

Motherhood and the Gender Productivity Gap*

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April 28, 2022

Abstract

Using Danish matched employer-employee data, I compare the relative pay of men and women to their relative productivity as measured by production function estimation. I find that the gender “productivity gap” is 8 percent, implying that almost two thirds of the residual gender wage gap is due to productivity differences between men and women. Motherhood plays an important role, yet it also reveals a puzzle: the pay gap for mothers is entirely explained by productivity, whereas the gap for non-mothers is not. In addition, the decoupling of pay and productivity for women without children happens during their prime-child bearing years. These estimates are robust to a variety of specifications for the impact of observables on productivity, and robust to accounting for endogenous sorting of women into less productive firms using a control-function approach. This paper also provides estimates of the productivity gap across industries and occupations, finding the same general patterns for mothers compared to women without children within these subgroups.

JEL Classification: J71, J31, J24

Keywords: Discrimination, Wage Gap, Labor Productivity

*Thank you to my advisor, Matthew Notowidigdo, and my committee members Lori Beaman and Jon Guryan for their very helpful advice and comments. I also thank David Berger, Stéphane Bonhomme, Matthias Doepke, Steven Durlauf, Martin Eichenbaum, Trevor Gallen, Brent Hickman, Jeff Grogger, Rune Vammen Lesner, John List, Lee Lockwood, Casey Mulligan, Seema Jayachandran, Rune Vejlin and participants at the Northwestern Applied Micro Reading Group and Applied Micro Seminar, ASU, Berkeley, the Chicago Federal Reserve, Conference on Labour Market Models and their Implications, Cornell, CeMENT, Harris School, H2D2 conference, DePaul, Duke, Nordic Data Workshop in Oslo, Purdue University, Stanford, UIC, and UIUC LER for helpful comments and discussions. Thank you to Henning Bunzel and LMDG, Department of Economics and Business, Aarhus University for access to the data. LMDG is a Dale T. Mortensen Visiting Niels Bohr professorship project sponsored by the Danish National Research Foundation. All mistakes are my own.

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1 Introduction

Women earn less than men and much of the gender wage gap has recently been attributed to motherhood (Angelov et al. [2016], Kleven et al. [2018]). This paper asks how much of the wage gap between men and women, and particularly between men and women with children, is explained by measurable productivity differences. Using Danish administrative data, I study how firm output varies with the gender and parenthood status of employees. I find that about 8 percentage points of the 12 percent (residual) gender pay gap can be explained by productivity differences between men and women. Productivity explains the entire pay gap associated with motherhood.

To measure the productivity gap, I use Danish data that matches worker characteristics with firm accounting information. I estimate a firm-level production function that takes labor, material goods, and capital as inputs and treats male and female labor units as perfect substitutes. The gender productivity gap is the number of efficiency units lost if a worker is female, holding other variables such as age, education, experience, and hours worked constant.

I find a sizable productivity gap of eight percent. However, this average masks differences between women over the lifecycle, particularly differences for mothers compared to non-mothers. For mothers, I find that the earnings gap is approximately equal to the productivity gap, suggesting that there is little or no discrimination in the form of uncompensated output against mothers. This is consistent with the literature arguing that the wage gap occurs primarily for women with children who work fewer and more flexible hours than their male counterparts (see for example Goldin [2014], Gicheva [2013], Angelov et al. [2016], and Kleven et al. [2018]) and that there may be some output loss associated with these work arrangements.

At the same time, there is evidence of uncompensated productivity among women without children. Although the wage gap is smaller for women without children, women without children are actually more productive than similarly aged men. In addition, I find that the disparity between wages and productivity for non-mothers happens especially during their prime child-bearing ages. After age 40, there are no meaningful differences in the relative productivity of mothers and non-mothers. Discrimination, then, is largest in the group with a smaller residual pay gap: young non-mothers¹.

¹Here I label differences between average pay and average productivity by gender/parenthood “discrimination,” as the wage gap literature often does. These differences between pay and productivity by gender/parenthood

This age path suggests that the pay gap between men and women without children but of childbearing age is due to statistical discrimination: if productivity falls with motherhood but employers cannot lower wages when women give birth, then employers may offer lower wages to productive women in anticipation of motherhood. I find mixed evidence for this hypothesis. Wages for women who have no children but will have children in the next three years are slightly lower than wages of women who have no children and will not have children soon, but the productivity of the former group is higher than the latter. However, I do not find a larger gap between pay and productivity for married or cohabiting women compared to single women without children (compared to men) even though marital status is a potential signal of the probability of children in the near future.

I present estimates of the productivity gap in the cross-section, over time, by industry, and accounting for selection of workforce composition based on unobservables using a control function approach which I discuss in Section 3. The control function approach does not change the overall estimate of the relative productivity of men compared to women. Consistent with the small role for selection in estimating relative productivity via the production function, using a wage decomposition as in Card et al. [2016], I also find no evidence that women work in lower wage firms within this subset of relatively large, private sector Danish firms.

This paper is the first to link parenthood by gender to productivity measures. The literature on the gender pay gap is extensive (see Altonji and Blank [1999], Olivetti and Petrongolo [2016], and Blau and Kahn [2017] for an overview) and recently has turned to understanding the role of motherhood². Whether mothers' lower pay reflects preferences or discrimination is an important unanswered question. In the Danish setting, Kleven et al. [2018] use an event study around the time of childbirth and find that mothers (relative to fathers) experience a permanent and substantial decrease in earnings growth explained in equal parts by a reduction in LFP, hours worked, and in wage rates. The authors find that the role of motherhood in explaining the wage gap has doubled since the 1980s. I study the importance of productivity difference between mothers and other workers as a potential explanation of the pay gap. The results suggest that

could arise from gender differences in worker preferences, for structural reasons, or due to firm-level statistical or taste-based discrimination.

²Mulligan and Rubinstein [2008] study the changing nature of female selection into the labor force from the 1970s to the 1990s finding that most of the apparent narrowing of the gender wage gap resulted from compositional changes in the female labor force. Since the 1990s, however, the gap has stagnated even as women's education relative to men's has increased leading to an interest in understanding what the "final" sources of the pay gap are (Goldin [2014], Blau and Kahn [2017])

while mothers indeed are paid less than similarly skilled men, this difference in pay is completely explained by productivity differences.

The literature linking relative productivity to relative pay was started by Hellerstein et al. [1999] which studies the relationship between wage gaps and gaps in marginal product for a variety of observable characteristics in the manufacturing industry in 1990. The authors find that with the exception of gender, differences in wages based on observables are equal to differences in marginal productivity. This paper differs from Hellerstein et al. [1999] primarily by introducing data on motherhood and its relationship to the productivity gap. This paper additionally builds on the work of Hellerstein et al. [1999] by using more recent data which cover a wider set of industries, and incorporates detailed differences in the occupations held by men and women in estimates of the productivity gap. As discussed by Blau [1977], and revisited in the case of the US by Blau and Kahn [2017] and in the case of Denmark by Gallen et al. [2017], an important component of the pay gap is occupation choice.³ Women may prefer working in low-wage occupations because these jobs allow fewer and more flexible hours [Goldin, 2014, Wasserman, 2017]. Conditional on occupation choice, this paper investigates whether and where gaps in productivity emerge. In addition, this paper incorporates the role of sorting based on firm unobservables using the Olley and Pakes [1996] control function approach. Card et al. [2016] find that men and women work in different firms in Portugal. This paper investigates the degree to which this is true in Denmark and empirically corrects estimates for the potential role of selection by women into less productive firms. I do not find evidence of sorting by women into lower-pay firms (controlling for individual effects) and accounting for sorting does not affect my estimates of the productivity gap.

In the same spirit as this study, Azmat and Ferrer [2017] document the difference between hours billed and new clients brought in to the firm for male vs. female lawyers. They find

³There is a large body of literature documenting the differences between women and men which may explain the gender wage gap, but are more subtle than differences in human capital accumulation, child-rearing, and occupational choice. As reviewed by Niederle and Vesterlund [2011], women have been documented in both the lab and the field to be less competitive than men, conditional on performance. This competitiveness factor has been studied extensively in recent years. See for example Bertrand [2011], Croson and Gneezy [2009], Flory et al. [2015], Buser et al. [2014], Apesteguia et al. [2012], Markussen et al. [2014], Kamas and Preston [2012], Berge et al. [2015], Zhang [2015], and Reuben et al. [2015]. Gneezy et al. [2009] argue that this link between gender and competition is reversed in a matrilineal society, implying that most of the link is driven by cultural rather than biological differences between men and women. Ichino and Moretti [2009] and Rockoff and Herrmann [2012] debate whether women are differentially absent from work due to menstruation. Small biological difference may turn into large differences in career pathways when mediated by social norms (see for example Fryer and Levitt [2010] and Bursztyn et al. [2017]).

that the large differences in the earnings of male and female lawyers (particularly mothers) are largely explained by these measures of productivity. A recent paper, Cook et al. [2018], studies the choices and experience profiles of men compared to women which explain the 7% gender pay gap among ride-share drivers. The pay of ride-share drivers is set by an algorithm, so they are studying a setting in which taste-based discrimination is not possible. These occupations—law and ride-share driving are interesting but somewhat specific and it is not possible to make conclusions about the economy overall.

The main contribution of this paper relative to Hellerstein et al. [1999] is a deeper probing of the role of motherhood.⁴ In fact, this paper is the first to investigate the role of motherhood in driving the gender productivity gap using production function estimation. This has important implications for a literature which is increasingly focused on motherhood as an important turning point in the careers of women (Kleven et al. [2018], Angelov et al. [2016]). The role of motherhood in explaining the gender productivity gap not only confirms that motherhood is associated with changes in the work women do, but also highlights a new problem: why are non-mothers still underpaid compared to men?

Before discussing the data and methods, I will highlight the past work on gender differences in pay to which this paper speaks. In general, women’s wages may be lower than men’s both due to statistical discrimination (if they are indeed less productive than men on average) as described in Aigner and Cain [1977] or due to taste-based discrimination⁵ as described in Becker [1971]. Gunderson [1989] discuss the very different policy implications of statistical and taste-based discrimination. I focus on identifying one particular type of phenomenon: gender differences in pay unexplained by differences in output. Such a gap would occur if, for example, women did not bargain as well as men for raises (for evidence, see a survey by Babcock and Laschever [2003] who find that women are 50 percentage points less likely than men to negotiate their starting salaries or Leibbrandt and List [2015] for field evidence). Another possibility would be that firms did not pass improvements in productivity on to female employees as much as male employees, as Black and Strahan [2001] demonstrate is the case for banks during a period with

⁴The discussion of why motherhood might be associated with different career choices for men relative to women has a long history. Decades ago, Becker [Becker, 1985] hypothesized that differences in demands on or abilities of women in the home production sector translate to differences in career choice. Hersch and Stratton [1997] provide early evidence of the effect of housework on market wages. The importance of finding flexible work arrangements to accommodate childrearing is emphasized in Goldin [2014] and Blau and Kahn [2013].

