Environmental Regulations, Imperfect Mobility, and the Gender Adaptation Gap

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Abstract

Is the transition to a green economy gender-neutral? The answer depends in part on how new regulations would interact with existing gender imbalances in the market and the extent to which workers are constrained in moving to green sectors. I develop a structural economic model that conceptualizes mobility costs for female and male workers and estimates a dynamic general equilibrium of a U.S. economy in which workers can change their sector in response to an energy tax. I find that female workers face twice the mobility costs of males to change their sector while leaving the market is equally costly for both and imposes higher costs. In after-tax scenarios, differences in the long-run welfare losses across genders are driven by mobility costs. I also study a particular case of a local labor market in which coal plays a substantial role, and gender segregation is more pronounced. My empirical setting exploits variation in coal-fired power plant closure announcements. I find that in anticipation of closure, female workers in carbon-intensive sectors are disproportionately affected. Both findings contribute to understanding the disparities women face in a green transition and reveal a mechanism for disparate effects by differentiating and quantifying mobility costs.

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1 Introduction

The employment effects of environmental regulations have long been debated, with an increasing focus on distributional effects. However, there is still a limited understanding of the prospects of female workers. In a labor market characterized by a high degree of gender segmentation, as carbon-intensive sectors are still predominantly male, a neutral policy is expected to have differential outcomes for female and male workers. Employment in carbon-intensive sectors is expected to decline, while workers can mitigate economic losses by transitioning into unregulated low-carbon sectors, yet switching jobs is costly. Is switching jobs more costly for men or women? Does gender segregation play a role in determining distributional effects?

To address these questions, I construct a dynamic general equilibrium model of costly intersectoral labor mobility to study gender differences in the presence of an energy tax. I model switching costs following the Artuç et al. (2010) (hereafter, ACM) and structurally estimate costs using Euler-type equation techniques. In contrast to their paper, I include female workers' moving decisions and introduce an additional non-market sector to loosen the assumption of inelastic labor supply. I constructed the non-market sector to represent home production, and the costs of moving to the home sector can be perceived as penalties for leaving the labor market.

In my model, mobility costs are characterized by monetary and non-monetary components. I find that the monetary costs of switching across market sectors are higher for female workers. Female workers must forego 2.2 times the average annual wages (normalized by the mean wage) to change their sector, while the cost is 1.6 for male workers. The importance of non-monetary factors in moving decisions is similar for both genders and small, indicating that expected wage differentials play a substantial role in their mobility decisions. However, leaving the labor market incurs higher costs than changing sectors for men and women, as costs are approximately four times the average annual wages. Non-monetary factors are more important for leaving market decisions, which indicates moving the decision to non-market is driven by other factors.[1] Results suggest substantial reallocation costs, varying by gender.

Simulating the impact of an energy tax, factoring in estimated mobility costs leads to reduced long-term present discounted values for women across all education levels. If long-term disparities are primarily driven by mobility costs, implementing policies that ease the transition for women can effectively eliminate these gender disparities. Therefore, I also study a counterfactual scenario in which women face the same mobility costs. Gender differences disappear in the long run, implying mobility costs act as a mechanism that perpetuates long-term disparities.

Local labor markets with a substantial dependence on carbon-intensive industries may exhibit distinct labor market responses to environmental regulations compared to the national level. The significance of local labor market structure is highlighted by Rendall (2018), as the rise of the service sector metropolitan statistical areas associated with higher female market hours, and there is evidence of a positive correlation between the prominence of extractive sectors and gender inequality (Baum and Benshaul-Tolonen, 2021). To incorporate these features, I study coal-fired power plant communities, which have a higher share of carbon employment than the national average, and gender segregation across sectors is more pronounced.[2]

Coal-fired power plant communities are undergoing plant closures as part of the transition towards a low-carbon economy. This shift started in the last decade and is anticipated to continue until 2040. I study the local labor market adjustments, exploiting variation in coal-fired power plant retirement announcements. Retirement announcements create a unique setting as the planned retirement decisions appear in the Energy Information Administration (EIA)-860 generator-level survey, typically five years prior to the actual retirement date. However, there is evidence suggesting that the time lag between announcements and actual retirements in the past decade is, in

[1] If moving to the home sector is driven by family reasons or a policy shock that causes higher unemployment, my model would capture this pattern as a higher importance of non-monetary factors.

[2] `https://cnee.colostate.edu/wp-content/uploads/2021/08/Supporting-the-Nations-Coal-Workers-report.pdf` Coal-related employment in these communities is higher than the national average, while in the next section, I show the gender breakdown.

fact, three years (Davis et al., 2021).[3] Possible anticipation of plant closures allows me to study local labor market response to transitions.

I link the EIA-860 power generator survey, which provides information about the generator's characteristics, location, and retirement decisions, to Public Use Micro Areas (PUMA) from the American Community Survey as a unit representing the local labor market. I find that in anticipation of closure, low-educated female workers are less likely to work in carbon sectors, while high-educated female workers are more likely to be unemployed. In contrast, male workers experience only a deduction in the number of hours worked. Results for female workers are greater in magnitude in places with higher capacity, indicating women are disproportionately affected in a labor market characterized by extensive carbon dependence.

This paper contributes to the literature in several ways. First, there has been a great interest in potential employment effects and distributional consequences of environmental regulations (Greenstone, 2002; Walker, 2011, 2013; Yamazaki, 2017; Yip, 2018; Curtis, 2018); yet the gender dimension has often been overlooked or examined in limited contexts. As resource booms have gender-specific impacts and change the labor allocation by gender (Maurer and Potlogea, 2021; Aragón et al., 2018; Kotsadam and Tolonen, 2016), little is known about the transition to a green economy. In a timely discussion, this paper shows there are disparate effects with long-run implications.

Differentiating and quantifying mobility costs as indicators of labor market frictions extends the discussions on environmental regulations and employment effects. While empirical studies highlight substantial transitional costs (Walker, 2013), a general equilibrium framework is necessary to fully understand the spillover effects and long-term implications (Hafstead and Williams III, 2018).[4] Current general equilibrium mod-

[3] The survey includes a question about planned retirements within the next five years, but it's important to clarify that reporting to the Energy Information Administration (EIA) is not legally binding. While EIA has extended the question to cover the next ten years, research suggests the relevant timeframe is shorter than this.

[4] Walker (2013) study sectoral reallocation of labor under the Clean Air Act (CAA), and workers in newly regulated plants experience earning loss of 20% of their preregulatory earnings, and regulated plants are subject to job destruction. As earning losses are greater for female workers, it is not clear the consequences or reasons.

els study mobility with certain limitations, typically by incorporating static or limited search frictions (Aubert and Chiroleu-Assouline, 2019; Hafstead and Williams III, 2020) or examining two extreme scenarios of labor market mobility: perfectly mobile workers or perfectly immobile workers (Castellanos and Heutel, 2019). This paper extends the mobility assumptions in a general equilibrium setting, and introduces heterogeneity in imperfect mobility across workers.

The significance of imperfect mobility in environmental regulation discussions lies in its impact on distributional outcomes. I find that female workers tend to incur greater mobility costs, which implies substantial long-term differences in welfare.[5] Given the limited attention previously to the gender dimension, this paper sheds light on the disproportionate impact of addressing mobility costs, representing one potential avenue for reducing gender disparities. Mobility costs might be one of the mechanisms that can explain the observed patterns in the transition to green jobs. (Gilbert et al., 2023; Curtis et al., 2023) document differences in acquiring green jobs and potential delays for workers, consistently indicating that women are falling behind. The findings of this paper suggest an explanation for possible delays for women in acquiring green jobs.

As labor market frictions are receiving increasing attention in the discussions of environmental regulations and their impact on employment, mobility costs have long been a subject of interest to trade economists, particularly in analyzing the distributional effects of trade policies. While substantial evidence demonstrates that moving costs vary with age and education levels among male workers (Artuç et al., 2010; Artuç and McLaren, 2015; Caliendo et al., 2019), understanding such costs for female workers is comparatively limited. Dix-Carneiro (2014) showed that low-educated female workers experience the highest mobility costs in the Brazilian labor market, consistent with the findings of this paper. [6] This paper provides an understanding of female moving

[5] This paper considers mobility costs as the aggregate value associated with job switching rather than differentiating different components of mobility costs. As Vona et al. (2018) argues, acquiring green skills is costly; while this is a factor that contributes to mobility costs, there are other factors that affect total costs.

[6] Dix-Carneiro (2014) finds mobility costs ranging from 1.4 to 2.7 times annual average wages but a high dispersion of these costs across the population. My preferred estimate is 2.2 times for female workers and 1.6 times for male workers, which is in the range of estimates of this paper.

costs and a penalty for leaving the market by carefully modeling the home sector. As it is needed to understand female workers' labor market opportunities in more detail, this paper can provide a benchmark for future studies.

Finally, this paper adds to our comprehension of the local labor market's dynamics in the context of coal-fired power plant closures, which is broadly in natural resource setting (Allcott and Keniston, 2018; Black et al., 2005; Feyrer et al., 2017). As part of the shift toward low-carbon energy sources, the rise of renewable sources is anticipated, coinciding with a decline in coal and coal-fired power plant demand worldwide. As coal mine closures and local labor market effects received attention (Black et al., 2005; Watson et al., 2023), coal-fired power plant closures are less studied. There is evidence for persistent local unemployment effects in Australia after coal-fired power plant retirements (Burke et al., 2019), but little is known about the U.S. The Inflation Reduction Act in the United States is expected to accelerate coal-fired power plant retirements in the next decade; these findings can shed light on expected disparate responses in the labor market.

2 Background

Environmental regulations would alter the distribution of employment among industries rather than the total employment level (Arrow et al., 1996). As technological, structural changes favored women (Black and Spitz-Oener, 2010), and the rise of the service sector helped the closing of the gender wage gap (Olivetti and Petrongolo, 2016; Ngai and Petrongolo, 2017), however, a green transition is unknown. According to the 2019 tables provided by The US Bureau of Labor, while carbon-intensive sectors (such as mining and utilities) have the lowest share of women, the service sector has the highest share of women in employment.[7] Segregation has implications since predominantly female jobs pay less than predominantly male (Macpherson and Hirsch, 1995), and industry choices are important in explaining the gender wage gap (Blinder, 1973;

[7] https://www.bls.gov/cps/aa2019/cpsaat14.htm

Oaxaca, 1973; Levanon et al., 2009). [8] Thus, environmental regulation, as changing the labor market structure, has paid little attention to the gender dimension. [9]

Large oil discoveries have positive effects on women's employment in the absence of crowding effect (Maurer and Potlogea, 2021), but Aragón et al. (2018) shows resource shocks affect men and women differently and highlight that gender should be considered in a natural resource context. They found a spillover effect as males increase in manufacturing and females decrease. As environmental regulations are expected to affect the entire nation, all market analysis is needed.

Trade literature establishes gendered effects of shocks (Keller and Utar, 2022) shows gender plays a key role in adjustment costs in case of a trade shock. Walker (2011, 2013) study sectoral reallocation of labor under the Clean Air Act (CAA), and workers in newly regulated plants experience earning loss of 20% of their preregulatory earnings, and regulated plants are subject to job destruction. The latter study shows that female workers experience much larger earnings losses. There is evidence that there will be job losses due to regulations.Greenstone (2002); Walker (2013). While overall employment effects are small (Yamazaki, 2017), effects are heterogeneous for different types of workers (Yip, 2018, 2020). Female workers received limited attention, as it is unclear whether new regulations will segregate the market or which mechanisms play a role in determining disparate outcomes. [10]

The significance of local labor market structure is highlighted by Rendall (2018), as the rise of the service sector metropolitan statistical areas associated with higher female market hours. Across countries there is a positive correlation between extractive industries (mining, oil, and natural gas) and gender inequality (Baum and Benshaul-

[8] In particular, Blau and Kahn (2017) show industry and occupation choices play a bigger role than in the past in explaining the gender gap.

[9] It is important to note that a portion of the gap exists that cannot be explained, and it is out of the scope of this paper.

[10] These studies are part of extensive literature on job displacement and associated costs. Earlier studies indicate that higher displacement costs for women (Jacobson et al., 1993; Crossley et al., 1994). Illing et al. (2021) find that women lose 35% more than men in displacement scenarios and identified key drivers of the gender earnings gap, including unemployment duration, wage losses, and part-time work. They also noted women's tendency to accept part-time jobs or stay at home, resulting in larger immediate earnings losses. Ivandić and Lassen (2023) find similar results. However, this paper considers mobility costs which is different than displacement.

Tolonen, 2021), which indicates local labor markets with carbon-intensive sectors have a potential to be correlated with gender inequality.

3 Theoretical Model

Both existing gender imbalance in the labor market and possible heterogeneity in mobility costs play a role in determining distributional effects. I borrow tools from trade economics to model costly interindustry labor mobility to improve environmental policy setting (Weber, 2020). I follow ACM on the structural cost parameter model while extending their model for out-of-market option and gender dimensions. To understand how the energy dependency of sectors affects labor allocation and existing imperfect gender substitution across sectors, I developed a nested energy-specific production side. Following sections explain the model in detail.

