ABSTRACT

Title of dissertation: TOPICS ON WAGE DIFFERENCES ACROSS LOCAL LABOR MARKETS

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It is well established that average wages differ across local labor markets. Researchers have found that this is partially explained by differences of worker ability, as reflected in observable dimensions of worker skill, such as education and labor market experience. However, the classical human capital explanation only partially explains differences in wages across metropolitan areas. In my dissertation, I consider two variations from this framework to explain why wage differentials across observably homogeneous workers persist.

First, I consider the role of unobserved dimensions of worker skill and the level of location amenities. I do this in the context of professional basketball, where worker skill and non-pecuniary employer characteristics are unusually well measured. I find strong evidence in support of the compensating differentials theory in this context. The analysis also demonstrates that when important measures of worker skill are omitted from the specification, the quality of the results is distorted and inference on the validity of the theory is misleading. The work also suggests that certain

specifications are sensitive to when we do not control for important portions of worker skills. The partially linear and the classic linear regression models outperform the Box-Cox alternatives in matching the hedonic estimates produced in the "full" specification case.

Second, I ask whether firms in a local market can exploit individual mobility costs and offer workers wages that are lower than the competitive rate. I describe a wage renegotiation model in which firms use information on worker mobility and on local labor market competition. The model predicts that workers with positive mobility costs receive lower wages, while the ability of firms to exploit these costs declines in the intensity of local competition.

To test this model, I construct measures of individual mobility costs and occupation-specific measures of local labor market competition. I find that individual mobility costs have a negative effect on wages and that this effect gets weaker the more competitive is the local labor market. Finally, the negative effect of mobility costs on wages is significantly lower for workers in highly unionized occupations, where individual wage renegotiation is less likely to occur.

TOPICS ON WAGE DIFFERENCES ACROSS LOCAL LABOR MARKETS

By

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Chapter 1: Introduction

There is an extensive literature that demonstrates important wage differences across workers exist, both within and across local labor markets. One of the principal explanations is that workers differ on levels of human capital. According to Schultz (1961), "Investment in human capital accounts for most of the impressive rise in the real earnings per worker." The author goes on to suggest that workers who invest more in human capital will earn higher wages compared to their counterparts and that human capital differences may be the most important explanation for the variation in wages across workers.

The discussion of the importance of human capital heterogeneity in explaining wage differences across workers was formalized based on the assumption that the labor market is perfectly competitive (Ben Porath, 1967; Becker, 1993). Each worker takes the price of human capital and its costs as given (e.g. education), and chooses the optimal level of investment to maximize her lifetime utility. Mincer (1974) extended the work of Ben Porath (1967) to produce a wage equation that suggests that wages are positively affected by the worker's level of education. At the same time, the Mincer wage equation suggests that after controlling for education, worker wages increase at a diminishing rate in the level of labor market experience that the worker accumulates after she completes her formal education. The earnings equation produced by Mincer is one of the most commonly used empirical tools in economics. Economists have used the Mincer earnings equation as a basis for research on a number of empirical issues. Notable examples are returns to formal education (see Card, 1999 for a review), wage differences across racial groups (Cain, 1988; O'Neil, 1990; Neal and Johnson, 1996), and wage differences across ethnic groups and between men and women (Oaxaca, 1973; Corcoran and Duncan, 1979; Reimers, 1983; Altonji and Blank, 1999).[1]

A second approach to explaining the significant wage differences across workers is based on the theory of compensating differentials. According to this theory, worker utility is affected not only by goods consumption, but also from the consumption of non-pecuniary employer characteristics, like location amenities, fringe benefits, and other employer attributes.[2] An extensive empirical literature – based on the models described by Rosen (1975) and Roback (1982) – uses variation in desirable location amenities, working conditions, and other important employer characteristics to explain wage differences across otherwise observably homogeneous workers. The wage equation in this context, also known as the hedonic wages equation, is a deviation from the classic wage equation since wages are affected by non-wage employer and local area characteristics in addition to the skills that workers bring to the market.

Researchers have produced some evidence that workers in jobs that feature unpleasant working conditions receive significant wage premiums (Lucas, 1977; Duncan and Stafford, 1980; Duncan and Holmlund, 1998; McNabb, 1989). In addition, some papers find that workers in jobs that involve higher risks of physical injury or death earn higher wages (Coates and Kumar, 1982; Duncan and Holmlund, 1998; Kim and Fishback, 1993). Moreover, workers in jobs with low employment or

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[1] See Willis (1999) for a thorough discussion on the evolution of the use of the wage equation to explain wage differences based on variation in human capital characteristics across workers.
[2] This theory is again formulated based on the assumption that labor markets are perfect. See Rosen (1988) for a review of the literature.

income security earn higher wages compared to workers in more secure employments (Viscusi, 1978; Olson, 1981; Coates and Kumar, 1982) and that workers living in locations with desirable amenities, also have higher wages (Roback, 1980; Blomquist et al, 1988).

On the other hand, many empirical studies question the strong connection between non-pecuniary job characteristics and wages. Hedonic coefficients are often found to be statistically insignificant, to have the opposite sign to the one predicted by theory, or both. In many cases, the results are sensitive to the wage equation specification.

Three potential explanations have been proposed to explain the inconsistencies in the empirical results. First, unobserved worker heterogeneity may bias the results against the theory's predictions (Brown, 1980; Duncan, 1976; Hwang et al, 1992; Lucas, 1977; Dorman and Hagstrom, 1988). This is true if non-wage job attributes are normal goods, thus these attributes are negatively correlated to unobserved ability. Second, measurement errors may affect the quality of the results and make inference on the validity of the theory very complicated (Atrostic, 1982; Brown; 1980). Reliable measures of working conditions are rarely available. In most data sources, working conditions are self-reported by the respondents or they are not available altogether. Third, results may be sensitive to the choice of the functional form of the wage equation, especially in the presence of the unobserved heterogeneity problem (Atrostic, 1982; Anglin and Gencay, 1996; Ekeland et al, 2001).

The second chapter presents a test of the validity of the compensating differentials theory by using a newly assembled dataset on players in the National

Basketball Association (NBA). While professional basketball is an insignificant fraction of employment, focusing on this industry has two principal advantages and lessons learned here may apply more generally to the labor market.

First, my data contains detailed measures of worker ability. Player statistics, personal characteristics, and other wage determinants are very well measured and are widely available. Specifically, I use three measures to capture player output: (a) *Minutes*, which is the total number of minutes the player plays per game, (2) *Offense*, which captures the offensive output of the player per game, and (3) *Defense*, which measures the defensive contribution of the player per game, which. These measures are commonly used by coaches and sportswriters to assess player skills. I also control for other worker characteristics that affect professional basketball players' wages: player experience, tenure, draft status, order in which the player was selected in the draft, whether the player attended college before entering the NBA, and height.

Second, employers are more homogeneous in professional basketball, compared to other employers examined in previous work. Employer heterogeneity is limited to location amenities and qualitative characteristics of the team and its coaching. To test the theory, I include measures of both of these factors. Location amenities are measured by local weather characteristics (rainfall, snowfall, and temperature conditions), population characteristics (population, crime rate, percentage of the local population in the player's racial category), and whether the team is located in Canada. Measures of team characteristics include whether the team has a coach with playoff experience, a coach that has won the NBA championship, the team winning percentage, and whether the team is the current NBA champion.

Using the classic wage equation and controlling for available measures of player quality I test whether location amenities and team characteristics affect wages. I find that undesirable location amenities (population, crime rate) have a significant positive effect on wages. Results suggest that undesirable weather characteristics (rainfall, snowfall, extreme temperature conditions) also have a significantly positive effect on wages, while players in locations with mild temperature conditions earn significantly lower wages. Furthermore, players who play for teams that are more successful or for teams that allow players to earn more from outside endorsement deals, have lower wages. These empirical results provide strong evidence that wages of professional basketball players are affected by non-pecuniary team and location characteristics, consistent with the theory of compensating differentials.

A straightforward test for whether unobserved heterogeneity distorts the hedonic estimates is to omit available player characteristics from the wage equation and observe how the estimates are affected. This test shows that omitting variables that capture important portions of worker heterogeneity may affect the quality of the estimates. Significant location amenities, like crime rate, rainfall, and snowfall lose statistical significance in certain specifications. At the same time, the effect of the team being located in Canada or the team having a coach with playoff experience are statistically insignificant or are underestimated in all “incomplete” specifications. The results demonstrate that in the presence of unobserved worker quality, the hedonic coefficients may be distorted to the point where the compensating differentials theory is falsely rejected.

Another important issue in the literature is whether the functional form of the wage equation may distort the hedonic estimates, especially when important portions of worker ability are not accounted for. I re-estimate the wage equation using six alternative models: the classic linear regression model, the partially linear regression model, the second order linear regression model, and three variations of the Box-Cox maximum likelihood estimation technique (single side transformation, restricted double-side transformation, and unrestricted double-side transformation). I compare across two different specifications, one in which all available player characteristics are included, and another in which important components of worker ability are not included on the right-hand side.

When all available player characteristics are included in the specification, hedonic coefficients do not differ across models. Estimated coefficients are extremely similar in size and statistical significance, suggesting that the choice of the regression model does not matter much in consistently estimating hedonic wages when important measures of worker quality are available. On the other hand, the choice of the statistical model is important when a substantial portion of player skill is omitted from the hedonic specification. Specifically, the partially linear regression model does extremely well in estimating hedonic wages that are similar to the ones obtained under the "full" specification case. Conversely, the Box-Cox maximum likelihood alternatives do very poorly in producing hedonic estimates that match in magnitude and statistical significance the estimates produced in the "full" specification cases. The classic linear regression model performs better than the Box-Cox models but not as well as the partially linear model.

This analysis illustrates that the compensating differentials theory is clearly substantiated in the context of professional basketball, where important measures of worker heterogeneity are available and firms are more homogeneous compared to employers examined in previous work. Furthermore, omitting significant measures of worker heterogeneity distorts the statistical inference on the validity of the theory, in some cases, to the point where the theory's predictions are falsely rejected. Finally, the choice of the functional form of the wage equation is only relevant when unobserved ability is an issue; the partially linear model outperforms the rival models in terms of consistently estimating hedonic wages.

These results enrich the discussion of how compensating differences may explain wage differences across observably similar workers in other contexts. It is possible that the theory is falsely rejected because of the problem of unobserved heterogeneity; credible conclusions on the validity of the theory can only be drawn when rich measures of worker quality are included in the hedonic wage equation. At the same time, allowing for a more flexible functional form of the wage equation may be a good idea, especially when unobserved heterogeneity is an issue.

The third chapter of my thesis asks whether firms exhibit oligopsonistic behavior in local labor markets and exploit worker mobility costs in setting wages. Many workers face important costs of moving across locations. In order to stay in their current location, workers may be willing to accept a wage offer that is lower than what they would if they had no moving costs or if they could costlessly find another job within the same labor market. My research considers whether the frictions faced by workers in moving across locations are used by employers to offer workers wages that are lower than their marginal product.

Previous theoretical work has shown that in the extreme case where only one employer is present in a given location, the monopsonistic firm may exploit workers mobility costs by offering them lower wages (Black & Loewenstein, 1991; Ransom, 1993). I develop a model that allows for different degrees of labor market competition, making it applicable to a wider range of occupation groups and not only to the college professors' case, which is considered in previous work.

In the model, each firm uses information on its own workers' mobility costs as well as on the local labor market competition when it renegotiates wages with each one of its workers. The firm observes a mobility cost signal for each of its workers, and knows the probability that the worker receives a wage offer from another firm within the same location. The model predicts that the firm offers lower wages to workers that signal high costs of moving across locations. The ability of firms to exploit moving costs to offer lower wages declines in the intensity of local labor market competition. A worker in a highly competitive local labor market has more opportunities to switch employers within her current location and therefore avoids moving across locations to raise wages. This makes the level of worker mobility costs irrelevant.

The model predicts that workers who are observably less mobile across locations will face lower wages compared to their counterparts, holding local competition equal. At the same time, holding worker mobility constant, workers in more competitive markets are less likely to suffer the wage exploitation. By construction, the model nests the extreme scenario of one employer in a given market (Black and Loewenstein, 1991), the case where we have a large number of employers within the same location, and all cases in between.

I test the model using a standard wage equation. Explanatory variables include measures of worker mobility costs, as well as measures of occupation-specific local labor market competition. Each metropolitan area is assumed a distinct labor market. A classic wage equation is estimated that includes the available measures of worker ability, a measure of worker mobility costs, a measure of local labor market competition, and the interaction of the two. According to theory, the measure of worker mobility costs should have a negative effect on wages, while the interaction should have a positive effect on wages.

Estimates are based on the 5% Public Use Micro Sample of the 2000 Decennial Census which contains a large number of observations on individuals and includes the individual's metropolitan area and occupation. This data also provides information on worker household characteristics that serve as measures of worker mobility costs. A worker that works in his state of birth is likely less mobile across metropolitan areas compared to a worker that works outside his state of birth. The same is probably true for workers that live in their spouse's state of birth. If the spouse of the worker works full time, the worker is less mobile across local markets since the spouse would have to quit her job or pay the search costs of finding a new one. Married workers whose spouse attends school, workers that have a disabled person in their household, and workers that have their parents or in-laws living in the same household are less mobile across metropolitan areas. Including these characteristics in a probit model, I show that they have a significant negative effect on the probability that a worker moves across metropolitan areas.

Three different measures of local labor market competition are used. The 2000 County Business Patterns provides information on both the total number of firms in each metropolitan area and the total number of firms in each metropolitan area, by industry. The third measure is constructed using unpublished 2000 Decennial Census data, which contains information on both the occupation and metropolitan area of the worker, but also the exact census in which each worker is working. Using this information, I produce a Herfindahl Index that captures the geographic concentration of occupation-specific employment opportunities in each metropolitan area.

Estimates of the wage equation using different measures of worker mobility costs and measures of local labor market competition in the specification demonstrate that both mobility costs and local labor market competition affect wages. I find that workers that face high mobility costs earn significantly lower wages compared to their counterparts. The negative effect of mobility costs on wages is higher for workers in smaller markets, where fewer employment opportunities exist. This evidence is not sensitive to the use of alternative measures of worker mobility costs or to different measures of local labor market competition.

Since the model assumes that each firm renegotiates wages separately with each of its workers, it is more likely that the model applies to occupations where wages are not subject to collective bargaining. Workers in occupations where a strong union presence exists are probably not affected by the predictions of this model. I test this hypothesis by including an interaction between worker mobility costs and the percentage of unionization in the occupation of the worker. This interaction effect is statistically significant and positive, that is, wage exploitation due to individual mobility costs is unlikely to occur for workers in highly unionized occupations.

Previous research has shown that important portions of wage differences across workers may be explained by differences in their human capital characteristics. According to the compensating differentials theory, wages are also affected by location amenities and other non-wage employer attributes. My research considers the statistical issues that are potential explanations of the ambiguous empirical evidence on the theory's validity. I conclude that in order to find consistent evidence of the theory compensating differences, worker ability must be well measured. The functional form of the wage equation does not seem to matter in consistently estimating hedonic wages when we control for an important portion of worker skill. However, in the absence of important measures of worker heterogeneity, the classic linear and the partially linear regression models outperform the Box-Cox maximum likelihood model in consistently estimating compensating differences.

My research also suggests that wage differences across homogeneous workers may differ across local markets, because of differences in the competitiveness across those markets. I describe a model which predicts that workers who are observably less mobile across locations receive lower wage offers compared to their counterparts and that the effect of worker immobility on wages declines in the competitiveness of the local markets. Empirical evidence show that worker mobility costs have a negative effect on wages, but that effect is lower for workers in highly competitive metropolitan areas, and lower for workers in highly unionized occupations where individual wage bargaining is less likely to occur.

Chapter 2: A New Test of Compensating Differences: Evidence on the Importance of Unobserved Heterogeneity

2.1 Introduction

Wage determination is one of the most widely discussed empirical issues in labor economics and many researchers have attempted to tackle it using various theories and accompanying statistical techniques. One of the most interesting and fruitful variations is the compensating differentials theory. According to this theory, workers value both goods consumption and the on-the-job consumption of job characteristics and amenities that are associated with the nature and location of their employment. The implied wage equation suggests that desirable job characteristics have a negative effect on wages, whereas undesirable amenities positively affect wages.

A basic test of the theory's validity is that the estimated monetary value of amenities bears the opposite sign of their utility value. The intuition is that workers are willing to forfeit part of their earnings to be in a working environment where a positive characteristic is present, while they should be compensated with higher wages for working conditions that reduce their utility.

Although the idea is very simple and intuitive, it has proven hard for researchers to establish strong connections between theory and microeconomic data. In many cases, the signs of the estimated parameters have not been compatible with the theory's predictions or do not have a significant effect on wages. Many are the possible explanations for these results. The most commonly discussed empirical flaw is selection due to unobserved worker ability. In the setting implied by the theory, if the unobserved part is correlated with the non-pecuniary job characteristics, hedonic wages estimates for these characteristics may be biased. Assuming that amenities are normal goods, then the direction of the bias would be the opposite of the sign of the hedonic wages for those amenities, producing signs that are not conformable with theory in cases where the bias is very large.

Furthermore, researchers do not have complete information on working conditions, which in most contexts are quite heterogeneous across industries and occupations. This may produce biased estimates of implicit wages if the omitted job characteristics are correlated with working conditions that are included in the hedonic wage equation. Moreover, even in cases where appropriate measures of working conditions may be available, their objectivity is questionable since in many cases they are self-reported by the worker.

Additionally, the functional form of the wage equation may also be an issue. Typically, the wage equation is estimated using the classic linear regression model. However, there are doubts on whether this model is appropriate to produce consistent estimates of compensating differences, especially since selection on unobservables is present. Researchers have suggested that in estimating the hedonic wages equation, a more flexible approach should be adopted. Omitted measures of worker skill and a potential non-linear relation between wages and amenities make it infeasible for the regression errors to be normally distributed. Using a more flexible approach may compensate for omitted measures of worker skill and for a potential non-linear relationship between wages and amenities, and provide more reliable and consistent hedonic estimates. Namely, the Box-Cox transformation technique is thought to perform better in terms of consistently estimating compensating differences, even if important components of worker heterogeneity are not available.

In this paper, I test the compensating differentials theory using information from a newly assembled dataset on professional basketball players. Professional sports data present a unique opportunity for economic research.[3] Professional sports data have rich measures of worker skill, which are standard in the industry, the errors in measurement of skill are limited, and employers are more homogeneous within this industry compared to in other contexts. Many of the problems that are widely considered to have an undesirable effect on the quality of the estimated hedonics are less of an issue in this context.

Using this data, I show that: (a) Workers implicitly receive positive compensating premiums for undesirable job characteristics and negative for desirable ones, as the theory suggests, (b) Omitting part of worker heterogeneity distorts the quality and the magnitude of the estimated differentials, (c) If worker heterogeneity is largely accounted for, the estimation results are not sensitive to the choice of the regression model, and (d) The Partially Linear and the Classic Linear regression models outperform the Box-Cox maximum likelihood alternatives when measures of worker ability are omitted from the specification.

2.2 Literature Review

Adam Smith was the first to articulate the notion that *"the monetary and non-monetary benefits of different employments must in general be equal."* His book, *"Wealth of Nations"* was the first documented discussion of the idea that workers

[3] See Kahn (2000) for a discussion

should receive positive compensation premiums for undesirable working conditions, making the sum of monetary and non-monetary benefits received equal between alternative job choices.

Formulation of this idea in a model comes down to a wage equation that satisfies the optimization conditions of both firms and workers. The implied wage equation includes measures of worker quality and all available job characteristics that may affect the worker's utility level.[4] By fully controlling for worker quality, one can produce consistent estimates of the implicit prices of such characteristics, which are their estimated coefficients in the wage equation.

Consistency with the theory implies that the estimated coefficients for desirable fringe benefits should be negative and those for undesirable job characteristics positive. One can explain this intuition using alternative approaches. For example, a negative coefficient means that workers are willing to forfeit part of their compensation in order to obtain fringe benefits that have a positive utility value. Put differently, the supply of labor for firms that have desirable amenities is high, pushing wages down.

There are many papers in the literature that attempt to connect the compensating differentials theory with microeconomic data.[5] Using the Survey of Economic Opportunity, Lucas (1977) finds that workers with jobs that are of a repetitive nature or feature other unpleasant working conditions pay more. Using the National Longitudinal Survey, Brown (1980) finds that wages are not significantly affected by unpleasant working conditions, such as working under stress or for

[4] Duncan (1976), was among the first to argue that the inclusion of non-pecuniary job characteristics in the wage equation is essential in order for researchers to explain wage differences.
[5] See Rosen (1998) for a review of the literature.

physical demanding jobs, while he estimates positive coefficients for other undesirable job characteristics, such as the probability of a fatal accident at the workplace. Duncan and Stafford (1980) test the theory by using the Time Use Survey, and conclude that jobs that require physical strength and feature inflexible working hours pay higher wages. Duncan and Holmlund (1998) estimate a positive wage premium for workers in Sweden that work under stress, when their jobs involve a risk of injury or death, and for workers that work in smoky or noisy environments. McNabb (1989) shows that workers in Britain receive positive wage premiums for poor working conditions, job insecurity, and inconvenient working hours.

Dorsey and Walzer (1983) use the Current Population Survey to estimate the hedonic prices for injury risk and fatality probabilities, getting results that are in general unsupportive of the theory. Similarly, Garen (1988) and Dorman and Hagstrom (1998) produce weak evidence of compensating premiums for jobs that feature high probabilities for on-the-work injury or fatality using the Panel Study of Income Dynamics. On the other hand, Kim and Fishback (1993) find that US rail workers are paid more when they face higher risks of getting injured at work, while by using the Quality of Employment Survey, Viscusi and Moore (1987) estimate positive hedonic wages for working environments that involve physical risk. Viscusi (1978) and Olson (1981) both conclude that workers that have low job and income security receive higher wages compared to workers in more secure employments. Coates and Kumar (1982) produce a similar result for workers in Canada that face income uncertainty. Finally, Roback (1980) finds that location amenities affect both wages and rents. Using the Current Population Survey, she finds that valuable local amenities carry a negative hedonic wage, while undesirable location characteristics a positive one.

Although there is evidence in favor of the compensating differentials theory, there are also rejections of this theory. Across many studies, hedonic estimates are often either statistically insignificant, have the opposite sign than is predicted by theory, or both. In addition to that, the magnitude and significance of estimated hedonic effects appears to be sensitive to model specification.

