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Commuting, children and the gender wage gap

Malte Borghorst* Ismir Mulalic† Jos van Ommeren‡

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Abstract

It has been documented that the gender pay gap strongly increases after the birth of the first child. We focus on Denmark and show that gender differences regarding commuting play an important role in explaining this. We offer 3 pieces of evidence. First, the gender pay and commuting gaps come into existence at the same moment: when the first child is born. Second, wage compensation for commuting is lower for women after the birth compared to men: about $3-4$ percentage points of the overall gender pay gap is due to gender differences related to compensation for commuting when having children. Third, women who get a child are much more likely to leave their job when they have a long commute, which is not true for men.

Using information on job moving through the lens of a dynamic search model, these results imply that the marginal cost of commuting increases substantially for women with a child. For female workers with a child, a one standard deviation increase in commuting distance induces costs equivalent to about 10% of their wage, whereas for all other workers these costs are equivalent to only 3-4% of their wages.

Keywords: commuting, wages, gender wage gap.

JEL Classification: J31, R41, J61, R23.

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1 Introduction

Over the last decades, wages for men and women have converged due to the reduced gap in education, skills, and labor participation.[1] However, women still earn substantially less than men, despite decades of equal-pay laws. This gender pay gap has been argued to be essentially a child penalty for women because a childbirth induces career interruptions and reduced working hours (Manning and Petrongolo, 2008; Blau and Kahn, 2017; Kleven et al., 2019; Card and Hyslop, 2021). This study shows that gender differences in commuting are an important determinant of this child penalty. Using administrative register data for the full working population in Denmark for the years 2003-2013 we apply an event study methodology – the birth of the first child – and demonstrate, that women not only earn substantially less but also strongly decrease their commute after the birth of the child relative to men. This finding makes sense as for many workers, adjusting the length of the commute through a job move is an important behavioral margin to optimise time devoted to labor as they are severely constrained in their choice of working hours (Böheim and Taylor, 2004).

Consistent with this finding, we show that women with a long commute are *several times* more likely to change jobs when they get a child, which is not true for men. We also show that workers with a higher wage are less likely to move jobs. Interpreting these results through the lens of a dynamic search model as in Gronberg and Reed (1994), van Ommeren and Fosgerau (2009) and Le Barbanchon et al. (2021), we estimate how much workers are willing to trade off wage for a shorter commute, i.e. we estimate the marginal cost of commuting. We show that this cost is the same for men and women before the birth of a child, but after the birth, it is substantially higher for women.

The sudden increase in the commuting cost for women after becoming a mother implies that the number of potential jobs within an acceptable commuting distance from the residence is reduced. This suggests that the gender pay gap may increase when getting a child, as women with children have fewer opportunities to find better jobs (Le Barbanchon et al., 2021). To investigate this, we estimate the effect of commuting distance on wages and use the event of the childbirth to estimate the role of children in this relationship. Our main

[1] See e.g. Blau and Kahn (2017), Altonji and Blank (1999) and Maasoumi and Wang (2019). Gallen et al. (2019) document this for Denmark.

finding here is that women with children are less compensated for longer commutes through higher wages compared to their male counterparts. These estimates imply that given the presence of a child, gender differences in compensation for commuting account for about 3-4 percentage points of the overall gender wage gap (of about 20 percentage points).

Our study refers to a range of literature. First, we contribute to a large body of literature that aims to explain the gender pay gap, see among others Goldin (2014) and Olivetti and Petrongolo (2016). Blau and Kahn (2017) provide a comprehensive review and find that conventional human capital factors, such as education and labor market experience, explain only a minor part of this gap, while gender differences in occupation and industry are identified as the most important factors in explaining it (Manning and Petrongolo, 2008). Although we are are agnostic to what extent monopolistic behavior plays a role in the gender wage gap, our results are consistent with the view that women with children prefer shorter commutes and that employers take advantage of this and therefore pay lower wages (Manning, 2003a, 2011; Hirsch et al., 2019).[2] Second, our study relates to literature which argues that this gap is essentially a child penalty for women, i.e. women's role as primary providers of childcare and home production (Polachek, 1981; Angelov et al., 2016). For example, many high-income jobs penalize the demand for flexibility and career breaks often associated with motherhood (Bertrand et al., 2010). Third, we relate to literature which emphasizes that the gap can be explained by higher commuting costs for women which results in restrictive job search, shorter commutes, and lower wages for women (Le Barbanchon et al., 2021; Farré et al., 2020; Petrongolo and Ronchi, 2020).[3] Fourth, we contribute to the urban economics literature which aims to estimate the marginal cost of commuting (i.e. the marginal willingness to pay for commuting).[4] Our starting point is that the labor market

[2] The literature also discusses other factors related to the gender wage gap: discrimination against women (Altonji and Blank, 1999), non-cognitive skills or psychological attributes (Croson and Donohue, 2003; Marianne, 2011; Azmat and Petrongolo, 2014) and anti-discrimination legislation aimed at removing entry barriers in male-dominated occupations (Goldin, 2006; Marianne, 2011; Olivetti and Petrongolo, 2016).

[3] Petrongolo and Ronchi (2020) show that women are more likely than men to quit their job given a long commute. See also Black et al. (2014) who argue that the presence of long commutes may foster specialization by family members in either market or home production to reduce commuting costs. Note that there is also a small literature that argues that women earn less because of monopsony related to job search, see Barth and Dale-Olsen (2009), but the role of commuting is ignored here.

[4] We have surprisingly few estimates of the commuting costs, although they play an important role in urban economic theory (see e.g., Wheaton (1974) and Fujita (1989)). Commuting costs determine urban spatial structure by influencing the size as well as the structure of cities (Lucas and Rossi–Hansberg, 2002;

is characterized by search behavior and therefore not fully competitive. This is important because there is a large literature that shows that frictions in the matching between workers and jobs make it difficult to estimate the compensating differential of job attributes (Hwang et al., 1992; Mulalic et al., 2013; Mas and Pallais, 2017). Hence, hedonic wage models, which are based on the competitive labor market assumption, are unlikely to provide compensating differentials for commuting (as well as other fringe benefits).[5] Fifth, our paper relates to a literature on the importance of, and economic valuation of, non-wage job characteristics for workers (van Ophem, 1991; Sullivan and To, 2014; Gronberg and Reed, 1994; Bonhomme and Jolivet, 2009). Important non-wage job characteristics include health insurance (Gruber and Madrian, 2004; Aizawa and Fang, 2020), employer-provided retirement benefits (Altonji and Paxson, 1992), employer-provided cars (Gutiérrez-i Puigarnau and Van Ommeren, 2011) and employer-provided parking (Van Ommeren and Wentink, 2012).

In the current paper, we estimate the marginal cost of commuting derived from information about job mobility given assumptions on the job search environment (as in Manning (2003a), van Ommeren et al. (2000), van Ommeren and Fosgerau (2009) and Le Barbanchon et al. (2021)). We offer several improvements. Our first, and main, improvement is that we improve the estimation procedure as introduced by Gronberg and Reed (1994), and which has been applied with minor changes in van Ommeren et al. (2000), Manning (2003b) and van Ommeren and Fosgerau (2009). In essence, this procedure estimates the effect of non-wage job characteristics (i.e., commuting distance) and wages on job mobility. The ratio of these effects provides information about the willingness to pay for these non-wage characteristics. The underlying idea is that workers search for a job where the distribution of wages of alternative jobs is given (Pissarides, 2000). Consequently, workers with higher wages are less likely to move jobs, because alternative jobs have become less attractive.

The fundamental econometric problem is that workers are heterogeneous, so the wage of the worker is an increasing function of the worker's productivity level, but also the distribution of wage offers shifts to the right for a higher level of productivity. For example, if one observes a worker with a high wage, then it may be the case that this worker is particularly

Ahlfeldt et al., 2015; Heblich et al., 2020; Baum-Snow, 2010).

[5]For some attempts to estimate hedonic wage models that include commuting as a job attribute, see Madden (1985) and Zax (1991).

productive (compared to another period), or that this worker had a lucky draw from job offers (Barlevy, 2008). Only in the latter case, there would be a strong incentive not to move to another job. Consequently, not controlling for worker productivity will result in an estimate of the marginal effect of wage which is biased towards zero. This bias may be large because it is generally thought that the relationship between wages and productivity is very tight (and even one-to-one according to fully competitive labor market models without search). The literature is aware of this issue, so in empirical applications, worker characteristics (e.g. education, age, sector) are used as controls (Manning, 2003a; van Ommeren and Fosgerau, 2009). However, most characteristics of the worker are unobserved. In the current paper, we will deal with this by including worker fixed effects.

Unfortunately, the inclusion of worker fixed effects, which controls for time-invariant unobserved heterogeneity, is not sufficient (and may make it even worse), because workers' wages strongly vary over time, because of productivity changes, so also there wage offer function changes over time.[6] Hence, we solve the econometric problem by combining the worker fixed effects with an IV approach. In essence, we are looking for an instrument that determines the wage of a worker, but not directly the wage offer distribution of this worker, as this would directly affect job mobility. We use the average wage of other workers with similar positions within the same firm as an instrument. Here, we also control for firm characteristics (e.g. firm size, average age of workers; adding additional firm controls doesn't appear to be fundamental for our results). Hence, the identifying assumption we make is that (changes over time in) the wage offer distribution of a worker are not related to (changes over time in) the average wage of other workers in the same firm.[7]

Our second improvement is that our study presents a significant advance in data quality compared to previous studies. We use administrative register data for the full work-

[6]For example, it implies that if we observe an associate professor who receives a wage increase from her current employer because of a top-five publication, it is plausible that her wage offer distribution would also be affected by this publication.

[7]Using an IV approach also reduces other econometric issues. First, it addresses the issue of measurement error which will be present, because the tax rate on labor income depends on other non-labor activities such as house ownership. So, for example, if the worker changes from renting to house ownership, the net income will change. In contrast to measurement error of income, measurement error in the instrument, i.e., the average net income of other workers, is much less, because it is based on a larger sample of workers. Second, it addresses the issue of fringe benefits offered to specific workers, such as company cars.

ing population of Denmark (rather than survey data) and we observe a precise measure of commuting distance.[8] This allows the econometric analysis to control for unobserved time-invariant worker characteristics using worker fixed effects and calculate our instrument, whereas previous studies essentially rely on cross-section identification with difficulties to find an instrument.

Our third improvement as in the analysis of wage compensation. We will estimate models that include household fixed effects. The inclusion of these fixed effects improves identification because according to urban economics theories that allow for spatial variation in jobs and residences, compensation for commuting occurs through higher wages as well as lower house prices (Wheaton, 1974; Fujita, 1989; Lucas and Rossi–Hansberg, 2002; Zenou, 2009; Ahlfeldt et al., 2015). Consequently, to measure compensation for commuting in the labor market, one ideally should either control for house prices, or even better for residential location, which we are able to do by including household fixed effects. Inclusion of household fixed effects, combined with worker fixed effects, implies that we essentially use information on changes over time in commuting distance of males and females who belong to the same household, and therefore, by construction, occupy the same residential location.