3.1 Setup and timing

Time is discrete, $t = \{0, 1, 2...., \}$, and at $t = 0$ workers see realization of their type. There are four different types of workers who differ in skill and gender. High- and low-educated groups consist of female and male workers. An individual is indexed by $i \in I \equiv \{fl, ml, fh, mh\}$.

There are four market sectors and one home sector, which are indexed by $j, k \in J$, where workers inelastically supply their labor. Market sectors are aggregated as Agriculture, Mining; Construction, Utilities, Transportation; Manufacturing, and Trade, Service. The Home sector can be considered as an outside option when workers are not employed by the market sectors [11]. Workers' problem is identical for home sector workers. First two market sectors are traditionally more carbon-intensive and will be referred to as carbon-intensive.

With the realization of shock, each worker i works for particular sector j at time t

[11] Home sector can be considered as a big sector which unemployed workers, non-employed or not in labor force population works and earns goods that is needed for the survival.

receives $w_{i,t}^j$ and an idiosyncratic benefit $\epsilon_{i,t}^j$ [12]. At each time t workers can either stay in the same sector or move to another sector but moving incurs a cost. Cost of moving from sector j to k for an individual i is C_i^{jk} and time invariant. Workers have rational expectations about future and forward looking.

3.2 Workers' utility

Following ACM, utility is additive separable, for worker i working for industry j at time t and takes the following form.

$$U_{i,t}^j = w_{i,t}^j + \max_k \{\epsilon_{i,t}^k - C_i^{j,k} + \beta E_t[V_{i,t+1}^k]\} \tag{1}$$

Lifetime expected utility of an individual is the sum of current wage and future utility. Wages and moving costs directly affect utility, so workers care about these two features in the decision-making process. If a worker decides to switch jobs a disutility occurs due to switching costs [13]. Cost and wages are additive and measured in terms of utility.

If an individual switches from sector j to k, in addition to monetary costs, there will be lost of non-monetary benefits of the past job but if worker choose k over other options there will be a non-monetary benefit from that job too. Thus, the total cost of switching from j to k for worker type i can be written as

$$\epsilon_{i,t}^j - \epsilon_{i,t}^k + C_i^{jk}$$

For marginal worker i cost of moving should be equal to expected future benefit.

$$C_i^{jk} + \epsilon_{i,t}^j - \epsilon_{i,t}^k = \beta E_t[V_{i,t+1}^k - V_{i,t+1}^j] \tag{2}$$

[12] The idiosynratic benefit can be considered as non-monetary benefit. Workers can like the job, sector, or colleagues, these features will be considered as idiosynratic benefit in this model.

[13] In this model, individuals age and education do not change over time so there is one moving cost for each type of worker.

Following ACM, the idiosyncratic benefit being employed in industry an Extreme Value Type 1 distribution.

In the beginning of t each worker solves the following problem:

$$V_{i,t}^{j} = \max_{k}\{w_{i,t}^{k} - C_{i}^{j,k} + \epsilon_{i,t}^{k} + \beta E_t[V_{i,t+1}^{k}]\}$$

3.3 Production side

Environmental regulations will affect labor demand through energy input. Each sector has different energy input structure and female and male workers are not perfect substitutes. There is evidence that female-male workers are more complements in "brown jobs" while they are perfect substitute in service sector.[14] To capture heterogeneous labor demand changes, I introduce a nested Constant Elasticity of Substitution (CES) production function for market sectors.

Output produced at time t in industry j bring aggregate labor and energy based on a Cobb-Douglas production function.

$$Y_t^j = A^j (L_t^j)^{\theta^j} (E_t^j)^{1-\theta^j} \text{ where } j \in J = \{\text{market sectors}\} \tag{3}$$

The efficiency term is A^j and does not change over time. The energy used in sector j at time t is E_t^j is, while the aggregate labor is L_t^j.

Aggregate labor is a composite of low and high educated subgroups. CES subaggregation allows imperfect substitution between low-educated and high-educated labor for each market sector.

$$L_t^j = [\alpha_1^j (L_{l,t}^j)^{\rho_1^j} + (1-\alpha_1^j)(L_{h,t}^j)^{\rho_1^j}]^{1/\rho_1^j} \tag{4}$$

Low- high-educated labor groups in industry j at time t are $L_{l,t}^j$ and $L_{h,t}^j$. Efficiency

[14] Existing literature that considers elasticity of substitution between female and male workers provide estimates ranging from 0.5 to 2.5. Olivetti and Petrongolo (2014) argues men and women are perfect substitutes but in "brawn" industries substitution is lower than service.

of the labor is α_1 while ρ_1 is degree of substitutability between education groups and represented by $-\infty < \rho_1 \leq 1$ and $\rho_1^j = 1 - 1/\sigma_s^j$ in which σ_s^j is elasticity of substitution between two education groups in industry i.

For each market sector, female and male workers in a particular education group will create CES education aggregator. This aggregation will allow female-male complementarity across skill groups and sectors.

$$L_{l,t}^j = [\alpha_2^j (L_{fl,t}^j)^{\rho_2^j} + (1-\alpha_2^j)(L_{ml,t}^j)^{\rho_2^j}]^{1/\rho_2^j} \tag{5}$$

$$L_{h,t}^j = [\alpha_3^j (L_{fh,t}^j)^{\rho_3^j} + (1-\alpha_3^j)(L_{mh,t}^j)^{\rho_3^j}]^{1/\rho_3^j} \tag{6}$$

The role of the α in equations 5 and 6 is analogous to equation 4. However, ρ_2^j is the degree of substitutability of female and male workers in the low-educated group in sector j, while ρ_3^j is for the high-educated group. They can be written as : $\rho_2^j = 1 - 1/\sigma_{lg}^j$ in which σ_{lg}^j is elasticity of substitution between females and males for the low-educated group in sector j while $\rho_3^j = 1 - 1/\sigma_{hg}^j$ is for the high- educated group.

There is one aggregate output of home sector, and this sector only utilizes the labor of each labor type. While each labor type's productivity in labor market differs, and represented by ω_i[15]. Efficiency of aggregate labor is A^{home}.

$$Y_t^{home} = A^{home} \sum_i^4 \lambda_i L_{i,t} \text{ where } i \in I = \{fl, ml, fh, mh\} \tag{7}$$

3.4 Equilibrium

Workers have identical preferences over consumption goods and worker i at time t gets utility from consuming goods from all sectors and it is additive separable to worker

[15] This model assumes everyone is single but individuals produce one single non-market output. Home sector is considered as what people eat while they are not in market sectors, so they engaged mostly in home production activities while looking for a job. As we know from home production literature females' productivity and high-educated people's productivity is higher in home sectors.

utility represented in equation 1.[16]

$$U(C_t) = log(C_t^j)$$

Good across sectors are aggregated by Cobb-Douglas aggregator.

$$C_t^j = \prod_{k=1}^{J} (c_{i,t}^k)^{\psi^k} \quad \text{where} \quad \sum_{k=1}^{J} \psi^k = 1$$

ψ^k is final consumption share of sector k good. Price index follows standard Cobb-Douglas form, in which P_t^k is price index of good purchased from industry k.

$$P_t = \prod_{k}^{J} (P_t^k / \psi^k)^{\psi^k}$$

All markets are clear, in which quantities supplied are equal to quantity demanded. Markets are perfectly competitive, thus firms are price-taking, and input prices equal their marginal products. Real wage for each worker at time t and sector j will be equal to marginal product of their labor. Appendix A.1 shows the derivation of wages for each type.

$$w_{i,t}^j = (\partial Y_t^j / \partial L_{i,t}^j) / P_t$$

3.5 Estimating Equation for Moving Costs

Following mobility assumptions in ACM, Caliendo et al. (2019), the idiosyncratic shocks are independent and identically distributed (i.i.d.) over time follow an Extreme Value (EV) Type 1 distribution with zero mean and $\pi^2\eta^2/6$ variance.[17] As used in most dynamic discrete choice models extreme value distributions enables closed-form

[16] This does not necessarily imply that their consumption is identical since they earn different wages they have different budget constraints.

[17] While this is restrictive, this allows the problem of worker at time t to be same at time $t + 1$

solutions. Cumulative distribution of shocks are:

$$F(\epsilon) = exp(-e^{-\epsilon/\eta})$$

$$m^{jk} = \frac{exp(\epsilon^j - \epsilon^k)/\eta}{\sum_{n=1}^{5}(exp(\epsilon^j - \epsilon^n)/\eta)}$$

With the extreme value type one distribution gross flow of workers who moves from industry$j$ to k is represented as being in industry j is greater than any other industry, which is quite similar expression to other multinominal choice models. Appendix A.2 explains in detail how to derive flows by using EV Type 1 properties.

$$(lnm_{i,t}^{jk} - lnm_{i,t}^{jj}) = \frac{\beta - 1}{\eta} C_i^{jk} + \frac{\beta}{\eta}(w_{i,t+1}^{k} - w_{i,t+1}^{j}) + \beta(lnm_{i,t+1}^{jk} - lnm_{i,t+1}^{kk}) + \mu_{i,t+1} \tag{8}$$

It is important to note that $E_t(\mu_{i,t+1}) = 0$ due to rational expectations. According to Equation 8, current gross flows from industry j to k for type i depend on future wage differentials across sectors for type i, future gross flows, and cost of moving for worker i across sectors, and these are sufficient statistics to recover moving costs across sectors. The coefficient of wage differentials, β/η, can be interpreted as the responsiveness of flows to wage differentials across sectors. As time discount factor, β is common for all workers and known.[18] Estimated β/η in which β is known, can be used to recover the cost which is C.[19]

Ordinary Least Square (OLS) estimation of Equation 8 will be biased since ob-

[18] This paper does not attempt to estimate time discount parameter, instead uses estimated values from literature. Since the magnitude of β could directly affect the estimated moving costs, and relative estimations, I provide estimates with different moving costs in Counterfactual Scenarios Section.

[19] This requires the strong assumption that, η is the same for all workers. Considering the meaning of η, the variance that flows are responsive to wages, this is a strict assumption. One can argue that female workers are less responsive to wage differentials for moving decisions but more driven by external factors (such as family obligations). To understand the restriction of this assumption, I estimate the moving cost for separate samples that η does not need to be fixed across gender groups.It will be explained in more detail in Counterfactual Scenarios.

servable factors that can explain gross flows between sectors can be correlated with expected wage differentials or expected future flows. [20] Following the literature, ACM, Caliendo et al. (2019), I use past wage differentials and past gross flows as instruments for future wages and flows. Exclusion restriction assumption will be unobservable factors are not correlated over time.[21]

Instruments lagged wage differentials and gross flows, and implemented generalized Method of Moments (GMM) is used for estimation.

4 Data

To estimate the moving costs across sectors and the model, I use multiple publicly available data sources. I estimate the key parameters of the model and calibrate several parameters.

4.1 Annual Gross Flows Across Sectors and Wages

Since moving costs are expected to be different across market sectors and outside of the market, first I define gross flows and average wages for each worker across market sectors. Then I explain how to consider the flows from home (outside of the market) and to home.

4.1.1 Across Market Sectors

I use the Current Population Survey (CPS) March Supplement (Flood et al., 2022) from 1976 to 2019 for annual gross flows across sectors and annual mean wages for each type [22]. I restrict the sample whose age is between 25 to 60, and workers who

[20] For example, a women workers can choose service sector over manufacturing due to flexible working hours, but this could also affect the expected wages since she may need to give up on earnings growth for the sake of flexibility

[21] This is a strict assumption that can be violated in many cases. However literature documents overweight the benefits of using it so I follow the literature for now.

[22] Estimating of switching costs requires knowing gross flows across sectors for each type. The March Supplement has the question "industry that longest job held in the last year" and current industry for each individual that is considered as gross flow for individual i.

finished bachelor's degrees or more are considered high-educated, while workers who do not have bachelor's degrees are considered low-educated. If workers stated they are were employed more than 26 weeks last year and earn less than 2000 or who stated more than 300,000 income, these observations also dropped from working in market sector sample.[23]

I aggregated market sectors into four main categories. The first sector is agriculture, mining; construction, utilities, transportation, and manufacturing, and trade, service. First two sectors are traditionally carbon-intensive and and will be referred as carbon-intensive for the rest of the paper. Table 1 shows descriptive statistics of the data. Sectoral segregation by gender is observable from data. In carbon-intensive sectors, the share of the low-educated men is much higher than the share of the low-educated women. As expected, segregation is less pronounced for the high-educated level. Women's mean wages are less than men's for every sector and education group. In addition, carbon-intensive sectors pay more than low-carbon sectors for each type.

Table 2 shows raw average gross flows between 1976 to 2019 for men and women.[24] Rows represent the origin sector while columns show destination sector. Diagonals shows stayers in particular sector. Independent of origin sector; female workers move to low-carbon than male workers.[25] For example, on average, 19.5% of women in construction,utilities, transportation sectors switch to trade and service sectors while only 9% of men in this sector switches to trade, and service. In carbon-intensive sectors female outflows are approximately the double of men outflows.

[23] Weeks less than 26 might be related to part-time workers which is out of scope of this paper, and high earner are in general move across industry or jobs due to better opportunities and with a raise.

