GENDER BASED SELF-SELECTION INTO INDUSTRIES AND OCCUPATIONS

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Abstract

In this paper, I investigate the relationship between the gender distribution across industries and occupations and the incidence and consequences of displacement. I first provide empirical evidence to support the idea that women self-select into less risky industries and occupations, that is industries and occupations with lower displacement rates and lower earnings growth. Using data from the Displaced Worker Survey (1984-2002), the corresponding Annual Demographic Supplement of the March CPS, and the Dictionary of Occupational Titles, I find that, even though women have a lower incidence of displacement in the aggregate, they are more likely to get displaced at the one-digit industry and occupation level than men. Displacement is also more costly for women, in terms of both employment and monetary consequences, which suggests that women's choice of safer sectors could be an insurance mechanism against the risk of displacement and its costly consequences. I then construct a dynamic occupational choice model in which occupation groups differ not only in the rate of human capital accumulation, but also in the risk and associated cost of displacement, as well as in the value of the non-monetary utility component. I calibrate the model for men and perform a number of counterfactual experiments for women. Preliminary quantitative results suggest that differences in displacement probabilities, together with differences in re-employment probabilities and in human capital penalty rates at displacement explain up to 15% of the gender occupational segregation. Allowing women to also have an extra preference for non-employment explains in a proportion of 60% why women avoid high risk occupations, that is occupations with higher displacement risk, higher earnings growth and higher human capital depreciation (or alternatively, lower human capital transferability).

Keywords: displacement, occupational self-selection, gender occupational segregation, occupational choice model, displacement risk

1.Introduction

Every major recession since the 1980s has hurt male dominated sectors harder that female dominated ones, as shown by the positive male-female unemployment gap (see Figure 1 in Appendix 2). By the late 2000's, women accounted for slightly less than half of the employed labour force, yet fewer and fewer women bear the burden of unemployment in difficult times. Can this be interpreted as systematic proof that women are clustered into safer, more secure sectors? A simple plot of displacement rates and employment shares in industries and occupations between 1984 and 2002 (see Figures 2 and 3 in Appendix 2) reveals that male dominated industries and occupations have, on average, higher total displacement rates compared to female dominated industries and occupations.

In this paper I am going to investigate the relationship between the gender distribution across industries and occupations and the incidence and consequences of displacement. I first document empirically the fact that women select into less risky industries and occupations, that is industries and occupations with low displacement risk and low earnings growth. I then look for potential explanations of this sorting behaviour.

One reason is the differential impact of the incidence and consequences of displacement on women versus men. Women are more likely to get displaced at the industry and occupation level, even though in the aggregate they get displaced less often then men. Being displaced is also more costly for women, in terms of both the employment and monetary consequences of displacement. Therefore women insure against the risk of costly displacement by selecting industries and occupations with low displacement risk.

I take these empirical findings to the model, in an attempt to quantify exactly how much of the gender occupational segregation can gender differences in the incidence and costs of displacement account for. The model I developed builds on Keane and Wolpin (1997), and is a dynamic occupational choice model in which occupation groups differ not only in the rate of human capital accumulation, but also in the risk and costs of displacement, and in the value of the non-monetary utility component associated to each occupation group.

In a first set of experiments, assuming that men and women attribute the same value to non-employment, I show that gender differences in the incidence and costs of displacement can only explain about 15% of the gender occupational segregation. However, allowing for gender differences in the value of non-employment, I show that gender differences in the incidence and costs of displacement can explain up to 60% of women's absence from high displacement risk occupations.

In light of these two sets of results, displacement risk might also be correlated with other factors that can explain the existing gender segregation in occupational choice. One potential such factor is the difference in skill attributes by occupation, and I present preliminary empirical evidence in support of this claim. However, further investigation is necessary in order to establish the exact nature of this relationship.

The scope of this paper is threefold. First, I contribute to the displacement literature by providing a detailed account of the differences in the incidence and costs of displacement for women compared to men. Although the displacement literature is rich and detailed[1], gender differences in the incidence and consequences of job loss have not been the main focus of existing research [2], nor has been their variation by industries and occupations investigated.

Second, I contribute to the literature on sorting and occupational segregation by gender, initially by establishing empirically the validity of the fact that women

[1]Reviewed in Fallick (1996), Kletzer (1998), and Farber (2004).

[2]Exceptions are Crossley, Jones and Kuhn (1994), Perrucci, Perrucci, and Targ (1997), and Koeber and Wright (2006). Highlights of gender differences in the costs of displacement also appear in Jacobson, LaLonde and Sullivan (1993), and Farber (2005).

self-select into low displacement industries and occupations, and then by further investigating gender differences in risk taking behaviour and preferences for risk[3], and gender sorting into occupations based on the trade-off between wages and different job characteristics, in particular displacement risk[4].

Third, I contribute to the literature of discrete choice structural models[5] by constructing a human capital model of occupational choice in the spirit of Keane and Wolpin (1997) which also allows for exogenous displacement risk across occupation groups. The model is used to assess the role of displacement risk on the gender distributions across occupations and on womens choice of low displacement risk occupations, and to provide quantitative measures of the extent to which differences in displacement risk across occupations explain occupational gender segregation.

Displacement risk is only one of many reasons why men and women might might choose different industries and occupations. The sources of gender occupational segregation have been classified in the literature in three main categories: neo-classical/human capital theories (with supply side and demand-side factors at play), institutional and labour market segmentation theories (dual labour markets and statistical discrimination theories), and feminist or gender theories (stereotypes of women and their abilities).[6] On the supply side, neo-classical human capital theories rely on differences between individuals in tastes and preferences (for example attitudes towards risk or various job attributes), differences in levels of human capital and/or skills and other endowments, as well as differences in wealth and/or other constraints.

[3]Hartog et al (2002), Dohmen at al (2005), Booth and Nolen (2009), and Borghans et al (2009), all conclude that women are more risk averse than men.

[4]DeLeire and Levy (2004), investigate sorting into occupations based on the risk of death on the job, while Grazier and Sloane (2008), look at sorting into occupations based on the risk of injury. Berkhout, Hartog, and Webbink (2006), Bonin et al (2007), Singh and Vijverberg (2007), and Jacobs, Hartog, and Vijverberg (2009), all investigate occupational choices based on economic risk, and in particular earnings risk. In all situations, women choose the less risky occupations, regardless of the measure of risk used in the analysis.

[5]See Keane and Wolpin (1994), Keane and Wolpin (1997), and Lee (2005).

[6]See Anker (1997) for a review.

On the demand side, there could be differences in skill requirements, and a taste for discrimination on the employers' side, to name just a few.

The goal of this paper is therefore not to account for and explain all sources of gender occupational segregation, but rather to isolate the impact of displacement risk on men and women's occupational choices.

An important, and very much quoted, implication of the research on gender occupational segregation is explaining the effect it has on male-female pay differentials. However, apart from being a source with important explanatory power of the male-female pay differentials, gender based occupational segregation is important in itself. Occupational segregation is a major source of labour market rigidity and economic inefficiency that negatively affects an economy's adaptability to adjust to change through the imperfect allocation of human resources, and a thorough knowledge of its determinants is a first step in designing and implementing more efficient social and economic policies.

The rest of the paper is organised as follows. In Section 2 I describe the different data sources used and present summary statistics. In Section 3 I first describe the methodology for the empirical analysis and then present results for the hypothesis of sorting into occupations based on displacement risk. In Section 4 I investigate potential sources of unobserved heterogeneity for the results in Section 3. In Section 5 I first describe the structural model of occupational choice with displacement risk, then discuss the calibration strategy and present results of counterfactual experiments. Section 6 concludes.

2.Data

In this paper I use three main data sources: the Displaced Worker Survey (DWS) of the Current Population Survey (CPS), the Annual Demographic Supplements to the

March CPS Files, and the Dictionary of Occupational Titles.

The Displaced Worker Survey (DWS) is a supplement of the Current Population Survey (CPS), administered every two years, in either January or February, starting in 1984. The DWS, as an alternative to the less accessible state level unemployment records, is the most comprehensive and widely used source of information on displaced workers in the US. The supplement collects information on displacement status, displacement reason [7], year of displacement [8], and lost job characteristics (weekly hours, weekly earnings, full-time/part-time status, private/government sector, industry and occupation, tenure on the lost job, etc). Since the DWS supplement follows the monthly CPS interview, information on the current (at the supplement interview date) labour force status and the current job characteristics, as well as individual demographic characteristics can also be retrieved for each individual in the DWS sample.

The advantages of using such a data set are obvious advantages like a large sample size [9], coming from a nationally representative sample, providing rich information on individual demographic characteristics, employment and earnings information collected over a long time period.

There are, however, a couple of aspects that need to be treated with caution when working with the DWS. First, the DWS collects information on only one job previously held and lost through displacement - the one with the longest tenure - thus ignoring multiple displacement events and therefore providing a lower bound for the true incidence of displacement. If we also add into account the retrospective nature of the survey, the possibility of the data being contaminated by recall bias is increased.

Second, the lack of extensive retrospective and current earnings information [10]

[7] There are six possible reasons for displacement: plant closing, position or shift abolished, slack work, seasonal job ended, self operated business failed, and other reasons.

[8] Before February 1994, the DWS tracks displacement up to five years prior to the survey date, while after this date it is displacement up to three years prior to the survey data that matters.

[9] Each monthly sample size is approximately 60,000 households, which translates into approximately 150,000 individual records for each survey year.

[10] The DWS only collects weekly earnings data for the pre- and post-displacement periods.

for the displaced workers in the survey and the lack of any retrospective earnings information for the non-displaced workers in the survey, limits the analysis of lost earnings for the displaced and allows no direct comparability with the control sample of non-displaced workers. I will address this by looking at a comparison sample of never displaced individuals constructed from the linked March CPS files in which the displacement information from the January/February CPS has been rolled over to the March CPS files.

Third, another potential source of selection bias is the issue of destructive attrition, which occurs following early notification when workers with better alternatives voluntarily quit, while those with no other alternatives stay and eventually become displaced. The early literature[11] on pre-notification concludes that early notification has small wage effects post-displacement and leads to small reductions in post-displacement joblessness. However, new evidence[12] based on administrative data sets conclude that early leavers are associated with lower costs of joblessness due to displacement. To the extent that there is no systematic difference in the way men and women react to advanced notification[13], destructive attrition is not going to bias the main results of this paper in a significant way.

The sample used for the main analysis in this paper consists of pooled cross-sections from the 1984 through 2002 DWS files[14], and contains all workers aged 20 to 64, that are currently either employed or have been displaced in any of the three years prior to the survey date, for any of the following three reasons: plant closing, position or shift abolished, slack work. Furthermore, I only keep those observations that have

[11]See Ruhm (1994) or Jones and Kuhn (1995), and Addison and Portugal (1991) for a review on advance notice.

[12]See Lengermann and Vilhuber (2002), and Schwerdt (2010).

[13]This assumption will be further addressed in Section 4 in the context of differences in risk preferences between men and women.

[14]Survey waves after 2002 were not included because of the switch to the 2000 Census classification of industries and occupations that cannot be longitudinally linked to the 1980 and 1990 Census Classifications used in previous years.

non-missing observations for the variables of main interest: individual demographic characteristics, and current and lost job characteristics, including weekly earnings. Summary statistics are available in Tables 1 and 2 in Appendix 3.

When estimating the incidence of displacement, I consider those currently employed who have not been displaced as a comparison sample for the displaced workers, in which case their current job characteristics retrieved from the monthly CPS survey attached to the DWS will be imputed as their previous job characteristics (the equivalent of pre-displacement job characteristics for displaced workers). I am assuming here that the distribution of workers across industries and occupations did not change significantly over a three year period, and there have been no voluntary complex job switches, i.e. job switches that also involved a change of industry and/or occupation.

