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 and estimate a dynamic structural general equilibrium model of the U.S. economy that conceptualizes mobility costs for female and male workers who 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 initial gender disparities are 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

Environmental regulations would likely alter the distribution of employment among industries rather than the total employment level (Arrow et al., 1996). As technological changes favor women (Black and Spitz-Oener, 2010), and the growth of the service sector contributes to narrowing the gender wage gap (Olivetti and Petrongolo, 2016; Ngai and Petrongolo, 2017), growth of green sectors which has different characteristics than male-dominated carbon-intensive sectors could potentially yield similar outcomes. Nonetheless, the question of whether women can effectively transition into these green jobs is unknown. There is evidence that women are not acquiring green jobs at the same rate as men (Gilbert et al., 2023), and the reasons for this disparity remain unclear. To gain insights on these issues, this paper studies the transition to a green economy, with a particular focus on women's economic opportunity and mobility.

Mobility constraints, which include adapting human capital, incurring explicit search costs, and forfeiting sector-specific productivity, can play a significant role in creating barriers for workers transitioning into low-carbon sectors. From a gender perspective, an additional factor is the existing gender segregation in the labor market. In a labor market characterized by substantial carbon-intensive industries that are predominantly male, an otherwise neutral environmental policy somcould yield different outcomes for male and female workers. In this paper, I examine the extent to which mobility constraints differ by gender and have an impact on adaptation to transition, and the extent to which the preexisting gender imbalance influences the distributional outcomes of environmental regulations.

To address mobility constraints, 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 Artuç et al. (2010) (hereafter, ACM) and estimate structural model of mobility costs using Euler-type equation techniques. In contrast to their paper, I include female workers' moving decisions to capture gender differences and introduce an additional non-market sector to loosen the assumption of inelastic labor supply. I construct a non-market sector to represent home production, with the costs of moving to the home sector 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 mobility decisions. However, leaving the labor market incurs higher costs than changing sectors for both men and women, as costs are approximately four times the average annual wages. Non-monetary factors are more important for the decision whether to leave the market, which indicates that whether to move to the non-market is substantially affected by reasons that are not related to wages.[1]

Mobility estimates suggest substantial reallocation costs, varying by gender. To understand the role of such costs in a context of environmental regulations, I simulate a general equilibrium of a simplified U.S. economy with an energy tax and estimated mobility costs. I find lower long-run present discounted values for women across all education levels relative to men. If long-term disparities are primarily driven by mobility costs, implementing policies that ease the transition for women can effectively eliminate these gender disparities. I study a counterfactual scenario in which women face the same mobility costs as men. Gender differences disappear in the long run, implying mobility costs act as a mechanism that perpetuates long-term disparities.

To account for the existing labor market structure, I study a particular local labor market experiencing a regulation-induced transition over the past decade. Local labor market responses to regulations can be different than at the national level, especially in terms of gender dynamics. The share of the service sector in the local labor market is associated with higher female market hours (Petrongolo and Ronchi, 2020; Rendall, 2018), and there is evidence of a positive correlation between the prominence of extractive sectors and gender inequality (Baum and Benshaul-Tolonen, 2021). Local markets with coal-fired power plants have a higher proportion of carbon-related employment relative to the national average, and gender imbalances are more pronounced.[2] As a part of the initial phase of the green transition, efforts are being made to reduce fossil fuel dependence in energy production and accelerate the closure of coal-fired power plants.

[1] If moving to the home sector is driven by factors like family or location preferences, 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. In the next section, I show female-male wage ratios in coal-fired power plant communities and the rest of the nation.

