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Commuting Patterns, the Spatial Distribution of Jobs and the Gender Pay Gap in the U.S.

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Abstract

This paper studies to what extent gender differences in commuting patterns explain the observed disparities between husband and wife in relation to earnings and wages. It is argued that the cost of commuting is higher for women because they bear a disproportionate share of housework and child-rearing responsibilities. Therefore, female workers tend to work relatively close to home. A ‘*job location wage gap*’ emerges because jobs located away from the central business district offer lower wages. Using pooled data from the American Community Survey, the results indicate that 10% of the gender pay gap among childless workers and more than 23% of the wage decline attributed to being a mother (“child pay penalty”) are explained by sex differences in commuting patterns. A conditional Oaxaca-Blinder decomposition indicates that short commutes are strongly associated with working in low-paying occupations and industries.

JEL codes: J31, R41, J61, R23

Keywords: Gender pay gap, job location, wages, commute time, wage gradient

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1 Introduction

It is well documented that the labor market outcomes of men and women have been steadily converging since the Late 1970s. However, the narrowing of the gender pay gap has significantly slowed down in the last decades, to the extent that there has been virtually no progress since 2002 (Blau and Kahn (2017), Blau and Kahn (2006), Blau and Kahn (2000)). Why do these labor outcomes fail to reach equality between genders? Can motives other than productivity differences and discrimination explain the lack of full convergence? These questions have very important policy implications and, not surprisingly, have been the object of study in recent papers. Some modern explanations focus on psychological traits associated with the sex of the worker, such as risk aversion, attitudes towards negotiation and non-cognitive skills (see Bertrand (2011) for an excellent review). Others emphasize the lack of workplace flexibility in certain occupations, which generates convexities in the pay scheme along hours worked favoring men over women (Goldin (2014)).

This paper adopts a different approach. It studies to what extent differences in commuting patterns of men and women explain the observed gender disparities in pay. The underlying rationale combines the uneven spatial distribution of jobs within urban agglomerations with a traditional household division of labor. The hypothesis is that women find commuting more costly as a result of bearing a disproportionate share of housework and child-rearing responsibilities in the family. Thus, they tend to work fewer hours and find jobs closer to home. A *job location gender wage gap* emerges because jobs located away from the city center tend to offer lower wages. The tendency of women to work relatively close to their homes is expected to be exacerbated when couples have children, potentially explaining a sizable portion of the “child pay penalty” (i.e., the gender pay gap associated with being a mother).

This paper presents a simple model of residential and job location in the context of household decision-making. It describes the choice process of couples in relation to how much and where to work, where to live and the number of children to have. The model emphasizes the division of tasks between husband and wife as households become larger. This model, in the spirit of those in the urban economics literature (White (1988), Crompton (1999) White (1999)), has the objective of guiding the empirical strategy. The regression specification used in the analysis consists of within-couple estimators. This approach is able to eliminate the main identification threats, which are the endogenously determined residential location and couple’s preferences for children. Alternative specifications that use a variety of fixed-effects

show that results are highly robust to different types of unobserved heterogeneity.

The data used in this paper contain all rounds of the American Community Survey (ACS, Ruggles et al. (2017)) from 2005 to 2016. Although the ACS has the drawback of not being longitudinal, it has the advantage of containing information about labor outcomes and commute variables, which are rarely jointly observed in other datasets. Additionally, the large sample size implies that results can be precisely estimated from a statistical perspective.

Results indicate that gender differences in commuting patterns can explain a sizable portion of the gender pay gap, particularly that associated with being a mother. Among couples without children, ten percent of the wage difference between husband and wife can be explained by commute variables (minutes traveling from home to work and departure time of the day), presumably measuring pay differentials in relation to job locations. Remarkably, above twenty-three percent of the “child wage penalty” can be attributed to this phenomenon. Gender differences in annual earnings, which enclose labor supply decisions, can also be significantly explained by commute variables.

Recent papers in the literature indicate that the gender pay gap is largely explained by the uneven distribution of men and women across industries and occupations (Blau and Kahn (2017)). The different commuting patterns between husband and wife may partially explain such finding to the extent that occupations and industries are not uniformly distributed within urban agglomerations (see Alonso et al. (1964)). This paper modifies the Oaxaca-Blinder decomposition (Oaxaca (1973), Blinder (1973), Fortin et al. (2011)) to quantify the relationship between gender differences in commuting patterns and the gender-based occupational/industry segregation. As opposed to the standard Oaxaca-Blinder method, which decomposes the unconditional gender pay gap, the modified approach presented here decomposes the *conditional* gender pay gap, requiring an auxiliary set of regressions.

The results of the decomposition indicate that three-fifths of the gender wage gap attributed to differential commuting behaviors of men and women corresponds to within-industry/within-occupation gender pay gaps, and two-fifths corresponds to women working in relatively low-paying occupations and industries.

The results in this paper are consistent with and complement those in Card et al. (2015). They perform a decomposition to understand what portion of the gender pay gap can be attributed to within-firm wage differences and what portion to the uneven allocation of men and women to high-paying firms. Card et al. (2015) measure precisely the contribution of these components, but they do not attempt to explain why, in the first place, women tend to

work in low-paying firms. A plausible explanation, although purely speculative for their case, is the one provided here. Low-paying firms locate away from the central business district and women tend to choose them because the commuting time is relatively short.

A natural limitation resulting from the empirical strategy adopted in the current paper is that singles, divorcees and widows are necessarily excluded from the sample. Thus, the results obtained should be interpreted exclusively as representative of people living with their spouses. Other papers in this literature face the same constraint (e.g. Blau and Kahn (2017)).¹

The rest of the paper is organized as follows. Section 2 discusses related papers. Section 3 shows a simple model that guides the empirical strategy. Section 4 discusses the potential sources of endogeneity in standard regressions and shows the empirical strategy to cope with them. Section 5 presents the data and descriptive statistics. Section 6 shows the main results of the paper. Section 7 discusses sources of heterogeneity across couples and presents additional results. Section 8 describes a modified Oaxaca-Blinder method to obtain conditional decompositions and shows the results of such procedure. Finally, section 9 concludes.

2 Short literature review

This paper lies in the intersection of labor economics and urban economics. Within the first of these fields, it joins the group of papers that have the objective of understanding the sources of gender disparities in pay, focusing on the intra-household division of tasks as the driving force.

One of the first studies on this topic is Becker (1981). This piece of research claims that men tend to specialize in the market sector, while women do it in housework and child-rearing activities, in part due to biological differences that give the latter a comparative advantage in these tasks. For this reason, women have the incentive to invest less in human capital that is specific to market activities. Additionally, Becker argues that housework consumes a sizable share of women's energy. Therefore, female productivity and earnings tend to be relatively low, even when men and women work the same number of hours.

Evidencing how the distribution of tasks in the family affects gender differences in labor

¹Blau and Kahn (2017) indicate that their “...sample is also restricted to family heads and spouses/cohabitators because the PSID only supplies the crucial work history information for these individuals” p792. Nonetheless, these authors supplement their PSID estimates with results obtained from the nationally representative Current Population Survey, finding little discrepancies between the two samples.

market outcomes is essential from a policy perspective. Previous papers indicate that the pay penalty for being a mother appears to be the main source of gender differences in earnings. For example, Waldfogel (1998) indicates that *“as the gap in pay between women and men has been narrowing, the gap between women with children and those without children has been widening”* p137, and Goldin (2014) states that *“women without children generally have higher earnings than women with children and ... the formers earnings are almost equal to those of comparable men”* p4.

The literature on measuring the “child pay penalty” is abundant (see Kleven et al. (2018), Chung et al. (2017) and Loughran and Zissimopoulos (2009) for recent evidence and Waldfogel (1998) for an excellent overview of the topic). They all conclude that having children is associated with a significant reduction in mother’s wages, but has a negligible impact on father’s pay. However, the empirical evidence on the underlying reasons is scarce. Some explanations include unobserved work effort (Becker (1981), discrimination (Goldin (1990) and lack of access to job-protected maternity leave (Berger et al. (2005)). The current paper contributes to this literature by studying commuting patterns as an alternative rationale for the child pay penalty.

Previous papers show that a large fraction of the gender wage gap can be “explained” (in the Oaxaca-Blinder decomposition sense) by gender differences in employment across occupations and industries (Blau and Kahn (2017)). Since industries are usually not uniformly distributed within cities (Alonso et al. (1964)), neither occupations as a result, this paper analyzes how commuting patterns relate to the gender occupational/industry segregation.

Closely related, recent papers analyze sex differences in pay in light of firm characteristics. For example, Card et al. (2015) quantify to what extent the allocation of female workers to low-paying firms explains the gender wage gap. Using Portuguese data, the authors find that such component accounts for ten percent. Card et al. (2015) provide novel and interesting insights, but they do not explain why, in the first place, women are matched to low-paying firms. A plausible explanation, although purely speculative for their case, is given here. Women prefer commuting shorter distances and, in accordance with urban economics literature, firms located away from the central business district pay less.

The current paper makes assumptions about the geographical distribution of wages and home prices that are based on urban economics papers. The first of these assumptions is that, in cities with decentralized employment (i.e., where jobs are not exclusively located at the central business district), wages should fall when firms sub-urbanize. A theorized

arguments for this pattern is that workers are willing to accept lower wages in exchange for shorter commutes (White (1999)). The empirical evidence is robust in this regard (Eberts (1981), Ihlanfeldt (1992), McMillen and Singell Jr (1992), White (1999)). The compensating differential argument of job proximity is directly measured in Mulalic et al. (2014) by exploiting firm reallocations. They find that wages increased 0.15% for each additional kilometer in commuting distance.

The second assumption taken from the urban economics literature, although non-essential for the empirical analysis, is that home prices fall with distance from the CBD (Muth (1969), Madden (1980)), and they do it at slower rate than wages.

The hypothesis in this paper is closely related to that in Madden and Chiu (1990). They study how gender differences in commuting patterns affect the gender wage gap. Contrary to the results shown below, they find no significant effect. Additionally, this paper relates to the literature that studies the differential commuting patterns of men and women (e.g., Madden (1981), Crampton (1999), Roberts and Taylor (2016), Tkocz and Kristensen (1994)) and the higher commuting cost that women face (Roberts et al. (2011)).