These observations have led economists to discuss statistical nuisances that may explain the inconsistencies in the empirical results. Brown (1980) indicates that the available demographic variables that are used as measures of worker ability do not capture a significant part of worker heterogeneity. Duncan (1976) presents evidence that non-pecuniary job characteristics are correlated with observable worker characteristics like education and experience. He argues that biased results may be produced in the case where important parts of worker heterogeneity are not available.

In related work, Hwang et al (1992) model the selection bias in this context and find that it maybe quite large under certain conditions,[6] while Dorman and Hargstom (1998) and Lucas (1977) informally discuss how unobserved worker heterogeneity may distort the hedonic estimates. Atrostic (1982) points out that the quantitative effect of variable omission, insufficient measures of labor market productivity and measurement errors is unknown, making inference on the validity of the hedonic wages theory very complicated.

[6] The authors show that the bias increases in the unobserved portion of worker ability is and in the conditional variance of wages given worker productivity.

Measurement errors in working characteristics could explain some of these inconsistencies. In available microeconomic data, respondents may give subjective responses about the quality of their workplace making the reliability of the empirical results questionable. In order to get around this issue, certain researchers have combined available microeconomic data with information on job characteristics coming from the Dictionary of Occupational Titles (Olson 1981) and the Bureau of Labor Statistics measures of work hazards by industry (Garen 1988). However, these measures are aggregated either by occupation or by industry and do not reflect the actual heterogeneity of working conditions across employers.

Furthermore, the sensitivity of the results to the linear specification of the wage equation that is often employed is not known to researchers, especially since the problem of unobserved heterogeneity is generally present. In fact, there is work that suggests that using the linear regression model may be inappropriate since the relationship between wages and job characteristics is more complex (Ekeland et al, 2001; Atrostic, 1982; Anglin and Gencay, 1996). The use of the Box-Cox transformation technique (Box and Cox, 1964) is often employed when estimating hedonic price equations (Blomquist et al, 1988; Atrostic, 1982, Atkinson and Halvorsen, 1990; Cheshire and Sheppard, 1995). Furthermore, Cropper et al (1988) show using simulations that the Box-Cox maximum likelihood model outperforms the linear regression model in the presence of selection on unobserved characteristics, when estimating hedonic rents. Intuitively, unobserved heterogeneity and non-linearities are reflected in the error term of the wage equation, putting in doubt the assumption that the errors are normally distributed. The Box-Cox maximum likelihood alternative chooses the optimal transformation for the dependent and independent variables, to maximize the probability that the normality assumption holds. If that is the case, consistent estimates of the hedonic parameters is feasible despite the data limitations.

In this paper, I estimate a hedonic wages equation in a setting where rich measures of worker ability are available. I also show how results are affected when important portions of worker heterogeneity is not accounted for in the specification, and whether the functional form is important both when good measures of worker ability are available and in the case where they are omitted from the specification.

2.3 A theory of compensating differences in professional basketball

To formulate the model, typical assumptions are employed. Workers are heterogeneous in terms of their marginal product but have homogeneous preferences for job characteristics. On the other hand, firms have the same technologies and costs for obtaining desirable non-pecuniary benefits. Let the preferences for basketball player *i* at location *k* be represented by:

$$u_{ik} = u(C_i, Z_k) \tag{1}$$

Note that C_i represents goods consumption and Z_k is the on-the-job consumption of location amenities and other working conditions at location *k*. The agent maximizes utility subject to a typical budget constraint, whereas the team minimizes costs subject to a function representing the production technology by choosing employment input and location. Furthermore, the firm's output is not affected by location characteristics but it is costly for firms to obtain desirable job characteristics.

The indirect utility and the minimum cost function for a player and a team located in city *k* are respectively represented by:

$$V_k = V(w_k, Z_k; a) \tag{2}$$

$$C_k = C(w_k, Z_k; b) \tag{3}$$

In equilibrium, wages optimally adjust to eliminate moving incentives for both players and teams, given player heterogeneity, preference and production parameters. So, in equilibrium we have:

$$w_k^* = w^*(Z_k; a, b) \quad \forall \;\; k=1,2,\ldots,K \tag{4}$$

$$\text{where: } \frac{dw}{dz} = -\frac{\frac{\partial V}{\partial Z}}{\frac{\partial V}{\partial w}} < 0 \tag{5}$$

Equation (4) is the price function for the on-the-job consumption of good *Z*. By using the indirect utility function, one can trivially produce (5), which suggests that in equilibrium, wages are decreasing in the level of the desirable amenity. The player implicitly pays a price for the on-the-job consumption level he enjoys by receiving lower wages. Similarly, if *Z* is an undesirable working condition, then the player receives higher wages as a premium for the utility loss he suffers from consuming *Z*.

From the team's perspective, the negative relation between wages and a desirable amenity suggests that a team gets "compensated" by the player for having a certain level of the desirable amenity. By the same token, the team pays a positive wage premium to the player for having a positive level of an undesirable working condition.

2.4 Data

I use data for players that compete in the National Basketball Association (NBA), the top professional basketball league in the US.[7] The NBA has franchise-like teams, which compete for the league championship on an annual basis. Each team employs a predefined number of basketball players and for which a contractual agreement has to be in place, according to league rules.

Player statistics that capture their on-court performance are widely available. The official statistics of the NBA are published both on the official website of the NBA and in annual league guides.[8] I compile the data for five seasons, between 1999 and 2003, and among other information, it includes the number of games each player played in each season, the number of points, rebounds, steals, blocked shots, assists, turnovers, and fouls the player produced. The data also reports each player's race, age, weight, height, position, place of birth, the year the player entered the league, and the order in which the player was selected at the annual league draft.

Salary information is obtained from different sources. The main source is the USA Today NBA salary database, which is based on research conducted by the newspaper.[9] Although salaries are not available in official league publications, the information is made available to the press by the league. Besides USA Today, I used

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[7] Some examples of economic papers that use professional basketball data are Hausman & Leonard (1997), Kahn & Sherer (1988), and Camerer (1989)

[8] The official website of the NBA is www.nba.com. Player statistics are reported in the website and are also available in print, in the Official NBA Register, which is issued yearly by Sporting News.

[9] Go to the official website of USA Today, for more information: www.usatoday.com.

published player salaries reports from newspapers like the Washington Post, the Dallas Morning News, and the Los Angeles Times, among others. I also use reports prepared by established basketball websites, like “BasketballReference.com” and “HoopsHype.com” to verify the salary information obtained from published newspaper reports.

Wages in the NBA are negotiated between the team and the player. When an agreement is reached, the two sides sign a contract that is final and binding for both sides. The rules under which the negotiation takes place are set by a Collective Bargaining Agreement (CBA). The CBA is an agreement between the league, the teams, and the National Basketball Players Association (NBPA) on the principles by which the employment of the athletes works, including compensation, insurance and working conditions.[10] Some of the conditions of the CBA have a significant effect on player compensation. In the next section, I discuss in more detail how the CBA may affect player wages and how I account for this variation in the specification of the wage equation.

Moreover, the CBA specifies the working conditions that govern the employment of the players, ensuring that certain standards of employment quality are maintained for players employed in any NBA franchise. This means that firm heterogeneity is limited in this context to the quality of the team’s coaching staff, the team’s administration, team success, and location related attributes. Measures that capture team success (team winning record, if the team qualified for the playoffs, and if the team are the current NBA champions), and the success of the coaching staff

[10] For more information on the collective bargaining agreement, see the official website of the NBPA, *www.nbpa.org*.

(playoff experience, coached team to the championship) are available. This information is obtained from the official reports of the NBA, as well as the Association of Professional Basketball Research.

To account for location amenities, additional data sources were used. Weather conditions, like temperature, snowfall, and precipitation are produced from the National Climatic Data Center and the Meteorological Service of Canada. Additionally, information on city population, crime rates, and other location characteristics are available from the US Census Bureau's "State and City Data Book 1997-98", the 2000 US Census, and from reports of the Canada Uniform Reporting Crime Survey and the 2001 Canadian Census.

2.5 Estimation Results

I estimate a classic hedonic wage equation that includes all available measures of player quality and team-specific characteristics that capture employer heterogeneity in terms of working conditions and location amenities. Formally, the wage equation is:

$$\log W_{it} = a + \sum_{k} P_{it}^{k} \beta^{k} + \sum_{m} Z_{it}^{m} \gamma^{m} + u_{it} \tag{6}$$

Note that $\log W_{it}$ denotes the logarithm of earnings for player i in year t. P includes variables that capture player output, other qualitative worker characteristics that have an effect on wages, while Z includes team-specific characteristics and location amenities.[11] I include three variables that capture player output - *Minutes*, *Offense*, and *Defense* - which represent the total number of minutes the player plays

[11] See Table 1 for variable description.

per game, his offensive output, and his defensive contribution. These statistics are commonly used by coaches and basketball analysts to evaluate player skill.[12] Other player characteristics are height, race, and nationality.

Controlling for player output, more experienced players are likely to earn more for two reasons: (1) Experienced players provide leadership and serve as locker room personalities for younger teams and for teams that make it to the playoffs, and (2) The CBA guarantees minimum compensations for veteran players, depending on the number of years they have been in the league.[13] Similarly, players that have been with the same team for a number of years earn more, not only because of all the intangible contributions they provide, but also since the CBA dictates that players that sign multi-year contracts with the team receive annual increases in their pay. The variable *Tenure* is thus included to capture this effect.

Another important aspect of player employment in the NBA is that prospective players enter the league by participating in an annual draft, were teams pick the rights to sign them.[14] Teams may also sign players that were either not draft-picked or players that do not have a contractual agreement with any other team; namely, players who are free agents. The order in which a player is selected in the draft directly affects the compensation he receives from the team that selected him. Players that are selected high in the draft receive higher compensations as per the

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[12] The standard measure of player performance is the TENDEX statistic, which was first used by the NBA. This statistic is a weighted sum of player statistics per game played (points, rebounds, steals, blocks). The statistic can be computed using different weights for each player statistic and can be broken down to two parts; one that measures offensive and the other measures defensive output. For the purposes of this paper, I break down the statistic into two parts and use equal weights for all characteristics. Note that the empirical results are not sensitive to the use of different weights to calculate the offensive and defensive output.

[13] For example, a 10-year veteran cannot earn less than one million dollars per year, as per the CBA.

[14] For more details on how the order of the draft is determined and how the draft is conducted, see the official website of the National Basketball Association (www.nba.com/draft)

CBA, while players that are not selected in the draft and are signed as free agents have an initial contract that is not protected by the CBA. In other words, whether the player entered the league through the draft, and if so, the order in which he was selected in the draft, are both very important wage determinants.

Finally, controlling for player output and other characteristics, players that enter the league directly from high school – that is, players that did not play college basketball in between – are likely to earn more. The reason is that such individuals are generally considered high quality basketball players and because of their young age, are thought to have more potential and more years to contribute positively to their teams. The intense demand for such young players that have the skills to play basketball at the high level of the NBA is likely to produce a premium in their final contracts.

There are two groups of non-wage employment characteristics. One group includes location amenities and the second, team characteristics that capture the probability that the player is in a successful environment that provides him with the potential to compete for the NBA championship and receive endorsement deals.

The list of location amenities I include in the wage equation are not very different from what other researchers have used. I assume that players dislike living in a metropolitan area with high crime rates or that it is heavily populated. At the same time, since more than 92 percent of players in the sample were born in the US, playing for a Canadian franchise may not be a very desirable situation and players may command a wage premium for that.

I also assume that players prefer locations that feature nice weather conditions, like low precipitation and mild temperatures. Therefore, I account for average snowfall, rainfall, and temperature, and for bad temperature conditions. Snowfall and rainfall averages will have a positive effect on wages if these characteristics affect player utility, while high average temperature – which captures mild weather a negative one. Additionally, adverse temperature conditions, namely high average temperature during the summer and very low average temperature during the winter, are not desirable, therefore, the estimated hedonic parameters for *Cold* and *Hot* are expected to be positive.

A second group of job characteristics is concerned with team success and player popularity, which possibly contribute to the player getting endorsement deals or higher future wages. First, I assume that a player is likely to be more popular if he plays for an NBA franchise that is located in a metropolitan area that it is either within the state of birth of the player or the state in which the player played college basketball. If so, the player's popularity would probably be higher in that situation, offering him the opportunity of getting more endorsement deals with local advertisers. It may also be the case that a white (or black) player has more advertising appeal in a city with a significant part of its population being white (or black).

In order to capture these effects, I include two variables in the specification, *Same Place* and *Same Race*. The first is a dummy that equals one if the player is employed in his state of birth or in the state that he played college basketball, whereas the latter is the percentage of the population in the team's metropolitan area that has the same race as the player. If these assumptions are correct, a player is willing to forfeit part of his earnings to play for an NBA team within his state of birth or the state he played college basketball in, or in a city that features a high proportion of the population that shares the same race as him. If this is in fact the case, then the estimated coefficients for these characteristics should be negative and significant.

Additionally, a player is assumed to value playing for a team that offers him a better chance to be successful and win an NBA championship. Being in a winning situation not only has non-pecuniary value to the player, but also increases his potential future earnings or endorsement deals. So, I construct four dummy variables that capture a team's potential for success: *Coach Playoff*, *Coach Ring*, *Winning Record*, and *Champs*. *Coach Playoff* equals 1 if the coach has previous playoff coaching experience, while *Coach Ring* equals 1 if the coach has led a team to an NBA championship in the past. At the same time, *Winning Record* equals 1 if the team had a winning record in the previous regular season, and *Champs* equals 1 if the team won the championship the year before.

Estimation results of equation (6), using the linear regression model, are summarized in Table 2. Note that the R-squared in all specifications is around .68. Considering that the typical R-square is around 0.3 when we estimate a Mincerian wage equation, this result supports the idea that the measures that I use in the wage equation capture skill differences across workers better than in other contexts. Player characteristics have the expected effect on wages. First, *Minutes*, *Offense* and *Defense*, which capture the player's statistical contribution, have a strong positive effect on wages across all specifications. Specifically, the estimated coefficients are around .008 for *Minutes*, .014 for *Offense*, and .011 for *Defense*, and are all statistically significant at the 1 percent level. These results suggest that a player that logs 5 percent more *Minutes* compared to the sample mean (24.77) earns 1 percent more on average. Similarly, a player earns 1 percent more on average if he has an offensive output that exceeds the sample mean by 10 percent, or a defensive output that exceeds the sample mean by 20 percent.

Second, experienced players or players that have been with the team for more than three years earn a significant wage premium, not only because of their intangible contributions to the team but also because of the favorable provisions of the CBA. The coefficients of *Experience* and *Experience Square* are around .078 and -.004 respectively, denoting the familiar wage-experience profile that is also found in other contexts. The estimated effect of *Tenure* on wages is around .085, suggesting that players that have been with the same team for more than 3 years earn around 8.5 percentage points more than their peers do.

Third, the estimated coefficient for *Drafted* is around .26 and is statistically significant at the 1 percent level in all specifications. This result suggests that players who enter the league through the draft earn higher wages, around 26 percentage points more than those who enter the league as free agents. Also, players that are picked higher in the draft clearly earn higher wages. The estimated coefficient for *Draft Number* is negative (around -.0067) and significant; the sample mean for *Draft Number* is 16. Intuitively, this result suggests that a player that is picked first in the draft earns 10.5 percentage points more than the average player does, whereas a player that is picked last in the draft (*Draft Number*=50), earns 20 percentage points less. Furthermore, the estimated coefficient for *High School* is around 0.09; players that enter the league directly from high school earn around .09 percentage points more. Due to the nature of the game, taller players receive higher compensations, even after controlling for individual statistics. Specifically, the estimated coefficient of *Height* is around .0059, implying that a player that is 2.10 meters tall earns 5.36 percentage points more, and a player that is 1.90 meters tall earns 6.18 percentage points less, than the average player (2.01 meters) does. Finally, the race or the nationality of a player, are unimportant predictors of wages.

The estimated effects of location amenities and other team characteristics are reported in columns (2)-(7) of Table 2. Most location characteristics perform very well. Players that work in cities that are highly populated or have high crime rates earn significantly more compared to their counterparts. The estimated elasticity of wages with respect to the city's population is .22, which means that if a player moves to a city that has 5 percent higher population compared to his current city, his wages will increase by 1.1 percentage points. For example, Houston and San Antonio feature similar location amenities, but Houston has 71 percent higher population. Controlling for player ability and other team characteristics, players employed by the Houston Rockets will earn on average 15.8 percentage points more than players who are employed by the San Antonio Spurs.[15] The hedonic price for *Crime* is around .05 and is statistically significant. This estimate suggests that if a player works in a city that has 1 percent higher crime rate than the sample mean (3.8%), he receives a wage premium of 3.9 percent. Both hedonic estimates do not vary significantly across specifications.

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[15] The hedonic wage for population can be interpreted either as the compensating differential for working in a heavily populated city or a premium to compensate players for working in large cities where the cost of living is higher.

It is the case that, players who play for a team based in Canada earn a significant wage premium, which is estimated to be around 20 percent. At the same time, both *Same Race* and *Same Place* have an estimated negative effect on wages, which is what one would expect. The coefficient for *Same Race* is statistically negative (-0.75) and significant, implying that a player who works in a city that has a *Same Race* percentage that is 10 percent higher than the sample mean (which is 37 percent) earns 3 percentage points less than what the average player makes. The estimated coefficient for *Same Place* is -.035; a player who works for a team within his state of birth or within the state in which he competed as a college basketball player, earns 3.5 percentage points less compared to the sample mean. However, this coefficient lacks statistical significance.

It is also the case that weather conditions have a significant effect on wages, providing further support of the theory's validity in this context. Undesirable weather conditions, like *Snowfall* and *Rainfall* produce highly significant positive coefficients. The hedonic wage for *Snowfall* is around .075 and is significant at the 5 percent level, and the respective price for *Rainfall* is around .076 and is significant at the 1 percent level. Variables that capture temperature conditions also have the expected effect on wages. Players that are employed in cities that feature mild weather, that is higher average temperature, earn less compared to their counterparts. Specifically, the hedonic coefficient for *Temperature* is around -.010 and it is significant at the 5 percent level. It seems that workers receive positive wage premiums for working in cities with very low average temperatures in the winter or very high average temperatures in the summer. The estimated coefficients for *Cold* and *Hot* are around .21 and .25 respectively and are highly significant.

Overall, weather conditions have the expected effect on wages, confirming the theory's prediction that workers earn higher wages as compensation for the existence of undesirable location amenities. To evaluate the importance of weather conditions in explaining player wage differentials across NBA cities, I perform the following exercise: using the estimated coefficients in the rightmost column of Table 2 and the actual values of the weather conditions for each of the cities in the sample, I calculate a hedonic index for weather amenities.[16] Using this index and the mean predicted wages for the whole sample and for each city separately, I can calculate the percentage deviation of mean predicted wages for each city from the sample predicted wages, due to differences in weather amenities.[17] If the percentage deviation due to weather amenities is negative for a specific city, it means that the city's weather conditions are on average more desirable to players, so they are willing to accept wages that are lower than the sample mean in order to work there. On the other hand,

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[16] The weather hedonic index for city *j* is constructed as follows: WHI_j = .0759*Snowfall $_j$ + .0755*Rainfall $_j$ - .0101*Temperature $_j$ + .2111*Cold $_j$ + .2480*Hot $_j$. Note that the hedonic wage estimates are those reported in Table 2, column 7.

[17] The sample predicted wage, evaluated at the sample means is:
$\hat{w} = \exp\left(\hat{a} + \sum_k \overline{P}^k \hat{\beta}^k + \sum_v \overline{A}^v \hat{\gamma}^v + \overline{WHI}\right)$, where $\overline{P}^k$ is the sample mean of player characteristic k, $\hat{\beta}^k$ the respective estimated coefficient, $\overline{A}^v$ is the sample mean of team characteristic *v* (it excludes weather characteristics), $\hat{\gamma}^v$ is the respective hedonic wage, and $\overline{WHI}$ is the weather hedonic index evaluated at the sample means. The mean predicted wage for city *j* (evaluated at the local weather amenities levels) is: $\tilde{w}_j = \exp\left(\hat{a} + \sum_k \overline{P}^k \hat{\beta}^k + \sum_v \overline{A}^v \hat{\gamma}^v + WHI_j\right)$. As a result the percentage deviation of the mean predicted wage for city *j* from the sample predicted wage, due to differences in the levels of weather amenities, is: $(\tilde{w}_j - \hat{w})*100/\hat{w}$. Note that the estimated coefficients are those reported in Table 2, column 7.

if the deviation is positive for a specific city, it means that players are compensated above the sample mean for the presence of relatively undesirable weather conditions in that location.

Table 3 summarizes the output of this exercise. The most desirable locations with respect to weather conditions are Californian cities; it is estimated that players are willing to earn on average 14.5 percentage points less than the sample mean to work in Los Angeles, 12.8 percentage points less to work in Oakland, and 11 percentage points less to work in Sacramento. This is an expected result since these locations feature mild weather, low precipitation averages, and no extreme temperature conditions. Similarly, due to desirable weather characteristics, players accept wages that are 9.6 and 9.3 percentage points lower than the sample mean to work in Phoenix and Charlotte respectively, 7.4 and 7.2 percentage points to work in Atlanta and Memphis respectively, and 2.6 percentage points to work in Indiana. Wage "penalties" due to desirable local weather conditions, are very small for players in Portland (1.1 percentage points), San Antonio (0.6), and Miami (0.2 percent).

On the other hand, players dislike locations with high precipitation averages and bad temperature conditions. It is not then surprising that due to relatively undesirable weather conditions, players receive a premium of 20.7 percentage points above the sample mean to work in Minneapolis, 16.5 to work in Utah, and 15.3 and 14.8 to work in Boston and Chicago respectively. That means that if, for example, the average player moves from a Los Angeles franchise (the Lakers or the Clippers) to the Minneapolis franchise (Minnesota Timberwolves) his wages would increase from

14.5 percentage points below to 20.1 points above the sample average, due to the significant differences in weather amenities across the two locations.

Moreover, because of undesirable weather conditions, players in Cleveland earn 12.2 percentage points more than the sample average, players in Milwaukee and Denver earn more than 11 percentage points above the sample mean, and players in Toronto earn close to 11 points more. These wage premiums are lower but still significant in size for the New York City area and Philadelphia. Specifically, players earn around 7.7 percentage points more than the sample mean to work in New York City and New Jersey, and 6.9 to work in Philadelphia. Wage premiums due to weather amenities are smaller for Houston (4.5 percentage points), Orlando (3.1), Washington DC (2.6), Dallas (2.2), and Seattle (1.0).