[24] I call it raw because, in literature, the argument is CPS flows can capture the five months of flows instead of yearly flows. I adjusted these flows to capture yearly movements in the analysis, but this table shows the unadjusted CPS flow rate. To estimate the moving costs, following the literature from CPS March Supplement do not reflect entire yearly flows (Kambourov and Manovskii, 2004). Following Artuç et al. (2010); Caliendo et al. (2019), I corrected observed flows which are representative of 5 months time period so I derived 12-month flows from observed data.

[25] I also have a breakdown of average gross flows into education levels, but there is no difference in moving rates across education groups. Low and high-educated women have the same moving pattern while low&high educated men move less than women but have similar patterns

4.1.2 Between Market to Home Sector

To estimate the cost of moving to *home sector*, wages and gross flows to home sector is needed. Gross flows to home can be recovered from CPS non-market flows. If an individual stated they did not work in the last year but they said currently employed this will be considered as gross flow from home sector to market sector.[26]

Potential wages for non-working people are not observable. This has been a long a central issue for labor economists and I borrow tools to estimate the potential wages for non-employed people to to recover how costly it is to from from market for each gender.[27] However as Heckman (1979) pointed out non-market sample is selected, and I apply sample correction, Appendix A.3 explains in detail construction of home sector.

I created a home sector where people who are not employed or not in labor force put their time. Value of time at home is calculated by the opportunity cost method [28]

Constructed home annual wage shows female wages are higher in-home sector in comparison to male wages. Findings are in line with literature that shows there is a positive gender gap in home sector (Albanesi and Olivetti, 2009). Table 3 and 4 show average flows across market and home sector and average home wages in home sector.

4.2 Parameters of the Model

The model is calibrated to 2005 U.S. economy. Gross output levels by industry, Y_0, is taken from Bureau of Economic Analysis (BEA) 2005 tables, and normalized.[29] Since aggregate production function follows Cobb-Douglas, θ is the cost share of labor. U.S. Bureau of Labor Statistics (BLS) released cost share of labor by industry. Initial

[26] This flow is constructed by using "workly" variable which indicates whether or not the respondent worked any time in the calendar year previous to the survey year and current status as "employed".

[27] I do not breakdown the sample into different education groups and different market sectors. Considering underrepresented of women in particular sectors further breakdown will create a small sample which will not create reliable estimates.

[28] While replacement cost is also considered as one other method, in practice results are similar. Home wage should be equal to time spend in home production activities multiply by opportunity cost of time for each individual. Construction of home annual wage will be equal to hours spend in home production for each type and year.

[29] Y_0 for the non-market sector was targeted to match with services such that represents perfect substitution for home production.

distribution of labor, L_0 is calculated by using CPS data for 2005. Initial distribution of energy, E_0 is taken from BEA Energy inputs by industry table.

Calibration of technology parameter, A, is done by calculation of production function. Since all parameters of production function can be recovered from data, except A.

$$A^j = Y_0^j (1/L_0^j)^{\theta^j} (1/E_0^j)^{1-\theta^j}$$

Elasticity of substitution between education and gender groups are critical for defining sectoral impact of an environmental regulation.[30] Following Katz and Murphy (1992), I calibrated elasticity between high educated to low educated workers (σ_1) 1.42 as a common value in literature.

Elasticity of substitution between female and male workers can change across sectors and education groups. Female and male workers are less substitutuable in low-educated group in comparison to high educated groups (Acemoglu et al., 2004), while goods sector substitution is lower than service sector (Olivetti and Petrongolo, 2014). Literature shows lower bound for substitution between 0.5 to 0.7 (Ghosh, 2018; Severini et al., 2019), while upper bound is 2.5 to 4. (Olivetti and Petrongolo, 2014), while evidence also shows it is between 1 to 1.4 (De Giorgi et al., 2015). This paper uses lower bound for carbon intensive low-educated workers while uses upper bound for non-carbon and high-educated workers.

Given elasticity of substitution parameter and FOC for wages, α_1 can be recovered. Rgiht hand side of the equation can be observed in data, and $\hat{\sigma}$ is taken from elasticity of substitution estimates. α_2 and α_3 is estimated similarly.

$$ln(\alpha_1^j/(1-\alpha_1^j)) = ln(w_{i0}^j/w_{i0}^j) + (1/\hat{\sigma})ln(L_{l0}^j/L_{h0}^j)$$

Calibration of λ_i, the home sector productivity of the labor, is driven by the home

[30] A possible energy tax will affect labor demand of the sectors according to elasticity of substitution. Literature highlights man and women is not perfect substitute for each sector which makes it crucial to differentiate the difference

sector wages. As in part 2.2, I calculated potential wages for home sector for each type. Ratio of wages will provide the efficiency of the labor according to 7.

$$w_i^{home} = (\partial Y^h / \partial L_i) \ \rightarrow w_f^{home} / w_m^{home} = \lambda_f / \lambda_m$$

Final consumption share of each sector ψ^j is the expenditure share of each sector's goods due to property of of Cobb-Douglas. Home sector final share is to match the expenditure share of services that are perfect substitute to home sector goods. Since home goods are considered perfect substitute for market services (Ngai and Petrongolo, 2017), I have subset the market services can be easily substituted by home goods. Following Aguiar et al. (2012), I looked at food away from home, alcohol away from home, vehicle maintenance, taking care of adults, personal services and sum their relative importance to find share of home sector in budget. Table 5 shows all parameters of the baseline model.

5 Results

5.1 Moving Costs Across Sectors

I estimated average moving costs across sectors for female and male workers by using Equation. As an initial analysis, I dropped the education groups because female data for some sectors have too little observation for different education groups. This estimation does not differentiate among sectors but rather calculates average moving costs resulting from any direction of gross flows.

Table 6 shows moving costs in terms of normalized average annual wages. To change industries among market sectors, female workers need to give up 2.24 times average wages while male workers pay 1.6 times the wages. Both estimations are statistically significant, suggesting that moving costs are not negligible and more pronounced for women. On the other hand η, is small with 0.68 which means that moving decisions across sectors are mostly driven by monetary reasons.

As a second step, I estimate the moving costs between home and market. Table 6, second column shows cost of swtining between market and non-market (home) sector. [31] Leaving the market sectors is equally costly for both genders, and it is more costly than switching across market sectors. Leaving market sector is almost double costly for women and third times costly for men relative to their counterparts who switches across market sectors. As expected, non-monetary features are more important for non-market moves.

If future moving costs are fully responsive to wage differentials, a low η variance should be estimated. If η is high that means other factors might play an important role for moving decisions. Estimation of η in Table fixes variance for both females and males and find relatively low value.[32]

5.2 Simulation: An Energy Tax

As in the equilibrium an energy tax 15% is introduced the model $t = 5$. Other prices are determined endogenously inside the model. [33]

However, to understand better the welfare effect, we need to analyze their expected discounted lifetime utilities. Table 7 shows long-run percentage changes for each type of worker for each sector. Female workers for both education levels and sectors experiences higher decreases in their welfare. In contrast, male workers experience modest decreases in long-run which shows their adaptability to regulations. As expected, being in the home sector has a bigger penalty than working in the market, which is true for each type of worker.

[31] This can be considered as penalty of leaving the market sector.

[32] I have also estimated η by using only female and only male data and both estimations. More detail next section. Since the estimation of η was similar for both samples, I assume variance is the same for everyone for the main model.

[33] One limitation of the model is having same moving costs across education levels and sectors. Low and high educated female workers have 2.24 moving costs, and low and high educated male workers have 1.6. However, wages are different for each education level in each sector.

5.2.1 Counterfactual Scenarios

Different Time Discount Rates and Separate Sample.

Table depicts the findings for two different future discounting parameters. Instead of estimating β, I used the most common discount factors in literature. As β gets low, moving cost should be smaller since individuals discount less future benefits of new sector. Estimated cost is lower with low β for both men and women.

To change their sectors, in preferred specification, female workers need to give up 3.55 times average wages while male workers pay 2.26 times the wages. Both estimations are statistically significant, suggesting that moving costs are not negligible and more pronounced for women. While the magnitude of moving costs decreases as β decreases, moving costs for women are still higher than for men.

One possible concern is future wage differentials, and gross flows may not capture the moving decisions. There might be other factors individuals take into consideration while changing sectors. (preference for a specific job, non-wage benefits, risk attributes, etc.) In the model, η aims to capture how much these factors affect the moving. Intuitively, women and men behave differently in the labor market, and we expect non-wage factors to affect their choices dissimilarly. Thus, I estimated moving costs using female-only and male-only samples, allowing variance to be independently estimated for each sample. Tables 8 and 9 show average moving cost and importance of non-monetary for each separate sample and relative results with different time discount values.

Estimations of separate samples are similar to the main results. Women have higher moving costs than men; the variance is close for each type. Thus, fixing variance to be the same for both types in the main analysis should not cause a limitation for the study.

Same Moving Costs

To understand the role of the moving costs in determining long-run welfare losses, I studied the counterfactual scenario in which there is a female workers have the same mobility costs as male workers. If differences in long-run is driven by market structure, even if there is a policy makes transition easy for women, there should be disparities in long-run welfare.

Table 10 shows results when female workers' mobility costs equal to male workers and provide a comparison with previous scenario. Loss gap between high-educated female and high-educate male closes, as low-educate women still slightly have more losses than low-educated men. Results suggest disparities in losses driven by mobility costs. Findings implying any policy targets women and their transition to green employment has potential to alleviate the long-run welfare gap.

6 Local Labor Markets

6.1 Research Design for Coal-Power Plant Retirement Announcement

Coal power plant closures can provide a setting that how local labor market adapt to environmental regulations. While EIA provides data on electric generators, it also provides whether there is a planned retirement for the generator and what is the planned date. It is often the case that EIA announces these retirement years before closure. [34] Reporting to planned retirements is not legally binding, but there is a question in the survey that specifically asks whether there is a planned retirement in 5 years.[35]. However, Davis et al. (2021) analyzed news, announcements and actual retirements in last decade, and found the median time between announcements and retirement was 3 years. If there is a heterogeneous adaptation, after announcement of retirement to actual closure we will observe the adaptation in the market. Composition of employment across sectors might response to expected retirement.

One concern will be if retirement decisions are driven by local labor market conditions, what is captured by this analysis might be misleading. Davis et al. (2021, 2022) work on power plant retirements in the U.S. and find retirement costs, efficiency, gas

[34] For example, EIA-860 shows which coal power plants will get retired in 2058, 2040, and closer future.
[35] Recent changes in EIA-860 survey made this timeline as 10 years

prices are significantly affecting the probability of getting retired; local variables such as median income, population density, unemployment rate, percent of male-female with higher education do not have a significant impact on the probability of getting retired. However, a local labor market which has a coal-power plant can be different than a local market which does not have a coal-power plant. Thus, I restrict the sample to only areas that has coal-power plant.

Capacity of the coal-power plant can affect both the employment level and dependency of the labor market to coal related jobs. For example, if the name plant capacity is less than 250 MW, it is associated with employment of 50 workers on average, while for more than 1000MW is associated with 200 workers. [36]

For this analysis I only consider coal-power plant PUMAs that are contain coal power plants. Areas that have electric generator but with different source was not included into model. [37] To understand which workers can adapt to changes easier, I start specify the following:

$$ln(workers_{pt}) = \beta_1 \left[Anticipation_{pt} \times Ever\ Retired_p\right] + \mathbf{X}'_{pt}\gamma + \mu_s + \theta_t + \epsilon_{pt} \tag{9}$$

Dependent variable is natural logarithm of the number of workers in PUMA p at time t, or the natural logarithm of the number of female and male workers. Since expectations of coal-power plant retirement should have a direct impact on carbon-intensive industries rather than non-carbon industries, I estimate the equation 14 for carbon and non-carbon industries separately. Dependent variable becomes natural logarithm of number of workers in carbon sector in PUMA p at time t. Anticipation is a binary variable equals to 1 if retirement entered EIA-860 list which is 5 years before the actual retirement. In second specification, it is one if it is 3 years before actual retirement. PUMA level controls, percentage white, percentage living in urban area,

[36] https://cnee.colostate.edu/wp-content/uploads/2021/08/Supporting-the-Nations-Coal-Workers-report.pdf

[37] Local labor markets without power plants would be different than local labor markets with power plants. This is also true for renewable sources vs coal power plant so sample is consist of coal-power plant commuting zones.

average income, percentage college graduate, percentage married, average age is in X_{pt}. Year fixed effects are included to account aggregate shocks that affect all PUMAs and state fixed effects to capture time-invariant employment related factors across states that might affect the dependent variable.[38] In order to account for capacity effects I consider 3 thresholds for the capacity, first specification considers all capacities, while second one considers only when capacities are greater than 250 MW , and the third one considers when it is greater than 1000 MW. [39]

Identification assumption is that labor composition of carbon and non-carbon sectors with active coal-power plants PUMAs would be same with PUMAs experienced a retirement except the anticipation of retirement coal-power plant in 5 (or 3) years. However, there can be unobservable characteristics of PUMAs, ϵ_{pt}, that might driving these composition. I provide a snapshot of the PUMAs characteristics in 2010 if they were different before these retirement decisions. In addition, Davis et al. (2021) explains in detail that retirement decisions are not related to local labor market conditions, rather driven by national factors (natural gas prices, renewable portfolios) or plant specific factors.[40] In addition, EIA documents many retirement between 2009 to 2019 were driven by stringent mercury regulations, plant age. [41] Watson et al. (2023) also argues it is driven by increasing cost of production rather than local effects.

