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Abstract

Although the neoclassical labor economics literature assumes that hours of work are determined solely on the supply side as a result of individual demand for leisure, an abundance of evidence points to the importance of employer demand factors in the market for hours of work. Despite the appeal of models allowing for simultaneity in the market for hours, the scarcity of appropriate data has made their estimation difficult. In this paper I attempt to incorporate labor demand into the problem of hours determination in an empirically tractable manner by exploiting the theoretically distinct roles played by commuting time at the individual and aggregate levels. Applying instrumental variables techniques to data from the 1990 U.S. Census yields larger cross-sectional wage elasticities of labor supply for both men and women than are generally found using conventional estimation methods.

1 Introduction

Much of the labor supply literature assumes that hours of work are determined solely on the supply side. The neoclassical model, in which the employee chooses hours to equalize the given wage rate with the opportunity cost of her time, frequently provides the theoretical basis for empirical labor supply analysis.[1] A main factor contributing to its popularity is undoubtedly the general nature of its assumptions, and the resulting capacity to accommodate a wide range of behavior. For example, the wage rate summarizes the demand for hours of work, but this does not restrict the employer's action to simply offering a wage and accepting the hours a worker chooses. As Pencavel (1986) notes in his handbook survey, this assumption is consistent with employers offering tied packages of wages and hours as long as the two are not systematically related, and provided the jobs available in the labor market represent the full range of hours of work. The neoclassical model has achieved only modest success in explaining variation in hours of work, however, especially for men.[2] This fact may fail to surprise for many reasons, including the recognition that measurement error and definitional ambiguity will lead to noisy and attenuated estimates. Yet the result persists despite efforts to address these issues. The small and insignificant estimates of wage elasticities of labor supply often found for both men and women (both cross-sectional and intertemporal) cast doubt on the ability of the supply side alone to tell the whole story regarding hours determination.[3]

One explanation for the poor performance of the neoclassical labor supply model may be that its simplicity is overly restrictive. The model assumes that labor affects both production and costs only in the form of total manhours; there is no scope for distinction between various aspects of labor, such as number of workers and worker hours. If different dimensions of labor impose different costs, or if their marginal productivities differ, wages will depend on hours.[4] Economists have long recognized this, dating back to at least a theoretical exposition by Lewis (1969). In his alternative labor market model, employers' technologies depend on

[1] Pencavel (1986), Killingsworth and Heckman (1986), and Killingsworth (1983) survey this vast literature; leading examples of dynamic models include Altonji (1986), MaCurdy (1981), and Card (1994).

[2] It is interesting to note that the neoclassical model has been more successful in explaining labor supply responses along the extensive margin than the intensive margin. Estimates of labor force participation elasticities of women, for whom the choice of working is viewed as being more endogenous, are generally found to be large. Yet this result is not exclusive to women; movements into and out of employment explain substantial time-series variation in aggregate measures of hours of work for men as well.

[3] Pencavel (1986), MaCurdy (1981), and Altonji (1986) are a few studies remarking on this widespread result for men; Schultz (1980) finds such a cross-sectional result for women.

[4] The model of coordination of inputs presented by Deardorff and Stafford (1976) suggests another avenue by which wages may depend on hours.

employee hours through fixed costs of employment.[5] In order to obtain the longer hours they desire to offset these costs, employers will be willing to offer compensating wages. Equilibrium is defined by the assignment of workers to firms, which creates a market wage-hours locus along which observed jobs fall.

An advantage of such an employer interest model over the neoclassical model is its ability to explain an excess of empirical facts. In the context of the employer interest model, the small observed correlations between wages and hours are interpreted not as a supply response, but rather as the net effect of offsetting supply and demand responses to wage changes. Not only is the model thus consistent with the findings above, it can also rationalize some additional empirical puzzles. For example, results obtained by Altonji and Paxson (1986, 1992) indicate that variance in hours worked is much smaller during a period of tenure with an employer than between employers, implying that employers constrain their employees' hours to some extent. This interpretation is further supported by the failure of the result to hold for the self-employed, as shown by Senesky (2000). Evidence presented by Ham (1986) shows that demand variables affect labor supply even when conditioning on the wage. This finding cannot be rationalized by the neoclassical model in which the wage represents a sufficient statistic for demand factors, and suggests instead that these factors are responsible for part of the variation in hours of work.[6]

Support for the employer interest model has important consequences in the context of estimation. As wages do not fully capture all of the relevant demand information in the presence of fixed costs of employment, they should be treated as endogenous in econometric labor supply equations. Otherwise, estimates will be based on information which is not purely the result of individual choice and will suffer from bias and inconsistency.[7] One straightforward method by which to obtain unbiased and consistent estimates of labor supply parameters like the wage elasticity is to use exogenous factors affecting firms' labor costs as instrumental variables. The response of hours to that variation in wages associated with shifts in labor demand can be confidently attributed to employee behavior.[8]

A primary difficulty in implementing such a strategy to estimate an employer interest model is the lack of

[5] Oi (1962) proposes that fixed costs arise from costs of hiring and training workers; others including Becker (1962) have hypothesized that searching, recruiting, administrative tasks, and supervision impose costs per worker as well.

[6] Card's (1987) survey presents a thorough discussion of these and other phenomena.

[7] More generally, biased estimates of neoclassical labor supply or demand equations will occur when the wage fails to separate the two sides of the market by summarizing all the relevant information about the other side; see Card (1987).

[8] Some other ways of incorporating such information involve specifying constraints explicitly in the empirical model and estimating with maximum likelihood (see Cogan (1980) and Rosen (1976)), directly estimating indifference surfaces (Heckman (1974)), or excluding from analysis the observations affected by demand factors (Card (1990), Senesky (2000)).

appropriate employer data. Most demand-side data available is highly aggregated, often at the industry and even country level.[9] This makes it extremely difficult even to learn about what affects the demand for hours, much less to make use of this information. To take a specific example, federal overtime laws in the U. S. are likely to affect the hours desired by employers, but have no empirical value in cross-sectional study because they exhibit no variation within the country. Without a feasibly estimable labor supply model derived from a theoretical framework that includes a systematic role for employer preferences, attempts to allow employers to partly determine hours proceed in an *ad hoc* manner. This practical obstacle helps to explain why the static labor supply literature has historically placed less emphasis on the issue of endogeneity, instead concentrating effort on the problems of sample selection and measurement error. In fact, while instrumental variables estimation procedures are common in this literature, their purpose is to address measurement error rather than simultaneity.

The goal of this paper is to isolate an observable dimension of labor demand which can function as a wage instrument in labor supply estimation. Ideally, we would like data on fixed employment costs for each individual's employer in order to estimate labor supply equations using instrumental variables. To make the empirical problem tractable in the absence of such information, my strategy is to construct a measure of labor demand using individual data on commuting time to work. I propose that average Primary Metropolitan Statistical Area (PMSA) commuting time is a plausible candidate for fixed employment costs to firms in the PMSA. Occupations within PMSAs even more closely approach the desired employer-level data, and may be used as the level of aggregation under additional conditions. Commuting time is generally thought of in terms of the fixed costs it imposes on workers, a feature retained in my model. However, I argue that the incidence of the costs imposed by commuting time varies with its level of aggregation. This argument represents an appeal to the recognized principle that a single variable may play different roles at different levels of aggregation.[10] The main idea is based on the implication of a hedonic model of intercity wage differentials that, at the city level, employers bear the cost of the disamenity of commuting time. It is this feature that I exploit to develop an empirically feasible econometric model of the market for hours that

[9]See Hamermesh (1991) and Stafford (1986) for a discussion of this problem.

[10]A leading example comes from the literature on intertemporal labor supply, in which wages can generate a negative (due to the income effect) or positive (due to the substitution effect) response of hours supplied, depending on whether we consider mean individual wages or within-individual deviations from the mean. See MaCurdy (1981), Altonji (1986), and Card (1994).

allows for employer preferences over employee hours as an alternative to the neoclassical labor supply model. Accepting this interpretation of aggregate commuting time, we gain a novel demand variable that has the advantage of being widely available in micro datasets.

Some stronger assumptions will be necessary in order to establish justification for treating aggregate commuting time as a demand instrument. Identification requires that, conditional on the wage, average commuting time affects desired hours of the employer. As I will discuss in Section 2, the fixed costs that employers face related to average commuting time can be attributed to the effects of each worker on co-ordination. Under the assumptions that firms' locations are fixed (or at least are chosen independently of observed differences in PMSA characteristics including commuting time), and that individuals have identical preferences over PMSA commuting time, individuals can escape any costs of average commuting time. Moreover, as I will show in Section 5, the grouped structure of average commuting time together with standard assumptions about the exogeneity of the other regressors permits unbiased estimation even when preferences for average commuting time are heterogeneous. If employers choose where to locate based on the relation of area conditions to their production and cost functions, estimates will suffer from attenuation bias. My analysis will not address this problem.

The remainder of the paper is organized as follows. Section 2 presents a model of the labor market and generates testable implications. After describing the data in Section 3, I discuss the results of analysis testing predictions of the model in the following section. Subsection 4.1 concerns the relationship between commuting time and wages, while subsection 4.2 concerns that between commuting time and hours. Section 5 describes the econometric framework used for estimating labor supply equations, with results discussed in Section 6. Section 7 concludes.

2 A conceptual framework

In order to include a role for employers in the determination of hours, I extend a conventional labor supply model by introducing the concepts of cities and firms. The resulting alternative model is similar to those developed by Rosen (1979) and Roback (1982) in its treatment of a city-level amenity, while additionally incorporating the problem of hours determination. The labor market aspect of the model follows Lewis

(1969) in specifying endogenous wages and fixed costs of employment to both individuals and firms.

Individuals and firms are located in cities, which are each associated with an average commuting time from home to work.[11] I treat average city commuting time s as fixed, since the marginal effect of a worker or firm is negligible. Differences in commuting time between cities relate to exogenous sources, such as geographical features of the landscape. Individuals are free to move between cities, but the locations of firms are assumed to be fixed and exogenous. In addition, I assume the average commuting time in a city equals the average commuting time for the employees of each firm in the city. To simplify the model for ease of exposition, I ignore the market for land here and restrict attention to the market for labor. However, the results derived are fairly general. The model below exploits the aggregation produced by the introduction of cities to allow commuting time to play a dual role, affecting both labor supply and labor demand.

2.1 Firms

The average commuting time in a city imposes fixed costs on employers due to its effects on coordination. Suppose that employee hours are complementary in production, as suggested by Deardorff and Stafford (1976), such that the firm's technology requires all employees to be working simultaneously. Coordination is disrupted by the hazard rate of delays associated with commuting, perhaps related to accidents. For every minute a worker spends in transit, there is a probability of encountering a delay. In order to make this clear, consider a specific example in which the probability of the number of delays x of duration d may be thought to follow a Poisson distribution, $P(x) = \frac{e^{-\lambda}\lambda^x}{x!}$, where λ represents the expected number of delays per minute. Thus, as a firm's number of employees n rises, the probability of all employees getting to work at a given time $P(0)^n$ falls. A longer average commute s increases each worker's impact in lengthening the expected delay to beginning the day's production, which can be expressed as $s\frac{r}{1-r}$, where $r = (1 - P(0)^n)\lambda d$. This is because the longer the commute, the more likely that delays will occur, and the longer the total delay on the way to work. The incidence of these costs in equilibrium lies at the heart of the discussion which follows.

Before proceeding to the choice problems, the reader will notice that the arguments I present refer to average commuting time as a fixed cost per day of work for both workers and firms. The relevant measure of

[11] In the following exposition, the terms "firm" and "employer" will be used interchangeably.

labor under consideration in this theoretical treatment is therefore days of work, defined over some unspecified time period. However, for the purposes of this discussion I will take the liberty of speaking as if the fixed costs apply to hours of work per week, since this will facilitate comparison with a dimension of labor supply that will be a focus of the empirical analysis. The implications of this approximation will be examined in more detail at that point.