3 Model

3.1 City structure

Assume that people live in circular cities as that depicted in Figure 1. The most expensive houses/apartments and the jobs that pay the highest wages are located at the city center, also called the central business district (CBD). Both, home prices and wages decrease with distance from the CBD. However, as Assumption 1 indicates, wages decline at a faster rate.²

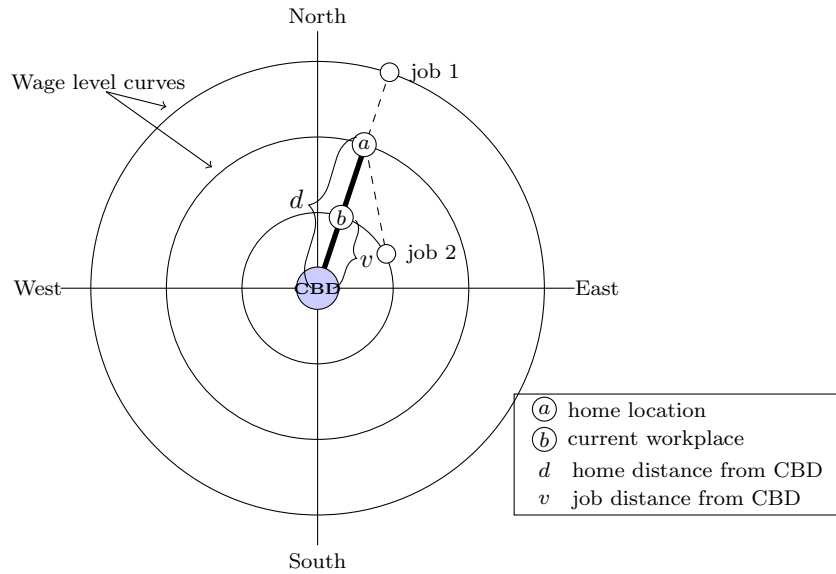
Assumption 1. *Let $p(d)$ be the price of a unit of housing located at distance d from the CBD and p'_d the price gradient (i.e., the derivative of $p(d)$). Similarly, let $w(v)$ be the wage of a job located at distance v from the CBD and w'_v the wage gradient, then*

$$\frac{w'_v}{w(v)} < \frac{p'_d}{p(d)} < 0 \quad \forall v, d$$

□

²The literature suggests several reasons for wages to decline with distance from the CBD. One of the leading explanations is that workers are willing to accept a lower pay because they commute less (see White (1999) for discussion on this topic).

Figure 1: City structure



Note: Housing prices and wages are lower in circumferences located more distantly from the CBD.

In this simple model, Assumption 1 is necessary for the existence of urban agglomerations. If the inequality sign in Assumption 1 were flipped, then any worker could simultaneously move his/her residence and job location away from the CBD in a way that the commuting time remains constant, and increase the purchasing power of his/her income as a result. Since all workers had the same incentives in such circumstances, then the urban agglomeration would disappear. This point will be apparent below.³

Commuting is costly to workers. So, if there are no frictions in the labor market, then the only relevant jobs are those located in the radius from where the worker lives to the city center (the segment from point a to the CBD in Figure 1). That is, conditional on the residential location a , a worker will never choose job 1 because his current workplace in point b requires the same commuting time and offers a higher remuneration. Similarly, this worker will never choose job 2 because his current work in point b pays the same and is located at a shorter distance from home. Proposition 1 summarizes these results.

Proposition 1. No out-commute, no circumferential commute. *In a circular city*

³As workers move their residential location away from the CBD, the housing prices they face decline at a rate $\frac{p'_d}{p(d)}$. Keeping constant the commuting cost implies finding jobs further away from the CBD, which wage offer declines at a rate $\frac{w'_v}{w(v)}$ with distance from the CBD. If wages declined at a slower rate than home prices (contrary to Assumption 1), then workers would have the incentive to move as far as possible from the city center, making the urban agglomeration unsustainable.

with no labor market frictions, any worker will hold a job located in the segment between his/her house and the city center. As a result, his/her job distance to the CBD will always be less or equal to his/her house distance to the CBD, i.e., $0 \leq v \leq d$.

Proposition 1 reduces the dimension of the location problem from six (latitude and longitude coordinates of the residence, the wife’s workplace and the husband’s workplace) to three (residence and job distances from the CBD), which is fundamental to the empirical approach since the exact residential and job locations are not observed in the data.

3.2 The maximization problem of couples

Consider a nuclear family of n members: a wife F , a husband M and $(n - 2)$ children. The utility function (1) of adult $i \in \{F, M\}$ depends on housing h , leisure l_i and the number of own children in the household. Other goods such as food and clothing are ignored for simplicity.

$$U^i = U^i \left(\frac{h}{n^\lambda}, l_i \right) + K^i(n - 2) \quad , i \in \{F, M\} \quad (1)$$

Notice that individual housing consumption h/n^λ consists of total home quantity h adjusted by household size. The parameter λ indicates that housing is a partial public good within the family. The polar cases are $\lambda = 0$ (pure public good) and $\lambda = 1$ (pure private good).⁴ The function $K^i(n - 2)$ in (1) is the utility that parent i derives from having children. Decisions regarding the ‘quality’ of children are non-essential and hence, ignored.⁵

Equalities (2) and (3) are time constraints. They indicate that the leisure time of each adult household member l_i is identical to the total endowment of time T minus the hours worked L_i , minus the time spent in traffic. This last quantity is defined as the absolute difference $|d - v_i|$ between the residential location d and the job location v_i multiplied by two since this distance is traveled twice daily. Then, the resulting quantity is divided by the average speed s to convert geographical distances into time equivalents (see Figure 1). The speed is assumed to be given by the infrastructure of the city, speed limits and level of congestion. The empirical section discusses these elements.

Constraints (2) and (3) describe the case for which both couple’s members participate in the labor market. The next section makes evident that this is the relevant case for the

⁴See Deaton and Paxson (1998) for modeling economies of scale in the household in this way.

⁵Becker and Lewis (1973) and Willis (1973) model fertility decisions assuming that parents derive utility from both the quantity and the ‘quality’ of children (healthy, educated, etc.).

empirical model.⁶

Couples are assumed to have a traditional household division of labor. For the sake of simplicity, this assumption is taken to an extreme case where only women spend time on certain tasks. In the wife's time constraint (2), R is a fixed amount of time spent on housework activities. Additionally, when a couple has children, it is assumed that only the mother uses part of her time to take care of them, which is indicated with the function $g(\cdot)$. The minimal properties of this time caring function are: i) $g(n - 2) > 0$ if $n > 2$ and ii) $g(n - 2) = 0$ otherwise. That is, childless women have more available time than mothers. The gradient of $g(n - 2)$ will be empirically revealed in other sections.

$$l_F = T - L_F - \frac{2|d - v_F|}{s} - R - g(n - 2) \quad (2)$$

$$l_M = T - L_M - \frac{2|d - v_M|}{s} \quad (3)$$

The sexual division of labor described in equations (2) and (3) is the only difference stressed in the model between a wife and her husband. The full specialization of women in non-market work certainly constitutes a polar case.⁷ However, the relevant conclusions needed for the empirical strategy remain qualitatively unchanged when men also spend time on housework and child-rearing activities, albeit they have to do it less frequently than women. Empirical evidence showing that women devote more time than men in non-market productive activities has been previously documented in the literature.

The budget constraint (4) indicates that family labor income $w(v_F)L_F + w(v_M)L_M$ and non-labor income y is spent entirely on housing. The direct cost of children, that includes food, clothing and education, is ignored as well as the expenditure on adult goods. Then, the cost of having children is the opportunity cost of the mother's time and the "need" for extra rooms in the house.

$$p(d)h = w(v_F)L_F + w(v_M)L_M + y \quad (4)$$

The household behaves in accordance with a collective model, maximizing a weighted sum

⁶The time constraint that considers the possibility of not working is

$$l_F = T - L_F - \mathbb{1}(L_F > 0) \frac{2|d - v_F|}{s} - R - g(n - 2)$$

where $\mathbb{1}(L_F > 0)$ is the indicator function that takes the value one if the argument is true and zero otherwise.

⁷The specialization of women in the care of children is theoretically modeled in Becker (1981).

of decision maker's utilities $\beta U^F + (1 - \beta)U^M$. As is common in the literature (Browning et al. (2014)), children are modeled as public goods for parents. For simplicity, let $\beta = 1/2$ and the utilities of the wife and the husband be identical to each other. Then, the household problem consists of maximizing (5), which results from replacing time constraints (2) and (3) in the corresponding utilities (1), subject to the budget constraint (4).

$$\begin{aligned} \max \frac{1}{2}U \left(\frac{h}{n^\lambda}, T - L_F - \frac{2|d - v_F|}{s} - g(n - 2) - R \right) + \dots \\ \dots \frac{1}{2}U \left(\frac{h}{n^\lambda}, T - L_M - \frac{2|d - v_M|}{s} \right) + K(n - 2) \end{aligned} \quad (5)$$

The couple determines its residential location, the hours each of its members will work, the location of their jobs (in an interior solution) and the number of children they want to have. For a given household size, the necessary first order conditions in relation to h , L_F and L_M are as follows.

$$- (U_h^{iF} + U_h^{iM}) \frac{h}{n^\lambda} \frac{p'_d}{p(d)} - \frac{2}{s} (U_l^{iF} + U_l^{iM}) = 0 \quad (6)$$

$$U_h^{iF} \frac{h}{n^\lambda} \left(\frac{w(v_F)L_F}{w(v_F)L_F + w(v_M)L_M} \right) \frac{1}{L_F} - U_l^{iF} = 0 \quad (7)$$

$$U_h^{iM} \frac{h}{n^\lambda} \left(\frac{w(v_M)L_M}{w(v_F)L_F + w(v_M)L_M} \right) \frac{1}{L_M} - U_l^{iM} = 0 \quad (8)$$

The first term in condition (6) is the benefit of moving the residence location to a greater distance from the CBD. If housing is not a pure public good ($\lambda > 0$), then larger families will usually benefit more from living farther away. Although this conclusion depends on the shape of the utility function, it will hold in the reasonable case when housing and leisure are gross complements.⁸ The cost of living at a greater distance (second term of condition (6)) is the loss of leisure time due to longer commutes. In the case represented here when both couple's members work, it will decrease the utility of the husband and the wife.

Equations (7) and (8) determine the allocation of hour worked. The first of these conditions balances the wife's benefits and the costs of working an extra hour conditional on participating in the labor force. The second of these equations does the appropriate for the husband. The ratio of conditions (7) and (8) results in the following equality.

$$\frac{U_h^{iF}}{U_h^{iM}} \frac{w(v_F)}{w(v_M)} = \frac{U_l^{iF}}{U_l^{iM}} \quad (9)$$

⁸See Deaton and Paxson (1998).