Finally, the results in Table 2 suggest that most indicator functions that capture team success do not have an important effect on wages. The only relevant dummy is *Coach Playoff* which has an estimated hedonic of .026 and is statistically significant at the 5 percent level. This suggests that players are willing to earn 2.6 percentage points less to play for a team that is coached by a coach with previous playoff experience. *Coach Ring*, *Winning Record*, and *Champs* do not have a significant estimated parameter and they do not seem to be relevant in explaining variation in wages across basketball players.

Overall, the results in Table 2 lead to two conclusions. First, the compensating differences theory receives support in the context of professional basketball players. Undesirable working conditions have a significant positive effect on worker wages, while desirable non-pecuniary attributes have a negative effect. Second, comparing the estimates across different specifications it is clear that the magnitude of the estimated parameters does not vary significantly, regardless of the list of amenities that are included in those specifications. The latter suggests that when an important portion of worker productivity is controlled for, unobserved employer heterogeneity in terms of working conditions or location amenities, does not significantly affect the hedonic estimates for the characteristics that are included in the wage equation.

2.6 The Effect of Unobserved Worker Heterogeneity

In the context of this paper, unobserved worker heterogeneity is less of an issue compared to other microeconomic data, so we are more confident in the consistency of the estimated hedonic wages. A straightforward way to test whether unobserved worker heterogeneity may lead researchers to false rejection of the compensating differentials theory is to omit components of worker quality in the current context and observe how it affects the results.

Table 4 summarizes the estimation results when *Minutes*, *Offense*, *Defense,* and other important components of player heterogeneity are omitted. Comparing these results with the "full" specification case, which is presented in column (7) of Table 2, there are certain location characteristics that perform equally well. Both *Log Pop* and *Crime Rate* have a significant positive effect on wages, which in most specifications are not very different compared to the estimates in Table 2. Additionally, the three variables that capture temperature conditions remain statistical significant and their signs are according to the theory's predictions.

On the other hand, *Same Race* does not bear a significant coefficient in specifications (1) through (4) in Table 4 and is only statistically important in specification (5). Similarly, the hedonic price of *Canada* is only significant in specifications (3) and (5), and equals .07 and .10 respectively. Even in these cases, the estimated coefficient is significantly smaller than the one in the "full" specification case, which is around .19.

In the absence of important components of worker quality, the estimated parameters of *Snowfall* and *Rainfall* are not statistically significant in none of the specifications in Table 4. Notably, the estimated coefficients in specification (4) are close to zero, while in (5) they are negative and insignificant. Finally, *Coach Playoff* does not bear a significant parameter in specifications (1) through (4), although it is estimated to have a significant negative effect on wages in specification (5).

Overall, the estimation results are sensitive to some extent to the omission of important measures of worker heterogeneity from the specification. The only employer characteristics that remain relevant across all specifications are the population of the metropolitan area, crime, and temperature conditions. *Canada* is important only in two specifications, while *Same Race* and *Coach Playoff* have a significant effect on wages only in one. Moreover, weather conditions like *Snowfall* and *Rainfall* lose their statistical significance and in one specification, they bear a negative estimated coefficient.

Based on specification (1), where only basic player information is included, there is some support for compensating differences. However, many location amenities and team characteristics are insignificant. This lack of consistent results would lead to some skepticism that basketball players value non-pecuniary team attributes. To a lesser degree, the same can be argued for specifications (2) and (4).

On the other hand, the theory gets more support in specification (3), and even more so, in (5). Even in those cases, the effect of characteristics, e.g. *Canada*, is underestimated compared to the full specification case, while precipitation variables remain insignificant.

In this context, it is clear that omitting important components of worker productivity may distort the estimates to a point where the researcher cannot infer with certainty that non-wage employer characteristics produce important wage variation. On the other hand, as it is apparent from specifications (3) and (5), even in the presence of substantial unobserved heterogeneity, evidence in favor of the compensating differentials theory may still be quite strong.

A similar exercise was conducted by Brown (1980). He shows that by adding variables that capture unobserved worker quality in the specification does not improve support for the compensating differences theory. Notably, that paper does not account for heterogeneity in location amenities. Therefore, we can better observe how the estimation results are affected by unobserved heterogeneity in this context, since in the "full" specification case, we infer with statistical certainty that location and other employer characteristics have a significant effect on player wages.

2.7 Alternative Functional Forms of the Wage Equation

Another issue is whether the underlying estimation method or the functional form affects the quality of the estimated coefficients, especially if there are unobserved components of worker heterogeneity. As discussed, there are papers in the literature that make the point that when there is selection on unobserved components of worker productivity, choosing the linear regression model may produce significantly biased hedonic estimates.

At the same time, even when worker heterogeneity is accounted for, there are doubts as to whether the relationship between wages and job characteristics is a linear one. Ekeland et al (2001) note that even though unobserved worker ability may still be an important issue, restricting the relationship between amenities and wages to be a linear one may be the reason for the inconsistent evidence in the literature. Allowing for flexible functional forms, either by adding non-linear terms in the right hand side of the wage equation or by utilizing the Box-Cox transformation technique, may produce empirical evidence that is more reliable in terms of inferring the validity of the theory. This, in fact, has been the strategy of researchers that have estimated hedonic price equations in the past (Atrostic, 1982; Blomquist et al, 1988).

I use my data to test the sensitivity of the hedonic estimates across different functional forms, both in the “full” specification case and when important measures of worker ability are omitted. I estimate the wage equation using six alternative models: (1) Classic Linear regression model, (2) Linear 2nd order model, which includes the squares of available worker characteristics in the specification, (3) Partially Linear regression model, (4) Box Cox maximum likelihood model, transforming only the dependent variable, (5) Box Cox with double-side transformation with the same parameter, and, (6) Box Cox with double-side transformation with separate parameters.

Table 5 presents the estimation results for these models when all measures of player quality are included in the specification. In columns (1)-(3), I report the hedonic estimates for the linear regression models. As the results suggest, the estimated coefficients across the linear regressions are similar in size and statistical significance. Undesirable location characteristics have a positive effect on wages, whereas desirable team and location amenities are negatively related to player earnings, as predicted by theory.

Additionally, columns (4)-(6) report the maximum likelihood estimates when variables are transformed using the Box-Cox transformation technique (Box and Cox, 1964). This transformation is shown to improve the plausibility of the assumption that the errors are normally distributed, especially in the case where there is selection on unobserved characteristics.[18] In its most general form, the model is as follows:

$$\frac{y^{\lambda}-1}{\lambda}=a+\sum_{\kappa}\alpha_k\frac{x_k^{\theta}-1}{\theta}+\sum_{m}d_k D_m(1)+u \qquad (6)$$

Note that y is the dependent variable, x includes the independent variables that are subject to transformation, and D denotes dummy variables that cannot be transformed. Also, λ is the transformation parameter for the dependent variable and θ for the right hand-side variables.[19] In order to make the results comparable across specifications, the maximum likelihood estimated parameters are transformed to capture the effect of each characteristic on the logarithm of earnings. If $\tilde{a}$ is the estimated parameter, and $\hat{a}$ the linearized coefficient, then the transformation is

[18] Box-Cox transformations are useful to improve the properties of the sample in cases where the disturbances of the simple linear regression model are problematic. The attractiveness of this transformation is that it allows the linear and log-linear models as special cases, depending on the estimated value of the transformation parameter. The estimated coefficients represent the marginal effects of the corresponding independent variables on the transformed dependent variable. To obtain the marginal effect on the untransformed dependent variable, one has to appropriately transform the estimated coefficient. See Linneman (1980) and Green (2000), p. 444-453 for more details.
[19] In this context, *Log Pop*, *Crime Rate*, *Same Race*, *Rainfall*, and *Temperature* are the only location and team characteristics that are subject to transformation.

$\hat{a} = \tilde{a}\bar{y}^{1-\lambda}$ if only the dependent variable is transformed (θ=1), $\hat{a} = \tilde{a}\left(\frac{\bar{x}}{\bar{y}}\right)^{\lambda-1}$ if we restrict both sides to be transformed by the same parameter (λ=θ), and $\hat{a} = \tilde{a}\frac{\bar{x}^{\theta-1}}{\bar{y}^{\lambda-1}}$ if we allow the two sides to be transformed by a separate parameter. The linearized parameter estimates of all three alternatives are summarized in columns (4)-(6) of Table 5.

First, the MLE estimated hedonics are similar in size and statistical significance across the three alternatives. Second, the compensating difference for *Same Place* is estimated to be around -.035 and it is statistically significant at the 10 percent level in the Box-Cox MLE models. Third, comparing the estimated hedonics of the simple linear regression in column (1) and those of the most flexible form of the Box-Cox transformation in column (6) - which marginally outperforms the other two models in terms of the value of the log-likelihood function - we see that in most cases the estimated coefficients are not statistically different between them.

Overall, based on the results in Table 5, we conclude that in the presence of a rich list of measures of worker ability, the functional form of the wage equation does not significantly affect the size and significance of the estimated coefficients. Although other researchers may have suggested that this might be true, to my knowledge, this is the first demonstration that the functional form does not matter when a significant portion of worker heterogeneity is accounted for, and where strong evidence exists in support of the theory.

As discussed, there is research work that shows the merits of using the Box-Cox transformation technique as a way of "solving" the selection on unobserved components of worker ability, when estimating hedonic wage equations. It is feasible in this context to check how different functional forms of the wage equation perform in terms of consistently estimating compensating differences in the absence of measures of worker heterogeneity. Specifically, I specify the wage equation similarly to the specification in Table 4, column 4, that is, I omit *Minutes*, *Offense*, *Defense*, *Drafted*, and *Draft Number*. Then, I estimate the wage equation using the First Order Linear, Partially Linear, and the three Box-Cox MLE models. The idea is to evaluate which models produce similar estimates for the hedonic wages, compared to the "full" specification cases in Table 5. Regression results are summarized in Table 6.

It is obvious that the Partially Linear model outperforms the classic linear regression model in this setting. Using the Partially Linear model, we obtain significant hedonic estimates for *Log Pop*, *Crime Rate*, *Canada*, *Same Race*, *Temperature*, *Cold*, *Hot*, and *Coach Playoff*, while the classic linear model does not produce statistically significant parameters for *Canada*, *Same Race,* and *Coach Playoff*. Also, the estimates produced by the Partially Linear model are closer to the ones obtained in the full specification case. This model, however, underestimates the hedonic premium of *Canada* and overestimates the effect of *Same Race*. On the other hand, the classic linear model overestimates the effect of *Crime Rate* and *Temperature*, compared to the complete specification case.

Furthermore, we conclude that all three Box-Cox MLE models perform quite poorly in the presence of unobserved heterogeneity. These models only produce statistically significant coefficients for crime and extreme temperature conditions, and based solely on the results they produce in this case, one would be hard pressed to argue that the compensating differentials theory has any support in the data in hand. In other words, in the absence of important measures of worker ability, the Box-Cox transformation does little in improving the estimates, at least in this context, and the linear regression models outperform the MLE models with regards to matching the hedonic wages estimated in the complete specification cases.

2.8 Conclusions

Evidence on the validity of the compensating differentials theory has been inconclusive, many argue because of the unobserved differences in worker ability. Additionally, there are concerns about the credibility of the relevant empirical results because of the poor observation and measurement of working conditions, and the distortion of the results that may be caused by the chosen functional form of the wage equation.

I utilize a dataset on professional basketball players, where richer measures of worker heterogeneity are available, there are limited measurement errors, and many important working conditions are observable. Using this information, I obtain significant evidence that the hedonic wages theory is strongly connected to the data in this context. I also conclude that different functional forms of the wage equation do not produce significantly different results, since the hedonic estimates are comparable in size and statistical significance across estimation models.

I also find that omitting worker characteristics that are important measures of player heterogeneity may distort the quality of the estimates. Certain parameters that have a significant effect on wages in the full specification lose significance or their magnitudes are smaller when I omit measures of worker ability. Moreover, the

Partially Linear regression model is more effective in estimating hedonics in the presence of unobserved worker heterogeneity, both compared to the classic linear regression model and the Box-Cox MLE alternatives.

The findings in this paper do not imply that the hedonic wages theory would be validated in other contexts had better measures of worker heterogeneity been available. It rather suggests that, when important components of worker heterogeneity are absent, empirical results are distorted, and may provide wrong inference on the validity of the compensating differentials theory. When the problem of unobserved worker quality exists it is difficult both to derive credible conclusions on whether the theory is connected to the data or not, and on the actual magnitude of the effect of job characteristics on wages.

Chapter 3: Labor Market Oligopsonistic Competition: The Effect of Worker Immobility on Wages

3.1 Introduction

Workers face important monetary and psychic costs of moving across locations. If migration across locations is costly, worker moving decisions become more complex since observed wage disparities across local markets may not suffice to cover the costs of migration. A worker finds it optimal to move from one location to another if the associated benefits exceed the costs that are relevant with such a move. Therefore, the presence of mobility costs is a possible explanation for the fact that workers optimally choose to stay in low-wage local markets, instead of migrating to alternative markets that have higher wages.

Although researchers in many disciplines - economics, sociology, psychology - concur that worker migration decisions are multidimensional and that wage differentials are not the sole consideration in such decisions, rarely have they asked whether worker mobility costs influence the wage setting behavior of employers. Because of the costs of migration, workers develop a positive taste towards staying in their current location, barring wage differences across markets. The question becomes if it is possible for employers in a local market to take advantage of workers that face positive mobility costs, and thus a taste for not moving, and offer them wages that are lower than the competitive rate.

With no costs of moving across markets, employers face an infinitely elastic labor supply and take the market wage rate as given. But even if workers have non-negative costs of moving across locations, under perfect competition, employers have no power in exploiting such costs in their wage setting behavior - even when such costs are public knowledge – when there is sufficient labor market competition within a local market. As a result, firms in all local markets offer the same perfectly competitive wage. Under this framework, migration is justified easily. Workers - especially those that face low costs of moving - choose to optimally migrate to an alternative location if there is an associated positive utility gain, either because wages in the destination are higher due to higher productivity or because of non-pecuniary utility gains, such as better location amenities.

This prediction is based on a rather strict assumption; each local market - be it a region, a state, or a metropolitan area - is large enough to prevent employers from exploiting the upward sloping labor supply they face from workers with positive mobility costs. In other words, labor market competition is extremely intense in all local markets and does not allow firms to exploit worker mobility costs in their wage setting behavior. This assumption is rather unrealistic since competition probably varies significantly both across local labor markets and across occupations within the same market.

If local competition is weak, then presumably employers in that market may be in a position to exploit worker costs of moving to another location. Consider the extreme case where we have a location with only one employer, that is, a local monopsony. A worker in such a market has two choices; accept the wage offer she receives from the monopsonistic firm or reject the offer and move to another location. Since the latter implies that the worker pays the associated cost of moving, the monopsonistic firm is in a position to exploit those costs and offer the worker a wage that is lower than her marginal revenue product of labor.

This extreme scenario is discussed by Black and Loewenstein (1991). The authors present a simple bargaining model, which predicts that workers that signal high costs of moving across locations receive lower wage offers compared to their counterparts. Their prediction contradicts the perfect market outcome and provides intuition for how wage discrimination based on worker mobility costs may occur. Of course, to derive this result they assume that a local monopsonistic firm exists, which is rare in the real economy. Their model is perhaps appropriate to describe the market for college professors, which is the scope of their paper, where employers are geographically isolated. However, that model is of little use in discussing the labor market conditions faced by workers in other occupations.

This paper contributes to the discussion of how worker mobility costs may affect employer wage setting behavior in two important ways. First, I describe a two period model where employers use information on worker mobility costs and on the intensity of the local labor market competition when they renegotiate wages with their own workers. The model predicts that workers that signal high mobility costs receive lower wage offers compared to their counterparts. At the same time, the model illustrates a clear interaction between worker mobility costs and local market competition. Specifically, the wage setting power that firms in a local market enjoy because of worker mobility costs is limited by the intensity of the local market competition. The more competitive a local labor market is, the less likely it is for wage discrimination to occur since workers enjoy more opportunities to switch employers within the location and avoid exploitation.

As a result, the model nests extreme local market conditions, such as the Black and Loewenstein paradigm and the “perfect market” scenario. In the first case, oligopsonistic exploitation is at its maximum, which is to say the monopsonist fully exploits worker mobility costs, whereas in the latter, exploitation is eliminated since workers can always switch employers within their current location. Furthermore, the model applies to all occupations, and not just college professors, which was the occupation group that was mostly discussed in this context in previous work (Black and Loewenstein, 1991; Ransom, 1993).

The second important contribution is that I produce empirical tests of the validity of this model. Firstly, I construct different measures of worker mobility costs, using a set of worker characteristics that capture worker immobility. To test the model I also need a measure at the metropolitan area level, by occupation, which captures the number of alternative employment opportunities a worker in a given occupation has within her current metropolitan area. As I discuss later, what consists a good measure of “alternative employment opportunities” differs significantly across occupations. There are occupations in which employment opportunities increase in the employer size of the metropolitan area (e.g. janitors, transportation workers, cleaning and maintenance workers, and repairers). However, there are occupation groups for which the employer size of the metropolitan area in the industry of the worker is a more appropriate measure of employment opportunities (e.g. college professors, physicians). Ideally, I would like to have information on how many firms in each metropolitan area employ workers in each occupation group, and how many workers in each occupation each firm employs. This would allow me to construct a measure of local competition at the occupational level, which would capture the competitiveness of each local market for a given occupation group.[20] Unfortunately, such information is not available. Instead, I use three different measures of competition; the total number of firms in the metropolitan area of the worker, the total number of firms in the metropolitan area and industry of the worker, and a Herfindahl Index that captures the geographic concentration of employment opportunities for each occupation at the metropolitan area level.

Using these measures, I produce a number of empirical exercises that provide formal tests on the validity of the model's predictions. Empirical evidence suggests that measures of worker mobility costs have a strong negative effect on wages, but that effect is significantly lower for workers in large, more competitive metropolitan areas. I also find that these results are robust to alternative specifications, using different measures of worker mobility costs or different measures of local labor market competition. Finally, I find that the negative effect of worker mobility costs on wages is significantly lower for workers in highly unionized occupations, where individual wage renegotiation is less likely to occur.

[20] From this point on, a "location" refers to a "metropolitan area" and "local labor market competition" refers to "labor market competition at the metropolitan area level."

3.2 Literature Review

In a perfectly competitive world, wage disparities across individuals are explained by differences in their human capital characteristics and innate ability (Schultz, 1961; Mincer, 1974; Becker, 1993), or by differences in employer technology. Additionally, such disparities may also occur in a hedonic environment, where employers differ across characteristics that are desirable to the workers, through compensating differences (Rosen, 1986; Roback, 1982). Empirically, researchers have used variation in worker productive characteristics to explain wage differences across individuals, most notably those across different racial groups (O'Neil, 1990; Neal and Johnson, 1996), ethnic groups and between men and women (Oaxaca, 1973; Corcoran and Duncan, 1979; Reimers, 1983).[21]

Others have tested how differences across employer characteristics may explain wage differences across individuals, in the form of compensating differentials.[22] Their results suggest that wages may differ across different employers because of important employer heterogeneity in working conditions and fringe benefits (Dorsey and Walzer, 1983; McNabb 1989; Dorman and Hagstrom, 1998), or location amenities (Roback, 1982; Blomquist et al, 1988).

Both lines of work are based on the premise that the labor market is perfectly competitive and both have been quite successful in explaining portions of the observed wage disparities across individuals and across locations. However, there is substantial empirical evidence that suggests it may be unrealistic to assume that labor supply is always infinitely elastic and employers have a passive role in the wage

[21] See Altonji and Blank (1999), for an extensive review of the relevant literature.
[22] See Rosen (1986), for a review.

setting process. In their famed paper, Card and Krueger (1994) produce evidence that an increase in the minimum wage may cause higher employment levels, a finding that is inconsistent with an infinitely elastic labor supply hypothesis.

In addition, there is evidence that wage differences are explained by employer characteristics that account for little variation in technology differences between them. Krueger and Summers (1987, pp. 18-47) note the persistence in wage differences across observably identical workers in different industries and conclude that market failures may be a reason for that persistency.[23] Davis, Haltiwanger, Katz, and Topel (1991) find that there is important wage dispersion across manufacturing plants, which can be partially accounted for by differences in their industry affiliation, size, age, location, and ownership type. Haltiwanger, Lane, and Spletzer (1999) find that such employer heterogeneity explains only a small fraction of the productivity differences across plants. Furthermore, a positive relationship between wages and firm size is found in numerous papers, but Brown and Medoff (1989) show that such differences persist even after accounting for differences in worker quality and working conditions.

Models of classic monopsony may explain some of this "curious" empirical evidence (Bronfenbrenner, 1956). For example, under a monopsonistic market, a carefully selected minimum wage results in an increase in the levels of employment that the monopsonist chooses. A pure monopsony model could also explain persistent wage differences across individuals that cannot be accounted for by productive differences across them. Wage disparities across workers of the same quality within

[23] The authors comment that: "Our conclusion that the inter-industry wage structure cannot plausibly be interpreted as a competitive outcome, has significance for both micro and macroeconomic issues" (pp. 42).

the same firm may be explained by classic monopsonistic wage discrimination. If the monopsonist observes worker characteristics, that allow it to group workers into different groups of labor supply elasticity, then the firm can offer lower wages to workers with lower elasticities. It is therefore possible for the employer to offer different wages to workers based on their non-productive characteristics that make them less responsive to marginal wage changes.

The existence of a pure monopsony is rare in the economy, so the explanations discussed above are of limited relevance. However, researchers have explored whether monopsonistic behavior may occur even in markets that feature more than one employer.[24] For example, if firms are different along dimensions that affect worker utility, then firms with higher levels of the desirable characteristic will enjoy an upward sloping labor supply (Boal and Ransom, 1997). In fact, Bhaskar and To (1999) formulate a model of firm differentiation in a competitive framework and show that such differentiation may explain how a minimum wage may in fact raise the level of employment.

Furthermore, Black and Loewenstein (1991) describe a model where the sole employer in a local market exploits the fact that workers suffer significant costs of changing employers, since such a decision involves relocation. In their model, wages are frontloaded; workers with positive mobility costs receive higher wages on the first period of employment, and face exploitation in the second period. Overall, their model predicts that workers with high mobility costs have lower lifetime wages than their counterparts. Ransom (1993) develops a model along those lines to explain why

[24] See Bhaskar, Manning and To (2002) for a discussion. Also, Boal and Ransom (1997) provide an insightful overview of the relevant literature.

returns to tenure for college professors appear to be negative, a result that was also found in previous research (Gordon, Morton and Braden, 1974).