When estimating the earnings growth for never displaced workers, I will no longer be able to use the comparison sample from the DWS because it only contains current job characteristics and earnings data. As an alternative, similarly to Farber (1997), I will make use of another comparison sample drawn from the Annual Demographic Supplement of the March CPS files (1984-2002), the second main source of data. The CPS is a monthly labour force survey of approximately 60,000 representative households administered by the Census Bureau for the Bureau of Labor Statistics. It is designed on a 4-8-4 rotation structure, meaning that each household is in the sample for four months, out of sample for the next eight months and in the sample again for the last four months. This structure allows for the creation of a panel with two time observations, one year apart, for each household in the sample. However, in any given month except March, information on earnings and hours is only collected if the respondent is in the outgoing rotation group, that is either the fourth month or the eight month in the sample. The Annual Demographic Supplement attached to the March files collects information on employment and earnings for the entire sample, which is why using March-to-March yearly comparisons is widely preferred. However, in the March sample I am not able to distinguish between displaced and non-displaced workers, as this information is only available in the DWS in either January or February, so the yearly earnings growth for never displaced workers is potentially underestimated, since the sample is “contaminated” with displaced workers. To overcome this shortcoming, I link each DWS survey to the March file of the corresponding year, and then link the March observations in the DWS year to the March observations of the previous year. The newly created sample is comparably smaller in size than the full March-to-March sample, but has the advantage of accurately identifying the displacement status of each worker in the sample.

The Dictionary of Occupation Titles is a collection of more than 12,000 occupations or jobs, each of which has a corresponding Census classification code, with information on skills, tasks, requirements and other characteristics. Poletaev and Robinson (2008) used factor analysis to identify a set of four main basic skills, or factors, that explain most of the variance in characteristics across all occupations. They are general intelligence, motor skills, physical strength, and visual skills. Factor scores were derived at the occupation Census code level in from the average characteristic ratings of the DOT codes that make up a Census code, and were weighted by the 1992 employment shares such that a factor unit represents a standard deviation of the factor for the employed population. Factors are normalised to have a mean of zero and a standard deviation of one. The vector of four factor scores for each three-digit Census occupation code was kindly provided by the authors.

3.Empirical Analysis

3.1.Methodology

I am defining sectoral[15] risk along three main dimensions: displacement incidence, employment effects of displacement, and monetary effects associated with displacement for each industry and occupation. Each category contains one or several indicators, as follows.

The incidence of displacement is measured by the rate of displacement. Following Farber (1997), this is defined as the ratio of the number of displaced workers to the numbers of workers who were either employed at the survey date or reported being displaced but were either unemployed or out of the labour force at the survey date.

The re-employment rate, the rate of switching industry, occupation, or both, the rate of full-time to full-time transitions, the number of weeks spent without a job post-displacement, and the number of jobs held post-displacement, are all measures of the employment effects of displacement. The re-employment rate is defined as the ratio of the number of displaced workers who have a job at the survey date to the total number of displaced workers. Similarly, the industry, occupation, and industry and occupation switching rates are the ratio of the number of displaced workers who, upon re-employment, switch their industry, occupation or both to the total number of displaced workers who are re-employed at the time of the survey. The full-time to full-time transitions rate represents the ratio of the number of displaced workers who were displaced form a full-time job and are employed in a full-time position at the time of the survey to the total number of displaced workers who are re-employed at the survey date.

The monetary effects of displacement are, on the one hand, the direct cost associated with the difference in weekly earnings of the displaced workers between the time

[15] I refer to a sector as being either an industry or an occupation.

of the survey and the pre-displacement period [16], and, on the other hand, the indirect cost associated with the change in weekly earnings that would have occurred had the workers not been displaced. This is approximated by the yearly difference in weekly earnings for a control group of never displaced workers from the March CPS files of the same years as the Displaced Worker Surveys.

I first characterise the predominantly female industries and occupations by looking at correlations between the main displacement indicators and the share of females in each sector. Then, using individual level data from the pooled 1984 to 2002 DWS, I am running probit and OLS regressions for the indicators of displacement and post-displacement consequences. The baseline specification includes only controls for individual characteristics and is illustrative of what groups in the population bears the burden of displacement. Then, for each dependent variable I am running two sets of regressions. In the first specification, similar to Farber (1997), I control for individual characteristics, lost job characteristics, and time-dummies. In the second specification, I add industry and occupation dummies corresponding to the job lost through displacement. In each specification I am particularly interested in the coefficient on the gender dummy. If they are significantly different from each other across specifications, I will interpret their difference as proof of women sorting into different industries and occupations compared to men.

More specifically, the first specification:

$$D_i = \alpha + \beta G_i + \gamma X_i + \delta Y_i + \tau T + \epsilon_i \tag{1}$$

and the second one:

$$D_i = \widetilde{\alpha} + \widetilde{\beta} G_i + \widetilde{\gamma} X_i + \widetilde{\delta} Y_i + \widetilde{\phi} Z_i + \widetilde{\tau} T + \widetilde{\epsilon_i} \tag{2}$$

[16] Earnings are deflated by the 1982-1984 = 100 CPI. Pre-displacement earnings are deflated using the CPI for the displacement year. Current earnings are deflated using the CPI for the survey month.

where: D_i is one of the indicators mentioned above, G_i represents a dummy variable for gender ($G = 0$ if man, and $G = 1$ if woman), X_i represents individual characteristics (age, race, marital status, and education), Y_i are the job characteristics of the pre-displacement job (full-time or part-time, and government or private sector job), Z_i are industry and occupation dummies of the pre-displacement job, and T are time dummies for each year of the DWS survey.

Equation (1) might be misspecified, in which case the gender coefficient β would suffer from omitted variables bias. Characteristics like industry, occupation, hours worked, tenure on the lost job, etc, can potentially all be correlated with gender and adding them in the second specification will attenuate the bias. Unfortunately, however, not all of them are available in the data [17], so I will only be able to add industry and occupation dummies as new regressors in specification (2). Since I am particularly interested in disentangling the main patterns of gender based sorting into industries and occupations, having any other explanatory variables omitted from both specifications should not affect the interpretation of my final results. Both β and $\widetilde{\beta}$ will be biased in the same direction, hence looking at their difference should be equivalent to looking at the true difference in coefficients.

3.2.Main Results

I start by looking at the characteristics of the predominantly female industries and occupations compared to the predominantly male ones. For this, I will look at correlations between the percentage of female employment in each one-digit industry and occupation and the following indicators associated with displacement in these industries and occupations: displacement rates, re-employment rates, industry switching rates, occupation switching rates, industry and occupation switching rates, full-time to

[17] Hours worked is one important variable missing from the DWS. Tenure on the current job is also not reported, which makes it difficult to use the tenure on the lost job variable when analysing the incidence of displacement, because of its absence from the comparison group.

full-time transition rates, number of weeks without a job post-displacement, number of jobs post-displacement, weekly earnings losses if displaced and weekly earnings gains if not displaced. In order to overcome any compositional effects, I am computing the indicators associated with displacement from the male population only.

Figures 4 to 11 in Appendix 2 show that predominantly female sectors are also sectors with lower displacement rates, higher re-employment rates, lower industry switching rates and higher occupation switching rates, lower full-time to full-time transition rates, fewer average number of weeks without any job post-displacement, fewer(more) average number of jobs post-displacement for industries(occupations), smaller earnings losses if displaced, and smaller earnings gains in general.

However, aggregated statistics at the industry and occupation level can hide important trends at the individual level. Table 3 in Appendix 3 presents results for the baseline specification using individual level data. As expected, younger individuals are more likely to be displaced than older individuals, but also more likely to be re-employed conditional on being displaced. Older displaced workers spend more time in unemployment and take on more part-time jobs post-displacement. College graduates have lower chances of suffering an involuntary job loss, and if this unlikely event happens, they are having higher chances of being re-employed than their high school graduates counterparts. Individuals with an educational attainment less that high-school are the category most prone to displacement, and conditional on displacement they are less likely to be re-employed, they spend more time in unemployment and take on more part-time jobs. Race does not seem to be a determinant of displacement probability, but not being white has a negative impact on re-employment chances post displacement. Married individuals are less likely to be displaced, and more likely to be re-employed post displacement. Even though women are being displaced less often than men, if they suffer from an involuntary job loss they are re-employed less often, they spend more time in unemployment and switch more towards part-time work engagements. Conditional on being displaced and re-employed, earnings losses are incurred across the board, with older workers losing more than young ones, but otherwise no significant differences being associated with either gender, race, or marital status. College graduates are the exception, in the sense that they are the only category with higher earnings post-displacement.

Table 1 below presents the gender marginal effects from the two specifications outlined in the previous section, where the dependent variable is the probability of being displaced. Each coefficient comes from a separate probit equation, with different levels of controls in different columns.

Table 1: Displacement Incidence - Probit

	(1)	(2)	Coeff. Different	N
Gender = Female	-0.043***	0.098***	yes	579,551
	[0.006]	[0.008]		
Individual Characteristics	yes	yes		
Lost Job Characteristics	yes	yes		
Industry & Occupation Dummies	no	yes		

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Marginal effects. Weighted by CPS sampling weights. Robust SE in brackets, clustered by age, gender, race, education, industry, occupation and year. Base categories: white male, 20-24 years old, high-school graduate, not married, full-time, private sector job, in 1984.

The negative gender coefficient in the specification with only individual characteristics, lost job characteristics, and time trends (column (1)) would lead to the conclusion that, in the aggregate - that is, when comparing women to men without taking into consideration their industry and occupation - women are less likely to be displaced than men. But when controls for industry an occupation are introduced (column (2)), the gender coefficient becomes positive, meaning that at each one-digit industry and occupation level, women are more likely to be displaced. The null hypothesis that the two coefficients are equal is strongly rejected. Women are more likely to be displaced from certain industries and occupations, but given that in the aggregate they are displaced less often than men, this suggests that women are sorting into industries and occupations with lower probabilities of displacement.

Table 2: Monetary Cost of Displacement - OLS

	(1)	(2)	Coeff. Different	N
Direct Earnings Loss - Displaced				
Gender = Female	-0.059***	-0.081***	no	21,437
	[0.011]	[0.013]		
Indirect Earnings Loss - Never Displaced				
Gender = Female	0.031***	0.035***	no	35,595
	[0.007]	[0.009]		
Indirect Earnings Loss - All March-to-March				
Gender = Female	0.035***	0.037***	no	65,229
	[0.005]	[0.006]		
Individual Characteristics	yes	yes		
Lost Job Characteristics	yes	yes		
Industry & Occupation Dummies	no	yes		

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Weighted by CPS sampling weights. Robust SE in brackets, clustered by age, gender, race, education, industry, occupation and year.

Following a similar interpretation for the gender coefficients in the weekly earnings losses specifications presented in Table 2, when controlling for one-digit industries and occupations, women loose more that men when they are displaced. But they also gain more when they are not displaced[18]. This coefficient, however, is greater than the one from the specification without controls for the non-displaced, which would suggest that women are selecting into lower earnings growth sectors.

The gender coefficients from the equations corresponding to all the other indicators of the employment cost of displacement are presented in table 3 and consistently show that when the industry and occupation of displacement are taken into account, women are faced with a heavier burden and a more costly displacement: they have lower probabilities of being re-employed, have higher probabilities of switching industries and occupations, they have lower probabilities of making full-time to full-time transitions, they spend more time into unemployment or out of the labour force and

[18]These coefficients need to be interpreted with a grain of salt, taking into consideration the fact that the hours worked variable is not present among the regressors because of data limitations in the DWS. With hours worked included (this is possible in the March CPS sample) the gender coefficient becomes not significantly different from zero.

consequently have fewer jobs post-displacement.