The remainder of the paper is organized as follows. In Section 2 we present and describe the data. We then first in Section 3 establish the relevance and extent of the gender pay and commuting gaps using an event study methodology, and then in Section 4 derive the marginal cost of commuting. We estimate and discuss the marginal cost of commuting in Section 5. Section 6 deals with the compensation for commuting. Finally, Section 7 presents the main conclusions.

2 Data

Our sample consists of longitudinal administrative register data for the full working population in Denmark. We observe for all workers demographic information (such as gender,

[8]In van Ommeren et al. (2000), the commuting distance was measured with substantial error, as only the residence and workplace municipalities were observed. Manning (2003a) and van Ommeren and Fosgerau (2009) observe commuting time which has the disadvantage that it is endogenously chosen, conditional on the distance and household income through the chosen travel modes.

number of children, and education) and labor market outcomes (such as annual wage, occupation, and sector).

We restrict our sample to workers who are employed between 2003 and 2013 and we censor observations of workers who move into non-employment, so all our job moves refer to job to job moves. This restriction makes it likely that the job moves (observed by us) tend to be voluntary, which will be a requirement of the approach introduced later on. Furthermore, we select observations of individuals who experience the birth of their first child either in this period or within up to 9 years before or 4 years after this period. This restriction is useful because workers without children may face different labor market conditions. We also impose a standard set of sample selection criteria of workers, i.e. we exclude workers younger than 19 or older than 45, workers who are in ongoing education, teleworkers, workers with an extremely low income (the lowest percentile) and workers with commuting distances exceeding 50 km. Commuting distance is calculated for each worker as the shortest route between the worker's residence and workplace location.[9]

In our analyses, we capture wages using annual net labor income. We focus on full-time workers, which facilitates interpretation of our empirical findings because for part-time workers we do not observe the exact number of hours worked. We define job mobility as a move from a (full-time) job to another job (which can be full-time or part-time). We have slightly more than 3 million observations.[10] Due to the childbirth and age selections, we focus on workers at the beginning of their career: workers are, on average, about 28 years in the period before the birth of their first child and about 35 years in the period after.

Table 1 reports descriptives for wages and commuting showing that wages for men exceed wages for women before and after the childbirth, but their difference is larger after the childbirth: the gender pay gap amounts to 12% before the childbirth and 24% after. It further shows that the Danish job market is characterized by high labor turnover and therefore by

[9]Statistics Denmark does not provide the exact residence and workplace addresses but provides the distances for the shortest route between these addresses. Note that the shortest distance may change over time even in the absence of job and residential relocations due to changes in road infrastructure (Börjesson et al., 2019; Mulalic and Rouwendal, 2020).

[10]Our original sample consists of about 10 million observations. We exclude observations with commuting distances outside the range (about one million observations), observations not referring to parents (about 4 million observations), part-time (about 0.5 million observations), censoring income (about 0.1 million observations) and observations with missing values (about 0.2 million observations).

Table 1: Wage and commute by gender and period (birth of first child)

	Men		Women	
	Mean	Std. Dev.	Mean	Std. Dev.
Before childbirth				
Commute (km)	13.20	11.91	12.26	11.72
Annual net income (DKK)	336,469	114,670	293,826	98,184
Job move	0.18	0.38	0.17	0.37
Residence move	0.19	0.39	0.19	0.39
Job tenure	2.80	2.63	2.43	2.14
Age	28.45	4.99	27.94	4.44
N	501,478		443,408	
After childbirth				
Commute (km)	15.04	12.24	12.65	11.03
Annual net income (DKK)	394,345	137,048	298,310	113,435
Job move	0.15	0.36	0.15	0.36
Residence move	0.09	0.29	0.09	0.28
Job tenure	4.36	3.90	3.94	3.43
Age	36.20	4.30	34.91	4.22
N	1,140,917		1,179,652	

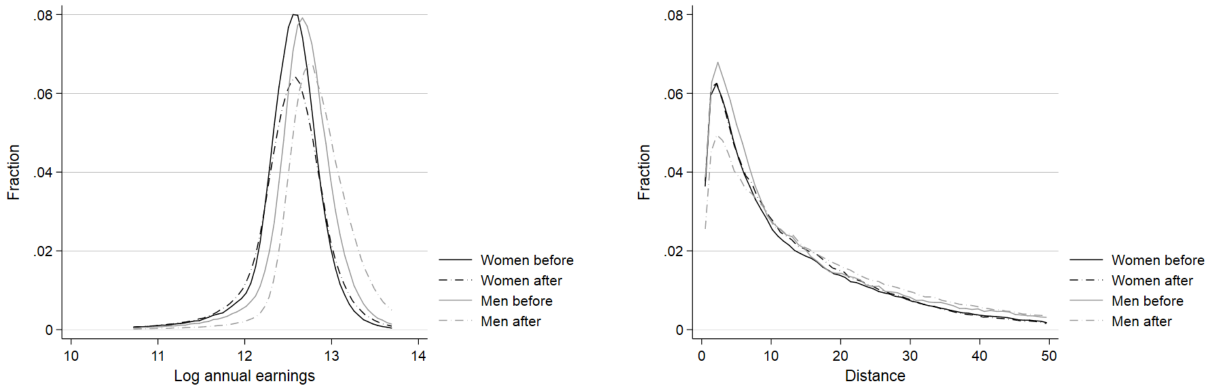
Notes: Full-time workers in the ten years around the birth of the first child. Observations of the year of the childbirth are excluded. 1 DKK ≈ 0.15 $.

short job durations (on average 3 years). Around 16% of workers move to another job within a year. Residential moving behavior is particularly important before the childbirth (about 19% of workers move residence each year), but this drops to 9% after the childbirth. The shares of men and women that move residence or job before and after the childbirth are similar.

The average commute for men and women before the birth of their first child is quite similar: men commute 13.2 km and women commute 12.3 km, so a difference of 1 km, about 8%. After the childbirth, however, it increases for men by almost 2 km to 15.0 km, while for women it increases by only 0.4 km to 12.7 km. The average increase in commuting distance for men after the birth of the first child is around 2.3 km, so by about 17%, longer, which is substantial. The time devoted to commuting increases then by approximately 30 minutes per week.[11]

[11] In Appendix B, using survey data, we show that the marginal effect of distance (in kilometres) on commuting time (in hours per trip) is about 0.025. We then multiply 0.025 with the increase in commuting distance (2.3 km) x 10 trips.

Figure 1: Wage, commuting and the first child



(a) Wage (b) Commuting distance (km)

Notes: Histograms for the annual earnings and commuting distance by gender and period.

In Figure 1a, we show distributions of log wage by gender and presence of a child. A remarkable feature of the distributions is that they are similar for men and women before the event, but not after: in particular the share of women with low wages increases, while for men the whole distribution moves to the right. In Figure 1b we show the commuting distributions. Note that after the childbirth the share of men with short commutes strongly drops, while for women this does not occur.

Finally, we have also examined to what extent changes in commuting distance are predominantly due to a residential move or due to a job move. It appears that the average (absolute) change in commuting distance is about 7 km given a residential move, whereas the (absolute) change in commuting distance given a job move is somewhat higher and equal to 9.4 km. Consequently, changes in commuting distance are mainly a labor market phenomenon and less a residential moving phenomenon, as residential moves, particularly of households with children, are mainly local.

3 Gender, wage and commuting gaps

We first aim to establish the relevance and extent of the gender wage and commuting gaps using a standard event study methodology based on the birth of the first child, following studies such as Kleven et al. (2019). We employ individual-level variation in the timing of the child's birth. Observed sharp changes in wage and commuting for mothers relative to fathers around the birth of the first child are likely orthogonal to unobserved determinants of these outcomes as they evolve smoothly over time. To reduce the selection effects of childbirth, we only select individuals who become a parent for the first time either during the period of observation or in the 10 years before or after the childbirth.

Event time is denoted by t (measured in years) and we observe the childbirth at time $t = 0$ (the actual childbirth occurs between -1 and 0). We focus on two outcome variables of worker i: wage and the length of the commute, both denoted by $y^g_{i,s,t}$. We then estimate the effect of childbirth at $t = 0$ on $y^g_{i,s,t}$, for each gender g separately, controlling for year s and age $h_{i,s}$:

$$y^g_{i,s,t} = \sum_{j \neq t'} \alpha^g_j \cdot \mathbb{I}[j = t] + \sum_k \beta^g_k \cdot \mathbb{I}[k = h_{i,s}] + \sum_l \gamma^g_l \cdot \mathbb{I}[l = s] + v^g_{i,s,t}, \tag{1}$$

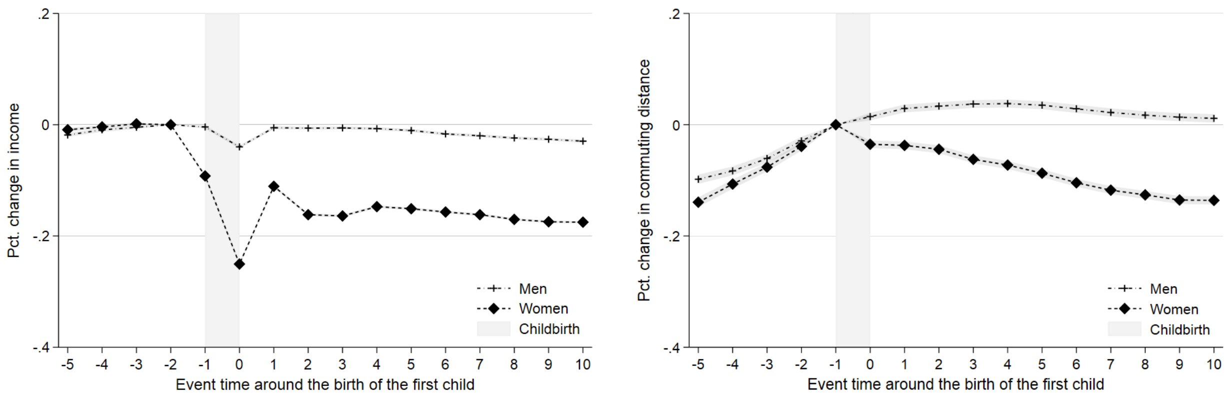
where event time effects are captured by α^g_j which yield the event time effect in relation to the year of the birth and $\mathbb{I}$ denotes an indicator variable.[12] In (1) we exclude α^g_j for $j \neq t'$ which is the reference category. This implies that the event time coefficients measure the impact of the birth of the first child relative to t'. When we focus on commuting distance then $t' = -1$, i.e. the last year before the worker is affected by the child birth. When we focus on wage then $t' = -2$, as we wish to allow for reduced wages due to maternity leave in the year before the childbirth. β^g_k captures the effects of a set of age dummies (to control for life cycle), γ^g_l a set of year dummies (to control for time trends), and $v^g_{i,s,t}$ is a (gender-specific) error term.[13] The estimated $\tilde{\alpha}^g_j$ are converted to percentage changes by $\tilde{\alpha}^g_t / \tilde{y}^g_{i,s,t}$, where $\tilde{y}^g_{ist}$ is the predicted outcome using the estimated coefficients (while excluding α^g_j), i.e. $\tilde{y}^g_{i,s,t} = \sum_k \tilde{\beta}^g_k \cdot \mathbb{I}[k = h_{i,s}] + \sum_l \tilde{\gamma}^g_l \cdot \mathbb{I}[l = s]$. It captures the event time effect at t as a share of the counterfactual outcome (i.e. no child at t').