The transition in coal-fired power plant communities started in the last decade and is anticipated to continue until 2040. I study local labor market adjustments, exploiting variation in coal-fired power plant retirement announcements. Retirement announcements provide a context for a gradual adjustment, with planned retirement decisions being documented in the Energy Information Administration (EIA)-860 generator-level survey, usually about five years before the retirement date. However, there is evidence suggesting that the time lag between announcements and actual retirements in the past decade is, in fact, closer to 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 (ACS) as a unit representing the local labor market. I find that in anticipation of a closure, low-educated female workers are less likely to work in carbon sectors, while high-educated female workers in carbon-intensive sectors are more likely to be unemployed. In contrast, male workers experience only a reduction in the number of hours worked. Estimates for female workers are greater in magnitude in places with higher capacity, suggesting 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 growing interest in potential employment effects and distributional consequences of environmental regulations (Greenstone, 2002; Walker, 2011, 2013; Yamazaki, 2017; Yip, 2018; Curtis, 2018), with some evidence that there exist gender-specific effects, but the extent of gender disparities and the mechanisms driving them remain unclear.[4] 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. As the introduction of new policies increases the pace of an energy transition, this paper

[3] The survey includes a question about planned retirements within the next five years, but reporting to EIA is not legally binding. While the EIA has expanded the question to cover the next ten years, Davis et al. (2021) shows the relevant timeframe is shorter.

[4] Walker (2013) studies sectoral reallocation of labor under the Clean Air Act finding that workers in newly regulated plants experience earning loss of 20% of their preregulatory earnings, with effects more pronounced for female workers. Yip (2018) provides evidence that British Columbia's carbon tax has differential impact on female and male workers.

identifies and adds the gender dimension to distributional effects discussions.

Second, this paper complements environmental regulations and employment effects studies by differentiating and quantifying mobility costs as indicators of labor market frictions. While existing empirical evidence provides displacement costs with heterogeneity by workers' characteristics, including gender (Walker, 2013), a general equilibrium framework is necessary to fully understand the spillover effects and long-term implications (Hafstead and Williams III, 2018).[5] Current general equilibrium models study mobility by incorporating static or search frictions (Aubert and Chiroleu-Assouline, 2019; Hafstead and Williams III, 2020) or by examining two extreme scenarios of labor market mobility: perfectly mobile workers or perfectly immobile workers (Castellanos and Heutel, 2019). I introduce imperfect mobility in a general equilibrium setting, which complements existing models in the environmental regulation and employment effects context.

Identifying mobility costs and their distributional consequences might be especially important in the green transition. With the anticipation of millions of jobs being created by this transformation, the question of which workers will be able to access these opportunities remains uncertain. I find that female workers tend to incur greater mobility costs, suggesting potential delays in their access to green jobs.[6] (Gilbert et al., 2023; Curtis et al., 2023) document differences in acquiring green jobs and delays for different types of workers by age and education, and Gilbert et al. (2023) also shows women falling behind acquiring green jobs. The findings of this paper suggest an explanation for potential delays: substantial mobility costs, particularly for female workers. In my model, mobility costs have long-term distributional effects and represent one potential avenue for reducing gender disparities in the long run.

Differentiating and quantifying mobility costs for various worker demographics will improve understanding of the underlying mechanisms behind observed patterns in green employment, ultimately achieving the goal of an equitable transition in the long run. Trade economists have traditionally emphasized the role of mobility costs in analyzing the distributional impacts of

[5] While Walker (2013) is closely related to this paper, there is a difference between displacement costs and mobility costs. In Walker's setting costs are associated with displacement which caused by CAA, while in my model I estimate total mobility costs which captures both voluntary and involuntary movements. Robinson (2018) provides an extensive discussion how to interpret these two specific costs.

[6] This paper considers mobility costs as the aggregate value associated with switching sectors 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.

trade policies, a perspective that parallels the context of the green transition. 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) shows that low-educated female workers experience the highest mobility costs in the Brazilian labor market, consistent with the findings of this paper.[7] Ashournia (2018) also shows that in the Danish economy female workers face higher costs. I provide estimates for sectoral mobility costs for females in the U.S. economy and costs associated with leaving the market. Given the potential importance of an outside option and its role in labor market decisions for female workers, this paper can provide a benchmark for future studies to estimate associated costs of unemployment and leaving the labor force.

Finally, this paper adds to our understanding of the dynamics within the local labor market in the context of coal-fired power plant closures. Natural resource booms and busts (Allcott and Keniston, 2018; Black et al., 2005; Feyrer et al., 2017) and coal mine closures (Watson et al., 2023) affects labor marker responses, while there is also evidence of persistent local unemployment effects in Australia after coal-fired power plant retirements (Burke et al., 2019). This paper identifies adjustments in anticipation of the closure of power plants in the U.S. over the past decade and highlights that adjustments start before actual closure. I find disproportionate effects for females in carbon-intensive sectors, implying that new regulations may exacerbate existing conditions. The Inflation Reduction Act is expected to accelerate coal-fired power plant retirements in the next 30 years, coinciding with a decline in coal and coal-fired power plant demand worldwide. There is a growing need to understand distributional effects on communities experiencing this transition.