Table 3: Employment Costs of Displacement - Probit and OLS

	(1)	(2)	Coeff. Different	N
Re-employment				
Gender = Female	-0.219***	-0.308***	yes	40,866
	[0.017]	[0.019]		
Industry Switch				
Gender = Female	0.164***	0.104***	yes	27,065
	[0.019]	[0.022]		
Occupation Switch				
Gender = Female	-0.023	-0.002	no	27,065
	[0.018]	[0.021]		
Industry & Occupation Switch				
Gender = Female	0.021	0.054*	no	27,065
	[0.019]	[0.022]		
FT-to-FT Transitions				
Gender = Female	-0.317***	-0.361***	no	23,763
	[0.022]	[0.025]		
Weeks Without Job Post-Displacement				
Gender = Female	1.582***	1.562***	no	27,065
	[0.213]	[0.244]		
Number of Jobs Post-Displacement				
Gender = Female	-0.091***	-0.085***	no	27,065
	[0.014]	[0.017]		
Individual Characteristics	yes	yes		
Lost Job Characteristics	yes	yes		
Industry & Occupation Dummies	no	yes		

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Marginal effects. Weighted by CPS sampling weights. Robust SE in brackets, clustered by age, gender, race, education, industry, occupation and year. Base categories: white male, 20-24 years old, high-school graduate, not married, full-time, private sector job, in 1984.

Taken together, these results suggest that women try to insure against the risk of displacement and its costly consequences, in both employment and monetary terms, by choosing safer sectors with lower displacement rates and lower earnings growth, so that, at the aggregate level, they experience lower displacement rates than men.

4.Sources of Unobserved Heterogeneity

Results in the previous section confirm the existence of gender based self-selection into industries and occupations in the context if displacement risk. The next natural steps are to determine why selection exists, and if possible, to determine not only what the underlying factors are, but also their relative importance. I follow the methodology described in DeLeire and Levy (2004) to further investigate the extent to which men and women sort into sectors based on their willingness to trade wages for disagreeable job characteristics, in this case the risk of displacement.

A model of compensating wages with worker heterogeneity would explain why workers would choose to sort into occupations[19] based on their preferences towards risk. More risk averse individuals will choose those sectors with lower risk of displacement. The fact that men are less risk averse than women is well documented in the literature[20], which would explain, at least partly, why women choose the low displacement risk sectors compared to men. Unfortunately, risk preferences are not readily observable in the data, so they will be approximated by family structure (marital status and presence of children[21]), with the hypothesis that single women with children have lower tolerance for risk than, for example, married men without children.

In a random utility model, an individual's occupational choice would depend on her individual characteristics, the characteristics of the occupations, and the wage she can receive in that occupation. If wages are a function of the same individual and occupation characteristics, they can be integrated out under certain assumptions[22] and a conditional logit model can be used for estimation. The coefficients on the occupational characteristics reflect the importance of that characteristic in the process of occupational choice.

I estimate ten different conditional logit models, one for each set of men, women,

[19]In this section I only focus on occupations, since measures of skill attributes are only available for occupations through the Dictionary of Occupational Titles.

[20]For recent experimental evidence see Hartog et al (2002), Dohmen at al (2005), Booth and Nolen (2009), and Borghans et al (2009).

[21]I present results using the presence of children under 6 years of age. Results with a variable indicating the presence of children under 18 years old are slightly weaker, but still significant.

[22]Two main assumptions are made: linear functional form, and error terms that are independently and identically distributed with type I extreme value distribution.

married men and women with and without children, and not married men and women with and without children. If displacement risk is the only occupational characteristic that influences occupational choice, then it is true that in general women are less tolerant to risk and choose occupations with lower displacement risk than men. This is true for all categories defined on the basis of family structure. This conclusion is based on results from a specification with only the mean probability of displacement for one-digit occupations included as a regressor, which are presented in Table 4. Not only is there a significant difference between the male and female coefficients in terms of magnitudes, but there is also a difference in their sign, with coefficients for all men categories being positive, while those for women are negative.

Table 4: Conditional Logit Model of Occupational Choice - Displacement Risk

	All Men	Married Men w/ child	Married Men w/o child	Single Men w/ child	Single Men w/o child
Displacement Risk	7.989*** [0.033]	8.771*** [0.074]	8.567*** [0.048]	11.894*** [0.291]	6.430*** [0.060]
N	594,265	119,543	281,377	7606	185,739
	All Women	Married Women w/ child	Married Women w/o child	Single Women w/ child	Single Women w/o child
Displacement Risk	-7.841*** [0.043]	-8.874*** [0.114]	-7.645*** [0.062]	-5.643*** [0.204]	-7.948*** [0.072]
N	521,127	75,465	243,104	21,196	181,362

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. One-digit occupation categories. Displacement risk refers to the probability of displacement from one-digit occupations. No controls for skill factors.

The risk of displacement, however, is definitely not the only characteristic of an occupation that is important in determining occupational choice. I will therefore add to the model measures of four different skill sets for each occupation - general intelligence, motor skills, physical strength, and visual skills. Table 5.a. below presents results for men, while Table 5.b. contains results for women.

As before, women are less tolerant to risk and choose occupations with much lower displacement risk than men. Among women, single parent women choose the safest occupations in terms of the risk of displacement, while married women without

Table 5a: Conditional Logit Model of Occupational Choice - Displacement Risk and Skill Characteristics, Men

	All Men	Married Men w/ child	Married Men w/o child	Single Men w/ child	Single Men w/o child
Displacement Risk	20.054*** [0.064]	24.219*** [0.154]	26.378*** [0.104]	7.687*** [0.490]	10.881*** [0.100]
General Intelligence	0.717*** [0.002]	0.839*** [0.005]	0.967*** [0.003]	-0.199*** [0.022]	0.365*** [0.004]
Motor Skills	-0.081*** [0.002]	-0.030*** [0.004]	-0.094*** [0.003]	0.034** [0.016]	-0.059*** [0.003]
Physical Strength	0.002 [0.002]	0.063*** [0.004]	0.063*** [0.003]	-0.193*** [0.019]	-0.122*** [0.004]
Visual Skills	0.232*** [0.002]	0.268*** [0.003]	0.279*** [0.003]	0.132*** [0.013]	0.181*** [0.003]
N	594,265	119,543	281,377	7606	185,739

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. One-digit occupation categories. Displacement risk refers to the probability of displacement from one-digit occupations. Skill characteristics are mean skill levels derived from factor scores at one-digit level occupations.

Table 5b: Conditional Logit Model of Occupational Choice - Displacement Risk and Skill Characteristics, Women

	All Women	Married Women w/ child	Married Women w/o child	Single Women w/ child	Single Women w/o child
Displacement Risk	-12.279*** [0.069]	-13.391*** [0.187]	-11.031*** [0.102]	-16.087*** [0.311]	-13.084*** [0.115]
General Intelligence	0.678*** [0.002]	0.698*** [0.006]	0.750*** [0.004]	0.194*** [0.012]	0.632*** [0.004]
Motor Skills	-0.360*** [0.003]	-0.274*** [0.007]	-0.350*** [0.004]	-0.454*** [0.014]	-0.399*** [0.004]
Physical Strength	-0.978*** [0.002]	-0.960*** [0.006]	-0.981*** [0.004]	-1.088*** [0.012]	-0.980*** [0.004]
Visual Skills	0.834*** [0.003]	0.822*** [0.009]	0.833*** [0.005]	0.886*** [0.014]	0.841*** [0.005]
N	521,127	75,465	243,104	21,196	181,362

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. One-digit occupation categories. Displacement risk refers to the probability of displacement from one-digit occupations. Skill characteristics are mean skill levels derived from factor scores at one-digit level occupations.

children are choosing more risky occupations in terms of displacement risk. Married women with children and single women without children do not seem to be different in their attitudes towards displacement risk. Among men, single parents are, as expected, the least tolerant to displacement risk, followed closely by single men without children.

Married men on the other hand, both with and without small children, are making the boldest of choices, with a clear preference for risky occupations.

In terms of the influence of other occupational characteristics, general intelligence and motor skills attributes of an occupation do not seem to influence men and women's choice of an occupation in a substantially different manner. However, it is clear that men's decisions are more influenced by the level of physical strength required by an occupation, while women's choices depend more on the level of visual skills.

The addition of occupational attributes based on their skill requirements suggests not only that demand side factors are important in explaining gender occupational segregations, but also raises two another potential sources of bias in the estimated coefficients. One is the correlation between the required levels of skill and the risk of displacement in an occupation[23], evidence of which comes from the fact that the magnitude of the coefficients on the risk of displacement changed with the addition of skill factors. The second is the fact that there might exist other occupational attributes, currently omitted from the analysis, that are correlated with displacement risk and that are disproportionately more appealing to either men or women.

5.Model

In order to have a better, more unified understanding of the results presented in the empirical part, more structure needs to be imposed on this problem. A structural model of occupational choice is going to allow us to achieve exactly that, and will also allow for more flexibility through the possibility of performing counterfactual experiments.

[23] A potential road-map to identify this problem is first, to establish empirically the fact that there exists gender sorting into occupations based on occupational attributes like skill requirements, and then to check how different - or similar - this sorting pattern is compared to the sorting based on displacement risk. This is one of the main topics in my current research agenda.

5.1.Model Set-Up

This life-cycle model of occupational choice builds on the dynamic discrete choice model developed by Keane and Wolpin (1997), and, while abstracting from the educational decision, it explicitly incorporates displacement related characteristics of occupational categories (like displacement and re-employment probabilities), into individuals' choices of labour market alternatives. The setup of the model is gender neutral, and the model period is one calendar year. Individuals will be indexed by i, the model period - which is identical to an individual's age, will be indexed by a, and the available labour market alternatives will be indexed by k.

Environment - The economy consists of one cohort of otherwise identical individuals who begin their working life at age $\underline{a} = 21$ and retire at age $\overline{a} = 60$. At each age a, individuals choose between three mutually exclusive alternatives in the labour market - work in either one of two occupation categories or be in the non-employment[24] category. The two occupation categories, generically denoted as "low-displacement" (LD) and "high-displacement" (HD), differ in their displacement and re-employment probabilities, their wage profiles, as well as the associated non-monetary utility rewards. Obviously, displacement and re-employment probabilities in the non-employment category are set to zero. Displacement probabilities (p), re-employment probabilities (q), and non-monetary utility rewards (α) vary not only by occupational category k, but also vary by the age[25] of the individual.

The model allows for period-by-period human capital accumulation. In this model's set-up, human capital is to be interpreted as occupation specific human capital, since general human capital enters the individuals' payoff function through the

[24]This category includes both unemployment and being out of the labour force.

[25]In the model individuals start their working life at age 21 and live for 40 years, up to age 60 when they retire. Their career is divided into four main age groups: 21 to 30, 31 to 40, 41 to 50 and 51 to 60. As observed in the data, displacement and re-employment probabilities, and non-monetary utility rewards, vary by occupation category as well as by age group.

age component. Occupation specific - and from here onwards human capital (hc) - is partially transferable upon an occupational switch[26] at rate δ, it is penalised in the event of displacement at rate gd in the period when displacement occurs, and it further depreciates with each non-employment spell at a rate of gs per period of non-employment.

In each period, displacement from either occupation occurs with probability $p_k(a)$, with the probability of displacement being lower from LD occupations compared to HD occupations. If displaced from occupation k at the end of the current period (a), at the beginning of the next period individuals are allowed to choose again between all three labour market alternatives with probability $q_k(a)$ - what in the model is referred to as the re-employment probability, and remain in non-employment for the entire period immediately following the period in which displacement occurred ($a+1$) otherwise. The probability of re-employment is higher in LD occupations compared to HD occupations.