Models in the existing literature provide important insight into how mobility costs may alter the wage setting behavior of employers, but do not account for cases where there is more than one employer in a local market. In this paper, I describe a model of wage determination, where employers in a local market use information they have on worker mobility costs and on the intensity of the local labor market competition when they renegotiate wages with their own workers. As a result, employers exploit worker costs of moving both within and across locations, by offering low wages to "high-cost" workers. The novelty of the model is that the wage setting power employers enjoy diminishes in the intensity of the local labor market competition. Because of that, the model applies to different occupation groups and motivates the empirical part of the paper.

Finally, there is considerable empirical work that assesses whether individual firms may enjoy an upward sloping labor supply curve as well as on the effect of potential employer market power on wages. Boal (1993) finds that coal-mining firms in the early 20th century faced labor supply elasticities that vary between 0.15 and 0.53. Sullivan (1989) and Hansen (1992) find that large hospitals may face an upward sloping labor supply. Furthermore, Link and Landon (1975) find that nurses' wages are lower the more concentrated employment is across hospitals, while Luizer and Thornton (1986) find a similar effect of the employment concentration of teachers across districts in Allentown, PA on the wages of certain groups of teachers.

However, to the best of my knowledge, there is no direct empirical evidence on the effect of individual mobility costs on the wages of workers in different occupations. There is also no evidence on how that effect, if any, differs across markets with different local market conditions. My empirical evidence suggests that workers with higher costs of moving may indeed face lower wages, especially if they are employed in small, less competitive metropolitan areas where employment opportunities in their occupation group are limited.

3.3 A Model of Wage Discrimination

Consider a two-period economy with an infinite number of firms that is partitioned into K number of locations. Each location is endowed with a fixed number of identical firms and an arbitrary number of workers. Let the total number of firms in location k be n_k, and the total number of firms in the rest of the economy, n_{-k}. All firms face constant returns to labor; the marginal revenue product of labor is thus constant and equal to p.

In the first period, employers have no information on worker mobility costs and therefore firms in all locations offer the same competitive wage rate to all workers. As a result, workers have no incentive to move to another location, regardless of their individual mobility costs. However, wages are only binding for the first period. Firms and workers renegotiate wages at the beginning of the second period.

The negotiation works as follows: First, the firm extends a final and binding wage offer to each one of its current workers.[25] Second, each worker observes the wage offer she gets from her current employer and potential offers she may receive from firms within her current location or from elsewhere. Finally, the worker chooses whether to stay with her current employer or switch to an alternative firm, if such an offer is available.

If a worker chooses to switch employers at the beginning of the second period, she suffers non-negative costs of moving, especially if the new employer is located outside her current location. In other words, when a worker switches to a new employer, she has to pay an associated cost of moving. I assume that these costs are higher when the new employer is located outside the worker's first-period location, compared to the case where the new employer is within the same location. Furthermore, I assume that these costs are privately known and the worker is the only one that knows their actual value.

While firms do not know the actual level of moving costs for each of its workers, they do observe a signal of those costs. Each employer chooses the wage offer to maximize its expected return from the negotiation, taking into account two important determinants of worker mobility. First, the worker may face positive costs of moving that limit the possibility that she will switch to an alternative employer, especially outside the current market. Second, the local labor market competition may be limited to the point where the worker may not receive a wage offer from a

[25] I assume that wage negotiation with a given worker is not affected by wages that other workers receive within the same firm nor by the existence of a perceived "fair wage." For example, Akerlof and Yellen (1990) and Johansen and Strom (2001) suggest that the willingness of a worker to continue working for the same firm and her work effort depends on the level of wages of other workers within the same firm and the level of the perceived fair wage.

competitor from within the local market. As a result, the wage offer will reflect these two frictions and it will predictably be lower than the market wage rate.

To formalize the discussion, consider the wage negotiation between worker *i* and firm *j* in location *k*. Denote individual moving costs for worker *i* as e_i when the worker switches employers within her current location and c_i, when the worker switches to an employer in an alternative location. As discussed, it is reasonable to assume that switching employers within one's location bears lower costs than moving to an alternative market, so that $c_i > e_i$, for all *i*. Although the employer does not know e_i and c_i, it observes a mobility cost signal, z_i, and the joint conditional distribution of moving costs $f(c,e \mid z)$. Also, assume that the corresponding conditional means are an increasing function of *z*, meaning that the expected moving costs for a worker increase with the observed value of *z*.

Finally, the worker may receive an alternative wage offer both from within her current location and from the rest of the economy. Let the corresponding rates of wage offer arrival be noted by $\lambda_k(n_k)$ and $\lambda_{-k}(n_{-k})$, where $\lambda_k(n_k)$ is the probability that a worker receives a wage offer from another firm from within market *k*, and $\lambda_{-k}(n_{-k})$ the probability of an offer arrival from a firm outside the local market. Both $\lambda_k(n_k)$ and $\lambda_{-k}(n_{-k})$ are increasing in the number of firms and are bounded between 0 and 1. The probability $\lambda_k(n_k)$ is equal to zero when the local market is monopsonistic, while it approaches one when there is a very large number of competitors within the market, ensuring that the worker will get both a wage offer from her current employer and an offer from the competitors. Similar conditions apply for $\lambda_{-k}(n_{-k})$. Assuming that the economy features a sufficiently large number of employers, the worker receives a wage offer from outside *k* with certainty, that is $\lambda_{-k}(n_{-k}) = 1$.

Based on these assumptions, the probability of a worker receiving an alternative wage offer only from outside market *k* is $(1 - \lambda_k)$ while the probability of receiving a wage offer from both an employer within *k* and an employer from outside *k* is λ_k. Since there is a large number of firms in the whole economy and only the current employer has information on the worker's mobility costs, alternative wage offers will be equal to the marginal revenue product of labor of the worker, *p*.

Each worker receives the offer from her current employer (w_k^j) but she may also receive the competitive offer *p*, from another employer within or outside her current location, or both. After receiving all offers, the worker chooses whether to stay with her current employer or move to another firm. Let the utility for worker *i* be $U_j^k = w_k^j$ if the worker stays with her current employer, $U_{-j}^k = p - e_i$ if the worker switches to another firm within the same market, and $U_j^{-k} = p - c_i$ if the worker switches to an employer outside the local market.

It follows that a worker changes employers within market *k* if an alternative wage offer from a firm in *k* arrives and that offer is such that $w_k^j < p - e_i$. Similarly, a worker rejects the offer of the current firm and moves outside market *k* if a wage offer from a firm outside *k* arrives and is such that $w_k^j < p - c_i$. In the event that an agent receives three offers, the choice the agent has is between staying with the current employer and moving within the current location. The worker never chooses to move to the employer outside her location over switching employers within her current location, since it is always true that $p-e_i > p-c_i$.

Firm j in location k chooses the wage rate it offers to worker i by taking into account both the information it has on the mobility of the worker, as well as the labor market conditions. If worker i accepts the wage offer, w_k^j, the firm receives a return of $p-w_k^j$, whereas if the worker rejects the offer, the firm has a zero return since it has to pay the competitive wage rate, p, to fill the vacancy. Therefore, the profit maximization problem for firm j is:

$$\max_{w_k^j}\{\lambda_k \cdot \Pr(w_k^j > p-e_i)+(1-\lambda_k)\cdot \Pr(w_k^j > p-c_i)\}\cdot(p-w_k^j) \tag{1}$$

To simplify things, I further assume that e_i and c_i are jointly and independently uniformly distributed over the intervals $e_i \in [o, e^*(z)], c_i \in [o, c^*(z)]$.[26] Under these assumptions, the first order condition produces the optimal wage offer:

$$w_k^j = p - \frac{c^*(z)\cdot e^*(z)}{2(1-\lambda_k)\cdot e^*(z)+2\lambda_k \cdot c^*(z)} \tag{2}$$

As a result, the oligopsonistic exploitation for a worker in location k, given z, defined as the difference between MRP_L and the wage offer is:

$$E_k = \frac{c^*(z)\cdot e^*(z)}{2(1-\lambda_k)\cdot e^*(z)+2\lambda_k \cdot c^*(z)} > 0 \tag{3}$$

It is obvious from the results in (2) and (3) that in the case where a worker signals positive costs of moving both across locations and to other employers within the same location, her employer offers her a wage rate that it is lower than the MRP_L.

[26] Both $e^*(z)$ and $c^*(z)$ are increasing in the observable z, and $e^*(z) < c^*(z)$.

The resulting oligopsonistic exploitation is positive and is a function of both the number of firms in the local market and the mobility cost signal, z. By using (2) and (3), we can show that:

$$\frac{dw_k^j}{dz} < 0 \quad , \quad \frac{dE_k}{dz} > 0 \tag{4}$$

In words, firms discriminate against workers that signal high mobility costs by offering them lower wages. The higher the moving cost signal a worker reveals to her employer, the lower the wage offer she receives when wages are renegotiated, and thus the higher the magnitude of oligopsonistic exploitation she faces. Therefore, the firm takes advantage of worker immobility to offer wages that are lower than the prevalent competitive wage rate. On the other hand, workers that signal zero costs of moving across locations are expected by their employer to have a reservation wage that equals the competitive wage rate. The latter group of workers receives a wage offer that is equal to their marginal revenue product of labor, regardless of the local labor market competition that the firm faces.

Wage discrimination in this model is a result of the mobility cost signal the worker sends her employer before wages are renegotiated. At the same time, worker mobility is affected by the degree of the labor market competition. The presence of alternative employment opportunities both within the worker's market and in the rest of the economy reduces the negative effect of mobility costs on wages. By using equations (2) and (3), we can show that:

$$\frac{dw_k^j}{d\lambda_k} > 0 \, , \, \frac{dE_k}{d\lambda_k} < 0 \tag{5}$$

It is easy to see that, keeping worker mobility costs equal, the wage offer increases in the intensity of the local labor market competition. As a result, the magnitude of exploitation decreases significantly when the worker has a higher probability of receiving competing offers from within the local market. This result is important since it suggests that worker mobility costs should matter more in smaller, less competitive local markets rather than in large local markets, where an abundance of alternative employment opportunities exists.

Consider two special cases of this model. First, consider the extreme case where the outside market is perfectly competitive, but where the local market has only one employer. This paradigm is the one Black and Loewenstein (1991) discuss in their paper. The local monopsony can fully exploit worker mobility costs in this case since workers have to pay the cost of moving to another location in order to avoid the wage penalty. In this case, exploitation reaches its maximum possible value, and one can show that it is equal to:

$$E_{(\lambda_k=0,\lambda_{-k}=1)} = \frac{c^*(z)}{2} \tag{6}$$

This result suggests that the firm penalizes a worker that has a mobility cost signal z by offering her a wage offer that is lower than the marginal revenue product of labor. The magnitude of exploitation is equal to the expected value of the moving costs the worker would suffer if she chose to relocate. This result is identical to the Black and Loewenstein paper. Although this is an interesting scenario, it is also unlikely to occur for workers in most occupations and in most local markets.

The second extreme case would be when location k features an infinite number of firms. In this case, each worker receives a wage offer from both within k

and from outside k with certainty. Exploitation in this case - keeping individual mobility costs equal - will take its minimum value and will equal the expected cost the worker pays to move within the location, given z:

$$E_{(\lambda_k = \lambda_{-k} = 1)} = \frac{e^*(z)}{2} \tag{7}$$

Overall, the intensity of the local labor market competition reduces the negative effect of mobility costs on wages, since it weakens the bargaining position of the employer. If the intensity of the local market competition is very weak, firms are in a better position to exploit costs the workers face to move across locations. On the other hand, in large and more competitive local markets, the bargaining position of employers is very small and thus exploitation is limited.

In conclusion, according to this model, firms may utilize information on worker mobility to offer lower wages to workers that signal high costs of moving both within, but more importantly across locations. The magnitude of exploitation increases in the mobility cost signal, and it decreases in the number of firms in the local market. The first observation suggests that wage differences across individuals within the same location may be explained by differences in characteristics that affect their costs of changing employers, while the latter suggests that such scenario is more plausible in local markets where labor market competition is limited and alternative employment opportunities are scarce. The model is constructed to capture the two extreme scenarios of local labor market competition – namely, monopsony and perfect competition – so it applies to different occupation groups and not only to college professors, which is the group mostly discussed in previous work.

3.4 Empirical Evidence

In this section, I describe a number of empirical exercises that provide formal tests of the predictions of the model. The model outlined in the previous section predicts a clear interaction between worker relocation costs and local market competition in the wage setting behavior of firms in local labor markets. Workers that signal high costs of moving across locations receive lower wages than their counterparts, whereas that effect is lower for workers in more competitive labor markets.

To test the predictions of the model, I estimate a wage equation that includes the typical control variables, a measure of individual mobility costs, a measure of occupation-specific local labor market competition, and an interaction between the two measures. According to theory, an appropriate measure of worker mobility costs should have a strong negative effect on wages. At the same time, that negative effect should be lower in metropolitan areas where local competition is more intense, so the effect of the interaction between the measures of moving costs and local market competition on wages should be positive.

Such an empirical test entails a number of challenges. First, appropriate measures of worker mobility costs are needed. Since such costs are not observed, I identify worker characteristics that are positively correlated with worker mobility costs, and at the same time, are plausibly not negatively correlated with unobserved ability. Second, a measure of local labor market competition that captures the variation in local competition across metropolitan areas and the variation in local competition across occupations within the same metropolitan area is needed. In the next section, I describe how I construct these measures.

3.4.1 Data

I use the 5% Public Use Micro Sample (PUMS) of the 2000 Decennial Census. This data contains information on worker demographics, as well as rich information on their employment and geographic characteristics. I constrain the sample to full-time employed males that are 35-64 years of age and live in an identifiable Metropolitan Statistical Area (MSA). The sample excludes self-employed workers.[27]

The 2000 PUMS contains a large number of observations for each of 283 metropolitan areas and reports the occupation of the respondent. This allows us to exploit the variation in local market competition across cities and across different occupational categories. Additionally, using the household records I obtain household characteristics that are used as proxies for worker mobility costs in the specification of the wage equation.

The data contain no information on workers' employment histories, so it is not useful to determine how wages may change when a worker moves across employers or on the tenure of a worker with the current employer. This is the main reason I constrain the sample to workers that are at least 35 years old, making sure that the sample includes workers that are more likely to have been with the same employer for some time.

[27] For a description of the sample, see Table 1.

To test whether the effect of worker mobility costs on wages declines in the intensity of the local market competition, I need measures of local labor market competition for each MSA, at the occupation level. The reason I need to produce tests of the model at the occupational level is that the intensity of the labor market competition in a given MSA is likely to vary significantly across different occupation groups. For example, New York City is the largest MSA in the US and it is reasonable to expect that New York City is a highly competitive market for lawyers. At the same time, a worker in the *Farming, Forestry and Fishing* category probably does not face the same competitive market in New York, since the overall number of employment opportunities for such workers are probably fewer than those available for a lawyer.

The point of this example is that competitive conditions do not only differ across metropolitan areas – as the model suggests – but also across occupations within the same metropolitan area. Therefore, I need a measure that captures total employment opportunities in each MSA, by occupation. Ideally, I would like to have information on the number of firms in each MSA that employ workers in each occupation group, and how many workers in each occupation each firm employs. Such information is unavailable from available data sources.

Because of the data availability issue, I initially construct two straightforward measures of local labor market competition by using information from the 2000 County Business Patterns. The CBP reports the number of employers - at the establishment level - for each of the MSAs that are available in the PUMS, by the industry classification provided by the North American Industry Classification

System (NAICS).[28] Using the CBP, I can construct two measures of local market competition: (a) Number of employers in the MSA of the worker, and (b) Number of employers in the MSA and 2-digit NAICS industry of the worker.[29] The assumption is that the larger the number of establishments in a MSA, the more employment opportunities a worker in that metropolitan area will have. In other words, the number of establishments in the metropolitan area of the worker serves as a good proxy for the local market competition.[30]

It is likely that employment opportunities for workers in certain occupations increase with the size of the MSA. For example, transportation workers, like limousine drivers, probably have less difficulty finding a job in a large metropolitan area like Los Angeles, CA compared to a smaller MSA like Kokomo, IN. The same is probably true for restaurant workers, workers in cleaning and maintenance occupations, workers in protective services, and workers in office and administrative support occupations. For the aforementioned occupations, the total number of firms in the MSA serves as a good measure of competition.

On the other hand, the number of firms in the industry of the worker may be a more appropriate measure of local labor market competition for other occupations. A farm worker in Wichita, KS probably has more opportunities to change employers within Wichita, KS, compared to a farm worker in Washington, DC. Again, using the number of total firms as an indication of local competition for farmers would not be appropriate in this scenario, since Washington, DC would appear as a "better" market

[28] For more information on the North American Industry Classification System (NAICS), go to the official website of the US Census Bureau, www.census.gov.
[29] Unfortunately, the CBP does not report similar information by occupation.
[30] See Table 2 for an overview of the 2000 County Business Patterns.

for such workers compared to Wichita, KS. The difference in the number of farms between the two MSAs would better reflect the differences in local labor market competition for farmers between Wichita and Washington.

Similarly, the number of colleges in a MSA is a more accurate measure of local competition for college professors rather than the total number of establishments in the MSA, and the total number of hospitals and clinics is a more appropriate measure of the local labor market competition for physicians and health care support workers. Therefore, there are occupations for which the total number of firms within the MSA and industry of the worker reflects local competition more accurately compared to using the total employer size of the MSA.

In the empirical analysis, I test the model by using both measures to investigate the sensitivity of the results to the use of one measure over the other. However, these measures of competition are not without their faults, since they do not account for differences in employment size across firms within the same MSA, and still do not account in full for the fact that an MSA may be an important employer for one occupational group, but not for another. In a later section, I define an alternative measure of labor market competition that gets around these issues.

3.4.2 Constructing Mobility Cost Indicators

According to the model, if employers in a local labor market have information on worker characteristics that may contribute to higher individual costs of moving across locations, then they would offer such workers lower wages. Testing the model would be straightforward if measures of individual moving costs were available. Since measures of worker moving costs are not available, I identify worker characteristics that may be positively related to unobserved individual relocation costs. Using the 5% PUMS from the 2000 Decennial Census, I have information on worker personal characteristics, as well as characteristics for his spouse, children and other members of his household. This information is utilized to identify indicators of individual mobility costs.

First, following the discussion of Sjaastad (1962), an agent would be reluctant to migrate out of his birthplace, since he would then lose the social network he enjoys there. It is reasonable to assume that people suffer important psychic costs in parting with their family and friends, so a move out of one's home state would yield a negative utility effect. Speare, Kobrin, and Kingkade (1982) comment that, "Households with Strong Bonds to an area, are more likely to seek a solution which enables them to stay in the area." The authors find using panel data for workers in Rhode Island that the probability of someone moving out of the state decreases significantly with the proportion of relatives, friends, and parents that the person has in the area. Therefore, it is reasonable to expect that a worker is less likely to migrate out of his state of birth than out of other states. One should expect a similar effect if the worker is married and the household is located in his spouse's state of birth. In all, a move to another state for a household that is located in either the head's or the spouse's state of birth, or both, bears significant psychic costs that make such a move less likely to occur.

One also expects that married workers whose spouses also work would be less likely to move across locations relative to others. There is considerable theoretical work that suggests that agents take into account their spouse's labor force status and her labor earnings when they face relocation decisions (Sandell, 1977; Mincer, 1978). Such households - keeping other costs equal - face higher relocation costs than others, since they either suffer the cost of the spouse quitting her job, or the search costs of finding a new one. Sandell (1977) finds that a family is less likely to migrate across states when the spouse is also employed, while Bartel (1979) shows that individual migration propensities may be higher when the spouse of the agent is not in the labor force. Furthermore, Bielby and Bielby (1992) suggest that families are more "reluctant to migrate" when the spouse is working or has acquired significant firm-specific human capital with her current employer.

Another source of immobility is whether the household has a disabled person, for example, the head's spouse or one of his children. This may cause higher monetary and non-pecuniary costs of moving for the household. First, there is evidence suggesting that workers may be hesitant to change jobs because they have employer-provided health insurance (Buchmueller and Valletta, 1996; Madrian, 1994). A worker that has either a disabled spouse or child may be more reluctant to change jobs, since he has the risk of losing existing benefits he enjoys from his current insurance (Klerman et al, 1992), or because many employers do not cover health expenses for preexisting conditions for new employees (Cotton, 1991). Second, there might be important monetary costs of making new living arrangements for the disabled members of the family at the new location. Finally, important non-pecuniary costs are also involved, if we consider the associated psychological effect that relocation may impose, especially on a disabled child, where the child would have to change schools, meet new friends, or receive treatment by new physicians or physical therapists.

Furthermore, if the parents or the in-laws of the household's head reside within the same household, presumably that would deter migration for the household. Moving to another location would mean either that the household would suffer the monetary cost of moving the parents with them or the psychic cost of relocating without them (Speare et al 1982). Finally, if the head's spouse attends college, relocation would mean that they either have to bear the costs of the spouse changing schools, quitting school, or the couple living apart until the spouse graduates. By using the household sample of the 2000 PUMS, I can identify which of these characteristics apply to each worker.[31]

In Tables 3 and 4, I present evidence that reinforce the point that the aforementioned characteristics may deter migration. First, as shown in Table 3, 24.84 percent of workers for whom the metropolitan area of residence is available for both in 1995 and in 2000 reported a different MSA of residence in 1995 and in 2000. However, only 13.75 percent of workers that live in their *State of Birth* reported a move across MSAs between 1995 and 2000, 11 percentage points less than the sample proportion. Only 14.56 percent of workers that live in their *Spouse State of Birth* have moved across MSAs, 10 percent less than the sample mean.

When the spouse has a full time job (*Spouse Works FT*) the household is 3 percentage points less likely to have moved whereas if the spouse or a child of the household's head is disabled (*Spouse or Child Disabled*), the household is 4 percentage points less likely to have moved across MSAs between 1995 and 2000. If

[31] For a description of mobility cost indicators, and their corresponding sample means, see Table 3.

the worker's spouse is in college (*Spouse in College*), the likelihood of a move is not significantly different than the sample proportion. Moreover, a household is estimated to be around 3 percentage points less likely on average to have moved from one MSA to another between 1995 and 2000 if the head's parents or in-laws reside in the same house (*Parents Present*), compared to the sample mean.