The firm chooses a number of employees N and hours per employee h to minimize costs subject to its production technology f, which is assumed to depend on total manhours,

$$\min_{h,N} Nhw(h,s) + Nv(s) \quad \text{subject to} \quad f(Nh) \geq Q.$$

(I assume that choices about employment and hours are separable from choices about capital inputs.) Total costs equal the sum of the wage bill and the fixed cost per employee $v(s)$, which is an increasing and concave function of commuting time. The fixed cost is what generates employer preferences over employee hours, since longer employee hours help to offset this cost.[12] I assume that the cost savings associated with longer hours permit employers to pay higher wages for them, compensating workers for these less desirable jobs.[13] Thus, wages are an increasing function of hours, and are further assumed to be subject to diminishing returns: $w = w(h),\ w_h > 0,\ w_{hh} < 0$.

The fixed costs per worker lead to two implications regarding the firm's desired employee hours. First, the firm will want an employee to work a minimum level of hours in order to recover the fixed cost of employing her. In addition, as the first order condition

$$hw_h = \frac{v}{h}$$

illustrates, the firm will tradeoff employees and hours of work until the marginal cost of an additional hour of work equals the average cost of an additional worker at the current level of hours. Higher fixed costs per employee will lead employers to desire longer hours per worker while reducing employment. Since longer commuting times increase fixed costs, employers in cities with long average commuting times will tend to offer jobs with longer hours. These employers should also hire fewer employees, although this issue will not be addressed here.

[12]However, notice that this result can also be achieved by replacing the assumption about fixed costs with an assumption about differing marginal productivities of employees and hours.

[13]Lewis (1969) gives a further reason to assume that wages depend on hours, showing that this avoids the absurd solution of employers asking employees to work all available hours.

2.2 Individuals

Individuals work in their cities of residence, and are assumed to be costlessly mobile between cities. Thus, we can think of their choice problems as proceeding in two stages: a choice of optimal demands given prices, followed by a choice of location. I ignore those who do not choose to do some work in the labor market.

The first stage corresponds to a labor supply model augmented to allow wages to be endogenous. Assuming that wages depend on both hours and average city commuting time s, the individual maximizes utility over consumption of a numeraire good x, hours h, and commuting time $s+t$, subject to her nonconvex budget constraint and her time endowment,

$$\max_{x,h,s+t} U(x,h,s+t) \quad \text{subject to} \qquad \begin{aligned} x &\leq w(h,s)h + E \equiv Y \\ h + L &+ s + t \leq T \end{aligned}$$

where L denotes leisure and E nonwage earnings. Utility functions are additively separable and homogeneous only with respect to average city commuting time s. For mathematical convenience, they are defined over hours rather than leisure. Notice that the specification allows for disutility of commuting beyond simply foregone earnings. Total commuting time is denoted $s+t$, where t represents the within-city component. The first order conditions imply that hours and commuting time are chosen to equalize their marginal costs, net of marginal benefits,

$$\frac{U_h}{U_x} + w + hw_h = \frac{U_{s+t}}{U_x} + hw_s.$$

In addition to the income effect on hours through the time endowment, average commuting time will have substitution and income effects on hours through its effect on wages as the following expression indicates:

$$\frac{\partial h}{\partial s} = \frac{\partial h}{\partial Y}\frac{\partial Y}{\partial s} + \frac{\partial h}{\partial w}\frac{\partial w}{\partial s} + \frac{\partial h}{\partial Y}\frac{\partial Y}{\partial w}\frac{\partial w}{\partial s}. \tag{1}$$

To see this graphically, consider Figure 1, which illustrates the decomposition of the effect of s on hours supplied shown mathematically in equation (1). The figure plots consumption C against leisure L. As I will show shortly, the change in s corresponds to an individual moving from one city to another in a non-equilibrium setting. Initially the individual is in city one and chooses point a, where her budget constraint

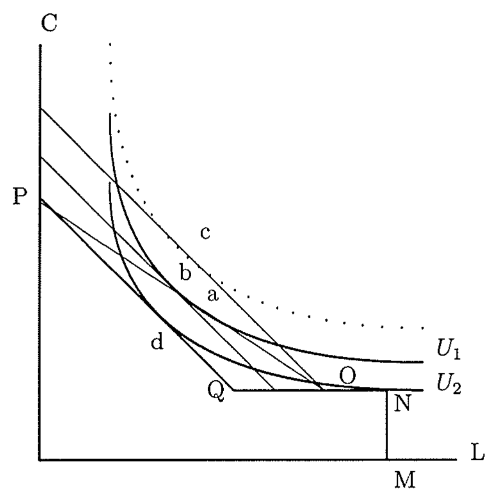

Figure 1: Decomposition of the effects of a change in city commuting time on hours supplied.

MNOP is tangent to indifference curve U_1. In city two, commuting time is longer but wages are higher, yielding budget constraint MNQP. Here she will choose point d, which yields lower utility U_2. The change is the net of the following three effects shown in the expression above. Hours will increase in response to the higher wages as a result of the substitution effect (the second term), represented by the move from point a to b. However, hours will decrease according to the income effect produced by the higher wages (the third term), from point b to c. Finally, the longer commuting time decreases her effective time endowment and hence potential income (the first term), producing an income effect in the opposite direction from point c to d.

The second stage of the individual's problem essentially involves choosing average city commuting time to maximize the indirect utility function

$$V(s) = U(x^s, h^s, (s+t)^s),$$

where the superscript s indicates the optimal consumer demand functions. The result of this maximization,

$$\frac{dV}{ds} = \frac{\partial U}{\partial x^s}\frac{\partial x^s}{\partial s} + \frac{\partial U}{\partial h^s}\frac{\partial h^s}{\partial s} + \frac{\partial U}{\partial s} = 0, \tag{2}$$

implicitly defines the equilibrium gradient of wages with average commuting time. This can be seen by substituting for the marginal utilities according to the first order conditions, and expanding the partial derivatives with respect to s on the right-hand side using the chain rule as in equation (1). The result comes about because commuting time may be thought of as a locational attribute traded implicitly through the

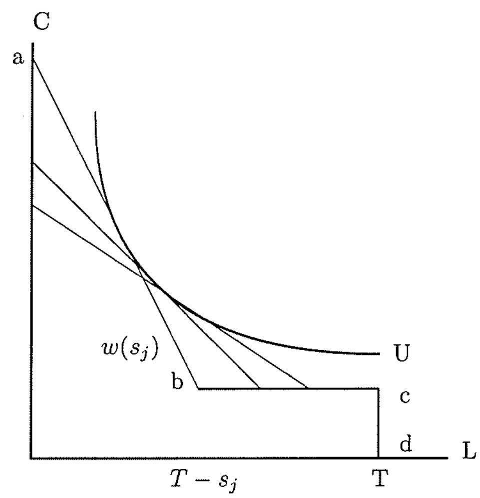

Figure 2: City wages and commuting times in equilibrium.

residential choice process.

2.3 Equilibrium

The maximization above indicates that in order to attract workers, wages at the city level must adjust to compensate employees for intercity differentials in commuting time, making them indifferent between city locations. Compensation covers all costs associated with average commuting time, including both its direct disutility and its fixed cost to hours of work. A simple graph makes this condition clear. Consider an individual's choice among several cities in equilibrium, represented by the graph in the plane of consumption and leisure shown in Figure 2. The cities, indexed by s_j, are associated with an average commuting time and hence an average wage rate, reflected in the differing horizontal intercepts $T - s_j$ and slopes $w(s_j)$. An individual's budget line in city j is *abcd*. As equation (2) indicated, any change in s leaves the individual on the same indifference curve. In terms of Figure 1, a change in s produces only a substitution effect due to the effect of s on wages. Clearly the effect of average commuting time on wages is determined by the shape of the individual's indifference curves. Heterogeneity in individual preferences over other locational attributes drives differences in the choice of location among cities offering the same utility in terms of hours and consumption.

The results make intuitive sense according to the concept that a cost is borne by the less mobile party. Since employee mobility gives precedence to their preferences, wages and rents must fully compensate them for the disamenity of average commuting time. This feature also explains why firms cannot pass on part of their fixed costs due to average commuting time to their workers. Employees can avoid any penalties for late arrival to work that their employer might impose by moving to another firm that is willing to bear the full cost. In fact, it is the relative immobility of firms that drives this result, so the assumptions of the model described here could be loosened to allow firms some freedom to move as well.

In equilibrium, an individual's actual hours of work on a job will be determined by the tangency of the labor supply and labor demand curves. Different cities present different fixed costs in the form of average commuting times, so labor demand will differ across cities. However, since individuals are fully compensated for the average commuting time, the distribution of labor supply functions will be the same across cities. Commuting time thus acts as a demand shifter. The systematic positive effect of average commuting time on labor demand implies that observed equilibrium hours will be higher in areas with longer average commutes.

Although the market for land has been ignored here, it is not difficult to see how land and other city attributes in general would enter the specification. An intuitive way to think about this is that after prices adjust to clear the explicit markets for labor and land, the mobility of individuals necessitates the clearing of implicit markets for locational attributes. If an individual's valuation of commuting time is fully capitalized in the land and labor markets, then conditional on both wages and rents, this attribute should not affect the labor supply decision. However, it is important to remember that this condition requires all individual valuations of commuting time to be equivalent.[14]

2.4 Implications

These results have important implications for the specification of the individual's optimal labor supply function. Individuals are fully compensated for the city-level component of their commuting time, s, so that conditional on wages and rents, it will play no role in their choice of hours of work. This reasoning, together with the assumption that average commuting time affects fixed costs of employment, establishes the theoretical justification for treating average commuting time as a labor demand instrument. The assumption of identical individual preferences for average commuting time is crucial to the theoretical argument for the exclusion of this factor from the labor supply function conditional on wages. Specifically, *all* individuals are

[14]A treatment of both land and labor markets is available from the author on request.

fully compensated for s since marginal utilities with respect to s are identical. If there is heterogeneity in valuations of average commuting time, the equilibrium gradient between average city real wages and average city commuting times defines the *average* of individuals' valuations of s.[15] However, the assumption of identical preferences for average commuting time can be relaxed in the context of the econometric model. The specific consequences of the alternative model's assumptions for the estimation of labor supply equations will be explored in detail in Section 5.

Some other simple practical implications of this model should now be clear. Mobility of workers and immobility of firms between cities lead to positively correlated average wages and commuting times at the city level as long as all individuals consider average commuting time a disamenity, whether employers play a role in determining hours or not. In addition, at the individual level, both models imply that hours should vary less in areas with higher fixed costs, where minimum acceptable hours of work will be higher on average. Fixed costs applying to both the employer and the employee or to the employee alone generate observationally equivalent results in this respect. Tests of these propositions will at least allow us to determine whether either of these models are supported by the data.

Examination of the relationship between average commuting time and hours of work provides a way in which to distinguish the neoclassical and alternative models. Consider the distribution of hours across cities that will be observed in equilibrium. The theoretical results of this model indicate that since average commuting time affects labor demand but not labor supply, conditional on wages, longer average hours and fewer part-time jobs will be observed in areas with longer average commutes. In contrast, the neoclassical model of hours determination, in which employers play no part, requires that employee preferences be reflected in a negative correlation between average city hours and commuting times conditional on wages, since higher time costs of working should reduce the labor market hours supplied by workers.[16] The finding of a positive empirical relationship between average commuting times and hours would allow us to reject the neoclassical model in favor of the alternative model that includes employer preferences. These are the predictions I will test in Section 4 to evaluate the appropriateness of the model. Hours will often be

[15] Concern for sorting behavior as described by Tiebout (1956) is usually expressed in the context of estimation of marginal valuations of locational amenities. However, similar biases will result if the disamenity plays the role of an instrument rather than a regressor.

[16] Workers should also substitute hours per day for days per week, since the fixed cost of commuting applies to the latter.

measured in logs rather than levels since that is how they will appear in the labor supply estimation. Different definitions of the aggregation level will be considered, in particular city-occupation groups in addition to cities.

