Family Friendly Occupations and the US Gender Wage Gap*

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PRELIMINARY

Abstract

A consistent finding in US labor market research is that wages are lower in predominantly female occupations. The roles of a number of specific occupational characteristics that may be of benefit to individuals juggling labor market and child-rearing responsibilities in explaining this relationship are investigated. These occupation level characteristics include the proportion of employees working part-time, the average hours of work among full-time workers and the average commuting time to work. The relationship between average occupation commuting time and wages is examined in detail. These characteristics can explain a significant portion of the lower wages paid in female-dominated occupations.

Keywords: gender wage gap, occupational characteristics, commuting time

JEL codes: J16, J24, J31, J71

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1 Introduction

Despite some narrowing over recent decades (see Jacobsen, 2007; Table 6.4), females and males still predominantly work in different occupations in the US, as in many countries. In 2000, approximately 52% of US female workers would have to change occupations to be distributed the same as US male workers.[1] It has been well established that the wages of both men and women in the US are lower in occupations where the workforce is predominantly female. See for example Macpherson and Hirsch (1995). Understanding why this relationship holds is important for our understanding of the labor market, and for evaluating the desirability of comparable worth and other policies aimed at altering the wage structure and narrowing the gender wage gap.

In the economics literature, a large number of potential explanations for differences across gender in the occupations that individuals are employed in have recently been investigated. These explanations include: on the job risk of death and injury (DeLeire and Levy, 2004; Grazier and Sloane, 2008), earnings losses after career interruptions (Adda et al, 2012), risk of layoff (Dan, 2010), cross-sectional earnings risk (Bonin et al, 2007), preferences for money (Fortin, 2008), personality and preferences (Borghans et al, 2008; Krueger and Schkade, 2008: Rosenbloom et al, 2008), and non-congitive traits (Fortin, 2008; Cobb-Clark and Tan, 2010; Antecol and Cobb-Clark, 2013).

This paper investigates the role of certain "family friendly" occupation characteristics in explaining gender differences in occupations and the gender wage gap. Even in the new millennium, females still bear the majority of family and home responsibilities in US households (Bureau of Labor Statistics, 2011). The focus of the investigation is the average commuting time to the job within an occupation. The prevalence of part-time work in the occupation and the average hours of work among full-time workers are also investigated. These three attributes of part-time flexibility, lower expectations of long work hours and shorter commutes may be of most value to those individuals (generally females) required to balance work and family responsibilities. Lower earnings in those occupations may thus reflect in part compensating differentials for these desirable job attributes.

The effect of part-time prevalence in an occupation on earnings and the gender wage gap has been explored previously (Macpherson and Hirsch, 1995, among others). Investigating the role of long hours in occupations on the gender wage gap is a natural extension, and has been

[1] This figure was constructed using the Duncan and Duncan (1955) index of occupation dissimilarity using US Census 2000 data over 475 occupations.

discussed as a potential explanation for occupation differences across genders by Cavallo and O'Neill (2004). The role of average commute times in an occupation has, as far as I am aware, not previously been investigated as a potential contributing factor to the gender wage gap.[2] The main focus of this paper is on this particular occupation attribute.[3]

The underlying concept here is that job location is related to worker productivity and thus to wages. Jobs located in city centers and industrial areas pay higher wages due to the higher productivity of workers in such locations. This could be due to agglomeration externalities, transport amenities, et cetera. Jobs located in suburban areas near where most people live are less productive, and thus pay less. Jobs in certain occupations such as finance, transport, and extraction are more likely to be in city and industrial areas, further from where most people live. Jobs in cafes, hairdressers and schools are more likely to be in suburban areas. If individuals with family responsibilities have higher preferences for jobs with short commutes (located in suburban areas near where they live), they are more likely to be employed in certain low pay suburban occupations.

Occupations differ on a multitude of dimensions and characteristics. Any or all of these could be driving both earnings and the employment decisions of men and women. To isolate the role of commuting time differences, I employ variation in commuting time by occupation across cities of different sizes. The relationships between occupation average commuting time and both earnings and the occupation choices of individuals with potentially different family responsibilities can be estimated while allowing for occupation fixed effects. Such occupation fixed effects should remove the influence of any other occupation characteristics on earnings and occupation choices on the estimates. While commuting times are equally low in suburban occupations in both large and small cities, commuting times in central city and industrial occupations are longer in large relative to small cities. The main findings are as follows. Irrespective of potential family responsibilities, females are more likely to work in occupations that have more family friendly attributes: shorter average commutes, higher part-time prevalence and shorter average hours among full-time employees. Females with children of school age are, however, more likely to work in these family friendly occupations than other females. Occupations with these family friendly characteristics pay consistently lower wages, holding fixed the observable

[2]The factors behind the observed shorter commuting time of females has been a long standing area of research in Urban Studies and Geography. MacDonald and Peters (1996) discusses several contributing factors and surveys the earlier literature.

[3]The role of additional measures of occupation flexibility (starting time, variation in commute times and variation in hours of work) are also explored, but these measures do not assist in explaining the gender wage gap.

productive characteristics of workers. The finding of lower earnings in short commute occupations is robust to controlling for fixed occupation effects and using variation in commutes by occupation across cities of different size. A significant proportion of the gender wage gap can be attributed to differences in these family friendly characteristics of occupations across genders. The estimates thus help us understand why earnings are lower in female-dominated occupations.

The outline of the paper is as follows. In Section 2, I discuss the potential relationships between occupation average and individual commute times with wage rates. This discussion is based on a theoretical model of job choice across locations in a city. In section 3, the occupation choices of individuals potentially with and without family responsibilities are explored. The main estimates relating individual and occupation characteristics to earnings are provided in Section 4. Estimates of the proportion of the gender wage gap attributable to differences in family friendly characteristics are also provided. Section 5 concludes.

2 Commuting times and earnings

The determination of both the living and working arrangements of individuals is a complex process. Individuals choose where to live and work to optimize wellbeing. Individual well-being (or utility) will be a function of earnings from working, non-monetary job attributes, housing costs and house / neighborhood quality. A shorter commute time, other things being equal, would generally be desired.[4] These choices are, however, constrained by opportunities. Housing availability is a function of historical building patterns, zoning regulations, geography and relative demand (reflected in prices and rents). Job availability is a function of firm (work) location.

Firms choose where to locate to optimize profits. Some firms may find it more optimal to locate near workers in residential areas (perhaps also to be near customers). Others may optimally choose to locate in city centers (due to agglomeration spill-overs) or industrial areas, again based on zoning regulations, but also on transportation links. Firm location may also be a function of history, with potentially large re-location costs. As a result, the residence and work locations of individuals we observe may or may not be an equilibrium outcome.

[4] Stutzer and Frey (2008) describe the significant negative effect that longer commutes can have on measures of subjective well-being.

2.1 A simplified model of occupation commutes

To illustrate the mechanisms in a world where equilibrium is reached, a simplified model of job and residence location choice in a city is presented in Appendix A. Individuals optimally choose a location specific occupation (city or suburb job) and a suburb to live in (near the city or further out), based on wages paid in different occupations, rental costs in different suburbs, and the individual's heterogeneous distaste for commuting.

Competitive firms can freely locate either in the city or in suburban areas, with potentially different production technologies depending on this location choice i.e. production amenities may differ across locations. Due to free mobility and optimal capital investment decisions, wage differences across city and suburban locations are determined by productivity differences alone. For wages to be higher in city (longer commute) occupations (as we will observe in the empirical analysis to follow), it must be the case that there are productivity benefits for firms locating in city areas, perhaps from spillovers, being closer to suppliers and customers, infrastructure, et cetera. If no such benefits existed, firms would not locate in city centers as they could not compete for workers, given worker distaste for (costs of) commuting.

Rents in suburbs near the city and further away are determined by supply and demand. Supply constraints are modeled using a simple mechanism where rents increase with the number of individuals choosing to live in a particular suburban area. This mechanism proxies the extra costs involved in attempting to add more housing to particular suburbs.

The model in Appendix A allows for multiple equilibria, depending on the particular values key parameters may take. I focus on an equilibrium where individuals live in both inner and outer suburban areas and work in both city and suburban occupations (as we observe). In this equilibrium, wages are higher in city jobs than suburban jobs, while rents are higher in suburbs close to the city relative to suburbs further out, otherwise no individual would choose to live in outer suburbs.[5] Individuals with the lowest distaste for commuting will choose to work in the city and live in outer suburbs, taking advantage of the lower rent in outer suburbs. A second group with distaste values in the middle of the distribution will choose to live in inner suburbs and work in city occupations. The remainder with the highest distaste for commuting will choose to live in outer suburbs and work in suburban occupations.

[5] In this model, there are no amenity differences across suburbs. Some readers may note the low rents in some inner suburb neighborhoods in some cities due to urban decay. Including amenity differences in this model is straightforward, and does not change the basic predictions of the model.

The model makes clear a number of issues. Earnings differences between long commute occupations (located in city centers) and short commute occupations (located in suburbs close to where people live) are driven by firm productivity differences alone. Thus we should not think of there being some "causal effect" of commuting time on earnings. Firm location "causes" wage differences. This implies that there is nothing to be gained from searching for "exogenous" variation in commuting times by occupation if the objective is purely to improve empirical estimation of the relationship between occupation commuting times and earnings .[6] If there was some variation in relative commuting times, i.e. if commuting from outer suburbs to the city became less time-consuming (via an improvement in transport links), then it would change the work location and suburb of residence decisions of some individuals. Some inner suburb individuals will move to the outer suburbs and still commute to city occupations, as commuting time from outer suburbs are now lower. A smaller number will move from the outer suburbs where they worked in local suburban jobs to inner suburbs and then will commute to city occupations (in response to inner suburb rent reductions). Overall, there will be more people working in the city but less people living in inner suburbs. This will mean that average commuting times of city workers may not fall much in the long run.

The model also illustrates that individuals with the greatest distaste for commuting choose to work in suburban jobs, and in this specific model of households with one worker only, they live in outer suburbs where rents are cheaper. Individual differences in commuting times among workers in the same (city) occupation reflect differences in distaste for commuting i.e. workers with the least distaste for commuting choose to live further from the city and pay lower rents. Wages do not differ by individual commuting distance differences within a (location-specific) occupation, but rents may.[7] Importantly, workers in city occupations are more likely to live in inner suburbs, pay higher rents but earn higher wages. Thus average commuting time differences between city and suburban occupation workers may be small relative to the observed wage

[6] This implication is based, however, on a world with competitive firms with free mobility. If firms are not mobile and competition is not perfect, then "exogenous" variation in commuting times might improve estimation.

[7] Along a similar vein, Timothy and Wheaton (2001) argued that wages in a particular working zone (an area) will be higher if the average commuting time of workers to that zone was higher. Higher average commuting times reflect the need for workers to commute from other zones i.e. the demand for workers in a zone exceeds the supply in the same zone. Individual commuting time differences should not be reflected in earnings differences, but instead should be capitalized into housing price / rent differences, i.e. lower prices for those houses positioned further from employment opportunities.

premium from working in city occupations, implying large compensating differentials for potentially small observed commuting time differences. It must be kept in mind when interpreting the estimates to follow, however, that city workers may be using part of the city occupation wage premium to pay for higher inner suburb rents.

Extensions of the basic model to allow for differences in worker productivity are also considered in Appendix A. For worker productivity differences to alter individual work location and residence decisions, it must be either that productivity and distaste for commuting are correlated, or that productivity differences interact with work location. If productivity and distaste for commuting were negatively correlated, more productive workers would choose to work in city occupations. Also, if there was some complementarity between productivity of workers and city occupations (high productivity workers are relatively more productive in city than suburban occupations), then again, more productive workers would choose to work in city occupations.

If high productivity types are more likely to work in city occupations (due either to complementarity or to a negative correlation between productivity and distaste for commuting), the observed average wage difference between city and suburban occupations will be larger than the wage gain that any specific worker with a particular productivity level would obtain from changing from suburban to city work. In the empirical analysis to follow, the relationship between occupation commuting time and earnings is estimated in a cross-section. As a robustness check, I also estimate the relationship using longitudinal data with individual fixed effects. The estimates of the relationship between occupation average commuting time and wages from the fixed effects estimates are somewhat smaller than from the cross-section, suggesting that there may be self-selection of high productivity types into city (long commute) occupations. This is not the only possible explanation of lower estimates when using fixed effects, however, as measurement error in recording occupations may cause greater attenuation in such estimates.

2.2 Individual commutes and earnings

In the simplest version of the model with frictionless and competitive markets and worker productivity homogeneity, wages differ across occupations but not within them. We will see the significant negative relationship between occupation average commuting times and earnings in Section 4. There remains, however, a less strong but still negative relationship between individual commuting times and earnings even within occupations. Several explanations for such a relationship at the individual level come to mind, where we relax the assumption of frictionless and competitive markets, and allow for unobserved (to the researcher) differences in worker productivity and firm location / specifics.

- Individual unobserved productivity differences may result in more productive workers who earn more being able to afford longer commutes. Dargay and Ommeren (2005) note the offsetting effects of higher income being able to buy the more expensive properties closer to city centers with the same higher incomes being able to afford the larger homes and sites that are generally available further from city centers. They estimate that higher income causally results in longer commutes.

- Individual firm heterogeneity in location may mean that some firms are located in city centers while others are in the suburbs, and they may employ individuals in the same occupations (e.g. city versus suburban lawyer). Productivity differences in city versus suburban firms may result in wage dispersion within occupations that is related to individual commutes.

- Specific firm / worker interactions (productivity) may mean that some workers are paid more to work in specific firms that are located further from home than another similar firm, and joint household location decisions may restrain the individual from moving closer to that specific firm.

- If there are frictions in labor markets, search models with job posting can create an "implicit" compensating differential (Manning, 2003). In this model, job openings arrive randomly, posted wages are heterogeneous, and individuals with distaste for commutes only accept low wage offers if the commute is shorter.

- Search models with random matching and ex-post bargaining also yield a negative relationship between individual commuting time and wages (Rupert et al, 2009). Individuals have a lower threat point in bargaining if the matched job has a shorter commute. In addition, a potential match is only accepted in the first instance if there is surplus in the match (productivity exceeds the worker's expected alternative).