⁵For evidence of taste-based discrimination, see Weber and Zulehner [2014], Hellerstein et al. [2002], Heyman et al. [2013], Pan [2015], and Goldin and Rouse [2000]

heavy barriers to entry and as suggested in Card et al. [2016] in the case of Portugal. This leaves out many important potential drivers of the labor market differences between men and women. For example, if women are not offered jobs at high productivity firms, or if women are not invested in or offered promotions despite being equally able to work in more demanding jobs (see for example Thomas [2015], Stearns [2017], Albrecht et al. [2015], and Albrecht et al. [2003]). This “mommy tracking” is difficult to distinguish from preferences, but may occur if many firms have a distaste for hiring women, or if firms are sufficiently risk averse and the distribution of female productivity differs from that of male productivity. Hiring/promotion based discrimination, both interesting and important, is not addressed here. Instead, I focus exclusively on the link between realized output and pay.

The paper proceeds as follows: Section 2 describes the data used in estimation. Section 3 provides the model and estimating equations. Section 4 presents results and Section 5 concludes.

2 Data

The data used in this paper are from three primary sources: a relatively new Danish register on employees called eIncome, a more commonly used Danish register on employees called IDA, and a detailed survey of firm accounts, called Regnskabsstatistikken (abbreviated FIRE). eIncome is register data covering all employees working in Denmark, from 2008. The data is reported monthly, by all employers to the Danish Customs and Tax Administration, who pass the data to Statistics Denmark’s eIncome Register to be used in calculation of national statistics at the monthly level. The primary advantage of this dataset is that it reports work by all employees in a given firm: their occupation, total pay for that month, and total hours worked in the month (as well as the dates of employment).

This dataset is distinct from the commonly used Danish IDA dataset, which is annual and has data on payments and hours based on the worker’s status in November of that year. The hugely improved hours variables in eIncome shrink the wage gap considerably. In particular, the gap falls from 16% to 10%. The main improvement is better tracking of workers who are not continuously employed in a firm and enter and exit the data only for a few months. In the IDA dataset, using bracketed hours worked and a November employment measure it is difficult to properly assign total hours worked at a given firm. Bracketing alone accounts for a two percentage point increase in the pay gap. Of course, there is some non-response even

in the eIncome dataset—about 15% of the hours data is imputed. All employees are included regardless of hours worked. Main jobs and side jobs are included. Employees who are not residents of Denmark are included. If an employee doesn't have pay for up to 45 days at a job, but subsequently returns to the same employer for pay (for example for training), he or she is included in the data for the months without pay.

The hours worked measure in IDA is based on employee contributions to retirement benefits. The brackets are four bins of weekly hours (0-8, 9-17, 18-27, 27+) or four bins of monthly hours, (0-38, 39-77, 78-116, 117+). The data also measure the fraction of the year worked. There is a large fraction of workers whose hours are not distinguished from one another but may in reality differ substantially. eIncome is not completely immune to this problem, though it is certainly less severe. In eIncome, salaried workers would be listed as working 37 hours a week, unless they clocked in overtime hours. Many likely do not, and work slightly less or slightly more than 37 hours per week. There is no reason to think this is orthogonal to gender—women work fewer hours on the margins we can measure, they may also work fewer hours on the margins we have more difficulty measuring. Indeed US time-use data (the American Time Use Survey) suggests that conditional on working full-time, mothers of older children work about one hour less per day than fathers and mothers of young children work about 40 minutes less per day than fathers.

The eIncome register can be linked with data on firm value added using a dataset called FIRE which contains information on firm accounts. The FIRE employer data is the basis for national accounts. As in Baggar, Christiansen, and Mortensen (2014), I follow the methodology for constructing value added and capital stock used in national accounting. The details of this procedure exactly follow Baggar, Christiansen, and Mortensen (2014) and are discussed in the data appendix. FIRE includes information on firms from tax records (such as revenue and the value of capital) and also contains detailed accounting measures from survey. Firms are surveyed based on size. Firms with more than 50 employees are surveyed annually, firms with 20-49 employees are surveyed every other year, firms with 10-19 employees are surveyed every 5th year, and firms with 5-9 employees are surveyed every 10th year.

Firms which are not in the survey in a given year have some of their information imputed into the dataset, though much of the imputation comes from tax records. Detailed information on the cost of intermediate goods, however, is completely imputed for a large fraction of firms in the data. My measure of value added is revenue less the cost of these intermediate inputs so

the measurement error generated by using imputed values is on the left hand side and does not systematically bias results. When information is imputed, it is based on industry-level averages weighted by employment and revenue. In the results reported, I use all data which was not completely imputed (that is, data taken from tax records combined with survey results). About 9,000 firms are actually surveyed in each year ⁶.

To supplement the worker-level information available in the income registers merged with FIRE—which is essentially occupation, hours worked, wages, and industry—I add demographic information on workers from IDA. This includes information on the birthdate of all children, year of marriage, education including major, age, and experience (which is constructed as the sum of hours worked in the labor market according to IDA).

2.1 Summary statistics

The earnings gap in Denmark is surprisingly similar to the gap in the US. Table 1 below provides estimates of the earnings gap in the US from Goldin [2014] compared to a similar population in Denmark and compared to my restricted sample of large industries in the FIRE database. The raw earnings gap is smaller in Denmark than in the US but it also is less explained by controlling for hours, education, and occupation. The smaller raw gap is consistent with Blau and Kahn [2003] who find that countries with more compressed wage distributions (such as Denmark) have smaller wage gaps.

The Denmark and US samples are restricted to ages 25-64. In Denmark, the raw gap is 27.7 log points, compared with 32 log points in the US. Controlling for age, hours worked, education, and occupation, the gap falls to 17.2 log points, compared with 19.1 log points in the US. The R-squared from the last wage regression in the US is about twenty percentage points lower than in Denmark. The lower R-squared in the US may reflect noise expected from survey data. Another explanation for the difference in the explanatory power of observables across countries may be that Denmark has a more compressed wage distribution (so there is less wage variation to explain). In addition, unions and collective bargaining determine wages to a greater extent in Denmark than the US. However, collective bargaining has become increasingly decentralized

⁶Restricting only to the set of firms surveyed in detail about their accounts, I estimate the relative productivity of women is 0.94, which is about 1-2 percentage points higher than my baseline estimates and not a statistically significant difference. The cost of using only firms that were actually surveyed is that I would not have power to study differences across industries, across occupation, by age, etc.

and wage dispersion has commensurately increased (Dahl et al. [2013]). In 2000, only 15% of the population has wages determined completely by collective bargaining, with no firm negotiation. In contrast, over the 1990s, the fraction whose wages are set completely outside the collective bargaining system grew from 5 to 20 percent. For the remainder of workers, collective bargaining sets minimum wages which are binding only for relatively low-skilled workers. For these workers, wage increases resulting from collective bargaining are determined by tenure and education (see Dahl et al. [2013] for a detailed description the these patterns and of wage bargaining in Denmark).

One advantage of the Danish register data compared with the American Community Survey survey in the US is that it provides information on the experience of a worker and also on the firm ID of the worker. Earnings may depend on experience (and women who take time off work to have children may have a different level of experience than men on the same age). Manning and Robinson [2004] argue that this difference in experience explains much of the gender pay gap in the British Household Panel Survey. Earnings may also vary by firm for observationally identical workers. This may reflect differences in non-wage compensation at different firms and in the presence of gender sorting may explain some of the earnings gap. In Table 2 below, I report the results of a regression of log earnings on hours, a quadratic in age, and sequentially add controls for 1. a quadratic in experience and education level dummies, 2. occupation and industry fixed effects (at the 3-digit ISCO level and the 2-digit NACE level, respectively), and 3. the interaction of firm fixed effects and occupation fixed effects.

Adding controls available with the rich Danish data, such as experience and occupation only causes the wage gap to fall slightly. Adding firm and occupation interactions and identifying the earnings gap using differences in the pay of women and men within a firm in a given occupation narrows the earnings gap to just under 12 percent on average in the years 2000-2011.

I focus my analysis on the six industries (measured at the two digit level) which have the largest number of firm-year observations in the FIRE database: Accommodation and food services, Construction, Manufacturing, Wholesale and retail trade, Other community, social and personal services, and Real estate, renting, and business activities. These make up more than 50 percent of the Danish economy⁷ and 98% of non-imputed firm-year observations. Table 3 below provides some summary statistics for the firms in each industry and the dataset overall.

⁷Measured by 2010 gross value added by industry tables available from Statistics-Denmark.

The wage gap varies by industry, ranging from 11%-19%. The fraction of the workforce in a given industry which is male also varies. In construction, a very large fraction of the labor force is male, while in other services, only half of workers are male. Notably, this study of productivity differences is focused on industries with relatively more men than average. Because there are no accounting statistics for public sector firms, this large portion of the Danish economy (and place of employment for women, disproportionately) is omitted from the analysis. The potential biases from this omission will be discussed in the next section.

3 Model and Estimation

The goal of this paper is to understand whether differences in the productivity of men and women, conditional on a set of observable characteristics, explains differences in the wages of men and women, conditional on the same set of observable characteristics. To answer this question, I estimate production functions assuming output is affected by the quantity of capital, the quantity of intermediate inputs, and the quantity of labor. Labor will be the sum of male and female labor, where I allow a unit of female labor to be more or less productive than a unit of male labor

$$\mathcal{L} = \beta L^F + L^M$$

Firms take these inputs and produce using some function F .

$$Y_{jt} = A_{jt}F(\mathcal{L}_{jt}, K_{jt}, M_{jt})$$

β measures the labor-preserving tradeoff between men and women: a $\beta < 1$ implies that women are less productive than men and $\beta > 1$ implies that women are more productive than men. Estimating this parameter, β , is the focus of this paper. I discuss the details of this function F in subsection 4.2. First, I discuss the measurement of labor.

3.1 Measuring labor inputs

As first noted in Griliches [1957] and more recently Fox and Smeets [2011], there is a difficulty in measuring the quantity of labor a firm has: an individual with a college degree produces more than an individual with primary school; an executive (likely) produces more than a janitor.

When measuring the labor a firm has access to, one must account for the *quality* of that labor. There are a number of possible ways to account for the quality of labor, which I discuss below.

My baseline specification relies on constructing efficiency units of labor from the market-wide male wage equation. In construction of the efficiency units, I assume that a woman with the same characteristics as a man would have the same returns to those characteristics, and attribute any deviation from this to gender-based productivity differences. I control for the quality of various characteristics by running an efficiency units regression on the subsample of male workers in the data of the form

$$\begin{aligned} \ln e_{it}^M = & \alpha^M + \gamma_1^M Age_{it} + \gamma_2^M Age_{it}^2 + \gamma_3^M Exp_{it} + \gamma_4^M Exp_{it}^2 + \gamma_5^M HS_{it} + \gamma_6^M Col_{it} + \gamma_7^M BA_{it} + \\ & + \sum_{j=1}^{4xx} \delta_j^M H_{it}^j + \sum_{o=1}^{NOCC} \omega_o^M \mathbf{1}\{OCC = o\}_{it} + \sum_{t=2000}^{2010} \phi_t^M Year_t + \varepsilon_{it} \end{aligned} \quad (1)$$

where e_{it}^M is male worker i 's labor market earnings in year t . Age , Exp , HS , Col , and BA measure a worker's age, hours of experience in the labor market, whether the worker has a high school or less, some college or trade school, or further education, respectively. The efficiency units regression also includes indicators of a worker's occupation at the three digit ISCO level, and year fixed effects. In this baseline specification, the amount of male labor in the firm J at time t is

$$L_{J(t)}^M = \sum_{i \in J(t), M} \widehat{e}_{it}^M$$

Like male labor in the firm, female labor is also measured using the returns to age, experience, occupation, education, and hours from the male wage equation (1), so that the amount of female labor in firm J at time t is

$$L_{J(t)}^F = \sum_{i \in J(t), F} \widehat{e}_{it}^M$$

Whether these characteristics are truly paid their marginal product is an interesting and potentially important question. Men in a given firm will on average be older than women in that firm. If younger workers are systematically underpaid, that will affect the interpretation of the gender productivity gap. The literature is not conclusive on this issue⁸, but I estimate the

⁸For example, Hellerstein et al. [1999] find a discrepancy between wage and marginal product only for gender. Dostie [2011] uses more age categories and finds on average concave wage and productivity profiles, where wages

gender productivity gap by age bins which should alleviate this concern.