In Table 4, I report the estimated marginal probability effects of these characteristics on the likelihood of being a mover, from probit models that also control for other available demographic characteristics. First, the results consistently show that people may be attached to their birthplace. More specifically, the results suggest that when the household is located in the head's state of birth, the household is around 15.5 percentage points less likely to relocate across MSAs compared to households that are not located in their head's state of birth. The estimated probability effect of the *Spouse State of Birth* is around -.11, suggesting that a worker that is married and lives in his spouse's state of birth is 11 percentage points less likely to relocate to another MSA compared to workers that are either single, or do not live in their spouse's state of birth. Both estimates are statistically significant at the 1 percent level across all specifications.

In addition, the estimated probability effect for *Spouse Works FT* is -.081 and is statistically significant at the 1 percent level, implying that a worker is on average 8.1 percentage points less likely to have moved between MSAs compared to workers that are either not married, or their spouse does not work full time. At the same time, if the spouse is in college, the worker is 1.3 percentage points less likely to move compared to his counterparts, whereas the respective negative effect of *Spouse or*

Child Disabled is 1.7. Finally, a worker is estimated to be almost 3 percentage points less likely to move if his parents or his in-laws reside in the same household compared to workers who are not living with their parents or in-laws. All aforementioned probability effects are statistically significant at the 1 percent level.

The evidence in Tables 3 and 4 illustrates the negative relationship between certain household characteristics and worker migration propensities. This evidence reinforces the argument that these characteristics are reliable proxies of individual mobility costs. To test the model's predictions, I use these characteristics to construct a measure of worker mobility costs. Specifically, I create an index that weighs each characteristic by its estimated marginal probability effect on the migration decision; I use the estimated probability effects from Table 4, column (3) to construct the index. More formally, the mobility cost index for worker *i*, is constructed as follows:

$$MCI_i = \frac{\sum_m D_{im} \cdot PR_m}{\sum_m PR_m} = \{.1554 * \textit{State of Birth} + .1108 * \textit{Spouse State of Birth} + \\ + .0808 * \textit{Spouse Works FT} + .0126 * \textit{Spouse in School} + \\ + .0293 * \textit{Parents Present} + .0161 * \textit{Person Disabled}\} / (.4051) \qquad (8)$$

Note that D_{im} is an indicator function that equals 1 if the moving cost indicator *m* applies to worker *i*, and 0 otherwise, while PR_m is the estimated marginal probability effect of characteristic *m* on the probability of being a mover. As equation (8) suggests, I add up each mobility cost indicator function - weighted by the respective marginal probability effect - and then I normalize the index by dividing by the sum of the estimated probability effects.

By construction, *MCI* is bounded between 0 and 1 and has a sample mean equal to .386 and a standard deviation equal to .306. Table 5 presents select groups of workers that lie on different percentiles of the *MCI* distribution.[32] First, Table 5 shows that 22.63 percent of workers in the sample have a *MCI* that is equal to zero, meaning that none of the mobility cost characteristics apply to them (group 1). Workers in group 2 (*Parents Present* is the only characteristic that applies to them) have an *MCI* of .0724 and account for only 1.59 percent of the sample. Group 3 includes workers that share only one of the mobility cost indicators; *State of Birth*. These workers account for 13.77 percent of the sample and have an *MCI* equal to .3835. Furthermore, workers in group 4 share only the two geographic indicators (*State of Birth* and *Spouse State of Birth*), account for 9.04 percent of the sample, and have an *MCI* that is equal to .6569. Finally, workers in group 5 – which includes workers that only share the three most important mobility cost indicators (*State of Birth*, *Spouse State of Birth*, and *Spouse Works FT*), have a *MCI* that is equal to .8564. This group of workers accounts for 15.35 percent of the sample.

Overall, there is substantial variation in the value of *MCI*. By construction, the *MCI* is significantly higher for workers that share characteristics that are highly related to worker mobility decisions. For example, workers in group 3 have a *MCI* that is 27 percentage points lower than the *MCI* of workers in group 4. At the same time, the *MCI* for workers in group 5 is 20 percentage points higher than the *MCI* of workers in group 4. In the next section, I use the *MCI* as an approximation of worker mobility costs in the wage specification, and if the model's intuition is valid, it should have a negative effect on wages.

[32] See Figure 1 for an illustration of the cumulative distribution function of the *MCI*.

3.4.3 Estimation Results

I use a classic human capital wage equation to test if mobility cost indicators have a negative effect on wages and whether that effect is lower in highly competitive local markets. The specification of the wage equation is:

$$\log w_{ik} = X \cdot \beta + \gamma \cdot M_i + \delta \cdot M_i \cdot F_k + \zeta \cdot F_k + u_{ik} \qquad (9)$$

In words, $\log w_{ik}$ is the logarithm of wages for worker *i*, in MSA *k*, and X includes all available demographic characteristics, such as age, age-squared, education, and race.[33] Additionally, M_i is a measure of mobility costs for worker *i* and F_k represents the total number of establishments in MSA *k*, or the total number of establishments in the industry of the worker in MSA *k*.

The parameters of interest are two: (1) γ, which captures the effect of individual moving costs on wages, and according to theory should be negative, and (2) δ, which captures the effect of the interaction between the measure of mobility costs and the measure of the local competition for the MSA of residence on wages, which should be positive. I estimate equation (9) using different measures of worker mobility costs, and the two measures of local competition, namely the total number of firms in the worker's metropolitan area, *Firms(M)*, and the total number of firms in the metropolitan area and industry of the worker, *Firms(M,I)*.

First, I use *State of Birth* and *Spouse State of Birth* as measures of mobility costs in the wage equation specification. The estimated parameters of interest are summarized in Table 6a; other available characteristics, as listed in Table 1, are included in the specification but produce typical coefficients and are therefore

[33] See Table 1 for all available worker characteristics.

omitted from the table. Results suggest that workers that live in their state of birth or their spouse's state of birth earn lower wages compared to their counterparts. In column (1), the respective estimated coefficients are -.029 and -.019 for *State of Birth* and *Spouse State of Birth* respectively and are statistically significant at the 1 percent level. In column (2) I also control for *Firms(M)* and the estimated coefficients for *State of Birth* and *Spouse State of Birth* are -.030 and -.019 and are still statistically significant. These estimates suggest that a worker that lives in his state of birth earns 3 percentage points less than a worker who lives outside his state of birth. At the same time, workers that live in their spouse's state of birth, earn 1.9 percentage points less than workers who are either single or are married and do not live in their spouse's state of birth.

State of Birth and *Spouse State of Birth* are used as proxies for worker mobility costs but in order to interpret their effect on wages as such, we have to dismiss the case that they are negatively correlated with unobserved ability. Workers tend to move out of MSAs that feature low wages and the population growth in such locations is likely to be negative. Workers may choose to stay in such locations either because they face important mobility costs or because they lack the ability or the entrepreneurship to pursue employment opportunities outside their current location. The issue is that if the latter is true, *State Own* and *Spouse State of Birth* are negatively correlated with unobserved ability and thus this correlation could be responsible for the estimated negative effect on wages.

I perform two sets of exercises that illustrate that these measures of individual immobility are not negatively correlated with unobserved worker ability. First, I regress wages on the MSA population growth (*Pop Growth*) and interactions between *Pop Growth* and these characteristics. *Pop Growth* is the percentage population growth in the MSA of the worker between 1990 and 1997, as reported by the US Census Bureau's "State and Metropolitan Area Data Book, 1997-98." I find that *Pop Growth* and its interactions with *State Own* and *Spouse State of Birth* do not significantly affect wages. Table A in the Appendix summarizes the results.

Second, I run the regressions restricting the sample to workers that live outside their *State of Birth*. The idea is to test whether wages for workers that have the ability or entrepreneurship to seek employment opportunities outside their state of birth are negatively affected when they are working in their spouses' state of birth. I find that *Spouse State of Birth* has a significant negative effect on wages of such workers. I also find that the *MCI* has a significant negative effect on wages when I restrict the sample to *State of Birth*=0. I find similar results when I restrict the sample to *Spouse State of Birth*=0. Table B of the Appendix summarizes the results.

In column (3) of table 6, I account for the total number of firms in the metropolitan area of the worker and the interaction between *Firms(M)* and the measures of mobility costs. The effect of *State of Birth* on wages rises to -.054, while the interaction effect is positive (.0022) and statistically significant. The coefficient of *Spouse State of Birth* also increases to -.034 with the respective interaction effect being positive (.0017) and statistically significant. These results confirm the intuition that workers that live in their own or their spouse's state of birth – and therefore send a signal of important psychic costs of moving to another location – earn significantly less compared to their counterparts. The positive interaction effects confirm that the effect of such immobility on wages is weak in large metropolitan areas that feature a high number of employers and thus more employment opportunities.

In the same table, I report results when I use *Firms(M,I)* as a measure of local competition. The results in column (5) are again supportive of the theory's intuition. Both characteristics bear a significantly negative coefficient, -.046 for *State of Birth* and -.034 for *Spouse State of Birth*, and at the same time, the interactions of these characteristics with *Firms(M,I)* have a significantly positive effect on wages; .0043 and .0049 respectively). So, workers that face such immobility earn less than others but that negative effect is stronger for workers that work in a metropolitan area that has a lower number of alternative employment opportunities in the industry of the worker.

To evaluate the economic importance of local competition on worker wages, I use the results in columns (3) and (5) of Table 6a to calculate the mean predicted income at different points of the *Firms(M)* and *Firms(M,I)* distributions. Specifically, I calculate the mean predicted income at different points of the *Firms(M)* and *Firms(M,I)* distributions, holding the mobility cost indicators and other worker characteristics constant. Table 6b reports the output of this exercise.

As reported in columns (1) and (2) of Table 6b, the sample mean of *Firms(M)* is 12.335, and the mean predicted income evaluated at this level of *Firms(M)* is 44,365 USD. Workers that lie on the 10^{th} percentile of the *Firms(M)* distribution earn on average 42,082 USD, which is 5.15 percentage points lower than the sample mean, holding mobility cost indicators and other worker characteristics equal. The predicted income of workers at the 25^{th} and 50^{th} percentiles of the *Firms(M)* distribution is 4.38

and 1.65 percentage points, respectively, lower than the predicted income evaluated at the sample mean of *Firms(M)*. On the other hand, workers on the 75th and 90th percentiles of the *Firms(M)* distribution earn on average 2.54 and 8.08 percentage points more compared to the sample mean. For example, a worker in Ann Arbor, MI - which lies on the 25th percentile of the *Firms(M)* distribution - earns 6.92 percentage points lower wages than a worker in Chicago, IL (75th percentile), holding mobility cost indicators and other personal characteristics equal.

Similarly, the sample mean of *Firms(M,I)* is 4.206 and the mean predicted income is 44,365 USD, as reported in columns (3) and (4) respectively. Workers at the 10th percentile of the *Firms(M,I)* distribution earn 1.88 percentage points less than the sample mean, holding mobility cost indicators and other characteristics constant. Workers at the 25th and 50th percentiles earn around .86 percentage points lower and .79 percentage points higher compared to the sample mean. Finally, workers in the higher levels of the *Firms(M,I)* distribution earn 3.42 percentage points (75th percentile) and 6.19 percentage points (90th percentile) more than the sample mean.

In a second set of analysis, I use the *MCI* as a measure of mobility costs; the results are presented in Table 7a. As expected, the *MCI* has a statistically significant negative effect on wages, which is -.1270 when we do not account for local competition in column 1, and -.1243 when we account for *Firms(M)* in column (2). In column (3), I add the interaction between *MCI* and *Firms(M)* to the specification. The effect of *MCI* is still negative (-.1739) and significant, while the interaction effect is positive (.0032) and statistically significant. Similar results are produced when I use *Firms(M,I)* as a measure of local competition, in columns (4) and (5) of Table 7a. The estimated coefficient for the *MCI* is -.1253 when I control for *Firms(M,I)* and -.1641 when I add the interaction between the *MCI* and *Firms(M,I)* in the specification. Both coefficients are significant at the 1 percent level. The interaction effect is estimated to be positive (.0075) and statistical significant.

The economic effect of *MCI* on worker wages is not very straightforward, therefore I use the results in columns (3) and (5) of Table 7a to evaluate the mean predicted income at different points of the *MCI* distribution, holding other worker characteristics and measures of local competition constant. I calculate the mean predicted income - evaluated at the sample means of the independent variables - at different points of the *MCI* distribution. Table 7b reports the output of this exercise.

The average worker has a *MCI* that is equal to .386 and the predicted income for such a worker is 44,365 USD. According to the results in column (2) of Table 7b, workers in group 1 (which do not share any of the mobility cost characteristics, i.e. they have an *MCI* that is equal to 0) are estimated to earn on average 46,809, which is 5.51 percentage points higher than the sample mean. In other words, keeping local competition and other worker characteristics constant, a worker that has none of the immobility characteristics in this context earns significantly higher wages compared to the average worker in the sample.

Workers at the 25^{th} percentile of the *MCI* distribution (group 2) earn 4.49 percentage points more than the sample mean, while workers that lie on the 50^{th} percentile of the *MCI* distribution earn about 0.21 percent more than the sample mean. On the other hand, workers on the 75^{th} and 90^{th} percentiles of the *MCI* distribution - which are workers with high mobility costs - earn 3.41 and 5.96 percentage points less than the sample average.

The results are very similar when we use the results from the *Firms(M,I)* specification instead. The numbers in Table 7b, column (4) show that workers on the 10th and 25th percentile of the *MCI* distribution earn 5.42 and 4.41 percentage points more than the average worker, respectively. On the other hand, workers in groups 4 and 5 earn 3.38 and 5.90 percentage points less than the mean predicted income of the whole sample, holding other characteristics and *Firms(M,I)* constant. Intuitively, based on the numbers in Table 7b, a worker in group 1 would earn around 5.7 percentage points less if he was working within rather than outside his state of birth (group 3). Also, a worker in group 3 (works in his state of birth) earns on average 6 percentage points less than a worker in group 5, who works in his state of birth and also is married and his spouse is local and works full time.

In order to calculate the effect of local competition on wages in this context, I conduct a similar exercise to the one in Table 6b. Specifically, I calculate the mean predicted income at different points of the *Firms(M)* and *Firms(M,I)* distributions, holding *MCI* and other worker characteristics equal. Table 7c reports the results, which are similar to those in Table 6b. Holding *MCI* and other worker characteristics constant, workers at the 10th percentile of the *Firms(M)* distribution earn 6.01 percentage points less than the average worker. Workers at the 25th and 50th percentiles of the *Firms(M)* distribution earn wages that are 5.14 and 2.04 percentage points lower than the sample mean. On the other hand, workers at the 75th and 90th percentiles of the same distribution earn higher wages than average (2.75 and 9.21

percentage points, respectively). Similar results apply when we move along the *Firms(M,I)* distribution.

Comparing the mean predicted wages for workers on the 25th percentile (Ann Arbor, MI) and those on the 75th percentile (Chicago, IL) of the *Firms(M)* distribution, we see that holding *MCI* and other worker characteristics equal, workers in Chicago earn 7.89 percentage points more than those in Ann Arbor. If we make the same comparison using the distribution of *Firms(M,I)* instead, workers on the 75th percentile earn wages that are 6.50 percentage points higher than the wages of workers on the 25th percentile.

Overall, the results in Tables 6 and 7 suggest that workers who are relatively less mobile across MSAs, earn significantly lower wages compare to their counterparts. However, the negative effect of the mobility cost indicators is significantly lower for workers in MSAs that feature a higher number of employers. Therefore, holding market competition constant, workers with high mobility costs earn lower wages, while when we hold worker immobility constant, local competition weakens the effect of mobility costs on wages. These results are robust to the use of different measures of worker mobility costs and local labor market competition in the wage equation specification.

3.5 An Alternative Measure of Local Labor Market Competition

The empirical results discussed in section 4.3 provide substantial support to the idea that workers who are observably less mobile across locations may suffer lower wages, especially if they are working in a MSA with weak local labor market competition. Two straightforward measures of local competition were employed, namely the total number of firms in the MSA of the worker and the total number of firms in the MSA and industry of the worker. These two measures are good indicators of the size of a local market and provide an appropriate approximation of the total number of employment opportunities in that market and the total number of employment opportunities in the industry of the worker.

Even though these measures are intuitively reasonable, they possess certain disadvantages. First, by using *Firms(M)* and *Firms(M,I)* as measures of local market competition, I do not account for differences in sizes across employers within the same MSA. This could be a source of concern for the accuracy of the measure. For example, a local market may have a relatively high number of employers, but at the same time, it may have a small number of large firms that enjoy the majority of the employment share in that market. As a result, the relatively high number of firms makes us believe that the market is competitive, when in fact it might not be, since a few employers have the power to control wages and employment outcomes.

Second, as previously discussed, the number of employment opportunities in a given MSA is probably quite heterogeneous across occupation groups. For example, New York City is the MSA with the highest number of establishments, according to the 2000 County Business Patterns. It is probably true that New York City is a competitive market for lawyers and financial advisors. However, it is a market where there are not so many opportunities for mining engineers or agricultural workers. Although it is true that *Firms(M)* is a good proxy for local employment opportunities for some occupations, it is not so great for others. Similarly, *Firms(M,I)* is a very good measure of local competition for "one-industry" occupations like agricultural workers, college professors, and physicians, but is not a very accurate measure for occupations that are found across many industries; lawyers, salesmen, and accountants are just a few examples.

One would like a measure that accounts not only for the size of the market but also for differences in market competition across occupations within that market. An appropriate measure would be a *Herfindahl Index* that captures how concentrated employment opportunities are across firms, within a metropolitan area, by occupation. The *Herfindahl Index* (*HI*) is a very popular measure of market concentration and has been used in numerous studies to evaluate the effect of market concentration on different market outcomes.[34] Researchers have found the *HI* to be very attractive since it possesses two important properties. First, it accounts for the size of the local market, and more specifically, it decreases in market size. Second, it increases in the dispersion of market share across firms, so it accounts for differences in size across employers within a local market. Overall, a high *HI* denotes weak market competition whereas a low *HI* denotes strong market competition.

Assume that we know the number of firms in each metropolitan area and how many workers, by occupation, are employed by each firm. By using this information, we can calculate the employment share of each firm on the total employment of the metropolitan area, by occupation. The *HI* for a specific occupation and MSA would simply be the sum of the square employment shares of each firm in the metropolitan area for that occupation. The maximum value of the *HI* is 1, meaning that employment in the market is perfectly concentrated, the local monopsony case. The

[34] See for example, Santerre and Neun (1986), Link and Landon (1975), and Luizer and Thornton (1986)

minimum value of the *HI* is 0, which suggests that employment in the market is perfectly dispersed, the perfect competition case.

If such an index were available, it would be higher for metropolitan areas that have a large number of firms employing workers in a specific occupation. For example, one would suspect that the *HI* for lawyers in New York City, NY would be significantly lower than the respective measure for lawyers in Charlottesville, VA since such workers have more employment opportunities in New York City. At the same time, local markets with a small number of employers or MSAs that have a number of very large employers for a specific occupation would have a higher *HI*, meaning that local competition for the specific occupation is weak.

In order to construct the *HI* for a specific MSA-Occupation pair, I need the number of workers in the specific occupation that each firm in that MSA employs. Unfortunately, a dataset that contains this information for the metropolitan areas in the sample is not available. Instead, I produce a version of the *HI* that is calculated using the spatial distribution of employment opportunities in a metropolitan area, by occupation.

To construct this index I use the unpublished 1/6 sample of the 2000 Decennial Census which reports not only the occupation of each worker, but also the worker's place of work. This information allows the identification of the city block where each respondent in the unpublished sample is employed at the time of the survey. Using the unpublished sample of the 2000 Census, I produce the number of workers, by occupation, employed in each block of all MSAs in the data,[35] and the

[35] I define 23 broad Occupation categories. These categories are in accordance to the Standard Occupational Classification (SOC), which is used by Federal Statistical Agencies to categorize

total number of workers, by occupation, in each MSA in the data. Therefore, for a given MSA, I can calculate the employment share of each of its blocks, by occupation. The *HI* for occupation *g* in MSA *k* is simply the sum of squared employment shares of all blocks in MSA *k* for occupation *g*:

$$HI_{gk} = \sum_b \left(\frac{E_{gkb}}{\sum_b E_{gkb}} \right)^2 = \sum_b \left(\frac{E_{gkb}}{E_{gk}} \right)^2$$

(10)

Note that E_{gkb} is the number of workers employed in block *b*, MSA *k*, occupation *g*, and E_{gk} is the total number of workers in MSA *k*, occupation *g*. The *HI* is bounded between 0 and 1, where 0 denotes perfect dispersion of employment opportunities across city blocks, and 1 denotes perfect concentration.

Table 9 illustrates the variation in the values of *HI* both across occupations and across metropolitan areas, by occupation. A metropolitan area is characterized as being a "concentrated" market for a specific occupation if the *HI* is higher than 0.10, "moderately concentrated" if the *HI* is between 0.10 and 0.18, and "highly concentrated" if the *HI* exceeds 0.18.[36] The first column of Table 9 lists the occupational groups, while columns (1)-(3) report the total number of metropolitan areas in each concentration category, by occupation.

Column (1) of Table 9 features the total number of concentrated markets, by occupation category. The numbers suggest that there is significant variation in the

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occupations. The SOC is reported in the PUMS and it is also reported in other datasets like the Current Population Survey. Table 8 illustrates how the sample breaks down into those categories.

[36] These classifications are based on the US Antitrust Department classifications that are used to classify industry concentration. For more information on the US Antitrust Department, and how it uses *HI* to classify industry concentration, go to www.usdoj.gov/atr.

total number of concentrated markets across occupation categories. First, a significant number of MSAs are concentrated markets for *College Professors* (196) and *Physicians* (108). This result is predictable since employers for these occupational categories are likely to be large and occupy a significant employment share of the market, especially in mid-size or small metropolitan areas. Second, there are occupations that are at least moderately concentrated in more than 20 MSAs. More specifically, workers in the *Farming, Forestry, and Fishing* category face concentrated labor markets in 67 metropolitan areas, *Scientists* in 45, workers in the *Computers and Mathematics* category in 39, *Architects and Engineers* in 31, and *Lawyers* in 22 MSAs.

Third, workers in around half the occupation groups face almost perfectly competitive markets in most, if not all, metropolitan areas, with the *HI* in most cases being below 0.10. These categories include *CEOs and Managers*, *Sales* occupations, *Food Preparation and Serving*, and *Cleaning and Maintenance*. Even though this result is perhaps not surprising for the latter two categories, one may argue that this is not an accurate indication of local marker conditions for the first two.