2.3 Occupation dispersion within cities and commuting time

Average commuting times in an occupation are likely to be lower if jobs in that occupation are more spread among residential areas where people live (the suburbs). Figure 1 presents a scatter plot of occupation average commuting times (the horizontal axis) against a measure of how dispersed the jobs in each occupation are among where people live (vertical axis). This measure of occupation dispersion OD^j in occupation j is based on the Location Quotient (LQ) measure employed in geography and urban economics to describe industry concentration in different regions. Here, I define the Location Quotient in terms of occupations as follows:

$$LQ_k^j = \frac{\text{\% of workforce in area } k \text{ working in occupation } j}{\text{\% of total national workforce working in occupation } j} \tag{1}$$

An LQ_k^j greater than 1 denotes that occupation j is relatively concentrated in area k. I construct a measure for each occupation combining area-specific LQ_k^j measures using worker residence area weights. The occupation dispersion measure (OD^j) for occupation j can be written as follows, where $k = 1, ..., K$ denotes specific areas and N_k denotes the number of workers who **live** in area k:

$$OD^j = \sum_{k=1}^{K} LQ_k^j \frac{N_k}{N} \quad \text{where} \quad N = \sum_{k=1}^{K} N_k \tag{2}$$

High values of OD^j (above 1) will occur in those occupations that are relatively concentrated (high LQ_k^j) in areas where most workers live (are dispersed), as individual area LQ_k^j's are combined using weights based on where workers live.

This occupation dispersion measure was constructed using data from the 2000 US Census 5% micro-data sample, using 1238 separate Census Place of Work Public Use Micro-data Areas (POW PUMAs) and 470 separate Census occupations.[8]

——————— INSERT FIGURE 1 HERE ———————

Note the expected significant negative relationship overall between occupation average commuting times[9] and occupation dispersion in Figure 1. There are, however, a number of occupations lying above and to the right of the general negative relationship. These occupations have relatively high dispersion measures but also longer commuting times on average. These occupations are generally in the construction trades and extraction, such as roofers, pavers, fence erecters, explosives workers, drillers, et cetera. Housing construction in particular will be dispersed among where people live, but due to the short-term contract nature of this kind of work, such workers may choose not to alter their living arrangements for every change in specific contract job location.

[8] All military employees and occupations were excluded from the analysis.

[9] These average commuting times in the occupation are for the one way commute to work, and were constructed using male employees only.

Note that the POW PUMA areas provided in the US Census micro-data are quite large geographical areas, with approximately 225 thousand residents each. The relationship depicted in Figure 1 may thus be subject to measurement error. Occupation dispersion measures were also constructed using data from the 2000 US Census Transport Planning Package (CTPP). This data source provides more detailed geographic breakdowns than the Census micro-data, but only provides occupation information at an aggregated level (23 occupation groups). The significant negative relationship between occupation average commuting time and occupation dispersion was more evident employing this data using Census Tracts as the appropriate geographical area (with approximately 4,000 residents each). As in Figure 1, the construction trades and extraction occupation group was positioned distinctly to the right of the otherwise clear negative linear relationship. Figures depicting this relationship for California and New York state are available upon request.

3 Gender, children and occupation attributes

The objective of this study is to increase our understanding of why female-dominated occupations pay lower wages. As discussed above, individuals with the highest distaste for commuting will choose to work near where they live in suburban jobs. This individual distaste for long commutes may be related to the need to provide care for children, before and after school and non-family child-care arrangements. These care requirements may also manifest in preferences for jobs where part-time work opportunities are more prevalent, and where expectations to work long hours in full-time jobs are lower. Jobs with these potentially "family friendly" and desirable characteristics of shorter commutes, higher part-time prevalence and lower expectations of long hours if full-time are likely to pay lower wages. Such jobs may also be more likely in specific occupations.

The relationship between occupation average wages and these "family friendly" characteristics of occupations is investigated in Section 4. In this section, I investigate whether individuals with potential family care responsibilities are more likely to be employed in occupations with higher average "family friendly" characteristics. Using individual level data from the US 2000 Census, the occupation level characteristics were constructed by averaging over all males employed in each occupation. By constructing the averages using male employees only, I avoid inducing a correlation between these occupation averages and the proportion of employees in an occupation that are female (PF). Constructing these averages over males and females together would result in correlations with PF, as females are more likely to have shorter commutes ,work part-time and to work fewer hours if full-time within occupations. Avoiding such correlations is extremely important in the estimates of Section 4, where I attempt to identify whether the negative relationship between wages and PF is attributable in part to these "family friendly" characteristics.

After constructing these average occupation level characteristics using all male employees, employees were then separated into groups based on age, gender, marital status and presence of children in the home by child age group. For each of these groups, averages were constructed for each of the three main "family friendly" occupation characteristics based on the occupation the individual was employed in. These averages are presented in Figure 2.

In Figure 2a, means of occupation average commuting times are presented for each demographic group. Clear inverted U-shaped patterns with age are present for both genders. Both the youngest (aged 16 to 24) and oldest (aged 55 to 64) employees are more likely to be in short commute occupations than other age groups. Females with dependent children of school age (aged 6 to 17) are employed in occupations with shorter average commutes, while there is little difference by marital status for females. For males, on the other hand, marital status is related to average commuting time of the occupation, with married males less likely to be in occupations with short commutes. The presence of dependent children is generally unrelated to occupation commuting time for males. Finally, regardless of age, presence of children or marital status, females are much more likely to be in occupations with short commutes than males.

——————— INSERT FIGURE 2 HERE ———————

In Figure 2b, means of part-time prevalence in the occupation are presented for each demographic group. Note the strong U-shaped pattern with age for both genders. Both young and old employees are more likely to be employed in occupations with a high part-time prevalence. For females, the presence of dependent children of school age (aged 6 to 17) is again related to being employed in occupations that are more "family friendly", that is, with higher part-time prevalence. Older females with only pre-school age dependent children actually are less likely to be in such occupations than those with no children (but this is likely to be a very select group). As with commutes, there is little difference among females by marital status in occupation part-time prevalence. For males, on the other hand, marital status is again related to the part-time prevalence of the occupation, with married males less likely to be in occupations with high part-time prevalence. The presence of children in the home is generally unrelated to part-time prevalence for males. Finally, regardless of the presence of children or marital status, females are much more likely to be in occupations with high part-time prevalence than males.

In Figure 2c, means of hours among full-time workers in the occupation are presented for each demographic group. In this case, there is a rough inverted U-shape with age for females, while for males this measure first rises with age then flattens out at older ages. For younger females, the presence of dependent children is related to lower average occupation full-time hours, but this is reversed for older females. For males, the presence of children is again less important than marital status. Married males are more likely to be in occupations with long full-time hours. Once more, irrespective of the presence of children or marital status, females are much more likely to be in occupations with fewer full-time hours than males.

For females, it appears that the presence of school-age children in the home is a strong driving force behind working in a "family friendly" occupation. The need to get children off to school and to pick them up afterwards is likely to be the source of this. For males, the presence of a spouse may allow them to work in occupations that are less "family friendly" but pay higher wages. There is also the possibility of reverse causality here: males in higher paying occupations may be more likely to be married.

While Figure 2 is strongly suggestive of females with family responsibilities being more likely to choose occupations with "family friendly" characteristics, there is always the possibility that other characteristics of occupations correlated with these "family friendly" ones are the underlying drivers of decisions. Here I attempt to isolate the effect of average commuting time alone on occupation decisions using variation in commuting time by occupation across cities of different sizes. Using such variation allows me to essentially difference out the effect of other occupation characteristics on decisions. I also use such variation in the next section when estimating the relationship between wages and occupation average commutes.

The idea here is as follows. As we would expect, average commuting times vary considerably across US cities, and are strongly related to city size. The top left hand panel of Figure 3 plots average commuting times in a city against population size. The 13 diamond markers in the plot represent the 13 largest US cities (Consolidated Metropolitan Statistical Areas - CMSAs). In decreasing size these cities are: New York, Los Angeles, Chicago, Washington DC, San Francisco (Bay Area), Philadelphia, Boston, Detroit, Dallas, Houston, Atlanta, Miami and Seattle. The square marker labeled "medium" is the average commute across 38 medium sized US cities

(MSAs), with populations of 0.9 to 3 million. The square marker labeled "small" refers to the remaining 192 cities (MSAs) identified in the Census micro-data, with populations from 0.1 to 0.9 million).

——————— INSERT FIGURE 3 HERE ———————

The top right panel of Figure 3 plots the standard deviation of average occupation commute times within each city against city population. For example, the point for New York at the right of the plot denotes the standard deviation of occupation average commute times in New York is nearly 5.5 minutes. Occupation average commute times were constructed separately for each city or city group (small and medium). To avoid small cell sizes, these occupation average commutes by city were constructed for 93 three digit Standard Occupation Classification (SOC) occupation groups, rather than separately by the 470 non-military occupations identified in the Census micro-data. Note the positive relationship between these standard deviations and city size. This tells us that the dispersion in travel times across occupations is larger in large cities. Occupations that are dispersed among the suburbs where people reside have low commuting times that vary little with city size. On the other hand, occupations that are more centralized in financial district or industrial areas have longer commutes in larger cities relative to smaller cities.

The bottom left panel of Figure 3 illustrates more clearly the "spreading out" effect of city size on commutes by occupation. Occupation average commutes for Los Angeles (LA) are plotted against occupation average commutes in medium sized cities. Commuting times by occupation generally lie in a line above the 45 degree line, with points very close to the line for low commute occupations. Thus local occupations have equally low commutes in large LA and medium sized cities, while jobs that are on average more distanced from residential areas have relatively longer commutes in larger LA.

The slope of the regression line in the bottom left panel of Figure 3 of 1.36 is what is plotted for LA in the bottom right panel. The slope coefficients from simple regressions of each city's occupation average commutes versus occupation average commutes in medium sized cities are all plotted here. Occupation average commutes in medium cities are used as the regressor in each case. The slope coefficient using medium cities themselves as the dependent variable is of course equal to one. These coefficients generally rise above one as city size increases.[10]

[10]The higher standard deviation and regression coefficient above 1 for "small" cities relative to "medium" cities reflects the effect of four specific occupation groups that had very long average commutes in "small" cities. These

If females with family responsibilities are actively choosing jobs with short commutes, they are more likely to be employed in occupations that are dispersed in the suburbs and have on average short commutes. This preference for short commute suburban occupations should be higher in large cities, as commutes to city center occupations will be relatively longer. To investigate this issue, I ran a simple regression at the individual level using as a dependent variable the average commuting time of all employees (males only) in the occupation that the individual is employed in. It is the same variable analysed in Figure 2. This variable was regressed on:

(1) indicators of marital status interacted with dependent children by child age group
(i.e. indicators for 7 of the 8 lines in Figure 2 - the base case being non-married individuals with no dependent children under age 18),
(2) interactions of the above 7 indicators with indicators for large and medium sized cities,
(3) a fourth order polynomial in age (capturing the age profiles observed in Figure 2a),
(4) 15 indicators of highest education level, and
(5) 7 indicators of immigrant status and race.

The results of these regressions of occupation average commutes are presented in Tables 1 and 2 for females and males respectively. Marginal effects from Probit estimates of the probability of employment are also provided, to provide some information on selection into employment.

Focusing first on females in Table 1, the coefficients on the marital status and dependent child indicators confirm the observations from Figure 2a. Females with dependent children of school age are less likely to be employed in occupations with long average commutes, while marital status alone has little effect. The coefficient estimates in column 3 highlight the negative effect of dependent children of pre-school age on the probability of being employed, and being married magnifies this negative effect.

——————— INSERT TABLE 1 HERE ———————

Coefficients on the interactions of the large city indicator with the married and dependent children indicators in column 1 of Table 1 reveal that having dependent children of any age lowers the likelihood of females working in long commute jobs. Marital status alone also has a negative effect in large cities, irrespective of the presence of dependent children. Note the large positive coefficient on the large city indicator alone here. Thus females (particularly single

occupation groups were: air transport workers; water transport workers; transport tourism and lodging attendants (includes flight attendants); and extraction workers. Jobs in these occupations generally lie outside or on the edge of city areas.

females with no dependent children under age 18) are more likely to be in long commute jobs in large cities than in small cities. This likely reflects the higher prevalence of "city centre" jobs in large cities, where agglomeration spillovers are potentially larger. The coefficients on the interactions with the indicator for medium sized cities are generally of the same sign but smaller size, as might be expected. Overall, these estimates support the hypothesis that females with dependent children of school age in particular are actively choosing occupations with shorter average commutes.

Note the estimated marginal effects on employment in column 3 reveal a more negative effect of dependent children on employment probabilities in large cities than in small cities. There is again a more muted response in medium sized cities relative to small cities. This may reflect the motivation of avoiding long commutes completely in large cities by dropping out of the workforce, or may reflect the higher earnings of spouses in large cities.

Turning now to the male estimates in Table 2, being married increases the likelihood of working in occupations with long average commutes, consistent with Figure 2a. The presence of dependent children also increases the likelihood of working in long commute occupations for single men living in small cities, but not for single men living in large cities (offsetting negative interaction effects). For married men, the presence of dependent children lowers average occupation commutes for men living in small cities, but not in large cities (offsetting positive interaction effects). The effects of marital status and presence of children are no different, however, in medium cities compared to small cities.[11]

——————— INSERT TABLE 2 HERE ———————

4 Earnings estimates

4.1 Individual characteristics

To investigate the relationships of individual and occupation characteristics with earnings, I employ the two step estimation procedure of Baker and Fortin (1999, 2001). In the procedure's first step, individual log hourly wages are regressed on a set of individual employee characteristics plus a set of indicator variables for each of the 470 individual non-military occupations

[11] These somewhat difficult to interpret estimates of the effect of dependent children by marital status and city size may reflect small numbers of single men with dependent children. Less than 3 per cent of males are single with dependent children in the estimation sample.

identified in the Census data. In the second step, the estimated coefficients on these occupation indicators are employed as the dependent variable in regressions at the occupation level on a set of occupation level characteristics. The estimates from the first step are presented in this sub-section.