Individuals are risk-neutral and at each age a maximize the expected discounted present value of their life-time utility by choosing one of the three available mutually exclusive career alternatives.

More specifically, the time-line of the model is as follows: in the initial period, prior to entering the labour market, each individual is endowed with one unit of human capital that can be used in any of the two occupation categories. At age 21, at the beginning of their working careers, agents draw a one-time preference parameter (ω) over the three mutually exclusive labour market alternatives[27]. This preference parameter evolves stochastically over time according to a specified transition probability (π). Knowledge of the preferred alternative in the labour market at each age a increases the total value of individual utility by the amount of the non-monetary component only if the preferred alternative is also the chosen alternative at age a.

[26] This includes both voluntary occupation switches and involuntary switches due to displacement.

[27] The initial period distribution of the preference parameter ω is exogenously set to match the data distribution of 21 year olds over the three mutually exclusive labour market alternatives.

Knowing the initial stock of human capital and the value of the preference shock, the individual chooses one of the three available alternatives - LD, HD, or NE - by comparing the expected discounted present value of each option and selecting the one that offers maximal life-time utility, and monetary rewards are earned for the current period.

If the LD or HD categories were chosen, at the end of the initial period individuals learn the value if the displacement shock[28]. In the event of displacement, individuals will adjust their stock of human capital to account for the penalty incurred with displacement, and they learn the value of a second shock, the re-employment shock. If there is a good realisation of the re-employment shock, they enter next period like any other non-displaced individuals, and therefore will be allowed to choose among all labour market alternatives. If, however, a bad realisation of the re-employment shock occurs, they will enter next period as non-employed persons, and will remain so for the entire duration of next period, without having the possibility of choice among the three available alternatives.

Starting from the second period and until retirement from the labour market, at the beginning of each period the preference parameter is updated, and then, depending on the realisation of last period's re-employment shock, the individual decides on his current period choice based on the maximal value of expected discounted present value of his remaining life-time utility (good realisation of the re-employment shock) or is directly assigned into non-employment (bad realisation of the re-employment shock). With knowledge of the current period's preference parameter, the current period's choice and last period's choice, the stock of human capital is updated to account for potential switches or depreciation due to non-employment, and current earnings are realised. Just like in the initial period, at the end of each period displacement and re-

[28]In other words, you cannot be displaced from non-employment. Alternatively, you can think of the probability of displacement - and the probability of re-employment - from non-employment as being equal to zero.

employment shocks are realised, human capital adjustments are made, and the cycle is repeated identically until retirement age is reached.

Preferences - At each age a, the individual's problem is to choose one of the three mutually exclusive career alternatives such as to maximise the expected discounted present value of his remaining life-time utility:

$$E\left[\sum_{\tau=a}^{\bar{a}} \beta^{\tau-a}\left(\sum_{k} d_k(a)U_k(hc, l, k_{-1}; a)\right)\right]$$

where $d_k(a) = 1$ if alternative k is chosen at age a, and $d_k(a) = 0$ otherwise; $U_k(\cdot; a)$ denotes the individual's total utility derived from category k at age a; $hc(a)$ denotes the individual's stock of human capital available at the beginning of period a; $l(a)$ indicates the individual's preferred labour market alternative at age a and is based on the updated value of the preference shock at the beginning of each period; $k_{-1}(a)$ denotes the individual's choice last period.

At each age a, individuals derive utility from consumption $c_k(hc, l, k_{-1}; a)$ and a non-monetary, alternative specific taste parameter $\alpha_k(a)$ if the chosen alternative at age a coincides with the preferred alternative at age a, i.e. $k(a) = l(a)$. Individual utility at age a is given by:

$$U_k(hc, l, k_{-1}; a) = c_k(hc, l, k_{-1}; a)e^{\alpha_k(a)\mathbf{I}(k(a)=l(a))}$$

Consumption at age a is equal to the individual's earnings when alternative k is chosen, and is further given by $c_k(hc, l, k_{-1}; a) = w_k(hc, l, k_{-1}; a)$, where $w_k(hc, l, k_{-1}; a) = [\delta(k_{-1}, k)hc(a)]^{\gamma_k}$ if $k = \{LD, HD\}$ and $w_k(hc, l, k_{-1}; a) = B$ if $k = NE$. In other words, if employed in either LD or HD occupations, individuals' earnings are a function of their adjusted, beginning of period, stock of human capital, and are equal to a constant amount B if non-employed. If employed in either LD or HD occupations, earnings grow at a rate of γ_k per period, with the growth rate being lower in LD occupations compared to HD occupations.

Human capital accumulates at a rate of one unit per model period, and is therefore directly proportional to the agent's age and the number of periods spent out of non-employment up to age a. It evolves according to the following law of motion:

$$hc(a') = [\delta(k_{-1}, k)hc(a) + 1\mathbf{I}(k(a) \neq NE)] [1 - gs_k\mathbf{I}(k(a) = NE)] [1 - gd_k\mathbf{I}(D(a) = 1)]$$

with $\delta(k_{-1}, k)$, the degree of human capital transferability between occupations being higher for LD occupations compared to HD occupations; gs_k, the rate of human capital depreciation while in non-employment being lower for LD occupations compared to HD occupations[29], and gd_k, the rate of human capital penalty in the event of displacement being lower for LD occupations compared to HD occupations. $\mathbf{I}$ represents the indicator function, $k(a)$ represents the current choice for period a ($k(a) = \{LD, HD, NE\}$), and $D(a) = 1$ is an indicator for displacement at age a. The alternative specific taste parameter $\alpha_k(a)$ represents the non-pecuniary benefit of choosing alternative k at age a, and enters the per-period utility function exponentially[30], conditional on the chosen alternative at age a also being the individual's preferred alternative at age a.

Individual Optimization Problem - As previously mentioned, individuals are risk neutral and maximize the expected discounted present value of life-time utility.

[29]Since one of the state variables is the individual's choice of labour market category in the period prior to the current period, this allows for different rates of depreciation of human capital while in non-employment only during the first period of non-employment following a job spell. If non-employment extends beyond one period, in all subsequent non-employment periods human capital will depreciate at a constant unique rate, regardless of the occupational category of the last job spell. In other words, the initial loss of human capital when entering non-employment is higher if an individual is entering non-employment from a HD occupation compared to a LD occupation, but if non-employment lasts for more than one period, in all subsequent periods of non-employment after the first one, human capital depreciates at the same rate - it's value is in between the two mentioned above. A switch from non-employment into either LD or HD occupations does not depreciate the value of human capital.

[30]An exponential taste parameter allows for proportional shifts in the utility function, whereas an additive taste parameter would change the levels of the utility function.

Maximization is accomplished by choice of the optimal sequence of control variables $d_k(a)$, with $k \in \{LD, HD, NE\}$, from the beginning of working age ($\underline{a}$) until retirement age ($\overline{a}$). The model is solved recursively from the retirement age ($\overline{a}$) backwards.

If at age a the individual has a choice between all three labour market alternatives, the individual's problem is:

$$V(hc, l, k_{-1}; a) = \max_k \{V_k(hc, l, k_{-1}; a)\}$$

where $k \in \{LD, HD, NE\}$, and $V_k(\cdot; a)$ represents the value to the individual of choosing alternative k.

If no choice is available and the individual is forced into non-employment at age a, his problem becomes:

$$\overline{V}(hc, l, k_{-1}; a) = V_{NE}(hc, l, k_{-1}; a)$$

At age $\overline{a} = 60$, there is zero continuation value to each alternative, therefore:

$$V_k(hc, l, k_{-1}; a) = U_k(hc, l, k_{-1}; a)$$

for all $k \in \{LD, HD, NE\}$.

At age $a < \overline{a}$, the value of choosing alternative k is given by:

$$
\begin{aligned}
V_k(hc, l, k_{-1}; a) = U_k(hc, l, k_{-1}; a) & \\
+ \quad & \beta(1 - p_k(a)) \left[\sum_{l'} \pi_{ll'} V(hc', l', k; a') \right] \\
+ \quad & \beta p_k(a) q_k(a) \left[\sum_{l'} \pi_{ll'} V(hc', l', k; a') \right] \\
+ \quad & \beta p_k(a)(1 - q_k(a)) \left[\sum_{l'} \pi_{ll'} \overline{V}(hc', l', k; a') \right]
\end{aligned}
$$

with $k, k' \in \{LD, HD, NE\}$. In other words, the value of choosing alternative k at age a is given by the direct utility derived from the choice of category k at age a, $U_k(\cdot; a)$ and the expected discounted value from next period on, taking into consideration the fact that with probability $1 - p_k(a)$ there is no displacement from occupation k and there is scope for voluntary switches next period; with probability $p_k(a)q_k(a)$ displacement from occupation k occurs, but because of the good realisation of the re-employment shock, there is scope for an involuntary switch next period; and with probability $p_k(a)(1 - q_k(a))$ the individual will be forced into non-employment next period.

Similarly, at age $a < \overline{a}$, the value of non-employment[31] is given by:

$$
V_{NE}(hc, l, k_{-1}; a) = B + \beta \left[\sum_{l'} \pi_{ll'} V(hc', l', k; a') \right]
$$

with $k' \in \{LD, HD, NE\}$. If the individual is voluntarily or involuntarily non-employed in the current period, he receives the constant non-employment benefit and next period will have the option of remaining non-employed or finding a job in one of the two occupational categories.

[31] The expression for the value of non-employment at age a can be derived from equation(*) considering $p_{NE}(a) = q_{NE}(a) = 0$.

5.2.Calibration

The parameters to be calibrated are:

- $\alpha_k(a)$ - non-monetary utility component taste parameter (3×4 matrix)
- π - transition probability matrix of the preference shock l (3×3 matrix[32])
- $\delta(k_{-1}, k)$ - human capital transferability matrix (2×2 matrix[33])
- gs_k - human capital depreciation parameter (3×1 vector)
- gd_k - human capital displacement penalty parameter (2×1 vector)
- γ_k - earnings growth parameter (2×1 vector)
- B - non-employment benefit.

The values for the other exogenous parameters of the model are established as follows:

- β - time discount rate, set at 0.95
- $p_k(a)$ - probability of displacement, estimated from the Displaced Worker Survey over the period 1984-2002[34]
- $q_k(a)$ - probability of re-employment conditional on displacement, estimated from the Displaced Worker Survey over the period 1984-2002

[32] In fact I am only calibrating the first 2 columns of the transition matrix, given the restriction that the elements in each row of the transition matrix must sum up to one.

[33] Only the off-diagonal parameters are calibrated, since the main diagonal parameters are fixed to 1, i.e. human capital is transferred one-to-one from one job to another, if the job switch does not involve an occupation switch.

[34] The sample used to generate displacement probabilities consists of men, high-school graduates, between the ages of 21 and 60 years old - see the section regarding the calibration of the model.

The model is calibrated to fit CPS data[35] over the period 1984-2002, for men, high-school graduates, between the ages of 21 and 60 years old. The targeted data sample moments are:

- proportion employed, by age and occupation category (from CPS March files)
- proportion not working, by age (from CPS March files)
- mean and standard deviation of log earnings, by age and occupation category (from CPS March files)
- one-period transition rates between all three labour market alternatives, by age (from linked CPS March files)
- mean log of earnings loss for those displaced and re-employed, by age and occupation category (from the Displaced Worker Survey files)
- one-period transition rates between labour market alternatives for those displaced, by age (from the Displaced Worker Survey files)

5.3.Quantitative Analysis - Counterfactual Experiments

Next, I perform a series of four main counterfactual experiments meant to pin down the relative importance of the incidence and costs of displacement in accounting for the differences in shares of men and women across labour market alternatives. In what follows I am going to refer to the model calibrated to match data moments for men as the baseline model for men, and to the counterfactual models as models for women.