In Figure 2, we show $\tilde{\alpha}^g_t / \tilde{y}^g_{i,s,t}$ based on the estimates of (1). Figure 2a shows a gender pay gap of about 15% immediately after childbirth compared to the year before pregnancy. It also shows that the wages of women and men follow the same trend before (and after)

[12]In our application, α^g_j range from -10 until $+9$.

[13]Age dummies are important because women are often younger than man when having their first child.

Figure 2: Wage, commuting and the first child



(a) Wage (b) Commuting distance

Notes: Full-time annual wage and commuting distance event time effects around the birth of the first child. The grey area marks the time interval of the birth of the first child. The shaded 95 percent confidence intervals are based on robust standard errors.

the birth. Women's wages drop substantially after the childbirth, while in contrast men's wages only slightly decrease. Moreover, the figure also shows that the effect of the birth of the first child is very persistent, i.e. it remains at the same level 10 years after the child's birth. These results are not novel to the literature.[14]

We now focus on the role of the childbirth on commuting distance, which is the main interest of the current paper. Figure 2b shows that the commuting distances of women and men follow the same upward trend before the birth of the child, but after the childbirth, women's commuting distance gradually reduces, while men's commuting distance uninterruptedly follows the trend a few years after the child birth and then stagnates.[15] The gender commuting distance gap ranges from about 5% immediately after childbirth (compared to the year before pregnancy) to about 15% ten years after. The resulting difference in commuting patterns after the childbirth hints towards an increase in the cost of commuting for women after having a child.[16]

[14]For example, these results are consistent with Kleven et al. (2019) who find that the gap remains in the long term (20 years). When we replicate the results with a similar sample (including part-time) our results do not fundamentally change.

[15]Importantly, although the commuting distance does not show a sharp change, we will, later on, show that the effects of commuting distance on job mobility will jump discretely around the childbirth.

[16]Additionally, we have tested whether the observed gender difference in commuting distance after the childbirth is sensitive to additional controls. For example, we have performed the same analysis with two additional control variables: education and the number of workers at the firm level. The results remain robust. The results are available from the authors upon request.

The latter result raises the question of whether the observed gender differences in the commuting distance are predominantly due to residential moving – which implies that households tend to make residential moves which make them locate closer to the workplace location of the new mother rather than the new father – or predominantly due to gender differences in workplace locations when moving job. To investigate this, we focus on sub-samples of workers that either do not move jobs or do not move residence (in the period starting 3 years before the birth), see Figure A.2 in Appendix A. These figures suggest that the gender differences in commuting distance after the childbirth are predominantly due to gender differences regarding the job location. This is consistent with the notion that residential moving is relatively rare in Denmark.

4 Marginal cost of commuting: theory

The purpose of this theoretical framework is threefold. First, using a standard search model, we will show that workers with a higher marginal cost of commuting (per unit distance), e.g. because they have children, have a lower arrival rate of acceptable jobs, as noted by Manning (2003b). Our contribution here is that we demonstrate that the arrival rate for acceptable jobs is inverse proportional to the *square* of the marginal cost of commuting when one considers two-dimensional geographical space. Second, we show how one can estimate the marginal cost of commuting, defined as the marginal monetary valuation of commuting distance using the information on job-to-job mobility, as noted in the literature (van Ommeren et al., 2000; Manning, 2003b; van Ommeren and Fosgerau, 2009).

We assume a labor market with jobs that are characterized by wages and commuting distance, and where employers post wages drawn from a wage distribution (Manning, 2003b). We also assume that space is homogenous: every point in space has the same level of employment, population, and wage distribution. We assume further that space is two-dimensional and workers are not allowed to move residence.

Workers get utility from wages, w, and disutility from distance to work, x. The utility is additive in the *logarithm of wages* and commuting. Hence, utility v can be written as an increasing function of $log(w) - \alpha x$, where α is a parameter. For simplicity we assume that

$v = log(w) - \alpha x$. We are interested to estimate the value of the instantaneous marginal cost of commuting, MCC, defined by $-(\partial v/\partial x)/(\partial v/\partial w) = \alpha w$. Hence, α can be interpreted as the (relative) marginal cost of commuting, i.e. the marginal cost of commuting relative to the wage.

Job offers come from a continuous wage offer cumulative distribution denoted by $F(w^*)$ with the corresponding density function denoted by $f(w^*)$. For now, we assume that this distribution is given for individual workers. Job offers at a distance x^* arrive at an exogenous Poisson arrival rate λ. In this setup, as we have assumed the absence of residential moving, workers will accept all job offers for which hold that $log(w^*) - \alpha x^* > log(w) - \alpha x$.

We now derive the voluntary job-to-job rate, θ, i.e. the arrival rate of jobs which increases utility. To derive θ, we introduce $\lambda(v^*)$ which defines the arrival rate of job offers that offer utility v^*. This arrival rate can be written as:[17]

$$\lambda(v^*) = \lambda \int_0^\infty f(v^* + \alpha x^*) 2\pi x^* dx^*. \tag{2}$$

We change the variable of integration to $log(w^*)$, so we get:

$$\lambda(v^*) = \frac{2\pi\lambda}{\alpha^2} \int_v^\infty (log(w^*) - v^*) f(log(w^*)) dlog(w^*). \tag{3}$$

Now consider a worker with a job offering $log(w^*)$ at a distance equal to x^*, i.e. a job which offers exactly utility v^*. This worker will accept all job offers v^* which exceed v. The job moving rate θ is then defined by:

$$\theta(w, x) = \int_v^\infty \lambda(v^*) dv^* = \frac{2\pi\lambda}{\alpha^2} \int_v^\infty \int_v^\infty (log(w^*) - v^*) f(log(w^*)) dlog(w^*) dv^*. \tag{4}$$

Equation (4) is useful for several reasons. First, it allows us to do comparative statics. Given (4), it is straightforward to see that an increase in the current wage or a decrease in the length of the commute will result in a lower job moving rate, i.e. $\partial\theta(w, x)/\partial w < 0$ and $\partial\theta(w, x)/\partial x > 0$.[18] Such a result is in line with intuition.

[17] Note that when job is at distance x^*, then the (log) wage offer is $v^* + \alpha x^*$. Space is two-dimensional and we, therefore, multiply the job offer density function with $2\pi x^*$.

[18] These predictions follow from the observation that the job moving rate depends negatively on v

Second, it allows us to investigate how α affects the job moving rate. Given (4) one can demonstrate that, conditional on the current wage and commuting distance, the job moving rate is inversely proportional to the ratio of the arrival rate λ and the *square* of the marginal cost of commuting α.[19] This ratio can be interpreted as a composite measure of the extent of frictions in the labour market, i.e. the monopsony power (Manning, 2003b). A labour market is more monopsonistic if α is high (classical monopsony), or λ is low (modern monopsony). An increase in α essentially reduces the arrival rate of acceptable jobs. This reduction is more than proportional because space is two-dimensional.[20]

Third, and most importantly for the current application, given (4), one can see that given information on the effects of wages and commuting distance on the job moving rate $\theta(w, x)$ one may derive the marginal cost of commuting, MCC, as:

$$MCC \equiv -\frac{\partial v/\partial x}{\partial v/\partial w} = -\frac{\partial\theta(w,x)/\partial x}{\partial\theta(w,x)/\partial w} = -\frac{\partial\theta(w,x)/\partial x}{\partial\theta(w,x)/\partial log(w)}w = \alpha w. \tag{5}$$

Consequently, MCC can be estimated using the ratio of the marginal effect of commuting distance on job mobility and the marginal effect of log wage on job mobility. In the current paper, we will estimate α using estimates of the effects of log wages and commuting distance on the job moving rate for workers in Denmark who get a child. Our key interest is to examine to what extent α depends on the presence of children, and whether or not this differs for men and women.

Arguably, the latter expression has been derived under restrictive assumptions. In van Ommeren et al. (2000), it is shown that (5) holds quite generally, including non-homogeneous space, endogenous job search, business cycles and job moving costs. Importantly for the current study, their analysis also implies that (5) does *not* hold for when workers move residence or expect changes in their commuting costs (e.g. because of having a baby), but in

$(\partial\theta(w,x)/\partial v < 0)$, whereas v depends positively on wages while negatively on distance.

[19] This result is similar to Manning (2003b) who assumes that space is one-dimensional, and therefore does not get the "square" result, but instead λ/α.

[20] The effect of α on the job moving rate is ambiguous, as for workers with a short commute, an increase in α reduces the job moving rate, whereas for those with a long commute, an increase in α increases the job moving rate. One can show this by differentiating $\theta(w, x)$ with respect to α: $\frac{\partial\theta(w,x)}{\partial\alpha} = -\frac{2\theta(w,x)}{\alpha} + \frac{\partial\theta(w,x)}{\partial x}\left(\frac{\partial v}{\partial x}\right)^{-1}\frac{\partial v}{\partial\alpha} = -\frac{2\theta(w,x)}{\alpha} + \frac{\partial\theta(w,x)}{\partial x}\frac{x}{\alpha}$. For x is equal to 0, the expression is negative, whereas for large values of x, the second term exceeds the first term, as the first term is bounded.

that case, the ratio of the marginal effects on job mobility is equal to the marginal *expected* cost of commuting, hence there is a subtle difference in interpretation. For example, for workers who are expected to change residence after they move jobs, one may argue that we estimate the expected monetary valuation of the commuting distance rather than the instantaneous monetary valuation of commuting distance.

The main restrictive assumption for the empirical application is that the wage offer distribution is *not* allowed to be correlated to the wage level of the worker. Given heterogeneous workers with different activity levels, this assumption will usually not hold, because the wage offer distribution is a function of the productivity. In the econometric approach, we deal with this by including controls (e.g. worker fixed effects) combined with an IV approach, where we use an instrument, the average wage of similar workers at the firm, which reflects the productivity at the firm (e.g. through capital investments) as well as exogenous changes in the environment of the firm (e.g. an increase in demand for its products), which directly affects the wage level of the individual worker in this firm, but not the wage offer distribution of this worker.

5 Marginal cost of commuting: empirical application

In this section, we turn to the estimation of the marginal cost of commuting. The first three subsections show how the marginal cost of commuting can be estimated using our econometric approach which is supported by a graphical approach. Subsection 5.4 reports our main findings of estimating the marginal cost of commuting and subsection 5.5 presents robustness checks.