The main argument forwarded by Baker and Fortin (1999, 2001) for employing this two-step procedure rather than the more common one-step method of including the occupation level characteristics directly in the individual log wage regressions (e.g. Macpherson and Hirsch, 1995) is to reduce potential coefficient bias. In the one-step method, if there are missing occupation level characteristics that are correlated with included regressors, all estimates, including estimates of coefficients on individual level characteristics, may be biased. By including the set of unrestricted occupation indicators in the individual level regressions, the potential for missing occupation level variables is averted, and coefficient estimates for individual level characteristics should be unbiased. Missing occupation level characteristics in the second step may, however, still be a source of bias in the estimates of the coefficients on these occupation level variables.

Summary statistics for the individual level variables included in the first step regressions are provided in Table 3. The data is from the 2000 US Census 5% micro-data sample. Details of sample and variable construction are provided in Appendix B. The gender wage gap is approximately 24% in this data, using constructed hourly wage rates. Females have marginally more years of schooling, and are more likely to be employed by not-for-profit and government employers. Regarding individual commuting time, females have one way commutes (the Census data collects commute time for the journey to work only) that are shorter by 4 minutes on average. Females are also more likely to begin their commute to work between the hours of 7 a.m. and noon, while males are more likely to start their commutes between midnight and 7 a.m.

————— INSERT TABLE 3 HERE —————

The estimates from the first step log hourly wage regressions by gender are provided in Table 4. The estimation results are generally in line with previous research.[12] Education attainment is strongly related to earnings, with education levels below the base category of a high school diploma related to earnings penalties, while post-secondary education is related to significant earnings premia. Immigrants and non-white individuals earn less on average than their US born white counterparts. Employees of not-for-profit groups generally earn less than private sector

[12]The positive relationship between part-time status (less than 35 hours of work per week) and earnings for males is an exception. This may be due to how hourly earnings was constructed using annual wage and salary income, weeks worked and usual weekly hours, rather than using a direct report of the hourly wage rate.

employees, while federal government employees in particular earn more.

——————— INSERT TABLE 4 HERE ———————

The variables that are generally not included in estimates of earnings functions are the individual commuting time and the time of starting the commute to work. A cubic in commuting time was included to describe the non-linear relationship. Individual earnings rise with commutes until commutes reach approximately one hour for both genders, then the relationship was quite flat beyond one hour. Female earnings rise further with individual commuting time than male earnings. Female earnings were approximately 13 per cent higher at one hour commutes relative to no commute, while for males earnings were 8 per cent higher. Note that these regressions include unrestricted indicators for 470 Census occupations, for 23 major industry groups and for 2,071 individual Census PUMA geographic locations based on where individuals live. Thus these relationships between commuting times and earnings are over and above the relationships with occupation, industry and living location. Potential explanations for positive relationships between individual commutes and earnings were outlined in the previous section, including unobserved individual and firm effects, and search frictions in labor markets.

Regarding individual commute starting times, earnings for both genders are higher for those starting their commutes prior to 6 a.m. or from 7 p.m. onwards relative to the base group of starting commutes from 8 to 8:59 a.m. For females, earnings are also higher for those starting between 6 and 7:59 a.m. Earnings for both genders are lower if starting mid-morning (9 to 11:59 a.m.). Thus there may exist compensating differentials for less desirable commute (job) starting times. Earnings are lower for individuals starting in perhaps more family friendly time periods from 8 to 11:59 a.m., which were also the starting times that were more prevalent among female employees.

4.2 Occupation average characteristics

The estimated coefficients on the occupation indicators from the first step are now employed as the dependent variable in the second step estimations at the occupation level. Summary statistics for the occupation level variables are provided in Table 5. The first variable is the proportion of females (PF) in the occupation. As expected, the mean of PF for females (0.666) is much higher than it is for males (0.304), given the high level of occupation segregation that remains in the US. The coefficient on PF in wage regressions is a particular focus in the comparable worth literature, including the studies of Macpherson and Hirsch (1995), Baker and Fortin (1999, 2001) and O'Neill (2003).

The next three occupation average variables in Table 5 are the main focus of this research. They were constructed using the Census 2000 micro-data, with the statistics provided based on occupation average characteristics constructed using male employees only. [13] The means of these occupation average characteristics in Table 3 highlight the higher proportions of females in occupations with characteristics that are more family friendly, as observed in Figure 2 above. For the interested reader, Appendix Table A1 provides a list of the occupations with the shortest and longest commuting times.

——————— INSERT TABLE 5 HERE ———————

The next group of variables in Table 5 - job zone, hazards, strength required and poor environment - were constructed using information from O*NET, the updated version of the Census Bureau's Dictionary of Occupation Titles (DOT). Variable construction is described in Appendix B. Each occupation is allocated to one of five job zones in O*NET, reflecting the amount of preparation (education and training) required for entry into that occupation. Occupations in zone 1 require essentially no or limited preparation, while occupations in zone 5 require extensive preparation.[14] There are only minor differences across genders in the job zones of occupations, with females more likely to be in occupations requiring extensive preparation (zone 5) and males more likely to be in occupations requiring some preparation (zone 2). A higher hazards measure reflects exposure to particular hazards on the job. A higher strength required measure is allocated to occupations where strength is a required ability. A higher poor environment measure denotes employment in an occupation that has environmental features that are generally unpleasant. For all three of these occupation based measures, males have higher means.

The next measure - fatal occupation injuries - is based on data reported by the US Bureau of Labor Statistics (BLS) on the numbers of such cases in each occupation.[15] Consistent with previous findings (e.g. DeLeire and Levy, 2004), males are in occupations with considerably higher levels of fatalities.

[13] Averages over female employees were highly correlated with the averages using male employees. Using averages constructed over male employees only resulted in much more conservative estimates (smaller in absolute value) of the relationships between these occupation average measures and earnings than if averages over both males and females were used, and marginally more conservative estimates than if averages using females only were used.

[14] These job zones are intended to be more broad than the measures included in the original DOT, and essentially replace the Specific Vocational Preparation (SVP) and General Education Development (GED) measures.

[15] Details of variable construction are again in the Appendix.

The last six measures in Table 5 were all taken from the Work Activities component of O*NET, using the Importance (IM) measure. Apart from the computing variable, these measures cover those attributes of occupations that some investigators have suggested females may be more attracted to due to preferences or personality. They include caring and teaching, as well as some related more specifically to interacting directly with people. Note that females are not more likely to work in occupations involving advising or teaching.

Estimates of the relationships between occupation characteristics and log hourly earnings (the second step) are provided in Tables 6 and 7 for females and males respectively. As discussed by Baker and Fortin (2001), there are at least three potential weighting schemes that can be employed when estimating these second step regressions: un-weighted, weighted using the number of observations in each occupation (or more specifically the sum of the Census person weights in each occupation), or weighted using the estimated variance (inverted) of the occupation indicator coefficients from the first step estimates. The choice between weighted and un-weighted estimation depends on one's beliefs about the greater potential source of error variance in the second step estimates. Using the estimated occupation coefficients from the first step should result in heteroscedastic errors in the second step estimates (noisier estimates of an occupation's coefficient if it is estimated using a smaller number of observations), thus implying weighted estimation is more appropriate. If, however, the variance of the error in the second step population model is large, un-weighted regression may be preferred. The estimates in Tables 6 and 7 use the estimated variance of the occupation indicator coefficients from the first step as weights.[16]

Four different model estimates at the occupation level are presented in Tables 6 and 7. In model 1, only the proportion female (PF) variable and job zone indicators are included. A negative relationship between hourly earnings and PF is estimated for both genders, with a marginally more negative relationship estimated for females. In model 2, the three "family friendly" characteristics are added to the regressions. These characteristics have the expected signs and are all statistically significant. Earnings are lower in occupations with higher part-time prevalence, lower hours among full-time workers and with shorter average commutes. The coefficients on the average commute variables for both genders are approximately four times the

[16]As found by Baker and Fortin (2001), the second step estimates were somewhat sensitive to the weighting scheme employed. Note, however, that estimates of the effect of occupation average commute times on earnings - the main focus of this analysis - were found to be very similar across weighting schemes. Estimates using the alternative weighting schemes are available upon request.

size of the steepest part of the equivalent gender commuting time effects in the individual level regressions of Table 4.[17] Note also that the negative relationship between occupation earnings and PF disappears after adding these three particular variables.

——————— INSERT TABLE 6 HERE ———————

——————— INSERT TABLE 7 HERE ———————

Consistent with previous findings (Macpherson and Hirsch, 1995; Baker and Fortin, 2001), the estimated relationship between PF and earnings is sensitive to the choice of other variables included in the estimated models. Model 3 includes a set of occupation level variables (described above) that have either commonly been included in such models in the previous literature, or have been discussed in the literature as potentially affecting earnings differences across occupations. Note that the estimated effect of PF on earnings is much more negative than in model 1. These additional variables do not all have the expected relationship with earnings. While occupations in higher job zones (more required preparation) have higher earnings, occupations with higher strength requirements and poorer working environments appear to earn less. Occupations with higher exposure to hazards, however, have higher earnings, as expected. The relationship of earnings with fatal injuries has an unexpected negative sign, but is imprecisely estimated.[18] Note that the hazards, strength and environment variables in particular are highly correlated with each other. The correlation coefficients among all the occupation level variables are presented in Table 8.

——————— INSERT TABLE 8 HERE ———————

Model 4 includes both the three “family friendly” occupation characteristics and the set of additional occupation level variables of model 3. Inclusion of the three “family friendly” variables lowers the size of the negative relationship between PF and earnings considerably, thus these three variables appear to account for a significant portion of the lower earnings in female-dominated occupations. Inclusion of the additional set of occupation level variables does generally result in smaller estimated effects of the three “family friendly” characteristics on earnings (model 4 versus model 2), but the effects retain their statistical significance, and the commuting time effect falls only slightly for females.

[17] The slopes of the cubic commute time functions are steepest at a zero commuting time, and at this point the slope equals the coefficient on commute time in levels.

[18] Previous research has found a negative relationship between earnings and fatal injuries at the industry level. These occupation level estimates are constructed after the effect of industry fixed effects have been removed in the first step individual estimates.

To gain some understanding of how much of the gender wage gap can be attributed to differences across genders in these occupation level characteristics, some simple Oaxaca (1973) and Blinder (1973) decompositions were constructed using the estimates of Tables 4, 6 and 7. In Table 9, a standard decomposition using the estimates from the first step regressions of Table 4 is presented. Individual level characteristics only are included here. The overall log hourly wage gap is 0.242. None of the individual level characteristics contribute much to the gender wage gap. Education differences contribute negatively to the gap, as females have on average higher levels of education. The Census does not have any measure of actual work experience of individuals, and the potential experience measure employed here differs very little across genders.[19] Differences in employer type only contribute a small amount to the gap. Females are more likely to work for low paying not-for-profit employers than males, but more likely to work for somewhat higher paying state and local government employers. Individual commuting time differences contribute a small amount to the gap (2%), while starting time differences contribute 2.5%. There is a large estimated contribution of industry differences (12.4%) to the gender wage gap, with males more likely to work in industries that pay higher wages (construction, utilities, manufacturing).[20]

——————— INSERT TABLE 9 HERE ———————

Table 10 presents Oaxaca-Blinder decomposition estimates based on the occupation level estimates of Tables 6 and 7. The percentage figures are calculated as a percentage of the overall gender log hourly wage gap of 0.242. Focusing on model 4, differences in the three "family friendly" characteristics all contribute significant amounts to the gender wage gap (summing to 18 per cent). The contribution of occupation average commute differences, at 6.2%, is over three times the size of the contribution of individual commute differences within occupation reported in Table 7. Job zone differences subtract from the gap, as females are marginally more likely to work in occupations requiring more preparation. Differences in hazards, strength requirements and poor work environments also subtract from the gap, due to the negative coefficients on these variables for all but hazards. While fatal injury differences across genders also appear to subtract from the gap, the estimate is based on coefficients that are imprecisely estimated.

——————— INSERT TABLE 10 HERE ———————

[19] O'Neill (2003) finds that actual work experience differences can account for a significant portion of the gender wage gap.

[20] All estimation results for models that do not control for major industry are available upon request.

4.3 Cross-city variation

The above estimates of the positive relationship between occupation average commute times and earnings may be biased due to missing characteristics of occupations that are correlated with average commuting times (firm location in a city). In this sub-section, I employ cross-city variation in commuting times by occupation (as discussed in Section 3) to provide further evidence that commuting time differences in particular are related to occupation earnings differences. To do this, I estimate individual level log hourly wage regressions essentially identical to those reported in Table 4, but now also adding a variable measuring commuting time by occupation within individual cities.

I construct this measure of commuting time by occupation within cities using the 93 occupations defined at the 3 digit SOC level. I construct these measures separately for the 13 largest US cities, for the group of 38 medium sized cities collectively, and for the group of 192 small cities collectively (the observations separately identified in Figure 3). Employees residing in non-metropolitan or mixed metropolitan / non-metropolitan areas were excluded from these regressions. Note that these regressions included the full set of unrestricted occupation indicators, which will capture any other differences in earnings across occupations. Thus the coefficients on occupation commuting time at the city level in these regressions should isolate the relationship between earnings and occupation commuting time differences alone. Note also that individual city (CMSA or MSA) indicators are included in these regressions.

The coefficients of interest from these regressions are those on the added occupation commuting time at the city level variable. For females, the coefficient equalled 0.0057 (t-statistic of 5.77), while for males it equalled 0.0045 (t-statistic of 5.20). Note that these t-statistics were constructed using standard errors that allowed for clustering at the city by occupation level. These estimated relationships are significant and relatively large, although they are only half the size of the estimates from the occupation level regressions of Tables 6 and 7. This may in part be due to measurement error in the city by occupation commute time variables attenuating coefficient estimates towards zero.

Here we have observed that differences in earnings between suburban and city occupations (short and long commutes) are larger in larger cities, where the differences in commuting times between city and suburban occupations are also larger. We must take care, however, not to interpret this as reflecting a causal effect of occupation commuting times on earnings. Earnings differences by occupation are driven by firm location productivity differences alone, given mobility (free entry and exit) of competitive firms. This finding thus suggests that firms located in city centres are more productive in larger cities, which in turn suggests that agglomeration spillovers may be higher in larger cities.