I also consider more detailed estimates of efficiency units—using eIncome data gives a finer measure of hours, and I allow for the interaction of occupation with industry and year in the calculation of efficiency units. Finally, eIncome includes monthly earnings based on both “take-home” pay (the narrow earnings definition) and earnings including benefits such as contributions to retirement accounts⁹. I use this broad definition of earnings when constructing efficiency units as a robustness check. If high-skilled men preferred to be paid retirement contributions rather than having money in the bank, then my efficiency units calculations would understate the returns to skill specifically for men. More generally, differences between the wage gaps using the two measures of income are potentially important for understanding the potential role for non-pecuniary benefits in generating wage differences.

An alternative specification of the labor units in a firm follows the Griliches [1957] method which has

$$\mathcal{L} = L \left[1 + (\phi_F - 1) \frac{F}{L} \right] \cdot \left[1 + (\phi_R - 1) \frac{R}{L} \right] \cdot \left[1 + (\phi_P - 1) \frac{P}{L} + (\phi_O - 1) \frac{O}{L} \right] \cdot \left[1 + (\phi_N - 1) \frac{N}{L} + (\phi_S - 1) \frac{S}{L} + (\phi_C - 1) \frac{C}{L} \right] \quad (2)$$

where F is the number of female workers, R is the number of married workers, G is the number of college workers, P is the number of 35-54 year old workers, O is the number of workers 55 and older, N is the number of unskilled laborers, S is the white collar, technical, and sales workers, and C are the number of high skilled workers. This categorization is (exactly) used in Hellerstein et al. [1999]¹⁰ to capture the quality of a firm’s labor force. ϕ_F is then equivalent to β as a measure of the productivity difference between a unit of female labor and male labor, accounting for differences in age, marital status, education, and occupation. Both methods assume that workers of different ages, occupations, etc. are perfect substitutes and that observable characteristics factor multiplicatively into productivity. The advantage of Equation (1) is that I can account more flexibly for returns to age, experience, hours worked, and occupation (rather

do not deviate significantly from productivity. However, Hellerstein and Neumark [2007] finds some evidence that wages are deferred over the life cycle.

⁹Other included benefits are the value of a free full-year of residence, the value of free summer residence, the value of a free pleasure boat, the value of a free TV license, the value of a free phone, the value of a PC, anniversary and severance pay, bonus income, and the value of “other” employee benefits as reported by the firm.

¹⁰They also had a category for Black workers which I omit in the context of Denmark.

than using large discrete bins), and this flexibility ties estimates directly to traditional estimates of the residual wage gap—I am able to measure the residual productivity gap accounting for the same differences in observables commonly used when measuring the residual wage gap. I discuss this in more detail in the next section. Since there are advantages to both methods, I present estimates of the productivity gap using both (1) to predict the labor units in a firm and estimating the production function using labor as in (2).

Fox and Smeets [2011] directly tackle the problem of measuring labor quality in production functions by experimenting with a variety of approaches in Danish data similar to the data I use in this paper. They find that despite the biases associated with measuring the quality of labor using the wage bill, these estimates perform as well as estimates using Griliches-type specifications. In principle, any firm-specific innovations to productivity get passed on to workers in a bargaining setting, so using the wage bill to stand in for labor quality correlates covariates and error terms. Empirically, however this does not seem to be a large source of bias. Using the wage-bill method, labor in the firm is given by $\mathcal{L} = \tilde{\beta}W^F + W^M$ where W^F is the sum of earnings of women employed at the firm and W^M is the sum of earnings of men employed at the firm. The benefit of using the firm’s wage bill method is that one asks whether a dollar paid to a man is as productive as a dollar paid to a woman, and one does not need to take a stand on how to model differences in returns to observables—they may differ and this is all summarized in wage differences. Here I distinguish between β in the baseline specification, which does not include wage discrimination by construction, and $\tilde{\beta}$ in this specification. A discriminatory firm which pays a woman less for the same output would result in a coefficient $\tilde{\beta}$ greater than 1.

A final possibility for measuring labor quality (also discussed in Fox and Smeets [2011]) is to take an ability-perspective: an AKM-decomposition of worker’s wages yields estimates of worker fixed effects and firm fixed effects. The worker fixed effects measure the ability of workers as rewarded by firms but take out everything that is constant within a firm over time (including firm productivity). So long as innovations in firm productivity are not predictive of worker moves (which is not an innocuous assumption), worker effects capture a worker’s underlying ability regardless of the firm employing him. Another benefit of using person effects as a stand-in for labor quality is that if women prefer front-loaded pay over their lifecycle, while men prefer back-loaded pay, using the current wage bill or efficiency units regressions from male wages will bias estimates of the productivity gap relative to the pay gap. A life-cycle measure of worker

ability gives an average measure of worker productivity. The form of the AKM decomposition used in this paper is

$$\ln e_{it} = \alpha_i + \theta_j + \sum_{t=2000}^{2010} \phi_t Year_t + \Phi_1 HS_{it} + \Phi_2 Col_{it} + \Phi_3 BA_{it} + \epsilon_{it} \quad (3)$$

so that firm J 's labor in period t is given by $\mathcal{L}_{J(t)} = \tilde{\beta} \sum_{i \in J(t), F} \hat{\alpha}_i + \sum_{i \in J(t), M} \hat{\alpha}_i$

3.2 Production function

In the baseline, I model firm value added (revenue minus the cost of intermediate inputs) as a translog function of labor and capital:

$$\begin{aligned} \log(Y_{jt} - M_{jt}) &= a_{jt} + \theta_i \\ + \sum_{i \in I} \mathbf{1}\{j \in i\} &\cdot (\alpha_{1,i} \log(\mathcal{L}_{jt}) + \alpha_{2,i} \log(K_{jt}) + \alpha_{3,i} \log(\mathcal{L}_{jt})^2 + \alpha_{4,i} \log(\mathcal{L}_{jt}) \log(K_{jt}) + \alpha_{5,i} \log(K_{jt})^2) \end{aligned} \quad (4)$$

where \mathcal{L}_{jt} is a measure of the firm's labor force which is the sum of male and female efficiency units as described above, K_{jt} is firm j 's value of capital stock, and a_{jt} is the log of revenue TFP, excluding industry fixed effects. I allow $\alpha_1, \dots, \alpha_5$ to vary by industry and include industry fixed effects (θ_i) at the NACE 2-digit level.

Profit maximizing firms which take wages as given will set the ratio of the price of labor equal to the ratio of marginal revenue product. In this case, a marginal unit of male or female labor has the same effect on revenue, up to a constant β , so that

$$\frac{w_{jt}^f}{w_{jt}^m} = \beta$$

where w_{jt}^f is the average cost to firm j of hiring an additional unit of female labor at time t and w_{jt}^m is the cost of hiring an additional unit of male labor, controlling for observable differences in the quality of labor which enter the efficiency units calculation (1).

One assumption in the estimation of the relative productivity of female labor, β , is that male and female labor are perfect substitutes. For legal or social reasons, firms may prefer to hire men and women in constant ratios. I relax the assumption of perfect substitutes and estimate

a CES aggregation of male and female labor. In particular I estimate (4) but using

$$\mathcal{L} = (\beta(L^F)^{\frac{\rho-1}{\rho}} + (L^M)^{\frac{\rho-1}{\rho}})^{\frac{\rho}{\rho-1}}$$

where ρ is the elasticity of substitution for labor by gender and L^F, L^M are estimated both in efficiency units and using the wage bill. As $\rho \rightarrow \infty$, men and women become perfect substitutes.

3.3 Selection

A long literature discusses the many problems econometricians have faced when estimating parameters of production functions. As noted by Marschak and Andrews [1944], if labor and capital choices were exogenously assigned, rather than chosen by firms based on productivity, then we could simply estimate (4) assuming a_{jt} is a shock process orthogonal to observed labor and capital. However, any unobserved component of TFP which is known to the firm (such as a firm fixed effect) will affect the optimal choice of labor and capital. This biases estimates of the coefficients on labor and capital $\alpha_1, \dots, \alpha_5$. The purpose of this paper is not to estimate labor and capital shares in Denmark, but rather to estimate the relative marginal product of men compared with women. For this purpose, endogeneity of input choice is not necessarily a problem. If firms hire a man or woman randomly, then β will not be correlated with productivity (or firm size). In some industries, this may be a reasonable approximation of hiring practices. Overall, however, it will be important to deal with the endogeneity of hiring choices. I borrow the classic Olley and Pakes [1996] control function approach to dealing with this endogeneity.

If some portion of A_{jt} is known to firms at the time they make their labor decisions, the labor share coefficients will be biased. If TFP is also correlated with the decision to hire a man relative to a women, this will bias estimates of β . This would be the case, for example, if a firm which anticipated a change in technology which made it more productive preferred to hire men, perhaps because it believed men were better able to work with new technology or because men were more interested in working with the new technology and only men applied for the new jobs. In both cases, if we can control for the unobservable known to the firm at the time they make hiring decisions, then we can control for the role of sorting by gender in the estimation of β .

Following Olley and Pakes [1996], I use investment to control for unobservables known to

the firm at the time they choose \mathcal{L} . The intuition for this control is straightforward: assuming investment has a monotonic relationship with the unobservable component of TFP known to the firm at the time they make their decisions (conditional on capital), then it will be possible to invert the optimal investment rule and use this inverted rule as a control for the unobserved TFP. I describe the assumptions in more detail in Appendix 2.

In this model, a_{jt} has a component which is a shock to the firm after they make labor and investment decisions, and also a known component (ω_t) which is unobservable to the econometrician directly. In other words, we can write $a_{jt} = \omega_{jt} + \varepsilon_{jt}$ where ω_{jt} is known by the firm and affects their optimal labor and investment decision. OP assume that ω_{jt} is a scalar which follows an exogenous first order Markov process—that the distribution $p(\omega_{t+1})$ depends only on the observed ω_{jt} . This assumption allows for simple firm fixed effects $p(\omega_{jt+1}|\omega_{jt}) = p(\omega_{jt+1}|\bar{\omega}_j)$, but is more general [Akerberg et al., 2007]. Conditional on capital, investment is then increasing in the unobservable ω_{jt} so that we can invert the optimal investment rule and write $\omega_{jt} = \phi(i_{jt}, k_{jt})$. I use a 5th-degree polynomial in investment and capital to represent the inverted investment rule. In Appendix 2 I discuss the assumption necessary for validity of a polynomial in investment and capital as a control function in more detail. Key, of course, to this exercise is the monotonicity of the investment in unobservable productivity. When I estimate an OP version of my main specification, I do so by 2-digit industry since the monotonicity assumption is not plausible when comparing across broad industries.