An important reason why workers in certain occupation groups appear to face competitive labor markets in most MSAs is the level of aggregation. Due to data confidentiality issues,[37] the *HI* is constructed for very broad occupational categories and, unfortunately, this may drive the index down in all metropolitan areas. For example, consider two workers in the *Sales* category, namely a car salesman and a software salesman. By aggregating these categories together, we consider a car

[37] Tabulating the unpublished 200 Census data using all occupation classifications (and not just the broad 23 categories used) is feasible. However, disclosure of the confidential data was conditional on calculating the *HI* for the 23 broad occupational categories.

dealership to be a potential employer of a software salesman and a software company a potential employer for a car salesperson. In other words, at this level of aggregation the *HI* is very likely to be lower than 0.10 for most metropolitan areas for sales occupations since we include all these employers in the calculation of the index. This issue can only be resolved by producing the *HI* at a lower level of aggregation, by occupation, and obtain access to the output for the purposes of this paper.

Overall, there is substantial variation in market concentration both across occupations and across metropolitan areas, by occupation. This variation can be exploited for the purposes of testing whether market competition matters in wage setting, especially in the presence of worker mobility costs. I merge the *HI* to the data, and use it as a measure of local labor market concentration in the wage specification. Since the *HI* measures the lack of competitiveness in the local market, one expects mobility costs to matter more for workers in concentrated markets, given their occupation classification. In other words, the interaction between *MCI* and *HI* should have a negative effect on wages. Estimation results are summarized in Table 10a.

Similar to the previous results, the *MCI* has a significant negative effect on wages even after controlling for market concentration. The estimated coefficient for *MCI* is -0.1278 when we control for market concentration, while the *HI* has a significant negative effect on wages (-0.9601). In the same table, I report the results when the interaction between *MCI* and *HI* is added in the specification. We see that the interaction effect is significantly negative (-0.6796), while the *MCI* still has a significant negative effect on wages (-0.1198). Since I construct the *HI* using city blocks, it is possible that the results are driven by the size of the city rather than the actual effect of market concentration on wages. The reason is that the number of city blocks is a function of city size and the *HI* is inversely related to the number of city blocks. In the rightmost column of Table 9, I report the estimates when we control for the population in the MSA of the worker. The coefficients of interest remain mostly unaffected, with the only difference being the lower effect of the *HI* on wages (-0.3823 in column 4, compared to -0.7293 in column 3).

To understand the effect of market concentration on wages, I calculate the mean predicted income at different values of the *HI* distribution. The output of this exercise is presented in Table 10b. First, the mean predicted income, evaluated at the sample means of *MCI*, other worker characteristics, and the *HI*, is 44,358 USD. Workers in a "perfectly competitive" market, where the *HI* is equal to 0, earn on average an estimated 44,823 USD or 1 percentage points more than the sample mean.

Workers in a moderately concentrated market (*HI*=.10) earn 8.53 percentage points less than the average worker, whereas workers in a highly concentrated market (*HI*=.18) have wages that are 15.51 percentage points lower than the sample mean.[38] The effect of market concentration on the wages of workers that lie on the upper levels of the *HI* distribution is very large. Workers in extremely concentrated markets (*HI*=0.50) earn wages that are on average 38.48 percentage points lower than the sample mean. Finally, in the extreme and unlikely case in which a worker was

[38] Referring back to Table 9, these results suggest that workers in 464 occupation-MSA pairs in this context earn between 8.53 to 15.51 percentage points less than the sample mean. As discussed earlier, the *HI* is calculated at a very high level of aggregation, which may drive the index down for certain occupation groups. If the *HI* could be produced at a more disaggregated level, the latter result would probably apply to an even higher portion of occupation-MSA combinations.

employed in a monopsonistic local market (*HI*=1) then he would face wages that are more than 60 percentage points lower than the sample mean.[39]

This set of results also shows that workers that are observably less mobile across locations experience significantly lower wages. Holding market concentration and other worker characteristics constant, workers that face high costs of moving across local markets experience lower wages. At the same time, the negative effect of worker immobility on wages is significantly higher for workers in local labor markets where employment opportunities in their occupation group are relatively concentrated, holding mobility cost indicators and other personal characteristics equal.

3.6 The Effect of Unionization on Exploitation

In the wage bargaining model discussed in this paper, firms use information on workers' mobility costs in their wage setting behavior. As a result, a worker that signals positive mobility costs receives a wage offer that is lower than the competitive rate. Since this result is based on the premise that each firm renegotiates wages separately with each worker, such outcome is less likely to occur when workers are members of a union, that is, when wages are collectively bargained.

For example, if the employer reaches an agreement with the union representatives on the compensation of the workers, it would be difficult for the firm

[39] Very few occupation-MSA pairs have a *HI* that is close to 1. This means that the prediction that workers in extremely concentrated local labor markets (or local monopsonies) earn substantially lower wages compared to the sample mean applies to a very small portion of workers in the sample, mainly college professors and physicians. If a more disaggregated version of the *HI* were available, we would probably have more occupation-MSA pairs with high values of the *HI*; the significant effect of extreme market concentration on wages would be relevant for more occupational categories. Nevertheless, the effect of local labor market concentration on wages is found to be important in this context solidifying the point that worker immobility may lead to lower wages especially for workers in less competitive local labor markets.

to demand that workers with positive costs of moving receive lower wages. Therefore, heterogeneity in terms of worker mobility costs will not be relevant in the wage bargaining for workers in highly unionized occupations, which is to say that the intuition of the model is more likely to apply to occupations were wages are individually set.

For this reason, we expect that mobility cost indicators should not matter as much for workers that are members of a union. To test this hypothesis we need information on each worker's union status, which unfortunately is not available in the 2000 Decennial Census. Instead, I use the March Supplement of the 2000 Current Population Survey (CPS) that reports not only the worker's occupation – categorized by the Standard Occupation Classification (SOC) coding – but also the worker's union affiliation. The idea is to construct a measure of unionization, by occupation, which captures the conditional probability that a worker is a union member, given his occupation category. More specifically, I calculate the percentage of workers that are union members for each one of the 23 broad occupational categories defined by the SOC.[40]

To test if individual mobility costs matter less for wages of workers in highly unionized occupations, I re-estimate equation (9), and I include the unionization rate (*Union*) and the interaction between *Union* and *MCI* in the specification. The unionization measure captures the likelihood of a worker being a union member, given his occupational group, and the interaction term captures the effect of unionization on the relationship between *MCI* and wages. Following the

[40] Table 8 features a breakdown of the sample into the 23 broad occupational categories defined by the SOC, and the CPS unionization rate for each category.

aforementioned intuition, the interaction between *Union* and *MCI* should have a positive effect on wages.

Table 11 reports the results. Columns (1)-(2) of the table show the estimation results when I use *MCI* as a measure of worker mobility costs and *Firms(M)* as a measure of market competition, while in columns (3)-(4) I use the *HI* to capture local labor market concentration. In column (2), the estimated effect of the *MCI* on wages is negative and statistically significant, and the *MCI*, *Firms(M)* interaction effect is significantly positive. At the same time, the interaction between *MCI* and *Union* is also positive (.0068) and significant, suggesting that workers in highly unionized occupations face lower wage penalties because of their observed immobility.

Using the *HI* as a measure of local market competition does not alter this result. The interaction between *MCI* and *Union* is still positive (.0063) and significant in column (4), suggesting that the effect of this interaction term is robust to the use of different measures of local competition. Overall, the results in Table 11 suggest that the negative effect of mobility costs on wages is lower for workers in highly unionized occupations, in which individual wage bargaining is likely to occur.[41]

3.7 Conclusions

In this chapter, I present a model of wage discrimination in which firms exploit worker mobility costs to offer workers lower wages when wages are

[41] I can use this result to provide another test for whether important mobility cost indicators, like *State of Birth* and *Spouse State of Birth*, are correlated with unobserved ability. Specifically, if the aforementioned characteristics are uncorrelated with unobserved ability they should not be important wage predictors for workers in highly unionized occupations. Therefore, I estimate the wage equation for workers that are in highly unionized occupations (Union >20%) and find that *State of Birth* and *Spouse State of Birth* do not have the same significant negative effect on wages as before. In fact, both coefficients are not significantly different to zero. See Table C of the Appendix for a summary of the results.

renegotiated. The model also suggests that the wage setting power firms enjoy in this context diminishes in the intensity of the labor market competition, along with the relevance of worker moving costs in wage setting.

Empirically, the model finds substantial support. Worker characteristics that serve as proxies for their individual moving costs have a strong negative effect on wages. At the same time, keeping individual mobility costs constant, the magnitude of exploitation is significantly higher for workers in small, less competitive metropolitan areas. Moreover, workers in highly unionized occupations are not subject to such discrimination, since individual wage bargaining is less likely to occur. Empirical results show that mobility costs have a strong negative effect on wages, but that negative effect is significantly lower for workers in occupations with a strong union presence, even after controlling for local market competition.

The findings in this paper contribute to the discussion of what explains the important wage differences across local markets. Higher wages in large metropolitan areas are in general connected with higher productivity or with undesirable local amenities and working conditions. It appears possible that another reason we observe higher wages in such markets is that the intensity of the local labor market competition in large metropolitan areas reduces the wage setting power employers enjoy in this context. Workers in smaller markets are more likely to face lower wages because of their observed immobility, because of the presence of relatively fewer employment opportunities within their current market. Overall, the intensity of the local labor market competition should have a central role in discussing what determines the important wage disparities across locations.

Appendix

Table A: Population Growth and the Effect of Mobility Cost Indicators on Wages

	(1)	(2)	(3)	(4)
State Own	-.0716** (.0150)	--	-.0462** (.0134)	--
Spouse State	-.0441** (.0092)	--	-.0297** (.0082)	--
MCI	--	-.2074** (.0314)	--	-.1638** (.0279)
State Own x Firms(M)	.0024** (.0004)	--	--	--
Spouse State x Firms(M)	.0018** (.0004)	--	--	--
MCI x Firms(M)	.0032** (.0009)	.0049** (.0009)	--	--
Firms(M)	.0032** (.0009)	.0031** (.0009)	--	--
Pop Growth	-.0016 (.0013)	-.0019 (.0014)	-.0024 (.0014)	-.0029 (.0015)
State Own x Pop Growth	.0014 (.0010)	--	.0014 (.0011)	--
Spouse State of Birth x Pop Growth	.0007 (.0007)	--	.0009 (.0007)	--
MCI x Pop Growth	--	.0021 (.0021)	--	.0024 (.0022)
R-Squared	0.3530	0.3544	0.3455	0.3473
Observations	788,728	788,728	788,728	788,728

Note: Dependent variable is the logarithm of wages. *MCI* is the mobility cost index, as defined in equation (9). *Firms(M)* is the number of firms in the MSA of the worker, in 10,000s. *Pop Growth* is the percentage population growth in the MSA of the worker between 1990 and 1997 (source: State and Metropolitan Area Data Book, 1997-98, US Census Bureau). Least Squares estimates, with standard errors clustered by metropolitan area, and reported in parenthesis. Not reported are the estimated effects of available demographic characteristics, listed in Tables 1a and 1b. * = statistically significant at the 5% level, ** = statistically significant at the 1% level.

Table B: Regression Results for Select Worker Sub-Samples

	(1)	(2)	(3)	(4)	(5)	(6)
State of Birth	--	--	--	-.0332** (.0071)	--	--
Spouse State of Birth	-.0177* (.0074)	--	--	--	--	--
MCI	--	-.2841** (.0233)	-.3468** (.0219)	--	-.1856** (.0167)	-.2531** (.0211)
Firms(M)	.0034*** (.0008)	.0034** (.0008)	.0027** (.0008)	.0039** (.0008)	.0039** (.0008)	.0029** (.0008)
MCI x Firms(M)	--	--	.0051** (.0009)	--	--	.0056** (.0009)
Sample Restriction	State of Birth = 0			Spouse State of Birth = 0		
R-Squared	0.3826	0.3069	0.3854	0.3756	0.3503	0.3776
Observations	403,733	403,733	403,733	488,206	488,206	488,206

Note: Dependent variable is the logarithm of wages. *MCI* is the mobility cost index, as defined in equation (9). *Firms(M)* is the number of firms in the MSA of the worker, in 10,000s. Least Squares estimates, with standard errors clustered by metropolitan area, and reported in parenthesis. Not reported are the estimated effects of available demographic characteristics, listed in Tables 1a and 1b. * = statistically significant at the 5% level, ** = statistically significant at the 1% level.

Table C: Unionization and the Effect of Mobility Cost Indicators on Wages

	(1)	(2)	(3)	(4)
State of Birth	-.0500** (.0062)	-.0005 (.0067)	--	--
Spouse State of Birth	-.0335** (.0054)	.0099 (.0053)	--	--
MCI	--	--	-.2538** (.0186)	-.0617** (.0163)
Firms(M)	.0049** (.0008)	.0052** (.0008)	.0034** (.0010)	.0032** (.0008)
MCI x Firms(M)	--	--	.0042** (.0009)	.0052** (.0010)
Sample Restriction	Union < 10%	Union > 20%	Union < 10%	Union > 20%
R-Squared	0.3223	0.2099	0.3263	0.2110
Observations	415,872	246,208	415,872	246,208

Note: Dependent variable is the logarithm of wages. *MCI* is the mobility cost index, as defined in equation (9). *Firms(M)* is the number of firms in the MSA of the worker, in 10,000s. Least Squares estimates, with standard errors clustered by metropolitan area, and reported in parenthesis. Not reported are the estimated effects of available demographic characteristics, listed in Tables 1a and 1b. * = statistically significant at the 5% level, ** = statistically significant at the 1% level.

Table 1: Variable Description

Log w	Logarithm of season salary
Minutes	Minutes played per game
Offense	Points per game + Assists per game – Turnovers per game
Defense	Rebounds per game + Steals per game + Blocks per Game
Experience	Number of years player has played in the NBA
Tenure	= 1 if player has been with the same team for more than 3 years, 0 else
High School	= 1 if player entered the NBA directly from high school, 0 else
Drafted	= 1 if player was drafted, 0 else
Draft no	Draft number, conditional on Drafted=1, 0 else
Black	= 1 if player is black, 0 else
Foreigner	= 1 if player is foreigner, 0 else
Log Pop	The logarithm of the population in the team's city
Crime	Crime rate in the team's city
Canada	= 1 if team is located in Canada
Same Place	= 1 if player played college basketball or was born in the team's state, 0 else
Same Race	The percentage of the population in the team's city that has the same race with the player
Snowfall	The average monthly snowfall in inches in team's city
Rainfall	The average monthly rainfall in inches in team's city
Temperature	The average daily temperature in team's city
Hot	= 1 if the May–October average daily temperature is above 80 degrees, 0 else
Cold	= 1 if the November–April average daily temperature is below 40 degrees, 0 else
Coach Playoff	= 1 if coach of the team has previous playoff experience, 0 else
Coach Ring	= 1 if coach of the team has won a championship, 0 else
Winning	= 1 if the team had a winning record the season before, 0 else
Champs	= 1 if the team are the current NBA champions, 0 else

Table 2: Estimation Results for the Hedonic Wage Equation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Minutes	.0074***	.0081***	.0083***	.0077***	.0085***	.0083***	.0083***
24.77 (10.18)	(.0017)	(.0017)	(.0017)	(.0017)	(.0017)	(.0017)	(.0017)
Offense	.0148***	.0145***	.0140***	.0145***	.0137***	.0140***	.0140***
10.98 (6.80)	(.0024)	(.0022)	(.0023)	(.0024)	(.0023)	(.0023)	(.0023)
Defense	.0121**	.0105**	.0105**	.0119**	.0103**	.0105**	.0105**
5.85 (3.39)	(.0048)	(.0048)	(.0048)	(.0048)	(.0048)	(.0048)	(.0048)
Experience	.0777***	.0775***	.0773***	.0779***	.0775***	.0773***	.0773***
3.52 (3.20)	(.0077)	(.0076)	(.0076)	(.0076)	(.0076)	(.0076)	(.0076)
Experience	-.0045***	-.0044***	-.0044***	-.0045***	-.0044***	-.0044***	-.0044***
Square	(.0006)	(.0006)	(.0006)	(.0006)	(.0006)	(.0006)	(.0006)
Tenure	.0842***	.0835***	.0853***	.0843***	.0854***	.0857***	.0857***
36.14%	(.0204)	(.0203)	(.0197)	(.0201)	(.0194)	(.0197)	(.0197)
Drafted	.2623***	.2601***	.2660***	.2653***	.2689***	.2670***	.2670***
87.86%	(.0446)	(.0449)	(.0448)	(.0443)	(.0444)	(.0449)	(.0449)
Draft Number	-.0067***	-.0066***	-.0068***	-.0067***	-.0068***	-.0068***	-.0068***
16.06 (14.41)	(.0008)	(.0008)	(.0008)	(.0007)	(.0008)	(.0008)	(.0008)
High School	.0937***	.0963***	.0903***	.0912***	.0878***	.0903***	.0903***
2.75%	(.0327)	(.0335)	(.0345)	(.0330)	(.0349)	(.0345)	(.0345)
Height	.0058***	.0059***	.0058***	.0059***	.0059***	.0058***	.0058***
201.22 (9.52)	(.0015)	(.0015)	(.0015)	(.0015)	(.0015)	(.0016)	(.0016)
Black	-.0048	-.0039	-.0041	-.0034	-.0040	-.0040	-.0040
80.24%	(.0172)	(.0176)	(.0238)	(.0170)	(.0238)	(.0236)	(.0236)
Foreigner	.0038	.0071	.0041	.0028	.0032	.0036	.0036
7.76%	(.0287)	(.0290)	(.0287)	(.0286)	(.0286)	(.0287)	(.0287)
Log Pop		.2249***	.2336***	--	.2366***	.2188***	.2234***
13.56 (.92)	--	(.0528)	(.0588)		(.0557)	(.0597)	(.0566)
Crime Rate		.0502**	.0501**	--	.0485**	.0496**	.0481**
3.82 (.31)	--	(.0200)	(.0199)		(.0194)	(.0203)	(.0198)
Canada		.2096**	.2003**	--	.2056**	.1986**	.1985**
4.31%	--	(.0903)	(.0963)		(.0986)	(.0981)	(.0981)
Same Race			-.0781**	--	-.0781**	-.0749**	-.0752**
.37 (.27)	--	--	(.0325)		(.0328)	(.0327)	(.0329)
Same Place			-.0347	--	-.0349	-.0352	-.0353
10.75%	--	--	(.0303)		(.0289)	(.0302)	(.0288)
Snowfall				--		.0751**	.0759**
1.58 (1.71)	--	--	--		--	(.0387)	(.0298)
Rainfall				--		.0767***	.0755***
2.87 (1.05)	--	--	--		--	(.0248)	(.0229)
Temperature				--		-.0101**	-.0101**
57.35 (8.23)	--	--	--		--	(.0049)	(.0049)
Cold				--		.2091***	.2111***
52.24%	--	--	--		--	(.0503)	(.0477)
Hot				--		.2458***	.2480***
18.75%	--	--	--		--	(.0749)	(.0743)
Coach Playoff				-.0268**	-.0264**		-.0260**
72.67%	--	--	--	(.0126)	(.0123)	--	(.0123)
Coach Ring				.0352	.0373		.0372
17.58%	--	--	--	(.0295)	(.0301)	--	(.0302)
Winning				.0258	.0246		.0244
55.37%	--	--	--	(.0225)	(.0217)	--	(.0217)
Champs				-.0180	-.0188		-.0189
3.13%	--	--	--	(.0272)	(.0292)	--	(.0288)
R-squared	0.6801	0.6822	0.6834	0.6822	0.6855	0.6835	0.6856

Notes: Dependent variable is the logarithm of wages (2065 observations). Independent variable names, means, and standard deviations are reported in the leftmost column. Year Fixed Effects and intercept are not reported. Standard errors are clustered by team and reported in parenthesis. *= significant at the 10% level, **= significant at the 5% level, ***=significant at the 1% level.

Table 3: Weather Conditions and Wage Differences across NBA Cities

	Mean Predicted Wages	Percentage Deviation from Sample Mean
Total Sample	$2,279,120	0.00
Los Angeles, CA	$1,949,890	-14.45
Oakland, CA	$1,987,100	-12.81
Sacramento, CA	$2,028,064	-11.02
Phoenix, AZ	$2,061,109	-9.57
Charlotte, NC	$2,067,220	-9.30
Memphis, TN	$2,110,990	-7.38
Atlanta, GA	$2,115,963	-7.16
Indiana, IN	$2,218,972	-2.64
Portland, OR	$2,254,231	-1.09
San Antonio, TX	$2,264,511	-0.64
Miami, FL	$2,274,122	-0.22
Seattle, WA	$2,308,815	0.98
Dallas, TX	$2,345,303	2.18
Washington, DC	$2,356,864	2.56
Orlando, FL	$2,372,133	3.06
Houston, TX	$2,415,347	4.48
Philadelphia, PA	$2,488,597	6.89
New York City	$2,510,259	7.61
Newark, NJ	$2,513,138	7.70
Toronto, Canada	$2,609,123	10.86
Denver, CO	$2,624,032	11.35
Milwaukee, WI	$2,629,894	11.54
Cleveland, OH	$2,648,233	12.15
Detroit, MI	$2,660,104	12.54
Chicago, IL	$2,729,053	14.81
Boston, MA	$2,744,334	15.31
Salt Lake City, UT	$2,781,478	16.53
Minneapolis, MN	$2,906,836	20.66

Note: Mean predicted wages are calculated as described in text.