4.4 Self-selection - fixed effects estimates

A common concern in studies of occupation and earnings is that the lower average earnings in certain occupations may be due to selection effects based on an unobservable component of an individual's productivity. For example, earnings may be lower in food preparation occupations that are located in suburban areas than in legal occupations that are predominantly located in city centers. This earnings difference may reflect the lower productivity of workers in food preparation relative to law. The discussion of the theoretical model including heterogeneity in worker productivity also illustrated that positive self-selection may occur if worker ability was relatively more productive in city (long commute) occupations, or if ability and distaste for commuting were negatively correlated.

The standard procedure for dealing with such selection concerns if some aspects of ability are not observed is to estimate earnings models using longitudinal data and controlling for a fixed unobserved individual effect. This procedure will control for any time-invariant productivity differences across individuals. The estimated effects of occupation characteristics on earnings are then identified via individuals that change occupations over time.

I employed data from the 2004 Survey of Income and Program Participation (SIPP) to estimate panel data models with individual fixed effects. In the SIPP, survey respondents are interviewed 3 times a year for up to four years. Information on employment and earnings is collected each survey wave. I attempted to estimate earnings models that were as close as possible to those estimated using Census data, with a few differences. One notable difference is the use of direct reports of the hourly wage rate, when it was provided, rather than relying on the constructed measure from the Census. There is, however, no individual commuting time or starting time information in the SIPP, so these variables were unable to be included. Details of SIPP sample and variable construction are provided in Appendix B.

Estimates from both pooled and fixed effect log hourly wage regressions using the SIPP data are presented for females and males in Appendix Tables A2 and A3 respectively. The pooled estimates are provided for comparison purposes, both to the fixed effects estimates and to the estimates using Census data. Note that a one step estimation strategy was employed here, rather than the two step strategy employed using the Census data. Occupation level characteristics were entered directly into the individual log hourly wage regressions. The one step estimation strategy is more amenable to fixed effects estimation.

The estimated coefficients on the individual characteristics from the pooled regressions are quite similar to those estimated using Census data. One exception is the negative coefficients on the part-time indicator estimated using the SIPP. This is the more standard finding in the literature i.e. lower wage rates for part-time workers. The use of a constructed hourly wage in the Census data may be the source of the zero (females) and positive (males) estimated part-time effects in Table 4.

The estimated coefficients on the occupation characteristics in the pooled regressions are also generally in line with those from model 4 in Tables 6 and 7 using Census data. Note that the occupation level measures for the three "family friendly" characteristics are the same measures as employed previously, that is, the measures constructed using the Census data. These Census occupation averages were linked to individuals in the SIPP data using the occupation individuals reported working in.

Turning now to the more important fixed effects estimates, the coefficients are generally attenuated towards zero relative to the pooled estimates. Again a notable exception is the coefficient on the individual level part-time indicator, which is positive rather than negative for both genders. Regarding the "family friendly" occupation level characteristics, the estimates for part-time prevalence generally maintain their size and statistical significance. The coefficients on average hours if full-time are no longer statistically significant, while for average commutes, the coefficients are smaller but are still statistically significant. Thus the estimated commuting time effects do not purely reflect selection on ability. The attenuated size of the estimates may be due in part to selection, but may also be due in part to compounding measurement error in occupation reports that arise in fixed effects estimates.

These fixed effects estimates of the commuting time relationship with earnings are essentially the same for females and males (0.0041 and 0.0034 to the fourth decimal point respectively). In the cross-section, the relationship for females was larger. If females have the highest distaste for commuting, then any self-selection bias in the cross-section should be larger for females. These estimates are thus consistent with this implication.

If there is self-selection bias in the cross-sectional estimates, as the fixed effects estimates suggest, it implies that the earnings gain that any individual may obtain from moving from a suburban to city occupation (short to long commute) will be less than the cross-section estimates imply. It may be the case, however, that the fixed effects estimates are understating the average earnings gain across the ability distribution, if we only observe low ability types switching occupations in the data. We may observe more low ability types switching if they are more likely to be at the margin of the city / suburb occupation choice. High ability types may always be observed in city occupations if ability is more productive in such occupations.

4.5 Commutes and firm size

Jobs in occupations with shorter average commutes (dispersed suburban jobs) may be on average in firms that are smaller in size. Previous research has shown the strong positive relationship between earnings and firm size, particularly in the US (Oi and Idson, 1999). Thus the negative relationship between occupation commuting time and earnings may be related to firm size effects.

Firm and work location size information is available in the SIPP micro-data, but commuting time is not.[21] Information is, however, collected in waves 3 and 6 of the 2004 SIPP on the number of miles driven to work and back each week by those individuals who report driving to work. Approximately 85% of employees drive to work in the US.[22] These commute driving miles should be highly correlated with commuting time.[23]

Estimates from simple regressions relating commute driving miles to overall firm size, work location size and indicators for whether the firm the individual works in has multiple work locations versus just one were constructed. These estimates revealed that those who drive further for employment work on average in larger work locations and particularly in larger firms. Working in a firm with multiple locations was also positively related to driving time.

As an explanation of the gender wage gap, however, firm or work location size differences do not provide any assistance. If anything, females tend to work in larger firms than males. Information on the proportion of employees working in different sized workplaces and firms by gender from the SIPP revealed that males are more likely to be working in work locations or firms with fewer than 25 employees. This result is primarily driven by more males working in

[21] Firm and work location information is not available in the US Census.

[22] Only around 5% take public transport, while the remainder car-pool, walk, ride a bike, take a taxi or hire car, et cetera.

[23] Average driving miles by occupation constructed from the SIPP data was highly correlated with average commuting times by occupation constructed from the US Census.

small construction and building related firms. Examples are roofers, electricians, and plumbers. These are occupations where jobs are dispersed in the suburbs, but commuting time is on average quite long. They are those occupations identified to the top and right of Figure 1.

4.6 Measures of occupation flexibility

The focus in the analysis thus far has been on three particular "family friendly" characteristics of occupations that I have found to be related to lower earnings. Job flexibility may also be attractive to individuals who need to balance work and family responsibilities. Such individuals may still choose to work in occupations with long commutes or long hours on average if there are some jobs within such occupations that have short commutes and short hours.

Two measures investigated here are based on variation in commuting times and in hours of work if full-time i.e. the second moments of these two variables. Specifically, measures of the coefficient of variation (standard deviation divided by the mean)[24] within occupations in commuting time and hours if full-time were constructed. Summary statistics for these two occupation level coefficients of variation are provided at the top of Appendix Table A4. The means of these measures of "flexibility" are essentially the same for females and males. Thus it does not appear that females are more likely to value occupations with flexibility measured in this way.

Individuals may also value occupations with variation in home leaving times, as it may provide the flexibility to juggle multiple responsibilities. Therefore, a measure reflecting the variation in home leaving times within each occupation was constructed as the sum of the squares of the proportion of employees in an occupation with starting times within each range.[25] Summary statistics for this variable are provided in the last row of Appendix Table A4. Higher values for this variable denote occupations where starting times are more concentrated within specific ranges, perhaps reflecting inflexibility in starting times. Note that means for this measure are also very similar for males and females.[26] Males are employed in occupations with starting times concentrated earlier in the morning, while females are in occupations with starting times concentrated later in the morning.

[24]Again, these measures were constructed for each occupation using male employees only.

[25]The starting time ranges used were those listed at the bottom of Table 3.

[26]Golden (2001) and McCrate (2005) investigated differences across genders in self-reports of start and end time flexibility in the job i.e. whether individuals had the opportunity to change their work schedules. They found that males were slightly more likely to have such flexibility than females. McCrate (2005) also found that earnings were not necessarily lower in jobs with such flexibility.

Occupation level regression estimates including these additional measures of occupation flexibility are presented in Appendix Table A5. Higher variation in commutes and hours if full-time are related to lower earnings, although the hours variation is not statistically significant for males. Thus it appears that earnings are lower in occupations offering greater flexibility along these two specific dimensions. In addition, occupation concentration in leaving times is positively related to earnings (yet not significant for males). Earnings thus seem to be higher in occupations with home leaving times that are more concentrated within specific parts of the day (less flexible). Higher earnings may be required to induce individuals to work in such occupations.

Even though these additional measures of occupation flexibility were found to be related to earnings in the expected directions, these measures cannot assist us in understanding the gender wage gap. As observed in Appendix Table A4, these three measures had essentially the same means across males and females. Thus it does not appear as if females are more responsive to occupation flexibility than males, at least along the three dimensions investigated here.

5 Conclusions

The analysis above illustrated the negative relationship between three specific "family friendly" occupation characteristics and earnings. Females were also much more likely to be working in such occupations, particularly if they had dependent children of school age. This strongly suggests that females may be trading off these "family friendly" characteristics for lower earnings. That is, the lower earnings in such occupations may be thought of as compensating differentials.

Differences in these "family friendly" characteristics were found to potentially "explain" up to 18 per cent of the US gender wage gap. These characteristics can in part rationalise why female-dominated occupation pay less overall, and why females might be choosing to work in such occupations. Thus these "family friendly" characteristics are at least if not more important in understanding occupation differences and the gender wage gap than aspects analysed in the recent literature, such as: risk of death, earnings and job risk, preferences for money, personality and non-cognitive traits.

There are, however a number of questions that remain to be answered. To begin, why are females more likely to be working in such "family friendly" occupations even if no dependent children are present in the home? Did they train for such occupations in expectation of potential family responsibilities, either to care for their own children or for other family members? Do females switch into “female-friendly” occupations once family responsibilities arrive, or are they working in such occupations prior to this? [27] Finally, have those occupations that females tend to work in developed “family-friendly” attributes in response to the desire of the majority female workers to have such job attributes? Goldin and Katz (2011, 2012) argue that certain professional occupations have become more flexible and “family friendly” over time as more females have entered. There is thus still work to do to fully understand the relationships identified here.

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Table 1: **Occupation Average Commute and Employment - Females**

	Occupation commute		Employment	
Variable	Coefficient	t-statistic	Marginal effect	t-statistic
married	0.031	1.69	-0.051	-31.0
child 0-5	-0.144	-3.09	-0.052	-11.9
child 6-17	-0.324	-11.3	0.013	4.33
child 0-17	-0.598	-10.6	-0.089	-17.4
child 0-5 * married	-0.052	-0.94	-0.125	-24.0
child 6-17 * married	-0.312	-8.97	-0.010	-2.94
child 0-17 * married	0.032	0.49	-0.095	-16.4
large city	0.804	49.8	0.004	2.84
married * large city	-0.284	-12.5	0.006	2.82
child 0-5 * large city	-0.134	-2.22	-0.023	-4.26
child 6-17 * large city	-0.213	-5.90	-0.018	-4.82
child 0-17 * large city	-0.131	-1.83	-0.018	-2.87
child 0-5 * married * large	0.420	5.90	-0.022	-3.45
child 6-17 * married * large	0.144	3.23	-0.025	-5.77
child 0-17 * married * large	0.250	3.04	-0.017	-2.47
medium city	0.464	26.3	0.024	14.5
married * medium city	-0.080	-3.24	-0.006	-2.79
child 0-5 * medium city	-0.093	-1.43	-0.012	-1.97
child 6-17 * medium city	-0.072	-1.83	-0.007	-1.71
child 0-17 * medium city	-0.034	-0.44	-0.015	-2.19
child 0-5 * married * medium	0.202	2.62	-0.009	-1.31
child 6-17 * married * medium	0.034	0.71	-0.013	-2.72
child 0-17 * married * medium	0.040	0.45	-0.007	-0.86
4th order polynomial in age	yes		yes	
Education indicators (15)	yes		yes	
Race and immigration indicators (7)	yes		yes	
observations	1,077,812		2,717,930	

Notes: 2000 US Census. Columns 1-2 – OLS estimates using average occupation commutes of male employees. Regressions include employees in analysis sample (see Appendix B). Columns 3-4 – Probit marginal effects of employment among all non-students aged 16-64.

Table 2: **Occupation Average Commutes and Employment - Males**

Variable	Occupation commute Coefficient	Occupation commute t-statistic	Employment Marginal effect	Employment t-statistic
married	0.330	13.8	0.054	41.7
child 0-5	0.365	3.65	0.067	14.2
child 6-17	0.249	3.93	0.065	18.5
child 0-17	0.405	2.73	0.053	7.16
child 0-5 * married	-0.386	-3.64	0.009	1.62
child 6-17 * married	-0.282	-4.13	0.020	4.95
child 0-17 * married	-0.522	-3.42	0.022	2.75
large city	0.588	29.4	0.008	8.30
married * large city	-0.069	-2.44	0.012	7.55
child 0-5 * large city	-0.325	-2.64	-0.028	-3.92
child 6-17 * large city	-0.158	-1.97	-0.009	-1.72
child 0-17 * large city	-0.489	-2.71	-0.007	-0.73
child 0-5 * married * large	0.413	3.18	-0.014	-1.81
child 6-17 * married * large	0.118	1.36	-0.024	-4.41
child 0-17 * married * large	0.536	2.89	-0.035	-3.22
medium city	0.292	13.4	0.021	19.1
married * medium city	-0.001	-0.04	-0.001	-0.58
child 0-5 * medium city	0.162	1.21	-0.016	-2.05
child 6-17 * medium city	-0.045	-0.52	-0.010	-1.73
child 0-17 * medium city	0.032	0.15	0.003	0.29
child 0-5 * married * medium	-0.058	-0.41	-0.001	-0.17
child 6-17 * married * medium	0.064	0.69	-0.003	-0.51
child 0-17 * married * medium	0.105	0.49	-0.019	-1.52
4th order polynomial in age	yes		yes	
Education indicators (15)	yes		yes	
Race and immigration indicators (7)	yes		yes	
observations	1,175,139		2,665,674	

Notes: 2000 US Census. Columns 1-2 – OLS estimates of average occupation commutes of male employees, include employees in analysis sample (see Appendix B) living in cities. Columns 3-4 – Probit marginal effects of employment among all non-students aged 16-64.