2 Background

Transitioning away from fossil fuels is expected to lower carbon-intensive employment while workers can mitigate possible economic losses by transitioning into unregulated low-carbon industries. The 2023 Job Creation and Local Economic Development report from the OECD

[7] 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.

highlights a gender disparity in the transition to a green economy, noting that women are notably underrepresented in green-task jobs across local labor markets.[8] Whether women would employed in green sectors, or existing conditions would persist is unclear.

Gender segregation across sectors is still pronounced, as carbon-intensive sectors (such as mining, utilities, and construction) have the lowest share of women in employment, and the service sector has the highest share.[9] 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; Oaxaca, 1973; Levanon et al., 2009).[10] Environmental regulations, which alter the labor market structure, would directly impact the economic opportunities of female workers, although the gender aspect has been relatively understudied.[11]

The impact of environmental regulations is expected to be particularly significant for employees working in regulated sectors. Yip (2018) shows evidence that the adverse employment consequences are more pronounced for women in the context of British Columbia's carbon tax implementation. Walker (2013) finds female workers face substantial earnings losses in the event of displacement as a response to Clean Air Act. [12] Research shows large oil discoveries have positive effects on women's employment when the crowding effect is absent (Maurer and Potlogea, 2021), but Aragón et al. (2018) demonstrates that the closure of coal mines disproportionately affects women in manufacturing and the service sector due to the crowding effect caused by inflow of male workers in the local labor market. It is evident that an examination of unregulated sectors is essential, as the crowding-out effect, a consequence of worker mobility, plays a crucial role in understanding the distributional impacts.

While regulations can impose costs on workers, such as wage decreases, workers have the

[8] https://www.oecd.org/cfe/leed/PH-JCLED-2023-3.pdf

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

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

[11] 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.

[12] Walker's study is a part of extensive literature on worker displacement and associated costs. Earlier studies indicate that higher displacement costs for women (Jacobson et al., 1993; Crossley et al., 1994). Recent studies suggest a mechanism for higher displacement costs for women. Illing et al. (2021) find that women lose 35% more than men in displacement scenarios and identifies 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 child care imposes a barrier for women to labor market recovery. However, this paper provides an estimate for total mobility, which is a combination of voluntarily job switches and displacement.

potential to mitigate these costs by transitioning to unregulated sectors. However, changing the sector incurs costs as workers are constrained to move to one sector. In response to trade shocks, trade economists have developed models to estimate mobility costs for labor adjustments. However, there has been relatively limited focus on the specific impact of these costs on female workers. Artuç et al. (2010); Caliendo et al. (2019); Artuç and McLaren (2015) estimate mobility costs for only male data, Dix-Carneiro (2014) female and less educated workers face higher mobility costs in Brazilian labor market. Ashournia (2018) estimates the cost of moving between 1.2 to 2.4, and higher for female workers in Danish economy. In this paper, I provide such estimates for U.S economy and my findings are in range of findings of Dix-Carneiro (2014) and Ashournia (2018).

As labor market transitions encompass moves to nonemployment, it becomes important to understand the associated costs of transitioning to nonemployment. Mentioned mobility studies often regard outside the workforce as residual sector which masks female comparative advantage. However, the home sector might play a different role than a residual one, as one gender may have a comparative advantage over the other. This paper model the home sector to represent women's comparative advantage and provide a benchmark for estimated costs of penalty for leaving the labor market.