3 Data

The following analysis uses data on minutes spent commuting one way to work from the 5% sample of the 1990 U. S. Census of Population. I consider data from two regions — the West coast (CA, OR, WA, AK, HI) and Mid-Atlantic (NY, NJ, PA) — to ease the computational burden while ensuring a diverse sample. I examine men and women aged 16 and older, and restrict the sample to those working both last week and last year in order to obtain data on annual salary, usual hours per week, weeks per year, and commuting time.[17] Those reporting educational attainment below the first grade were excluded, as were those working in the military. I focus on individuals living in primary statistical metropolitan areas (PMSAs). Non-metropolitan or unidentifiable PMSAs (coded as non-MA, mixed PMSA/non-PMSA, or two or more PMSAs) were dropped. The sample is further restricted to those whose imputed wage is at least $1 but less than $100 in order to prevent extreme outliers from dominating, yielding a data file of 1,277,953 individuals. The data includes 12 broad occupational and 13 industrial indicators for the individual's current job, and represents 71 PMSAs with sample sizes ranging from 2045 (Yuba City, CA) to 161,303 (Los Angeles-Long Beach, CA) with a mean of 17,999. It also provides demographic information on sex, age, marital status, race, and hispanic ethnicity. In addition to the labor market variables noted above, data on salary, total personal earnings, total personal income, and total family income will be crucial to my analysis. These measures are used in creating three derived variables: the wage rate, defined as salary divided by the product of hours per week and weeks per year; other family income, defined as total family income minus total personal income; and other personal income, defined as total personal income minus total personal earnings. Tables A–D present sample means as well as keys for PMSA and occupational codes.

Various PMSA characteristics are also included in some analysis. Variables measuring population, popu-

[17]A caveat is that salary and labor supply information refer to the previous calendar year, while commuting time refers to the previous week. The inclusion criteria regarding work behavior in the past week and past year raise the issue of selection bias, which I do not address here.

lation growth, and population density describe the levels and rates of change of PMSA size. Other variables capture regional price differentials (price of gasoline, typical monthly electric bill, median housing value), as well as rates of unemployment and crime. The reporting dates vary from 1986 to 1990.[18]

4 Testing predictions of the behavioral model

4.1 Effects of commuting time on wages

The model developed in Section 2 predicted that areas with longer commuting times should have higher wages. The correlation between aggregate wages and commuting times should reflect individual valuations of commuting time, the compensating wage paid to employees to offset their costs of commuting and make them indifferent between locations. As a first examination of this relationship, I compare the standard wage measure to one which accounts for commuting time by adding commuting hours to working hours, assuming a five-day workweek.[19] If differences in commuting time drive wage differences across PMSAs, then corrected wages should have smaller variance. Table 1 presents decompositions of the total wage variance into within and between variances at the PMSA and PMSA-occupation levels. The results indicate that commuting time explains 20% of the total variance in wages. Moreover, it explains more variance between PMSA and PMSA-occupation cells (33 and 22%) than within cells, suggesting that average commuting time has a large impact on cross-PMSA wage differentials.

Next I turn to more direct evidence of the link between wages and commuting. A scatterplot of mean wages and commuting times shown in Figure 3 reveals a clear positive relationship (correlation 0.77). Fitting a regression line through these points indicates that 5 extra minutes commuting in one direction raises the hourly wage by $1.85, as shown in line 1a of Table 2. This is a large effect considering that for someone working 40 hours a week, this additional 50 minutes of commuting each week yields an additional $74.00 per week. For the average worker with an hourly wage of $12.34, this more than compensates for his lost time. If we believe that the entire premium results from a demand for compensation, this implies that

[18]The source for most of these variables is the *City and County Data Book* (1988). The exceptions are population, calculated as PMSA cell size from the Census data; unemployment rate, reported by the Bureau of Labor Statistics; gas price, reported by *American Cost of Living Survey* (1994); and housing value, reported by the 1994 edition of the *CCDB*.

[19]Specifically, the corrected wage is defined as salary / (weeks per year * (hours per week + (time * 10/60))).

workers consider the inconvenience of the extra commuting time to be very large. Moreover, the fit of the regression is remarkably good ($R^2 = .59$). An examination of PMSA-occupation means reveals a similarly large relationship. Controlling for PMSA-level and individual-level characteristics drives the estimated effect of commuting time towards zero, not surprisingly given the small sample sizes and collinearity among the regressors. These results indicate that aggregate commuting time generally represents a significant cost to employers, if not always substantial.

4.2 Effects of commuting time on hours

Having discovered that PMSA- and PMSA-occupation-level commuting times appear to reflect a substantial cost to employers in terms of higher wages, I consider whether this hypothesis finds support from other evidence. Specifically, I examine whether PMSAs with high fixed costs of work, represented by commuting time, are associated with longer and less variable hours as theory suggests. I examine the effect of commuting time on four measures relating to the log hours distribution by estimating an OLS regression of PMSA or PMSA-occupation means:

$$hours\ measure_j = \beta_0 + \beta_1 time_j + u_j$$

This equation essentially represents a reduced-form labor supply regression. Hours will frequently be measured in logs to facilitate comparison with later analysis. Results discussed in this section are displayed in Table 3.

First, the variance of hours measures, including log hours per week, log weeks per year, and log total hours per year should be negatively related to PMSA commuting time. This follows logically from the idea that in PMSAs with high fixed costs of working, the equilibrium level of hours should be high, and since individuals' time endowments bound hours from above, the variance of individual hours around the PMSA mean should be low. In fact, simple regressions reveal that this is the case. As shown in lines 1a–1c, a 5 minute increase in one-way commuting time significantly decreases log hours variance and log weeks variance by .015, and log annual hours variance by .05. These amounts represent 10, 10, and 12% of the total variances. By PMSA-occupation cells, the effects are even larger (6, 25, and 33% respectively). The models also fit remarkably well, as the R^2 statistics attest.

High fixed costs of work (to employers or employees) also imply that hours should have a higher minimum threshold. One way to approach this issue is by examining the effect of average commuting time on the related measure of prevalence of part-time jobs by PMSA. The operational definition used for this concept is the percentage of employees working less than 35 hours per week. As shown in line 2, I find that at the PMSA level, a 5 minute increase in one-way commuting time decreases the percent of employees working less than 35 hours per week by a significant 0.02 percentage points, 11% of the average percentage. At the PMSA-occupation level, the effect is even larger: a 0.1 percentage point decrease for a 5 minute increase in commuting time. (This larger effect relates to the fact that the range of percentages of part-time workers is much wider, from 0% to 100%, among PMSA-occupation cells than among PMSA cells, from 13% to 29%.) Again, the regressions fit well, with adjusted R^2 statistics of at least .25.

A comparison of labor supply equations across PMSAs may also be illuminating. If fixed costs of work represented by average PMSA commuting times are high enough on average, they may on average constrain individuals' labor supply responses to wage changes. I estimate simple cross-sectional labor supply regressions

$$\ln hours_i = \beta_0 + \beta_1 \ln wage_i + X_i\gamma + u_i$$

for each group j. The matrix X includes controls for age, age-squared, education, other family income, other personal income, sex, marital status, interaction of sex and marital status, black, and hispanic ethnicity. These regressions should fit better in PMSAs where individual fixed costs of work are lower. In fact, regressions of the R^2 statistics from these equations on mean commuting time at the PMSA and PMSA-occupation levels support this hypothesis. Lines 3a and 3b show that an extra 5 minutes of average commuting time reduces the fit of a weekly hours equation by 0.01, and of an annual weeks equation by 0.005.

Finally, we can examine whether cross-sectional wage elasticities of weekly hours, estimated by the coefficients β_1 in the model above, vary with commuting time, as shown in lines 4a–4c. We expect that labor supply will be less elastic in areas with high fixed costs. Uncompensated wage elasticities of weekly and annual hours are negative on the whole, indicating a dominant income effect. A five-minute increase in one-way commuting time reduces (makes more positive) the elasticity of weekly hours by about 0.01, and of annual hours by about 0.05. In other words, longer commuting time does tend to push elasticity estimates towards zero. The effect of commuting time on the weeks elasticity is also positive, but since the mean elasticity is very close to 0 (0.005), the interpretation is unclear. These effects are even larger by PMSA-occupation, where the average elasticities are even more negative, although the R^2 statistics are much lower. The fact that annual weeks are generally more responsive to commuting time than weekly hours seems surprising, since weekly hours correspond more closely to the unit of time for which commuting is truly a fixed cost, days per week.

The reader should bear in mind that since commuting time represents a fixed cost of work per day, annual or weekly days worked would be the most appropriate measure of labor supply to use in this paper's analysis. Measures such as annual and weekly hours can substitute for this ideal but unavailable data, a choice justified by theory as well as by convenience and convention. Discontinuity in the days per week function will induce discontinuity in the hours per week function, which will have a minimum equal to the product of the minimum of days per week and of hours per day.[20] The same reasoning applies to show discontinuity in the hours per year function as well. Nevertheless, the aggregated measures fail to reflect the full labor supply responses to the discontinuity, since such responses may involve substitution between the components, of which the net effect may be quite small. For example, a worker choosing a schedule of 4 days a week at 10 hours per day in response to higher daily fixed costs will look the same in terms of weekly hours as someone working 8 hours a day, 5 days a week. Thus, analysis both here and later in the paper will underestimate the effects of daily fixed costs like commuting.

These results that variance of log hours, percentage of employees working short weekly hours, goodness of fit of labor supply equations, and wage elasticities all decrease in PMSAs characterized by longer commutes provide strong evidence that mean PMSA commuting time represents a fixed cost of work. The fact that the cost has greater impacts at the PMSA-occupation level suggests that at this level of aggregation, the measure better reflects fixed costs of employment.

It is also of interest to consider whether the effects of commuting time described above differ for men and women. Time in transit to work may impose differing costs of work to men and women due to their differing opportunity costs of time. As Table 4 shows, effects of mean commuting time on mean wages are significantly higher for men than for women at the PMSA and PMSA-occupation levels, except when demographic and

[20]This is especially true if the reservation price of days per week is high relative to that of hours per day, in which case the range defined in part by the minimum of days per week will be smaller. In the absence of evidence relating to the reservation prices above, the actual appropriateness of these measures is unclear.

PMSA controls are included. However, as lines 2–3 show, commuting time tends to decrease the variance of log hours per week only slightly more for women than for men; reductions in the percentage of workers with part-time hours are approximately the same. These results indicate the potential importance of examining the effects of commuting time on labor supply for men and women separately.

5 An econometric framework for estimating labor supply equations

The preceding sections have shown that not only does aggregate commuting time impose financial costs on employers, it also affects actual variance in log hours of work. These results indicate that this measure should be a powerful instrument for demand-side factors, such as firms' costs of employment, affecting working hours. My main interest now is in using this instrument to obtain estimates of the uncompensated cross-sectional wage elasticity of hours of work.

Consider the following expressions for hours supplied and demanded corresponding to optimal hours choices for the employee and employer derived in Section 2, using a simple parameterization:

$$S: \quad \ln h_{ij} = \ln w_{ij}\beta_1 + X_{ij}\beta_2 + \tilde{t}_{ij}\beta_3 + u_{ij} \tag{3}$$

$$D: \quad \ln h_{ij} = \ln w_{ij}\delta_1 + X_{ij}\delta_2 + \bar{t}_j\delta_3 + \xi_{ij} \tag{4}$$

where i indexes individuals, j indexes groups, and each group contains N_j individuals. I consider only those individuals who are working and ignore issues of selection.[21] In my empirical analysis, I will experiment with two levels of aggregation of the instrument, PMSA and PMSA-occupation.[22] X represents a matrix of individual and PMSA characteristics and a constant term, while t denotes commuting time. Note that only deviations of individual commuting time from the group mean, denoted $\tilde{t_{ij}}$, appear in the labor supply equation since we have assumed that employees are fully compensated by employers through the wage for the group-level component of their commuting time. In contrast, within-group commuting time does affect

[21]The high rates of labor force participation for both men and women in the Census suggest that such issues may be relatively unimportant.

[22]Variation in commuting times across occupations in a PMSA will be driven by differences in their intracity locations. Here again, as with PMSA commuting time, if the commuting times associated with these locations are a job characteristic for which individuals are compensated, PMSA-occupation commuting time can function as a demand instrument.

individuals' hours, representing a fixed cost to working for which they are not fully compensated. The errors in each equation are assumed to be $i.i.d.$ and uncorrelated with the regressors X. The demand equation error ξ_{ij} is also orthogonal to $\bar{t}_j$.