Table 3: **Summary statistics - Employees in 2000 US Census**

	Females		Males	
	mean	st. dev.	mean	st. dev.
Hourly wage	15.56	12.65	20.51	18.14
Years of schooling*	13.90	2.38	13.67	2.75
Age	40.21	10.98	39.70	11.03
Part-time	0.190		0.049	
Married	0.604		0.666	
Immigrant	0.112		0.142	
Black	0.100		0.076	
Hispanic	0.081		0.106	
American native	0.013		0.012	
Asian	0.040		0.041	
Pacific Islander	0.002		0.002	
Other race	0.041		0.057	
Non-profit employee	0.119		0.048	
Federal govt. employee	0.031		0.036	
State govt. employee	0.066		0.044	
Local govt. employee	0.100		0.067	
Commute (minutes)	23.68	21.36	27.70	25.46
work at home	0.013		0.011	
leave for work				
- 0 to 5:59 am	0.072		0.157	
- 6 to 6:59 am	0.168		0.251	
- 7 to 7:59 am	0.364		0.291	
- 8 to 8:59 am	0.198		0.120	
- 9 to 11:59 am	0.086		0.057	
- 12 to 6:59 pm	0.076		0.081	
- 7 to 11:59 pm	0.022		0.033	
Observations	1,494,545		1,621,748	

Notes: US 2000 Census data. Averages constructed using population weights provided with the Census data. * Constructed from highest education attained categories (see Appendix A).

Table 4: **Individual level regressions (step 1)**

	Females		Males	
	coeff.	t-stat	coeff.	t-stat
4th grade or less	-0.209	-20.1	-0.246	-33.4
5th or 6th grade	-0.182	-26.4	-0.197	-42.7
7th or 8th grade	-0.147	-24.2	-0.157	-37.5
9th grade	-0.139	-25.8	-0.165	-43.7
10th grade	-0.113	-27.3	-0.126	-39.5
11th grade	-0.093	-22.5	-0.101	-32.7
12th grade, no diploma	-0.043	-12.5	-0.046	-17.0
Some college (<1 year)	0.055	33.7	0.054	32.1
College ≥ 1 yr, no degree	0.083	59.2	0.082	60.1
Associate degree	0.120	70.9	0.114	64.2
Bachelor's degree	0.251	158.4	0.241	147.1
Master's degree	0.436	193.0	0.367	151.4
Professional degree	0.321	61.9	0.386	61.3
Doctorate degree	0.508	81.7	0.471	93.7
Potential experience (PE)	0.057	67.6	0.060	67.2
PE^2 / 10	-0.028	-40.0	-0.024	-33.1
PE^3 / 1,000	0.062	28.3	0.049	21.4
PE^4 / 100,000	-0.052	-22.2	-0.041	-17.1
Part-time	-0.007	-5.06	0.050	15.6
Married	0.008	9.03	0.121	118.6
Immigrant	-0.076	-38.7	-0.091	-47.3
Black	-0.012	-6.31	-0.064	-32.2
Hispanic	-0.020	-7.9	-0.048	-20.3
American native	-0.055	-13.2	-0.065	-15.1
Asian	-0.011	-3.75	-0.049	-16.1
Pacific Islander	-0.015	-1.53	-0.019	-1.83
Other race	-0.021	-6.88	-0.023	-8.72

Notes: Table continued on next page.

Table 4 (cont.): **Individual level regressions (step 1)**

	Females		Males	
	coeff.	t-stat	coeff.	t-stat
Non-profit employee	-0.010	-5.78	-0.067	-24.2
Federal govt. employee	0.159	51.1	0.094	31.3
State govt. employee	0.074	32.6	-0.015	-5.69
Local govt. employee	0.056	26.0	-0.006	-2.71
Commute (minutes)	0.0035	32.0	0.0022	20.6
Commute^2 / 100	-0.0029	-13.3	-0.0019	-9.64
Commute^3 / 10,000	0.0007	7.02	0.0006	6.29
work at home	0.037	6.53	0.044	7.19
leave for work				
- 0 to 5:59 am	0.027	13.4	0.020	10.2
- 6 to 6:59 am	0.026	17.5	0.002	1.29
- 7 to 7:59 am	0.017	13.8	0.000	-0.12
- 9 to 11:59 am	-0.032	-15.4	-0.050	-19.0
- 12 to 6:59 pm	0.006	2.69	-0.010	-4.25
- 7 to 11:59 pm	0.048	14.6	0.019	6.85
Occupation (470)	Yes		Yes	
Industry (24)	Yes		Yes	
PUMA (2071)	Yes		Yes	
Observations	1,494,545		1,621,748	
R-squared	0.4166		0.4446	

Notes: Dependent variable is the natural log of the hourly wage rate. Estimates constructed using Census provided population weights. Coefficient t-statistics based on White robust standard errors.

Table 5: **Occupation variable summary statistics**

	Females		Males	
	mean	st. dev.	mean	st. dev.
Proportion female	0.666	0.242	0.304	0.239
Proportion Part-Time (males)	0.085	0.072	0.049	0.052
Mean hours FT (males)	44.31	2.35	45.42	2.85
Mean commute (males)	26.44	3.48	27.70	4.45
Job zone 1	0.057	0.232	0.052	0.222
Job zone 2	0.294	0.456	0.323	0.468
Job zone 3	0.285	0.452	0.292	0.455
Job zone 4	0.226	0.419	0.236	0.425
Job zone 5	0.138	0.346	0.097	0.296
Hazards	1.658	0.472	2.006	0.648
Strength required	1.615	0.522	1.863	0.595
Poor environment	1.817	0.375	2.309	0.692
Fatal injuries (per million hours)	0.010	0.027	0.038	0.073
Computers	3.619	0.909	3.249	1.002
Caring	3.091	0.788	2.705	0.598
Advising	2.654	0.628	2.754	0.619
Teaching	3.144	0.614	3.123	0.526
Work with public	3.234	0.828	2.892	0.910
Relationships	3.821	0.444	3.622	0.526
Observations	470		470	

Notes: Sources: US Census 2000, O*NET and US Bureau of Labor Statistics. Occupation means were constructed using the US Census provided individual male weights.

Table 6: **Occupation level regressions - Females**

	Model one		Model two		Model three		Model four	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
Proportion female (PF)	-0.159	-5.81	-0.039	-1.29	-0.255	-6.61	-0.191	-4.75
Proportion Part-Time (male)			-0.359	-3.14			-0.259	-2.32
Mean hours FT (male)			0.014	4.63			0.011	3.22
Mean commute (male)			0.014	7.30			0.013	6.74
Job zone 2	0.141	4.38	0.078	2.46	0.038	1.24	0.022	0.72
Job zone 3	0.288	8.93	0.192	5.88	0.099	2.95	0.067	2.05
Job zone 4	0.393	12.0	0.268	7.81	0.166	4.44	0.142	3.93
Job zone 5	0.474	13.6	0.358	9.89	0.212	5.27	0.183	4.71
Hazards					0.110	4.41	0.102	4.33
Strength required					-0.063	-2.57	-0.040	-1.70
Poor environment					-0.049	-1.85	-0.069	-2.72
Fatal injuries (per mill. hours)					-0.039	-0.36	-0.153	-1.46
Computers					0.064	6.20	0.049	4.59
Caring					0.042	2.77	0.051	3.56
Advising					0.055	3.09	0.037	2.18
Teaching					-0.060	-3.96	-0.037	-2.50
Work with public					0.009	0.99	0.021	2.46
Relationships					0.047	2.10	0.012	0.55
Observations	470		470		470		470	
R-squared	0.4763		0.5637		0.6100		0.6566	

Notes: First step estimates of sample variance of occupation indicator coefficients used as weights.

Table 7: **Occupation level regressions - Males**

	Model one		Model two		Model three		Model four	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
Proportion female (PF)	-0.133	-5.46	0.000	-0.01	-0.178	-4.91	-0.103	-3.02
Proportion Part-Time (male)			-0.848	-6.66			-0.682	-5.12
Mean hours FT (male)			0.013	5.83			0.010	4.42
Mean commute (male)			0.009	6.98			0.010	8.04
Job zone 2	0.133	4.29	0.041	1.38	0.067	2.21	0.008	0.28
Job zone 3	0.253	8.11	0.130	4.22	0.115	3.48	0.045	1.46
Job zone 4	0.406	12.9	0.247	7.66	0.188	5.03	0.123	3.54
Job zone 5	0.448	12.8	0.296	8.45	0.223	5.56	0.154	4.14
Hazards					0.052	2.24	0.060	2.83
Strength required					-0.069	-3.12	-0.035	-1.75
Poor environment					-0.002	-0.07	-0.043	-2.18
Fatal injuries (per mill. hours)					-0.015	-0.18	-0.167	-2.15
Computers					0.031	3.16	0.028	3.06
Caring					0.008	0.59	0.014	1.11
Advising					0.051	2.93	0.034	2.15
Teaching					-0.012	-0.75	0.000	-0.01
Work with public					-0.003	-0.40	0.016	2.14
Relationships					0.055	2.76	0.008	0.45
Observations	470		470		470		470	
R-squared	0.4968		0.6117		0.5856		0.6677	

Notes: First step estimates of sample variance of occupation indicator coefficients used as weights.

Table 8: **Correlation among occupational measures**

	Prop. Female	Prop. PT	FT hours	Commute	Hazards	Strength	Poor Envir.
Prop. Female (PF)	1						
Proportion PT	0.45	1					
FT hours	-0.34	-0.37	1				
Commute	-0.26	-0.33	0.02	1			
Hazards	-0.49	-0.06	-0.12	-0.01	1		
Strength	-0.36	0.19	-0.19	-0.18	0.81	1	
Poor Environment	-0.67	-0.14	-0.06	0.14	0.87	0.74	1
Fatal injuries	-0.41	0.01	0.10	0.23	0.38	0.38	0.51
Computers	0.32	-0.31	0.09	0.18	-0.64	-0.77	-0.60
Caring	0.44	0.30	-0.06	-0.33	0.15	0.25	-0.10
Advising	-0.13	-0.40	0.46	0.09	-0.16	-0.31	-0.21
Teaching	0.03	-0.09	0.20	-0.27	0.10	0.07	0.01
Work with public	0.32	0.31	0.13	-0.28	-0.14	0.04	-0.16
Relationships	0.33	-0.18	0.36	0.04	-0.52	-0.57	-0.57

	Fatal Injuries	Work with Computers	Caring	Advising	Teaching	Work Public	Relation-ships
Fatal injuries	1						
Computers	-0.38	1					
Caring	-0.03	-0.07	1				
Advising	-0.12	0.42	0.19	1			
Teaching	-0.04	0.11	0.44	0.55	1		
Work with public	0.01	0.02	0.52	0.06	0.13	1	
Relationships	-0.26	0.55	0.33	0.60	0.28	0.35	1

Notes: Sources: US Census 2000, O*NET and US Bureau of Labor Statistics. Correlations were constructed using the US Census provided individual person weights.

Table 9: **Decomposition of mean log wage gap - individual characteristics**

	log points	per cent
Raw log wage gap	0.242	100.0
Education	-0.009	-3.7
Potential experience	0.000	-0.1
Part-time	-0.003	-1.2
Married	0.004	1.7
Immigrant	-0.003	-1.1
Race	0.000	-0.1
Employer	0.002	0.8
Commute	0.005	2.0
Work at home	0.000	0.0
Start time	0.006	2.5
Industry	0.030	12.4
TOTAL	0.032	13.1

Notes: Decomposition employs average of male and female regression coefficients.

Table 10: **Decomposition of mean log wage gap - occupation characteristics**

	Model 1		Model 2		Model 3		Model 4	
	level	%	level	%	level	%	level	%
Proportion female (PF)	0.053	21.8	0.007	2.9	0.078	32.4	0.053	22.0
Proportion Part-Time (male)			0.021	8.9			0.017	6.9
Mean hours FT (male)			0.015	6.2			0.012	4.8
Mean commute (male)			0.014	5.9			0.015	6.1
Job zone	-0.009	-3.8	-0.008	-3.3	-0.005	-2.0	-0.005	-2.0
Hazards, strength, environment					-0.001	-0.3	-0.013	-5.5
Fatal injuries					-0.001	-0.3	-0.005	-1.9
Computers					-0.018	-7.3	-0.014	-5.9
Care, teach, advise, public, relate					-0.013	-5.4	-0.027	-11.1

Notes: Decomposition employs average of male and female regression coefficients.