First, I re-solve the model taking all the parameter calibrated to fit the data for men, except the probabilities of displacement, which correspond to the probabilities of displacement of women, high-school graduates, between the ages of 21 and 60 years

[35] I am using the Displaced Worker Survey from 1984 to 2002 and the March CPS files from 1984 to 2002

old, in the Displaced Worker Survey over the period 1984 to 2002. So, if women had the same preference parameters, and human capital accumulation and depreciation parameters as men, how much would the difference in displacement rates between men and women explain from the difference between the shares of men and women in low and high displacement occupations, and in non-employment? Figure 12 in Appendix 2 presents the results. If differences in displacement probabilities between men and women are the unique source of gender segregation across labour market alternatives, then we would expect the model for women to be very different from the model for men, and in fact to be exactly overlapping the data for women. In fact, the higher probabilities of displacement for women compared to men account for approximately 15% of the fact that more women than men choose low displacement occupations and non-employment, while fewer women than men choose high displacement occupations.

In the second experiment, all the parameters of the model are again kept at their value in the baseline model for men, except the displacement and re-employment probabilities, which correspond to those of women in the Displaced Worker Survey, with similar characteristics as before. Results are presented in Figure 13 in Appendix 2. Allowing for differences in both displacement and re-employment probabilities by gender does not change the quantitative result obtained in experiment 1. So, differences in the re-employment probabilities have little explanatory power for the difference in the distribution of men and women across the three labour market alternatives.

Building on the second experiment, in the third experiment I allow not only for different displacement and re-employment probabilities for men and women, but also for different rates of penalty of human capital at displacement between men and women. The human capital displacement penalty rates for women are the result of a new calibration of the baseline model, in which the only data moments targeted are the earnings losses of displaced women, in the Displaced Worker Survey over the period 1984 to 2002. Results are presented in Figure 14 in Appendix 2. The combined effect of different displacement probabilities, re-employment probabilities, and different rates of human capital penalty at displacement between men and women, is slightly larger than the effect observed in the second experiment, accounting for approximately 16% of the gender occupational segregation.

In the last experiment, the fourth factor with potential explanatory power in the gender segregation across labour market alternatives is an extra preference for non-employment of women. In the context of this model these translate into higher transition probabilities for the preference parameter for women compared to men for such transitions as those from low and high displacement occupations into non-employment, and lower transition probabilities for women compared to men for such transitions as those from non-employment into low and high displacement occupation categories. They result from a new calibration of the baseline model to match flows into and out of non-employment for women, in the linked March CPS files over the period 1984 to 2002. Results of the fourth experiment are presented in Figure 15 in Appendix 2. Allowing women to have an extra preference for non-employment compared to men explains in a 60% proportion why women are reluctant to take on jobs in the high-displacement occupation category, but does little to explain differences in the distribution of men and women in the low-displacement occupation category. The extra preference of women for non-employment can be thought of as a higher value of the outside option for women, or anything that gives women an increased value of the non-monetary utility component in the non-employment state compared to be men, whether it is household production, or bearing and caring for children.

Other important potential sources of differences between men and women's choice of occupations that were raised in the empirical part of this paper are differences in demographic structure of men and women, differences in skill endowments[36] between men and women, and differences in the level of skill requirements across occupations.

[36] Think more about physical strength, motor skills and visual skills, rather than general intelligence.

In order to have a more comprehensive explanation of the role played by the incidence and consequences of displacement in gender occupational segregation, all of the issues mentioned above, as well as their interaction with displacement risk need to be accounted for in future versions of the model. They are all important aspects to be explored in future research projects.

6.Conclusion

This paper builds on three main observational facts: the fact that there exist differences in displacement rates across industries and occupations, the fact that there are differences in male/female employment shares across industries and occupations, and the fact that the share of women employed across industries and occupations is inversely related to displacement rates in those industries and occupations. I explore these facts to investigate the relationship between the gender distribution across industries and occupations and the incidence and consequences of displacement.

I first document existing gender differences in the incidence and cost of displacement across industries and occupations and then establish empirically the validity of the fact that women self-select into low displacement industries and occupations. Women are less likely to be displaced overall, however they are more likely to be displaced at the industry and occupation level than men. Women also face stronger negative employment and monetary effects of displacement: once displaced, women are less likely to be re-employed, they switch industries and occupations more often, they make fewer full-time to full-time transitions, they spend longer time in unemployment and therefore take fewer jobs post-displacement, and they incur bigger monetary losses. So, to insure against the costly risk of displacement, women self-select into less risky industries and occupations. Women prefer industries and occupations characterised by lower displacement rates, lower human capital depreciation (or alternatively higher human capital transferability), and lower earnings growth.

I then develop a gender neutral occupational choice model with exogenous displacement risk to assess the role of displacement risk on gender distributions across industries and occupations and on womens choice of low displacement industries and occupations. I calibrate the model to fit CPS data on men and perform a number of counterfactual experiments for women. Allowing women to have higher displacement risk, lower re-employment risk, and higher human capital penalty at displacement accounts for approximately 20% of the gender occupational segregation. If women are also allowed to have an extra preference parameter for non-employment, this explains in a proportion of approximately 60% why women stay away from high-displacement occupation categories.

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Appendix 1 - Data

1980 Census Classification of 1-Digit Industries

1. Agriculture
2. Mining
3. Construction
4. Manufacturing - durables
5. Manufacturing - non-durables
6. Transportation
7. Communications
8. Utilities services
9. Wholesale trade
10. Retail trade
11. Financial and insurance services
12. Private household services
13. Repair services
14. Personal services
15. Entertainment services
16. Hospitals
17. Medical services
18. Educational services
19. Social services
20. Other professional services
21. Forestry and fishing
22. Public administration
23. Armed forces (omitted)

1980 Census Classification of 1-Digit Occupations

1. Managerial occupations
2. Professional occupations
3. Technicians
4. Sales occupations
5. Administration occupations
6. Private household occupations
7. Protection occupations
8. Service occupations
9. Craft and repairs occupations
10. Operators occupations
11. Transport occupations
12. Handlers
13. Farmers
14. Armed forces (omitted)

Table 1: Examples of Industries and Occupations with Highest and Lowest Risk of Displacement and the Fraction of Female Employment (3-digit classification levels)

INDUSTRY	Fraction Displaced	Fraction Female
Highest risk:		
Mfg-leather and leather prod	0.226	0.591
Mining	0.198	0.148
Mfg-apparel and other finished textile prod	0.179	0.761
Mfg-toys, amusement and sporting goods	0.175	0.481
Private household services	0.142	0.855
Mfg-lumber and wood prods, ex furniture	0.138	0.157
Mfg-primary metals	0.135	0.150
Mfg-machinery, ex electrical	0.134	0.243
Construction	0.132	0.103
Mfg-fabricated metals	0.130	0.242
Lowest risk:		
Insurance and real estate	0.042	0.564
Other professional services	0.041	0.480
Goods producing-other agricultural	0.040	0.231
Utilities and sanitary services	0.038	0.207
National security and internal affairs	0.036	0.374
Admin of human resource programs	0.027	0.674
Hospitals	0.025	0.781
Other public administration	0.023	0.488
Educational services	0.013	0.687
Justice, public order and safety	0.008	0.310

OCCUPATION	Fraction Displaced	Fraction Female
Highest risk:		
Construction labourers	0.217	0.043
Fabricators, assemblers, inspectors, samplers	0.154	0.391
Other handlers, equipment cleaners, helpers, labourers	0.138	0.245
Machine operators, and tenders, except precision	0.135	0.421
Other transportation and material moving occupations	0.131	0.043
Construction trades	0.124	0.023
Other precision production, craft, and repair	0.113	0.229
Forestry and fishing occupations	0.112	0.046
Freight, stock, and material handlers	0.107	0.232
Engineering and science technicians	0.097	0.231
Lowest risk:		
Health technologists and technicians	0.034	0.832
Health assessment and treatment occupations	0.029	0.870
Teachers, college and university	0.026	0.407
Mail and message distribution	0.025	0.378
Private household service occupations	0.020	0.962
Lawyers and judges	0.019	0.240
Teachers, except college and university	0.018	0.747
Officials and administrators, public admin.	0.017	0.444
Health diagnosing occupations	0.011	0.219
Farm operators and managers	0.006	0.180

Appendix 2 - Figures

Figure 1: Male vs. female unemployment rates, BLS, January 1980 to Sept 2009

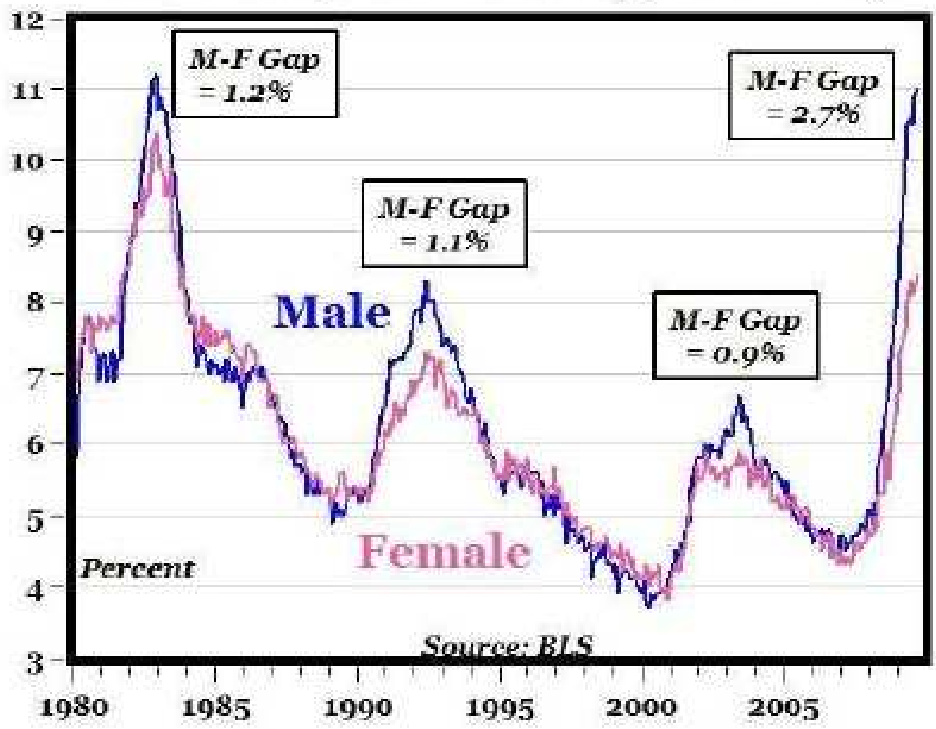


Figure 2: Employment shares and displacement rates by gender in 1-digit industries, CPS DWS, 1984 to 2004 averages