A natural question is: do men and women select into firms with different productivities? In addition to checking for the role of selection using production function estimation, I check for selection using the method outlined in Card et al. [2016]. I estimate the average firm effects for men and women in the sample of connected firms in the data used in the production function estimation (relatively large, private sector firms). I discuss the details of this procedure in Appendix 2. I find that there is no difference in the average firm effects for men compared to women in this subsample.¹¹ This suggests that sorting is unlikely to bias estimates of the relative productivity of men compared to women. Confirming this, I find little evidence of systematic sorting within industries using OP. I discuss these results, as well as the main results, below.

¹¹This contrasts with the role of firm-level sorting in the overall Danish economy. Focusing on an establishment level definition of the firm and including both the private and public sector, Gallen et al. [2017] find that 2.7 percentage points of the log pay gap can be explained by sorting in Denmark in the 2000s.

4 Results

4.1 Estimates of the productivity gap

Table 4 presents my baseline estimates of the relative productivity of women compared to men via the translog production function in (4). I find that one unit of female labor is equal to about .92 units of male labor. The relative productivity of female labor is closer to .94 when using the 2008+ eIncome sample for estimation. This is driven by the better hours measures available in that data, rather than a broader definition of earnings (comparing column 2 to column 3 relative to column 3 and column 4). Columns including non-wage benefits are those which use the full definition of income available in eIncome, including payments to retirement accounts and the value of other non-monetary benefits, such as a computer, home, etc. Finally, detailed efficiency units allow for the interaction of occupation with industry and year in the calculation of efficiency units and use the finest level of education major choice. Using a more detailed definition of efficiency units, the productivity gap falls to just four percent, indicating very little difference between a unit of male labor and a unit of female labor. Note, however, when making efficiency units categories too fine, the interpretation of the productivity gap becomes more confounded with differences in returns to (for example) majors between men and women.

While the efficiency units method summarized in (1) is my preferred specification, I also report alternative specifications of efficiency units of labor. In Table 5, column (1), $\tilde{\beta}$ is the coefficient on the female wage bill, where total labor is measured as the sum of the male wage bill and $\tilde{\beta}$ times the female wage bill in the firm. The interpretation of $\tilde{\beta}$, then, is the productivity of a dollar spent on female labor relative to a dollar spent on male labor. I find that female labor is more productive per dollar, consistent with the evidence in Table 4 which shows a smaller productivity gap than pay gap. The estimates are three percent smaller when using the eIncome dataset (columns 2 and 3) and do not depend on whether non-wage benefits are included in the definition of the wage bill.

Column 4 of Table 5 is the measure of relative productivity using predicted individual fixed-effects from an AKM decomposition of wages as effective labor. Similar to the wage bill measure, the AKM measure of $\tilde{\beta}$ can be interpreted as the relative productivity of a female unit of labor measured in average lifetime wages (rather than current period wages) compared to a male unit of labor. Discrimination in the sense of uncompensated productivity is largest using the AKM

method. The benefit of the AKM method is that if men and women have different preferences for backloading pay over the lifecycle, then the efficiency wage regressions in (1) may be biased. Since the predicted individual fixed effects in this estimate of the production function does not vary with TFP, it does not have the same mechanical bias that is induced when using the wage bill.¹² Column 5 of Table 5 gives the Griliches estimate of the relative productivity of women as estimated in Hellerstein et al. [1999]. The gap is quite small (5 percent), given the coarse categories used in estimation: 3 age bins, 4 occupation bins, married vs. single, and male vs. female. All regressions use a translog production function with 2-digit industry fixed effects and industry-specific coefficients on labor and capital.

To deal with the possibility of selection of women into less (or more) productive firms, I take two approaches. First, I decompose log worker earnings into individual and firm fixed effects, controlling for education, age, and year fixed effects. I use the method outlined in Card et al. [2016] to do this, but focus on the connected subset of my sample of private-sector firms. Separately for the male and female sample, I regress

$$\ln e_{it} = \alpha_i + \phi_{j(i,t)}^{G(i)} + X'_{it}\beta^{G(i)} + r_{it}$$

where $\ln e_{it}$ are the log earnings of worker i at date t , $j(i,t)$ is the id of the firm employing worker i at date t , $G(i)$ indicates gender, and X_{it} is a vector of controls which includes year dummies interacted with education dummies and quadratic and cubic terms in age interacted with education dummies. The difference between firm effects $E(\phi_{j(i,t)}^F|m)$ and $E(\phi_{j(i,t)}^F|f)$ summarizes the degree to which men and women work in firms with different average pay. I find only a 0.005 log point difference between these expressions, suggesting the sorting by gender across private sector firms is not a large factor in the gender pay gap. Nonetheless, I can also use the Olley-Pakes control function approach described in Section 4.3 to account for TFP-based sorting by gender. Including a 5th-order polynomial in investment and capital in equation (4) does not change my estimates, but this may be because the assumptions underlying the OP method are not valid when looking across wide industries.

Turning to a by-2-digit industry application of Olley-Pakes does result in a slightly larger role for selection in some sub-industries. Figure 1 gives a histogram of the difference between the

¹²However, as noted before, Fox and Smeets [2011] argue that the wage bill measure works well for practical purposes, despite this bias.

productivity gap estimated using a translog production function at the 2-digit industry level¹³, and a specification which adds to this production function the OP “control” for unobserved productivity which the firm uses when optimizing its factor choices. The vast majority of my productivity gap estimates do not change when adding the OP control. Interestingly, those that do change move both in the positive and negative direction, suggesting there is some positive sorting of women into more productive firms (this is especially true in manufacturing sub-industries). More generally, women tend to sort into less productive firms, but the magnitude of this is small on average and concentrated in a small number of industries.

Implicit in the production function estimated thus far is an assumption that male and female labor are perfect substitutes. This need not be the case. If firms hire male and female labor in some fixed proportion, then total labor is the CES aggregation of male and female labor in the firm (not the sum). Table 6 gives the coefficient on female labor under a CES specification for total labor. There is a substantial fall in the estimated productivity of women relative to men. Intuitively, the first order condition¹⁴ (which is not used in estimation) would imply that β should fall when the fraction of female labor matters to firms: women are more scarce than men in the labor force, yet they are paid less. The wage bill estimate of discrimination also falls. The elasticity of substitution between male and female labor is between 5 and 10, depending on the specification. These fairly large estimates suggest that perfect substitutes is not an unreasonable assumption.

Next, I explore the source of the gap in productivity between men and women. The literature finds that the wage gap increases over a woman’s life-cycle, markedly rising when she has children, and falling again only after mid-life (Kleven et al. [2018], Goldin [2014]). If mothers take more time off work to care for children (even in ways not measured by register data on hours worked) then we would expect this group to be driving up the productivity gap. If the productivity gap is instead driven by innate differences between men and women, some other factors correlated with gender, or mis-measurement, it would show up both for mothers and for non-mothers. I find that the productivity gap is driven only by mothers. Women without children are as productive as their male counterparts. I expand on this result in the next section.

¹³I also require that the sub-industry have at least 100 observations in the data.

¹⁴The FOC is $\beta \left(\frac{L_{jt}^f}{L_{jt}^m} \right)^{-\frac{1}{\rho}} = \frac{w_t^f}{w_t^m}$.

4.2 Motherhood

Bertrand et al. [2010] find that in a sample of recent US MBA recipients, the gender gap in career disruptions and female preference for shorter work hours was driven largely by mothers. In Denmark, recent work by Kleven et al. [2018] has argued the much of the Danish wage gap occurs with motherhood. This has changed markedly over time. While the presence of children can explain 40% of the gender earnings gap in 1980, children can explain 80% of the gap in 2011. The “child-penalty” comes in the form of (roughly equally) lower labor force participation of mothers, fewer hours of work for mothers, and lower wage rates for mothers. In my sample, I consider only mothers who have selected into work and those who are working in industries with good output data, notably excluding the public sector. For these reasons, I find that motherhood explains less of the earnings gap—women with children are paid 85 cents on the dollar and women without children are paid 90 cents on the dollar compared to men without children. Nonetheless, mothers face the largest earnings gap. This paper is the first to study whether motherhood also affects the difference between earnings and productivity.

Wage gaps don’t only differ across mothers and non-mothers, however. A literature started with Lundberg and Rose [2002] finds that fathers actually earn *higher* wages than non-fathers, controlling for many correlated factors. Using the PSID, Lundberg and Rose [2002] find a wage gap of 4.2 percent for fathers relative to men without children. Fathers also work more hours than men without children. Approximately the same relationship holds in Denmark for fathers compared with non-fathers. Women earn less as mothers and men earn more as fathers, both in Denmark and the US. This result would be implied by a model of household specialization with human capital accumulation (market and non market specific)—on average men invest in their careers to increase household market income and women invest in household production to increase household non-market output.

Register data makes it possible to incorporate whether or not a worker has a child into the estimates of relative productivity. In Figure 2 I plot the wage gap, measured using a wage regression of log earnings on a quadratic in experience, education dummies, industry, occupation, and hours fixed effects, as well as the interaction of parenthood, gender, and age categories in three year intervals. For each age category, I plot the pay of fathers, mothers, and women without children relative to men without children. As expected, the wage gap is largest for mothers and smallest (negative) for fathers in most age bins. Figure 3 plots the productivity

gap for fathers, mothers, and women without children relative to men without children (the productivity analogue of Figure 2). As women move past childbearing age, both the residual productivity and pay of mothers and non-mothers converge¹⁵. However, when women are in their prime childbearing years, mothers are substantially less productive than non-mothers, and non-mothers, fathers, and men without children have approximately the same level of productivity. Women without children are actually more productive than men without children. This is not true of wages: in all age brackets women’s wages are lower than men’s wages.

One channel through which motherhood may affect productivity is a flexibility penalty described in Goldin [2014]. As reported in Appendix Table 14, if I split occupations into above vs. below median flexibility using the Goldin [2014] O*NET classification, I do not find that women are substantially less productive in the most inflexible jobs. In fact, women are substantially less productive in flexible jobs, relative to men and only slightly less productive in inflexible jobs.¹⁶

The age-decomposition by parenthood in Figure 3 suggests that women’s productivity declines substantially when they have children. Selection may be an issue, of course. Many women leave the private sector when they have children in Denmark (Pertold-Gebicka et al. [2016]). Those who shifted from private to public sector within 2 years of child’s birth had about 1/10th a standard deviation less education and made about 10k less in earnings than those who stayed in the private sector, controlling for age and year. This suggests that my estimates are a lower bound of the productivity gap between mothers and non-mothers, since mothers in the private

¹⁵Note that there are strong cohort effects which I do not control for in wage regressions. Older mothers and non-mothers in the sample are from a different cohort than younger mothers and non-mothers. This is not a lifecycle analysis because the level of observation for productivity calculations is the firm, not an individual worker.