Equation (9) indicates that, *Ceteris Paribus*, the extra responsibilities that the wife has at home increase her marginal utility of leisure and consequently reduces her labor supply to make such condition balance. Additionally, when couples have children, part of the mother's time is devoted to child-rearing, which increases her marginal utility of leisure further (right-hand side of equality (9)) generating an extra reduction in her relative labor supply. These conclusions are summarized in Proposition 2.⁹

Proposition 2. *In couples with a traditional household division of labor, the optimization of time allocation implies that women work fewer hours than men even among childless couples. Additionally, the labor supply gap between a husband and his wife becomes wider in larger families.*

The first order conditions in relation to the job location of the wife v_F and the job location of the husband v_M are as follows.

$$(U_h'^F + U_h'^M) \frac{h}{n^\lambda} \left(\frac{w(v_F)L_F}{w(v_F)L_F + w(v_M)L_M} \right) \frac{w'(v_F)}{w(v_F)} + \frac{2}{s} U_l'^F \begin{cases} < 0 & \text{if } v_F = 0, \\ = 0 & \text{if } 0 < v_F < d, \\ > 0 & \text{if } v_F = d. \end{cases} \quad (10)$$

$$(U_h'^F + U_h'^M) \frac{h}{n^\lambda} \left(\frac{w(v_M)L_M}{w(v_F)L_F + w(v_M)L_M} \right) \frac{w'(v_M)}{w(v_M)} + \frac{2}{s} U_l'^M \begin{cases} < 0 & \text{if } v_M = 0, \\ = 0 & \text{if } 0 < v_M < d, \\ > 0 & \text{if } v_M = d. \end{cases} \quad (11)$$

Proposition 1 indicates that the location of the wife's and the husband's jobs, measured as distance from the CBD v_F and v_M , are bounded from above and from below. Then, conditions (10) and (11) do not necessarily hold with equality. Moreover, the result of the optimization process implies that the left-hand sides (10) and (11) cannot be simultaneously equal to zero. If this was the case, their summation would be:

$$- (U_h'^F + U_h'^M) \frac{h}{n^\lambda} \frac{\bar{w}'_v}{\bar{w}(v)} - \frac{2}{s} (U_l'^F + U_l'^M) = 0 \quad (12)$$

where $\frac{\bar{w}'_v}{\bar{w}(v)} \equiv \left(\frac{w(v_F)L_F}{w(v_F)L_F + w(v_M)L_M} \right) \frac{w'(v_F)}{w(v_F)} + \left(\frac{w(v_M)L_M}{w(v_F)L_F + w(v_M)L_M} \right) \frac{w'(v_M)}{w(v_M)}$ is the within-couple weighted average of the rate at which wages decline with distance to the CBD. In the case where female and male wages decline at the same rate, then $\bar{w}'_v/\bar{w}(v) = w'_v/w(v)$. Equalities (12)

⁹In the case that working is too costly to the wife, she leaves the labor force (condition (7) holds with inequality). Since at least one member has to generate income in the couple, the husband always work.

and (6) implies that $w'(v)/w(v) = p'(d)/p(d)$. However, this statement violates Assumption 1.

The solution to the maximization problem is the husband working at the CBD (the left-hand side of condition (11) is negative) since he is the couple's member specialized in market activities. On the other hand, the extra responsibilities that the wife has at home reduce her marginal utility of leisure, which increases the incentives to find a job closer to home (U_l^F in condition (10)). Additionally, when the couple has children, the time spent by the mother taking care of them results in an additional increase in the marginal utility of leisure, making condition (10) more likely to hold with equality or to reverse the sign of the inequality. That is, the mother becomes more likely to commute less ($0 < v_F < d$) or not commute at all ($v_F = d$).

Proposition 3. *The commuting time gap between the husband and the wife is non-negative and becomes wider in relatively large families.*

4 Empirical strategy

The city structure presented in section 3 indicates that the wage rate per unit of human capital decreases with distance from the CBD. For exposition purposes, let the functional form of this relationship be exponential.

$$w = w_0 e^{-\phi v} \quad (13)$$

where w_0 is the wage level at the CBD and ϕ is the percentage wage decline for each additional distance unit away from the city center.

At each distance v , wages vary in relation to the characteristics of the worker. Then, taking the log of expression (13) and including additional variables result in regression (14).

$$\ln(w_{ik}) = \beta_0 + \beta_1 fem_{ik} + \beta_2 children_k + \beta_3 fem_{ik} \times children_k + X_{ik} \underbrace{\Gamma - \phi v_{ik} + \mu_k + \epsilon_{ik}}_{unobserved} \quad (14)$$

The dependent variable is the (log) wage of individual i in household k . The added variables on the right-hand side are: a gender indicator (fem_{ik}) that takes the value one if the worker is a woman and zero otherwise, the number of children living in the household ($children_k$) and human capital proxies (X_{ik} includes polynomials of age and years of education). The coefficient β_1 measures the gender wage gap for reasons other than job location,

including unobserved productivity differences and discrimination. The wage ‘penalty’ associated with having an extra child is β_2 for men and $\beta_2 + \beta_3$ for women. The unobservables other than the job location v_{ik} in the regression are disaggregated into those that vary across couples (μ_k) and those that are idiosyncratic to the individual (ϵ_{ik}).

Standard wage equations ignore the job location v_{ik} , in part because this variable is rarely observed. The location of jobs is expected to be correlated with both the *female* indicator and the number of children. This is one of the conclusions from the model presented in section 3, which suggests that women, especially those with children are likely to work relatively close to their home.

In addition to the omission of the job location, another problem with regression (14) is that the number of children is endogenously determined by a bargaining process within couples, resulting in a family-specific unobserved component μ_k . The bargaining process is likely to affect not just the number of children, but labor market outcomes as well.¹⁰

The proposed solution to these two problems is as follows. The job location v_{ik} is not observed in the data. However, the ACS survey contains information about the commute time of each person in the household. The time constraints (2) and (3) in the previous section indicates that the time spent in traffic, now denoted com_{ik} , is the differences between residential location and job location adjusted by the average speed, i.e. $com_{ik} = \frac{2}{s}(d_k - v_{ik})$. Then, adding and subtracting ϕd_k on the right-hand side of regression (14) gives the following expression.

$$\begin{aligned} \ln(w_{ik}) = & \beta_0 + \beta_1 fem_{ik} + \beta_2 children_k + \beta_3 fem_{ik} \times children_k + \dots \\ & \dots + X_{ik}\Gamma + \underbrace{\beta_4}_{\phi s/2} com_{ik} - \underbrace{\phi d_k + \mu_k + \epsilon_{ik}}_{unobserved} \end{aligned} \quad (15)$$

This procedure solves the problem of omitting job location v_{ik} by replacing this variable with the observed commute time com_{ik} . However, it adds another equally serious problem. The error term in the regression now contains residence location d_k , which is clearly correlated with commute time and the number of children in the family accordingly to the model previously presented. However, both d_k and μ_k vary across but not within households. Then, the effect of residence location and family-specific preferences on wages can be eliminated by computing regression (15) after taking the difference between couples’ members.

¹⁰In a collective model, the component μ_k can be written as a function $\mu_k = f(\mu_{Fk}, \mu_{Mk}; \theta)$, where μ_{Fk} and μ_{Mk} are the unobserved ‘taste’ component of each couple’s member in case they lived separately, and the relative female bargaining power θ_k .

Let Δ be the operator that takes the difference between the wife and her husband in selected variables. After applying this operator on both sides of expression (15), the within-couple estimating equation becomes:

$$\Delta \ln(w_k) = \beta_1 + \beta_3 \text{children}_k + \Delta X_k \Gamma + \beta_4 \Delta \text{com}_k + \Delta \epsilon_k \quad (16)$$

Regression (16) recovers all the parameters of interests, β_1 is the gender gap for childless individuals, β_3 is the (negative of the) relative female “child penalty” and β_4 is the “job location pay gap”.¹¹ The within-couple analysis of regression (16) is numerically identical to estimating a wage equation with couple fixed-effects.

The exercise performed in section 6 consists of computing regression (16) with and without the commute time variable to understand what part of the gender gap and the child penalty is explained by this phenomenon.

5 Data and descriptive analysis

The source of information is the American Community Survey(ACS), which is carried out by the U.S. Census Bureau and publicly provided by IPUMS-USA (Ruggles et al. (2017)). The ACS is a repeated cross-sectional nationally representative survey. Its annual sample size is approximately one percent of the U.S. population. The dataset used in this paper contains twelve survey years covering the period 2005-2016.

The sub-sample used for the analysis is restricted to i) heterosexual couples, ii) in nuclear families, iii) where the children in the household, if any, are sons and daughters of both couple’s members (i.e. no households with stepdaughters, stepsons or foster children), and iv) the wife’s age in the couple ranges from 25 to 55.^{12,13} The exclusion of single, divorced, and widowed individuals is the consequence of the empirical strategy described in the previous section, which analyzes within-couple outcomes. The rest of the conditions are imposed to obtain a relatively homogeneous set of households. Relaxing them, particularly the age range of the wife and the inclusion of households with stepdaughters and stepsons, does not

¹¹As previously indicated, the female child penalty is $\beta_2 + \beta_3$. However, previous studies suggest that the child penalty for men is negligible, i.e., $\beta_2 \approx 0$, leaving β_3 as good approximation (e.g., Kleven et al. (2018)).

¹²In this age range, both members of the couple are likely to have completed their education and not retired from the labor force.

¹³The reason for analyzing only nuclear families (i.e., families consisting of the mother, the father, and their children) is because, in three-generation households, grandparents can take care of children affecting the job location decision of the mother.

change the results significantly.

Table 1 shows descriptive statistics as a function of the number of children in the household. Panel A describes commuting patterns and Panel B labor variables. Overall, men's outcomes vary relatively little with household size and in most of the cases, no clear trend can be inferred. On the other hand, women's outcomes significantly change with household size.

Column 1 Panel A shows that men with no children spend on average 27.6 minutes in traffic going to work, the same amount of time as men with four children. In contrast, women's commuting time monotonically declines with household size (column 2). As a result, the average traffic difference between husband and wife goes from 2.8 minutes for couples with no children to six minutes for couples with five children. This pattern is consistent with Proposition 3.