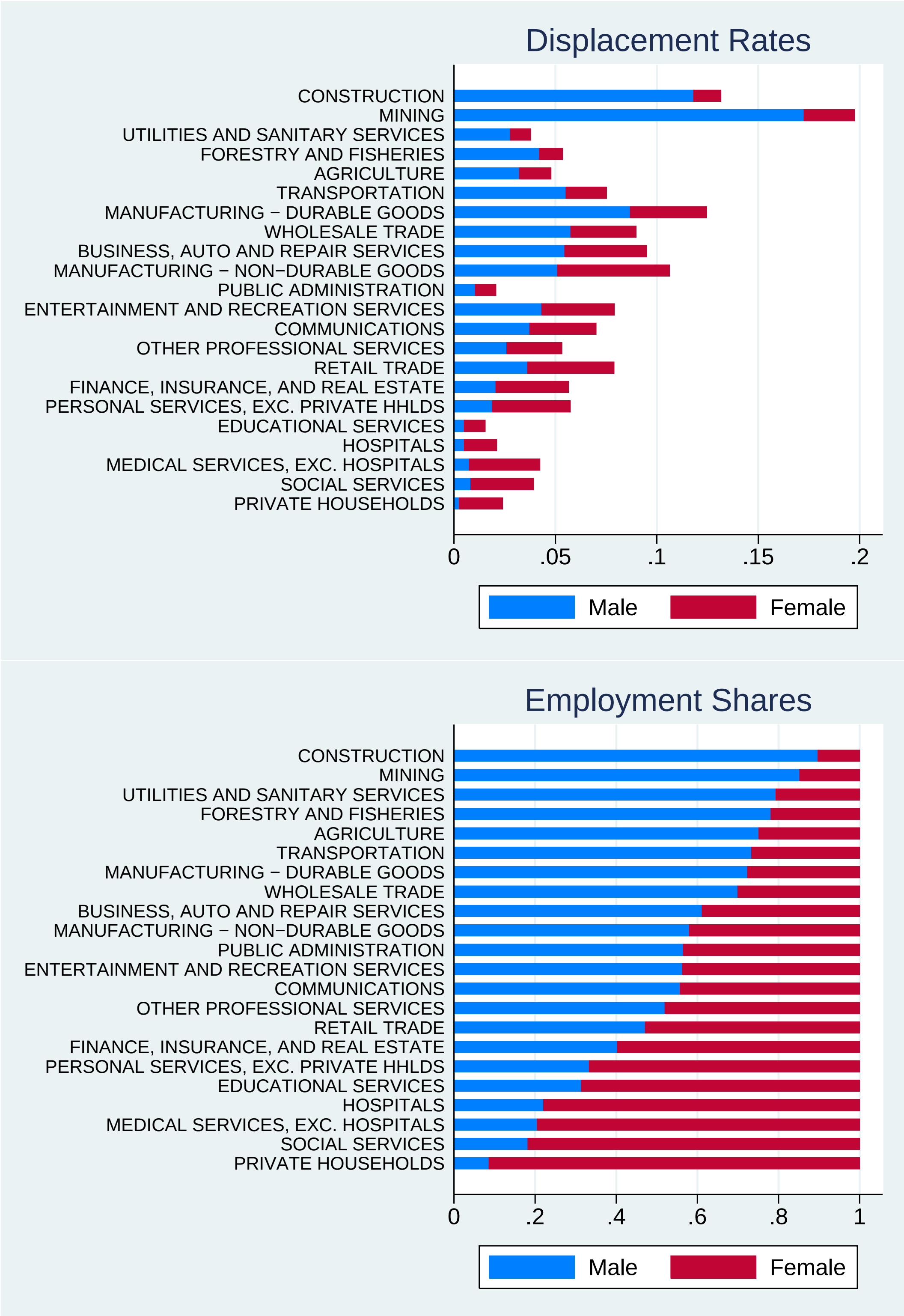


Figure 3: Employment shares and displacement rates by gender in 1-digit occupations, CPS DWS, 1984 to 2004 averages

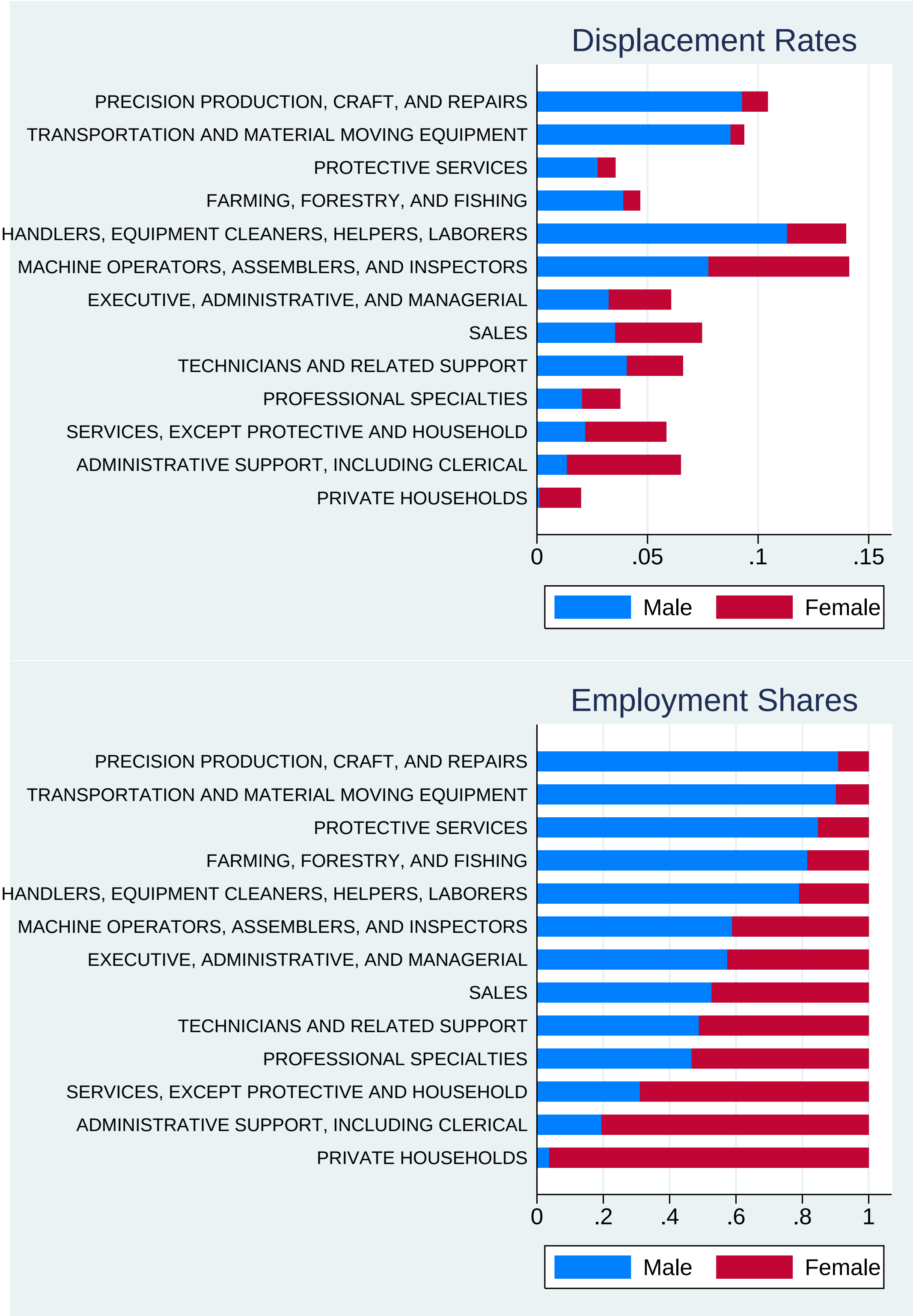
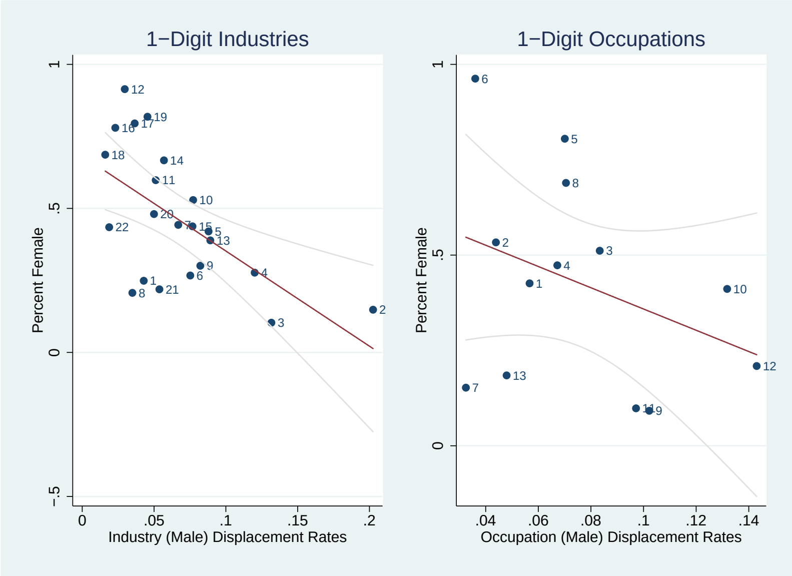


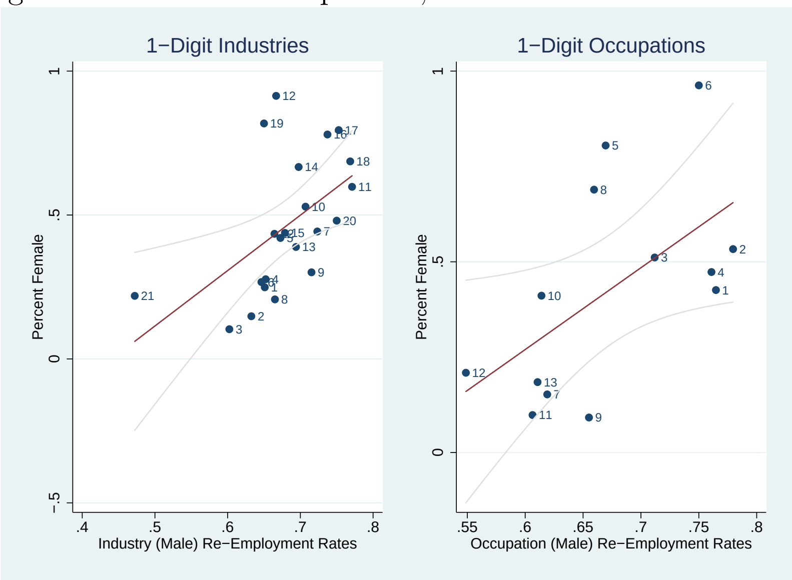
Figure 4: Correlations between female employment shares and (male) displacement rates in one-digit industries and occupations, CPS DWS 1984-2002 averages



Correlation Coefficients

Industry	-0.601***	Occupation	-0.351

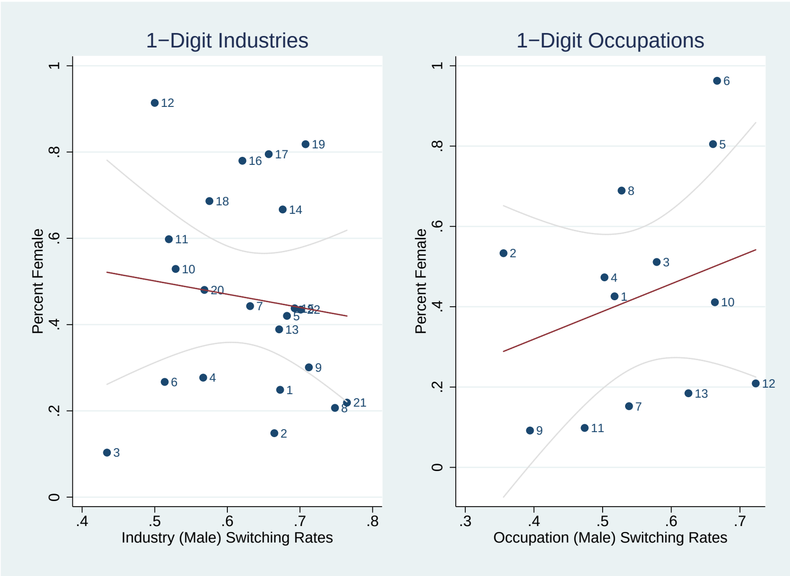
Figure 5: Correlations between female employment shares and (male) re-employment rates in one-digit industries and occupations, CPS DWS 1984-2002 averages