Figure 1: **Occupation Dispersion and Average Commuting Times**

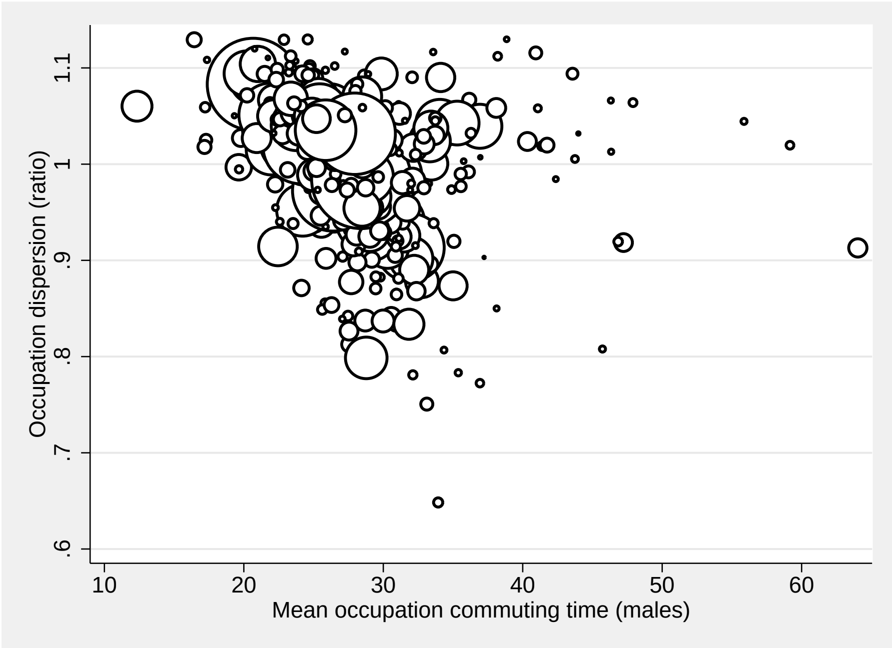
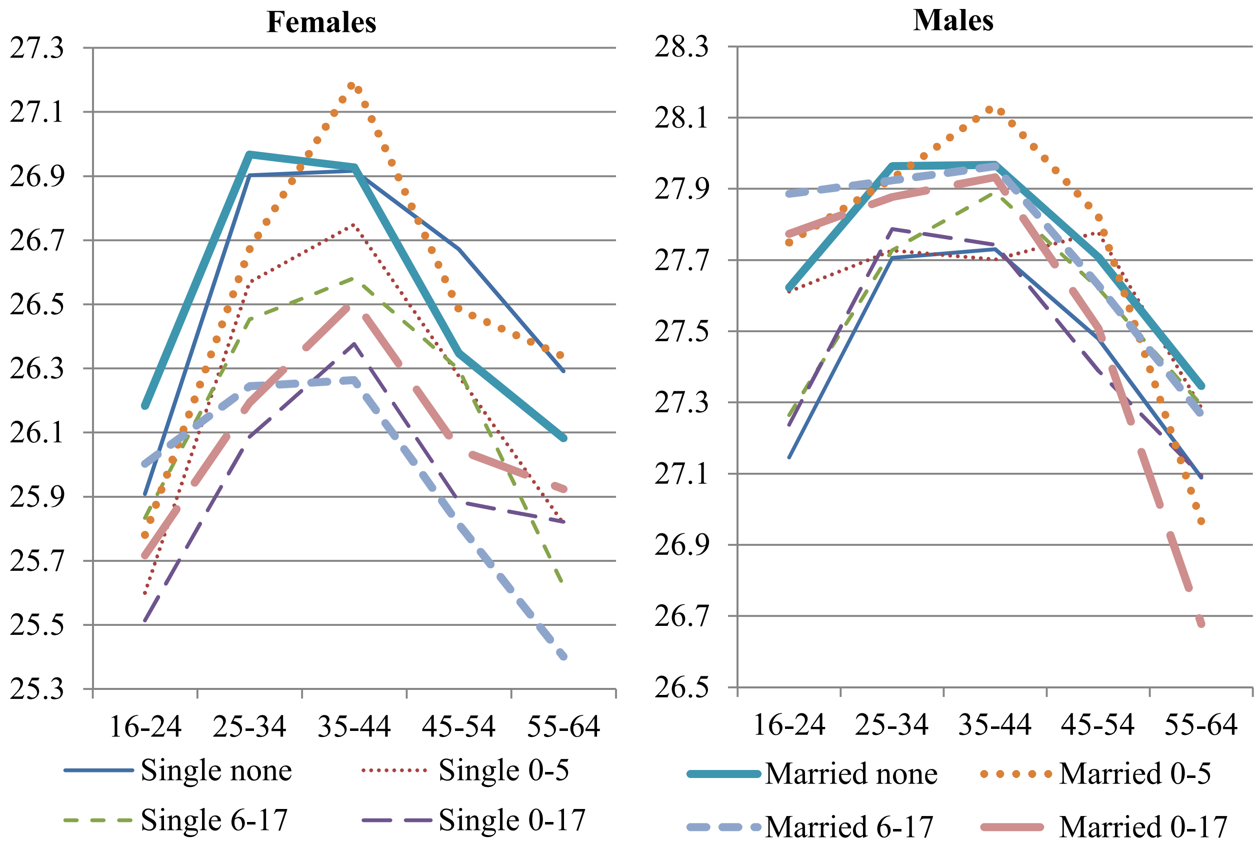


Figure 2a: **Average commuting time in the occupation**



Notes: Each data point is the average of the occupation characteristic for the group.
0-5 = children aged 0 to 5 only in the home, 6-17 = children aged 6 to 17 only in the home,
0-17 = children aged both 0 to 5 and 6 to 17 in the home

Figure 2b: **Part-time prevalence in the occupation**

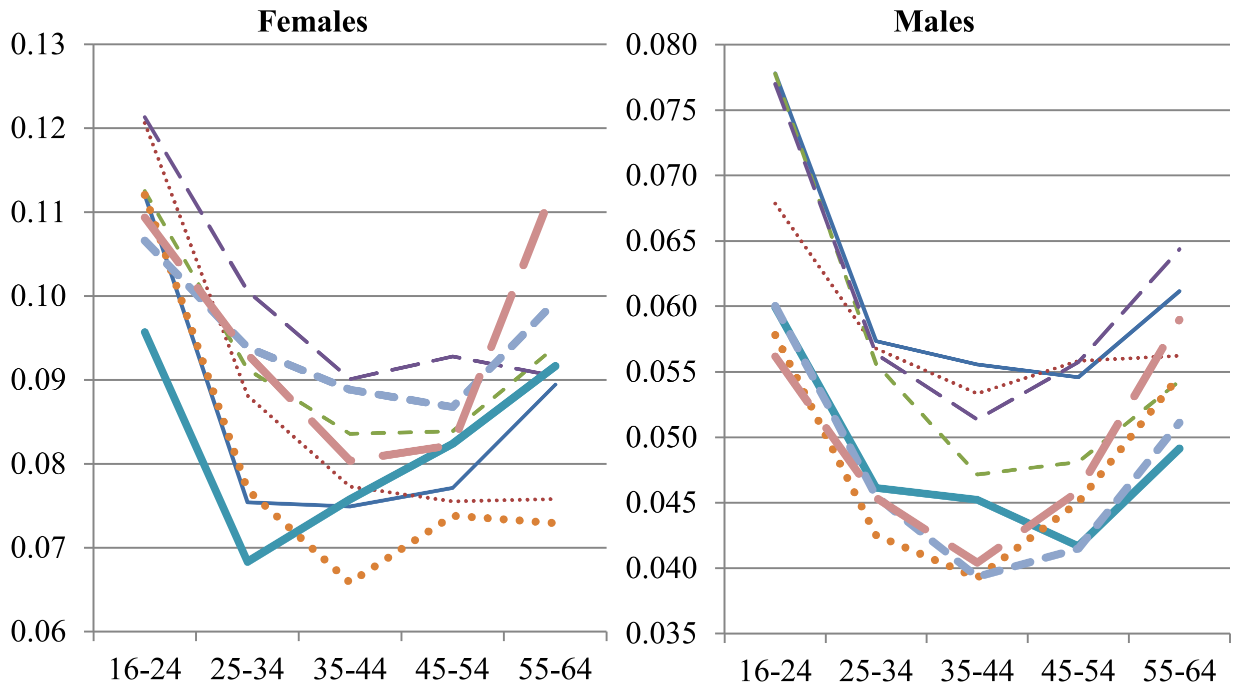
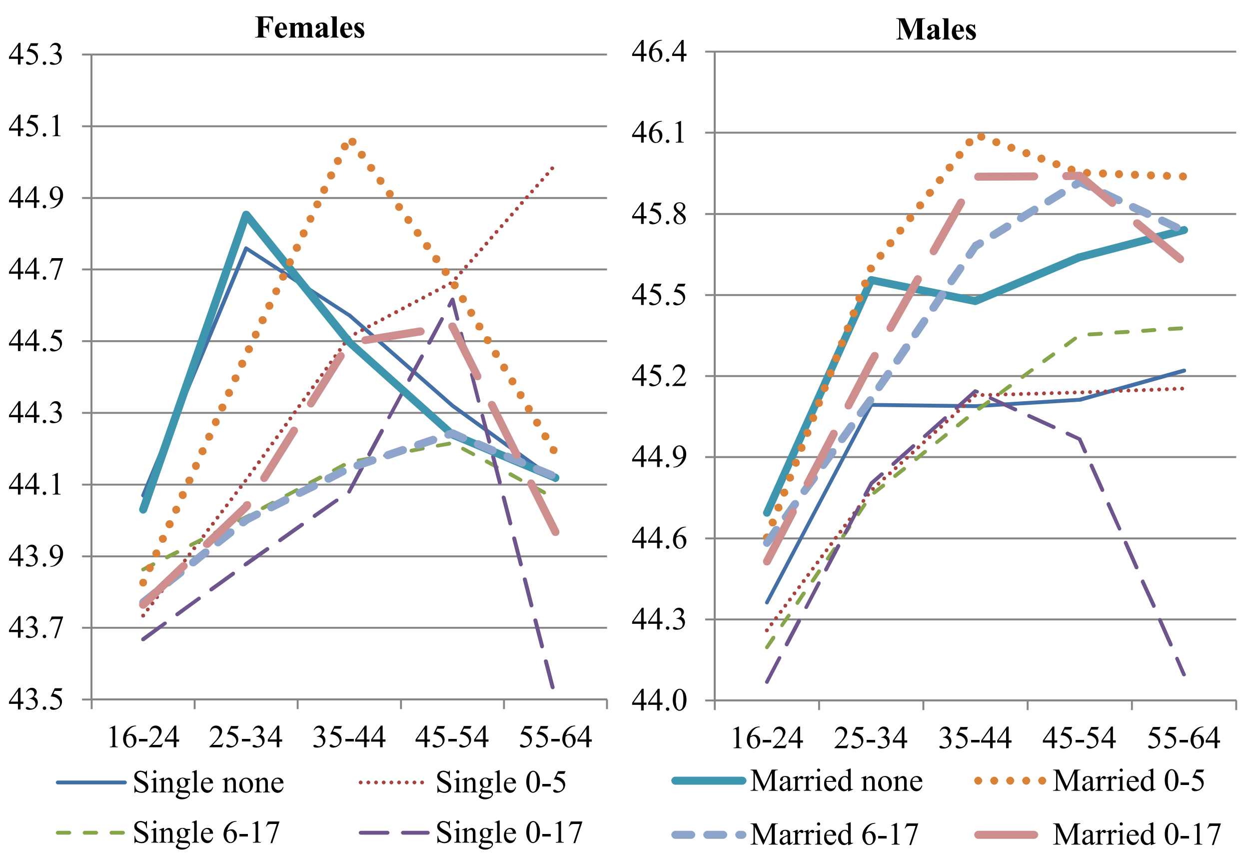
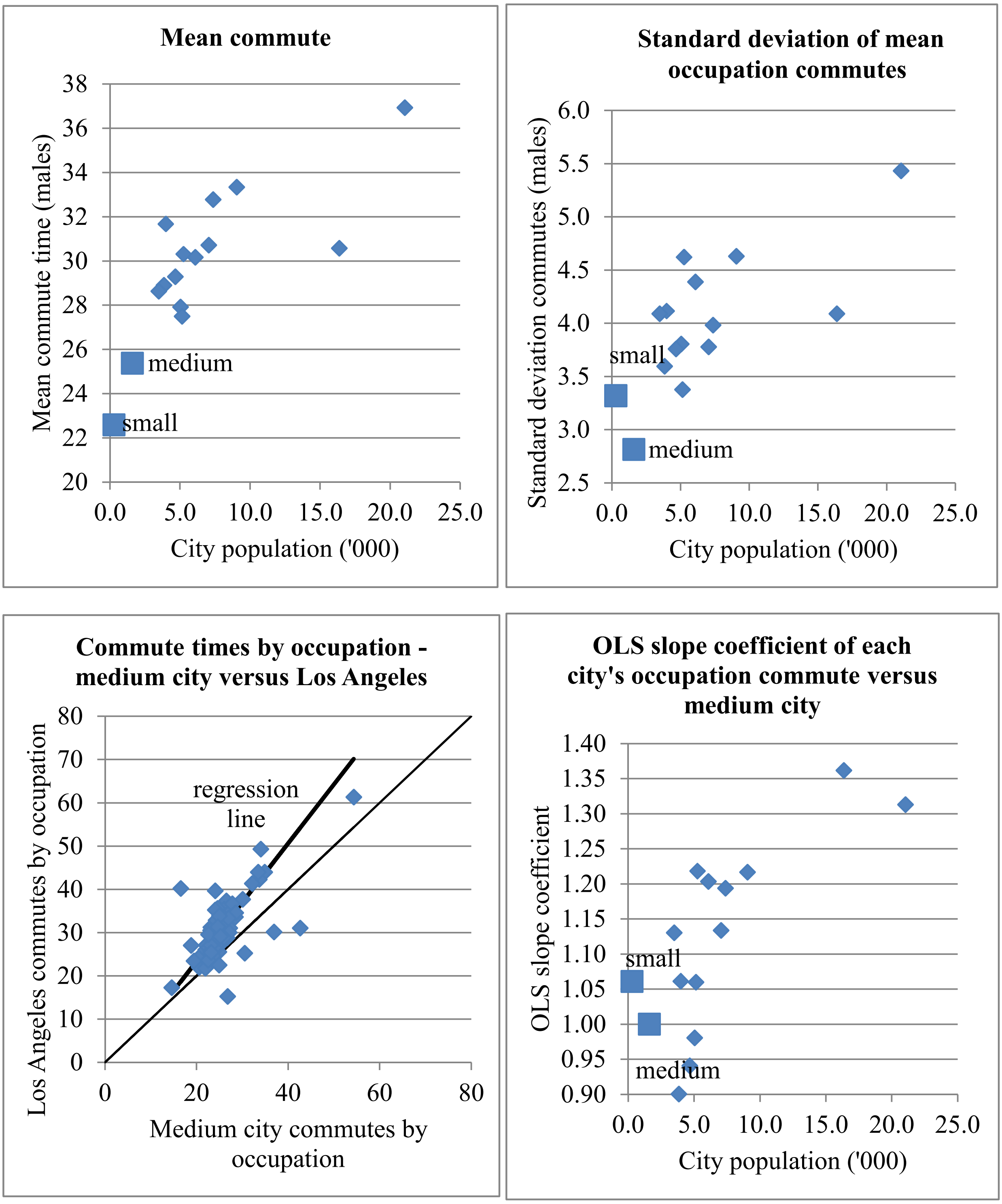


Figure 2c: **Average hours if full-time in the occupation**



Notes: Each data point is the average of the occupation characteristic for the group.
0-5 = children aged 0 to 5 only in the hom(none = no children under age 18 in the home,
0-17 = children aged both 0 to 5 and 6 to 17 in the home

Figure 3: **City-based measures of commuting time by occupation**



A Theoretical Model

Consider the following simplified model of work and residence location choices in a city. Individuals optimally choose a location specific occupation to work in and a suburb to live in according to the following linearized indirect utility function, where w_j is the market wage in occupation j, r_k is rent in suburb k, t_i is a heterogeneous parameter reflecting individual i's distaste for commuting, while d_{jk} is the commuting time from suburb of residence k to location of occupation j.

$$U_{ijk} = w_j - r_k - t_i \cdot d_{jk} \tag{A.1}$$

The individual's heterogeneous distaste for commuting t_i is assumed to be distributed uniformly over the range T_l to T_u (i.e. $t \sim U[T_l, T_u]$), where $T_u > T_l > 0$. We could think of T_l as the monetary cost of commuting per unit of time, while individuals have some non-negative individual distaste for commuting over and above the monetary cost. The total number of individuals in the city is normalized to equal 1, and they supply labor inelastically.