5.1 Econometric approach

We aim to estimate the parameters α to derive the marginal cost of commuting as derived in the previous section. This is not the first study that exploits information on job mobility to derive the marginal cost of commuting (van Ommeren et al., 2000; Manning, 2003b; van Ommeren and Fosgerau, 2009). Our main contribution here is that we can fundamentally improve on these studies because we have a large sample of panel observations over a long period, so we can identify the parameters of interest using worker fixed effects, whereas the previous studies essentially rely on strategies identifying parameters of interest without worker fixed effects. More fundamentally, we also introduce an instrumental variable approach to deal with the issue that workers differ in their wage offer distribution.

In the labor economics literature, there are several approaches to estimate the effects on job mobility, all of which have been applied in the context of the effect of commuting on job mobility. Survival analysis has been applied by van Ommeren et al. (2000), discrete choice models by van Ommeren and Fosgerau (2009) and linear probability models by Manning (2003b). In the current paper, we apply the latter approach, as we wish to deal with a large number of worker (and other, for example household) fixed effects, which is less straightforward to include for the other approaches.

We aim to estimate the causal effects of wage and commuting distance on job mobility. We will differentiate both effects by gender, g, and the presence of a child, c. One complication, as is common with annual data, is that we observe the commuting distance at the end of the year and average wage per year. Consequently, in the year that the worker moves, the average wage is a combination of the before-the-move wage and after-the-move wage, which is problematic because we wish to know the effect of before-the-move wage on job mobility. To deal with this, we define a job move in year t, when the actual move takes place the year after. Given this definition, we use a job moving dummy indicator $J_{i,t}$ which captures whether a worker, i in year, t, moves job. We then use the following two-way fixed effects specification, to estimate the effects of log wage and commuting distance on job mobility:

$$J_{i,t} = \alpha_{g,c} \cdot x_{i,t} + \beta \cdot log(w_{i,t}) + \gamma \cdot X_{i,t} + \delta_{g,c} + \lambda_i + \kappa_t + \varepsilon_{i,t}, \tag{6}$$

where our main interest is in the marginal effects of commuting distance, $x_{i,t}$ and log wage, $log(w_{i,t})$, which are captured by the coefficients and $\alpha_{g,c}$ and β respectively. Importantly, $\alpha_{g,c}$ is gender and child-specific. We also include $\delta_{g,c}$, which is a gender and child interaction term, which allows job mobility to change over time for reasons not captured by commuting distance or wages.[21] $X_{i,t}$ consists of a vector of additional controls, which includes marital

[21]For example, we allow for the situation that women with children receive less job offers for unobserved reasons.

status, sector, firm size, the average age of workers at the firm, job tenure, and region fixed effects. We include worker λ_i and year κ_t fixed effects and $\varepsilon_{i,t}$ is an idiosyncratic error term. We emphasize here that we include worker fixed effects, so we control for time-invariant worker characteristics. Consequently, we examine whether changes in wage levels of workers affect their job mobility.

The above approach can be criticized, as it is assumed that changes in wages are exogenous, i.e. these changes are not correlated to changes in the wage offer distribution. This assumption is unlikely to hold. For example, if we observe that a worker receives a higher wage while staying at the same job, it is very plausible that the productivity of this worker has increased, and therefore the wage offer distribution of this worker also has changed.

To address this issue, we will use an instrumental variable approach, where we use the (log of the) average wage of similar workers that work at the same firm as an instrument, where similar is defined as belonging to the group of workers who get children during the observed time interval and who are in the same job category, where we distinguish between 7 broad job categories (e.g., manager).[22] The underlying idea of this instrument is that productivity improvements *at the firm level* reflect into individual worker's wage increases, which do not affect the wage offer distribution of this worker. These productivity improvements at the firm level should be contrasted with the productivity improvements at the individual level, which do affect the wage distribution of a worker.

The underlying assumption is that the average wage of the firm does not directly affect individual job moving decisions, except through its effect on the individual wage of the worker. To minimize the possibility that the average wage has a direct effect, we also control for a range of firm characteristics, including firm size, and the average age of workers at the firm, as these factors may have an effect on the job mobility of workers beyond the effect through the average wage. However, we will also add additional firm-level control variables, such as average education and gender share to examine the robustness of the underlying assumption.[23]

[22]We have also examined other specifications with other definitions of similar. For example, when we include older workers in the same job category, then the first-stage impact of the instrument becomes smaller, so the instrument becomes less convincing.

[23]Note that we do *not* include firm fixed effects. In that case, one effectively uses differences in the average wage growth experienced by the same worker at different firms as an instrument of the wage change. The

We will also examine a range of alternative specifications. For example, our estimates could be biased, because of unobserved household or residential location characteristics such as the local transport context (e.g. the supply of public transport). To deal with these issues, we will include for each worker belonging to the same household, h, household fixed effects, η_h. Hence, we essentially compare (instrumented) changes in wages and commuting distance of men and women workers who belong to the same household before and after they receive a child.

5.2 Gender-specific wage effects

In the labor economics literature, there is a discussion to what extent the effects of wage on job mobility are gender specific, as these differences might be indicative of monopsony power by firms. A general finding is that these effects are very similar, see for example the book by Manning (2003a).[24] To examine this further we have estimated models where we also allow $\beta^w_{g,c}$ to vary by child and gender, so we have 4 endogenous variables:

$$J_{i,t} = \beta^w_{g,c} \cdot log(w_{i,t}) + \beta^x_{g,c} \cdot x_{i,t} + \gamma_{g,c} \cdot X_{i,t} + \delta_{g,c} + \lambda_i + \kappa_t + \varepsilon_{i,t}, \tag{7}$$

and where we use 4 instrumental variables in the first stage (the average wage in the firm interacted with group). Furthermore, we have estimated models where we estimate each model separately for both genders.

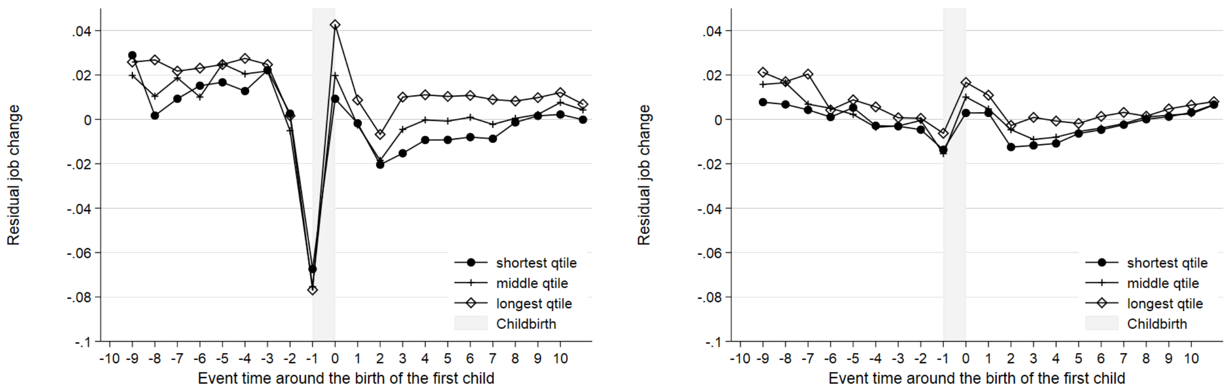
5.3 Graphical approach

To support our econometric results discussed, later on, we have examined the effect of commuting distance on job mobility graphically for several distance quantiles definitions (e.g. 3 quantiles, 5 quantiles, et cetera). Here, we control for worker fixed effects and the same

first-stage effect of the average wage is then close to zero, resulting in an instrument that is either weak or not robust to minor changes in specification. This makes sense, because given firm fixed effects, identification comes from differences in changes in wage for firms that employed the worker, whereas, without firm fixed effects, identification comes from differences in changes in wage levels across firms.

[24]The only exception we are aware of is the study by Barth and Dale-Olsen (2009) that differentiates firms based on their gender composition.

Figure 3: Job changes by distance quantiles



(a) Women (b) Men

Notes: We estimate a regression as in (6), but where we exclude commuting distance as an explanatory variable, i.e. $J_{i,t} = \beta \cdot log(w_{i,t}) + \gamma \cdot X_{i,t} + \delta_{g,c} + \lambda_i + \kappa_t + \varepsilon_{i,t}$. The figures display the estimated job mobility residuals $\hat{\varepsilon}_{i,t}$.

controls used in our econometric approach later on.[25] The results for these different quantiles definitions are very similar. In Figure 3 we show job mobility for 3 distance quantiles.

There are several messages in this figure. First, and most importantly, workers belonging to a higher commuting distance quantile tend to move jobs more, and this effect is particularly visible for women with children. Second, there is an extreme drop in job mobility of females just before the birth, which is likely due to a combination of reasons, including the effect of a Danish law which states that if women announce that they are pregnant, they cannot be fired, which reduces the incentives to search for another job.

As job mobility just before childbirth appears to be an extreme outlier, which may potentially affect the estimates of the econometric analysis, in a robustness check of the econometric analysis we will exclude observations in the year before the birth.

[25] Because we use controls, we apply the following two-step procedure. We first estimate a regression as in (6), but where we exclude commuting distance as an explanatory variable:

$$J_{i,t} = \beta \cdot log(w_{i,t}) + \gamma \cdot X_{i,t} + \delta_{g,c} + \lambda_i + \kappa_t + \varepsilon_{i,t}.$$

In the figures, we show the estimated residuals $\hat{\varepsilon}_{i,t}$.

5.4 Empirical results

Our main results using different specifications to identify the marginal cost of commuting by estimating (6) can be found in Table 2. All coefficients are estimated precisely and have expected signs. In all specifications, the wage is instrumented and it appears that the instrument is very strong with high F-values and has the expected positive sign. For example, for the specification shown in column [1], the effect of the log average wage on the individual's log wage is about 0.13, with a F-value equal to 4187.

In column [1], which is our preferred specification, it is shown that the effects of commuting distance on job mobility are very similar for men and women before they have children, with coefficients equal to 0.0010 and 0.0007, respectively. Hence, given a hypothetical increase of about one standard deviation in the length of the commute, which is equal to almost 12 km, job mobility rates increase by about 0.012. After the birth of the child, the estimated effect of distance is about the same for men, and equal to 0.0009, but for women, the estimated effect is about 0.0025, so almost 3 times the estimated effect for their male counterparts. This supports our claim that gender differences regarding commuting play an important role after the birth of the first child. *Women who get a child are much more likely to leave their job when they have a long commute, which is not true for men.* This result is novel to the literature, as previous studies speculated about this effect, but failed to show this, see e.g. van Ommeren and Fosgerau (2009). We will see that in all other specifications these results remain robust.