Correlation Coefficients

Industry	0.521**	Occupation	0.711***

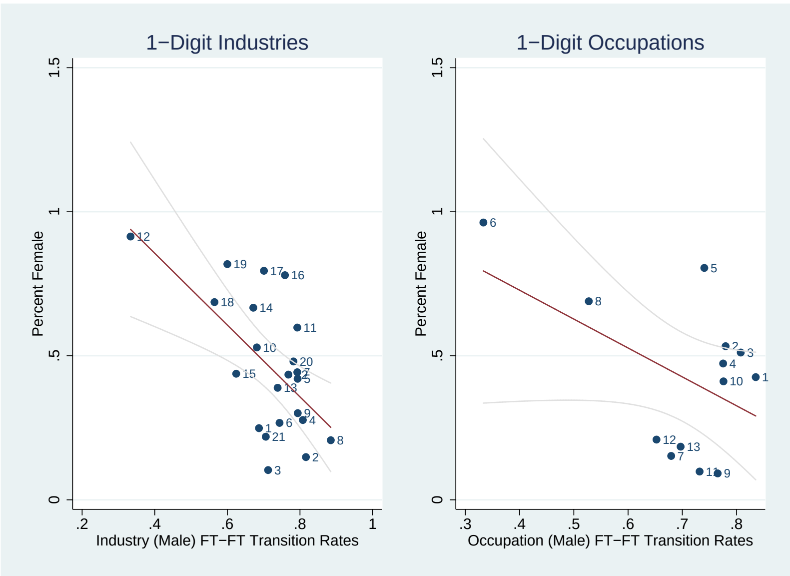
Figure 6: Correlations between female employment shares and (male) industry and occupation switching rates in one-digit industries and occupations, CPS DWS 1984-2002 averages



Correlation Coefficients

Industry	-0.304	Occupation	0.372

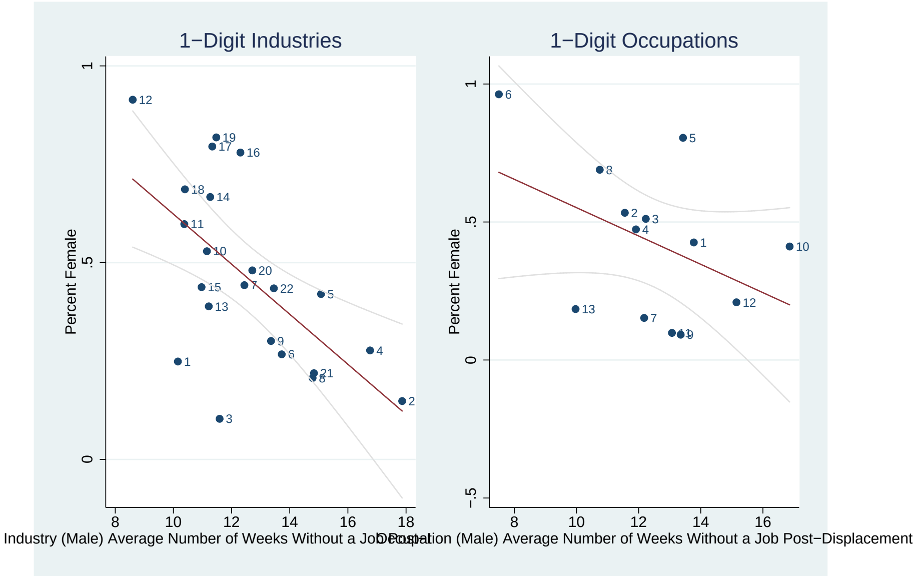
Figure 7: Correlations between female employment shares and (male) full-time to full-time transition rates in one-digit industries and occupations, CPS DWS 1984-2002 averages



Correlation Coefficients

Industry	-0.619***	Occupation	-0.494*

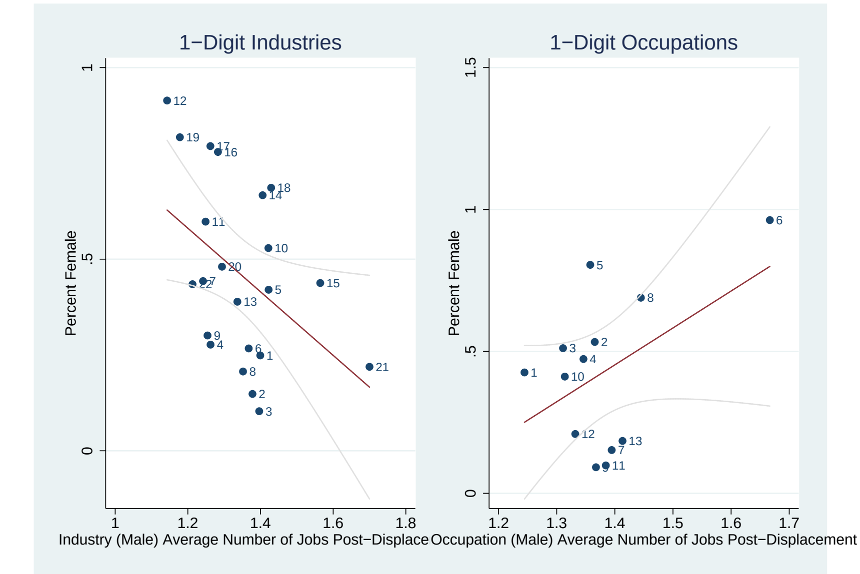
Figure 8: Correlations between female employment shares and (male) average number of weeks without a job post-displacement in one-digit industries and occupations, CPS DWS 1984-2002 averages



Correlation Coefficients

Industry	-0.597**	Occupation	-0.391*

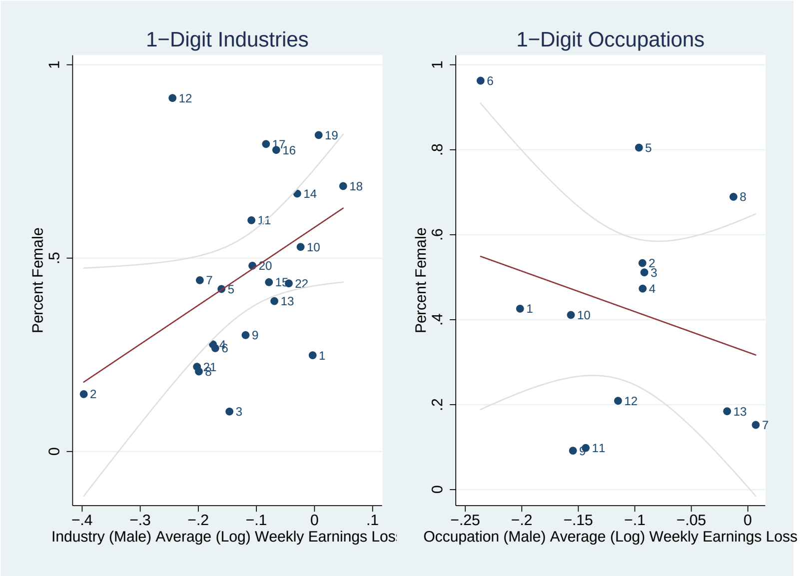
Figure 9: Correlations between female employment shares and (male) average number of jobs post-displacement in one-digit industries and occupations, CPS DWS 1984-2002 averages



Correlation Coefficients

Industry	-0.314**	Occupation	0.532*

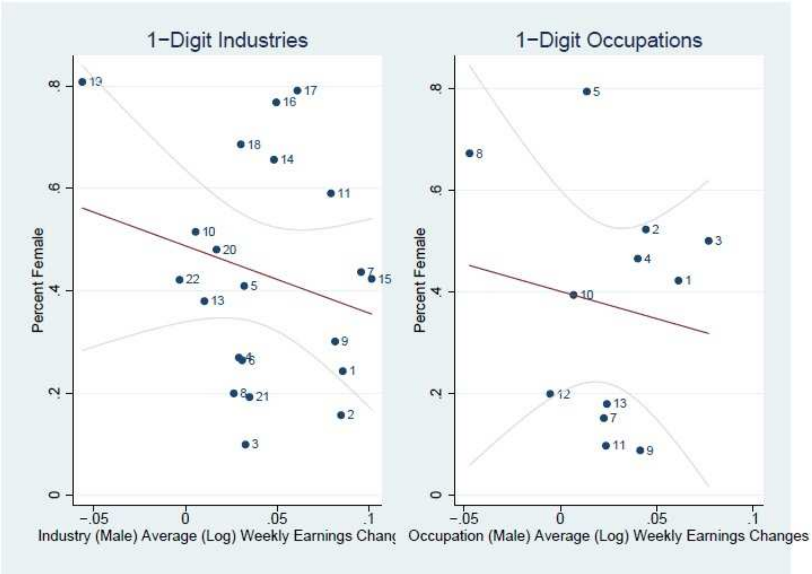
Figure 10: Correlations between female employment shares and (male) average (log) weekly earnings losses for displaced workers in one-digit industries and occupations, CPS DWS 1984-2002 averages



Correlation Coefficients

Industry	0.549***	Occupation	-0.237

Figure 11: Correlations between female employment shares and (male) average (log) weekly earnings gains for non-displaced workers in one-digit industries and occupations, CPS March files 1984-2002 averages