¹⁶Goldin [2014] argues that mothers require more flexible hours than non-mothers and that flexible job structure may be less productive, especially in traditionally inflexible occupations. Translating ISCO codes to the (to the extent possible) to the 92 professions in the ACS with flexibility measures from O*NET used in Goldin [2014], I categorize each 4 digit ISCO occupation into being either below median flexibility (for example, chief executives), being above median flexibility (for example, pharmacists), or missing flexibly data. I then estimate the production function in (4) using

$$\mathcal{L}_{jt} = \hat{E}_{j,t,M,inflex} + \beta_{F,nf} \hat{E}_{j,t,F,inflex} + \beta_{M,f} \hat{E}_{j,t,M,flex} + \beta_{F,f} \hat{E}_{j,t,F,flex} + \beta_{M,o} \hat{E}_{j,t,M,o} + \beta_{F,f} \hat{E}_{j,t,F,o} \quad (5)$$

where

$$\hat{E}_{j,t,G,O} = \sum_{i \in j(t), G, occ \in \{O\}} \widehat{e}_{it}^M$$

for person i working in firm j at time t of gender G (M or F) in occupation occ which is in the set of 46 occupations categorized as Flexible (*flex*), 46 occupations categorized as Not-Flexible (*inflex*), or another occupation (o). The results of this exercise are in Appendix Table 14. To summarize, I find that indeed, conditional on working in jobs requiring long, inflexible hours, women are more productive than men (by nearly 40 percent). Conditional on working in hours-flexible jobs, women are less productive than men, also by about 40 percent. In other jobs, women are less productive than men but only by about 10 percent.

sector are positively selected.

The decline in productivity for women with children may affect wages before the children are born. If wages are sticky down, then employers may have limited scope for adjusting wages in response to this 20% productivity decline. The probability of having a child at age 30 is 13.8% in Denmark. Fertility rates are similarly high for all the prime child-bearing years. Suppose, for the purpose of this example, that the length of a wage contract is 4 years. Then employers would want to pay a 28 year old woman 7% less than a man because of risk of childbirth. In other words, taking into account childbearing probabilities, the expected productivity of a 28 year old non-mother over the next four years is seven percent less than her male counterpart's.

If employers are able to somehow predict future childbearing and use this prediction to inform wages even for women without children, then we would expect to see a larger gap between pay and productivity for women who are going to have children in the near future relative to women who are not going to have children in the near future. Of course, some part of this is endogenous: women who are underpaid may decide to have children. As described in Table 7, the data are consistent with statistical discrimination. Women are relatively more productive in the years when they are about to have children, but they are also paid less than other childless women in those years (especially in older age-brackets). The same general pattern hold for men, but the difference between women and men is statistically significant at the ten percent level¹⁷.

Another (less direct) test of whether employer expectations concerning future childbirth are driving the gap between pay and productivity of women without children is whether there is such a gap for women who are not married or cohabiting (and therefore less likely to have children soon). The Danish data contains information on whether a person is married or cohabiting with a partner, so I can perform a decomposition of the productivity gap based on marital status as well as gender. Overall, married/cohabiting childless women's relative productivity gap is higher than the wage gap compared to single women without children, especially when young, but as in Table 8, this difference is not larger than the same difference for men. This is not consistent with a story in which marriage signals to employers that a woman without children is likely to have children very soon. Notably, marriage and cohabitation are by no means perfect predictors of future children: the probability of having her first child in the subsequent four years is 29% for married or cohabiting women without children compared to 5% for single women without

¹⁷Point estimates are extremely noisy at this level, especially in older years when few women and men have their first children within three years.

children. This is also weaker test of statistical discrimination since it is not clear whether employers know a woman’s relationship status at the time they make hiring and wage setting decisions, but nonetheless it casts doubt on the extent of statistical discrimination by employers.

4.3 Estimates by industry and occupation

Estimates of the productivity gap vary widely across industries. Figure 4 plots the OP-estimated productivity gap by 2 digit industry, as well as the wage gap by industry. There is a very slightly positive correlation of 0.02 between the series. A regression of the wage gap on the productivity gap gives a coefficient of 0.115. The distribution of relative productivity is wide both within and across industries, with accommodations and food services as well as other services having generally smaller productivity gaps than manufacturing and construction.

At the 2-digit industry level, all standard errors are close to ten percentage points or more. Aggregating up to larger industry groupings and estimating the productivity gap by industry with 2-digit fixed effects, gives substantially more precise estimates of the productivity gap. I report these results (and associated wage gaps) Table 9. Interestingly, the relationship between the wage gap and the productivity gap for mothers is very strong in all industries other than construction¹⁸: in real estate and renting, other services, wholesale and retail trade, and manufacturing, the wage gap (generally close to 20 percent) is within two percentage points of the productivity gap. In accommodations and food services the gap is closer to three percentage points, while in construction the gap is 7 percentage points.

For women without children compared to men, there is a positive relationship between the pay and productivity gap across industries (the higher the pay gap the higher the productivity gap, excluding construction). The difference between pay and productivity does vary somewhat across industries, ranging from just under twenty percent in real estate and renting, and just over 30 percent in accommodations and food services and construction. Across industries, the difference between pay and productivity of non-mothers is around ten times higher than that for non-mothers.

It is also possible to disaggregate β by occupation¹⁹: Table 10 reports the results of produc-

¹⁸Gender preferences can translate to differences in wages directly via compensating differentials: when risk-taking, physical and otherwise is rewarded and women shy away from risky jobs, they will on average be paid less than men.

¹⁹The role of discrimination and performance for high-level workers has been studied recently using a Norwegian policy change that forced firms to increase the number of women on their boards to 40%. Matsa and Miller [2013]

tion function estimation in (4) when labor is given by

$$\mathcal{L}_{jt} = \sum_{o \in \mathbf{O}} \beta_{F,c}^o \hat{E}_{j(t),F,c}^o + \beta_{F,nc}^o \hat{E}_{j(t),F,nc}^o + \beta_M^o \hat{E}_{j(t),M}^o$$

where $\hat{E}_{j(t),\cdot}^o$ are the sum of efficiency units in firm j estimated *excluding occupation fixed effects* in category \cdot , where these categories are female with children, female without children, and male, respectively. The set of occupations \mathbf{O} is management at the highest level, job requires knowledge at the highest level (from school teachers to researchers), job requires knowledge at the medium level (e.g. tech.), office jobs, sales, service, and care jobs, craftsman jobs, blue collar jobs, military, and agriculture, forestry, fishing requiring basic level knowledge, along with large heterogenous categories unknown and other.²⁰

There is not a strong relationship between the pay and productivity of either mothers or non-mothers across occupations. The relative productivity of women without children is everywhere higher than that of women with children, and generally higher than the productivity of men in the same occupation. However, women seem to be substantially less productive than men in low skilled jobs, without commensurately low pay. These are jobs in which union contracts have the largest influence on wages and retention, which may explain why women appear to be so dramatically over-compensated. Women without children are in every occupation paid less than their relative productivity, while women with children are generally (but not everywhere) over paid.

5 Conclusion

This paper presented estimates of the relative productivity of men and women, accounting for age, education, experience, occupational choice, and hours worked. Overall, I find that

find that firms that increased the number of women on their board in response to this policy change had fewer layoffs than comparison firms in Sweden. This increased their labor costs and reduced short-term profits. This suggests that women at high levels in a company (or the boards that picked them) do have different preferences and management styles than men, on average. It's difficult to generalize the results of this policy change since the women who were newly put on boards differed significantly on observables from women already on boards, as did their companies. It's also not clear that the policy had any long-run effect on the gender wage gap. In recent work, Bertrand et al. [2018] find that this reform did not affect the probability that women enrolled in business programs, changed relative female wages, or affected women's fertility and marital decisions, even though the policy change was tangible and women knew that they would be more likely to be put on a company board in the future.

²⁰In estimation, β_M for the category "unknown" is restricted to be 1 (so all estimates are productivity relative to men in occupations unknown).

the productivity of women is about 8 percent lower than men, controlling for age, education, experience, and hours worked. This implies that productivity differences explains just under two-thirds of the residual gender pay gap. This productivity difference may arise from differences in the effort, extra (undocumented) hours worked, or effectiveness of men relative to women.

While on average, the pay gap is quite close to the productivity gap, this is not true over all of the lifecycle. In particular, women without children are estimated to be as productive if not more productive than men without children, but they are paid less than these men. Mothers, on the other hand, are substantially less productive than fathers and are paid commensurate with this productivity gap. The data provides mixed support for a statistical discrimination mechanism: the gap between productivity and pay for women who are going to have children soon relative to women who are not going to have children soon is significantly larger than the same difference for men. On the other hand, marriage or cohabitation is not a strong predictor of the divergence between pay and productivity.

The results reported above are generally robust to various different specifications of a firms quantity/quality of labor: the baseline estimate uses an efficiency units approach which predicts returns to various observables correlated with gender, another method is to use the wage bill to represent labor quality, another method uses person fixed effects from a wage decomposition, and a final method estimates the relative productivity of various observables directly as inputs in the production function. The results are also robust to using more detailed wage and hours measures (which exist only from 2008 onward). My baseline estimates are robust to controlling for the potential role of sorting by women into less productive firms. Finally, the general pattern that women without children are as productive as men, while mothers are substantially less productive holds across industries and occupations.

Like the wage approach, the productivity approach in this paper implies that motherhood is central to the discussion of the gender pay gap. However, while differences in pay between men and women are largest for mothers, I find that differences in pay which cannot be explained by productivity are largest for women without children. The factors driving the gap between the pay and productivity of women without children (preferences, discrimination, occupation sorting) is an interesting avenue for future research.

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Figures

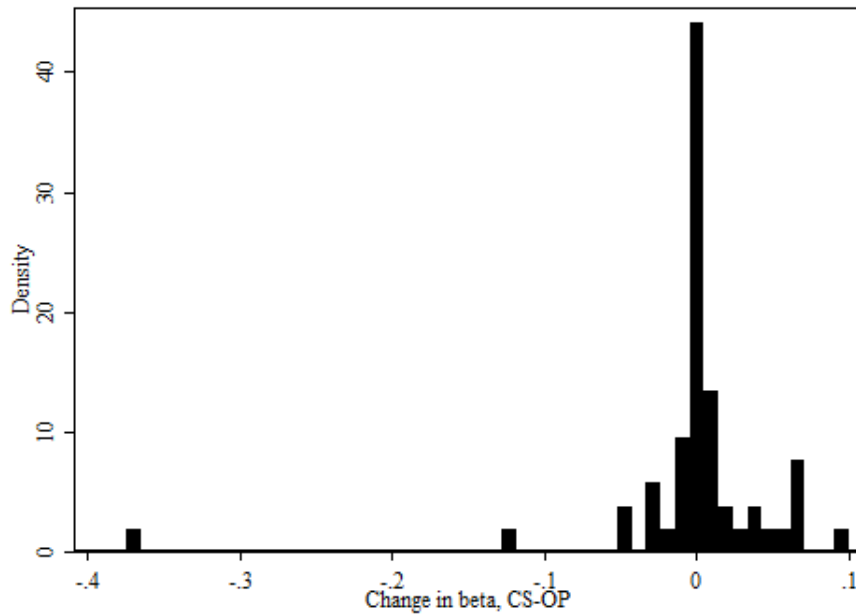


Figure 1: This figure shows the difference between estimates of the productivity gap (by 2-digit NACE industry) with and without the OP control function. Estimates without an OP control function are the coefficients on female labor efficiency units in a translog (in capital and the sum of male and female labor) production function which include detailed industry fixed effects. Estimates with an OP control add a fifth-order polynomial in investment and capital to this production function in order to approximate unobserved productivity known to the firm at the time it makes its labor and investment choices. The difference between the coefficients on female labor in these two production functions captures the role of selection of women into lower TFP-firms in explaining the gap between male and female productivity. I find that in most industries, there is no meaningful selection (captured by a large mass at 0). If there is selection, it is not always negative (though it is more often negative). There are 54 unique sub-industries with at least 100 observations in the data.