Focusing on the same column, it appears that the effect of log wage on job mobility is negative, with a coefficient equal to about -0.29. This estimate implies that a 10% increase of the current wage decreases job mobility by roughly 0.03, which is about 16% of the mean job mobility rate of 0.18. The order of magnitude of this estimate seems to make sense intuitively. For example, it suggests that a doubling of the wage in the current job would prevent most workers from leaving voluntarily ($0.18 - 0.7 \times 0.29 \approx 0$). This estimate implies a job moving elasticity with respect to the wage of about -1.2 (0.21/0.18), which is in line with the estimates obtained by Barth and Dale-Olsen (2009) for workers in the manufacturing industry in Norway (using a different methodology with different types of

Table 2: Job mobility

		[1]	[2]	[3] Women	[4] Men	[5] No anticipated residence move	[6] No anticipated childbirth
Distance (km)							
Women	before	0.0007***	0.0008***	0.0007***		0.0005***	0.0010***
		(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)
	after	0.0025***	0.0024***	0.0024***		0.0024***	0.0026***
		(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)
Men	before	0.0010***	0.0011***		0.0009***	0.0009***	0.0009***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)
	after	0.0009***	0.0010***		0.0011***	0.0010***	0.0010***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)
Log. wage							
		-0.294***		-0.269***	-0.309***	-0.229***	-0.286***
		(0.017)		(0.031)	(0.020)	(0.019)	(0.018)
Women	before		-0.418***				
			(0.0215)				
	after		-0.207***				
			(0.0171)				
Men	before		-0.379***				
			(0.0193)				
	after		-0.232***				
			(0.0187)				
Controls		yes	yes	yes	yes	yes	yes
Worker fixed effect		yes	yes	yes	yes	yes	yes
MCC (% of annual wage) per 12km increase (1 std.)							
Women	before	-0.028	-0.023	-0.032		-0.029	-0.044
		(0.005)	(0.004)	(0.006)		(0.008)	(0.007)
	after	-0.100	-0.138	-0.109		-0.126	-0.109
		(0.007)	(0.013)	(0.013)		(0.012)	(0.008)
Men	before	-0.039	-0.035		-0.037	-0.046	-0.036
		(0.005)	(0.004)		(0.005)	(0.008)	(0.006)
	after	-0.044	-0.052		-0.043	-0.052	-0.045
		(0.005)	(0.006)		(0.005)	(0.007)	(0.005)
No. of observations		2,387,501	2,387,501	1,210,891	1,176,610	2,040,011	2,236,505

Notes: The sample consists of full-time workers. All specifications include the following controls: a gender and child interaction term, marital status, job tenure in linear and squared form, number of workers in the firm, average age of workers at the firm, as well as year controls. Log wage is instrumented using the average wage of similar workers of the same firm. The first stage results are available from the authors upon request. *MCC* is estimated using the ratio of the marginal effect of commuting distance on job mobility and the marginal effect of log wage on job mobility, see equation (5). Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

instruments), which increases confidence in our results.

In column [2], as explained above, we allow the log wage coefficients to be gender and period (i.e. before and after the birth of the first child) specific, where we use the four interactions of the average wage in the firm with gender and period as instruments. These estimates imply that men are somewhat more sensitive to wage increases than females, in line with the idea that employers have more monopsony power over women than men, as hypothesized by Manning (2003a), and empirically supported by Barth and Dale-Olsen (2009). However, the gender differences of the effect of wage are statistically not different from each other at conventional significance levels. To investigate this further, we re-estimate [1], but now for women and men separately, columns [3] and [4], while imposing that the effect before and after the birth is the same in order to improve the power of the test. However, a formal t-test of gender differences still does not reject the null hypothesis of equality (the t-value is equal to 1.58). We will therefore continue assuming that there are no gender differences in wage effects.

The estimates in column [2] also suggest that workers are more responsive to wages before having a child. However, it appears that this result is sensitive to specification. When we as a robustness check estimate the same model while excluding $\delta_{g,c}$, then we find that the the difference in the effect of wage before and after the childbirth disappear. Subsequently, we will continue to assume that the effect of wage is neither gender specific (for which there is no evidence in our data) nor child specific (for which the evidence is less robust).

In the last 2 columns of the table, we estimate models for a more selective sample. In Section 4, we have explained that the interpretation of the marginal cost of commuting as defined by (5) changes if workers expect to change residence or get a child after accepting a new job, because the estimate refers then to marginal expected commuting costs. We do not observe the expectations of households, but it is plausible that few households adapt their job mobility decisions because they expect to move residence or to get a child in more than 3 years. In line with this idea, we exclude observations of workers in the 3 years before moving residence or getting a child, which gives similar results (see columns [5] and [6])).[26] Our main finding is that the estimates are hardly affected, so we are safe to assume that these estimates can be used to calculate the marginal cost of commuting, i.e. the marginal willingness to pay for a (one-way) commuting distance of 1 km. The results for MCC are shown in the panel below the estimated coefficients.

[26] This also addresses the issue that job mobility the year before the childbirth is an extreme outlier for women, as noticed by the graphical approach, see Section 5.3.

To improve interpretation, we will focus here on a one-way commuting distance increase of about 12 km, as this is the standard deviation of the commuting distance in our data, as a percentage of annual wage.

Our headline results, using (5) and our estimates of column [1] of Table 2, demonstrate that for men, irrespective of whether or not they have a child, and for women before having a child, the MCC given a one standard deviation increase of commuting distance is about 3-4% of the wage.

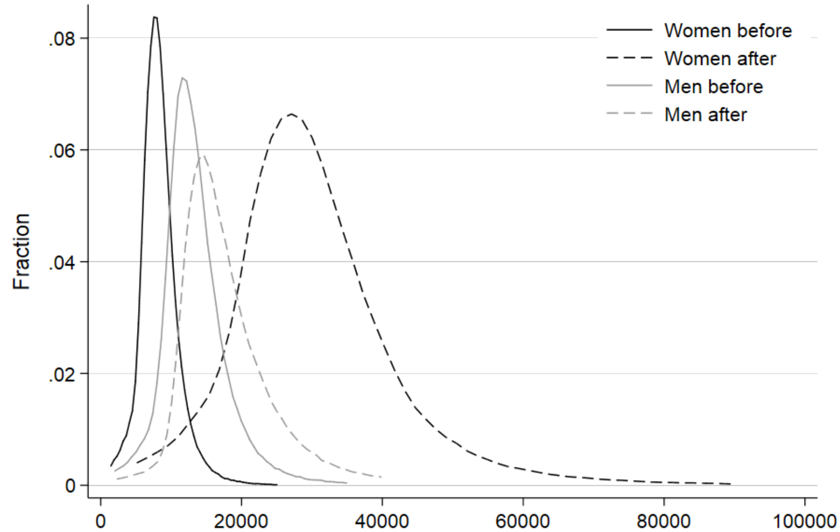
When having a child, the MCC given a one standard deviation increase of commuting distance is substantially higher for women and equal to 10% of the wage. The latter finding is in line with the idea that (full-time) women with children often have more childcare and household responsibilities than men, hence their marginal disutility of commuting will be higher. Clearly, the estimated marginal costs of commuting are very similar for different model specifications shown in Table 2.

Our assumption that utility is additive in the logarithm of wages and commuting implies that MCC is proportional to the wage, see (5), hence our estimate implies that there is a distribution of marginal commuting costs. Figure 4 shows the estimated distributions of the annual marginal commuting costs per 12 kilometer (in DKK), using the estimated coefficients from model [1] in Table 2 and the distribution of annual wage. It shows that the MCC distributions are very similar for men before and after they have children, with a mean of about 13,400 DKK and 17,600 DKK respectively. For women, the distributions before and after having a child are quite different: before the birth, the mean is about 8,400 DKK, whereas after the birth of the child, the MCC distribution for women shifts to right with the mean of about 30,000 DKK.

In this study, we estimate commuting costs using commuting distance. The main advantage of the latter measure compared to an alternative measure used in the literature, commuting time, is that distance does not depend on the mode of transport, which is endogenously chosen. However, it also has a disadvantage as it does not directly give insight into the marginal cost of commuting *time* (rather than distance), which may be either expressed in terms of (leisure) time lost or in monetary terms, which are also useful measures.

To calculate the marginal cost of commuting time, we have to make additional assump-

Figure 4: Marginal (annual) commuting costs per kilometer (in DKK), by period and gender



Notes: The marginal cost of commuting MCC per 12 kilometer (1 std. dev.) has been computed using the estimated coefficients from model [1] in Table 2 and the observed distribution of annual wage.

tions. We will assume that workers commute each day back and forth between the residence and the workplace (without combining these trips with other trips, e.g. dropping children at school, which may reduce the effective commuting time) and assume that the the number of hours worked per day 7.4 for full-time workers (in line with other studies). Furthermore, we need to have information about the effect of a marginal increase in commuting distance on commuting time. To derive the latter, we use the Danish National Travel Survey (NTS), which provides information on the commuting behavior of about 80,000 randomly selected individuals who fill out a one-day travel diary.

For the population of young workers we are interested in, the marginal effect of distance on one-way commuting time (in hours) is about 0.025, see Appendix B.[27] This estimate implies, given i.e. a 40 km increase, the (one way) commuting time increases exactly by one hour, which makes sense. It follows that the marginal effect of distance on *daily* commuting

[27] According to the speed literature, the effect of travel distance on travel time is diminishing, because the marginal increase in travel time is less for longer distances, see, for example, Couture et al. (2018). In line with that, we estimate the marginal effect of distance on travel time using a log-log specification, see Table B.2 in Appendix B. We find a coefficient of 0.58, almost identical to the estimates reported for the United Kingdom by Van Ommeren and Dargay (2006). For this specification, the average marginal effect is equal to the product of the estimated coefficient and the average inverse speed (the ratio of travel time and travel distance). Given an estimate of 0.58 (see Table B.2) and an average inverse speed of about 0.043 (see Table B.1), it appears that the average marginal effect is 0.025.

time is about 0.050. The implied MCC for one hour of commuting per day before the childbirth is then 52% of hourly wage for women without children and for men.[28] For female workers with children, the MCC for commuting time is substantially higher, about 1.25 times the hourly wage, i.e. it exceeds the hourly wage.[29]

How do these estimates compare with the literature? Note that in most previous studies (van Ophem, 1991; van Ommeren and Fosgerau, 2009; Manning, 2003b), commuting time rather than commuting distance was used as a proxy for commuting costs, so one can only compare with our implied commuting time estimates. Nevertheless, it appears that our implied estimates of MCC for commuting time are *substantially* less than the estimates obtained in those studies (at least a factor two). One explanation is that it is plausible that the estimated coefficients of log wage were downward biased in those studies. Another explanation is that we have a sample of young workers, which is in line with our finding that the MCC appears to be higher for older workers with children as indicated by our estimates in column [2] of Table 2.

The only study we are aware of which also uses distance (van Ommeren et al., 2000), finds roughly the same point estimate, but the confidence interval of this estimate is very large, so their point estimate must be interpreted as suggestive. Important for the current study which focuses on the role of children and gender, the current study is the first study that can differentiate between the MCC between men and women, and demonstrates the importance of the presence of children with precisely estimated point estimates.