The gender differences in commuting time do not appear to be large. For them to be economically meaningful, i) women should be able to travel substantially less distance in order to suffer a significant wage penalty and ii) women's dis-utility from commuting few extra minutes should be important enough to justify the resulting wage loss. Although the relevance of commuting patterns in explaining the gender wage gap is ultimately an empirical question and the object of this paper, it is important to analyze in more detail how the variables are measured.

There are reasons to believe that sex differences in commute time underestimate the gender gap in travel distances. One of them is that women are more likely to commute during rush hours. Columns 5 and 6 in Panel A evidence this fact. They show the proportion of men and women traveling to work during peak hours, which is defined as an interval containing the mode of the depart time distribution (see Figure 2). Women are consistently seven to eight percentage points more likely to commute when the traffic is slower.

Related to the previous point, columns 3 and 4 show that the average time workers leave their houses to work differs by gender. Without taking this fact into account, the use of commute time as a metric for geographic distance is likely inaccurate. Men tend to leave the house earlier, at 7:45 am approximately, with no variation across households with zero to three children. Women appear to adjust more their schedule as their family grows. The average departure time ranges from 8:02 am for women with no children to 9:08 am for women with five children.

Additionally, women may also travel shorter distances per unit of time if they are respon-

sible for dropping off children at the daycare or school. Unfortunately, this statement cannot be directly empirically analyzed since the data do not include such information. However, its relevance should not be underestimated.¹⁴

Panel B presents labor outcome variables. Columns 1 to 4 show variations on the intensive margin of the labor supply. These variables are used to build hourly wages (see data appendix). Conditional on being employed, the proportion of women working 50 to 52 weeks is smaller in larger households. This pattern is not observed among men. Similarly, the hours worked per week is relatively invariant for men across households of different sizes (44 to 45 hours per week), but declining for women as the number of children increases (from 40 hours per week among childless women to 33 hours per week when she has 5 children). The observed labor supply pattern is consistent with Proposition 2.

Panel B columns 5 and 6 show the annual earnings of men and women belonging to households of different sizes. Similarly to previous outcomes, the husband to wife earnings' gap is larger in households with relatively many children.

Figure 3 shows the association between commute time and (log) hourly earnings, computed as the ratio of annual earnings to the product of weeks worked in the year and hours worked per week (see data appendix for a detailed description). For the ease of comparison, the curves are scaled to have a value of one for workers commuting in the range from zero to five minutes. The left panel indicates that men and women who commute more, earn higher hourly earnings. For example, the hourly earnings of men who spend 26 to 30 minutes in traffic going to work (i.e. the average in the sample) are six percent higher than those who commute 0 to 5 minutes. The wage gradient is steeper for women. Female workers who spend 26 to 30 minutes in traffic going to work earn eleven percent more than female workers who spend 0 to 5 minutes on traffic.

Men and women in the sample used to compute Figure 3 are couples. That is, for every woman used to compute the female commute profile, a man living in the *same residence* (i.e. her husband) is used to compute the male profile. Then, the gender patterns in the graph suggest that men and women have different behaviors in relation to commuting. A plausible explanation suggested by the model in section 3 is that the burden of being in traffic is higher for women. Then, women require a higher compensation for commuting an extra minute.¹⁵ Figure 3 right panel is consistent with this idea. The commute profile

¹⁴If relevant, the unobserved mother's responsibility of taking children to the daycare or school underestimate the importance commute variables in explaining the gender pay gap.

¹⁵Roberts et al. (2011) presents empirical evidence showing that commuting is psychologically costlier for

of women with children, for whom the marginal utility of leisure is higher, is steeper than that of women with no children. On the other hand, the commute profiles of men with and without children are indistinguishable.

6 Main results

Table 2 presents estimates of equation (16) with the only caveat that the variable *children* is included as a set of indicators.¹⁶ Column 1 in Panel A shows the wage regression excluding commute variables. This set of coefficients is used as a benchmark for comparison. It indicates that women’s wages are 22% lower than men’s wages when no child is present in the household (regression constant estimate). The gender wage gap increases two percentage points when couples have one child, 6.9 points when couples have two children and continues to increase with household size until it reaches more than 12 percentage points for couples with four and five children.

Column 2 in Panel A follows the specification in column 1, but it includes an additional regressor that measures the worker’s commute time in minutes. As predicted by the model, both the gender gap and the ‘child wage penalty’ decline. Conditioning on the workers’ travel time to work reduces the gender wage gap 5% when no child lives in the house. The ‘child wage penalty’ declines a remarkable 26% among couples with one child. In larger families, the portion of the child wage penalty explained by commute variables is smaller, but remains economically important (around ten percent).

Column 3 shows the results when *all* commute variables are included among regressors. These covariates are a polynomial of degree five in travel time from home to work and 48 dummy indicators (one of them omitted) of 30-minute intervals for departure time to work. This set of indicators is relevant since spending the same amount of time on the road at different moments of the day implies traveling unequal distances (see Panel A in Table 1).

Consistent with the model in section 3, the inclusion of commute variables in the regression reduces the measured gender wage gap, particularly that associated with being a mother. Eleven percent of wage differences between husband and wife is explained by sex disparities in commuting patterns when the couple has no children (percentage difference

women.

¹⁶For example, the variable *one child* takes the value 1 if the couple has one child living with them and zero otherwise, the variable *two children* takes the value 1 if the couple has two children and zero otherwise, and so on. The sample includes only families with at most five children. Then, the omitted category is the couples without children.

in the estimated regression constant across columns 1 and 3). The percentage of the “child wage penalty” explained by such phenomenon is 40% when one child is present, 24% when two children are present, and 21% when three or more children live in the household.

Figure 3 suggests that the wage gradient in relation to commuting time is steeper for women. Consequently, column 4 in Table 2 shows the result of including the interactions of the five polynomial terms in travel time to work with a female indicator in addition to all the regressors included in column 3.¹⁷ In this specification, the constant measures the gender wage gap among childless couples *in the hypothetical case of zero commute time*. Since the wage gradient in relation to travel time to work is allowed to be different across genders, then this value is not comparable to the those from the previous three columns. Therefore, the “adjusted” constant evaluates the gender wage gap among childless couples evaluated at the commute time sample mean, making quantities comparable across columns.

The estimates show that the adjusted constant in column 4 and the regression constant in column 3 are almost identical. The rest of the estimates in column 4 indicates that a slightly larger fraction of the “child wage penalty” is explained by commute variable in relation to those in column 3.¹⁸

Panel B in Table 2 repeats the analysis of Panel A but replacing the dependent variable with the difference in (log) annual earnings between the wife and her husband. The gender gap and the “child pay penalty” are expectedly larger in this case than in the previous one. Women adjust the location and hours worked as a result of housework and childrearing responsibilities. However, the portion explained by commute variable is lower, around twelve percent.

Are there differences across couples with different levels of education? Table 3 shows to what extent the role of commute variable in explaining the gender wage gap varies

¹⁷In this specification the effect of ϕ in equation (15) is allowed to be different for women ϕ_f and men ϕ_m . Then, the within-couple estimating equation (16) becomes:

$$\Delta \ln(w_k) = \beta_1 + \beta_3 \text{children}_k + \phi_m \Delta \text{com}_k + \underbrace{\phi_d \text{com}_{fk}}_{\text{added term}} + \Delta X_k \Gamma + \Delta \epsilon_k \quad (17)$$

where $\phi_d = \phi_f - \phi_m$ and com_{fk} is the commute time of the wife in household k . The results presented in Column 3 of Table 2 correspond to this specification with the caveat that the commuting time is included as a polynomial of degree five with the objective of adding flexibility to functional form.

¹⁸The adjusted constant is computed as $\text{cons} + \phi_d \overline{\text{com}}$ from regression (17), where $\overline{\text{com}}$ is the average commute time in the sample. Notice that when the gradient is assumed to be the same across genders, then there is no need to adjust the constant.

across couples with different levels of education. The sample is partitioned in four groups. Panel A shows the estimates of regression (16) for couples where both members have at least a college degree.¹⁹ Column 1 shows the estimates when no commute variables are included among regressors. This is the same specification as that in Table 2-column 1, but excluding year of education from the regressors since this variable is used to partition the sample. Column 2 shows the results when a polynomial in commute time and departure dummies are included among regressors (column 3 in Table 2 excluding years of education). Panels B, C, and D show analogous results as those in Panel A, but for couples of different levels of education.

The comparison of results in Panels A and B suggest that the location of jobs (proxied by commute variables) is more explicative of the gender wage gap among childless couples when both members are unskilled than among childless couples when both members have a college degree. The regression constant declines 6% from column 1 to column 2 in Panel A while 15% from column 3 to column 4 in Panel B. However, the job location accounts for a remarkably similar share of the child penalty gap. For example, it explains 25% of the child penalty among skilled couples with two children (Panel A) and 26% of the child penalty among unskilled couples with the same number of children (Panel B). Panel D analyzes couples where the husband holds a B.A. degree and the wife has a lower level of education. The results are similar to those Panels A and B.

Panel C shows results when the wife has a college degree and the husband has a lower level of education. Contrary to other cases, the regression constant is positive. Among childless couples, women earn 8% more than their spouses. Interestingly, the ‘child wage penalty’ appears to be shared equally across couples’ members when the first child arrives. The *one child* coefficient in the first row is statistically not different than zero. However, women appear to hold most of the child-rearing responsibilities in larger families. Similarly to other panels in the table, the coefficients of the children indicator variables are negative when the couple has two or more children.

¹⁹Costa and Kahn (2000) calls ‘power couples’ those in which both members are college educated.

7 Heterogeneity across couples and cities: a concern for the empirical approach?

Specification (16) is expected to eliminate the main identification threats, which are the endogenous residential location and couple-specific preferences. However, some concerns may remain in this econometric model from the fact that the data is not longitudinal. First, the sample used to compute the regressions contains couples working in cities of different sizes and average commuting time. The estimates may be biased if the size of the urban agglomeration is correlated with the number of children in the family.

Panel A in Table 4 shows the results of estimating equation (16) including commuting zone fixed effect *after* within-couple variables are calculated. The definition of commuting zones is taken from the Bureau of Economic Analysis.²⁰

A consequence of including fixed effects is that the constant is not identified anymore. Thus, the gender wage gap among couples with no children cannot be measured, only the “child pay penalty” for each family size is obtained. The results are remarkably similar to those in Table 2 indicating that omitted city characteristics are not relevant after differentiating outcomes within couples’ members.