Table 4: Estimated Compensating Differences with Unobserved Player Heterogeneity

	(1)	(2)	(3)	(4)	(5)
Experience	.1466*** (.0080)	.1145*** (.0095)	.1505*** (.0073)	.1196*** (.0087)	.1154*** (.0082)
Experience Square	-.0082*** (.0007)	-.0061*** (.0008)	-.0084*** (.0007)	-.0065*** (.0008)	-.0067*** (.0007)
Tenure	--	.2071*** (.0225)	--	.1978*** (.0209)	.1580*** (.0222)
Drafted	--	--	--	--	.5147*** (.0430)
Draft Number	--	--	--	--	-.0127*** (.0009)
High School	--	--	.2639*** (.0782)	.2445*** (.0713)	.1421** (.0647)
Height	--	--	.0084*** (.0013)	.0082*** (.0013)	.0041*** (.0012)
Black	.0580 (.0447)	.0321 (.0437)	.0872** (.0414)	.0619 (.0400)	-.0005 (.0373)
Foreigner	.1683*** (.0508)	.1476*** (.0503)	.0943** (.0457)	.0767* (.0440)	.0724* (.0362)
Log Pop	2291*** (.0677)	.2296*** (..0699)	.1771*** (.0314)	.1794*** (.0334)	.1835*** (.0178)
Crime Rate	.0919 (.0506)	.0928* (.0499)	.0840* (.0489)	.0760* (.0482)	.0467* (.0245)
Canada	.1219 (.0999)	.1519 (.1034)	.0737* (.0413)	.0580 (.0444)	.0958*** (.0285)
Same Race	-.0458 (.0612)	-.0738 (.0555)	-.0274 (.0545)	-.0551 (.0485)	-.1193** (.0473)
Same Place	-.0334 (.0535)	-.0301 (.0469)	-.0186 (.0548)	-.0551 (.0484)	-.0438 (.0368)
Snowfall	.0616 (.0434)	.0310 (.0438)	.0353 (.0281)	.0073 (.0285)	-.0108 (.0211)
Rainfall	.0475 (.0410)	.0258 (.0407)	.0248 (.0313)	.0052 (.0305)	-.0265 (.0237)
Temperature	-.0105* (.0055)	-.0210*** (.0065)	-.0140** (.0061)	-.0193*** (.0061)	-.0103** (.0051)
Cold	.1886*** (.0477)	.2380*** (.0498)	.1677*** (.0252)	.2147*** (.0272)	.2060*** (.0208)
Hot	.2616** (.1209)	.3090** (.1236)	.2245** (.1105)	.2300** (.1106)	.2194** (.0953)
Coach Playoff	-.0129 (.0182)	-.0137 (.0195)	-.0186 (.0174)	-.0191 (.0182)	-.0278** (.0126)
Coach Ring	.0206 (.0410)	.0093 (.0395)	.0255 (.0377)	.0144 (.0363)	.0314 (.0289)
Winning Record	-.0090 (.0239)	-.0155 (.0236)	-.0094 (.0223)	-.0157 (.0219)	.0114 (.0221)
Champs	.0247 (.0389)	.0046 (.0472)	..0180 (.0390)	-.0009 (.0471)	-.0257 (.0465)
R-squared	0.3472	0.3845	0.3865	0.4204	0.5774

Notes: Dependent variable is the logarithm of wages (2065 observations). *Minutes*, *Defense*, and *Offense* are omitted from all specifications. Year Fixed Effects and intercept are not reported. Standard errors are clustered by team and reported in parenthesis. *= significant at the 10% level, **= significant at the 5% level, ***=significant at the 1% level.

Table 5: Estimation of the Wage Equation using Alternative Models

	LINEAR REGRESSION MODELS			BOX-COX MLE MODELS [a]		
	First Order (1)	Second Order [b] (2)	Partially Linear [c] (3)	Only LHS (4)	Both Sides Restricted (5)	Both Sides Unrestricted (6)
Log Pop	.2234*** (.0566)	.1867*** (.0501)	.2173*** (.0625)	.2232** (.029)	.2449** (.035)	.2199** (.031)
Crime Rate	.0481** (.0198)	.0430** (.0192)	.0489** (.0211)	.0541*** (.003)	.0254*** (.002)	.0565*** (.003)
Canada	.1985** (.0981)	.1554* (.0867)	.2059* (.1086)	.1939** (.046)	.1815** (.047)	.1930** (.048)
Same Race	-.0752** (.0329)	-.0557** (.0256)	-.0945** (.0431)	-.0733** (.034)	-.0675* (.052)	-.0731** (.045)
Same Place	-.0353 (.0288)	-.0315 (.0270)	-.0348 (.0304)	-.0354* (.054)	-.0345* (.061)	-.0356* (.055)
Snowfall	.0759** (.0298)	.0661** (.0263)	.0720** (.0316)	.0725* (.051)	.0873** (.030)	.0704** (.047)
Rainfall	.0755*** (.0229)	.0625*** (.0217)	.0707*** (.0233)	.0745** (.039)	.1283* (.052)	.0696** (.048)
Temperature	-.0101** (.0049)	-.0089* (.0048)	-.0104** (.0049)	-.0096** (.049)	-.0093** (.045)	-.0097** (.047)
Cold	.2111*** (.0477)	.1777*** (.0449)	.2236*** (.0518)	.2131** (.019)	.1980** (.030)	.2123** (.024)
Hot	.2480*** (.0743)	.2316** (.1040)	.2158** (.1051)	.2321*** (.001)	.2877*** (.004)	.2292*** (.003)
Coach Playoff	-.0260** (.0123)	-.0245** (.0120)	-.0266** (.0124)	-.0258** (.047)	-.0257** (.048)	-.0257** (.048)
Coach Ring	.0372 (.0302)	.0391 (.0275)	.0410 (.0313)	.0380 (.175)	.0368 (.185)	.0381 (.0183)
Winning Record	.0244 (.0217)	.0307 (.0213)	.0234 (.0330)	.0240 (.202)	.0195 (.185)	.0247 (.203)
Champs	-.0189 (.0288)	-.0126 (.0266)	-.0158 (.0330)	-.0254 (.497)	-.0287 (.445)	-.0254 (.0442)
R-squared	0.6856	0.6934	0.6721	--	--	--
LR test [d]	2.065	1.4455	7.228	--	--	--
Ramsey F-test [e]	1.73 (.183)	0.90 (.454)	2.60 (.080)	--	--	--
Log Likelihood	--	--	--	-41.543	-45.387	-41.445

Notes: Dependent variable is the logarithm of wages (2065 observations). Estimated coefficients for personal characteristics are not reported. In parenthesis, are reported the clustered standard errors by team in columns (1)-(3) and the p-values of the LR test in columns (4)-(6). *= significant at the 10% level, **= significant at the 5% level, ***=significant at the 1% level.

a= For comparison purposes, the Box-Cox coefficients are linearized, as discussed by Linneman (1980) and Greene (2001). The optimal transformation coefficients are 2.660 for specification (4), 2.811 for specification (5), and 2.643 (0.838 for the independent variables) in specification (6). All transformation parameters are statistically significant at the 1% level.

b= 2[nd] Order Specification includes the squares of *Minutes*, *Offense*, *Defense*, *Draft Number* and *Height.*

c= Specification includes dummy variables for each quartile of the distributions of *Minutes*, *Offense*, *Defense*, *Draft Number* and *Height*.

d= The LR test statistic is distributed χ^2_3 (Critical values: 9.49 - 5% , 13.28 - 1%), Null Hypothesis: No higher order terms are omitted in specification. See Wooldridge (2001), p.125-126.

e= The F-Statistic and p-value for the RESET misspecification test (Ramsey ,1969) are reported. The null hypothesis is that there is no omission of higher order or interaction terms in the specification. This statistic is derived by taking the fitted values from the model being tested and producing higher order terms of its fitted values. These terms are included in the base model and a standard F-test is performed to determine whether they are jointly significantly different from zero.

Table 6: Estimation of the Wage Equation with Unobserved Player Heterogeneity

	LINEAR REGRESSION MODELS		BOX-COX MLE MODELS		
	First Order (1)	Partially Linear (2)	Only LHS (3)	Both Sides Restricted (4)	Both Sides Unrestricted (5)
Log Pop	.1794*** (.0334)	.1754*** (.0205)	.1817 (.191)	.2709 (.198)	.2617 (.192)
Crime Rate	.0760* (.0482)	.0467* (.0282)	.0842 (.001)	.0257*** (.000)	.0463** (.032)
Canada	.0580 (.0444)	.0786*** (.0253)	.0650 (.745)	.0629 (.752)	.0589 (.750)
Same Race	-.0551 (.0485)	-.1134** (.0455)	-.0588 (.211)	-.0576 (.219)	-.0546 (.217)
Same Place	-.0551 (.0484)	-.0360 (.0368)	-.0180 (.472)	-.0176 (.481)	-.0172 (.477)
Snowfall	.0073 (.0285)	-.0229 (.0207)	.0053 (.953)	.0251 (.799)	.0893 (.801)
Rainfall	.0052 (.0305)	-.0347 (.0238)	.0040 (.963)	.1297 (.744)	.1420 (.837)
Temperature	-.0193*** (.0061)	-.0107** (.0048)	-.0201 (.243)	-.0100 (.237)	-.0127 (.234)
Cold	.2147*** (.0272)	.2095*** (.0206)	.2245* (.069)	.2115* (.086)	.1559* (.087)
Hot	.2300** (.1106)	.2766*** (.0310)	.2073*** (.006)	.1983*** (.008)	.2201*** (.007)
Coach Playoff	-.0191 (.0182)	-.0299* (.0153)	-.0199 (.331)	-.0197 (.335)	-.0191 (.332)
Coach Ring	.0144 (.0363)	.0302 (.0269)	.0165 (.571)	.0169 (.559)	.0185 (.543)
Winning Record	-.0157 (.0219)	.0105 (.0223)	-.0139 (.485)	-.0142 (.476)	-.0141 (.482)
Champs	-.0009 (.0471)	-.0169 (.0376)	-.0006 (.904)	-.0055 (.914)	-.0035 (.909)
R-Squared	0.4204	0.5676	--	--	--
Log Likelihood	--	--	-680.515	-677.584	-674.748
LR Test	5.369	3.924	--	--	--
Ramsey F-Test	0.91 (0.451)	0.83 (0.487)	--	--	--

Notes: Dependent variable is the logarithm of wages (2065 observations). Not included in the specifications are *Minutes*, *Offense*, *Defense*, *Draft Number*, and *Drafted*. For a description of the statistical models and the specification tests, see notes of Table 4. Note that the specification in column (2) includes dummy variables for each quartile of the distributions of *Experience* and *Height*. Estimated coefficients for personal characteristics are not reported. In parenthesis, are reported the clustered standard errors by team in columns (1)-(3) and the p-values of the LR test in columns (4)-(6). *= significant at the 10% level, **= significant at the 5% level, ***=significant at the 1% level. The optimal transformation coefficients are 2.672 for specification (3), 2.785 for specification (4), and 7.068 (2.736 for the independent variables) in specification (6). All transformation parameters are significant at the 1% level.

Table 7a: Sample Description

	Sample Proportions		Sample Proportions
Education		Race	
Less 9th Grade	3.47%	White	82.30%
9th-12th Grade	7.45%	Black	7.90%
High School Diploma	54.62%	American Indian	0.46%
College Degree	20.30%	Chinese	1.11%
Graduate Degree	11.85%	Japanese	0.38%
PhD	2.29%	Other Asian	2.48%
Married	77.25%	Other Race	3.67%
Has Children	58.04%	Multiple Races	1.69%
Disabled	10.37%	Hispanic	8.62%
No English	3.08%	Foreigner	14.52%

Note: Author's tabulations of the 5% PUMS of the 2000 Decennial Census. Sample includes full-time (30+ weeks of work, 30+ hours of work per week) male workers, ages 35-64, living in an identifiable metropolitan statistical area and reported positive earnings. Observations: 788,728.

Table 7b: Sample Description

	Sample Mean	Standard Deviation
Age	46.525	7.674
Income	57,384	54,097
Log Wage	10.700	0.688

Note: Author's tabulations of the 5% PUMS of the 2000 Decennial Census. Sample includes full-time (30+ weeks of work, 30+ hours of work per week) male workers, ages 35-64, living in an identifiable metropolitan statistical area and reported positive earnings. Observations: 788,728.

Table 8a: Number of Establishments at the Metropolitan Area level

Summary Statistics (across all MSAs)	
Mean	38,171
St. Dev.	59,196
Minimum	1,170
Maximum	491,578
Number of Establishments	Number of MSAs
Over 300,000	2
Over 200,000	7
Over 100,000	28
Over 50,000	60
Over 10,000	194
Less than 10,000	89

Source: Author's tabulations of the 2000 County Business Patterns. Summary statistics reported only for the 283 metropolitan areas included in the PUMS.

Table 8b: Total Number of Establishments, select Metropolitan Areas

Metropolitan Statistical Area	Total Number of Establishments
New York City, NY	491,578
Los Angeles-Long Beach, CA	452,564
Atlanta, GA	226,766
Detroit, MI	104,588
Houston-Brazoria, TX	197,076
Washington DC	152,872
San Jose, CA	91,310
Orlando, FL	89,858
Charlotte, SC	84,362
Indianapolis, IN	84,114
Cincinnati, OH	76,656
Pueblo, CO	6,374
Jacksonville, NC	5,204
Anniston, AL	5,132
Yuma, AZ	5,074
Kokomo, IN	4,580
Charlottesville, VA	1,540

Source: County Business Patterns 2000.

Table 9: Moving Cost Indicators and Relocation Decisions

	Sample Proportions	Proportions	
		Non-Movers	Movers
Total Sample	100%	75.16%	24.84%
State of Birth	42%	86.25%	13.75%
Spouse State of Birth	30%	85.44%	14.56%
Spouse Works FT	40%	78.81%	21.19%
Spouse In School	4%	74.58%	25.42%
Spouse or Child Disabled	7%	79.24%	20.76%
Parents Present	2%	78.90%	21.10%

Note: Mover is a worker that reported a different metropolitan area of residence for 1995 and 2000. Non-Mover is a worker that reported the same metropolitan area of residence for 1995 and 2000. Metropolitan Area of residence in 1995 and 2000 is only available for 262,623 respondents.

Table 10: Marginal Probability Effects of Moving Cost Indicators on Migration Decisions

	(1)	(2)	(3)
State of Birth	-.157 (.002)**	-.155 (.002)**	-.155 (.002)**
Spouse State of Birth	-.114 (.002)**	-.111 (.002)**	-.111 (.002)**
Spouse Works FT	--	-.081 (.002)**	-.081 (.002)**
Spouse In School	--	-.013 (.004)**	-.013 (.004)**
Parents Present	--	--	-.029 (.007)**
Spouse or Child Disabled	--	--	-.016 (.004)**
Married	.069 (.002)**	.113 (.002)**	.114 (.002)**
Has a Child	-.034 (.002)**	-.042 (.002)**	-.042 (.002)**
Education: 9th – 12th Grade	.000 (.000)	.006 (.006)	.006 (.007)
Education: High School Diploma	.041 (.006)**	.048 (.006)**	.048 (.006)**
Education: College Degree	.103 (.007)**	.108 (.007)**	.107 (.007)**
Education: Graduate Degree	.140 (.008)**	.141 (.008)**	.141 (.008)**
Education: PhD	.210 (.011)**	.213 (.011)**	.212 (.011)**
Age / 10	-.049 (.014)**	-.012 (.014)	-.011 (.014)
Age Square / 100	.003 (.000)**	.002 (.002)	-.001 (.002)
Foreigner	-.085 (.003)**	-.085 (.003)**	-.085 (.003)**
Hispanic	.022 (.004)**	.019 (.004)**	.020 (.004)**
Race: Black	-.030 (.003)**	-.026 (.003)**	-.025 (.003)**
Race: American Indian	.167 (.015)**	.165 (.015)**	.166 (.015)**
Race: Chinese	.012 (.008)	.019 (.008)*	.020 (008)*
Race: Japanese	.018 (.015)	.015 (.015)	.015 (.015)
Race: Other Asian	.022 (.006)**	.025 (.006)**	.027 (.006)**
Race: Other Race	.054 (.007)**	.053 (.007)**	.053 (.007)**
Race: Multiple Races	.196 (.032)**	.199 (.032)**	.201 (.032)**
Pseudo R-Squared	0.0896	0.0953	0.0954

Note: Dependent variable equals 1 if respondent is a *Mover*, 0 otherwise (262,623 observations). Mover is a worker that reported a different MSA of residence in 1995 and in 2000. Probit maximum likelihood estimates of the marginal probability effects are reported, with standard errors in parenthesis. For sample means and proportions, see Tables 1a, 1b, and 3. *= significant at the 5%, level **=significant at the 1% level.

Table 11: Select Groups of Workers and the *MCI* Distribution

	MCI	Sample Proportion	Percentile
Group 1: No Mobility Cost Indicators	.0000	22.63	10th
Group 2: Parents Present	.0724	1.59	25th
Group 3: State of Birth	.3835	13.77	50th
Group 4: State of Birth, Spouse State of Birth	.6569	9.04	75th
Group 5: State of Birth, Spouse State of Birth, Spouse Works FT	.8564	15.35	90th

Note: *MCI* is constructed as described in equation 8. Mean *MCI* = .3862, Standard Deviation =.3061.

Table 12a: The Effect of Mobility Cost Indicators and Local Competition on Wages

	(1)	(2)	(3)	(4)	(5)
State of Birth .4869	-.0286** (.0070)	-.0297** (.0057)	-.0536** (.0078)	-.0296** (.0057)	-.0456** (.0067)
Spouse State of Birth .3791	-.0185** (.0053)	-.0195** (.0049)	-.0344* (.0050)	-.0192** (.0049)	-.0342** (.0045)
Firms(M) 12.335 (12.245)	--	.0048** (.0008)	.0033** (.0009)	--	--
State Own x Firms(M) 5.234 (9.521)	--	--	.0022** (.0004)	--	--
Spouse State x Firms(M) 3.986 (8.464)	--	--	.0017** (.0004)	--	--
Firms(M,I) 4.206 (5.297)	--	--	--	.0109** (.0022)	.0077** (.0023)
State Own x Firms(M,I) 1.748 (3.775)	--	--	--	--	.0043** (.0010)
Spouse State x Firms(M,I) 1.332 (3.332)	--	--	--	--	.0049** (.0008)
R-Squared	0.3442	0.3509	0.3510	0.3495	0.3503
Observations	788,728	788,728	788,728	788,728	788,728

Note: Dependent variable is the logarithm of wages. *MCI* is the mobility cost index, as defined in equation (8). *Firms(M)* is the number of firms in the MSA of the worker, in 10,000s. *Firms(M,I)* is the number of firms in the MSA and industry of the worker, in 1,000s. Least Squares estimates, with standard errors clustered by metropolitan area, and reported in parenthesis. Not reported are the estimated effects of available demographic characteristics, listed in Tables 1a and 1b. * = statistically significant at the 5% level, ** = statistically significant at the 1% level.

Table 12b: Mean Predicted Income at different points of the *Firms(M)* and *Firms(M,I)* Distributions

	(1) *Firms(M)*	(2) Mean Predicted Income (in US $)	(3) *Firms(M,I)*	(4) Mean Predicted Income (in US $)
Mean	12.335	44,365 (0.00)	4.206	44,365 (0.00)
10th Percentile	1.230	42,082 (-5.15)	0.209	43,532 (-1.88)
25th Percentile	2.836	42,422 (-4.38)	0.668	43,633 (-0.86)
50th Percentile	8.436	43,631 (-1.65)	2.267	44,715 (0.79)
75th Percentile	16.762	45,491 (2.54)	5.553	45,883 (3.42)
90th Percentile	27.256	47,950 (8.08)	10.696	47,111 (6.19)

Note: Predicted income is evaluated at the sample means of all characteristics. Predicted income in column (2) is calculated using the estimation coefficients from the specification in Table 6a, column (3). Predicted income in column (4) is calculated using the estimation coefficients from the specification in Table 6a, column (5). In parenthesis is reported the percentage deviation from the mean predicted income.

Table 13a: The Effect of the Mobility Cost Index and Local Competition on Wages

	(1)	(2)	(3)	(4)	(5)
MCI 0.386 (0.306)	-.1270** (.0159)	-.1243** (.0134)	-.1739** (.0162)	-.1253** (.0136)	-.1641** (.0142)
MCI x *Firms(M)* 4.226 (6.239)	--	--	.0045** (.0009)	--	--
MCI x Firms(M,I) 1.416 (2.513)	--	--	--	--	.0075** (.0024)
Firms(M) 12.335 (12.245)	--	.0048** (.0008)	.0032** (.0009)	--	--
Firms(M,I) 4.269 (5.251)	--	--	--	.0109** (.0022)	.0105** (.0021)
R-Squared	0.3458	0.3524	0.3530	0.3511	0.3516
Observations	788,728	788,728	788,728	788,728	788,728

Note: Dependent variable is the logarithm of wages. *MCI* is the mobility cost index, as defined in equation (8). *Firms(M)* is the number of firms in the MSA of the worker, in 10,000s. *Firms(M ,I)* is the number of firms in the MSA and industry of the worker, in 1,000s. Least Squares estimates, with standard errors clustered by metropolitan area, and reported in parenthesis. Similarly to Table 6a, not reported are the estimated effects of all available demographic characteristics. *= statistically significant at the 5% level, ** = statistically significant at 1% level.

Table 13b: Predicted Income across the *MCI* Distribution

	(1) *MCI*	(2) Mean Predicted Income (in US $)	(3) Mean Predicted Income (in US $)
Mean	0.386	44,365 (0.00)	44,365 (0.00)
10^{th} Percentile (Group 1)	0.000	46,809 (5.51)	46,768 (5.42)
25^{th} Percentile (Group 2)	0.072	46,356 (4.49)	46,321 (4.41)
50^{th} Percentile (Group 3)	0.384	44,457 (0.21)	44,450 (0.19)
75^{th} Percentile (Group 4)	0.657	42,852 (-3.41)	42,867 (-3.38)
90^{th} Percentile (Group 5)	0.856	41,719 (-5.96)	41,749 (-5.90)

Note: See Table 5 for definitions of worker groups 1-5. Predicted Income evaluated at sample means of all characteristics. The predicted income in column (2) is calculated using the estimation coefficients from the specification in Table 7a, column (3). The predicted income in column (3) is calculated using the estimation coefficients from the specification in Table 7a, column (5). In parenthesis is reported the percentage deviation from the mean predicted income.

Table 13c: Mean Predicted Income at different points of the *Firms(M)* and *Firms(M,I)* Distributions

	(1) *Firms(M)*	(2) Mean Predicted Income (in US $)	(3) *Firms(M,I)*	(4) Mean Predicted Income (in US $)
Mean	12.335	44,365	4.206	44,365
10^{th} Percentile	1.230	41,699 (-6.01)	0.209	42,117 (-5.07)
25^{th} Percentile	2.836	42,085 (-5.14)	0.668	42,377 (-4.48)
50^{th} Percentile	8.436	43,458 (-2.04)	2.267	43,295 (-2.41)
75^{th} Percentile	16.762	45,584 (2.75)	5.553	45,243 (1.98)
90^{th} Percentile	27.256	48,412 (9.12)	10.696	48,470 (9.25)

Note: Predicted income is evaluated at the sample means of all characteristics. Predicted income in column (2) is calculated using the estimation coefficients from the specification in Table 7a, column (3). Predicted income in column (4) is calculated using the estimation coefficients from the specification in Table 7a, column (5). In parenthesis is reported the percentage deviation from the mean predicted income.