As PUMA level analysis provide insight on composition of the workers carbon and non-carbon sectors with the anticipation of the retirement, individual level analysis can provide whether sub-populations are more likely to work in carbon sectors by the anticipation or by anticipation whether any group is more likely to be in unemployed group. To capture these effects I start specifying the following equation:

[38] Since coal PUMAs are dispersed in many states using state and PUMA fixed effects will absorb all variation so I use only state fixed effects

[39] One can expect the local labor market can be different in an area that has multiple generators, higher Name Plate Capacity compared to an area with one generator that has less than 250 MW plant. To account possible differences I created sub-samples for different capacities to compare similar capacities with each other.

[40] If high maintenance cost plants are concentrated with one area rather than distributed randomly identification assumption would be violated. However, we do not have evidence for this kind of pattern.

[41] https://www.eia.gov/todayinenergy/detail.php?id=44636

$$Y_{ipt} = \beta_1 \left[Anticipation_{pt} \times EverRetired_p \right] + \mathbf{X}'_{ipt}\gamma + \mu_s + \theta_t + \epsilon_{ipt} \tag{10}$$

Dependent variable equal to 1 is worker i in PUMA p at the t is unemployed, or employed in carbon-intensive sector. Individual level controls like age, marital status, race, living in urban area are included. State and year fixed effects are also included to account for possible aggregate shocks. I estimate this equation on sub-samples of different education and gender group for each capacity thresholds. The dependent variable is binary variable and including of fixed effects can create additional problems with logistic and probit estimations. So I use linear probability model with fixed effects that is more suitable in this setting. (Greene, 2004)

Expectations for retirement can play a role in different labor market behavior. While workers can adjust at an extensive margin (by leaving sectors), they can also adjust in the intensive margin (by decreasing the number of hours they work) To capture whether intensive margin adjustments are happening, if it is happening, which type of worker and which places, I specify the following:

$$Y_{ipt} = \beta_1 \left[Anticipation_{pt} \times EverRetired_p \right] + \mathbf{X}'_{ipt}\gamma + \mu_s + \theta_t + \epsilon_{ipt}$$

Dependent variable is number of hours worked per week for worker i at PUMA p at time t. Individual level controls like age, marital status, race, living in urban are with state and year fixed effects. I estimate this equation on sub-samples of different education and gender group for each capacity thresholds.

6.2 Coal-Power Plants and American Community Survey

Energy Information Administration (EIA) generator level data, EIA-860, contains detailed information on electric generators and plants. For each generator which technology is used (such as conventional steam coal, natural gas fired combined cycle, wind, hydroelectric, solar), generator nameplate capacity in megawatss (MW), power plant that generator is part of, and which utility owns the power plant.[42] The most critical information for this study is EIA-860 contains the information about status of the generator, active or retired. For active generators whether there is a planned retirement while for retired generators which date generator got retired. It is not legally binding to report planned retirement date but there is a specific question consider 5 year window for retirement is in survey. [43] In addition, existing literature show that on average there are three years between the retirement announcement and actual retirement.

To understand which local labor market is expected to show anticipation effects, I aggregated the generator level data to obtain plant level data. I sum across the generator nameplate capacity to obtain plant level capacity and planned retired capacity for year. EIA-860 survey provides detailed information on the location of the plant level data, including state, county, utility ID, and zipcode. It is expected that one local market will be served by multiple plants, or one plant can be in intersection of multiple local markets. Thus, I matched the zipcode of the power plants to American Community Survey Public Use Microdata Areas (PUMA) by using existing weights in crosswalk prepared by University of Missouri.[44] I created a coal-power plant data by PUMA showing total capacity , if there is a retirement, when was the first retirement happened, when is the last retirement, when maximum capacity got retired, operational capacity.[45] Table 11 shows how many generators per PUMA and total coal-fired

[42] Nameplate capacity is the highest value that generator is capable of producing in MW rounded to the nearest tenth. Each power plant might have more than one generator with different nameplate capacities. Each utility might have different power plants with different technologies.

[43] Survey recently changed the question "If this generator will be retired in the next ten years, what is its estimated retirement date? If you expect this generator to be retired in the next 10 years, enter your best estimate for this planned retirement date in the format of month, day, year " instead of 5 year retirement window.

[44] `https://mcdc.missouri.edu/cgi-bin/uexplore?/data/corrlst/zip2_xxx`

[45] There can be multiple retirements in a PUMA and in this study I considered the PUMA as retired when the maximum capacity got retired. Instead of considering total retired capacity, I consider the total PUMA capacity to understand the infusion of coal-power plant in the community. For example, Each PUMA may or may not contain only one type of coal-power plant generator. One generator might be retired in 2015 while the bigger capacity is expected to get retired in 2020. To assign the status of PUMA in these situations, I have created when first generator got retired in PUMA and when the highest capcity retired in PUMA.

capacity in a PUMA and how many are still active in 2019, and what are the expected retirements an d expected PUMAs from these retirements in next 20 years. Active capacity of coal-power plants is 243956 MW with 631 generators in 2019. Among active capacity 51,930 MW is expected to get retired in next 45 years. from 2019.[46]

I spatially link PUMA coal-power plant data to yearly American Community Survey (ACS) from 2010 to 2019, that provides employment status, gender, age, education level, industry, wages, occupation, marital status of individuals. I follows the same process that agriculture, mining, utilities,construction, transportation as carbon-intensive sectors while the remaining as non-carbon sectors. Individuals who are between 24 to 65 are considered, college graduates will be referred as high-educated workers while any education level below college will be taken as low-educated.[47] As shown in Table 12, PUMAs with an anticipated coal-fired power plant and always active coal-fired power plants were similar in 2010.

6.3 Anticipation Effects in the Local Labor Market

As coal power plant retirement enters the EIA-860 survey or public announcements are made for the retirement, the expectation in the local labor market will alter the behavior of the workers. Rational workers in expected sectors might start looking for outside options, or respond at the intensive margin.[48]

As workers in carbon-intensive sectors are expected to be affected directly, I work sub-samples of carbon sector and non-carbon sector separately. As mentioned in research design part, total capacity in PUMA might indicate different labor markets, so I consider 3 different sub-samples in terms of capacities. First specification considers all

IF they were in the same time which means anticipation effects only occurred between planned and retired date, if there is a 3-5 year effects which create an anticipation effect in the community.

[46] This paper does not consider the period between 2019 to 2023 since COVID-19 might change the retirement priorities, or affected one communities differently than other might confound the analysis.

[47] PUMAs in 2010 to 2012 follows 2000 Census boundaries and PUMA identifier while 2012 to 2019 follows 2010 PUMA boundaries and identifier. I used crosswalk supplied by IPUMS between 2000 to 2010 PUMAs and obtained a unified 2010 PUMA identifier between 2010 to 2019.

[48] I exclude the post-retirement period since that period will be more related to mass layoffs and displacement workers. On the contrary, this paper is build on workers behaviour.

capacities, while neither total number of workers or female and male workers respond to being enlisted in EIA-860 form, female workers tend to leave the sectors, and female representation in carbon sector decreases by 7% due to anticipation of retirement in next 3 years. This effect gets stronger for the places which has higher capacities, it doubles in PUMAs have more than 250 MW capacity, and almost triples and becomes 22% for the PUMAs that has more capacity than 1000 MW. [49] This shows that as carbon sectors are more influential (more capacity is correlated with more employment), female workers tend to leave these sectors more due to anticipation. There is no significant effect from male workers and both female and male workers do not move in anticipation of retirement in non-carbon sectors.

As known there is an existing gender imbalance in the carbon intensive sectors. While using natural logarithm has many benefits, dealing with skewness in the data, percentage change, this may mask the possible make movements of male workers.[50] I conducted the same analysis but with number of workers instead of logarithm of the workers. Table 15 shows results for the level of workers. As coal-power plant in the PUMA enlisted in EIA-860 data, on average 13 male workers leave carbon intensive sectors in these PUMAs by the anticipation of retirement. While almost same number of men leaves the carbon-intensive sector by anticipation of retirement in 3 years, now also female workers leave these sectors. As expected all outflows are happening in carbon-intensive sectors while female and male are responding at different times, and magnitudes.

Previous analysis changes in composition of the carbon sectors employment in anticipated PUMA. To understand individual responses, and allow for additional breakdown of the data by the educational group, I look at whether likelihood of being employed is changing by the anticipation. I look at the employed low-educated female population in all capacities and other capacities, as the anticipation which is 3 years before the

[49] Share of carbon-intensive employment in PUMAs with coal-fired power plant is higher than rest of the country. However, share of female employment in carbon-intensive sectors is lower than rest of the country. Results are less likely to be driven by over average employment of women in carbon sectors.

[50] Assume there is only 10 women in carbon intensive sector while 900 men, even a movement of one women can drive the results and can be considered as high percentage while 90 men should be

retirement, they are less likely to be employed in carbon sectors. While anticipation does not affect the likelihood of employed in carbon sectors for high-educated female workers, this shows that As literature shows mentions leavers and stayers are 2 different groups, leavers are below average productivity while stayers are considered above average productivity.

Is one group more likely to be unemployed compared to another group? To understand if one group is push outside of the labor marker I have checked the likelihood of being unemployed for different sub groups. High educated female workers in anticipated PUMAs are more like to be unemployed than high educated female workers who are in non-anticipated PUMAs. This finding is consistent for PUMAs with different capacities. All other specifications are not significant, stating anticipation is not increasing the likelihood of unemployment for male workers and low-educated female workers. This suggest that low-educated female workers leave carbon-intensive sectors but end up in non carbon sectors while high educated female workers more likely to become unemployment. in PUMAs like capacities are greater 1000 MW these unemployment effects disappear which means that when carbon sectors has the potential to absorb possible layoffs there is no anticipation effects on unemployment. High educated female workers might have high reservation wage which makes them to leave carbon sectors while spend some time to job shopping while the results in low-educated female workers states they switched from carbon to non-carbon sectors. On the other hand, male workers do not engage in any of these extensive margin adjustments.

Low-educated male workers are the only ones who decreases the number of hours worked per week as the anticipation of retirement. Capacities plays the same role as PUMAs greater than 1000MW they do not decrease the number of hours worked but high-educated male workers increases the number of hours they work. Which shows that in high capacity places, both female and male workers form different expectations than low-capacity places.

7 Conclusion

The transition to a green economy, aimed at reducing the dependence on carbon-intensive sources, is expected to change employment across sectors. Distributional effects will depend on to which extent workers can adapt to changes and how the existing labor market structure interacts with new regulations. This study examines the distributional impacts, primarily emphasizing the gender dimension. There is limited evidence on the labor mobility of female workers, and carbon-intensive sectors are predominantly male-dominated.

One key finding is that the cost of switching market sectors is significantly higher for female workers compared to their male counterparts, and leaving the market imposes a higher cost. As mobility costs have significant long-run distributional consequences, policies that reduce such barriers for women can potentially eliminate gender differences in the long run.

I also find the anticipation of coal-fired power plant closures displaces women in carbon-intensive sectors. However, my current analysis can not differentiate whether the employer or employee initiates these separations. Future work with longitudinal data with worker histories can shed light on the mechanism. As I find that high-educated women are more likely to be unemployed, possible unemployment duration and after-separation wages will help understand how women adapt to negative resource shocks in the local labor market.

This study brings the gender dimension to the distributional effects of environmental regulations discussions, an aspect which is often studied within limited scopes. The findings underscore the significance of recognizing this gender dimension, emphasizing that mobility costs can give rise to disparities. Furthermore, in local markets with pre-existing gender imbalances, gender inequality may be exacerbated.

8 Figures and Tables

Table 1: Mean Wages for Each Type of Worker in Market Sectors

	Current Population Survey 1976-2019			
	Low-Educated Female		**Low-Educated Male**	
	Mean Wage	Observation	Mean Wage	Observation
Ag, Mining	25,344	8,811	38,585	41,403
	(26076.7)		(34852.2)	
Cons, Util, Trans	32,218	40,539	44,242	203,357
	(22403.5)		(33472.8)	
Manu	27,793	99,501	44,783	212,806
	(19138.8)		(29823.4)	
Tra, Serv	26,390	593,889	41,327	432,669
	(22044.8)		(33716.8)	

	High-Educated Female		**High-Educated Male**	
	Mean Wage	Observation	Mean Wage	Observation
Ag, Mining	44,877	2,536	70,424	5,905
	(38969.2)		(64556.3)	
Cons, Util,Trans	52,267	9,156	73,126	28,257
	(45448.5)		(61788.3)	
Manu	58,912	17,753	83,331	48,779
	(47452.1)		(62225.5)	
Tra, Serv	47,700	270,775	77,303	252,907
	(42701.2)		(75364.7)	

‡ Mean wages are in 2005 dollars and standard deviations are in parentheses.