I control for employee and locational characteristics which are presumed to be exogenous factors affecting choices of hours. While the inclusion of individual traits is fairly standard, the role of PMSA attributes in a labor supply equation may not be obvious. I attempt to strike a balance after weighing arguments for and against their inclusion. First, a useful way to think about the econometric model is to remember that implicit markets exist for all PMSA and job attributes, including commuting time, in addition to the explicit market for hours of work. As with commuting time, if individual valuations of an attribute differ, or if part of its valuation is capitalized in the land market through lower rents, the wage does not provide full compensation for all individuals. In such a case the attribute should be included in the labor supply equation to avoid the risk of omitted variables bias. Among PMSA characteristics are prices such as rents (proxied here by median housing value). While rents are clearly related to amenities in a more complex way, they have a straightforward role in the labor supply equation as the price of another good that is taken into account by individuals choosing consumption of leisure. It is important to recognize that the equations I estimate thus represent a lower-dimensional slice of a larger hedonic system, and may be considered structural only along the dimensions of hours of work and commuting time. With respect to the other dimensions they are in reduced form.

This logic brings me next to a familiar projection argument. In order to abstract from the effects of potentially endogenous factors on the wage, I want to use only that variation in the wage which is related to commuting time, to the extent that this reflects the influence of demand factors, to identify the wage coefficient. The qualification in the preceding statement makes an important point. I am not interested in isolating the effect of commuting time on wages for its own sake, but only in so far as it reflects something which is costly to employers. If commuting time is actually correlated with other factors which impact firm costs, it has the advantage of providing a convenient proxy for more general demand effects. The exclusion of controls thus has the additional advantage of lending greater power to the elasticity estimator.

These considerations govern the choice of control variables, although specific choices are, in the end, a matter of judgment rather than empirical evidence. Variables relating to the tightness of the labor market, price levels, and pure amenities should be included, since they are exogenous determinants of the wage. I assume that such variables include population levels, growth, and density; the unemployment rate; and the crime rate. These choices are not uncontroversial. For example, while Ham (1986) interprets the unemployment rate as an employment cost, Abowd and Ashenfelter (1981) present an argument for treating it as a disamenity. However, some assumptions about the nature of the compensation for each amenity must be made in order to proceed.

5.1 Estimation procedures

The simplest approach to estimating the parameters in the labor supply equation (3), in particular the uncompensated wage elasticity β_1, uses the method of OLS. However, the behavioral model indicates that both the wage and the individual-level component of commuting time are endogenous to the individual, which makes this strategy problematic. Employers offer wages that depend on the hours an employee works, and within-PMSA commuting time is chosen jointly with hours of work. This induces correlation between the wage and the error term, $Ew'u \neq 0$, leading to bias and inconsistency in the OLS estimator of β_1. The sign of the bias is ambiguous, depending on the interactions between the income and substitution effects and the wage-hours-commuting time locus. The endogeneity of within-group commuting time leads to similar bias in its coefficient estimate. An obvious way to address the issue of bias is to implement an instrumental variables procedure. The exogenous demand variables (in this case, the single variable average commuting time) provide instruments for the wage.[23] The aggregate instrument breaks the correlation of the wage and the error within groups, removing the bias due to omitted individual-level taste variables. The wage is identified off the aggregate-level variation.

[23]Without instruments for within-group commuting time, its coefficient is biased, but as this parameter is not our main concern we ignore this problem.

5.1.1 Instrumental variables estimator

In order to examine this IV estimation strategy more closely, rewrite the error term in equation (3) to include both group-level and individual-level components:

$$\ln h_{ij} = \ln w_{ij}\beta_1 + X_{ij}\beta_2 + +\tilde{t_{ij}}\beta_3 + \mu_j + \nu_{ij}. \tag{5}$$

Both μ and ν are assumed to have mean 0, with ν homoskedastic and μ heteroskedastic. Furthermore, I assume that individual characteristics X are uncorrelated with tastes, $EX'u = 0$. This is a conventional random effects specification that allows tastes to be correlated within groups. The probability limit of the IV estimator of β_1 can be written as

$$plim\hat{\beta_1}^{IV} = \beta_1 + \frac{plim\ \bar{t}'M_X\mu}{plim\ \bar{t}'M_Xw}$$

where $\bar{t} \equiv \bar{t}_j$ and M_ω is defined as $I - P_\omega = I - \omega(\omega'\omega)^{-1}\omega'$. Identification of β_1 requires that the instrument must be correlated with the endogenous variable. As the group-level instrument is orthogonal by construction to the individual-level (within-group) error, the assumption required for unbiasedness and consistency of the estimator is that the instrument is orthogonal to the group-level error component.[24] In other words, individuals cannot choose their PMSA of residence based on differing tastes related to commuting, which could occur if wages do not fully compensate all individuals for this disamenity. Significantly different OLS and IV estimates would imply that average commuting time does affect wages. Specifically, in the context of the model described above, the interpretation of this result would be that wages are endogenous in the labor supply equation and that employers have a distinct interest in employee hours beyond their interest in total manhours. Of course, with only one instrument I cannot rule out the possibility that average commuting time relates to individual tastes for hours using an overidentification test. The empirical results on the relationship between average commuting time and hours, however, support the claim that this relationship is primarily the result of demand factors.

Although the aggregation of commuting time may be considered a practical asset in terms of its exogeneity to variation within groups, the use of an aggregate instrument entails the typical problems of bias in estimates of standard errors that are associated with aggregate variables in general. These problems relate to the effects

[24] This estimator is similar to the Wald estimator employed by Angrist (1991), which uses year effects as instruments in the estimation of intertemporal labor supply elasticities. Interestingly, his approach also yields large elasticity estimates.

of sorting similar to those described above. Since the instrument varies only at the group level, errors are likely to be correlated within groups, implying that OLS standard errors will be biased downward and will appear too precise. Robust variance calculations correct these biases.[25]

5.1.2 Contrast estimator

If the assumption above of identical individual preferences for commuting time fails and individuals do care about average commuting time even conditional on the wage, the group-level error μ will be correlated with the instrument, $E\bar{t}'\mu \neq 0$, leading to bias in the IV estimator. The bias of the IV estimator will be positive if, on average, individuals who prefer longer hours of work tend to locate in cities with longer average commutes, and negative if they tend to locate in cities with shorter commutes. Another way to think about this is that, to the extent that the average component of some workers' commuting time is undercompensated by the wage, this component will again function as a cost that reduces their hours supplied. Notice that bias can exist even in wage elasticity estimates of labor supply measures whose choice is little affected by commuting time. For instance, while commuting to work represents a fixed cost per day of work, elasticity estimates of the supply of annual weeks of work may be biased if individuals' preferences over commuting time are correlated with their preferences for weeks of work.

The model remains estimable even allowing for such correlation of tastes with average commuting time. We can exploit the assumption that individual characteristics X are uncorrelated with the error terms ν and μ by using as an instrument only that variation in mean PMSA commuting time that is correlated with the PMSA means of these characteristics. In other words, we use $\bar{X}$ as an instrument for the instrument. Such an estimator, which I call the Contrast estimator, is defined as

$$\hat{\beta_1}^C = \frac{\bar{t}'P_{\bar{X}}M_X h}{\bar{t}'P_{\bar{X}}M_X w}.$$

This estimator relies on differences in the relationship between hours and wages within and between groups, so it has the advantage of being robust to more forms of omitted variables than the IV estimator which uses only group means as instruments. The estimator will be unbiased and consistent if tastes for work are

[25]Detailed discussions of bias due to grouped variables may be found in Moulton (1986), while Shore-Sheppard (1996) and Hoxby and Paserman (1998) focus specifically on grouped instruments. Greenwald (1983) derives expressions relating properties of the disturbances to bias in OLS standard errors.

independent of (observable) individual characteristics, regardless of the correlation of tastes for work with average commuting time, so no additional orthogonality assumptions are needed.[26] However, this savings is made possible at the cost of additional assumptions on the relationship of the covariates X to other variables. Identification of the estimator depends crucially on the presence in the labor supply equation of these covariates, which must be correlated with wages as well as with mean commuting time. Choice between the Contrast and IV estimators thus depends on whether we believe more endogeneity exists in the instrument $\bar{t}$ or in the mean regressors $\bar{X}$.[27]

The estimator described here is similar to one proposed by Hausman and Taylor (1981) to estimate time-invariant effects in a panel data setting in that both depend on the presence of control variables in the regression and on the independence of these control variables from the error.[28] However, there are some important differences. First, Hausman and Taylor use a time-series panel of individuals over time, while I focus on a geographic cross-section of individuals in different cities. My city-level effects are analogous to their time-invariant individual effects. Second, they use individual means of the conditioning variables X as instruments for the time-invariant regressors, while I use group means of X as instruments for the instrumented regressor. Thus, their strategy applies to an OLS context while mine applies to an IV context. In fact, I follow exactly their procedure in my two first stage OLS regressions.

This estimation strategy is also related to the approach taken by Boozer and Rouse (1998) to estimate the effects of school quality on student achievement when quality is correlated with state-level error terms. In this case, their endogenous regressor is not time-invariant, and is moreover correlated with school-level errors as well. They allow for both state and school fixed effects and derive an estimator from these general orthogonality conditions. The econometric model set up by Boozer and Rouse corresponds more closely to the one I describe here than the Hausman and Taylor model does, although they also operate in an OLS

[26]To see this, note that the assumption of the independence of X from the error terms implies that $plim\ \bar{t}' P_{\bar{X}} M_X u = plim\ \bar{t}' P_{\bar{X}} u - plim\ \bar{t}' P_{\bar{X}} P_X u = 0$. See the Appendix for all derivations and a statement of the orthogonality condition that uniquely defines this estimator.

[27]It is interesting to note that the Contrast estimator may also be interpreted as a weighted difference of the IV estimator and a group-level IV estimator (denoted IV-b; a group-level IV estimator replaces the observations of all variables by their group means). The intuition is that both estimators will share similar biases since the potential covariance between the instrument and the error is at the group level. The difference in the estimators arises because the identifying covariation between mean commuting time and the wage (conditional on the variance in the covariates) is necessarily smaller in the group-level regression. The ratio of these covariances (IV to group-level IV) $\hat{\alpha}$ is thus equivalent to the inverse ratio of the biases in the two estimators, and is used as a weight in defining the Contrast estimator, $\hat{\beta_1}^C = \frac{\hat{\beta}^{IV-b} - \hat{\alpha}\hat{\beta}^{IV}}{1-\hat{\alpha}}$, where the less-biased estimator is given more weight. I use this definition to obtain estimates of β_1. Standard errors are calculated using the Delta method. I have not yet explored efficient estimation procedures.

[28]See also Amemiya and MaCurdy (1986), who nest the Hausman and Taylor approach in a more general framework.

setting.[29]

5.1.3 Instrumental variables estimator with fixed effects

While the discussion above shows the advantages of a grouped instrument, it also highlights a disadvantage. Essentially, the instrument removes bias from omitted individual-level variables at the expense of inflating the bias from omitted group-level variables.[30] To see this, first note that the bias due to differences in tastes for commuting in the expressions above can be interpreted as a form of omitted variables bias. Consider a conventional instrumental variables estimator, in which the instrument is individual-level commuting time. This IV estimator will have two components of bias, due to omitted factors varying at both levels,

$$plim\hat{\beta}_1^{CIV} = \beta_1 + \frac{plim\ t'M_X\nu}{plim\ t'M_Xw} + \frac{plim\ t'M_X\mu}{plim\ t'M_Xw}.$$

The second term on the right-hand side represents the bias due to omitted group-level variables. A comparison of the bias due to omitted group-level variables in the IV estimator above shows that my IV estimator magnifies this bias relative to the conventional IV estimator by $\frac{plim\ t'M_Xw}{plim\ \bar{t}'M_Xw} > 1$.

This argument illustrates the exceptional importance of controlling for PMSA and PMSA-occupation traits that might influence individuals' choice of location. An obvious way to achieve this is by including variables covering a wide range of characteristics in the matrix X, although in terms of the contrast estimator this involves a tradeoff of power and bias as discussed above. Another approach exploits the availability of two levels of aggregation by allowing for fixed PMSA effects, removing the bias associated with individual preferences over PMSAs. Since the PMSA is a broader grouping than the PMSA-occupation, the dimension of variation within PMSAs but between occupations can be used to identify the wage. This estimation strategy, denoted IV-FE, practically involves the use of PMSA-occupation instruments and the inclusion of PMSA fixed effects in the second stage. Such a specification is especially appealing if there are doubts that the PMSA-level controls in the first stage capture the effects of all relevant PMSA characteristics, since it abstracts from these characteristics altogether. Under the assumption of random PMSA-occupation effects, the IV-FE estimator proposed here will be free from bias.