5.5 Sensitivity analysis

We have performed several sensitivity analyses of our preferred specification [1] of Table 2. First, we have also applied an event time methodology, where we let the distance coefficients vary per year. Second, we focus on non-linear effects of distance. Third, we examine the

[28]Given our estimates of column [1] of Table 2, the MCC (per km) is about 0.0034 (-0.0010/0.294) of the daily wage. The MCC for one hour of commuting per day is then 0.068 (0.0034/0.050) of the daily wage, as the marginal effect of distance on daily commuting time is 0.050. Given a number of hours worked per day equal to 7.4, the MCC for one hour of commuting per hour worked is exactly half the hourly wage (7.4 * 0.068=0.5).

[29]We have assumed that workers commute each day. Note that given the, maybe more plausible, assumption that workers do not commute to work one day a week, e.g. because of working from home or because of a business trip, then the MCC for commuting time is about 25% higher.

importance of additional firm level controls to examine the robustness of using our firm level instrument. Fourth, we examine a range of alternative specifications, including where we control for household fixed effects.

5.5.1 Event time methodology results

In the previous analyses, we have assumed that the estimated coefficients discretely jump after the birth of the first child, implicitly assuming that they do not vary over time otherwise.[30] To investigate this further, we therefore also estimate models that exploit an event time methodology, i.e. we re-estimate our preferred specification, but we allow the (gender-specific) distance coefficients β_g^x to vary over time, i.e. these coefficients vary by year j relative to the event of the birth. Consequently, we essentially estimate:

$$J_{i,t} = \sum_j \alpha_{g,j} \cdot x_{i,t} + \beta \cdot log(w)_{i,t} + \gamma \cdot X_{i,t} + \lambda_i + \kappa_t + \varepsilon_{i,t}, \tag{8}$$

where we instrument $log(w_{i,t})$.

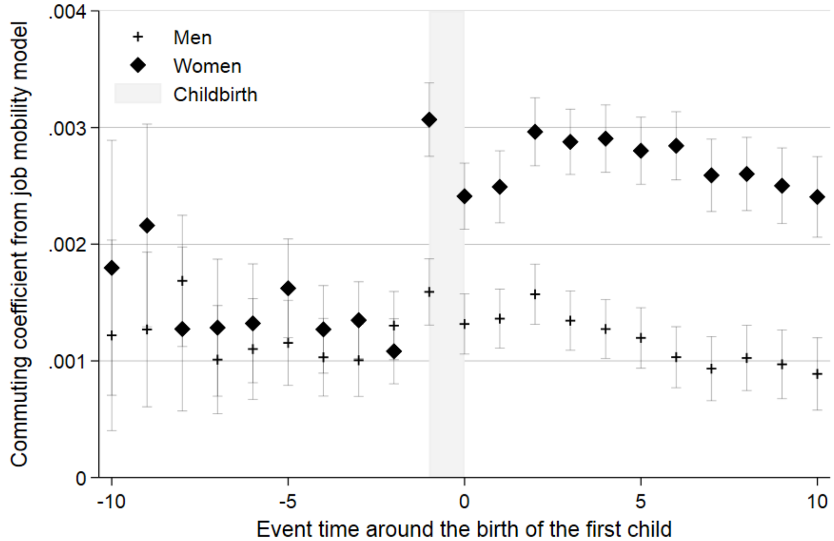
In Figure 5, we show the estimated distance coefficients for men and women around the year of the birth. It clearly shows that the coefficients for men are very similar for the different years before and after the event. In addition, the coefficients of women are indistinguishable to the male coefficients before the childbirth, but jump discretely after the childbirth. Consequently, we believe that the jump in the coefficients for women when they get a child supports our methodology, and therefore our findings.

5.5.2 Non-linear distance effects

We have also investigated whether the distance on job mobility is linear, see Appendix C. It appears that linearity is a reasonable assumption for our data. For example, when we impose that all distance effects are not gender-child specific and we include the square and the cube of distance, then the latter two terms are statistically insignificant. We have also estimated piecewise linear distance specifications with two knots (at 10 and 20 km), i.e. we

[30]Recall that we didn't observe such a discrete change in the average distance, as distance, as opposed to the effect of distance, is slowly changing over time, as we have seen earlier.

Figure 5: Job mobility: commuting distance coefficients



Notes: Estimated coefficients of commuting distance on job mobility around the birth of the first child when including individual fixed effects and other controls.

estimate separate (gender-child specific) coefficients for short, medium and long distances. In this case, the distance coefficients are very similar. When we estimate the same model for the different gender-child samples, the coefficients suggest, linearity cannot be rejected for males (using a standard F test).

5.5.3 Additional firm level control variables

In our IV approach, we use as an instrument the average wage (of similar workers) within the firm. In these estimations, we control for firm size as well as the average age of the workers belonging to the firm to avoid the criticism that the average wage has a direct effect on individual wage. Nevertheless, one criticism of the above estimation procedure is that we do not control sufficiently for firm characteristics, which may invalidate the instrument if these firm characteristics are correlated to the instrument and affect job mobility directly. To address this issue, we have estimated model specifications with additional firm-level control variables, such as more detailed sector controls, average education shares, the share of male workers, and region dummies. These results are shown in Table A.1 in Appendix A.

For convenience, we focus on a basic specification where we do not estimate gender-child specific coefficients of distance, but we constrain these coefficients to be the same. The results of this specification are reported in the first column of Table A.1. We now find that the MCC of a standard deviation increase in commuting distance is about 7.9% of the wage. Arguably, controlling for sectors is potentially important, as it has been known for many years that wages are structurally higher in certain sectors, whereas there are also substantial job mobility differences between sectors. In case that the sectoral wage differences and sectoral job mobility differences are correlated with each other, then the instrument would be invalid. This suggests that controlling for sectors is essential. To address this, we add additional controls for sectors at NACE 2 (88 sectors) and even NACE 3 (272 sectors) levels, respectively, as shown in columns [2] and [3]. The effects of commuting distance remain the same, whereas the effect of wage is slightly less pronounced. These point estimates imply that MCC of a one standard deviation increase in distance increases in absolute values from -0.079 to -0.094 and -0.103, respectively. The confidence intervals for the latter estimates increase now somewhat, and they overlap. Consequently, the estimates are insensitive to sector controls, even when we control for sector in a very detailed way.

Similarly, adding controls for the share of workers with a certain educational level or share of male workers results in almost identical results (see columns [4] and [5]). Column [6] shows that including regional fixed effects (5 regions) does not affect the estimation results. Finally, we have also re-estimated models only for larger firms, see column [7]. We find that the effects of distance and wage are slightly less pronounced resulting in somehow larger MCC. In conclusion, it appears that for all these additional specifications, the effects of commuting distance and wage are very robust.

5.5.4 Alternative specifications

We have also estimated a range of alternative specifications. Again, we focus on a basic specification where we do not estimate gender-child specific coefficients of distance, but we constrain these coefficients to be the same. The results of this specification are reported in the first column of Table A.2 of Appendix A. First we have estimated a specification where we add household fixed effects, so we additionally control for unobserved time-invariant household characteristics. This essentially means that we identify the effects of interest by comparing the behavior of men and women within the same household (i.e. a husband and wife). It appears that the MCC results are almost identical, see column [2]

Then we have have investigated also the robustness of the results using several other specifications, which also appear in the literature (no worker fixed effects, household fixed effect rather than worker fixed effects, no instrumenting of wage), see Table A.2 in Appendix A. First, we show a specification where we do *not* control for worker fixed effects, but replace these fixed effects with a range of control variables including age, gender, and education, see column [3]. In this case, it appears that the effect of distance is robust. In contrast, although the instrument is very strong (with the first-stage coefficient of about 0.56), it appears that there is a positive effect of the wage on job mobility, which doesn't make sense from an economic point of view. Clearly, the instrument is invalid without worker fixed effects, because of worker sorting. Second, we show a specification where we do not control for worker fixed effects but replace these fixed effects with household fixed effects, see column [4]. It appears that the estimated effects of wages are quite different. This reinforces our previous conclusion that the average wage is only valid as an instrument given worker fixed effects. Again, the effects of commuting distance remain robust. Third, in column [5], we show a specification where we do not instrument the wage. It appears now that the estimated effect of wage is about 5 times lower, suggesting that workers are hardly sensitive to wage increases, because the specification ignores that a wage increase also shifts the wage offer distribution. Again, we find that the effects of commuting distance remain the same.

Hence, in conclusion, it appears that the effects of commuting distance are extremely robust, whereas the effect of wage is *not* and depends on the methodology used. In our context, it is essential not only to use worker fixed effects, but also to instrument the wage.

6 Compensation for commuting

We are also interested in the question of whether women with children receive a different compensation for the length of their commute than men. According to standard urban economic theory, which allows for spatial variation in locations of jobs and residences, given the assumption of a perfect labor market with complete information – i.e. no job search frictions

– workers' wage would be equal their marginal productivity, and compensation differences for commuting for workers employed at the same workplace location would not exist, while workers at different residential locations would be compensated for the difference in the commuting costs by different levels of housing prices (Wheaton, 1974; Fujita, 1989). At the same time, commuting compensation would exist for workers who reside at the same residential location (so compensation in the housing market through house prices does not occur), but are employed at different workplace locations (Lucas and Rossi–Hansberg, 2002; Ahlfeldt et al., 2015). This result is important for our study, because it implies that if one aims to investigate commuting compensation in the labor market through higher wages, then in the hedonic wage regression one must control for residential location. Furthermore, according to standard economic theory, employers and workers are assumed to be price takers, so firms do not differentiate compensation for commuting based on the characteristics of workers, suggesting that women with children receive the same level of commuting compensation as other workers. On the other hand, it is possible through sorting that women with children sort themselves into jobs were different levels of commuting compensation are offered.

These predictions somewhat change given the presence of search frictions due to incomplete information. Theoretical studies indicate that search frictions may induce employers to differentiate wages based on the length of the commute also for workers employed at the same workplace location due to monopsony power. For reviews we refer to Zenou (2009) and Mulalic et al. (2013). This suggests that women with children may be treated differently from men with children, see Manning (2003a); Barth and Dale-Olsen (2009).[31]

To investigate this further, we employ a standard hedonic wage regression with the logarithm of wage as dependent variable, where we include gender-child specific effects of com-

[31] These differences may come into existence for example when firms have more monopsony power over women workers with children. It is then not clear then whether women with children receive less or more compensation for commuting compared to men. If firms are not constrained in exercising their monopsony power, firms would then pay lower wages for women with children, independent of the commuting distance, but more compensation for distance (Van Ommeren and Rietveld, 2005). On the other hand, if firms are constrained in exercising their monopsony power by, for example, unions, which is the institutional environment for Denmark, firms and workers may bargain about a higher wage, conditional on a threshold wage agreed with the unions. In this case, it is also plausible that firms pay less compensation for commuting towards women with children because the resulting wage is closer to their marginal productivity.

muting distance:

$$log(w_{i,h,t}) = \beta_{g,c} \cdot x_{i,h,t} + \gamma \cdot X_{i,h,t} + \lambda_i + \kappa_t + \eta_h + \varepsilon_{i,h,t}, \tag{9}$$

where we include individual fixed effect, λ_i, household fixed effect, η_h, and the same control variables as in the job mobility model.[32] Our preferred specification is a specification with individual and household fixed effects, as reported in column [1] of Table 3, but we also show other specifications without both fixed effects to investigate their importance.