Table 2: Average Gross Flows Across Market Sectors 1976-2019

	Female and Male Workers			
	Ag, Mining	Cons, Util, Trans	Manu	Tra, Serv
Ag, Mining	0.814	0.056	0.033	0.096
	0.794	0.014	0.024	0.168
Cons, Util, Trans	0.010	0.867	0.033	0.090
	0.005	0.775	0.025	0.195
Manu	0.010	0.043	0.837	0.109
	0.004	0.010	0.846	0.140
Tra, Serv	0.007	0.037	0.035	0.920
	0.002	0.009	0.015	0.973

Note: Rows represent origin sector while columns show destination sector. Diagonals show the stayers in particular sector. Gross flows of female workers are shown in blue. This table shows gross flows from CPS sample,however literature argues gross flows from CPS only capture 5-month mobility.For the mobility costs estimations I correct flows to represent annual flows.

Table 3: Average Gross Flows across Market and Home Sector

Female and Male Workers		
	Any Market Sector	Home Sector
Any Market Sector	0.901	0.099
	0.877	0.123
Home Sector	0.125	0.875
	0.089	0.911

Note: As Table 2, rows represent origin sector while columns show destination sector. Home sector is defined as non-employed people put their time.

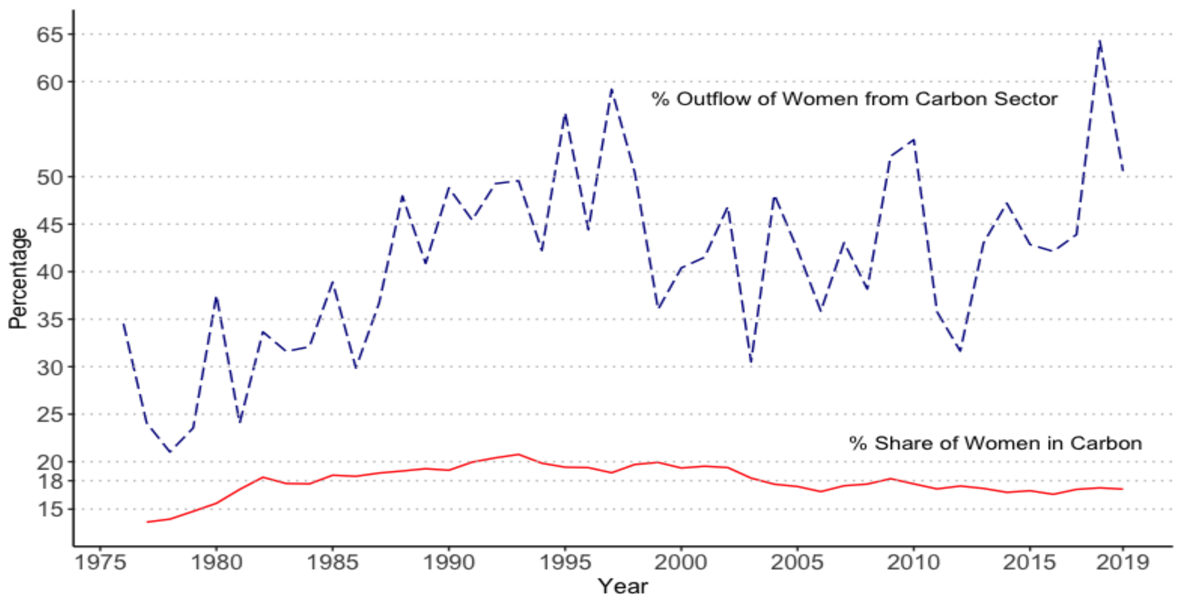

Figure 1: Female Share in Carbon Sectors and Female Carbon- NonCarbon Flows

Note: CPS March Supplement from 1976 to 2019 is used to calculate both percentages. Percentage outflows are calculated among female workers who worked in a carbon-intensive sector in the past year but started working in a non-carbon sector in the current year.

Table 4: Constructed Home Sector Wages and Relation to Market Sector

	Home Wages	Market wages
Female Workers	18,509	30,794
Male Workers	16,022	47,138

Note: Home wages are constructed for each year by using ATUS and AHTUS surveys which is a sub-sample of CPS. Market wages are also representing the sub-sample to be in harmony with the home sample. Appendix A.3 explains in detail how to obtain home wages.

Table 5: Model Parameters

	Model Specific Matched Parameters					
	Carbon Sectors		**Non-Carbon Sectors**		**Home**	**Source**
	Ag.,Min.	Tran.,Util.,Cons.	Manu.	Tra.,Ser.		
A^j	0.32	0.48	1.27	1.22	0.5	In Text
θ^j	0.92	0.35	0.89	0.84	1	Matched to BLS data
ψ^j	0.07	0.37	0.22	0.25	0.09	Matched BLS consumption share
α_1^j	0.91	0.95	0.81	0.47		See Appendix
α_2^j	0.17	0.15	0.34	0.65		In Text
α_3^j	0.17	0.08	0.28	0.5		In Text
	Model Free Parameters					
σ_1^j	1.5	1.5	1.5	1.5		Katz and Murphy (1992)
σ_2^j	0.7	0.7	0.7	1.2		Olivetti and Petrongolo (2014)
σ_3^j	1.7	1.7	1.7	1.7		Ghosh (2018)
	Estimated Parameters					
		Female Workers		**Male Workers**		
λ_i		1.17		1		Home Productivity
C_i		2.24		1.6		Moving Costs Market-Market
C_i		4.14		4		Moving Costs Home-Market
η		0.68		0.68		Non-monetary benefit

Table 6: Average Moving Costs for Female and Male Workers

	Average Moving Costs	
	$\beta = 0.9$	
	Across Market Sectors	Between Market and Home
Female	2.24 (4.98)	4.14 (3.34)
Male	1.60 (6.67)	4.01 (2.89)
η- Non-Monetary Importance	0.68 (8.27)	3.30 (11.60)

† T-Statistics are in parenthesises

Table 7: Long-run Welfare Changes after Tax with mobility - Simulation Results

	% Δ Present Discounted Lifetime Values		
	Carbon Sectors	Non-Carbon Sector	Home
Low-educated Female	-1.4	-2.4	-6.9
Low-educated Male	$+0.01$	-0.21	-5.4
High-educated Female	-3.43	-4.76	-7.26
High-educated Male	-0.8	-1.24	-6

Simulations are based on mobility costs estimated in Table 6, in which female workers have higher mobility costs.

Table 8: Average Moving Costs with Different Discount Factors

	Average Moving Costs			
	$\beta = 0.95$		$\beta = 0.97$	
	Across Market Sectors	Market-Home	Across Market Sectors	Market Home
Female	2.98 (3.004)	4.15 (1.614)	3.55 (2.041)	3.60 (0.822)
Male	2.02 (4.507)	4.09 (1.390)	2.26 (3.140)	3.66 (0.727)
η- Non-Monetary Importance	0.85 (7.151)	3.75 (10.70)	0.93 (6.671)	3.96 (10.33)

† T-Statistics are in parenthesises

Table 9: Average Moving Cost for Separate Samples

	Average Moving Costs Across Market Sectors			
	Only-Female Sample		Only-Male Sample	
	$\beta = 0.97$	$\beta = 0.90$	$\beta = 0.97$	$\beta = 0.90$
Cost	3.30 (1.569)	2.04 (2.717)	1.87(3.108)	1.32 (6.554)
η- Non-Monetary Importance	0.87 (2.316)	0.62 (3.023)	0.766(6.462)	0.557(8.067)

† T-Statistics are in parenthesises

Table 10: Long-run Welfare Changes Counterfactual Scenario

	% Δ Present Discounted Lifetime Values					
	Different Moving Costs			Same Moving Costs		
	Carbon	Non-Carbon	Home	Carbon	Non-Carbon	Home
Low-educated Female	-1.4	-2.4	-6.9	-0.7	-1.1	-5.6
Low-educated Male	$+0.008$	-0.21	-5.4	-0.3	-0.7	-4.9
High-educated Female	-3.43	-4.76	-7.26	-1.3	-1.9	-6.5
High-educated Male	-0.8	-1.24	-6	-1.2	-1.8	-6

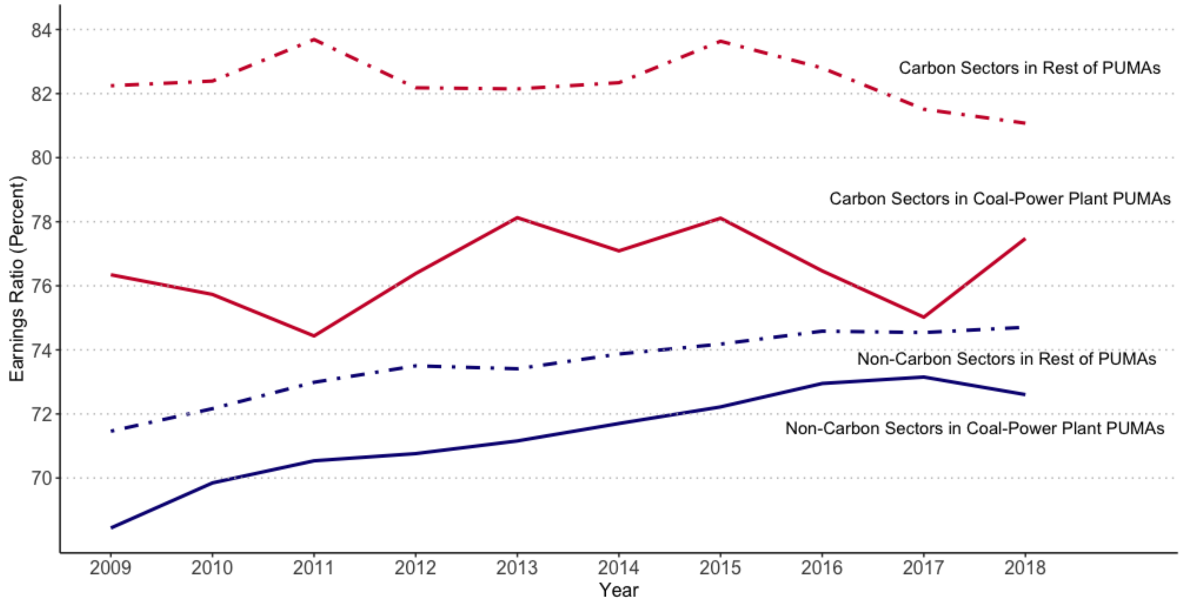

Figure 2: Female-to-Male Earnings Ratio Trends in Coal-Fired Power Plant PUMAs and Rest of other PUMAs

Note: I calculated average wage for women and men who employed in carbon-intensive in PUMAs which has active or retired coal-fired power plant by using ACS from 2010 to 2019. Rest of PUMAs represent the averages in PUMAs in entire nation which does not have a coal-fired power plant.

Table 11: Coal-Power Plant Retirements

Coal-Power Plant Retirements			
Retirement Year	Total Capacity (MW)	Total Number of Generators	Number of PUMAs†
2010	1,534	28	3
2011	2,254	30	5
2012	9,719	58	15
2013	6,568	48	9
2014	4,588	44	6
2015	16,391	103	24
2016	7,791	49	12
2017	4,973	24	4
2018	11,627	30	14
2019	14,352	59	17
Total Retired by 2019	79,797	473	109
Active by 2019	243,956	631	192
Planned Retirements			
2020-2024	30,454	96	54
2025-2029	8,554	17	11
2030-2045	12,922	22	13

Note: PUMA sample is restricted to places with more than 60MW capacity since smaller capacities are trivial. PUMA retired year is taken as the year that maximum retirement occurred in PUMA. Total Capacity and Number of Generator columns do not have these restrictions.

Table 12: Coal-Power Plant PUMA Characteristics

	PUMA Active		PUMA Anticipated	
2010 Indicators	Mean	SD	Mean	SD
Population	$872,699$	$1,410,469$	$1,289,965$	$2,067,923$
White Share	0.85	0.13	0.84	0.14
Non-Urban Share	0.38	0.33	0.32	0.32
College Graduate Share	0.253	0.08	0.258	0.09
Unemployment Rate	7.58	2.37	8.74	2.26
Female LFPR	67.1	5.03	67.6	5.61
Average Income	$36,439$	7854	$36,219$	6992
% Carbon Employment	18.1	4.53	16.4	3.13
% Women Employment in Carbon	16.7	3.57	17.4	4.75
Total Observations (2010-2019)	$2,077,088$		$1,121,628$	

Note: PUMA Active indicates that Public Use Micro Areas that has an active coal power plant in 2010 and these coal-power plants never experienced retirement in the next year. PUMA Anticipated shows characteristics of PUMAs have active coal-power plant in 2010 but in later years they experience retirement in some capacity. Carbon-intensive sectors defined as agriculture, mining, construction, utilities, transportation.