[29]The connection to the estimator presented here is perhaps easiest to see under the "weighted difference" interpretation, in which components of the bias terms are actually estimated and then expunged.

[30]See Hanushek, Rivkin, and Taylor (1996), Boozer and Rouse (1998), and Hausman and Taylor (1981).

Now, however, we may be concerned about the exogeneity of the identifying PMSA-occupation variation in commuting time. If tastes for occupations are correlated with tastes for commuting, the fixed-effects IV estimator will be biased as well. The better (less-biased) choice to the researcher between the IV-FE estimator and the IV estimator using the PMSA-occupation level instrument is ambiguous in this case. In fact, the potential for such sorting is also relevant to the researcher's choice between the IV estimators using the two averages of commuting time as instruments. Although the PMSA-occupation instrument is more disaggregated than the PMSA instrument, it may have more bias if selection into PMSA and occupation is less random than selection into PMSA alone. These issues should be kept in mind when examining and interpreting results of estimation. Results will suggest which sources of bias may be present. Observational differences that cannot be attributed to sampling error between the IV-FE and PMSA-occupation IV estimators, or between the PMSA-occupation IV and PMSA IV estimators, indicate sorting behavior at one or both levels.

The preceding discussion highlights the reason why individual commuting time fails to identify the wage, while aggregate commuting time can do so even if preferences for average commuting time are not identical among individuals. Identification of the IV estimator does not come from the orthogonality of the instrument itself to the aggregate error component in the labor supply equation, but from the orthogonality of the control variables X to the error, along with their covariance with city-level commuting time. Results of estimation using the methods described above to remove possible biases due to sorting will be presented in the following section.

6 Results of estimation of labor supply equations

Using this framework, I estimate labor supply equations for three hours measures: log hours per week, log weeks per year, and log annual hours. Analysis is performed for men and women separately, a choice justified theoretically as well as empirically. Men's and women's hours choices will differ if their outside alternatives differ. Although both face the same choices of market work, home production, or leisure, rates of and especially trends in labor market participation vary greatly by sex. In the past century, the participation rate of men in the U.S. has always exceeded that of women, and divergent trends have narrowed the gap.

Furthermore, results in the previous section showed that the effects of commuting time on hours of work differ for men and women. Clearly some aspect of the choice problem individuals face is systematically different between sexes, suggesting that they should be treated separately.

However, I do not further stratify the sample according to marital status, as many studies of labor supply do, especially those concerning women. Instead, I merely allow for differing intercepts. This specification avoids selection bias due to the possible endogeneity of marriage, while aiming to improve explanatory power.[31] Controls for individual characteristics X include a constant term, age, age-squared, education, other family income, other personal income, and dummies for being married, black, and hispanic. Controls for PMSA traits include unemployment rate, crime rate, and sets of variables relating to population and price levels. The instrument t identifying the log wage is the aggregate mean of commuting time. Both PMSA level and PMSA-occupation level specifications will be estimated, with the latter including controls for PMSA size and size-squared. All IV estimators will allow for random group effects in the second stage, which may be interpreted as average tastes for hours if I assume endogenous PMSA or PMSA-occupation choice.[32]

Results of estimation of the labor supply model for the dependent variables weekly hours, annual weeks, and annual hours of work are shown in Tables 5M and 5F. For the sake of brevity, this discussion will focus on the results for weekly hours.[33] Column 1 presents OLS estimates. The log wage coefficient estimates for both men and women are negative and close to zero; both estimates are insignificant. In comparison, the IV estimates in columns 2 and 3 are positive for men and women, exceeding the OLS estimates by at least .1 and up to .6. Each instrument does appear to explain a significant amount of wage variation, as the F statistics and partial R^2 statistics indicate, although the PMSA-occupation instruments appear superior to the PMSA instruments.[34] Only the PMSA-occupation-level instrument yields significant estimates, however. IV estimates are larger when using the less aggregated PMSA-occupation instrument (.17 for men and .63 for women), and are roughly three times larger for women than for men. These differences between the OLS and IV results indicate that ignoring employers' preferences over employee hours leads to substantial

[31] A specification excluding marital status as a regressor altogether produces very similar results.

[32] Results from specifications excluding PMSA-level regressors yielded very similar parameter estimates.

[33] While full sets of parameter estimates are not shown, coefficients are generally significant and of the correct sign.

[34] It is especially important to perform such evaluation in this case, where an extremely large data set is used. As Bound, Jaeger, and Baker (1995) show, in such a situation even a small correlation of the instruments with the error will be magnified.

understatement of labor supply elasticities, as we suspected. Although this analysis has ignored the possibility of employer sorting, I have shown that this would lead to attenuation bias in the elasticity estimates, reinforcing the result of downward bias in OLS estimates.

Including fixed PMSA effects in the PMSA-occupation IV specification to eliminate potential sorting bias yields even larger estimates, shown in column 4. Wage elasticities of hours per week increase almost by a factor of 2 for men (to .33) and by 1.5 for women (to .93). At mean hourly wages ($11.31) and weekly hours (36) for women, this implies that a $1.00 increase in the wage will lead to an increase of almost 3 hours per week on average. The differences between the IV and IV-FE estimates imply that bias due to individual sorting into PMSAs or PMSA-occupations may affect one or both of these estimators.

The Contrast estimator provides an alternative means by which to correct for sorting bias. I compute this estimator only for the PMSA-occupation instrument, as results suggest that the Contrast estimator using the PMSA instrument is insignificant.[35] As shown in column 5, this estimator indicates slightly smaller downward bias for men, implying a true uncompensated elasticity of annual hours of .45. In contrast, for women there is little bias in the elasticity of weekly hours, and a small (though potentially insignificant) *upward* bias in the elasticities of annual weeks and hours, suggesting a true uncompensated elasticity of annual hours of .97.

A comparison of the estimators reveals further details about the nature of the sorting bias, which is a likely source of their differences. In the most general case of individual sorting into both PMSAs and occupations, only the Contrast estimator will produce unbiased results. The IV-FE estimator is robust only to PMSA sorting and the IV estimator is vulnerable to both types. Thus, PMSA sorting drives the difference between the IV-FE and IV estimators, while occupational sorting drives the difference between the Contrast and IV-FE estimators. According to this reasoning, PMSA sorting generates downward bias in elasticity estimates while occupational sorting produces upward bias. An intuitive way to think about these biases is to cast them in terms of omitted variables. For instance, the negative PMSA-sorting bias could be attributed to an omitted PMSA-level disamenity, such as cold or wet weather, which increases wages while making it more difficult to work and decreasing hours supplied. The results indicate that even if individuals sort into

[35]The component IV and IV-b estimators based on the PMSA instrument are insignificant.

PMSAs due to differing tastes for average commuting time, the IV estimator is indeed less biased than the OLS estimator, which fails to account for employers' interest in employee hours and underestimates the wage elasticity even more dramatically. Interestingly, PMSA sorting bias in estimates for women exceeds that for men, consistent with greater responsiveness of women to these types of factors. The differences between men and women in the bias of IV estimates could indicate an avenue for further research.

Results for annual weeks and annual hours are qualitatively similar to the results for weekly hours. OLS estimates of the log wage coefficient are significant but small in absolute value, positive for women but of mixed sign for men. (Mathematically, the annual hours elasticity is simply the sum of the weekly hours and annual weeks elasticities.) IV estimates are usually insignificant when the PMSA-level instrument is used, but are large and significant using the PMSA-occupation-level instrument. The substantial wage elasticities for annual hours are even more remarkable given that the way in which the wage measure is constructed tends to bias this estimate towards -1. In the between regressions, although the PMSA-level instrument yields insignificant log wage estimates for both annual weeks and annual hours, the PMSA-occupation-level instrument produces large positive coefficients.

Since most estimates of cross-sectional labor supply elasticities found in the literature apply to annual hours, the estimates here can be compared to those obtained using conventional methods. Few empirical treatments of simultaneity in the market for hours of work exist, however, which makes direct comparison with similar instrumental variables approaches difficult. Most IV strategies employed are intended to deal with problems of measurement error in wages or hours variables, or comprise part of a procedure to correct for sample selection. In fact, to my knowledge, the only other study using demand instruments for the wage is Oettinger's (1999) research which looks at the intertemporal supply of days of work. However, it is interesting to note that he also finds downward bias in the intertemporal wage elasticity when the estimation procedure does not account for demand factors. Given these distinctions, it may be most illuminating to compare the IV estimates of annual hours elasticities found here with similar OLS estimates. PMSA-occupation IV and IV-FE estimates of the uncompensated wage elasticity of annual hours for men (.31 and .64) far exceed OLS estimates found by each of 14 studies from the 1970's and 1980's surveyed by Pencavel (1986), almost all of which are actually negative. Ashenfelter and Heckman's (1974) estimate is -.16, and the average over these studies is -.12.

For women, the PMSA-occupation IV and IV-FE wage elasticity estimates of annual hours shown here (1.02 and 1.58) are also much larger than estimates produced using OLS. For example, Schultz (1980) computes OLS estimates of uncompensated wage elasticities of annual hours for employed married women whose husbands are also employed, stratified by age and race. These estimates range from .01 to .24.[36] Clearly, accounting for employer preferences in hours determination dramatically changes our inferences on the responsiveness of labor supply to wage levels.

In sum, aggregate commuting time appears to be a powerful instrument for the wage, and yields wage elasticity estimates which are roughly three times larger for women than for men. The instrument performs better when aggregated into PMSA-occupation groups than into PMSA groups. In both cases, IV estimates of wage elasticities of several labor supply measures are shown to exceed OLS estimates. Correction for potential sorting bias strengthens this result, while suggesting that the IV estimates tend to understate the true elasticities for men and for the weekly hours of women.

7 Conclusions

The results of this paper demonstrate that aggregate commuting time plausibly captures one dimension of employer interest in employee hours, serving as a valuable instrument for fixed employment costs. Not only does mean PMSA (and PMSA-occupation) commuting time impose financial costs on employers through higher wages, it also tends to increase actual hours of work, a result which is inconsistent with the neoclassical model. For instance, log hours vary less and fewer people are observed working part-time in areas characterized by long commutes. The interpretation and use of average commuting time, which has the advantage of wide availability in micro datasets, as a factor affecting labor demand allows estimation of labor supply equations with endogenous wages through instrumental variables procedures. Log wage coefficient estimates obtained for several labor supply measures using these methods are positive, and are always larger for women than for men. The finding of downward bias in OLS estimates due to the effects of omitted variables attests

[36]Ashenfelter and Heckman use the 1960 U.S. Census of Population, and Schultz uses the 1967 Survey of Economic Opportunity. For both men and women, some of the difference of my results from the others cited here could be due to my use of more recent data.

to the importance of incorporating demand factors into the problem of hours determination, as well as to the usefulness of this particular instrument.

First-stage results indicate that the less aggregated PMSA-occupation instrument has superior explanatory power for the wage, lending greater credence to the larger (and significant) estimates it yields. For annual hours, these wage elasticity estimates are .31 for men and 1.02 for women. While individuals' PMSA locations may not be unrelated to average commuting times even after conditioning on the wage, as these strategies assume, I show that bias in the IV estimator arising from this source can be eliminated through simple manipulations of various conventional estimators or through the inclusion of PMSA fixed effects. These strategies generally produce even larger elasticity estimates that exceed those usually found using conventional methods.

Overall, the results support the importance of employer interest in determining hours of work. The empirical framework developed here opens a channel through which to gain insight into a host of issues relating to employer and employee choices of hours of work. Further consideration of this issue may help to improve our estimates of labor supply parameters, as well as deepen our understanding of the role of employers in the labor market.