The estimates reported in column [1] have several messages. First, in line with theories that allow for search frictions, we find a positive effect of commuting distance. Second, compensation for commuting tends to be higher for males than for females. These levels of compensation are small, but not negligible. For example, for men with children, we find a coefficient of about 0.0060, and for women with children, we find a coefficient of 0.0020. This implies that a standard deviation increase in commuting distance raises wage by about 0.3-0.8%. Recall our previous finding where we show that the commuting costs increase by about 5.2% of wage given a standard deviation increase in commuting distance. Consequently, the wage compensation is in the range of 6-15% of the commuting costs. These results are in line with the empirical literature which finds that, on average, workers receive low levels of compensation for their commuting distance due to monopsony. For example, Mulalic et al. (2013) report that Danish workers are compensated for 15-20% of their commuting costs through higher wages (in the long run, but less in the short run).[33] This suggests although job search frictions from commuting are important to workers, as expressed in their job mobility behavior, these frictions do not play a major role in terms of commuting compensation offered by employers. Furthermore, women with children receive less compensation for commuting than their male counterparts.

These results qualitatively hold if we exclude either worker fixed effects or household

[32] We estimate the effects of commuting distance on wages. Given the assumption of a frictionless labor market, one may interpret our results as causal as we address omitted variable bias. In contrast, according to search theory, one cannot interpret these effects as causal because workers accept job offers and therefore simultaneously accept commuting distance as well as wage, so one should interpret the effect as associations.

[33] In this study, the confidence intervals of the estimates were too large to demonstrate a difference in compensation between men and women.

Table 3: Compensation for commuting by gender and period

	[1] Househ. and indiv. FEs	[2] Household FE	[3] Individual FE	[4] Cross section
Women				
No child	0.0025***	0.0025***	0.0019***	0.0078***
	(0.0006)	(0.0006)	(0.0006)	(0.0004)
Children	0.0020***	0.0113***	0.0020***	0.0179***
	(0.0006)	(0.0004)	(0.0005)	(0.0003)
Men				
No child	0.0045***	0.0084***	0.0049***	0.0188***
	(0.0006)	(0.0006)	(0.0006)	(0.0004)
Children	0.0060***	0.0217***	0.0062***	0.0305***
	(0.0005)	(0.0004)	(0.0005)	(0.0003)
Time var. cont.	yes	yes	yes	yes
Time invar. cont.	no	yes	no	yes
Household FE	yes	yes	no	no
Individual FE	yes	no	yes	no
No. of observations	2,702,648	2,702,648	2,702,648	2,702,648

Notes: Dependent variable is log wage. Time variant controls include: a gender and child interaction term, family status, job tenure and firm size. Time invariant controls include: worker age and education. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

fixed effects, but the sizes of the estimates are quite different. In particular, these results indicate that including worker fixed effects is paramount when analyzing the compensation for commuting. When we exclude worker fixed effects, we find higher levels of compensation for women with children than for women without children (see column [2]), but these levels of compensation are still lower than for their male counterparts.

We have also examined to what extent the unobserved household characteristics affect the estimated coefficients. We have therefore estimated the model also without household fixed effect, see column [3]. It appears that the effect of commuting distance on wages is essentially the same. However, using household fixed effects instead of individual fixed effects, we find coefficients similar to the cross-sectional model, see column [4]. This suggests that the individual fixed effects are essential to identifying commuting compensation.

The above analysis allows us to investigate the importance of commuting for the overall gender pay gap using a decomposition methodology, as introduced by Blinder (1973) and Oaxaca (1973), which differentiates between two potential mechanisms. First, gender differ-

Table 4: Contribution of commuting to gender pay gap

	[1]	[2]	[3]	[4]
	Household and individual FEs		Individual FEs	
	No child	Children	No child	Children
Commuting differential	0.0005***	0.0012***	0.0005***	0.0013***
$(\bar{x}_m - \bar{x}_w) \cdot \hat{\beta}_m$	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Compensation differential	0.0180*	0.0365***	0.0263***	0.0387***
$\bar{x}_w \cdot (\hat{\beta}_m - \hat{\beta}_m)$	(0.0078)	(0.0068)	(0.0072)	(0.0064)

Notes: The decomposition is based on methodology introduced by Blinder (1973) and Oaxaca (1973). We use in columns [1] and [2] the estimated coefficients as reported in column [1] of Table 3 and in columns [3] and [4] the estimated coefficients as reported in column [3] of Table 3. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

ences in the length of the commuting distance (”the gender commuting gap”), which will be labeled as the *gender commuting differential*, will affect the gender pay gap. Following the gender pay decomposition literature, we will measure this differential, using the estimated coefficients for men (as reported in Table 3) multiplied with the average gender difference in the commuting distance. Second, differences in the compensation for the same commuting distance may also contribute to the gender pay gap, which we will call the *gender compensation differential*. This differential is estimated using the average commuting distance of women multiplied with the gender difference in commuting distance coefficients (as reported in Table 3).

Table 4 shows the contribution of commuting into the gender wage gap for workers with and without children. Columns [1] and [2] report the results for model with both household and individual fixed effects, see column [1] of Table 3. We find that the commuting differential doubles (from 0.05 to 0.12 percentage points) after the childbirth, but this increase is economically small compared to the increase in the size of the compensation differential, which doubles (from 0.0180 to 0.0365). This decomposition suggests that after a childbirth, the compensation differential for commuting contributes 3.65 percentage points to the gender wage gap — which is in the order of 20 percentage points, as we have shown above — whereas the gender commuting differential does hardly contribute to the gender wage gap.

We emphasise here that the gender composition differential for commuting is higher for workers with children than for workers without children, but their difference is equal to 1.85 percentage points (3.65-1.80) with a standard error of 1.12 percentage points, so formally we cannot reject the null hypothesis that the gender composition differential is higher for workers with children than for workers without children at the 5% level, but the presence of a gender composition differential for workers with children of 3.65 percentage points is highly statistically significant with a standard error of 0.68 percentage points. It appears that these results remain unchanged when we exclude household fixed effect, see columns [3] and [4] in Table 4. This confirms once again that the individual fixed effects are crucial to identifying commuting compensation.

7 Conclusion

This article analyses the contribution of gender differences with respect to commuting due to the presence of children to the persistent gender wage gap using administrative register data for the full working population in Denmark. We show that these gender differences are important.

We offer several pieces of evidence using the childbirth as an event for identification. First, we show that the gender pay and commuting gaps come into existence at exactly the same moment: when the first child is born. Second, wage compensation for commuting is reduced for women after the birth, but not for men: around 3.6 percentage points of the child-induced gender pay gap is due to gender differences related to compensation for commuting. Third, women who get a child are much more likely to leave their job when they have a long commute – the marginal effect of distance on job mobility is about 3 times higher – which is not true for men.

Our findings are consistent with the notion that gender differences in commuting patterns are important for understanding the gender wage gap and possible gender discrimination due to monopsony in the labor market, as argued by Manning (2003a,b) and Le Barbanchon et al. (2021). A subtle, but important, contribution here is that we show that these gender differences are only important when children are present.

In line with job search theory, we also demonstrate that workers with higher wages are less likely to move to another job. It appears that the elasticity of job mobility with respect to wage is about -1.2. Here we improve on previous studies such as Gronberg and Reed (1994) and van Ommeren and Fosgerau (2009) by using an approach employing a combination of worker fixed effects and instrumental variables.

Using this information on job moving through the lens of a dynamic search model, these results imply that the marginal cost of commuting increases substantially for women after the birth. A one standard deviation increase in commuting distance induces costs equivalent to about $3 - 4\%$ of the wage for all workers, except for female workers with children for which these costs are equivalent to about 10% of wage.

Policies to reduce the gender pay gap appear to have had little effect, as discussed at length in the labor economics literature (Manning and Petrongolo, 2008). In this literature, policies regarding commuting subsidies have not been discussed, but these policies potentially contribute to this gap. Different forms of income tax reductions for workers with long commutes can be found in many European countries (Potter et al., 2006). Commuters in Denmark with a one-way commute that exceeds 12 km are entitled to a tax deduction.[34] In particular, male commuters benefit from this tax deduction (the share of men receiving the subsidy is 0.46, whereas the share of women is 0.40). This kind of subsidy is likely inefficient and have been shown to increase commuting distances (Paetzold, 2019). Our empirical findings indicate that removing this commuting subsidy (maybe only for males) is unlikely to reduce the gender wage gap, as the gender wage gap induced by commuting is predominantly due to the lower compensation for commuting received by women with children rather than that these women commute much less.

[34]In 2019, commuters were entitled to deduct 1.96 DKK, about 0.20 US dollars, from gross income per kilometer driven.

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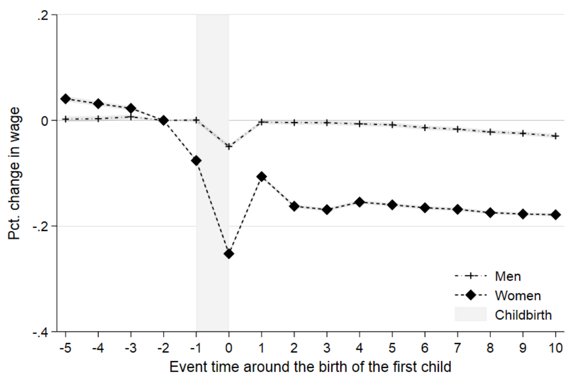
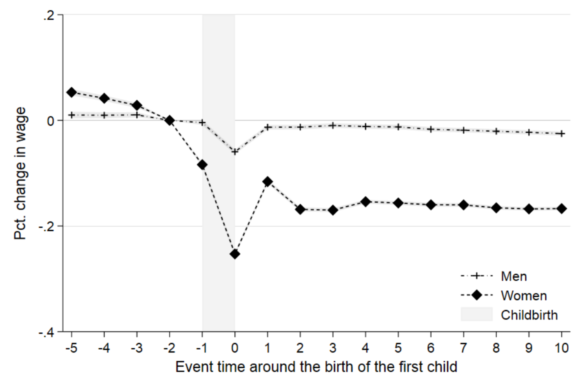
Appendices

A Additional estimation results

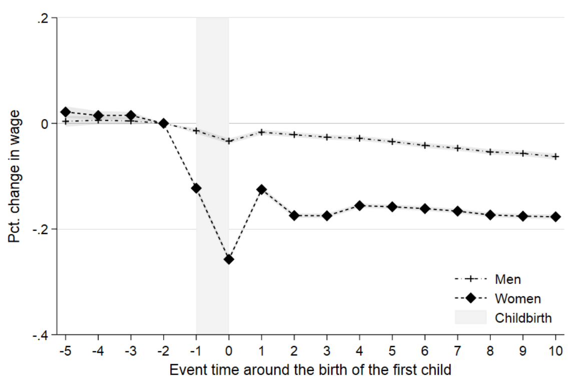
Figure A.1: Event study results for different samples: wage