Table 13: Number of Workers by Anticipation of Retirement

	Ln(worker)	Ln(female)	Ln(male)
Panel A: All Capacities			
Carbon Sectors			
Anticipation<5	-0.0552 (0.0401)	-0.0583 (0.0412)	-0.0554 (0.0409)
Anticipation<3	-0.0516 (0.0392)	-0.0780* (0.0400)	-0.0469 (0.0405)
Observations	302,083		
Non-Carbon Sectors			
Anticipation<5	-0.0346 (0.0377)	-0.0331 (0.0385)	-0.0363 (0.0371)
Anticipation<3	-0.0315 (0.0365)	-0.0290 (0.0368)	-0.0344 (0.0364)
Observations	1,476,976		
Panel B: Capacities>250 MW			
Carbon Sectors			
Anticipation<5	-0.0717 (0.0429)	-0.0810 (0.0445)	-0.0717 (0.0440)
Anticipation<3	-0.0861 (0.0477)	-0.1377** (0.0476)	-0.0772 (0.0493)
Observations	246,663		
Non-Carbon Sectors			
Anticipation<5	-0.0561 (0.0404)	-0.0569 (0.0403)	-0.0545 (0.0410)
Anticipation<3	-0.0613 (0.0410)	-0.0614 (0.0399)	-0.0606 (0.0425)
Observations	1,185,925		
Panel C: Capacities>1000 MW			
Carbon Sectors			
Anticipation<5	-0.0732 (0.0692)	-0.1010 (0.0722)	-0.0692 (0.0697)
Anticipation<3	-0.1424* (0.0748)	-0.2228** (0.0928)	-0.1282 (0.0742)
Observations	129,888		
Non-Carbon Sectors			
Anticipation<5	-0.0529 (0.0532)	-0.0534 (0.0524)	-0.0496 (0.0544)
Anticipation<3	-0.1168 (0.0710)	-0.1198 (0.0686)	-0.1099 (0.0750)
Observations	584,160		
State-Year FE	Yes	Yes	Yes

Note: Anticipation < 5 represents the time that generator announce retirement in EIA-860, and Anticipation < 3 is the median time between the actual announcement and closure. Carbon Sectors are defined as in paper which is utilities, transportation, construction, mining and agriculture. Non-Carbon Sectors are manufacturing, trade, and service sector. Regressions include state and year fixed effects. For PUMA level controls for average working population age, percentage white, percentage high-educated, percentage living in urban area, percentage married, average total income in PUMA. Standard errors are two-way clustered at the PUMA and year. Significance codes: * p<0.05; ** p<0.01; *** p<0.001.

Table 14: Number of Workers by Anticipation of Retirement -Level Analysis

	Worker	Female	Male
Panel A: All Capacities			
Carbon Sectors			
Anticipation<5	-16.20* (8.787)	-2.716 (1.907)	-13.49* (6.971)
Anticipation<3	-17.97* (8.286)	-3.386* (1.827)	-14.59* (6.602)
Observations	302,083		
Non-Carbon Sectors			
Anticipation<5	-67.21 (48.98)	-38.56 (26.82)	-28.65 (22.29)
Anticipation<3	-63.44 (48.44)	-37.19 (27.00)	-26.26 (21.64)
Observations	1, 476, 976		
Panel B: Capacities>250 MW			
Carbon Sectors			
Anticipation<5	-13.72 (7.752)	-2.435 (1.735)	-11.28 (6.175)
Anticipation<3	-20.66* (10.48)	-4.448 (2.440)	-16.21* (8.228)
Observations	246,663		
Non-Carbon Sectors			
Anticipation<5	-60.79 (42.76)	-35.03 (23.27)	-25.76 (19.63)
Anticipation<3	-63.74 (54.59)	-36.86 (28.46)	-26.89 (26.30)
Observations	1,185,925		
Panel C: Capacities>1000 MW			
Carbon Sectors			
Anticipation<5	-7.611 (11.07)	-0.6267 (1.502)	-6.984 (9.751)
Anticipation<3	-20.98 (12.41)	-3.777* (1.947)	-17.20 (10.69)
Observations	129,888		
Non-Carbon Sectors			
Anticipation<5	-11.11 (37.16)	-5.464 (20.78)	-5.642 (16.50)
Anticipation<3	-66.13 (55.54)	-35.92 (28.76)	-30.21 (26.84)
Observations	584,160		
State-Year FE	Yes	Yes	Yes

Note: Anticipation < 5 represents the time that generator announce retirement in EIA-860, and Anticipation < 3 is the median time between the actual announcement and closure. Carbon Sectors are defined as in paper which is utilities, transportation, construction, mining and agriculture. Non-Carbon Sectors are manufacturing, trade, and service sector. Regressions include state and year fixed effects. For PUMA level controls for average working population age, percentage white, percentage high-educated, percentage living in urban area, percentage married, average total income in PUMA. Standard errors are two-way clustered at the PUMA and year. Significance codes: * p<0.05; ** p<0.01; *** p<0.001.

Table 15: Likelihood of being Employed in Carbon-Intensive Sectors by Different type of Workers and Capacities

	Carbon Employment		
	(1)	(2)	(3)
Low-Educated Female			
Anticipation	-0.0033 (0.0021)	-0.0043* (0.0023)	-0.0110** (0.0047)
Observations	635,723	516,481	266,165
High-Educated Female			
Anticipation	-0.0015 (0.0025)	-0.0011 (0.0030)	0.0022 (0.0063)
Observations	302,072	237,298	108,570
Low-Educated Male			
Anticipation	-0.0050 (0.0050)	-0.0054 (0.0060)	0.0011 (0.0135)
Observations	740,404	601,391	312,398
High-Educated Male			
Anticipation	-0.0066 (0.0060)	-0.0031 (0.0066)	0.0065 (0.0121)
Observations	273,513	214,220	95,946
State-Year FE	Yes	Yes	Yes
Subset	All Capacities	Capacities>250	Capacities>1000

Note: Dependent variable is carbon employment and equals to 1 if employed in carbon-intensive sectors. Anticipation represents 3 year before the actual retirement. Carbon Sectors are defined as in paper which is utilities, transportation, construction, mining and agriculture and this is on sample that stated employed. Non-Carbon Sectors are manufacturing, trade, and service sector. Regressions include state and year fixed effects, and individual level controls such as age, race, marital status, living in a metropolitan area. Standard errors are two-way clustered at the PUMA and year. Significance codes: * $p<0.05$; ** $p<0.01$; *** $p<0.001$.

Table 16: Likelihood of being Unemployed

	Unemployment		
	(1)	(2)	(3)
Low-Educated Female			
Anticipation	0.0021 (0.0019)	-0.0002 (0.0021)	-0.0024 (0.0043)
Observations	684,934	556,180	286,114
High-Educated Female			
Anticipation	0.0044** (0.0013)	0.0056 **(0.0020)	0.0013 (0.0052)
Observations	311,402	244,477	111,681
Low-Educated Male			
Anticipation	0.0035 (0.0020)	0.0014 (0.0027)	-0.0028 (0.0046)
Observations	802,946	651,922	337,992
High-Educated Male			
Anticipation	-0.0014 (0.0012)	-0.0004 (0.0017)	-0.0049 (0.0031)
Observations	282,052	220,823	98,736
State-Year FE	Yes	Yes	Yes
Subset	All Capacities	Capacities>250	Capacities>1000

Note: Dependent variable is being unemployed and equal to 1 if an individual is unemployed. This is on the employed population. Standard errors are two-way clustered at the PUMA and year. Significance codes: * p<0.05; ** p<0.01; *** p<0.001.

Table 17: Intensive Margin Adjustments by Different Type of Workers and Capacities

	Usual Hours Worked Per Week		
	(1)	(2)	(3)
Low-Educated Female			
Anticipation	-0.0892 (0.0832)	-0.0871 (0.0680)	-0.0681 (0.1244)
Observations	579,772	471,398	242,720
High-Educated Female			
Anticipation	0.0275 (0.0874)	0.0513 (0.1283)	0.0741 (0.1890)
Observations	283,252	222,896	102,148
Low-Educated Male			
Anticipation	-0.2772** (0.1016)	-0.1931* (0.0987)	0.0264 (0.1416)
Observations	666,242	542,576	281,275
High-Educated Male			
Anticipation	0.0988 (0.1132)	0.0081 (0.1023)	0.3040* (0.1418)
Observations	247,686	194,087	87,051
State-Year FE	Yes	Yes	Yes
Subset	All Capacities	Capacities>250	Capacities>1000

Note: Dependent variable is usual hours worked per week. This is on the employed population.Standard errors are two-way clustered at the PUMA and year. Significance codes: * p<0.05; ** p<0.01; *** p<0.001.

References

Acemoglu, Daron, David H Autor, and David Lyle, "Women, war, and wages: The effect of female labor supply on the wage structure at midcentury," *Journal of Political Economy*, 2004, *112* (3), 497–551.

Aguiar, Mark, Erik Hurst, and Loukas Karabarbounis, "Recent developments in the economics of time use," *Annu. Rev. Econ.*, 2012, *4* (1), 373–397.

—, —, and —, "Time use during the great recession," *American Economic Review*, 2013, *103* (5), 1664–1696.

Albanesi, Stefania and Claudia Olivetti, "Home production, market production and the gender wage gap: Incentives and expectations," *Review of Economic Dynamics*, 2009, *12* (1), 80–107.

Allcott, Hunt and Daniel Keniston, "Dutch disease or agglomeration? The local economic effects of natural resource booms in modern America," *The Review of Economic Studies*, 2018, *85* (2), 695–731.

Aragón, Fernando M, Juan Pablo Rud, and Gerhard Toews, "Resource shocks, employment, and gender: evidence from the collapse of the UK coal industry," *Labour Economics*, 2018, *52*, 54–67.

Arrow, Kenneth J, Maureen L Cropper, George C Eads, Robert W Hahn, Lester B Lave, Roger G Noll, Paul R Portney, Milton Russell, Richard Schmalensee, Kerry Smith et al., "Benefit-cost analysis in environmental, health, and safety regulation," *Washington, DC: American Enterprise Institute*, 1996, pp. 1–17.

Artuç, Erhan and John McLaren, "Trade policy and wage inequality: A structural analysis with occupational and sectoral mobility," *Journal of International Economics*, 2015, *97* (2), 278–294.

—, Shubham Chaudhuri, and John McLaren, "Trade shocks and labor adjustment: A structural empirical approach," *American Economic Review*, 2010, *100* (3), 1008–45.

Aubert, Diane and Mireille Chiroleu-Assouline, "Environmental tax reform and income distribution with imperfect heterogeneous labour markets," *European Economic Review*, 2019, *116*, 60–82.

Baum, Sarah and Anja Benshaul-Tolonen, "Extractive Industries and Gender Equality," *Review of Environmental Economics and Policy*, 2021, *15* (2), 195–215.

Black, Dan, Terra McKinnish, and Seth Sanders, "The economic impact of the coal boom and bust," *The Economic Journal*, 2005, *115* (503), 449–476.

Black, Sandra E and Alexandra Spitz-Oener, "Explaining women's success: technological change and the skill content of women's work," *The Review of Economics and Statistics*, 2010, *92* (1), 187–194.

Blau, Francine D and Lawrence M Kahn, "The gender wage gap: Extent, trends, and explanations," *Journal of Economic Literature*, 2017, *55* (3), 789–865.

Blinder, Alan S, "Wage discrimination: reduced form and structural estimates," *Journal of Human resources*, 1973, pp. 436–455.

Burke, Paul J, Rohan Best, and Frank Jotzo, "Closures of coal-fired power stations in Australia: local unemployment effects," *Australian Journal of Agricultural and Resource Economics*, 2019, *63* (1), 142–165.

Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro, "Trade and labor market dynamics: General equilibrium analysis of the china trade shock," *Econometrica*, 2019, *87* (3), 741–835.

Castellanos, Kenneth A and Garth Heutel, "Unemployment, labor mobility, and climate policy," Technical Report, National Bureau of Economic Research 2019.

Crossley, Thomas F, Stephen RG Jones, and Peter Kuhn, "Gender differences in displacement cost: Evidence and implications," *Journal of Human Resources*, 1994, pp. 461–480.

Curtis, E Mark, "Who loses under cap-and-trade programs? The labor market effects of the NOx budget trading program," *Review of Economics and Statistics*, 2018, *100* (1), 151–166.

_, Layla O'Kane, and R Jisung Park, "Workers and the Green-Energy Transition: Evidence from 300 Million Job Transitions," Technical Report, National Bureau of Economic Research 2023.

Davis, Rebecca J, J Scott Holladay, and Charles Sims, "Coal-fired power plant retirements in the US," Technical Report, National Bureau of Economic Research 2021.

_, _, and _, "Coal-fired power plant retirements in the United States," *Environmental and Energy Policy and the Economy*, 2022, *3* (1), 4–36.

Dix-Carneiro, Rafael, "Trade liberalization and labor market dynamics," *Econometrica*, 2014, *82* (3), 825–885.

Feyrer, James, Erin T Mansur, and Bruce Sacerdote, "Geographic dispersion of economic shocks: Evidence from the fracking revolution," *American Economic Review*, 2017, *107* (4), 1313–1334.