If the data were longitudinal, the optimal empirical strategy would consist of comparing husband and wife outcomes, before and after having children. This approach is not feasible in the ACS. However, a cohort analysis provides a valuable alternative. I construct cohorts using not just the birth year, but also other time-invariant characteristics. Two couples are considered to belong to the same cohort if the husbands were born in the same year, belong to the same race group and have the same level of education; wives across couples must also share the birth year, race and education, and both couples must have gotten married in the same year. Since the data contain several survey years, then the fixed-effects estimator compares similar couples observed at different ages with different number of children (i.e., similar couples observed at different life stages).

The unobserved heterogeneity across families cannot be completely eliminated using cohort fixed-effects. However, if this were a significant problem in the original strategy proposed in section 4, then results would be considerably different in this alternative approach, but they are not. Panel B shows the results of including cohort fixed-effects *after* within-couple differences are calculated. As in the previous case, they are almost identical to those shown

²⁰Similar results are obtained when county fixed-effects are used.

in Table 2.

A corollary of Table 4 is that the remarkable similitude of results when different types of fixed-effects are included suggests that the strategy of differentiating the outcomes across couples members successfully deals with most endogeneity concerns.

8 Commuting and the distribution of workers across industries and occupations

If, as previous papers in the literature suggest, industries and occupations are not uniformly distributed within urban agglomerations, then sex differences in commuting patterns may explain part of the uneven allocation of male and female workers across these dimensions (i.e., commuting differences across genders may explain a portion of the gender occupational/industry segregation). This section proposes a simple modification of the Oaxaca-Blinder decomposition to empirically measure this conjecture. Contrary to the original technique that partitions the total *unconditional* gender pay gap into components associated with its determinants, the method in this section performs a *conditional* decomposition of the gender pay gap. In doing so, it measures the extent to which sex differences in commuting patterns between otherwise observationally identical women and men explain the uneven gender allocation of workers into more profitable occupations and industries.^{21,22}

8.1 A conditional decomposition of the contribution commute variables to the gender wage gap

The previous sections presented empirical evidence showing that commute variables can explain a sizable portion of the gender pay gap. The approach consisted in comparing the results of regression (16) with and without commute variables. That is, the differences in the coefficients obtained from these regressions, reproduced in (18) and (19) for convenience,

²¹Alonso et al. (1964) renowned bid-rent theory indicates that industries are located in concentric rings around the CBD, but at different distances to it.

²²The original Oaxaca-Blinder decomposition is explained in Oaxaca (1973), Blinder (1973) and Fortin et al. (2011).

are measures of the “job location pay gap”, which estimates are shown in Table 2.²³

$$\Delta \ln(w_k) = \beta_1 + \beta_3 \text{children}_k + \Delta X_k \Gamma + \beta_4 \Delta \text{com}_k + \Delta \epsilon_k \quad (18)$$

$$\Delta \ln(w_k) = \tilde{\beta}_1 + \tilde{\beta}_3 \text{children}_k + \Delta X_k \tilde{\Gamma} + \Delta \tilde{\epsilon}_k \quad (19)$$

In regression (18), β_1 and β_3 (linearly) combined measure the expected gender pay gap among couples with n children and where the wife and the husband commute the same distance and have the same human capital variables. That is,

$$\beta_1 + \beta_3 n = E(\Delta \ln(w_k) | \text{children}_k = n, \Delta X_k = 0, \Delta \text{com}_k = 0) \quad (20)$$

Similarly, $\tilde{\beta}_1$ and $\tilde{\beta}_3$ in regression (19) measure the expected gender gap among couple with n children, where the wife has the same human capital as her husband, but she **does not necessarily** commute the same distance as him.

$$\tilde{\beta}_1 + \tilde{\beta}_3 n = E(\Delta \ln(w_k) | \text{children}_k = n, \Delta X_k = 0) \quad (21)$$

The coefficients β_1 , β_3 , $\tilde{\beta}_1$ and $\tilde{\beta}_3$ on the left-hand side of equalities (20) and (21) are those reported in Table 2. They will be decomposed to answer the question of interest.

Decomposing the conditional gender pay gaps Consider augmenting regressions (18) and (19) by including vectors of occupational indicators for women occ_{fk} and men occ_{mk} separately.

$$\Delta \ln(w_k) = \alpha_1 + \text{occ}_{fk} \Psi_f - \text{occ}_{mk} \Psi_m + \alpha_3 \text{children}_k + \eta \Delta \text{com}_k + \Delta X_k \Theta + \Delta \mu_k \quad (22)$$

$$\Delta \ln(w_k) = \tilde{\alpha}_1 + \text{occ}_{fk} \tilde{\Psi}_f - \text{occ}_{mk} \tilde{\Psi}_m + \tilde{\alpha}_3 \text{children}_k + \Delta X_k \tilde{\Theta} + \Delta \tilde{\mu}_k \quad (23)$$

Given J occupations in the economy, the j^{th} entry in row vector occ_{ik} takes the value one if individual $i \in \{female, male\}$ in household k works in occupation j and zero otherwise. If the worker is female (male), then occ_{mk} (occ_{fk}) is a vector of zeros. The dimension of occ_{ik} is $J - 1$ since one occupation is omitted to avoid collinearity. Ψ_i and $\tilde{\Psi}_i$ are a gender-specific conformable vectors of coefficients.

²³The previous section included the number of children as a series of dummy variable rather than a single variable ‘children’ measuring the number of kids in the household. In this specification, children_k in regressions (18) and (19) represents a vector of indicators, which j -th component takes the value one if the couple has a number of children equal to j and zero otherwise. β_3 and $\tilde{\beta}_3$ are conformable vector of coefficients.

Let Z be the vector with the regressors ($children_k, \Delta X_k, \Delta com_k$), and let z be the particular values of this vector ($n, 0, 0$). Taking the expectation of expression (22) conditional on $Z = z$ but not on the occupational indicators occ_{fk} and occ_{mk} gives.

$$E(\Delta \ln(w_k)|Z = z) = \alpha_1 + \alpha_3 n + E(occ_{fk}|Z = z)\Psi_f - E(occ_{mk}|Z = z)\Psi_m$$

Adding and subtracting $E(occ_{fk}|Z = z)\Psi_m$ to the right-hand side of this expression and doing the corresponding algebra gives:

$$\underbrace{E(\Delta \ln(w_k)|Z = z)}_{T_1} = \underbrace{\alpha_1 + \alpha_3 n + E(occ_{fk}|Z = z)\Delta\Psi}_{R_1} + \underbrace{E(\Delta occ_k|Z = z)\Psi_m}_{S_1} \quad (24)$$

Expression (24) is a **conditional** Oaxaca-Blinder decomposition. The left-hand side T_1 is the average gender wage gap when $Z = z$ (i.e., when the couple has n children, and the wife has the same level of human capital and commutes the same distance as the husband). The component R_1 on the right-hand side is the gender pay gap that would be observed (in the Oaxaca-Blinder sense) if men were allocated across occupations in the same way as women of similar characteristics are (i.e., $E(occ_{fk}|Z = z)$), and the within-occupation gender pay gap $\Delta\Psi = \Psi_f - \Psi_m$ were as the one currently observed. The component S_1 is the portion of the conditional gender pay difference T_1 that would be observed if women earned the same as men in each occupation Ψ_m and the currently observed uneven allocation of men and women across occupations $E(\Delta occ_k|Z = z)$ remained such.

The right-hand side of (20) and left-hand side of (24) are identical. Then, combining these two equalities gives the decomposition of the regression coefficients of interest.

$$\underbrace{\beta_1 + \beta_3 n}_{T_1} = \underbrace{\alpha_1 + \alpha_3 n + E(occ_{fk}|Z = z)\Delta\Psi}_{R_1} + \underbrace{E(\Delta occ_k|Z = z)\Psi_m}_{S_1} \quad (25)$$

The computation of decomposition (25) requires the estimation of the conditional expectations $E(\Delta occ_k|Z = z)$. This can be done is a separate step computing a set of auxiliary regressions.

$$\Delta occ_k = \delta_0 + \delta_1 Z_k + error \quad (26)$$

The system (26) contains $J - 1$ equations, one for each occupation in the vector Δocc_k . Then, δ_0 and δ_1 are $J - 1$ -dimensional column vectors and δ_2 is an $(J - 1 \times dim(Z))$ matrix of coefficients. Replacing the conditional expectations $E(\Delta occ_k|Z = z)$ obtained from equations

(26) in the decomposition (25) gives a simple expression for S_1 .

$$S_1 = (\delta_0 + \delta_1 z) \Psi_m \quad (27)$$

The component R_1 in decomposition (25) is obtained by computing the difference $T_1 - S_1$ or by estimating an additional set of auxiliary regression for $E(occ_{fk}|Z = z)$.

The previous procedure can also be used to decompose expression (21). Let \tilde{Z} be the vector containing the regressors ($children_k, \Delta X_k$). Contrary to Z in decomposition (24), the variable Δcom_k is excluded from \tilde{Z} . Let \tilde{z} be the particular values of this vector ($n, 0$). Then,

$$\underbrace{\tilde{\beta}_1 + \tilde{\beta}_3 n}_{T_2} = \underbrace{\tilde{\alpha}_1 + \tilde{\alpha}_3 n + E(occ_{fk}|\tilde{Z} = \tilde{z})\Delta\tilde{\Psi}}_{R_2} + \underbrace{E(\Delta occ_k|\tilde{Z} = \tilde{z})\tilde{\Psi}_m}_{S_2} \quad (28)$$

As before, the set of auxiliary regressions can be written as follows:

$$\Delta occ_k = \zeta_0 + \zeta_1 \tilde{Z}_k + error \quad (29)$$

and the resulting occupational segregation component S_2 is

$$S_2 = (\zeta_0 + \zeta_1 z) \tilde{\Psi}_m \quad (30)$$

The conditional decompositions (25) and (28) simplify to the standard of Oaxaca-Blinder approach when no Z or \tilde{Z} variables are included. This result is expected and desirable from a statistical perspective. A conditional approach like the one presented here should reduce to an unconditional one when the conditioning set is empty.