Correlation Coefficients

Industry	-0.397*	Occupation	-0.150

Figure 12: Experiment 1

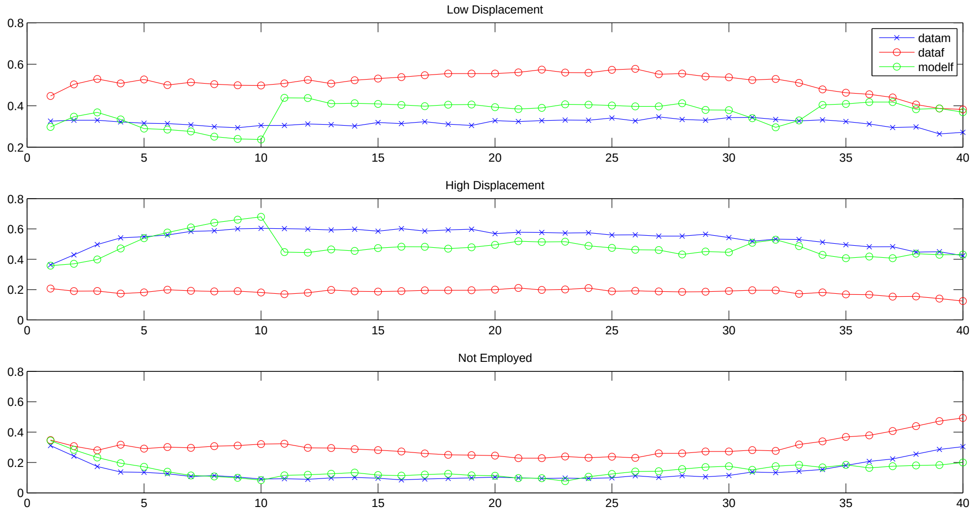


Figure 13: Experiment 2

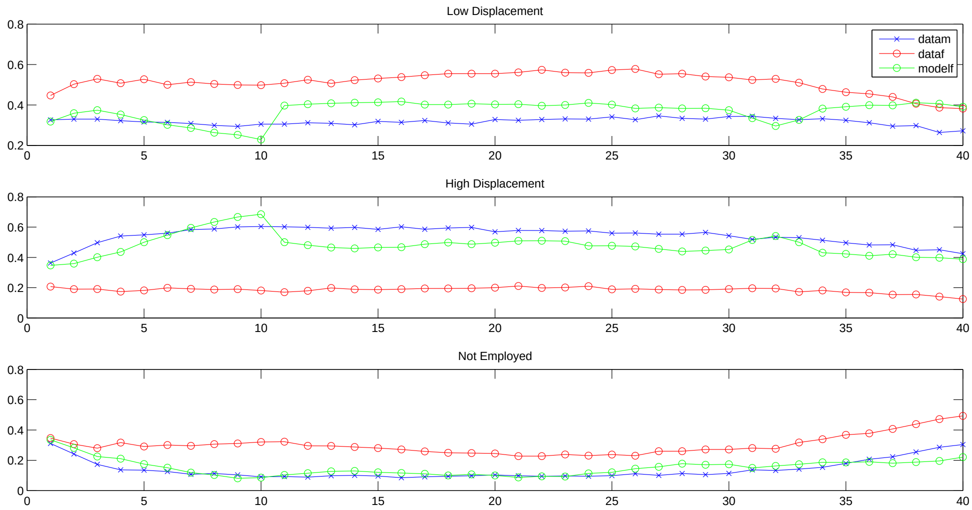


Figure 14: Experiment 3

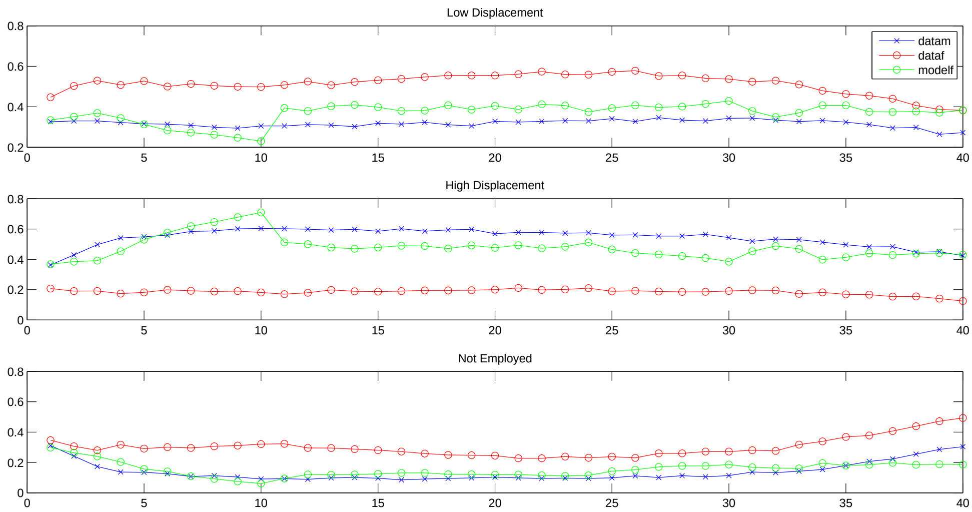
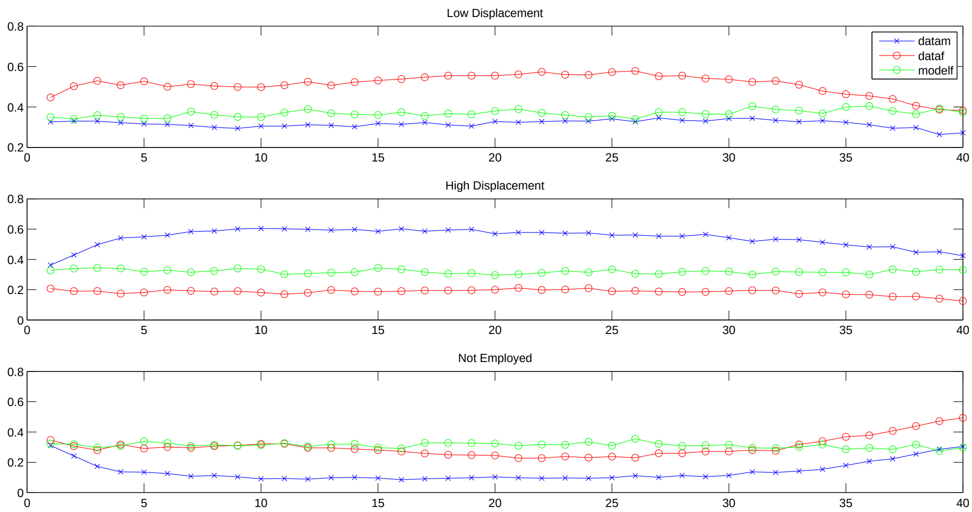


Figure 15: Experiment 4



Appendix 3 - Tables

Table 1: Summary statistics - DWS sample, 1984 - 2002

	Non-Displaced			Displaced		
	Male	Female	Total	Male	Female	Total
Gender	52.8%	47.2%		58%	42%	
Age Category						
20-24	10.20%	11.50%	10.80%	13.50%	13.60%	13.60%
25-34	28.30%	27.90%	28.20%	32.80%	32.10%	32.50%
35-44	28.40%	28.70%	28.60%	26.90%	26.80%	26.90%
45-54	21.10%	21.00%	21.10%	17.20%	18.50%	17.70%
55-64	11.90%	10.80%	11.40%	9.50%	9.10%	9.30%
Race						
White	88.70%	85.70%	87.30%	88.50%	84.80%	86.90%
Non-white	11.30%	14.30%	12.70%	11.50%	15.20%	13.10%
Marital Status						
Married	69.30%	62.20%	66.00%	62.60%	54.70%	59.30%
Not married	30.70%	37.80%	34.00%	37.40%	45.30%	40.70%
Education						
Less HS	12.10%	8.90%	10.60%	15.70%	12.70%	14.40%
HS grad or more	58.90%	65.10%	61.80%	64.60%	69.30%	66.60%
Coll or more	29.00%	25.90%	27.50%	19.70%	18.00%	19.00%
Full-Time/Part-Time						
FT	86.00%	68.50%	77.80%	93.70%	80.40%	88.10%
PT	14.00%	31.50%	22.20%	6.30%	19.60%	11.90%
Class of Worker						
Private	70.70%	72.00%	71.30%	96.30%	94.00%	95.40%
Government	14.40%	20.00%	17.00%	3.20%	5.60%	4.20%
Self-empl	14.90%	8.00%	11.60%	0.50%	0.30%	0.40%

Note: "Full-Time/Part-Time" and "Class of Worker" are job characteristics that refer to the pre-displacement period. All the individual demographic characteristics are at the current survey date.

Table 2: Summary Statistics - Displacement Characteristics - DWS sample, 1984 - 2002

	Male	Female	Total
Incidence of Displacement			
Displacement Rate	8.00%	6.50%	7.50%
Displacement Reason			
Plant closed down	28.42%	31.10%	29.60%
Insufficient work	31.91%	22.22%	27.64%
Position or shift abolished	12.88%	15.71%	14.12%
Seasonal job completed	4.68%	3.67%	4.24%
Self-operated business failed	2.77%	1.81%	2.35%
Some other reason	19.35%	25.48%	22.05%
Year of Displacement			
Displacement Year			
1 year before survey	44.56%	43.42%	44.08%
2 years before survey	29.68%	30.53%	30.04%
3 years before survey	25.76%	26.05%	25.88%
Employment Effects of Displacement			
Re-employment Rate	66.50%	61.20%	64.30%
Industry Switch Rate	57.40%	63.90%	60.00%
Occupation Switch Rate	50.90%	51.10%	51.00%
Industry & Occupation Switch Rate	38.40%	40.10%	39.10%
FT-to-FT Transition Rate	80.80%	70.80%	77.20%
Number of Weeks w/o Job Post-Displacement	13.58	14.69	14.02
	[17.86]	[18.90]	[18.28]
Number of Jobs Post-Displacement	1.45	1.36	1.42
	[1.29]	[1.14]	[1.23]
Monetary Effects of Displacement			
(Log) Weekly Earnings Loss (if displaced)	-0.128	-0.123	-0.126
	[0.633]	[0.685]	[0.655]
(Log) Weekly Earnings Change (if never displaced)	0.030	0.041	0.036
	[0.446]	[0.473]	[0.460]
(Log) Weekly Earnings Change (March-to-March)	0.026	0.039	0.033
	[0.459]	[0.488]	[0.473]

Table 3: Displacement Incidence and Costs of Displacement - Baseline Specifications

	Displacement	Re-empl	Industry Switch	Occupation Switch	Ind.Occ Switch	Ft-Ft	Weeks w/o Job	Nr.Jobs	Earnings Loss (log)
Age category = 25-34	-0.044*** [0.008]	0.013 [0.019]	-0.150*** [0.023]	-0.159*** [0.023]	-0.191*** [0.023]	0.107*** [0.027]	2.461*** [0.282]	-0.118*** [0.022]	-0.101*** [0.013]
Age category = 35-44	-0.124*** [0.009]	-0.002 [0.022]	-0.193*** [0.026]	-0.210*** [0.025]	-0.250*** [0.025]	0.119*** [0.030]	3.719*** [0.327]	-0.196*** [0.023]	-0.145*** [0.014]
Age category = 45-54	-0.170*** [0.010]	-0.289*** [0.025]	-0.200*** [0.031]	-0.244*** [0.031]	-0.271*** [0.032]	0.075* [0.037]	5.561*** [0.429]	-0.295*** [0.029]	-0.217*** [0.019]
Age category = 55-64	-0.154*** [0.016]	-0.671*** [0.040]	-0.165** [0.059]	-0.214*** [0.059]	-0.227*** [0.061]	-0.308*** [0.066]	7.970*** [0.855]	-0.493*** [0.032]	-0.367*** [0.046]
Gender = Female	-0.101*** [0.006]	-0.165*** [0.015]	0.168*** [0.019]	-0.013 [0.018]	0.027 [0.019]	-0.305*** [0.022]	1.573*** [0.241]	-0.066*** [0.016]	-0.009 [0.011]
Education = Less HS	0.147*** [0.009]	-0.350*** [0.021]	-0.099*** [0.028]	-0.049 [0.028]	-0.023 [0.029]	-0.250*** [0.033]	1.896*** [0.360]	-0.073** [0.023]	-0.055*** [0.016]
Education = College or more	-0.216*** [0.007]	0.318*** [0.021]	0.005 [0.022]	-0.183*** [0.022]	-0.168*** [0.023]	0.171*** [0.027]	-1.246*** [0.280]	-0.022 [0.019]	0.048*** [0.014]
Race = Non-white	0.011 [0.009]	-0.299*** [0.021]	0.081** [0.029]	0.089** [0.028]	0.093** [0.029]	-0.097** [0.033]	2.507*** [0.384]	-0.078** [0.024]	-0.013 [0.015]
Marital status = Married	-0.114*** [0.006]	0.078*** [0.016]	-0.054** [0.019]	-0.067*** [0.019]	-0.081*** [0.019]	0.128*** [0.023]	0.175 [0.244]	-0.078*** [0.018]	-0.009 [0.011]
N	579,551	40,866	27,065	27,065	27,065	23,763	27,065	27,065	21,437

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Coefficients of the probit equations are normalised to represent the derivative of the probability of the outcome with respect to a change in the independent variable. Weighted by CPS sampling weights. Robust SE, clustered by age, gender, race, education, industry, occupation and year. The base categories are white male, 20-24 years old, high-school graduate, not married, displaced prior to 1984. Time dummies not presented. No controls for lost job characteristics and industry & occupation dummies.