Individuals choose between two location-specific occupations:

(1) a city occupation paying w_c (e.g. lawyer), and

(2) a suburban occupation paying w_s (e.g. supermarket checkout operator).

Individuals also choose between two suburb areas:

(1) suburbs near the city with rent r_n (inner or near suburbs), and

(2) suburbs further away with rent r_o (outer suburbs).

If an individual chooses a suburban occupation, the commuting distance d_{jk} is assumed to be zero irrespective of the suburb lived in ($d_{sn} = d_{so} = 0$). If a city occupation is chosen, $d_{cn} = 1$ while $d_{co} = 1 + \alpha$ where $\alpha > 0$, i.e. outer suburbs are more distant from the city that inner (near) suburbs by α.

Firms are competitive and produce a composite consumption good Y according to the following standard constant returns to scale Cobb-Douglas production function.[1]

$$Y_j = X_j \cdot N_j^{\beta} \cdot K_j^{1-\beta} \tag{A.2}$$

Competitive firms can freely locate either in the city or in suburban areas, with the technology parameter X_j governing production potentially differing depending on this location choice i.e. production amenities may differ across locations. Output is assumed tradeable across cities and

[1]The Cobb-Douglas production function is employed for illustrative purposes only. The main tenor of the results will follow in more general constant returns to scale production functions.

even between the city and suburbs,[2] with the price determined externally to any city (price is normalized to equal 1). Firms can rent capital K on competitive markets at p_k per unit.

Firm profit maximization results in an equilibrium wage in each occupation as follows.

$$w_j = \frac{\partial Y_j}{\partial N_j} = \beta(1-\beta)^{(1/\beta-1)} p_k^{(1-1/\beta)} \cdot X_j^{1/\beta} = \Omega(\beta, p_k) \cdot X_j^{1/\beta} \tag{A.3}$$

Due to free mobility and optimal capital decisions, wages are determined by production function parameters and the cost of capital. For wages to be higher in city (longer commute) occupations (as we observe), it must be the case that there are productivity benefits ($X_c > X_s$) for firms locating in city areas, perhaps from agglomeration spill-overs, being closer to suppliers and customers, infrastructure, et cetera. If no benefits existed, firms would not locate in city centers as they could not compete for workers, given worker distaste for (costs of) commuting.

To keep the model as simple as possible, I follow Moretti (2011) by assuming the following equation for rent determination in the two suburb areas.

$$r_k = z + \rho_k \cdot N_k \qquad \text{where } \rho_k \geq 0 \quad k = n, o \tag{A.4}$$

This rental determination equation has rents increasing with the number of individuals choosing to live in a particular suburban area. This mechanism proxies the extra costs involved in attempting to add more housing to particular suburbs. It would seem appropriate for $\rho_n > \rho_o$, i.e. that it is more costly to squeeze more housing into inner suburbs that are constrained from expanding relative to outer suburbs, where it may be possible to expand outside current residential boundaries. If ρ_n were infinite, for example, the number of houses in inner suburbs would essentially be fixed at some level N_n. Lower values of ρ_k reflect more elastic supply of housing.

In this model, certain values for model parameters will yield specific equilibria. For example, if parameter values were such that $w_c < w_s + T_l$, no individual would choose to work in the city, as wages would not be high enough to overcome positive commuting costs. If $w_c > w_s + (1 + \alpha) \cdot T_u$, then all individuals would choose to work in the city. To generate equilibria where individuals work in both the city and suburban areas, we will focus on parameter values (values of $X_c, X_s, \alpha, \beta, p_k, T_l$ and T_u) such that $T_l < w_c - w_s < (1 + \alpha) \cdot T_u$.

Consider an equilibrium where individuals live in both inner and outer suburban areas and work in both city and suburban occupations. The parameter values that lead to such an equilibrium will be discussed below. In such an equilibrium, where necessarily $r_n > r_o$ (otherwise no

[2] Output of city and suburban firms being different to each other but still tradeable across cities would not change the model predictions to any important extent. Price differences across goods would change equilibrium wages in each occupation, akin to a change in X_j.

individual would choose to live in outer suburbs), individuals will choose their optimal living and working arrangements depending on their individual t_i.[3] Those with commuting distaste values in a range $T_l \le t_i < T_1$ will choose to work in the city and live in outer suburbs, as they have the least distaste for commuting, and will take advantage of the lower rent in outer suburbs.[4] A second group with distaste values in a range $T_1 \le t_i < T_2$ will choose to live in inner suburbs and work in city occupations. The remainder with the highest distaste values in the range $T_2 \le t_i \le T_u$ will choose to live in outer suburbs and work in suburban occupations. No individuals choose to live in inner suburbs and work in suburban occupations in this simplified model, as wages are the same as in outer suburb jobs while rent is higher.[5]

To describe the equilibrium here, we solve for T_1 and T_2, the values of t_i where individuals are indifferent between adjacent choices. At T_1, individuals working in the city are indifferent between living in inner versus outer suburbs, thus equation (A.5) must hold.

$$w_c - r_n - T_1 = w_c - r_o - (1+\alpha)\cdot T_1 \quad \Rightarrow \quad r_n - r_o = \alpha \cdot T_1 \tag{A.5}$$

Note also for this low t_i group, individuals must prefer working in a city versus suburban occupation while living in an outer suburb. For this condition to hold, it requires:

$$w_c - r_o - (1+\alpha)\cdot t_i > w_s - r_o \quad \Rightarrow \quad t_i < (w_c - w_s)/(1+\alpha) \tag{A.6}$$

The value for T_1 constructed using condition (A.5) ensures that condition (A.6) holds for all $t_i < T_1$, i.e. (A.5) is the binding constraint here (see equation (A.10) below).

At T_2, individuals are indifferent between working in the city and living in inner suburbs versus living and working in outer suburbs. Thus equation (A.7) must hold.

$$w_c - r_n - T_2 = w_s - r_o \quad \Rightarrow \quad r_n - r_o = (w_c - w_s) - T_2 \tag{A.7}$$

Using the assumed uniform distribution for t_i, we can write the following for N_{cn}, the number

[3] In this model, there are no amenity differences across suburbs. Some readers may note the low rents in some inner suburb neighborhoods in specific cities due to urban decay. Including amenity differences in this model is straightforward, and if preferences for such amenities A_k were homogeneous across the population, individuals would optimize over $r_k - A_k$ rather than just r_k. In this case, r_o may be less than r_n in equilibrium if $A_n < A_o$, but $r_n - A_n$ must be greater than $r_o - A_o$.

[4] This category will be non-empty as long as $r_n - r_o > \alpha \cdot T_l$, i.e. as long as there is a group with low distastes for commuting, or housing supply is such that rents are a certain amount higher in inner versus outer suburbs.

[5] Extensions to the model that may yield equilibria where individuals choose to live in inner suburbs but work in suburban jobs include: (a) heterogeneous preferences for inner suburb living, (b) joint household location decisions where one household member may choose to work in the city and another member in a suburban occupation, and (c) certain output produced in the suburbs is non-tradeable or costly to trade.

of individuals choosing to live in inner suburbs and work in the city, where $T = T_u - T_l$.

$$N_{cn} = \int_{T_1}^{T_2} f(t_i)\, dt_i = \frac{T_2 - T_1}{T} \quad \Rightarrow \quad T_2 - T_1 = N_{cn} \cdot T \tag{A.8}$$

We can combine equations (A.5), (A.7) and (A.8) with the rent determination equations (A.4) to solve for the following:

$$N_{cn} = \frac{(1+\alpha)\rho_o \ + \ \alpha\,(w_c - w_s)}{(1+\alpha)(\rho_n + \rho_o) \ + \ \alpha T} \tag{A.9}$$

$$T_1 = \frac{1}{1+\alpha}\left[(w_c - w_s) \ - \ N_{cn} \cdot T\right] \tag{A.10}$$

$$T_2 = \frac{1}{1+\alpha}\left[(w_c - w_s) \ + \ \alpha \cdot N_{cn} \cdot T\right] \tag{A.11}$$

The following comparative statics for N_{cn} - the number of individuals living in inner suburbs and working in the city - are in line with expectations:

1. N_{cn} falls with ρ_n i.e. as the supply of inner suburb housing becomes more inelastic.
2. N_{cn} rises with ρ_o i.e. as the supply of outer suburban housing becomes more inelastic.
3. N_{cn} rises with $(w_c - w_s)$, the wage gap, as city occupations pay a larger premium.
4. N_{cn} falls with T, the variation in distaste for commuting.
5. N_{cn} rises with α, the additional commute from outer suburbs to the city.

The comparative statics for $N_o = N_{co} + N_{so}$, the total number of people living in outer suburbs irrespective of where they work, are the opposite of the above. The solutions for N_{co} and N_{so} - the two components of N_o - are as follows.

$$N_{co} = \left[\frac{(w_c - w_s)(\rho_n + \rho_o)/T - \rho_o}{(1+\alpha)(\rho_n + \rho_o) \ + \ \alpha\, T}\right] \ - \ \frac{T_l}{T} \tag{A.12}$$

$$N_{so} = \frac{T_u}{T} \ - \ \left[\frac{(w_c - w_s)[(\rho_n + \rho_o)/T \ + \ \alpha] \ + \ \alpha\rho_o]}{(1+\alpha)\ (\rho_n + \rho_o) \ + \ \alpha\, T}\right] \tag{A.13}$$

While N_{co} rises with the wage gap $(w_c - w_s)$, N_{so} falls. It can also be shown that N_{co} falls as the additional commute from outer suburbs α increases, while N_{so} rises. Intuitively, N_{so} and N_{co} rise with ρ_n and fall with ρ_o.[6] The total number of individuals working in the city is $N_c = N_{cn} + N_{co} = 1 - N_{so}$. Thus N_c will have the opposite comparative statics to N_{so}.

[6]These populations will fall with ρ_o as long as $(w_c - w_s) < T + (1+\alpha)\rho_n$, i.e. as long as the wage gap is not too large. This same requirement must also hold for there to be a positive number of people living in outer suburbs.

We can also solve for the parameter values that ensure $r_n > r_o$, the requirement for this particular equilibrium to hold:

$$\frac{\rho_n}{\rho_o} > \frac{T}{(w_c - w_s)} - 1 \tag{A.14}$$

The equilibrium thus requires the elasticity of inner suburb housing supply to be relatively low, and it must decrease as the wage gap increases. In the case where ρ_o equals zero i.e. the supply of housing in outer suburbs is perfectly elastic, the condition collapses to $w_c - w_s > 0$. In the case where ρ_n is infinite, and thus the supply of inner suburb housing is fixed at some level N_n^*, the required condition is $N_n^* < (w_c - w_s)/T$.

A.1 Model extension - worker productivity differences

Let us now assume that there are two types of workers in the economy, with high and low ability (productivity). To begin, we will assume that both types have exactly the same distribution of the distaste for commuting parameter t_i. If we assume that the high ability types are equally more productive than low ability types in city and suburban jobs, we have $w_c^h - w_s^h = w_c^l - w_s^l > 0$ where $w_c^h > w_c^l$ and $w_s^h > w_s^l$. In this specific case, the points of indifference between adjacent decisions in equations (A.5) and (A.7) are the same for high and low ability types ($T_1^h = T_1^l$ and $T_2^h = T_2^l$). Thus adding worker productivity heterogeneity to the model in this specific manner will not change the model predictions in any interesting way.

A more interesting case is where there is complementarity between ability and working in city occupations i.e. high ability types are relatively more productive in city versus suburban jobs. The city versus suburban occupation wage premium may be larger for high ability workers relative to low ability workers ($w_c^h - w_s^h > w_c^l - w_s^l$ and again $w_c^h > w_c^l$ and $w_s^h \geq w_s^l$). In this case, $T_1^h = T_1^l$ but $T_2^h > T_2^l$ (rents are the same for low and high ability workers living in the same suburb). High ability workers are more likely to choose to work in city occupations and live in inner suburbs (can afford the higher rents) than low ability workers. However, high ability workers are no more likely to work in city occupations and live in outer suburbs than low ability workers, as the relevant tradeoff (binding equation (A.5)) is based on rent differences only, not on city-suburb wage premia. Overall, high ability workers are more likely to work in city occupations, and low ability workers are more likely to live in outer suburbs, irrespective of where they work.

If there is complementarity between ability and working in city occupations as defined above, the higher average earnings of city workers may in part reflect higher ability, as these types are more likely to choose to work in city occupations. If females have the highest distaste for commuting, only high ability females will choose to work in city occupations. A mixture of high and low ability males may choose to work in city occupations. The observed mean wage difference between city and suburban occupations among females is thus likely to be larger than that for males. This is precisely what we observe in the empirical analysis, with a larger estimated effect of average occupation commuting time on female wages than male wages.

A further potential extension to the model would be to allow for a correlation between individual ability and distaste for commuting. There is no inherent reason to suspect that such a correlation exists, but some may think that females (with potentially higher distaste for commuting) may be less productive than males in potentially competitive city occupations. Let us assume that high ability types do have lower distaste for commuting. Even without complementarity between ability and city occupations, high ability types would then be more likely to work in city occupations.