A Appendix

In this appendix I derive the expressions for bias in the various estimators discussed in the text. Consider the following equations:

$$h = w\beta_1 + X\beta_2 + Pu + Qu \tag{6}$$

$$w = Pt\gamma_1 + X\gamma_2 + \epsilon \tag{7}$$

where both hours and wages are $(N = \sum_j N_j) \times 1$ vectors measured in logarithms. P represents the between operator $I_j \otimes \frac{i_{N_j} i'_{N_j}}{N_j}$ where i_{N_j} denotes an N_j x 1 vector of ones and I_j denotes a $J \times J$ identity matrix, and Q represents the within operator $I_{ij} - P$. It is a familiar result that P and Q are projection matrices such that $P + Q = I$ and $PQ = 0$. Assume that $EX'u = 0$. The error components Pu and Qu represent a random effects specification. Assume that the within-group error Qu is homoskedastic with mean 0 and variance σ^2 but that the between-group error Pu is heteroskedastic with variance $E\mu\mu' = I_j \otimes \Sigma_{N_j}$, $\Sigma_{N_j} = \rho_j i_{N_j} i'_{N_j}$. Furthermore, both Pu and Qu are correlated with the wage, so that $Ew'u \neq 0$, and Pu is correlated with Pt, $Et'Pu \neq 0$. The error ϵ is assumed to be homoskedastic with mean 0 and orthogonal to all regressors and to u. Define the symmetric and idempotent matrix projecting off the space spanned by the regressors X as $M_X = I - X(X'X)^{-1}X'$.

A.1 Contrast estimator

A.1.1 Definition

The instrumental variables estimate of β_1 is

$$\begin{aligned}
\hat{\beta_1}^{IV} &= (\hat{w}' M_X \hat{w})^{-1} \hat{w}' M_X h \\
&= (w' M_X Pt(t' P M_X Pt)^{-1} t' P M_X w)^{-1} w' M_X Pt(t' P M_X Pt)^{-1} t' P M_X h \\
&= \frac{t' P M_X h}{t' P M_X w}
\end{aligned}$$

where the last equality follows in the case of exact identification (t is a column vector). The probability limit of the estimator can be written as

$$plim\ \hat{\beta_1}^{IV} = \beta_1 + \frac{plim\ t' P M_X u}{plim\ t' P M_X w}.$$

Consistency of the IV estimator requires

1. $plim\ \frac{1}{n}X'X = Q_X$ positive definite

2. $plim\ \frac{1}{n}t'Pw \neq 0$

3. $plim\ \frac{1}{n}X'u = 0$

4. $plim\ \frac{1}{n}t'Pu = 0$.

We may similarly define the group-level IV estimator, where all variables are aggregated to the PMSA level,

$$\hat{\beta_1}^{IV-b} = \frac{t'PM_{PX}h}{t'PM_{PX}w},$$

with probability limit

$$plim\ \hat{\beta_1}^{IV-b} = \beta_1 + \frac{plim\ t'PM_{PX}u}{plim\ t'PM_{PX}w}$$

where $M_{PX} = I - PX(X'PX)^{-1}X'P$. Consistency of the IV-b estimator requires

1. $plim\ \frac{1}{n}X'PX = Q_{PX}$ positive definite

2. $plim\ \frac{1}{n}t'Pw \neq 0$

3. $plim\ \frac{1}{n}X'Pu = 0$

4. $plim\ \frac{1}{n}t'Pu = 0$.

Suppose that individual tastes are correlated with commuting time at the group level, such that $Et'Pu \neq 0$ and both the IV and IV-b estimators are inconsistent (and biased). We may still obtain a consistent (and unbiased) estimate of β_1 in this case by exploiting the independence of the regressors X and the error u. Consider using only the variation in mean commuting time related to the variance in mean X as an instrument rather than mean commuting time itself. This yields the Contrast estimator

$$\hat{\beta_1}^{C} = \frac{t'PP_{PX}M_Xh}{t'PP_{PX}M_Xw}$$

with probability limit

$$plim\ \hat{\beta_1}^{C} = \beta_1 + \frac{plim\ t'PP_{PX}M_Xu}{plim\ t'PP_{PX}M_Xw}. \tag{8}$$

The instrument is the predicted value from a regression of mean commuting time on mean X, $P_{PX}Pt$, rather than mean commuting time Pt itself. Note that mean Xs must be used rather than the regressors X themselves as these must be included as control variables.[37] Notice that we may also consider using the projection of Pt onto $f(x)$ as long as $Ef(x)u = 0$ and $f(X)$ can be excluded from the labor supply equation. The unique orthogonality condition identifying this estimator defined by the numerator of the bias term above. The expression above makes it easy to see the conditions required for consistency of the Contrast estimator:[38]

1. $plim\ \frac{1}{n}X'X = G_X$ positive definite

2. $plim\ \frac{1}{n}X'PX = G_{PX}$ positive definite

3. $plim\ \frac{1}{n}X'QX = G_{QX}$ positive definite

4. $plim\ \frac{1}{n}X'w \neq 0$

5. $plim\ \frac{1}{n}t'PX \neq 0$

6. $plim\ \frac{1}{n}X'Pu = 0$

7. $plim\ \frac{1}{n}X'Qu = 0$.

Conditions (1) – (5) ensure that the estimator is well-defined. (Condition (3) is needed to ensure $X'X \neq X'PX$, in which case the IV and IV-b estimators would be identical and the contrast estimator undefined.) Conditions (4) and (5) replace the IV condition $plim\ \frac{1}{n}t'Pw \neq 0$. Conditions (6) and (7) correspond to the assumptions required to establish consistency of IV estimators, replacing the condition $plim\ \frac{1}{n}t'Pu = 0$. However, notice that in this context, PX plays the role of an instrument for Pt. Notice also the absence of an orthogonality condition between Pt and u. In this way, the approach resembles that of Hausman and Taylor (1981) as described in the text.

[37]The estimate of the coefficient on X will simply be the OLS estimate.

[38]To establish unbiasedness, stronger conditions replacing $plim$ with $E(\cdot)$ are required.

A.1.2 Interpretations

The Contrast estimator can be computed by estimating the following regression using OLS:

$$h = wb + M^* w\theta + \epsilon$$

where

$$M^* = I - M_X P_{PX} Pt\Big(t'PP_{PX}M_X P_{PX}Pt\Big)t'PP_{PX}M_X.$$

The estimator $\hat{b}$ is equivalent to $\hat{\beta_1}^C$. (See the discussion in Davidson and MacKinnon (1993).) The second term is a vector of residuals from a regression of w on the instrument $M_X P_{PX} Pt$, which regressor may be obtained in two steps: first obtaining predicted values from a regression of Pt on PX, and then taking the residuals from a regression of this predicted values on X.

To cast the estimator in a GMM framework, note that the Contrast estimator of β maximizes the criterion function

$$C = (h - w\beta_1 - X\beta_2)'\ M_X P_{PX} Pt\Big(t'PP_{PX}M_X P_{PX}Pt\Big)^{-1} t'PP_{PX}M_X\ (h - w\beta_1 - X\beta_2)$$

according to the first order condition

$$w'M_X P_{PX} Pt\Big(t'PP_{PX}M_X P_{PX}Pt\Big)^{-1} t'PP_{PX}M_X\ (h - w\beta_1 - X\beta_2) = 0.$$

Dividing out the scalar terms, we find again the orthogonality condition identifying the Contrast estimator,

$$\begin{aligned} t'PP_{PX}M_X u &= 0 && (9) \\ t'PX(X'PX)^{-1}X'Pu - t'PX(X'X)^{-1}X'u &= 0, \end{aligned}$$

which requires the key conditions that $X'u = 0$ and $X'Pu = 0$.

It is interesting to note an alternative interpretation of the Contrast estimator as a weighted difference of the IV and IV-b estimators.

$$\begin{aligned} \hat{\beta_1}^C &= \frac{t'PP_{PX}M_X h}{t'PP_{PX}M_X w} \\ &= \frac{t'P(P_X - P_{PX})h}{t'P(P_X - P_{PX})w} \end{aligned}$$

$$
\begin{aligned}
&= \frac{t'P(M_{PX}-M_X)h}{t'P(M_{PX}-M_X)w} \\
&= \frac{t'P(M_{PX}-M_X)h}{t'PM_{PX}w}\cdot\frac{t'PM_{PX}w}{t'P(M_{PX}-M_X)w} \\
&= \left[\frac{t'PM_{PX}h}{t'PM_{PX}w}-\frac{t'PM_Xh}{t'PM_Xw}\cdot\frac{t'PM_Xw}{t'PM_{PX}w}\right]\frac{t'PM_{PX}w}{t'P(M_{PX}-M_X)w} \\
&= \frac{\hat{\beta}^{IV-b}-\hat{\alpha}\hat{\beta}^{IV}}{1-\hat{\alpha}}
\end{aligned}
$$

(The intuition behind the second equality is that the expressions $t'P(P_{PX} - P_X)$ and $t'PP_{PX}M_X$ both denote projection of Pt onto PX but off of X. We multiply the top and bottom of the first expression by -1 to derive the equality.) The weight $\hat{\alpha}$ is the inflation of the bias in the IV-b estimator relative to the IV estimator,

$$\hat{\alpha} = \frac{t'PM_Xw}{t'PM_{PX}w}.$$

The estimator places more weight on the less biased estimator. Mathematically, $\alpha = 1$ in the unidentified case. As α grows to infinity, the estimator converges to the IV estimator. Consistency is established by the Slutsky theorem. This specification is the one used here to calculate the Contrast estimator. Standard errors were calculated according to the Delta method using a diagonal variance matrix, ignoring nonzero covariances between estimators. This strategy should avoid downward finite-sample bias due to correlation between estimates of covariances and first derivatives; see Altonji and Segal (1996).

A.1.3 Hausman tests

To further compare the Contrast and IV estimators, it is illuminating to consider performing a Durbin-Wu-Hausman (DWH) test based on the vector of differences between the Contrast and IV estimates. The test is based on the fact that the Contrast estimator is consistent under weaker conditions.

$$
\begin{aligned}
\hat{\beta}^c - \hat{\beta}^{IV} &= (t'PP_{PX}M_Xw)^{-1}t'PP_{PX}M_Xh - (t'PM_Xw)^{-1}t'PM_Xh \\
&= \left(t'PP_{PX}M_Xw\right)^{-1}\left[t'PP_{PX}M_X\left[I - w(t'PM_Xw)^{-1}t'PM_X\right]h\right]
\end{aligned}
$$

Since the first term is a scalar, we want to test whether

$$
\begin{aligned}
& t'PP_{PX}M_X[I - w(t'PM_Xw)^{-1}t'PM_X]h = 0 \\
\Rightarrow\ & t'PP_{PX}M_X\left[I - w(t'PM_Xw)^{-1}t'PM_X\right]u = 0. \qquad (10)
\end{aligned}
$$

This test is based on the F statistic for $\delta = 0$ in the following equation:

$$h = M_w^{P_{M_X Pt}} P_{PX} M_X Pt\delta + \epsilon \tag{11}$$

where

$$\begin{aligned} M_w^{P_{M_X Pt}} &= I - w\left[w' M_X Pt(t'PM_X Pt)^{-1} t'PM_X w\right]^{-1} w' M_X Pt(t'PM_X Pt)^{-1} t'PM_X \\ &= I - w(t'PM_X w)^{-1} t'PM_X. \end{aligned}$$

(I use the initial "M" projection matrix ($= I - z(z'z)^{-1}z'$) in equation (11) rather than including a component (z) as an additional regressor because $M_w^{P_{M_X Pt}}$ is an oblique projection matrix and cannot be nicely decomposed into the $z(z'z)^{-1}z'$ form. This is like the GLS projection matrix $X(X'\Omega^{-1}X)^{-1}X'\Omega^{-1}$. It is related to the predicted residuals from the IV regression). If the IV estimator is consistent ($X'u, X'Pu, t'Pu = 0$), then $\hat{\delta} = 0$. If the condition $t'Pu = 0$ does not hold, the Contrast estimator will still be consistent although the IV estimator will not.

The estimate $\hat{\delta}$ is

$$\hat{\delta} = \left[t'PP_{PX} M_X M_w^{P_{M_X Pt}} P_{PX} M_X Pt\right]^{-1} t'PP_{PX} M_X M_w^{P_{M_X Pt}} h$$

and the F statistic is

$$F = \frac{h'P^*h/1}{h'M^*h/n-k-1}$$

where

$$P^* = M_w^{P_{M_X Pt}} Pt\left[t'PP_{PX} M_X M_w^{P_{M_X Pt}} P_{PX} M_X Pt\right]^{-1} t'PP_{PX} M_X M_w^{P_{M_X Pt}}.$$

We use the variation in the instrument Pt predicted by X, but not PX, that is not related to the covariance of Pt and w conditional on X.