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 [13]. 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 receives $w^j_{i,t}$ and an idiosyncratic benefit $\epsilon^j_{i,t}$ The idiosyncratic benefit can be considered as non-monetary benefit. Workers can like the location, sector, or colleagues, these features will be considered as idiosyncratic benefit in this model. 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^{jk}_i 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.

$$V^j_{i,t} = w^j_{i,t} + \max_k \{\epsilon^k_{i,t} - C^{j,k}_i + \beta E_t[V^k_{i,t+1}]\} \tag{1}$$

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 sectors a disutility occurs due to

[13] 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.

switching costs.[14] 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 j, but if worker choose k over other options there will be a non-monetary benefit of being in sector k. Thus, the total cost of switching from j to k for worker type i can be written as

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

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

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

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

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

Following ACM, the idiosyncratic benefit being employed in industry has an Extreme Value Type 1 distribution with zero mean and and $\pi^2\eta^2/6$ variance.

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.[15] 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

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

[15] 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.

Cobb-Douglas production function.

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

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, while the aggregate labor is L_t^j.

Aggregate labor is a composite of low-and high-educated subgroups. CES sub-aggregation allows imperfect substitution between two education groups 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- and high-educated labor groups in industry j at time t are $L_{l,t}^j$ and $L_{h,t}^j$. Efficiency 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 j.

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[16]. Efficiency of aggregate labor is A^{home}.

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

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 utility represented in equation 1.[17]

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

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.

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

[16] 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. We know from home production literature females' productivity and high-educated people's productivity is higher in home sectors.

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

3.5 Estimating Equation for Moving Costs

Following mobility assumptions in ACM and 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 a zero mean and a variance of $\pi^2\eta^2/6$. As used in most dynamic discrete choice models, extreme value distributions enables closed-form solutions with tractability and iid assumption would allow for aggregation of idiosyncratic decisions. Cumulative distribution of idiosyncratic shocks are represented as:

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

With the EV Type 1 distributional assumption, gross flow of workers transitioning from industry j to k, denoted as m^{jk}, can be written as a function involving the variance of costs, η, and the differences in expected utility along with explicit costs, C^{jk}. Appendix A.2 explains in detail how to derive flows by using EV Type 1 properties. Gross flows from industry j to k will be written as:

$$m_i^{jk} = \frac{exp[((1/\eta)(\beta E_t(V_{i,t+1}^k - V_{i,t+1}^j)) - C_i^{jk}]}{\sum_0^N exp[((1/\eta)(\beta E_t(V_{i,t+1}^n - V_{i,t+1}^j)) - C_i^{jn}]}$$

Gross flows from j to k is represented as value of being in industry k is greater than any other industry n, which is similar expression to other discrete choice models. This expression tells that for worker type i, industry with higher lifetime utility should experience higher gross flows. Using marginal mover's decision, gross flows representation and the fact that staying in same sector does not incur any costs, moving costs can be recovered under rational expectations assumption. Following equation will recover monetary and non-monetary components of mobility costs.

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

According to Equation 8, current gross flows from industry j to k for type i depend on future wage differentials between sectors for type i, expected future gross flows, and cost of moving for worker i. It is important to note that $E_t(\mu_{i,t+1}) = 0$ due to rational expectations, and under rational expectations future gross flows are sufficient statistics for expected future gross flows. Under these assumptions, both left and right hand-side of equation 8 can be identified in data, ultimately C and η can be recovered.

The coefficient of wage differentials, β/η, can be interpreted as the sensitivity of flows to wage differentials across sectors. The time discount factor, β is common for all workers and known.[18] For a specific time discount value, if the flows exhibit greater responsiveness to wage differentials, this would suggest a lower value of η, indicating a low variance of idiosyncratic shocks. Since this would imply that non-monetary factors have a limited influence on moving decisions after accounting for wage differentials, I will refer to η as the importance of non-monetary factors for the rest of the paper.

Estimated β/η in which β is known and a common η for all workers, can be used to recover the differential monetary cost, C, for both female and male workers. [19] Explicit mobility costs are represented by C, and for the remainder of the paper, I will use the term "mobility costs" to refer to C. The Ordinary Least Squares estimation of Equation 8 may be biased, as unobservable factors that could explain gross flows between sectors might be correlated with expected wage differentials.[20] Following the literature, in particular Artuç et al. (2010) and Caliendo et al. (2019), I use lagged flows and wages as instruments for wages. Instruments, $(lnw^k_{i,t-1} - lnw^j_{i,t-1})$, $(lnm^{jk}_{i,t-1} - lnm^{jj}_{i,t-1})$,$(lnm^{jk}_{i,t-2} - lnm^{jj}_{i,t-2})$, are used to estimate Equation 8 with Generalized Method of Moments (GMM) method. Exclusion restriction assumption is unobservable factors, $\mu_{i,t+1}$, are not correlated over time. While this assumption may appear restrictive, the literature places significant emphasis on its advantages, with a more detailed explanation available in Artuç et al. (2010).