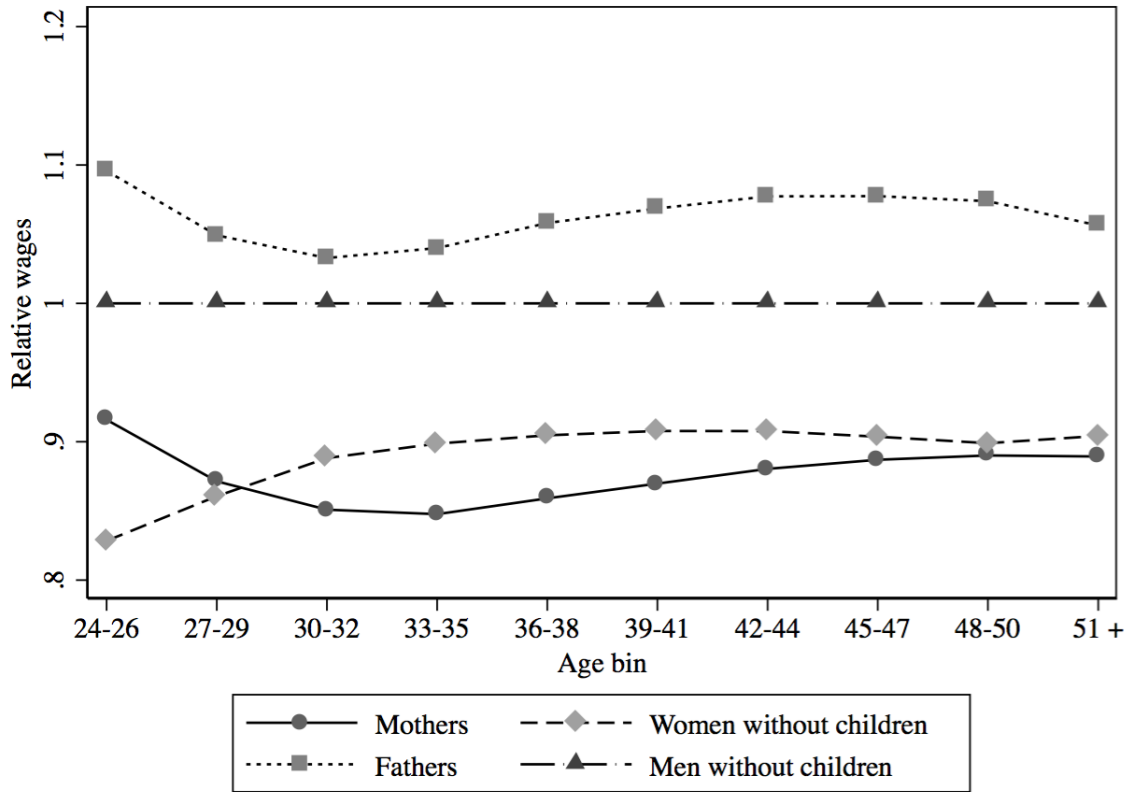


Figure 2: This figure shows the relative wages of women without children compared to men without children of the same age, as well as mothers and fathers compared to men without children of the same age. Relative wages are measured using a wage regression with 2 digit industry fixed effects, 3 education fixed effects, a quadratic in experience, and year fixed effects. For each age category, I normalize the wages relative to those of men without children of the same age.

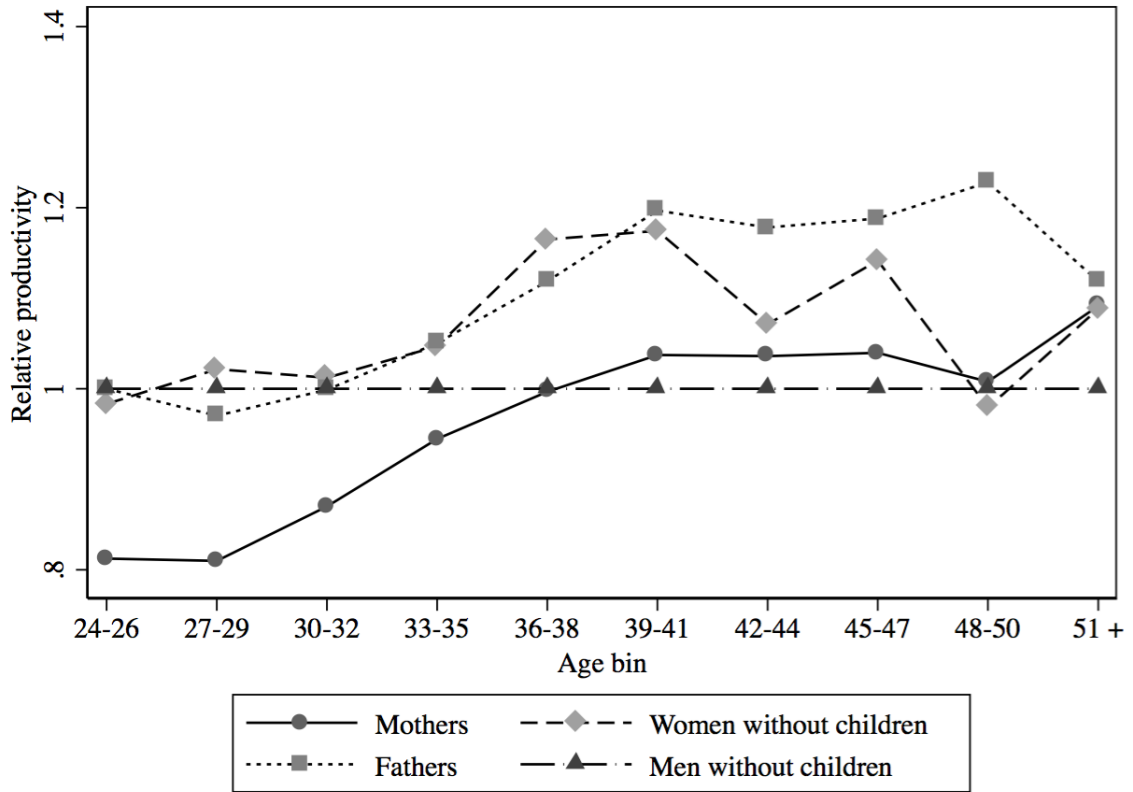


Figure 3: This figure shows the relative productivity of women without children compared to men without children of the same age, as well as mothers and fathers compared to men without children of the same age. Relative productivity is measured using the baseline translog production function with industry specific shares and fixed effects, and the baseline specification for efficiency units but omitting age from the efficiency units. I model efficiency units of the interaction of 12 age bins and 4 gender/parenthood categories as perfect substitutes.

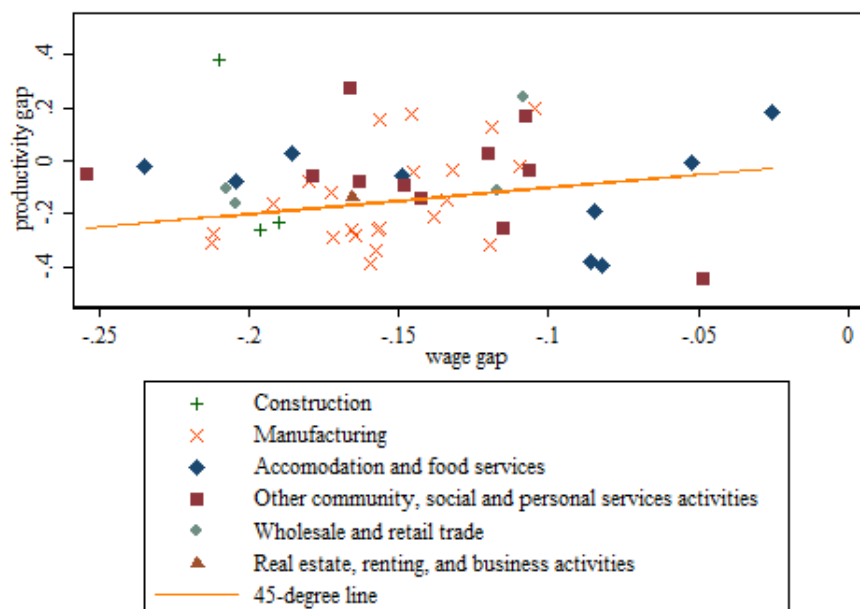


Figure 4: This figure displays a scatter of the wage gap and productivity gap, using an investment control function and translog production function, estimated by industry at the 2-digit NACE-level. Larger industry groups (1 digit level) are represented by different symbols. These are: Accommodations and food services, Construction, Manufacturing, Wholesale and Retail Trade, Other community, social, and personal services, and Real estate, renting, and business activities. The 45 degree line also graphed. The slope of a regression of the productivity gap on the wage gap is 0.11 and clearly, the correlation is very weak at the sub-industry level. Standard errors on the productivity gap when measured at the 2-digit level are large (and variable), ranging between 2 percentage points and thirty percentage points.

Tables

Table 1: The pay gap in Denmark vs. US

Sample	Variables included	Coefficient on female	Standard error	R ²
US	Basic	-0.320	0.0010	0.102
US	Basic, time	-0.196	0.0009	0.353
US	Basic, time, education	-0.245	0.0008	0.475
US	Basic, time, education, occupation	-0.191	0.0010	0.563
Denmark (FIRE)	Basic	-0.277	0.0011	0.095
Denmark (FIRE)	Basic, time	-0.193	0.0006	0.727
Denmark (FIRE)	Basic, time, education	-0.200	0.0006	0.750
Denmark (FIRE)	Basic, time, education, occupation	-0.172	0.0006	0.781

Dependent variable is log earnings. The sample is 2009 to 2011. All regressions include a quadratic in age and year dummies. US regressions also include race. Hours controls are added in the second regressions. Hours are bracketed in Denmark (see the data appendix) and indicate hours per week and weeks per year in the US. Education indicates primary, high school, or more advanced schooling in Denmark, and similar groups in the US, and is added in the third row. Occupation dummies at the 3 digit level are added in the final row. Goldin's ACS sample includes only individuals ages 25-64. For comparison, I restrict to only these ages in the FIRE sample. The number of observations is 3,291,168 in the US, and 2,879,216 in the restricted FIRE sample.

Table 2: Conditional pay gap 2000-2011

	(1)	(2)	(3)	(4)
Female	-0.1740 (0.0002)	-0.1628 (0.0002)	-0.1393 (0.0003)	-0.1184 (0.0003)
Experience	N	Y	Y	Y
Occupation, Industry FE	N	N	Y	Y
Firm \times Occ FE	N	N	N	Y
R-squared	0.8430	0.8442	0.8562	0.8924
N	15613056	15613056	15613056	15613056

Dependent variable is log earnings. All regressions include hours and year controls, a quadratic in age, and education level dummies. Experience indicates a quadratic in experience (measured as hours of employment). Occupation is at the 3 digit ISCO level. Standard errors in parentheses.