Similarly, to test the difference between the Contrast and group-level IV estimators,

$$\hat{\beta}^c - \hat{\beta}^{IV-b} = (t'P(M_{PX} - M_X)w)^{-1}\left[t'P(M_{PX} - M_X)\left[I - w(t'PM_{PX}w)^{-1}t'PM_{PX}\right]h\right],$$

we want to test whether

$$t'P(M_{PX} - M_X)\left[I - w(t'PM_{PX}w)^{-1}t'PM_{PX}\right]u = 0.$$

A.2 Conventional IV estimator

Consider the conventional IV estimator, which uses t as an instrument. Its probability limit is

$$plim \hat{\beta}_1^{CIV} = \beta_1 + \frac{plim\ t'M_X u}{plim\ t'M_X w}$$

$$= \beta_1 + \frac{plim\ t'M_X Pu}{plim\ t'M_X w} + \frac{plim\ t'M_X Qu}{plim\ t'M_X w}.$$

To compare the bias due to aggregate-level error in the CIV and IV estimators, notice that $t'M_X Pu = t'PM_X u$ given the random effects assumption. Bias in the IV estimator will equal group-level bias in the conventional IV estimator times ψ, where $\psi = \frac{t'(P+Q)M_X w}{t'PM_X w}$. Since in general $\psi > 1$, this implies that the IV estimator inflates group-level bias.

A.3 Employer sorting

Suppose instead that employer but not individual tastes are correlated with commuting time at the group level, $Et'\epsilon \neq 0$. In this case I assume $Et'u = 0$ in addition to $EX'u = 0$. The probability limit of the IV estimator is

$$plim\ \hat{\beta}_1^{IV} = plim\ (\hat{\gamma}_1{}'t'PM_X Pt\hat{\gamma}_1)^{-1}\hat{\gamma}_1{}'t'PM_X h$$

where $plim\ \hat{\gamma}_1 = \gamma_1 + plim\ (t'PM_X Pt)^{-1}t'PM_X P\epsilon$. Expanding this expression yields

$$plim\ \hat{\beta}_1^{IV} = \beta_1 \cdot plim\ (D'(t'PM_X Pt)^{-1}D)^{-1}D'(t'PM_X Pt)^{-1}t'PM_X w$$

where

$$D = t'PM_X P\epsilon + t'PM_X w.$$

If the instrument t is a single variable, this reduces to

$$plim\ \hat{\beta}_1^{IV} = \beta_1 \cdot \frac{plim\ t'PM_X w}{plim\ (t'PM_X P\epsilon + t'PM_X w)}.$$

The IV estimator will suffer from attenuation bias and inconsistency since $Et'PM_X P\epsilon \neq 0$. In the case of employer sorting β_1 cannot be identified.

A.4 IV with fixed effects

Now consider another estimation strategy, which hinges on the fact that there are two levels of aggregation that we use, PMSA and PMSA-occupation. PMSA fixed effects can be included in equation 6 if we use the PMSA-occupation level instrument. Let P_2 and Q_2 be the between occupation and within occupation projection matrices, respectively. Rewriting equations 6 and 7,

$$h = w\beta_1 + X\beta_2 + Pu + QQ_2u + QP_2u \tag{12}$$

$$w = PP_2t\gamma_1 + X\gamma_2 + \epsilon \tag{13}$$

notice that the within PMSA error component has been replaced by the sum of within PMSA-occupation and within PMSA-between occupation components, such that $QQ_2u + QP_2u = Qu$. Pu is now a regressor. Define the IV-FE estimator as the IV estimator associated with these equations,

$$\hat{\beta_1}^{IV-FE} = (w'M_{[X,Pu]}PP_2t(t'P_2PM_{[X,Pu]}PP_2t)^{-1}t'P_2PM_{[X,Pu]}w)^{-1}$$

$$w'M_{[X,Pu]}PP_2t(t'P_2PM_{[X,Pu]}PP_2t)^{-1}t'P_2PM_{[X,Pu]}h$$

whose probability limit includes a bias term relating to $QQ_2u + QP_2u$. Notice that $M_{[X,Pu]} = M_X - R$, where $R = Pu(u'PX)^{-1}X' + X(X'Pu)^{-1}u'P + Pu(u'Pu)^{-1}u'P$. Again working with the exactly identified case for ease of exposition, the probability limit is

$$plim\ \hat{\beta_1}^{IV-FE} = \beta_1 + \frac{plim\ t'P_2PM_{[X,Pu]}(QQ_2u + QP_2u)}{plim\ t'P_2PM_{[X,Pu]}w}$$

$$= \beta_1 + \frac{plim\ t'P_2PM_X(QQ_2u + QP_2u) - t'P_2PR(QQ_2u + QP_2u)}{plim\ t'P_2P(M_X - R)w}.$$

Using this new notation, the probability limit of the IV estimator using the PMSA-occupation level instrument PP_2t is

$$plim\ \hat{\beta_1}^{IV} = \beta_1 + \frac{plim\ t'P_2PM_X(QQ_2u + QP_2u) + t'P_2PM_XPu}{plim\ t'P_2PM_Xw}.$$

It is useful to note the following interpretations of the error components: $t'P_2PM_XPu$ represents sorting into PMSAs and $t'P_2PM_XQP_2u$ represents sorting into occupations within PMSAs. Assume random effects within PMSA-occupation, $EXQQ_2u = 0$. The difference between these estimators is

$$\hat{\beta_1}^{IV} - \hat{\beta_1}^{IV-FE} = \frac{t'P_2PM_XQP_2u + t'P_2PM_XPu}{t'P_2PM_Xw} - \frac{t'P_2PM_XQP_2u - t'P_2PRQP_2u}{t'P_2PM_Xw - t'P_2PRw}.$$

If no sorting into PMSAs or occupations occurs, then $\hat{\beta}_1^{IV} = \hat{\beta}_1^{IV-FE}$ and neither estimator is biased. If individuals sort into PMSAs but not into occupations, the IV-FE estimator will be unbiased under the assumption of random effects within PMSA-occupation ($Et'P_2PM_XQQ_2u = 0$), while the IV estimator remains biased. If individuals sort into both PMSAs and occupations, both estimators will be biased. It is unclear which estimator will be more biased, as such an evaluation depends on two factors. If $t'P_2PM_Xw > 0$, the IV-FE estimator will tend to have more bias since the identifying covariation between PMSA-occupation commuting time and the wage is smaller. If correlation between PMSA-occupation commuting time and individual tastes is positive, the IV estimator will have more bias if sorting into PMSAs is more of a problem, and the IV-FE estimator will have more bias if sorting into occupations is more of a problem.

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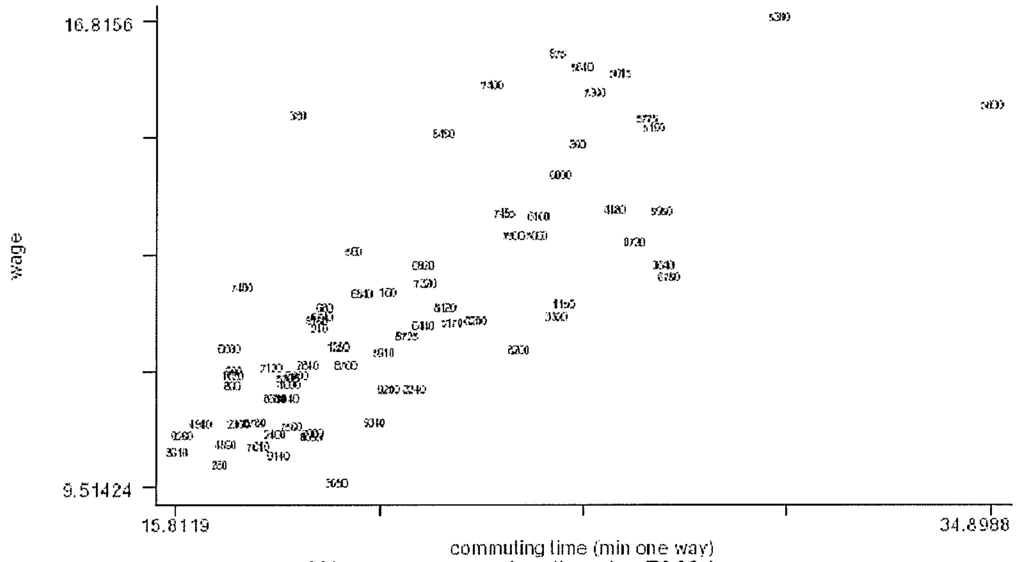
[43] U. S. Bureau of the Census. *County and City Data Book: 1994.* Washington, D. C.: U. S. Government Printing Office, 1994.

Table 1: Wage variances (column percentages)

Type	Wage	Corrected wage	Percent of wage variance explained by commuting time
Sample: PMSA			
Total	119.33	95.67	20%
Within	116.27 (97%)	93.63 (98%)	19%
Between	3.07 (3%)	2.04 (2%)	33%
Sample: PMSA-occupation			
Total	119.33	95.67	20%
Within	102.67 (86%)	82.59 (86%)	20%
Between	16.67 (14%)	13.08 (14%)	22%

Notes: Samples denote the cells relevant for within and between calculations. Corrected wage has been adjusted to include commuting hours in hours worked, assuming a 5-day workweek, according to the formula (wage*hrs)/(hrs+((time*10)/60)).



Wage v. commuting time by PMSA

Figure 3

Table 2: OLS regressions of wage on commuting time (standard errors)

Sample:		PMSA Coefficient	PMSA-occ Coefficient
Dependent variable: wage			
	Sample mean	12.34	11.47
		(0.22)	(0.12)
1a.	No controls	0.37	0.39
		(0.04)	(0.02)
		{0.59}	{0.31}
1b.	Size controls	0.30	0.38
		(0.05)	(0.02)
		{0.62}	{0.39}
1c.	Size, demographic controls	0.001	0.013
		(0.002)	(0.001)
		{0.93}	{0.89}
1d.	Size, demographic, PMSA controls	0.003	0.010
		(0.003)	(0.001)
		{0.95}	{0.91}
	n=	71	852

Adjusted R^2s shown in curly brackets. Size controls for the PMSA sample include PMSA population and population-squared; for the PMSA-occupation sample the controls also include PMSA-occupation cell size and size-squared. Demographic controls include education, age, age-squared, other family income, other personal income, and dummies for married, black, and hispanic. PMSA controls include population growth and density, unemployment and crime rates, median housing value, monthly electric bill, price of gasoline, annual precipitation, and annual heating and cooling degree days. All controls include a constant term.

Table 3: OLS regressions of hours measures on commuting time (standard errors)

Sample:		PMSA		PMSA-occ		Size controls:	
		Coefficient	Sample mean[1]	Coefficient	Sample mean[1]	PMSA	PMSA-occ
Dependent variable:							
1a.	Variance of ln weekly hours	-0.003	0.15	-0.02	0.17	-	c
		(0.001)	(0.02)	(0.001)	(0.14)		
		{0.29}		{0.26}			
1b.	Variance of ln annual weeks	-0.003	0.17	-0.01	0.20	b	c
		(0.001)	(0.03)	(0.001)	(0.15)		
		{0.20}		{0.16}			
1c.	Variance of ln annual hours	-0.01	0.42	-0.03	0.46	-	c
		(0.002)	(0.06)	(0.002)	(0.32)		
		{0.28}		{0.24}			
2.	Percent with weekly hours < 35	-0.004	0.19	-0.02	0.21	-	c
		(0.001)	(0.03)	(0.001)	(0.16)		
		{0.25}		{0.25}			
3a.	Adjusted R^2 from weekly hours eq.	-0.002	0.18	-0.004	0.17	b	-
		(0.001)	(0.03)	(0.001)	(0.11)		
		{0.15}		{0.03}			
3b.	Adjusted R^2 from annual weeks eq.	-0.001	0.09	-0.0003	0.10	a	d
		(0.001)	(0.02)	(0.0007)	(0.09)		
		{0.19}		{0.04}			
4a.	Weekly hours elasticity	0.002	-0.03	0.02	-0.13	-	-
		(0.001)	(0.03)	(0.01)	(1.64)		
		{0.04}		{0.005}			
4b.	Annual weeks elasticity	0.003	0.005	0.04	-0.10	-	-
		(0.001)	(0.02)	(0.01)	(1.82)		
		{0.30}		{0.01}			
4c.	Annual hours elasticity	0.01	-0.03	0.07	-0.22	-	-
		(0.00)	(0.05)	(0.02)	(2.87)		
		{0.18}		{0.01}			
	n=	71		852			

Adjusted R^2s shown in curly brackets. 1=Quantities in parentheses for sample means are standard deviations. Size control specifications were chosen by compared values of adjusted R^2. The following codes denote these specifications: a=PMSA population, b=a and population-squared, c=b and PMSA-occupation cell size and size-squared, d=PMSA-occupation cell size and size-squared. Labor supply regressions used to calculate elasticities in lines 4a-4c included demographic controls.