Fisher, Kimberly, Sarah M. Flood Jonathan Gershuny, Joan Garcia Roman, and Sandra L. Hofferth., "Integrated Public Use Microdata Series," *American Heritage Time Use Study Extract Builder: Version 1.2 [dataset]. Minneapolis, MN: IPUMS, https://doi.org/10.18128/D061.V1.2*, 2018.

Flood, Sarah M., Liana C. Sayer, Daniel Backman, and Annie Chen., "Integrated Public Use Microdata Series," *American Time Use Survey Data Extract Builder: Version 3.2 [dataset]. College Park, MD: University of Maryland and Minneapolis, MN: IPUMS, https://doi.org/10.18128/D060.V3.2*, 2023.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry, "Integrated Public Use Microdata Series," *Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS, https://doi.org/10.18128/D030.V10.0*, 2022.

Ghosh, Pallab K, "A study of the long-run substitutability between men and women," in "in" IZA Conference mimeo 2018.

Gilbert, Ben, Hannah Gagarin, and Ben Hoen, "Distributional Equity in the Employment and Wage Impacts of Energy Transitions," Technical Report, National Bureau of Economic Research 2023.

Giorgi, Giacomo De, Marco Paccagnella, and Michele Pellizzari, "Gender Complementarities in the Labor Market," in "Gender Convergence in the Labor Market," Emerald Group Publishing Limited, 2015, pp. 277–298.

Greene, William, "The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects," *The Econometrics Journal*, 06 2004, *7* (1), 98–119.

Greenstone, Michael, "The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of manufactures," *Journal of Political Economy*, 2002, *110* (6), 1175–1219.

Hafstead, Marc AC and Roberton C Williams III, "Unemployment and environmental regulation in general equilibrium," *Journal of Public Economics*, 2018, *160*, 50–65.

_ and _ , "Jobs and environmental regulation," *Environmental and Energy Policy and the Economy*, 2020, *1* (1), 192–240.

Heckman, James J, "Sample selection bias as a specification error," *Econometrica: Journal of the econometric society*, 1979, pp. 153–161.

Illing, Hannah, Johannes F Schmieder, and Simon Trenkle, "The gender gap in earnings losses after job displacement," Technical Report, National Bureau of Economic Research 2021.

Ivandić, Ria and Anne Sophie Lassen, "Gender gaps from labor market shocks," *Labour Economics*, 2023, *83*, 102394. European Association of Labour Economists (EALE) Conference 2022.

Jacobson, Louis S, Robert J LaLonde, and Daniel G Sullivan, "Earnings losses of displaced workers," *The American Economic Review*, 1993, pp. 685–709.

Kambourov, Gueorgui and Iourii Manovskii, "nA Cautionary Note on Using (March) CPS Data to Study Worker Mobility, oMimeo," *University of Pennsylvania*, 2004.

Katz, Lawrence F and Kevin M Murphy, "Changes in relative wages, 1963–1987: supply and demand factors," *The Quarterly Journal of Economics*, 1992, *107* (1), 35–78.

Keller, Wolfgang and Hâle Utar, "Globalization, gender, and the family," *The Review of Economic Studies*, 2022, *89* (6), 3381–3409.

Kotsadam, Andreas and Anja Tolonen, "African mining, gender, and local employment," *World Development*, 2016, *83*, 325–339.

Levanon, Asaf, Paula England, and Paul Allison, "Occupational feminization and pay: Assessing causal dynamics using 1950–2000 US census data," *Social Forces*, 2009, *88* (2), 865–891.

Macpherson, David A and Barry T Hirsch, "Wages and gender composition: why do women's jobs pay less?," *Journal of Labor Economics*, 1995, *13* (3), 426–471.

Maurer, Stephan E and Andrei V Potlogea, "Male-biased Demand Shocks and Women's Labour Force Participation: Evidence from Large Oil Field Discoveries," *Economica*, 2021, *88* (349), 167–188.

Ngai, L Rachel and Barbara Petrongolo, "Gender gaps and the rise of the service economy," *American Economic Journal: Macroeconomics*, 2017, *9* (4), 1–44.

Oaxaca, Ronald, "Male-female wage differentials in urban labor markets," *International Economic Review*, 1973, pp. 693–709.

Olivetti, Claudia and Barbara Petrongolo, "Gender gaps across countries and skills: Demand, supply and the industry structure," *Review of Economic Dynamics*, 2014, *17* (4), 842–859.

__ **and** __ , "The evolution of gender gaps in industrialized countries," *Annual review of Economics*, 2016, *8*, 405–434.

Rendall, Michelle, "Female market work, tax regimes, and the rise of the service sector," *Review of Economic Dynamics*, 2018, *28*, 269–289.

Severini, Francesca, Francesco Felici, Noemi Ferracuti, Rosita Pretaroli, and Claudio Socci, "Gender policy and female employment: a CGE model for Italy," *Economic Systems Research*, 2019, *31* (1), 92–113.

Vona, Francesco, Giovanni Marin, Davide Consoli, and David Popp, "Environmental regulation and green skills: an empirical exploration," *Journal of the Association of Environmental and Resource Economists*, 2018, *5* (4), 713–753.

Walker, W Reed, "Environmental regulation and labor reallocation: Evidence from the Clean Air Act," *American Economic Review*, 2011, *101* (3), 442–47.

__ , "The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce," *The Quarterly Journal of Economics*, 2013, *128* (4), 1787–1835.

Watson, Brett, Ian Lange, and Joshua Linn, "Coal demand, market forces, and US coal mine closures," *Economic Inquiry*, 2023, *61* (1), 35–57.

Weber, Jeremy G, "How Should We Think about Environmental Policy and Jobs? An Analogy with Trade Policy and an Illustration from US Coal Mining," *Review of Environmental Economics and Policy*, 2020, *14* (1), 44–66.

Yamazaki, Akio, "Jobs and climate policy: Evidence from British Columbia's revenue-neutral carbon tax," *Journal of Environmental Economics and Management*, 2017, *83*, 197–216.

Yip, Chi Man, "On the labor market consequences of environmental taxes," *Journal of Environmental Economics and Management*, 2018, *89*, 136–152.

__ , "Labor Market Adjustments Through Part-Timers: Evidence from British Columbia's Carbon Tax," Technical Report, mimeo 2020.

A Appendices

A.1 Derivation of Wages for Market Sectors

Production Function:

$$Y_t^j = A^j (L_t^j)^{\theta_j} (E_t^j)^{1-\theta_j}$$

Output produced at time t in sector j is Y_t^j. Aggregate labor used for production of j is L_t^j. Energy used in sector j at time t is E_t^j Wages are equal to the marginal product of labor. In the model, wages differ by type and sector, so the model creates 16 different wages.

$$W_{i,t}^j = \frac{\partial Y_t^j}{\partial L_{i,t}^j} \times P_t^j$$

There are wages for 4 different workers which differentiates in each sector j. Low educated female workers who works in sector j earn $w_{fl,t}^j$.

$$w_{fl,t}^j = A^j \theta_j \alpha_1^j \alpha_2^j E^{1-\theta_j} L_{f,l}^{\rho_2^j - 1} [\alpha_2^j L_{f,l}^{\rho_2^j} + (1-\alpha_2^j) L_{m,l}^{\rho_2^j}]^{\rho_1^j/\rho_2^j} + (1-\alpha_1^j)[\alpha_3^j L_{f,h}^{\rho_3^j} + (1-\alpha_3^j) L_{m,h}^{\rho_3^j}]^{\rho_1^j/\rho_3^j}]^{\theta_j/\rho_1^j} \times [\alpha_2^j L_{f,l}^{\rho_2^j} + (1-\alpha_2^j) L_{m,l}^{\rho_2^j}]^{(\rho_1^j/\rho_2^j)-1}$$

Low educated male workers who works in sector j earn $w_{ml,t}^j$.

$$w_{ml,t}^j = A^j \theta_j \alpha_1^j (1-\alpha_2^j) E^{1-\theta_j} L_{m,l}^{\rho_2^j - 1} [\alpha_2^j L_{f,l}^{\rho_2^j} + (1-\alpha_2^j) L_{m,l}^{\rho_2^j}]^{\rho_1^j/\rho_2^j} + (1-\alpha_1^j)[\alpha_3^j L_{f,h}^{\rho_3^j} + (1-\alpha_3^j) L_{m,h}^{\rho_3^j}]^{\rho_1^j/\rho_3^j}]^{\theta_j/\rho_1^j} \times [\alpha_2^j L_{f,l}^{\rho_2^j} + (1-\alpha_2^j) L_{m,l}^{\rho_2^j}]^{(\rho_1^j/\rho_2^j)-1}$$

High educated female workers who works in sector j earn $w_{fh,t}^j$:

$$w_{fh,t}^j = A^j \theta_j (1-\alpha_1^j) \alpha_3^j E^{1-\theta_j} L_{f,h}^{\rho_3^j - 1} [\alpha_2^j L_{f,l}^{\rho_2^j} + (1-\alpha_2^j) L_{m,l}^{\rho_2^j}]^{\rho_1^j/\rho_2^j} + (1-\alpha_1^j)[\alpha_3^j L_{f,h}^{\rho_3^j} + (1-\alpha_3^j) L_{m,h}^{\rho_3^j}]^{\rho_1^j/\rho_3^j}]^{\theta_j/\rho_1^j} \times [\alpha_3^j L_{f,h}^{\rho_3^j} + (1-\alpha_3^j) L_{m,h}^{\rho_3^j}]^{(\rho_1^j/\rho_3^j)-1}$$

High educated male workers who works in sector j earn $w_{mh,t}^j$:

$$w^j_{mh,t} = A^j\theta_j(1-\alpha^j_1)(1-\alpha^j_3)E^{1-\theta_j}L^{\rho^j_3-1}_{m,h}[\alpha^j_2 L^{\rho^j_2}_{f,l}+(1-\alpha^j_2)L^{\rho^j_2}_{m,l}]^{\rho^j_1/\rho^j_2}+(1-\alpha^j_1)[\alpha^j_3 L^{\rho^j_3}_{f,h}+(1-\alpha^j_3)L^{\rho^j_3}_{m,h}]^{\rho^j_1/\rho^j_3}]^{\theta_j/\rho^j_1}$$
$$\times [\alpha^j_3 L^{\rho^j_3}_{f,h} + (1-\alpha^j_3)L^{\rho^j_3}_{m,h}]^{(\rho^j_1/\rho^j_3)-1}$$

A.2 Derivation of Estimating Equation for Moving Costs

I derive estimating equation for moving costs using distributional effects of idiosyncratic benefits, and this part of proof follows ACM. Probability of choosing k over different alternatives means that for worker i utility in sector k is greater than other alternatives j:

$$m^{jk}_i = Pr(V^k_i > V^j_i) = Pr(U^k_i - U^j_i + \epsilon^k_i > \epsilon^j_i)$$

Imposing the CDF of EV Type 1 and treating ϵ^j_i as an conditioning variable, we can calculate the probability of k is chosen for all $j \neq k$ conditional on ϵ^j_i.

$$m^{jk}_i = P^{jk}_i = \int f(\epsilon^k_i)\prod_{j\neq k} F(\epsilon^k_i + \underbrace{[\beta((E_t[V^k_i - V^j_i - C^{jk}_i]) - E_t[V^i_n - V^i_j - C^{jn}_i])]}_{\text{Option value being in k compared to any sector n}})d\epsilon^k_i$$

I call the option value of being in k as x^k and being in j as x^j to simpliyf the notation. Inserting pdf and CDF of EV Type 1 distribution with η variance and γ direction parameter we will obtain the following.

$$m^{jk}_i = \int(1/\eta)(exp(-\epsilon^k_i/\eta - \gamma)exp(-exp(-\epsilon^k_i/\eta - \gamma))\prod_{j\neq k} exp(-exp(-(x^k - x^j + \epsilon^k_i)/\eta - \gamma))d\epsilon^k_i$$

Since $exp(-exp(-\epsilon^k_i/\eta - \gamma) = exp(-exp(-(x^k - x^k + \epsilon^k)/\eta - \gamma))$ we can rewrite equation:

$$m^{jk}_i = (1/\eta)\int exp(-\epsilon^k_i/\eta - \gamma)\prod_{j} exp(-exp(-(x^k - x^j + \epsilon^k_i)/\eta - \gamma))d\epsilon^k_i$$

Using the fact that product of exponential is the sums of the exponents, transformation of exponential of products will result in following:

$$m_i^{jk} = (1/\eta) \int exp(-\epsilon_i^k/\eta - \gamma) exp(-\sum_j exp(-(x^k - x^j + \epsilon_i^k)/\eta - \gamma)) d\epsilon_i^k$$

Factoring out ϵ_i^k from summation will result in:

$$m_i^{jk} = (1/\eta) \int exp(\underbrace{-exp(-\epsilon_i^k/\eta - \gamma)}_{\text{If we call this term as c}} \sum_j exp(-(x^k - x^j)/\eta - \gamma)) \quad \underbrace{exp(-\epsilon_i^k/\eta - \gamma) d\epsilon_i^k}_{\text{This term will be derivative of c}}$$

$$m_i^{jk} = (1/\eta) \int exp(c \sum_j exp(-(x^k - x^j)/\eta - \gamma)) dc$$

Computing integral will give us

$$m_i^{jk} = (\frac{exp(c \sum_j exp(-(x^k - x^j)/\eta - \gamma))}{\sum_j exp(-(x^k - x^j)/\eta - \gamma)})\Big|$$

$$m_i^{jk} = \frac{exp(x^k/\eta)}{\sum_j exp(x^j/\eta)}) = \frac{exp(\beta((E_t[V_i^k - V_i^j - C_i^{jk}])/\eta)}{\sum_j exp(-(x^k - x^j)/\eta)}$$

Staying in the same sector does not incur a cost, $C_i^{jj} = 0$, and $V_i^j - V_i^j = 0$

$$\epsilon_{i,t}^j - \epsilon_{i,t}^k = \beta E_t[V_{i,t+1}^k - V_{i,t+1}^j] - C_i^{jk} = \eta[ln m_i^{jk} - ln m_i^{jj}]$$

Staying in one sector has an option value that can be measured as aggregate "staying flows" but responsiveness varies with variance of ϵ

$$E_t[\max_k(\epsilon_{i,t}^j - \epsilon_{i,t}^k)] + \beta E_t[V_{i,t+1}^j] = -\eta(ln m_i^{jj})$$

A.3 Construction of the Home Sector

Definition of home production follows Aguiar et al. (2013), and includes activities involving core home production related to home ownership, obtaining goods and services related to households, and care for others (excluding children). I use the American Time Use Survey (ATUS) and American Heritage Time Use Survey (AHTUS), which use information from randomly selected individuals from the CPS sample.[51] The sample is similar to the CPS sample with those age between 25 to 60 who stated currently not working (including unemployed, both laid off and looking for a job, or not in the labor force). I calculated the average time spent in home production according to each gender and year.