The role of commute variable in explaining the gender occupational segregation

The difference in the left-hand sides of expressions (25) and (28) is the portion of the gender wage gap associated with gender differences in commuting patterns. This quantity can be decomposed into within-occupation gender pay gaps associated with gender differences in job location ($R_1 - R_2$) and gender differences in the selection of workers to occupations ($S_1 - S_2$).

$$T_2 - T_1 = (R_2 - R_1) + (S_2 - S_1) \quad (31)$$

8.2 Results of the conditional decomposition

Table 5 shows the results of implementing the conditional Oaxaca-Blinder decomposition previously described. This table consists of six panels vertically stacked. Each of them decomposes a relevant dependent variable (hourly wages or annual earnings) by either occupation, industry, or occupation conditional on industry.²⁴

Rather than showing the decomposition of the linear combination $\beta_1 + \beta_3 n$, Table 5 shows the decomposition of β_1 and β_3 separately to facilitate the comparison with previous tables. The values in column T_1 are identical to those in columns 1 in Table 2. These are the quantities to analyze when no commute variables are included in the regression. Columns R_1 and S_1 decompose the conditional gender wage gap and the ‘‘child wage penalty’’ shown in column T_1 into gender differences in pay within categories (either occupations or industries) and gender differences in the distribution of workers across categories.

Panel A column S_1/T_1 indicates that 40% of the ‘job location gap’ among childless couples (regression constant) is attributed to women working in low-paying occupations. The other 60% is attributed to within-occupation gender wage inequality.

The values in column T_2 are identical to those in columns 3 in Table 2. They correspond to regression (16) when commute variables are included among covariates. Columns R_2 and S_2 decompose the conditional gender wage gap T_2 as previously indicated. Conclusions are qualitatively similar to the case when no commute variables were included.

The most interesting results in Table 5 are those contained in the last two columns. They decompose the fraction of the gender pay gap attributed to job location (i.e., the quantity $(T_2 - T_1)$ in expression (31)). The goal is to answer whether sex differences in commute variables are associated with women choosing different occupations (industries) or whether women are paid less even when they work in the same occupations (industries) as men. Both of these possibilities are consistent with urban economics models.

²⁴The conditional decomposition by occupation computes regressions (22) and (23). The decomposition by industry replaces the vectors of occupational indicators occ_{mk} and occ_{fk} by industry indicators ind_{mk} and ind_{fk} . The decomposition by occupation conditional on industry modifies regressions (22) and (23) by including industry indicators in the following way.

$$\Delta \ln(w_k) = \alpha_1 + occ_{fk} \Psi_f - occ_{mk} \Psi_m + \phi \Delta ind_k + \alpha_3 children_k + \eta \Delta com_k + \Delta X_k \Theta + \Delta \mu_k \quad (32)$$

$$\Delta \ln(w_k) = \tilde{\alpha}_1 + occ_{fk} \tilde{\Psi}_f - occ_{mk} \tilde{\Psi}_m + \tilde{\phi} \Delta ind_k + \tilde{\alpha}_3 children_k + \Delta X_k \tilde{\Theta} + \Delta \tilde{\mu}_k \quad (33)$$

When regressions (32) and (33) are used, the within-couple industry indicators Δind_k are also included in regressions (18) and (19) as regressors for the technique to be consistent. The results of regressions (32) and (33) are very similar when industry ‘returns’ are allowed to be gender specific (i.e., include the difference $\tilde{\phi}_f ind_{fk} - \tilde{\phi}_m ind_{mk}$ instead of $\tilde{\phi} \Delta ind_k$).

The results of the decomposition indicate that the tendency of women to commute less is substantially associated with them working in low-paying occupations. On average, 40% to 50% of the gender gap attributed to sex differences in job location is explained by gender occupational segregation (Panels A and D, column $S_2 - S_2/T_2 - T_1$).

The conditional decomposition by industry gives quantitatively similar results. Panels B and E show that the uneven distribution of men and women across industries explains more than 40% of the gender pay gap and the ‘child pay penalty’. The rest can be attributed to within-industry gender inequality.

Panels C and F show the decomposition of (log) hourly wages and (log) annual earnings by occupation conditioning on the wife and her husband to be in the same industry. The last two columns of the table indicate that commute time is significantly associated with gender occupational segregation even among workers in the same industry.

9 Summary and conclusions

This paper analyzes to what extent the differential commuting patterns of women and men explain the gender pay gap and the *child pay penalty* (i.e., the gender pay gap associated with being a mother). The paper hypothesizes that women find commuting costlier as a result of holding a disproportionate share of housework and child-rearing responsibilities. Then, they tend to find jobs located closer to home. A ‘job location pay gap’ as a plausible explanation of the gender pay gap emerges because job located away from the central business district tend to offer lower wages.

The results using a within-couple estimator show that commute variables, which proxy job location, explain ten percent of the gender pay gap among childless, and between twenty to forty percent of the child wage penalty. Consistent with an uneven distribution of jobs within urban agglomerations suggested in the literature, a significant share of the ‘job location gap’ can be related to women working in less profitable occupations and industries.

The hypothesis of this paper provides a plausible underlying explanation for some of the recent findings in the labor economics literature; that women work in firms, occupations, and industries that pay relatively less. The mechanisms behind these findings have not been pinned down. The results in this paper indicate that the interaction between job locations in urban agglomerations and the sexual division of task in the household are important channels.

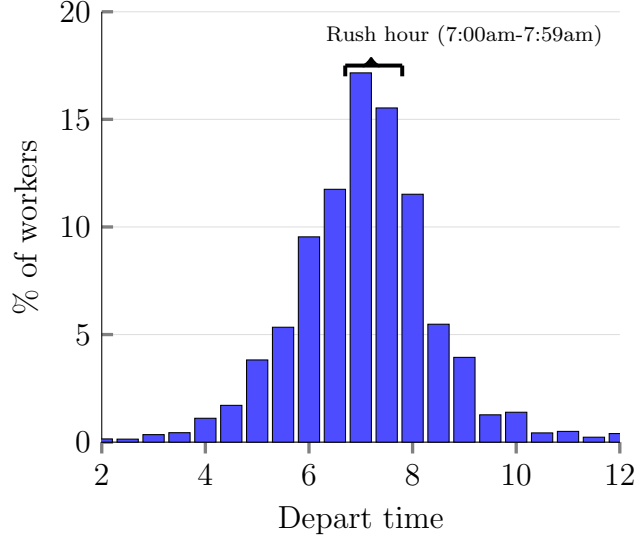
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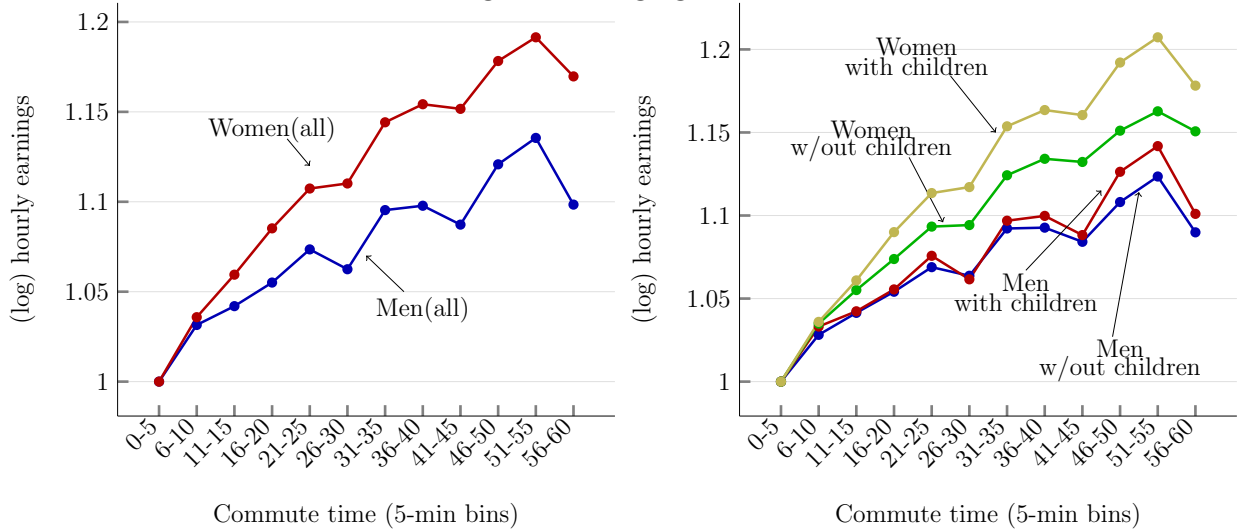
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Figure 2: Histogram depart time to work



Note: Computed using all workers from the ACS 2005-2016, including single, divorced and widowed individuals absent in the sample to estimate the regressions. Bars show the share of workers in 30-minute bins.

Figure 3: Wage gradient



Note: Each point is computed as the average (log) hourly wages within five-minute bins. Average values for men and women that arrive to work in 5 minutes or less are normalized to one.

Table 1: Descriptive statistics

Panel A									
Commuting patterns									
children	Commute in minutes			Time depart to work			Commute during rush hour [§]		
	(1)	(2)	(1)-(2)	(3)	(4)	(3)-(4)	(5)	(6)	(5)-(6)
	men	women	diff	men	women	diff [#]	men	women	diff
0	27.6	24.9	2.8	7:45am	8:02am	-16.7	0.29	0.36	-0.071
1	28.6	24.4	4.2	7:45am	8:05am	-19.8	0.30	0.39	-0.086
2	28.7	23.5	5.2	7:44am	8:13am	-28.2	0.32	0.39	-0.071
3	28.4	22.2	6.2	7:48am	8:30am	-41.5	0.30	0.35	-0.048
4	27.6	21.6	6.0	7:56am	8:51am	-55.6	0.28	0.30	-0.019
5	27.0	21.0	6.0	8:09am	9:08am	-58.8	0.27	0.26	0.009
Obs.	1,570,266	1,570,266		1,570,266	1,570,266		1,570,266	1,570,266	
Panel B									
Labor outcomes									
children	Hours worked per week			Worked 50+ weeks			Annual earnings		
	(1)	(2)	(1)-(2)	(3)	(4)	(3)-(4)	(5)	(6)	(5)-(6)
	men	women	diff	men	women	diff	men	women	diff
0	44.3	40.0	4.3	0.90	0.85	0.04	48,800	34,500	14,300
1	44.4	38.1	6.4	0.91	0.82	0.09	50,000	33,400	16,600
2	44.7	36.6	8.1	0.91	0.80	0.11	53,900	33,300	20,600
3	44.8	35.0	9.8	0.90	0.76	0.14	52,800	29,000	23,800
4	44.6	33.9	10.8	0.89	0.73	0.17	48,900	24,800	24,100
5	44.2	33.2	11.0	0.88	0.72	0.16	44,400	21,700	22,700
Obs.	1,570,266	1,570,266		1,570,266	1,570,266		1,570,266	1,570,266	

Note: Sample consists of i) heterosexual couples, ii) in nuclear families, iii) where the children in the household, if any, are sons and daughters of both couple's members (i.e. no households with stepdaughters, stepsons or foster children), and iv) the wife's age in the couple ranges from 25 to 55.