B Data construction

The US Census 2000 sample employed in estimation was constructed as follows.

1. The sample was limited to non-military employees (no self employed or employers) with positive usual hours, aged 16 to 64, working within the US (excluding Puerto Rico), and not enrolled in education since February 1, 2000. Individuals with any of the following characteristics allocated by the Census Bureau were also excluded: wage and salary income, hours of work, weeks of work, occupation, commuting time or employment status.

2. Hourly wage rates were constructed by dividing wage and salary income from 1999 by weeks worked in 1999 and usual weekly work hours. Individuals with constructed hourly wage rates above $200 or below $1 were excluded.

3. Potential work experience was constructed by subtracting a generated years of schooling variable from age minus 5. This generated years of schooling variable was constructed from reports of highest education level attained. For individuals attaining post-school levels, years were allocated as follows: (1) some college, but less than 1 year = 13, (2) one or more years of college, no degree = 14, (3) associate degree = 15, (4) bachelor's degree = 16, (5) master's degree = 17, (6) professional degree = 18, and (7) doctorate degree

= 20. Mid-points were allocated for grade ranges, and for those who attended grade 12 but did not receive a degree were allocated 11.5. For those with less than 9 years of schooling, potential work experience was calculated as age minus 15. The small number of individuals with a calculated negative potential experience were excluded.

4. Part-time workers were indicated by usual weekly work hours of less than 35.

The occupation characteristics constructed using information from O*NET (version 15.0) were constructed as follows.

1. Job zones were in some instances provided for occupations at a more detailed level than those identified in the Census. In those instances, the Census occupation group was allocated the highest zone among the individual occupations in O*NET within that group.

2. Hazards is the simple average of the context (CX) measures (ranging from 1 to 5) for the following exposures in work contexts: contaminants; radiation; disease or infections; high places; hazardous conditions; hazardous equipment; and minor burns, cuts, bites or stings.

3. Strength required is the simple average of the importance (IM) measures (range 1 to 5) for: static strength, explosive strength, dynamic strength and trunk strength.

4. Poor environment is the simple average of the context (CX) measures (range 1 to 5) for the following work contexts: sounds, noise levels are distracting or uncomfortable; very hot or cold temperatures, extremely bright or inadequate light; cramped work space or awkward positions; and exposed to whole body vibration.

5. The other occupation level characteristics were also measured using the importance (IM) variable. The full titles of these work activities are:

    (a) Computers - Interacting With Computers

    (b) Caring - Assisting and Caring for Others

    (c) Advising - Provide Consultation and Advice to Others

    (d) Teaching - Training and Teaching Others

    (e) Work with public - Performing for or Working Directly with the Public

    (f) Relationships - Establishing and Maintaining Interpersonal Relationships

The number of fatal injuries by occupation over the period 2003 to 2010 were taken from the BLS's Census of Fatal Occupational Injuries (CFOI). These numbers were transformed into the annual number of fatalities per million work hours within each occupation using information on hours worked from the 2000 US Census micro-data. Usual weekly work hours of employees were multiplied by 52 weeks and summed using Census person weights to construct annual work hours by occupation.

The US SIPP 2004 sample employed in estimation was constructed using the same criteria as outlined for the US Census above, with the following differences.

1. Hourly wages were constructed by using the actual report of the hourly wage rate if one was reported. If no hourly wage rate was reported, or the rate reported was top-coded at $28, then the hourly wage rate was calculated by dividing monthly wage and salary earnings by (usual weekly hours times 365/(12*7)).

2. The SIPP micro-data provides information on up to two jobs held by individuals each wave. Information was employed only for a job that was held at the time of interview. If both reported jobs were held at the time of interview, information from the job with the highest reported weekly hours of work was employed.

3. In around 4% of cases, individuals reported that their weekly hours of work varied, rather than reporting a figure for usual weekly hours. These individuals were controlled for in the estimates using an indicator.

4. There are no PUMA details provided in the SIPP. To control for residence, individual state indicators and these state indicators interacted with an indicator of city residence were included.

5. To control for differences in the time period when individual surveys took place, separate indicators for month times year of interview were included.

Table A1: **Occupations with the shortest and longest commutes**

Occupation	**time**
Ten shortest commutes	
Clergy	12.34
Farm, ranch, & other agricultural managers	16.44
Religious workers, other	17.18
Funeral Directors	17.23
Directors, religious activities & education	17.29
Animal trainers	17.36
Funeral service workers	19.32
Bartenders	19.64
Barbers	19.66
Preschool & kindergarten teachers	19.74
Ten longest commutes	
Financial examiners	45.72
Hoist & winch operators	46.32
Rail-track laying & maintenance equipment operators	46.34
Elevator installers & repairers	46.84
Transportation attendants	47.23
Miscellaneous extraction workers	47.91
Sailors & marine oilers	55.87
Ship & boat captains and operators	59.17
Aircraft pilots & flight engineers	64.03
Derrick, rotary drill, service unit operators, roustabouts - oil, gas, & mining	75.87

Notes: 2000 US Census, commutes based on male employees only.

Table A2: **SIPP Wage Regressions - Females**

	Pooled		Fixed Effects	
	coeff.	t-stat	coeff.	t-stat
Less than 1st grade	-0.282	-2.53	-0.064	-0.95
1st to 4th grade	-0.189	-3.82	-0.050	-1.49
5th or 6th grade	-0.175	-6.20	0.020	1.19
7th or 8th grade	-0.174	-5.99	-0.022	-0.78
9th grade	-0.094	-3.34	0.037	1.29
10th grade	-0.117	-4.38	0.011	0.59
11th grade	-0.103	-6.07	-0.057	-3.33
12th grade, no diploma	-0.063	-2.76	0.011	0.36
Some college, no degree	0.056	6.33	0.001	0.06
Certificate / diploma	0.022	1.84	0.006	0.28
Associate degree	0.160	8.55	0.043	1.60
Bachelor's degree	0.298	16.41	0.064	2.40
Master's degree	0.462	19.90	0.073	1.98
Professional degree	0.571	12.15	0.073	0.84
Doctorate degree	0.595	12.03	0.114	1.44
Potential experience	0.042	6.58		
PE^2 / 10	-0.019	-3.93	0.009	3.65
PE^3 / 1,000	0.040	2.66	-0.039	-3.76
PE^4 / 100,000	-0.033	-2.02	0.041	3.24
Part-time	-0.093	-5.33	0.033	6.07
Hours vary	-0.130	-8.51	0.002	0.48
Married	0.031	4.89	0.010	1.51
Black	-0.041	-3.79		
Asian	-0.072	-3.92		
Hispanic	-0.104	-8.37		
Non-profit employee	-0.008	-0.44	0.011	0.94
Federal govt. employee	0.207	8.71	0.077	2.72
State govt. employee	-0.001	-0.05	0.042	2.16
Local govt. employee	0.031	1.60	0.012	0.67

Table A2 (cont.): **SIPP Wage Regressions - Females**

	Pooled		Fixed Effects	
	coeff.	t-stat	coeff.	t-stat
Proportion female	-0.054	-0.69	0.035	1.32
Prop. Part-Time (male)	-0.432	-2.19	-0.603	-8.88
Mean hours FT (male)	0.013	2.38	0.002	1.00
Mean commute (male)	0.018	6.64	0.004	2.85
Job zone 2	0.084	1.43	0.068	4.76
Job zone 3	0.107	1.91	0.082	5.10
Job zone 4	0.225	3.92	0.098	5.29
Job zone 5	0.294	4.07	0.103	4.93
Hazzards	0.177	3.51	0.048	2.91
Strength required	-0.106	-2.18	-0.085	-6.45
Environmental bads	-0.007	-0.15	0.025	1.53
Fatal injuries (mill. hrs)	-0.011	-0.05	-0.138	-1.05
Computers	0.037	1.51	-0.017	-2.77
Caring	0.037	1.62	0.010	1.20
Advising	0.041	1.59	0.017	1.73
Teaching	-0.031	-1.53	-0.012	-1.39
Public	0.005	0.35	-0.001	-0.27
Relationships	0.024	0.72	-0.005	-0.42
Industry (20)	Yes		Yes	
State (51)	Yes		Yes	
City times state (47)	Yes		Yes	
Month of survey (48)	Yes		Yes	
Observations	146,019		146,019	
Individuals			24,463	
R-squared within			0.0737	
R-squared between			0.2840	
R-squared TOTAL	0.4956		0.2523	

Notes: The pooled regression t-statistics allow for clustering at the occupation level. The fixed effects t-statistics are based on White robust standard errors.

Table A3: **SIPP Wage Regressions - Males**

	Pooled		Fixed Effects	
	coeff.	t-stat	coeff.	t-stat
Less than 1st grade	-0.311	-4.44	0.141	2.67
1st to 4th grade	-0.212	-8.01	0.020	0.59
5th or 6th grade	-0.173	-7.53	-0.017	-0.45
7th or 8th grade	-0.151	-7.11	0.007	0.34
9th grade	-0.142	-5.81	0.019	0.58
10th grade	-0.069	-4.44	-0.002	-0.08
11th grade	-0.048	-2.86	-0.014	-0.84
12th grade, no diploma	-0.086	-4.08	-0.081	-3.75
Some college, no degree	0.091	7.93	0.029	2.16
Certificate / diploma	0.069	5.15	0.043	1.51
Associate degree	0.139	10.06	0.040	1.51
Bachelor's degree	0.274	15.45	0.049	1.66
Master's degree	0.397	16.78	0.140	3.15
Professional degree	0.554	13.00	0.067	0.74
Doctorate degree	0.526	15.29	0.195	1.76
Potential experience	0.038	6.67		
PE^2 / 10	-0.010	-1.98	0.013	5.47
PE^3 / 1,000	0.006	0.35	-0.066	-6.01
PE^4 / 100,000	0.003	0.15	0.080	5.51
Part-time	-0.170	-10.75	0.021	2.30
Hours vary	-0.089	-8.22	-0.018	-3.23
Married	0.110	16.48	0.013	1.68
Black	-0.111	-9.68		
Asian	-0.087	-5.16		
Hispanic	-0.156	-12.83		
Non-profit employee	-0.100	-3.15	-0.039	-1.64
Federal govt. employee	0.201	8.68	0.037	0.98
State govt. employee	-0.047	-2.27	0.021	0.67
Local govt. employee	-0.011	-0.53	0.029	1.21

Table A3 (cont.): **SIPP Wage Regressions - Males**

	Pooled		Fixed Effects	
	coeff.	t-stat	coeff.	t-stat
Proportion female	-0.124	-1.94	-0.003	-0.11
Prop. Part-Time (male)	-0.685	-4.16	-0.628	-6.31
Mean hours FT (male)	0.011	2.71	0.000	-0.12
Mean commute (male)	0.012	5.52	0.003	3.26
Job zone 2	0.017	0.76	0.020	1.44
Job zone 3	0.067	2.65	0.038	2.46
Job zone 4	0.131	3.81	0.049	2.33
Job zone 5	0.191	3.86	0.075	3.12
Hazzards	0.072	2.84	0.022	1.47
Strength required	-0.075	-2.57	-0.048	-3.43
Environmental bads	-0.040	-1.69	-0.017	-1.19
Fatal injuries (mill. hrs)	-0.146	-1.35	0.009	0.15
Computers	0.019	1.59	-0.003	-0.55
Caring	0.013	0.62	-0.001	-0.11
Advising	0.054	2.58	-0.001	-0.08
Teaching	-0.025	-1.10	0.012	1.15
Public	-0.013	-1.25	-0.014	-2.56
Relationships	0.049	1.90	0.007	0.58
Industry (20)	Yes		Yes	
State (51)	Yes		Yes	
City times state (47)	Yes		Yes	
Month of survey (48)	Yes		Yes	
Observations	146,398		146,398	
Individuals			24,244	
R-squared within			0.0588	
R-squared between			0.2106	
R-squared TOTAL	0.4925		0.1924	

Notes: The pooled regression t-statistics allow for clustering at the occupation level. The fixed effects t-statistics are based on White robust standard errors.

Table A4: **Occupation flexibility summary statistics**

	Females		Males	
	mean	st. dev.	mean	st. dev.
FT hours variation (male)	0.170	0.022	0.170	0.024
Commute variation (male)	0.887	0.083	0.899	0.088
Concentration in leaving time (male)	0.251	0.069	0.253	0.056
Observations	470		470	

Notes: Sources: US Census 2000. Means were constructed using the US Census provided individual person weights.

Table A5: **Extended occupation level regressions - occupation flexibility measures**

	Females		Males	
	coeff.	t-stat	coeff.	t-stat
Proportion female (PF)	-0.193	-5.11	-0.101	-2.96
Proportion Part-Time (male)	-0.041	-0.36	-0.453	-3.04
Mean hours FT (male)	0.024	5.39	0.018	4.46
Mean commute (male)	0.013	6.93	0.008	5.67
Job zone 2	0.016	0.57	0.014	0.49
Job zone 3	0.051	1.68	0.055	1.81
Job zone 4	0.107	3.15	0.127	3.68
Job zone 5	0.139	3.74	0.153	4.11
Hazards	0.086	3.91	0.049	2.38
Strength required	-0.008	-0.34	-0.034	-1.71
Poor work environment	-0.066	-2.77	-0.025	-1.28
Fatal injuries (per mill. hours)	-0.109	-1.11	-0.114	-1.48
Computers	0.046	4.48	0.019	2.05
Caring	0.064	4.75	0.020	1.61
Advising	0.025	1.61	0.030	1.93
Teaching	-0.040	-2.85	-0.002	-0.15
Work with public	0.018	2.22	0.021	2.72
Relationships	0.006	0.32	0.010	0.57
FT hours variation (male)	-0.731	-1.92	-0.421	-1.01
Commute variation (male)	-0.306	-3.85	-0.373	-4.81
Concentration in leaving time (male)	0.622	5.66	0.110	1.08
Observations	470		470	
R-squared	0.7256		0.6824	

Notes: First step estimates of sampling variation of occupation indicator coefficients used as weights.