Table 3: Cross-industry summary statistics

	Accom./food	Constr.	Manuf.	W/R trade	Other serv.	Real est.
w^f/w^m	0.8808	0.8083	0.8331	0.8418	0.8737	0.8485
fraction men	0.5911	0.8992	0.6919	0.6782	0.5152	0.5935
firm size	6.50	5.65	10.04	7.15	7.18	5.28
N	298370	135808	72000	69215	11799	18920

This table provides summary statistics on variables of interest across industries. w^f/w^m is the average wage gap control for quadratics in age and experience, education level, occupation fixed effects at the 3-digit ISCO level, hours worked, and year. Wage regressions are run by industry. The fraction men are averages measured at the person level. Firm size is measured treating the firm as the unit of observation.

Table 4: Estimates of β (relative female productivity)

	(1)	(2)	(3)	(4)	(5)
β	0.919	0.928	0.941	0.940	0.960
	(0.008)	(0.007)	(0.009)	(0.010)	(0.009)
w^f/w^m	[0.861]	[0.861]	[0.901]	[0.900]	[0.920]
industry-specific shares	N	Y	Y	Y	Y
better hours (2008+)	N	N	Y	Y	Y
including non-wage benefits	N	N	Y	N	Y
detailed efficiency units	N	N	N	N	Y
R^2	0.8489	0.851	0.853	0.8523	0.853
N	852,729	852,729	258,978	258,978	258,978

This table gives estimates of β , the coefficient on female efficiency units in the translog production function regression (4) using (1) to form efficiency units. β can be interpreted as the relative productivity of female labor, controlling for differences in the quality of that labor captured by age, experience, education, and occupation. All regressions include 2-digit industry fixed effects and columns 2-5 allow the coefficients on labor and capital to vary at the 1-digit industry level. Standard errors are bootstrapped (50 samples) at the person level to account for estimation error in forming predicted efficiency units and then, for each estimate of efficiency units, cluster bootstrapped at the firm-level in the production function estimation step. The last row of the table, w^f/w^m is relative female wages, residual of quadratics in age and experience, education level fixed effects, and occupation fixed effects. Columns (3)-(5) use a subset of the data (2008 onward) in estimation because more detailed measures of hours worked are available in that time-period. This does reduce the productivity gap by about two percentage points. Columns (3) and (5) also include non-wage benefits in the estimation of efficiency units. Column (5) estimates efficiency units allowing for the interaction of occupation with industry and year the finest level of education major choice.

Table 5: Alternative measures of β

	(1)	(2)	(3)	(4)	(5)
	Wage Bill	Wage Bill (2008 +)	Wage Bill (2008+ including non-wage benefits)	AKM	Griliches ($\beta = \phi_F$)
$\tilde{\beta}$	1.0624 (0.0035)	1.0332 (0.0055)	1.0350 (0.0055)	1.0961 (0.0101)	
β					0.9519 (0.0060)
R^2	0.8654	0.8724	0.8725	0.8184	0.6412
N	714,254	258,978	258,978	641,916	852,729

This table gives estimates of β , the coefficient on female efficiency units in the translog production function regression (4) using the wage bill (columns 1-3), person fixed effects from an AKM decomposition (column 4), and equation (2) (column 5) to measure effective labor. A coefficient larger than one on wage bill and AKM estimates is consistent with a productivity gap which is smaller than the wage gap, as in Table 4 above. The interpretation of these coefficients is that one dollar paid to female labor is more productive than one dollar paid to male labor. In contrast, column (5), though less than 1 is *also consistent with Table 4*. This is a measure of the relative productivity of a unit of female labor (not a dollar spent on female labor). All regressions use specification (4) to estimate the production function and include 2-digit industry fixed effects and allow the coefficients on labor and capital to vary at the 1-digit industry level. Standard errors are clustered at the firm-level.

Table 6: Imperfect substitutes: relative productivity of female labor (β) and the elasticity of substitution (ρ)

	(1)	(2)	(3)
β	0.868 (0.008)	0.872 (0.008)	
$\tilde{\beta}$			1.029 (0.004)
ρ	5.425 (0.089)	5.496 (0.092)	9.327 (0.264)
N	852,729	852,729	714,254
industry specific shares	N	Y	Y
wage bill	N	N	Y

This table gives estimates of β , the coefficient on female efficiency units in the translog production function regression (4) allowing total labor to be a CES combination of male and female efficiency units, where ρ is the elasticity of substitution between male and female labor. All regressions include 2-digit industry fixed effects and columns 2 and 3 allow the coefficients on labor and capital to vary at the 1-digit industry level. Standard errors are bootstrapped (50 samples) at the person level to account for estimation error in forming predicted efficiency units and then, for each estimate of efficiency units cluster bootstrapped at the firm-level in the production function estimation step.

Table 7: Productivity-pay gap for men and women without children

age	Men, children soon	Women, no children soon	Women, children soon
24-26	0.123 [-0.001]	-0.176 [-0.190]	0.188 [-0.164]
27-29	0.209 [-0.009]	-0.040 [-0.151]	0.120 [-0.145]
30-32	0.160 [-0.027]	-0.097 [-0.125]	0.104 [-0.136]
33-35	0.058 [-0.036]	0.180 [-0.093]	0.135 [-0.138]
36-38	0.062 [-0.055]	-0.167 [-0.086]	0.066 [-0.149]
39-41	0.075 [-0.078]	-0.326 [-0.110]	0.385 [-0.168]
42-44	-0.178 [-0.068]	-0.662 [-0.100]	0.166 [-0.160]
F-Test for $(\Delta \text{ productivity} - \Delta \text{ pay})_{\text{women}} > (\Delta \text{ productivity} - \Delta \text{ pay})_{\text{men}}$:			0.0885

This table splits the productivity and wage gap (in hard brackets) for women and men without children into one for men without children who will have children in the next 3 years (men, children soon), women without children who will not have children in the next three years (women, no children soon), and women without children who will have children in the next three years (women, children soon). All estimates are relative to men without children who will not have children in the next three years. Also included in the regressions (but not reported) are categories for fathers and mothers by age. Age categories for 45 years and beyond are not reported because very few women have children after this age. All regressions include 2-digit industry fixed effects and allow the coefficients on labor and capital to vary at the 1-digit industry level. The F-test reported is a test of the sum of the coefficients for relative productivity for women without children who will have children soon compared to women without children who won't have children soon minus the sum of relative wages for this groups, minus the same difference for men. Women are significantly (at the 10 percent level) more underpaid when they are going to have children in the next three years relative to men.

Table 8: Productivity-pay gap for men and women without children by marriage

age	men, married/cohabiting	women, single	women, married/cohabiting
24-26	0.087 [0.031]	-0.107 [-0.171]	0.107 [-0.148]
27-29	0.108 [0.019]	-0.011 [-0.139]	0.169 [-0.124]
30-32	0.132 [0.027]	0.041 [-0.101]	0.115 [-0.098]
33-35	0.198 [0.039]	0.240 [-0.081]	0.073 [-0.089]
36-38	0.094 [0.043]	0.194 [-0.072]	0.323 [-0.086]
39-41	0.234 [0.050]	0.452 [-0.065]	0.172 [-0.080]
42-44	0.270 [0.053]	0.099 [-0.060]	0.258 [-0.079]
F-Test for $(\Delta \text{ productivity} - \Delta \text{ pay})_{\text{women}} > (\Delta \text{ productivity} - \Delta \text{ pay})_{\text{men}}$:			0.9834

This table splits the productivity and wage gap (in hard brackets) for women and men without children into one for men without children who are married or cohabiting, women without children who are single, and women without children who are married or cohabiting. All estimates are relative to men without children who are single. Also included in the regressions (but not reported) are categories for fathers and mothers by age. Age categories for 45 years and beyond are not reported because very few women have children after this age. All regressions include 2-digit industry fixed effects and allow the coefficients on labor and capital to vary at the 1-digit industry level. The F-test reported is a test of the sum of the coefficients for relative productivity for married/cohabiting women compared to single women without children minus the sum of relative wages for this groups, minus the same difference for men.

Table 9: Gender productivity gap by industry and parenthood

	Accom./food	Constr.	Manuf.	W/R trade	Other serv.	Real est.
female, no children	1.231 (0.015) [0.926]	1.127 (0.042) [0.794]	1.043 (0.038) [0.839]	1.135 (0.031) [0.886]	1.160 (0.074) [0.906]	1.075 (0.082) [0.879]
female, children	0.852 (0.009) [0.828]	0.881 (0.021) [0.815]	0.846 (0.020) [0.831]	0.813 (0.017) [0.811]	0.829 (0.047) [0.848]	0.834 (0.045) [0.830]
N	298,370	135,808	72,000	69,215	11,799	18,920
R^2	0.770	0.819	0.848	0.704	0.600	0.7470

This table gives estimates of β , the coefficient on the category of efficiency units listed in the first column in a translog production function where the labor of men, women with children, and women without children are treated as perfect substitutes. Standard errors are in parentheses. Relative wages, residual of the same factors which enter efficiency units estimation, are in brackets. Both relative wages and relative productivity are compared to an omitted category of all men. Across industries, relative wages and relative productivity line up nearly perfectly for mothers, but are unrelated for non-mothers.

Table 10: Gender productivity gap by occupation and parenthood

	M	HS	MS	WC	S	C	LS
$\beta_{F,nc}^o/\beta_M^o$	1.045 (0.111) [0.803]	1.154 (0.036) [0.888]	1.240 (0.030) [0.834]	0.992 (0.019) [0.909]	1.073 (0.022) [0.935]	1.129 (0.036) [0.884]	0.744 (0.067) [0.877]
$\beta_{F,c}^o/\beta_M^o$	0.940 (0.048) [0.752]	0.816 (0.020) [0.858]	0.867 (0.014) [0.791]	0.753 (0.010) [0.865]	0.552 (0.013) [0.827]	0.907 (0.022) [0.874]	0.570 (0.025) [0.870]
N individuals	509,790	1,138,811	2,007,428	1,560,069	1,581,954	2,433,454	1,520,541

This table gives the ratio of relative productivity coefficients by occupation. The first row of coefficients is the relative productivity of women without children relative to men and the second row of coefficients is the relative productivity of women with children compared to men in the same occupation (o). o is one of the 11 occupations described below modeled as perfect substitutes in a translog production function. Bootstrapped standard errors are in parentheses. Relative wages, residual of the same factors which enter efficiency units estimation, are in brackets.

Occupation codes: M = Management at the highest level, HS = Job req. knowledge at the highest level (from school teachers to researchers), MS = Job req. knowledge at the medium level (e.g. tech.), WC = Office jobs, S = Sales/Service/Care, C = Craftsman jobs, LS = Blue collar jobs. Occupation data is only available for a person's main job. About 30 thousand person-year observations list the primary job as *military* and another 30 thousand in the category *agriculture, forestry, fishing requiring basic level knowledge*, the estimates for these productivity gaps are in Appendix Table 15, along with large heterogenous categories *unknown* and *other*.