[#] Difference in minutes.

[§] Rush hour defined as that between 7:00am to 7:59am based on relative frequencies of departure time.

Table 2: Commute variables, the gender pay gap and the ‘child pay penalty’

Panel A: (log) hourly wages							
	without commute variables (1)	with commute time (linear) (2)	with all commute variables (3)	plus female interac. (4)	% difference		
					(2)-(1)	(3)-(1)	(4)-(1)
Commute time		0.0037 (0.0000)***	polynomial	polynomial			
One child	-0.0206 (0.0017)***	-0.0153 (0.0017)***	-0.0123 (0.0017)***	-0.0126 (0.0017)***	-25.7%	-40.3%	-38.8%
Two children	-0.0685 (0.0016)***	-0.0594 (0.0016)***	-0.052 (0.0016)***	-0.0514 (0.0016)***	-13.3%	-24.1%	-25.0%
Three children	-0.1167 (0.0023)***	-0.1039 (0.0023)***	-0.0919 (0.0023)***	-0.0894 (0.0023)***	-11.0%	-21.3%	-23.4%
Four children	-0.1263 (0.0044)***	-0.1143 (0.0044)***	-0.0998 (0.0044)***	-0.0962 (0.0044)***	-9.5%	-21.0%	-23.8%
Five children	-0.1227 (0.0100)***	-0.1111 (0.0099)***	-0.0957 (0.0098)***	-0.0911 (0.0098)***	-9.5%	-22.0%	-25.8%
Const. (no child)	-0.2249 (0.0012)***	-0.2138 (0.0012)***	-0.2005 (0.0012)***	-0.2748 (0.0037)***	-4.9%	-10.8%	
Adj. const.				-0.204 (0.001)***			-9.3%
Age (polyn. degree 5)	yes	yes	yes	yes			
Years of educ.	yes	yes	yes	yes			
Commute time polynomial	no	degree 1	degree 5	degree 5			
Comm. time x female	no	no	no	yes			
Departure dummies	no	no	yes	yes			
N	1,570,266	1,570,266	1,570,266	1,570,266			

Panel B: (log) annual earnings							
	without commute variables (1)	with commute time (linear) (2)	with all commute variables (3)	plus female interac. (4)	% difference		
					(2)-(1)	(3)-(1)	(4)-(1)
Commute time		0.0054 (0.0000)***	polynomial	polynomial			
One child	-0.1095 (0.0023)***	-0.1017 (0.0023)***	-0.0961 (0.0022)***	-0.0967 (0.0022)***	-7.1%	-12.2%	-11.7%
Two children	-0.2407 (0.0022)***	-0.2275 (0.0022)***	-0.2108 (0.0022)***	-0.2096 (0.0022)***	-5.5%	-12.4%	-12.9%
Three children	-0.3774 (0.0032)***	-0.3588 (0.0031)***	-0.329 (0.0031)***	-0.3233 (0.0031)***	-4.9%	-12.8%	-14.3%
Four children	-0.4626 (0.0060)***	-0.4451 (0.0060)***	-0.4041 (0.0058)***	-0.3958 (0.0058)***	-3.8%	-12.6%	-14.4%
Five children	-0.4899 (0.0135)***	-0.473 (0.0134)***	-0.4278 (0.0131)***	-0.4171 (0.0131)***	-3.4%	-12.7%	-14.9%
Const. (no child)	-0.3796 (0.0016)***	-0.3634 (0.0016)***	-0.3371 (0.0016)***	-0.5336 (0.0049)***	-4.3%	-11.2%	
Adj. const.				-0.345 (0.002)***			-9.1%
Age (polyn. degree 5)	yes	yes	yes	yes			
Years of educ.	yes	yes	yes	yes			
Commute time polynomial	no	degree 1	degree 5	degree 5			
Comm. time x female	no	no	no	yes			
Departure dummies	no	no	yes	yes			
N	1,570,266	1,570,266	1,570,266	1,570,266			

* p<0.05, ** p<0.01, *** p<0.001

Note: Standard errors in parenthesis. All regressions are computed after taking within-couple differences of variables as indicated in equation (16). Regressors include a polynomial of degree five in age and a polynomial of degree three in years of educations. Commuting time is included as a polynomial of degree 1 in column 2 and as a polynomial of degree 5 in columns 3 and 4. Departure dummies are forty eight indicators (30-minute intervals each, one of them being the omitted one) of the departure time to work.

Table 3: Heterogeneity across couples' formal education

	Panel A: wife and husband with college degree			Panel B: wife and husband without college degree		
	without commute variables	with all commute variables	difference	without commute variables	with all commute variables	difference
	(1)	(2)	(2)-(1)	(3)	(4)	(4)-(3)
One child	-0.0227 (0.0032)***	-0.0122 (0.0031)***	-46.3%	-0.0169 (0.0026)***	-0.0103 (0.0025)***	-39.1%
Two children	-0.0903 (0.0030)***	-0.0684 (0.0029)***	-24.3%	-0.0548 (0.0025)***	-0.0406 (0.0025)***	-25.9%
Three children	-0.1662 (0.0044)***	-0.1312 (0.0043)***	-21.1%	-0.0869 (0.0034)***	-0.07 (0.0034)***	-19.4%
Four children	-0.2122 (0.0091)***	-0.1678 (0.0089)***	-20.9%	-0.0746 (0.0061)***	-0.0591 (0.0060)***	-20.8%
Five children	-0.2296 (0.0226)***	-0.1856 (0.0222)***	-19.2%	-0.0789 (0.0129)***	-0.0642 (0.0127)***	-18.6%
Const. (no child)	-0.1866 (0.0022)***	-0.1753 (0.0022)***	-6.1%	-0.2462 (0.0018)***	-0.209 (0.0018)***	-15.1%
Age (polyn. degree 5)	yes	yes		yes	yes	
Years of educ.	no	no		no	no	
Commute time polynomial	no	degree 5		no	degree 5	
Comm. time x female	no	no		no	no	
Departure dummies	no	yes		no	yes	
N	515,999	515,999		644,765	644,765	

	Panel C: wife skilled - husband unskilled			Panel D: wife unskilled - husband skilled		
	without commute variables	with all commute variables	difference	without commute variables	with all commute variables	difference
	(1)	(2)	(2)-(1)	(3)	(4)	(4)-(3)
One child	-0.0028 (0.0041)	0.0032 (0.0041)	-214.3%	-0.0309 (0.0058)***	-0.0195 (0.0057)***	-36.9%
Two children	-0.0343 (0.0040)***	-0.0216 (0.0039)***	-37.0%	-0.1017 (0.0057)***	-0.0805 (0.0055)***	-20.8%
Three children	-0.0685 (0.0059)***	-0.0478 (0.0058)***	-30.2%	-0.1556 (0.0080)***	-0.1193 (0.0079)***	-23.3%
Four children	-0.1136 (0.0122)***	-0.0927 (0.0120)***	-18.4%	-0.1774 (0.0151)***	-0.1418 (0.0148)***	-20.1%
Five children	-0.1817 (0.0294)***	-0.1523 (0.0290)***	-16.2%	-0.0953 (0.0326)**	-0.0565 (0.0319)	-40.7%
Const. (no child)	0.0776 (0.0029)***	0.082 (0.0029)***	5.7%	-0.4971 (0.0041)***	-0.4521 (0.0041)***	-9.1%
Age (polyn. degree 5)	yes	yes		yes	yes	
Years of educ.	no	no		no	no	
Commute time polynomial	no	degree 5		no	degree 5	
Comm. time x female	no	no		no	no	
Departure dummies	no	yes		no	yes	
N	252,012	252,012		157,490	157,490	

* p<0.05, ** p<0.01, *** p<0.001

Note: Standard errors in parenthesis. All regressions are computed after taking within-couple differences of variables as indicated in equation (16). Regressors include a polynomial of degree five in age. Commuting time is included as a polynomial of degree 5 in columns 2 and 4. Departure dummies are forty eight indicators (30-minute intervals each, one of them being the omitted one) of the departure time to work.

Table 4: Heterogeneity among couples across personal attributes and urban agglomerations

	(log) hourly wages			(log) annual earnings			% difference (5)-(4) (6)-(4)
	without commute variables	with commute variables	plus female interac.	without commute variables	with commute variables	plus female interac.	
	(1)	(2)	(3)	(4)	(5)	(6)	
Panel A: Commuting zone fixed-effects							
One child	-0.0211 (0.0017)***	-0.0129 (0.0017)***	-0.0130 (0.0017)***	-0.1102 (0.0023)***	-0.0970 (0.0022)***	-0.0972 (0.0022)***	-12.0% -11.8%
Two children	-0.0696 (0.0016)***	-0.0533 (0.0016)***	-0.0525 (0.0016)***	-0.2420 (0.0022)***	-0.2125 (0.0022)***	-0.2106 (0.0022)***	-12.2% -13.0%
Three children	-0.1177 (0.0023)***	-0.0932 (0.0023)***	-0.0906 (0.0023)***	-0.3786 (0.0032)***	-0.3307 (0.0031)***	-0.3245 (0.0031)***	-12.7% -14.3%
Four children	-0.1274 (0.0044)***	-0.1011 (0.0044)***	-0.0975 (0.0044)***	-0.4632 (0.0060)***	-0.4051 (0.0058)***	-0.3969 (0.0058)***	-12.5% -14.3%
Five children	-0.1237 (0.0100)***	-0.0970 (0.0098)***	-0.0925 (0.0098)***	-0.4900 (0.0135)***	-0.4285 (0.0131)***	-0.4178 (0.0131)***	-12.6% -14.7%
Age (polyn. degree 5)	yes	yes	yes	yes	yes	yes	
Years of educ.	yes	yes	yes	yes	yes	yes	
Commute time polynomial	no	degree 5	degree 5	no	degree 5	degree 5	
Comm. time x female	no	no	yes	no	no	yes	
Departure dummies	no	yes	yes	no	yes	yes	
N	1,570,266	1,570,266	1,570,266	1,570,266	1,570,266	1,570,266	
Panel B: Cohort fixed-effects							
One child	-0.0151 (0.0022)***	-0.0077 (0.0022)***	-0.0079 (0.0022)***	-0.0943 (0.0030)***	-0.0827 (0.0029)***	-0.0830 (0.0029)***	-12.3% -12.0%
Two children	-0.0619 (0.0023)***	-0.0458 (0.0022)***	-0.0454 (0.0022)***	-0.2143 (0.0031)***	-0.1853 (0.0030)***	-0.1840 (0.0030)***	-13.5% -14.1%
Three children	-0.1142 (0.0031)***	-0.0908 (0.0031)***	-0.0893 (0.0031)***	-0.3673 (0.0042)***	-0.3212 (0.0041)***	-0.3171 (0.0041)***	-12.6% -13.7%
Four children	-0.1288 (0.0057)***	-0.1022 (0.0056)***	-0.0999 (0.0056)***	-0.4818 (0.0077)***	-0.4204 (0.0075)***	-0.4144 (0.0075)***	-12.7% -14.0%
Five children	-0.1223 (0.0128)***	-0.0976 (0.0126)***	-0.0950 (0.0126)***	-0.5055 (0.0175)***	-0.4457 (0.0169)***	-0.4389 (0.0169)***	-11.8% -13.2%
Age (polyn. degree 5)	yes	yes	yes	yes	yes	yes	
Years of educ.	yes	yes	yes	yes	yes	yes	
Commute time polynomial	no	degree 5	degree 5	no	degree 5	degree 5	
Comm. time x female	no	no	yes	no	no	yes	
Departure dummies	no	yes	yes	no	yes	yes	
N	1,247,274	1,247,274	1,247,274	1,247,274	1,247,274	1,247,274	