Table 14: Sample Breakdown by Occupation

	Mean Income (St. Dev.)	Observations (PUMS)	Unionization Rate (CPS March 2000)
Legal Occupations	140,561 (107,626)	6,224	3.49%
Physicians, Health Diagnostic	125,995 (105,241)	14,347	7.27%
CEOs & Managers	91,981 (77,898)	116,147	5.47%
Business & Finance	75,387 (67,629)	32,343	8.67%
Computers & Mathematics	70,390 (42,005)	30,609	5.13%
Scientists	67,416 (47,864)	9,248	7.01%
College Professors	66,613 (43,657)	9,900	14.29%
Architects & Engineers	65,746 (47,864)	39,129	1.53%
Sales	64,769 (63,415)	81,597	2.34%
Arts, Media, and Entertainment	60,591 (52,012)	12,474	8.38%
Teachers, Librarians, Archivists	47,288 (22,048)	18,651	38.08%
Installation, Repairers, Mechanics	42,715 (22,321)	62,870	24.62%
Office & Administrative Support	42,173 (31,288)	53,830	8.00%
Health Care Support	41,472 (35,140)	7,482	14.22%
Construction	40,724 (25,672)	62,679	26.33%
Production	40,723 (23,711)	96,000	18.39%
Community & Social Services	40,159 (25,220)	10,532	12.43%
Transportation	39,304 (29,522)	71,888	26.00%
Personal Care Services	35,240 (29,340)	5,154	7.78%
Protective Services	34,499 (26,568)	7,841	43.82%
Cleaning and Maintenance	28,435 (21,742)	23,608	23.61%
Food Preparation and Serving	26,203 (22,565)	12,426	7.21%
Farming, Forestry, Fishing	25,694 (27,608)	3,749	6.81%

Note: Data: 2000 Decennial Census, 5% PUMS. Sample includes full-time (30+ weeks, 30+ hours per week) employed males, ages 35-64 that live in an identifiable MSA, and reported positive earnings. Total Observations: 788,728. Occupation Categories based on the 2000 Standard Occupational Classification (SOC), which is used by the Federal Statistical Agencies to classify workers into occupational categories. A detailed description of each category is available at the Bureau of Labor Statistics website, www.bls.gov. Both the 2000 PUMS and the CPS report SOC. Unionization Rate is the percentage of workers in each occupation category that are union members, as reported from respondents in the Current Population Survey, March Supplement 2000.

Table 15: Number of Concentrated Markets, by Occupation

Occupation Group	(1) Number of Concentrated Markets $HI \geq 0.10$	(2) Number of Moderately Concentrated Markets $.18 \geq HI > .10$	(3) Number of Highly Concentrated Markets $HI > 0.18$
College Professors	196	90	106
Physicians	108	89	19
Farming, Forestry, Fishing	67	62	5
Protective Services	52	49	3
Scientists	45	36	9
Computers and Mathematics	39	30	9
Architects and Engineers	31	23	8
Lawyers	22	22	0
Health Care Support	19	17	2
Arts, Media, and Entertainment	16	15	1
Production	13	11	2
Installers, Repairers, Mechanics	10	8	2
Personal Care Services	3	3	0
Business and Finance	3	3	0
Construction	2	1	1
CEOs and Managers	1	1	0
Food Preparation & Serving	1	1	0
Office and Administrative Support	1	1	0
Teachers, Librarians, Archivists	1	1	0
Transportation	1	1	0
Community and Social Services	0	0	0
Cleaning & Maintenance	0	0	0
Sales	0	0	0
Totals	631	464	167

Note: The Herfindahl Index is calculated for 264 metropolitan areas and 23 occupation groups. Occupation groups are defined by the Standard Occupation Classification. A MSA is a *concentrated* market for a given occupation if the Herfindahl Index is higher than 0.10, whereas a market with an *HI* that is higher than 0.18 is *highly concentrated*. These classifications are based on the US Antitrust Department classifications of industry concentration.

Table 16a: The Effect of Mobility Costs and Occupation Concentration on Wages

	(1)	(2)	(3)	(4)
MCI 0.386 (.306)	-.1270** (.0159)	-.1278** (.0156)	-.1198** (.0170)	-.1272** (.0143)
MCI x *HI* .0039 (.0113)			-.6796** (.2297)	-.7399** (.2221)
HI (Occ, MSA*)* .0101 (.0246)		-.9601** (.2036)	-.7293** (.1747)	-.3823* (.1663)
Population 3.016 (3.968)				.0134** (.0036)
R-Squared	0.3458	0.3467	0.3467	0.3529
Observations	788,728	788,728	788,728	788,728

Note: Dependent variable is the logarithm of wages. *MCI* is the Moving Cost Indicator, as defined in equation (9). *HI* (Occ, MSA) is the Herfindahl Index for the Occupation of the worker in the MSA of the worker. *Population* is the total population (in millions) in the MSA of the worker (source: State and Metropolitan Area Data Book, 1997-98). Least Squares estimates, with standard errors clustered by Metropolitan Area, and reported in parenthesis. Not reported are the estimated effects of available demographic characteristics, listed in Tables 1a and Tables 1b. *= statistically significant at the 5% level, ** = statistically significant at 1% level.

Table 16b: Predicted Income across different values of the Herfindahl Index

	(1) Herfindahl Index	(2) Mean Predicted Income (in US $)
Mean	0.010	44,378 (0.00)
Perfect Competition	0.000	44,823 (1.00)
Moderate Concentration	0.100	40,591 (-8.53)
High Concentration	0.180	37,495 (-15.51)
Extreme Concentration	0.500	27,299 (-38.48)
Monopsony	1.000	16,626 (-62.53)

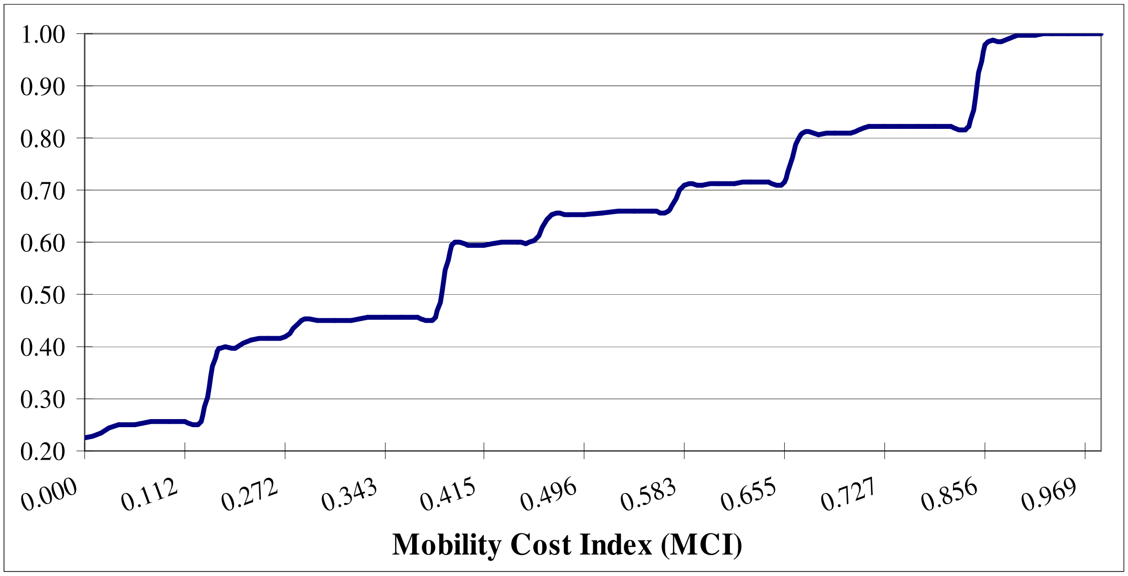
Note: Predicted income is evaluated at the sample means of all characteristics. Predicted income in column (2) is calculated using the estimation coefficients from the specification in Table 7a, column (3). Predicted income in column (4) is calculated using the estimation coefficients from the specification in Table 7a, column (5). In parenthesis is reported the percentage deviation from the mean predicted income.

Table 17: The Effect of Unionization on the Magnitude of Exploitation

	(1)	(2)	(3)	(4)
MCI 0.386 (.306)	-.1243** (.0134)	-.2702** (.0175)	-.1278** (.0156)	-.2065** (.0211)
MCI x *Firms(M)* 4.226 (6.239)	--	.0048** (.0008)	--	--
MCI x HI (Occ, MSA*)* .0039 (.0113)	--	--	--	-.6622** (.2216)
MCI x Union 5.676 (6.924)	--	.0068** (.0005)	--	.0063** (.0052)
Firms(M) 12.335 (12.245)	.0048** (.0008)	.0031** (.0009)	--	--
HI (Occ, MSA*)* .0101 (.0246)	--	--	-.9601** (.2036)	-.7322** (.1726)
Union 13.981 (10.250)	-.0112** (.0005)	-.0138** (.0005)	-.0133** (.0007)	-.0156** (.0007)
R-Squared	0.3524	0.3539	0.3467	0.3475
Observations	788,728	788,728	788,728	788,728

Note: Dependent variable is the logarithm of wages. *Union* is the percentage of workers in the worker's occupation category that were union members, as reported from respondents in the Current Population Survey, March Supplement 2000. See Table 9 for more details. Other variables, as described in notes of previous tables. Least Squares estimates, with standard errors clustered by Metropolitan Area, and reported in parenthesis. Not reported are the estimated effects of available demographic characteristics, listed in Tables 1a and 1b. *= statistically significant at the 5% level, ** = statistically significant at the 1% level.

Figure 1: The Cumulative Distribution Function of the Mobility Cost Index



Note: *MCI* is constructed as described in equation (8) in text. Mean = .386, Standard Deviation = .306.

Bibliography

Altonji J.G. and Blank R.M. (1999), “Race and Gender in the Labor Market”, *Handbook of Labor Economics: Volume III*, Elsevier, pp. 3143-3248.

Anglin M.P. and Gencay R. (1996), “Semiparametric Estimation of a Hedonic Price Function”, *Journal of Applied Econometrics*, Vol.11, No.6, pp. 633-648.

Atrostic B.K. (1982), “The Demand for Leisure and Non-Pecuniary Job Characteristics”, *American Economic Review*, Vol. 72, No. 3, pp. 428-440.

Bartel A.P. (1979), “The Migration Decision: What Role Does Job Mobility Play?“, *American Economic Review*, Vol. 69, No. 5, pp. 775-786.

Becker G. (1993), “Human Capital”, 3rd Edition, Chicago: University of Chicago Press, chapters 3-4.

Bhaskar V., and To T. (1999), “Minimum Wages for Ronald McDonald Monopsonies: A Theory of Monopsonistic Competition”, *Economic Journal*, Vol. 109, No. 455, pp. 190-203.

Bhaskar V., Manning A., and To T. (2002), “Oligopsony and Monopsonistic Competition in Labor Markets”, *Journal of Economic Perspectives*, Vol. 16, No. 2, pp. 155-174.

Bielby W.T, and Bielby D.D. (1992), “I Will Follow Him: Family Ties, Gender-Role Beliefs, and Reluctance to Relocate for a Better Job”, *American Journal of Sociology*, Vol. 97, No. 5, pp. 1241-1267.

Black D.A., and Lowenstein M.A. (1991), “Self-Enforcing Labor Contracts with Costly Mobility: The Subgame Perfect Solution to the Chairman’s Problem”, *Research in Labor Economics*, Vol. 12, pp. 63-83.

Blomquist C.G., Berger M.C., and Hoehn J.P. (1988), “New Estimates of Quality of Life in Urban Areas”, *American Economic Review*, Vol. 78, No. 1, pp. 89-107.

Boal W.M. (1995), “Testing for Employer Monopsony in Turn-of-the-Century Coal Mining”, *Rand Journal of Economics*, Vol. 26, No. 3, pp. 519-536.

Boal W.M., and Ransom M.R. (1997), “Monopsony in the Labor Market”, *Journal of Economic Literature*, Vol. 35, No. 1, pp. 86-112.

Box G.E.P., and Cox D.R. (1964), “An Analysis of Transformations”, *Journal of the Royal Statistical Society*, Vol. 26, No. 2, pp. 211-252.

Bronfenbrenner M. (1956), “Potential Monopsony in the Labor Market”, *Industrial and Labor Relations Review*, Vol. 9, No. 4, pp. 577-588.

Brown C. (1980), “Equalizing Differences in the Labor Marker”, *Quarterly Journal of Economics*, Vol. 94, No.1, pp. 113-134.

Brown C., and Medoff J. (1989), “The Employer Size-Wage Effect”, *Journal of Political Economy*, Vol. 97, No. 5, pp. 1027-1059.

Buchmueller T.C., Valletta R.G. (1996), “The Effects of Employer-Provided Health Insurance on Worker Mobility”, *Industrial and Labor Relations Review*, Vol. 49, No. 3, pp. 439-455.

Camerer C.F. (1989), “Does the Basketball Market Believe in the Hot Hand?”, *American Economic Review*, Vol. 79, No. 5, pp. 1257-1261.

Card D., and Krueger A.B. (1994), “Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania”, *American Economic Review*, Vol. 84, No. 4, pp. 772-793.

Coates M.L., and Kumar P. (1982), "Occupational Earnings, Compensating Differentials and Human Capital: An Empirical Study", *Canadian Journal of Economics*, Vol. 15, No. 3, pp. 442-457.

Corcoran M., and Duncan J.G. (1979), "Work History, Labor Force Attachment, and Earnings Differences between the Races and Sexes", *Journal of Human Resources*, Vol. 14, No. 1, pp. 3-20.

Cotton P. (1991), "Pre-Existing Conditions Hold American Hostage to Employers and Insurance", *Journal of the American Medical Association*, Vol. 265, pp. 2451-2453.

Cropper L.M, Deck B.L, and McConnell E.K. (1988), "On the Choice of Functional Form for Hedonic Price Functions", *Review of Economics and Statistics*, Vol. 70, No. 1, pp. 255-260.

Davis S.J., Haltiwanger J., Katz L.F. and Topel R. (1991), "Wage Dispersion between and within US Manufacturing Plants, 1963-86", *Brookings Papers on Economic Activity, Microeconomics*, Vol. 1991, pp. 115-200.

Dorman P., and Hagstrom P. (1998), "Wage Compensation for Dangerous Work Revisited", *Industrial Relations and Labor Review*, Vol. 52, No. 1, pp. 116-135

Dorsey S., and Walzer N. (1983), "Workers' Compensation, Job Hazards, and Wages", *Industrial Relations and Labor Review*, Vol. 36, No. 4, pp. 642-654.

Duncan J.G. (1976), "Earnings Functions and Non-pecuniary Benefits", *Journal of Human Resources*, Vol. 11, No. 4, pp. 462-483.

Duncan J.G., and Holmlund B. (1983), "Was Adam Smith Right After All? Another Test of the Theory of Compensating Wage Differentials", *Journal of Labor Economics*, Vol. 1, No. 4, pp. 366-379.

Duncan J.G., and Stafford P.F. (1980), "Do Union Members Receive Wage Differentials?", *American Economic Review*, Vol. 70, No. 3, pp. 355-371.

Ekeland I., Heckam J.J., and Nesheim L. (2001), "Identification and Estimation of Hedonic Models", *CEMMAP Working Paper*, CWP07/02.

Fishback P.V., and Kim S.W. (1993), "Institutional Change, Compensating Differentials and Accident Risk in American Railroading 1892-1945", *Journal of Economic History*, Vol. 53, No. 4, pp.796-823.

Garen J.E. (1988), "Compensating Wage Differentials and the Endogeneity of Job Riskiness", *Journal of Labor Economics*, Vol. 70, No. 1, pp. 9-16.

Gordon N.M., Morton T.E., and Braden I.C. (1974), "Faculty Salaries: Is There Discrimination by Sex, Race and Discipline?", *American Economic Review*, Vol. 64, No. 3, pp. 419-427.

Haltiwanger J.C., Lane J.I., and Spletzer J.R. (1999), "Productivity Differences across Employers: The Roles of Employer Size, Age and Human Capital", *American Economic Review*, Vol. 89, No. 2, *Papers and Proceedings of the One Hundred Eleventh Annual Meeting of the American Economic Association*, pp. 94-98.

Hansen K. (1992), "Registered and Practical Nurses in California: Competition Versus Oligopsony in the 1980s", *Working Paper*, Ohio State University.

Hausman J.A., and Leonard G.K. (1997), "Superstars in the National Basketball Association: Economic Value and Policy", *Journal of Labor Economics*, Vol. 15, No. 4, pp. 586-624.

Hwang H., Reed W.R., and Hubbard C. (1988), "Compensating Wage Differentials and Unobserved Productivity", *Journal of Political Economy*, Vol. 100, No. 4, pp. 904-921.

Kahn L.M., and Sherer P.D. (1988), "Racial Differences in Professional Basketball Players' Compensation", *Journal of Labor Economics*, Vol. 6, No. 1, pp. 40-61.

Kahn L.M. (2000), "The Sports Business as a Labor Market Laboratory", *Journal of Economic Perspectives*, Vol. 14, No. 3, pp. 75-94.

Klerman J., Buchanan J., and Leibowitz A. (1992), "Labor Turnover and Health Insurance", *US Department of Labor, Pension and Welfare Benefits Administration, Health Benefits and the Workplace, Washington DC: GPO*, pp. 43-55.

Krueger A.B., and Summers L.H. (1987), "Reflections on Inter-Industry Wage Structure", *Unemployment and the Structure of Labor Markets*, New York: Basil Blackwell, pp. 18-47.

Leibowitz A., Klerman J.A., Waite L.J. (1992), "Employment of New Mothers and Child Care Choice: Differences by Children's Age", *Journal of Human Resources*, Vol. 27, No. 1, Special Issue on Child Care, pp. 112-133.

Link C.R., and Landon J.H. (1975), "Monopsony and Union Power in the Market for Nurses", *Southern Economic Journal*, Vol. 41, No. 4, pp. 649-659.

Link C.R., and Landon L. (1976), "Market Structure, Non-Pecuniary Factors and Professional Salaries: Registered Nurses", *Journal of Economics and Business*, Vol. 8, No. 2, pp. 151-155.

Lucas R.E.B (1977), "Hedonic Wage Equations and Physic Wages in the Returns to Schooling", *American Economic Review*, Vol. 67, No. 4, pp. 549-558.

Luizer J., and Thornton R. (1986), "Concentration in the Labor Market for Public School Teachers", *Industrial and Labor Relations Review*, Vol. 39, No. 4, pp. 573-584.

Madrian B.C. (1994), "Employment-Based Health Insurance and Job Mobility: Is There Evidence of Job-Lock?"**,** *Quarterly Journal of Economics*, Vol. 109, No. 1, pp. 27-54.

McNabb R. (1989), "Compensating Wage Differentials: Some Evidence from Britain", *Oxford Economic Papers*, Vol. 41, No. 2, pp. 327-338.

Mincer J. (1978), "Family Migration Decisions", The *Journal of Political Economy*, Vol. 86, No. 5, pp. 749-773.

Neal D.A., and Johnson W.R. (1996), "The Role of Premarket Factors in Black-White Wage Differences", *Journal of Political Economy*, Vol. 104, No. 5, pp. 869-895.

O'Neil J. (1990), "The Role of Human Capital in Earnings Differences Between Black and White Men", *Journal of Economic Perspectives*, Vol. 4, No. 4, pp. 25-45.

Oaxaca R. (1973), "Male-Female Wage Differentials in Urban Labor Markets", *International Economic Review*, Vol. 14, No. 3, pp. 693-709.

Olson C.A. (1981), "An Analysis of Wage Differentials Received by Workers on Dangerous Jobs", *Journal of Human Resources*, Vol. 16, No. 2, pp. 167-185.

Ramsey J.B. (1969), "Tests for Specification Errors in Classical Linear Least Squares Regression Analysis", *Journal of the Royal Statistics Society*, Series B, No. 31, pp. 350-371.

Ransom M.R. (1993), "Seniority and Monopsony in the American Labor Market", *American Economic Review*, Vol. 83, No. 1, pp. 221-233.

Reimers C.W. (1983), "Labor Market Discrimination Against Hispanic and Black Men", *Review of Economics and Statistics*, Vol. 65, No. 4, pp. 570-579.

Roback J. (1982), "Wages, Rents and the Quality of Life", *Journal of Political Economy*, Vol. 90, No. 6, pp. 1257-1278.

Rosen S. (1986), "The Theory of Equalizing Differences", *Handbook of Labor Economics, Vol. I, Ch. 12*, Amsterdam: North-Holland, pp. 641-691.

Sandell S.H. (1977), "Women and the Economics of Family Migration", The *Review of Economics and Statistics*, Vol. 59, No. 4, pp. 406-414.

Santerre R.E., Neun S.P. (1986), "Stock Dispersion and Executive Compensation", The *Review of Economics and Statistics*, Vol. 68, No. 4, pp. 685-687.

Schultz T. (1961), "Investments in Human Capital", *American Economic Review*, pp. 1-17.

Showalter H.M. (1994), "A Monte Carlo Investigation of the Box-Cox Model and a Non-Linear Least Squares Alternative", *Review of Economics and Statistics*, Vol. 76, No. 3, pp. 560-570.

Sjaastad L.A. (1962), “The Costs and Returns of Human Migration”, *Journal of Political Economy*, Vol. 70, No. 5, Part 2: Investment in Human Beings, pp. 80-93.

Speare, S.Jr., Kobrin F., and Kingkade W. (1982), “The Influence of Socioeconomic Bonds and Satisfaction on Interstate Migration”, *Social Forces*, Vol. 61, No. 2, pp. 551-574.

Sullivan D. (1989), “Monopsony Power in the Market for Nurses”, *Journal of Law Economics*, Vol. 32, No. 2, pp. 135-178.

Viscusi W.K, and Moore M.J. (1987), “Workers’ Compensation: Wage Effects, Benefit Inadequacies and the Value of Health Losses”, *Review of Economics and Statistics*, Vol. 69, No. 2, pp. 249-261.

Viscusi W.K. (1978), “Wealth Effects and Earnings Premiums of Job Hazards”, *Review of Economics and Statistics*, Vol. 60, No. 3, pp. 408-416.