(a) Job fixed and residence flexible



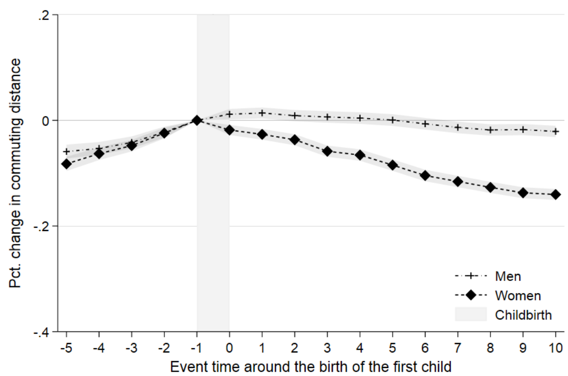
(b) Job flexible and residence fixed (t=-3)



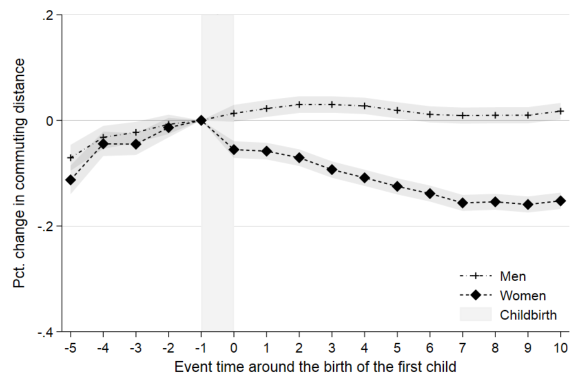
(c) Job and residence fixed

Notes: Wage event time effects around the birth of the first child. The grey area marks the parent around the birth of the first child. The shaded 95 percent confidence intervals are based on robust standard errors. The estimates from the specifications we have presented graphically are available from the authors upon request.

Figure A.2: The Event study results for different samples: commuting distance



(a) Job fixed (from t=-3)



(b) Residence fixed (from t=-3)

Notes: Commuting distance event time effects around the birth of the first child. The grey area marks the parent around the birth of the first child. The shaded 95 percent confidence intervals are based on robust standard errors. The estimates from the specifications we have presented graphically are available from the authors upon request.

Table A.1: Job mobility models (2SLS): additional firm level control variables

	[1] Main specification	[2] Sector FE NACE 2	[3] Sector FE NACE 3	[4] Education	[5] Share men	[6] Regional FE	[7] Large firms > 100
Coefficients							
Distance (km)	0.00135***	0.00138***	0.00137***	0.00136***	0.00135***	0.00137***	0.00128***
	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00013)
Log wage	-0.205***	-0.175***	-0.159***	-0.157***	-0.172***	-0.208***	-0.097***
	(0.023)	(0.0231)	(0.024)	(0.023)	(0.023)	(0.023)	(0.044)
First stage							
Avg. wage	0.127***	0.123***	0.120***	0.123***	0.127***	0.126***	0.158***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
F-Test	4,187	4,065	3,986	4,033	4,035	4,122	1,247
(MCC (% of annual wage) per 12km increase (1 std.)							
	-0.079	-0.094	-0.103	-0.104	-0.094	-0.079	-0.158
	(0.009)	(0.013)	(0.016)	(0.016)	(0.013)	(0.009)	(0.072)
Controls							
Time var. cont.	yes	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes
No. of observations	2,387,501	2,387,501	2,387,501	2,387,501	2,387,501	2,387,501	1,142,183

Notes: The sample consists of full-time workers. All specifications include the following controls: a gender and child interaction term, marital status, job tenure in linear and squared form, number of workers in the firm, average age of workers at the firm, as well as year controls. Log wage is instrumented using the average wage of similar workers of the same firm. The first stage results are available from the authors upon request. *MCC* is estimated using the ratio of the marginal effect of commuting distance on job mobility and the marginal effect of log wage on job mobility, see equation (5). Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.2: Alternative specifications of the job mobility model

	[1] 2SLS Main specification	[2] 2SLS Worker and household FE	[3] 2SLS Cross section	[4] 2SLS Household FE	[5] OLS Worker FE
Coefficients					
Distance (km)	0.00135***	0.00147***	0.00120***	0.00166***	0.00132***
	(0.00007)	(0.00008)	(0.00004)	(0.00006)	(0.00007)
Log wage	-0.205***	-0.213***	0.024***	-0.027**	-0.039***
	(0.023)	(0.027)	(0.005)	(0.007)	(0.002)
First stage					
Avg. wage	0.127***	0.111***	0.560***	0.370***	-
	(0.002)	(0.002)	(0.003)	(0.003)	-
F-Test	4,187	3,176	26,888	14,216	-
MCC (% of annual wage) per 12km increase (1 std.)					
	-0.079	-0.083	0.610	-0.751	-0.404
	(0.009)	(0.011)	(0.135)	(0.200)	(0.029)
Controls					
Time var. cont.	yes	yes	yes	yes	yes
Time invar. cont.	no	no	yes	yes	no
Individual FE	yes	yes	no	no	yes
Household FE	no	yes	no	yes	no
Year FE	yes	yes	yes	yes	yes
No. of observations	2,702,648	2,702,648	2,702,648	2,702,648	2,702,648

Notes: The sample consists of full-time workers. All specifications include the following controls: a gender and child interaction term, marital status, job tenure in linear and squared form, number of workers in the firm, average age of workers at the firm, as well as year controls. Log wage is instrumented using the average wage of similar workers of the same firm. The first stage results are available from the authors upon request. MCC is estimated using the ratio of the marginal effect of commuting distance on job mobility and the marginal effect of log wage on job mobility, see equation (5). Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B Marginal effect of distance on commuting time

We use the Danish National Travel Survey (NTS) to estimate the marginal effect of distance on commuting time. The NTS provides information on the travel behavior of randomly selected individuals who fill out a one-day travel diary. Information is collected continuously throughout the year. We use NTS for the years 2006-2019 and select individuals (18-70 years old) who report commuting trips and exclude observations with missing information and observations for which the one-way commuting distance exceeds 108 km (99 percentile), the one-way commuting time exceeds 95 minutes (99 percentile), or the average commuting speed is below 3.6 km/h (1 percentile) or above 79.5 km/h (99 percentile). Given these selection criteria, we exclude 6.7% of commuting trips. Our final sample includes 81,577 commuting trips.

Table B.1 provides descriptives. On average, the one-way commuting time is 21 minutes, the one-way commuting distance is about 14 km and the speed is 36 km/h. The mean inverse speed is 0.045. The most popular commuting mode is the car (65%), while only 9% of workers commute with public transport. Bicycle use is very common: more than 29% of workers commute by bicycle. For the sample of workers between 25-45 years, which is the relevant population for our paper, the descriptive statistics are almost identical.

Table B.1: Descriptive statistics for Danish national travel survey

	All commuters		Comm. 25-45 years	
	Mean	Std. dev.	Mean	Std. dev.
Trip length (km)	14.20	15.40	14.60	15.58
Trip time (minutes)	21.35	16.51	21.73	16.44
Trip speed (km/h)	35.82	20.03	36.35	20.12
Trip inverse speed (h/km)	0.045	0.040	0.043	0.038
Car (share)	0.65	0.48	0.65	0.48
Public transport (share)	0.09	0.20	0.09	0.29
Walking (share)	0.04	0.04	0.04	0.19
Bicycle (share)	0.21	0.41	0.22	0.41
Male (share)	0.49	0.50	0.49	0.50
Age (year)	43.43	12.08	36.50	5.77
Number of obs. (commuting trips)	81,577		37,524	

According to the speed literature, the effect of distance on travel time is diminishing, because the marginal increase in travel time is less for longer distances, see, for example, Couture et al. (2018). In line with that, when we regress travel time on travel distance, we use a log-log specification, see Table B.2. In the first model [1], we find a coefficient of 0.58, slightly higher than the value reported for the United Kingdom by Van Ommeren and Dargay (2006). When we estimate the models for the sample of workers between 25-45 years, the estimated coefficients are almost identical, see column [2]. Finally, we re-estimate the latter model separately for women and men, see columns [3] and [4]. Again it appears that the coefficient is about 0.58.

Table B.2: Travel distance and travel time

	All commuters	Commuters 25-45 years		
			Man	Woman
Dep. variable	log(time)	log(time)	log(time)	log(time)
	[1]	[2]	[3]	[4]
log(distance)	0.5792***	0.5846***	0.5945***	0.5771***
	(0.0013)	0.0019	(0.0027)	(0.0027)
const.	-2.5231***	-2.5354***	-2.5755***	-2.5028***
	(0.0030)	0.0045	(0.0066)	(0.0062)
R-squared	0.7197	0.7200	0.7316	0.7086
Number of obs.	81,577	37,524	18,443	19,081

Notes: Standard errors are in parentheses, *** $p < 0.01$.

We are interested in the marginal effect of commuting distance (measured in km) on commuting time (measured in hours). Given a log-log specification, the average marginal effect is equal to the product of the estimated coefficient and the average inverse speed (the ratio of travel time and travel distance). Given an estimate of 0.58 (see Table B.2) and an average inverse speed of about 0.045 and 0.043 respectively (see Table B.1), it appears that the mean marginal effect is 0.026 for the full sample and 0.025 for the sample of commuters 25-45 years, receptively.

C Functional Form

Table C.1: Linear probability job mobility model

	[1] Overall	[2] Women no child	[3] Women child	[4] Men no child	[5] Men child	[6] Polynomial
Spline						
<10km	0.0013***	-0.0003	0.0037***	0.0007	0.0017***	
	(0.0002)	(0.0006)	(0.0004)	(0.0006)	(0.0005)	
10km-30km	0.0010***	0.0002	0.0024***	0.0005**	0.0010***	
	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	
30km-50km	0.0011***	0.0024***	0.0024***	-0.0000	0.0004	
	(0.0002)	(0.0006)	(0.0005)	(0.0005)	(0.0004)	
Polynomial						
distance						0.0012***
						(0.0004)
distance^2						-0.0001
						(0.00002)
distance^3						0.0000001
						(0.0000003)
Number of obs.	2,507,138	353,792	907,456	403,204	842,686	2,507,138
F test for spline	0.47	6.29	3.05	0.41	0.70	
R^2	0.054	0.084	0.069	0.067	0.057	0.054

Notes: The sample consists of full-time workers. All specifications include the following controls: a gender and child interaction term, marital status, job tenure in linear and squared form, number of workers in the firm, average age of workers at the firm, as well as year controls. Log wage is instrumented using the average wage of similar workers of the same firm. The first stage results are available from the authors upon request. MCC is estimated using the ratio of the marginal effect of commuting distance on job mobility and the marginal effect of log wage on job mobility, see equation (5). Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.