* p<0.05, ** p<0.01, *** p<0.001

Note: Standard errors in parenthesis. All regressions are computed after taking within-couple differences of variables as indicated in equation (16). Regressors include a polynomial of degree five in age and a polynomial of degree three in years of educations. Commuting time is included as a polynomial of degree 5 in columns 2, 3, 5 and 6. Departure dummies are forty eight indicators (30-minute intervals each, one of them being the omitted one) of the departure time to work.

Table 5: Conditional decomposition

	without commute variables				with commute variables				difference		
	components		R_1/T_1		S_1/T_1		components		$(R_2 - R_1)/(T_2 - T_1)$		
	T_1	R_1	S_1	R_1/T_1	T_2	R_2	S_2	R_2/T_2	S_2/T_2	$(S_2 - S_1)/(T_2 - T_1)$	
Panel A											
One child	-0.021	-0.013	-0.008	61.5%	-0.01	-0.01	0.00	61.2%	38.8%	62.1%	37.9%
Two children	-0.069	-0.050	-0.019	73.0%	-0.05	-0.04	-0.01	76.5%	23.5%	61.9%	38.1%
Three children	-0.117	-0.087	-0.030	74.2%	-0.09	-0.07	-0.02	78.2%	21.8%	59.2%	40.8%
Four children	-0.126	-0.094	-0.033	74.0%	-0.10	-0.08	-0.02	78.7%	21.3%	56.5%	43.5%
Five children	-0.123	-0.087	-0.036	70.9%	-0.10	-0.07	-0.02	76.3%	23.7%	51.7%	48.3%
Const. (no child)	-0.225	-0.133	-0.091	59.3%	-0.20	-0.12	-0.08	60.8%	39.2%	47.2%	52.8%
Panel B											
One child	-0.021	-0.013	-0.008	61.7%	-0.01	-0.01	0.00	63.1%	36.9%	59.8%	40.2%
Two children	-0.069	-0.050	-0.018	73.0%	-0.05	-0.04	-0.01	77.0%	23.0%	60.7%	39.3%
Three children	-0.117	-0.088	-0.029	75.0%	-0.09	-0.07	-0.02	79.4%	20.6%	58.9%	41.1%
Four children	-0.126	-0.095	-0.031	75.4%	-0.10	-0.08	-0.02	80.2%	19.8%	57.2%	42.8%
Five children	-0.123	-0.091	-0.032	74.2%	-0.10	-0.08	-0.02	78.8%	21.2%	58.0%	42.0%
Const. (no child)	-0.225	-0.161	-0.064	71.5%	-0.20	-0.15	-0.05	75.2%	24.8%	41.8%	58.2%
Panel C											
One child	-0.016	-0.013	-0.003	79.6%	-0.01	-0.01	0.00	82.4%	17.6%	75.3%	24.7%
Two children	-0.060	-0.050	-0.010	84.0%	-0.05	-0.04	-0.01	86.9%	13.1%	73.5%	26.5%
Three children	-0.102	-0.086	-0.016	84.5%	-0.08	-0.07	-0.01	87.5%	12.5%	71.6%	28.4%
Four children	-0.110	-0.093	-0.017	84.7%	-0.09	-0.08	-0.01	87.9%	12.1%	69.9%	30.1%
Five children	-0.108	-0.088	-0.020	81.4%	-0.09	-0.07	-0.01	85.5%	14.5%	63.9%	36.1%
Const. (no child)	-0.181	-0.133	-0.048	73.4%	-0.17	-0.12	-0.05	73.1%	26.9%	77.4%	22.6%
Panel D											
One child	-0.109	-0.094	-0.016	85.4%	-0.10	-0.08	-0.01	88.2%	11.8%	65.5%	34.5%
Two children	-0.241	-0.204	-0.037	84.8%	-0.21	-0.18	-0.03	87.1%	12.9%	68.8%	31.2%
Three children	-0.377	-0.317	-0.061	84.0%	-0.33	-0.28	-0.04	86.6%	13.4%	65.8%	34.2%
Four children	-0.463	-0.395	-0.067	85.4%	-0.40	-0.36	-0.05	88.5%	11.5%	64.5%	35.5%
Five children	-0.490	-0.418	-0.072	85.3%	-0.43	-0.38	-0.05	88.8%	11.2%	61.7%	38.3%
Const. (no child)	-0.380	-0.222	-0.158	58.4%	-0.34	-0.20	-0.14	59.8%	40.2%	47.7%	52.3%
Panel E											
One child	-0.109	-0.096	-0.013	87.9%	-0.10	-0.09	-0.01	90.6%	9.4%	68.8%	31.2%
Two children	-0.241	-0.211	-0.030	87.7%	-0.21	-0.19	-0.02	89.8%	10.2%	72.7%	27.3%
Three children	-0.377	-0.330	-0.047	87.6%	-0.33	-0.30	-0.03	89.9%	10.1%	71.6%	28.4%
Four children	-0.463	-0.412	-0.051	89.0%	-0.40	-0.37	-0.03	91.4%	8.6%	72.5%	27.5%
Five children	-0.490	-0.437	-0.053	89.1%	-0.43	-0.39	-0.04	91.4%	8.6%	73.7%	26.3%
Const. (no child)	-0.380	-0.272	-0.107	71.7%	-0.34	-0.25	-0.08	75.1%	24.9%	44.9%	55.1%
Panel F											
One child	-0.101	-0.093	-0.008	92.2%	-0.09	-0.09	-0.01	93.8%	6.2%	78.5%	21.5%
Two children	-0.224	-0.203	-0.021	90.6%	-0.20	-0.18	-0.02	92.0%	8.0%	79.2%	20.8%
Three children	-0.351	-0.314	-0.036	89.6%	-0.31	-0.28	-0.03	91.3%	8.7%	76.3%	23.7%
Four children	-0.433	-0.392	-0.041	90.6%	-0.39	-0.36	-0.03	92.5%	7.5%	75.0%	25.0%
Five children	-0.463	-0.417	-0.047	89.9%	-0.41	-0.38	-0.03	92.2%	7.8%	71.3%	28.7%
Const. (no child)	-0.305	-0.218	-0.087	71.5%	-0.28	-0.20	-0.08	71.0%	29.0%	77.9%	22.1%

Data appendix

Table 6: Descriptive statistics

	Men		Women	
	mean	sd	mean	sd
(log) Hourly wages	2.902	0.699	2.652	0.694
(log) Annual earnings	10.56	0.79	10.06	0.94
Years of education	14.27	2.85	14.56	2.67
Age	43.27	9.19	41.11	8.46
Number of children in hh	1.268	1.103	1.268	1.103
The couple has:				
o No child	0.319	0.466	0.319	0.466
o One child	0.251	0.433	0.251	0.433
o Two children	0.304	0.460	0.304	0.460
o Three children	0.100	0.301	0.100	0.301
o Four children	0.022	0.147	0.022	0.147
o Five children	0.004	0.064	0.004	0.064
Travel time to work (min)	28.27	23.43	23.98	19.43
Time depart to work [#]	7:45am	3.162	8:10am	2.798
Hours worked per week	44.52	9.77	37.80	10.70
Weeks worked previous year:				
o 1-13 weeks	0.008	0.090	0.020	0.142
o 14-26 weeks	0.012	0.107	0.024	0.153
o 27-39 weeks	0.022	0.146	0.047	0.212
o 40-47 weeks	0.035	0.184	0.070	0.255
o 48-49 weeks	0.021	0.144	0.025	0.155
o 50-52 weeks	0.902	0.297	0.814	0.389
Observations	1,570,266		1,570,266	

[#]standard errors in minutes

Hourly wages: Computed as annual earnings divided by the hours worked per week times the number of weeks worked in the previous year. Annual earnings are deflated using CPI (base 1999). The number of weeks worked in the previous year is reported in categories (see Table 6). The number of weeks used to compute wages is the mid-point of the range reported (e.g. those reporting working 50 to 52 weeks, a value of 51 is used for the wage calculation). Results are robust to alternative calculations such as using the min or the max of the range.

Annual earnings: Respondent's total pre-tax wage and salary income. The reference period is the previous 12 months. Sources of income include wages, salaries, commissions, cash bonuses, tips, and other money income received from an employer. This variable is deflated using CPI-index (base 1999).

Number of children in the household: Integer indicating the number of own children in the household. Given the criteria to select the sample. This value corresponds to the biological children of both household members.

Travel time to work: Minutes did it usually take for a person to get from home to work in the previous week of the interview. Travel time is from door to door. Only workers who report this variables are considered in the analysis. Workers for whom the this variable has been imputed are discarded from the analysis.

Time depart to work: Time that the respondent usually left home for work last week. Imputed values are ignored in the analysis.

Hours worked: Number of hours per week that the respondent usually worked, if the person worked during the previous year. The reference period is the previous 12 months.

Weeks worked previous year Number of weeks that the respondent worked for profit, pay, or as an unpaid family worker during the previous year. Responses are given in intervals (1-13 weeks, 14-26 weeks, and so on), instead of the precise number of weeks.

Occupation Harmonized occupation coding scheme based on the Census Bureau's 1990 ACS occupation classification scheme.

Industry Harmonized Census Bureau industrial classification scheme (1990). This is a consistent long-term classification of industries.