Model Appendix

Assumptions underlying the Olley-Pakes control function approach to the selection problem:

Assumption 1: Factor prices are constant across firms

The assumption that factor prices are constant across firms allows us to infer that firms which choose different levels of investment do so because they predict that their TFP will differ in the next period. If firms face different labor prices, particularly by gender, then β may still be biased due to unobservables (factor prices). In Denmark this assumption is not particularly offensive, since wages are set in no small part by collective bargaining and generally are compressed relative to the US.

Assumption 2: Labor is a non-dynamic input

This assumption *would* be unreasonable in countries where it was difficult to re-adjust the labor force every year. Denmark, however, prides itself on a “Flexicurity” system. This is the combination of a very flexible labor market—it’s very easy to fire and hire workers in Denmark—combined with a secure safety net in the case of unemployment. In Denmark and the US, just over 25% of employees are new hires in each year, and about 25% separated from their employer in the same period. In Norway, these rates are closer to 17%. In Italy, they are about 15% [OECD, 2010]. See Appendix Figure 5 for a graph of cross-country separation and hiring data.

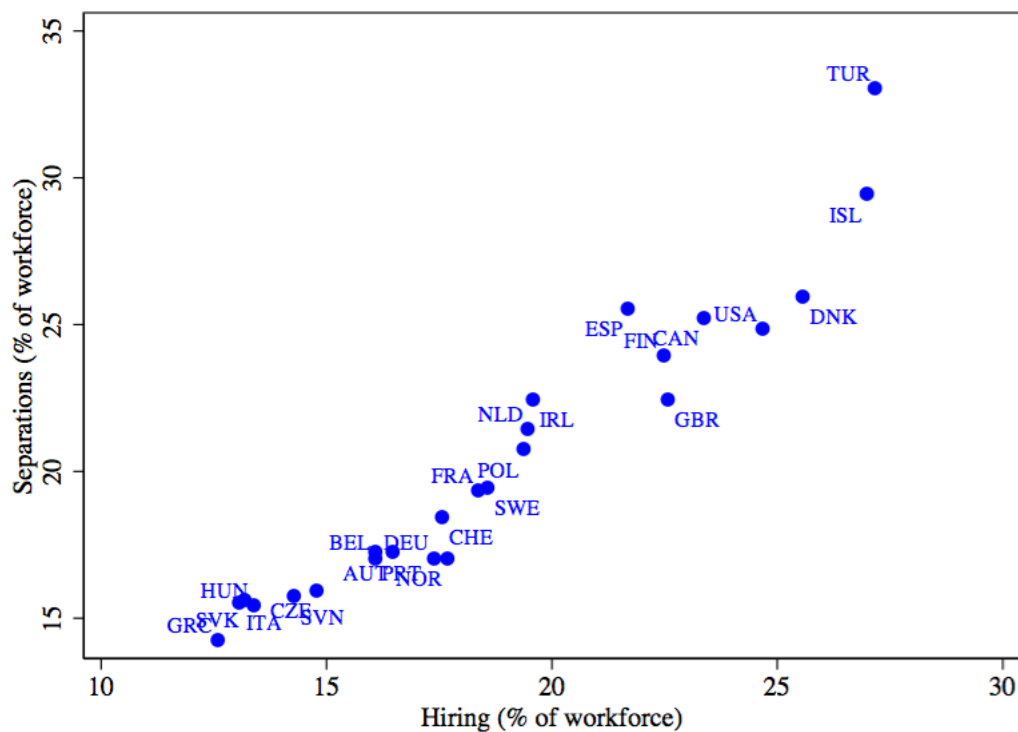


Figure 5: This figure is directly replicated from OECD data on relative workforce flexibility, OECD [2010] Figure 2.1, see Annex 3.A1. Country averages of reallocation rates expressed in percentage of total dependent employment and adjusted for industry composition. Austria: 2002-07; Belgium: 2000-07; Canada: 2000-06; the Czech Republic: 2001-07; Denmark: 2000-06; Finland: 2000-07; France: 2000-06; Germany: 2000-06; Greece: 2000-05; Hungary: 2000-05; Iceland: 2002-07; Ireland: 2000-05; Italy: 2000-06; the Netherlands: 2000-07; Norway: 2000-04; Poland: 2004-05; Portugal: 2000-06; the Slovak Republic: 2002-06; Slovenia: 2002-07; Spain: 2000-05; Sweden: 2000-06; Switzerland: 2000-07; Turkey: 2007; the United Kingdom: 2000-07; and the United States: 2000-06.

Assumption 3: Conditional on capital, investment is monotonically increasing in the unobservable ω_{jt}

These assumptions rule out, for example, adjustment costs which differ across firms within an industry. Scalar investment is given by $i_{jt} = i_t(\omega_{jt}, k_{jt})$. Pakes (1994, Theorem 27) shows

that when $i > 0$, $i_t(\omega_t, k_t)$ is increasing in ω for every k , so that we can invert the investment rule and write $\omega_{jt} = \phi(i_{jt}, k_{jt})$.^{21,22}

Approximating this investment rule with a flexible, higher-order polynomial in k and I yields the equation

$$\log(Y)_{jt} = a_t + \psi_1 \log(\mathcal{L})_{jt} + \psi_2 k_{jt} + \phi(i_{jt}, k_{jt}) + \varepsilon_{jt} \quad (6)$$

where $\phi(i_{jt}, k_{jt})$ is a flexible 3rd degree polynomial in i and k . Since labor does not enter the ϕ polynomial, the labor share and β are identified simply by running this regression.

Akerberg et al. [2004] (ACF) note that there is a simultaneity problem if investment and labor are truly chosen simultaneously—in this case labor demand can be written $\mathcal{L}(\omega, k)$, problematically. Indeed, if labor can be written as a flexible polynomial in i and k , then there is perfect collinearity between ϕ and inputs in \mathcal{L} , making estimated labor coefficients meaningless. ACF suggest a 2-step solution to this problem, as well as a timing assumption which corrects the problem. In the Danish context and with yearly data, this timing is not particularly offensive. More formally:

Assumption 4: Labor is chosen first, then investment is chosen based on an information set correlated but not collinear with the information used to choose labor.

As suggested by Akerberg et al. [2004] to eliminate the problem posed if i and labor are chosen based on exactly the same information set and factor prices do not vary across firms.²³ In general, all that is needed for identification is different adjustment speeds of various factors (see, Bond and Soderbom [2005]).

To estimate capital share, ψ_2 , we can use the knowledge of ψ_1 and β obtained in the first stage to write

$$\log(Y)_{jt} - \psi_1 \log(\mathcal{L})_{jt} = a_{jt} + \omega_{jt} + \varepsilon_{jt}$$

Since ω is a first order Markov process, we can decompose it into its expectation given information at time $t - 1$, $g(\omega_{j,t-1})$ and a residual, ξ_{jt} . In addition, we estimate the combination of

²¹Ericson and Pakes [1995] discuss the conditions for this invertibility in equilibrium in more detail.

²²The general formation also includes firm age as a state variable, but omitting age does not affect the invertibility in equilibrium and simplifies the problem, since the relationship between firm age and productivity is not of interest in this paper.

²³See Akerberg et al. [2007] for an extensive discussion of OP and alternatives.

capital effects in the first stage. Let the first stage coefficient on capital be κ_{jt} . We now have

$$\log(Y)_{jt} - \psi_1 \log(\mathcal{L})_{jt} = a_t + \psi_1 k_{jt} + g(\kappa_{j,t-1} - a_{t-1} - \psi_2 k_{j,t-1}) + \xi_{jt} + \varepsilon_{jt}$$

This paper is focused on the estimation of β , which is identified in the first stage in the case of firm entry and exit, measurement error in investment, and lumpy levels of investment [Akerberg et al., 2007].

Data Appendix

Table 11: Hours and jobs per person-firm-year-month in eIncome

Entries per p-f-y-m	Percent of p-f-y-m observations	25th pctile hours/month	50th pctile hours/month	75th pctile hours/month
1	98.88%	91	157.61	160.33
2	0.98%	6	22	62
3	0.025%	5	17	51
4+	0.0015%	3	8	31

This table describes the distribution of number of separate entries an individual (p) in a given firm (f) in a given year (y) and month (m) has in the eIncome data. The eIncome register is formed from taking monthly payroll statements which include occupation, hours worked, and various compensation breakdowns (take-home pay, adding fringe benefits, adding retirement contributions, etc). Multiple worker observations within a firm in a month (p-f-y-m) may arise because a worker changes occupations/job types in a month or has multiple occupations in a given month in a given firm, or they may arise due to a break in the employment spell in a month (resumed in the same month). There are a total of 135430660 person-firm-year-month observations. 98.88% of these have only one record and virtually all the rest have only two records. These data are used to construct efficiency units when estimates use the 2008+ sample of firms.

Table 12: Efficiency units estimation

More than high school	0.145
	(0.0003)
College	0.434
	(0.0004)
Age	0.061
	(0.0001)
Age ²	-0.001
	(0.0000)
Experience	0.021
	(0.0001)
Experience ²	-0.000
	(0.0000)

This table gives the estimated coefficients on education (omitted category is high school diploma or less), a quadratic in age, and a quadratic in experience. Regressions also include hours bins interacted with the fraction of the year worked, occupation fixed effects at the 3-digit ISCO level, and year fixed effects. Standard errors are in parenthesis.

Table 13: Griliches detail

$\phi_F - 1$ (female)	-0.0482 (0.006)
$\phi_R - 1$ (married)	0.298 (0.007)
$\phi_P - 1$ (35-54 year old)	1.038 (0.015)
$\phi_O - 1$ (55 and older)	0.709 (0.016)
$\phi_N - 1$ (unskilled laborers)	0.135 (0.013)
$\phi_S - 1$ (white collar, technical, and sales workers)	0.497 (0.009)
$\phi_C - 1$ (high skilled workers)	0.565 (0.016)
α_1	1.192 (0.011)
α_2	0.421 (0.006)
α_3	-0.007 (0.000)
α_4	-0.089 (0.001)
α_5	0.054 (0.002)

This table provides details of estimates using specification (2) for constructing \mathcal{L} in the production function (4).

Table 14: Job-flexibility
and relative productivity

$\beta_{F,nf}$	1.387 (0.065)
$\beta_{M,f}$	1.554 (0.046)
$\beta_{F,f}$	1.166 (0.052)
$\beta_{M,o}$	1.338 (0.034)
$\beta_{F,o}$	1.229 (0.032)

This table provides details of estimates by occupation flexibility, as in equation (5).

Table 15: Gender productivity gap by occupation and parenthood

	Agriculture	Other	Military	Unknown occupation
$\beta_{F,nc}^o/\beta_M^o$	0.756 (0.174)	1.008 (0.036)	0.535 (0.300)	1.180 (0.012)
$\beta_{F,c}^o/\beta_M^o$	0.519 (0.110)	0.561 (0.019)	-0.130 (0.007)	0.854 (0.006)
N	37,326	1,720,432	30,207	4,194,407

This table gives the ratio of relative productivity coefficients by occupation for the three omitted occupation categories in Table 10. These are omitted because the sample size is small and/or the categories are not informative. The first row of coefficients is the relative productivity of women without children relative to men and the second row of coefficients is the relative productivity of women with children compared to men in the same occupation (o). o is the occupation listed in the column heading and modeled as perfect substitutes in a translog production function with the occupations in 10. Bootstrapped standard errors are in parentheses.