Table 4: OLS regressions on commuting time, by sex (standard errors)

Sample:	PMSA		PMSA-occ	
	Men	Women	Men	Women
Dependent variable:				
1a. Wage	0.39	0.32	0.32	0.22
	(0.04)	(0.03)	(0.02)	(0.02)
	{0.55}	{0.59}	{0.19}	{0.18}
1b. Wage (size controls)	0.30	0.26	0.25	0.19
	(0.05)	(0.05)	(0.03)	(0.02)
	{0.60}	{0.61}	{0.28}	{0.25}
1c. Wage (size, demog, PMSA controls)	0.04	0.05	0.08	0.08
	(0.04)	(0.03)	(0.02)	(0.01)
	{0.93}	{0.95}	{0.73}	{0.80}
2. Variance of ln weekly hours	-0.002	-0.004	-0.01	-0.01
	(0.0004)	(0.0008)	(0.001)	(0.001)
	{0.22}	{0.29}	{0.17}	{0.17}
3. Percent with weekly hours < 35	-0.003	-0.004	-0.011	-0.01
	(0.0007)	(0.0008)	(0.0007)	(0.001)
	{0.21}	{0.27}	{0.22}	{0.12}

Adjusted R^2s shown in curly brackets. For definitions of controls, see notes to Table 2. All regressions above except those reported in lines 1c and 3 are significantly different for men and women at the 1% level of significance.

Table 5M: Estimated Log Wage Coefficients for Men (Huber-White standard errors)

Estimation method:	OLS	IV	IV	IV-FE	Contrast
Agg. level of instrument time:		PMSA	PMSA-occ	PMSA-occ	PMSA-occ
	(1)	(2)	(3)	(4)	(5)
Dependent variable:					
Log weekly hours	-0.037	0.043	0.167	0.327	0.261
	(0.004)	(0.035)	(0.021)	(0.007)	(0.029)
Log annual weeks	0.015	0.009	0.147	0.316	0.194
	(0.003)	(0.028)	(0.017)	(0.009)	(0.022)
Log annual hours	-0.022	0.052	0.313	0.643	0.454
	(0.006)	(0.052)	(0.032)	(0.012)	(0.044)
First-stage statistics					
F for identifying instrument	-	12.84	123.72	-	-
Adjusted R^2	-	0.349	0.358	0.358	-
Partial R^2	-	0.004	0.016	-	-

All regressions (all columns excluding 5) include a constant term, other family income, other personal income, age and its square, education, and indicators for race, Hispanic ethnicity, and marital status; as well as the PMSA characteristics population and its square, population density and growth rate, unemployment rate, crime rate, median housing value, monthly electric bill, and gasoline price. Regressions in columns 3 and 4 also include PMSA-occupation cell size and its square. Regressions in columns 2, 3, and 4 include the deviation of individual commuting time from the group mean, while those in column 1 includes individual commuting time. The Contrast estimator was calculated as a weighted sum of IV estimators as described in the Appendix, with an inflation factor α of 5.18.

Table 5F: Estimated Log Wage Coefficients for Women (Huber-White standard errors)

Estimation method:	OLS	IV	IV	IV-FE	Contrast
Agg. level of instrument time:		PMSA	PMSA-occ	PMSA-occ	PMSA-occ
	(1)	(2)	(3)	(4)	(5)
Dependent variable:					
Log weekly hours	-0.009	0.112	0.625	0.934	0.638
	(0.005)	(0.111)	(0.068)	(0.010)	(0.105)
Log annual weeks	0.023	-0.112	0.392	0.642	0.330
	(0.002)	(0.128)	(0.049)	(0.011)	(0.077)
Log annual hours	0.015	0.001	1.017	1.576	0.968
	(0.005)	(0.183)	(0.112)	(0.016)	(0.175)
First-stage statistics					
F for identifying instrument	-	4.90	62.11	-	-
Adjusted R^2	-	0.26	0.27	0.27	-
Partial R^2	-	0.001	0.015	-	-

All regressions (all columns excluding 5) include a constant term, other family income, other personal income, age and its square, education, and indicators for race, Hispanic ethnicity, and marital status; as well as the PMSA characteristics population and its square, population density and growth rate, unemployment rate, crime rate, median housing value, monthly electric bill, and gasoline price. Regressions in columns 3 and 4 also include PMSA-occupation cell size and its square. Regressions in columns 2, 3, and 4 include the deviation of individual commuting time from the group mean, while those in column 1 includes individual commuting time. The Contrast estimator was calculated as a weighted sum of IV estimators as described in the Appendix, with an inflation factor α of 2.80.

Table A: Means of individual characteristics (standard deviations)

Sample:	All	Men	Women	PMSA means	PMSA-occ means
Variable:					
Commuting time	24.83	26.46	22.87	21.30	20.84
	(19.07)	(19.84)	(17.91)	(3.84)	(4.97)
Wage	13.73	15.76	11.31	12.34	11.47
	(10.92)	(12.44)	(8.13)	(1.86)	(3.52)
Female	0.46	0.00	1.00	0.45	0.43
	(0.50)	(0.00)	(0.00)	(0.02)	(0.26)
Married	0.58	0.63	0.53	0.61	0.59
	(0.49)	(0.48)	(0.50)	(0.04)	(0.11)
Age	38.17	38.25	38.08	37.92	37.70
	(12.88)	(12.89)	(12.87)	(0.90)	(2.56)
Black	0.07	0.06	0.08	0.04	0.04
	(0.25)	(0.24)	(0.27)	(0.04)	(0.06)
Hispanic	0.03	0.03	0.03	0.02	0.02
	(0.18)	(0.18)	(0.18)	(0.02)	(0.05)
Education	13.36	13.36	13.35	13.17	12.77
	(2.79)	(2.97)	(2.56)	(0.46)	(1.50)
High school graduate	0.86	0.84	0.87	0.86	0.82
	(0.35)	(0.37)	(0.33)	(0.04)	(0.15)
Self-employed	0.04	0.06	0.02	0.04	0.04
	(0.20)	(0.23)	(0.15)	(0.01)	(0.04)
Weeks last year	46.72	47.63	45.64	46.33	45.65
	(10.65)	(9.81)	(11.48)	(0.94)	(3.33)
Hours/week	39.44	42.12	36.23	39.25	38.82
	(11.48)	(10.94)	(11.28)	(0.85)	(4.41)
Salary	26699.03	32889.97	19293.88	23637.13	21558.94
	(25216.80)	(29573.67)	(15801.06)	(4033.00)	(8764.64)
Other family income	27111.84	21897.16	33349.25	23737.13	23369.76
	(32716.50)	(28631.39)	(36037.54)	(5105.41)	(7664.37)
Other personal income	1591.58	1999.89	1103.19	1425.18	1352.64
	(5809.31)	(6850.70)	(4188.13)	(295.77)	(602.88)
% with commuting time=0	0.02	0.02	0.02	0.02	0.03
	(0.13)	(0.13)	(0.13)	(0.01)	(0.05)
n=	1,277,953	696,041	581,912	71	852

Table B: Means of PMSA characteristics (standard deviations)

Variable:	
Population	17,999.34
	(26,710.19)
Unemployment rate (%)	6.00
	(2.36)
Population density / sq. mi.	4,956.47
	(4,093.40)
Population growth (% change)	5.33
	(11.76)
Annual crime rate / 100,000 pop.	7,697.06
	(4,723.76)
Annual precipitation (in.)	31.25
	(13.45)
Annual heating degree days	4,642.07
	(1,938.75)
Annual cooling degree days	783.87
	(667.18)
Gasoline price ($ / m. Btu)	9.04
	(0.50)
Monthly electricity bill ($ / 750 kWh)	57.28
	(16.34)
Median housing value ($)	110,049.30
	(73,556.81)
n=	71

Table C: Occupation codes

Code:	Occuption:	n:
1	Executive/Administrative/Managerial	183,431
2	Professional specialty	199,118
3	Technicians and related support	52,586
4	Sales	146,239
5	Administrative support, incl. Clerical	233,601
6	Private household service	5,847
7	Protective service	25,148
8	Other service	119,003
9	Farming/Forestry/Fishing	17,151
10	Precision production, craft, repair	134,198
11	Machine operation/assembly/inspection	70,423
12	Transportation and material moving	91,208

Table D: PMSA codes

Code:	SMSA:	n:
160	Albany-Schenectady-Troy NY	17,660
240	Allentown-Bethlehem-Easton PA	9,793
280	Altoona PA	2,454
360	Anaheim-Santa Ana CA	54,257
380	Anchorage AK	3,616
560	Atlantic City NJ	4,803
680	Bakersfield CA	8,591
860	Bellingham WA	2,581
875	Bergen-Passaic NJ	27,202
960	Binghamton NY	4,880
1150	Bremerton WA	3,729
1280	Buffalo NY	18,099
1620	Chico CA	2,731
2360	Erie PA	5,219
2400	Eugene-Springfield OR	5,116
2840	Fresno CA	10,488
3240	Harrisburg-Lebanon-Carlisle PA	12,689
3320	Honolulu HI	18,542
3610	Jamestown-Dunkirk NY	3,966
3640	Jersey City NJ	9,731
3680	Johnstown PA	5,582
4000	Lancaster PA	8,042
4480	Los Angeles-Long Beach CA	161,303
4890	Medford OR	2,427
4940	Merced CA	2,684
5015	Middlesex-Somerset-Hunterdon NJ	26,825
5170	Modesto CA	6,260
5190	Monmouth-Ocean NJ	21,813
5380	Nassau-Suffolk NY	58,724
5600	New York NY	121,224
5640	Newark NJ	35,630
5700	Niagara Falls NY	4,529
5775	Oakland CA	43,557
5910	Olympia WA	3,005
5950	Orange County NY	6,283
6000	Oxnard-Ventura CA	13,816
6160	Philadelphia PA	83,540
6280	Pittsburgh PA	32,982
6440	Portland OR	21,816
6680	Reading PA	7,498
6690	Redding CA	2,488
6740	Richland-Kennewick-Pasco WA	2,687
6780	Riverside-San Bernardino CA	40,023
6840	Rochester NY	23,372
6920	Sacramento CA	27,951
7080	Salem OR	3,791
7120	Salinas-Seaside-Monterey CA	6,149
7320	San Diego CA	47,804
7360	San Francisco CA	32,344
7400	San Jose CA	33,763
7480	Santa Barbara-Santa Maria-Lompoc CA	7,425
7485	Santa Cruz CA	4,057
7500	Santa Rosa-Petaluma CA	6,796
7560	Scranton-Wilkes-Barre PA	10,736
7600	Seattle WA	40,239
7610	Sharon PA	2,833
7840	Spokane WA	6,677
8050	State College PA	2,920
8120	Stockton CA	7,844
8160	Syracuse NY	13,381
8200	Tacoma WA	11,222
8480	Trenton NJ	6,889
8680	Utica-Rome NY	6,310
8720	Vallejo-Fairfield-Napa CA	9,003
8725	Vancouver WA	4,557
8760	Vineland-Millville-Bridgeton NJ	2,789
8780	Visalia-Tulare-Porterville CA	4,388
9140	Williamsport PA	3,198
9260	Yakima WA	2,741
9280	York PA	7,844
9340	Yuba City CA	2,045