Figure 3 shows trends in time spent at home production for non-employed men and women. Women spend on average 250 hours in home production in a year, while it is 150 hours for men. When both genders are not engaged in labor market work, women still spend more time in home production, and this gap has not closed in recent years.

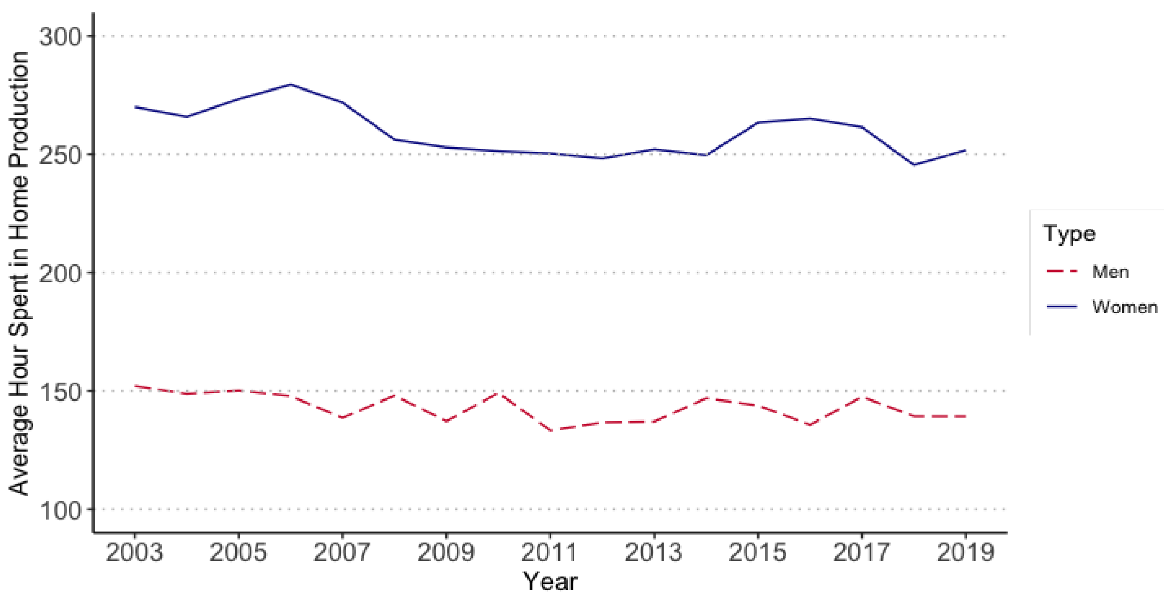

Figure 3: Yearly Time Spent in Home Production for Non-Employed Women and Men

Potential wages for workers who are in *home sector* will equal to time spent in home production multiply by their opportunity cost of time. As non-employed population is a selected group, to calculate the opportunity cost of time , first I use Heckman Selection model. In the

[51] ATUS is between 2003 and 2019, while AHTUS covers the period between 1975 and 2000. There are early years that are not covered by AHTUS, and in the final stage to, home wages are interpolated to cover those years.

first stage, using entire ATUS Flood et al. (2023) and Fisher et al. (2018), a probit model of the probability of working is estimated, controlling for the individuals' age, education, marital status, and having kids under 5.

$$Pr(D = 1|Z) = \Phi(Z\mu)$$

Potential home wages are estimated in second stage by the following equation.

$$w^* = X'\beta + \rho\sigma_u\lambda(Z\mu)$$

The second stage estimates the earnings equation controlling for the individual's age, level of education, and living in a metropole, and I estimate potential wages for non-employed sample.

Table 18 depicts the first stage results and inverse mills ratio, while potential wages are predicted by outcome equation section.

Table 18: Heckman Sample Selection

	Estimate	
Probit Selection Equation:		
Sex	-0.4610^{***}	(0.007)
Age	-0.0278^{***}	(0.001)
Education	0.4677^{***}	(0.008)
Having Children under 5	-0.3218^{***}	(0.008)
Marital Status	-0.0534^{***}	(0.004)
Outcome Equation:		
Sex	-280.651^{***}	(5.419)
Age	6.8137^{***}	(0.251)
Education	467.4161^{***}	(5.423)
Living in Metropol	130.7470^{***}	(4.487)
Inverse Mills Ratio	-109.5518^{***}	(22.230)
Observations	133,624	
14 free parameters (df = 133611)		
Adjusted R-Squared:0.2539		

Note: Significance codes: * p<0.05; ** p<0.01; *** p<0.001.

Two pieces, time spent in home production and potential hours wages, can be used to construct a home wage for each year for men and women. Trends in constructed home wage are shown in Figure 4. As expected home sector can be considered as a sector in which women have a comparative advantage compared to men.

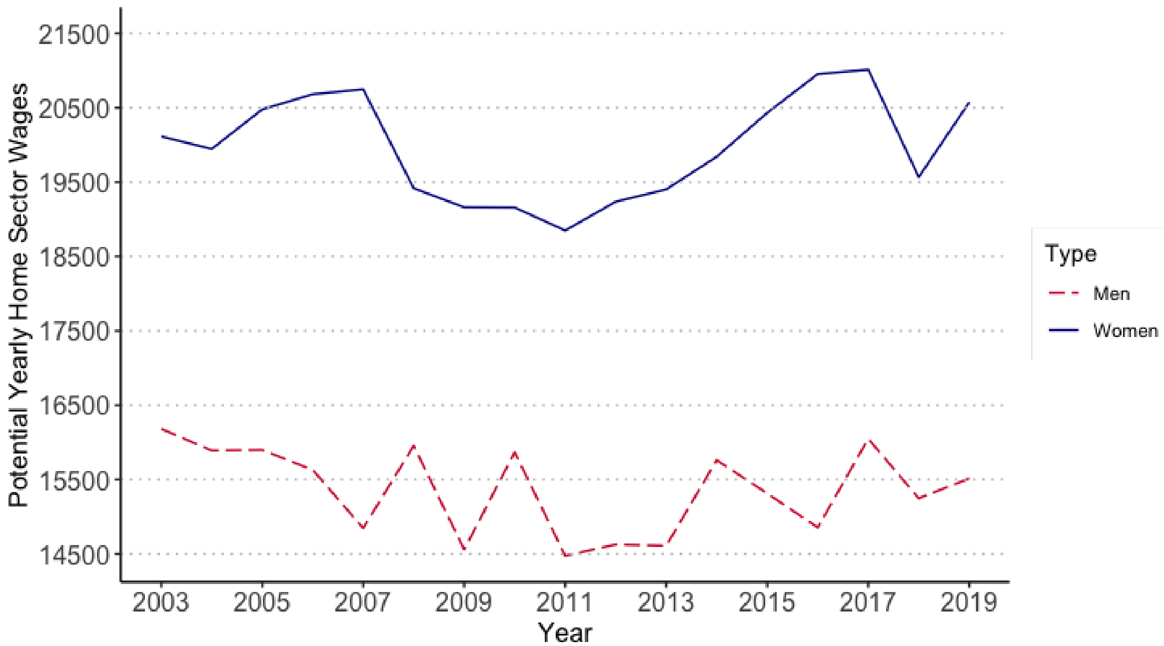

Figure 4: Trends in Potential Constructed-*Home* Wages for Non-Employed

A.4 Coal-fired Power Plant Retirements

Since the anticipation effects begin before the actual retirement of coal-fired power plants, examining the retirement effects will be biased. Individuals who are left before retirement differ from those who experience layoffs. In particular, Walker (2013) argues, leavers have lower than average productivity while stayers are associated with above than average productivity. As results should be interpreted cautiously, I study the effect of the impact of retirement on the wages of both female and male workers across all educational backgrounds. Big capacities retirements are associated with displacement of workers of mass layoffs which is different than anticipation effects.

Similar to specification in anticipation part, to understand if there is a disparate impact when plant is closed (or retired), I estimate the following baseline equation.

$$Y_{ipt} = \beta_1 \left[PostClosure_{pt} \times Closure_p\right] + \mathbf{X}'_{ipt}\gamma + \lambda_s + \theta_t + \epsilon_{ipt}$$

Closure is equal to one if coal-power plant has the majority of the capacity retired in the PUMA. Other variables are same as Anticipation Section. The coefficient of interest, β_1, is the effect of finalizing the coal-fired power plant retirement. Dependent variable is log(wage) for individual i lives in PUMA p at time t.

Table 19 shows wage effect for each sub-sample for different capacities of power plant areas. In Panel A, where all capacities are considered, only male sample experience adverse wage effects. However, when breaking down the total groups by carbon intensity of sector, only female workers in carbon sectors will have a reduction in wages. For the PUMA to have an initial capacity of more than 250 MW, female and male workers in carbon-intensive sectors will have negative effects, while female workers have slightly more than male workers. For places with an initial capacity of 1000 MW, losses of females are doubled, while for males, it stays the same as earlier specifications. This shows that in places with high carbon-intensive industry shares, male workers can be absorbed by big carbon industries and have a smooth transition. Table 20 shows results are driven by high-educated women and low-educated men in carbon sectors.

Table 19: Coal-Power Plant Retirement Effects on Wages

	Total		Carbon		Non-Carbon	
	Female	Male	Female	Male	Female	Male
Panel A: All Capacities						
Retirement	-0.0065 (0.0116)	-0.0248^{*} (0.0130)	-0.0322^{*} (0.0156)	-0.0250 (0.0151)	-0.0047 (0.0115)	-0.0223 (0.0139)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	989,257	1,049,110	59,147	282,517	930,110	766,593
Panel B: Capacities>250 MW						
Retirement	-0.0111 (0.0145)	-0.0314^{*} (0.0162)	-0.0566^{*} (0.0256)	-0.0426^{*} (0.0195)	-0.0080 (0.0141)	-0.0247 (0.0171)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	767,200	815,774	45,890	223,868	721,310	591,906
Panel C: Capacities>1000 MW						
Retirement	-0.0252 (0.0197)	-0.0418 (0.0249)	-0.1054^{***} (0.0213)	-0.0497^{*} (0.0261)	-0.0212 (0.0202)	-0.0361 (0.0292)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	362,147	387,703	22,004	113,804	340,143	273,899

Note: Each column represents the sub-sample. Regressions include controls for age, race, education, metropolitan status, marital status. Standard errors are two-way clustered at the PUMA and year. Significance codes: * $p<0.05$; ** $p<0.01$; *** $p<0.001$.

Table 20: Retirement Effects on Wages by Education Group, Capacities > 250MW

	Log(Wage)			
	(1)	(2)	(3)	(4)
Carbon Sectors				
retired	-0.0835** (0.0322)	-0.0387 (0.0247)	-0.0185 (0.0359)	-0.0446* (0.0200)
Observations	10,791	35,099	27,739	196,129
Non-Carbon Sectors				
retired	0.0086 (0.0193)	-0.0195 (0.0134)	-0.0206 (0.0226)	-0.0297 (0.0163)
Observations	238,521	482,789	189,232	402,674
Subset	High-Educ Female	Low-Educ Female	High-Educ Male	Low-Educ Male
Year-State FE	Yes	Yes	Yes	Yes

Note: Each column represents the sub-sample. Regressions consider two separate panel. The first one is carbon-intensive and second one is non-carbon sectors. Regressions include controls for age, race, education, metropolitan status, marital status. Standard errors are two-way clustered at the PUMA and year. Significance codes: * $p<0.05$; ** $p<0.01$; *** $p<0.001$.