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

[19] Estimation relies on the assumption that η is same for all workers. Considering the meaning of η, as the variance indicating the responsiveness of flows to wages, this could be a restrictive assumption. One can argue that female workers are less responsive to wage differentials for moving decisions, placing more emphasis on external factors like family obligations. To understand the restriction of this assumption, I estimate the moving cost for separate samples that η does not need to be same across gender groups. It will be explained in more detail in the Counterfactual Scenarios.

[20] For example, a female worker may switch to service sector from manufacturing because of flexible working hours. However, this choice could also be correlated with wages differentials, as she may have to forego potential earnings growth in favor of flexibility.

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 elasticity of substitution 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,I first define gross flows and average wages for each worker across market sectors. Then, I elaborate on how to account for flows from home (outside 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.[21] I restrict the sample whose age is between 25 to 60, and workers who 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.[22]

I aggregated market sectors into four main categories. The first comprises agriculture and mining, the second includes construction, utilities, and transportation, the third is manufacturing, and the fourth involves trade and services. The first two sectors are traditionally carbon-intensive and will be referred to as such throughout the rest of the paper. Table 1 shows observations and mean wages for each type of worker in every aggregated sector. In carbon-intensive sectors, the proportion of low-educated men is significantly higher than that of low-educated women. As anticipated, the segregation is less evident at higher education levels. On average, women's wages are lower than men's across all sectors and education groups. On average, carbon-intensive sectors offer higher pay compared to low-carbon sectors for each

[21] 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.

[22] Workers who work more than 26 weeks are considered full-time employed.

worker type.

Table 2 shows raw average gross flows between 1976 to 2019 for men and women.[23] Rows represent the origin sector while columns show destination sector. Diagonals show stayers in particular sector. Independent of origin sector; female workers move to low-carbon than male workers.[24] For instance, on average, 19.5% of women in the construction, utilities, and transportation sectors transition to trade and service sectors, while only 9% of men in this sector make the same switch. In carbon-intensive sectors, female outflows are roughly double those of men.

4.1.2 Between Market Sector to Home

To estimate the cost of moving to *home sector*, data on wages and gross flows to home sector are needed. Gross flows to home can be derived from CPS non-market flows. If an individual indicated they did not work in the last year but claimed to be currently employed, this will be regarded as a gross flow from the home sector to the market sector.[25]

Potential wages for non-working individuals are not observable which has been a central issue in labor economics. The value of home production offers an avenue to calculate home wages, as my model considers home sector where people who are not employed or not in labor force put their time. Potential wages for workers who are in home sector will equal to time spent in home production multiply by their opportunity cost of time.[26] As non-employed sample is a selected group, I follow Heckman (1979) to correct sample selection, and estimate weekly wages for non-employed. Appendix A.3 explains in detail construction of home sector and home wages.

Table 3 depicts average flows across any market and home sector. For female workers, flows

[23] The term ”raw” is used here because, in existing literature, the contention is that CPS flows can account for five months of flows rather than yearly flows (Kambourov and Manovskii, 2004). In my analysis, I adjusted these flows to represent movements over a year; however, the data presented in this table depicts the unadjusted CPS flow rate. Following Artuç et al. (2010); Caliendo et al. (2019), I derived 12-month flows from observed data to recover mobility costs.

[24] I also analyzed average gross flows by education levels, finding no difference in moving rates among these groups. Low and high-educated women exhibit similar moving patterns, while low- and high-educated men move less than women.

[25] Flow from home to market is constructed by using ”workly” variable which indicates whether the respondent worked any time in the calendar year previous to the survey year and current status as ”employed”. Flow from market to home is the opposite direction.

[26] 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.

from the market to the home sector are higher, and once in the home sector, the tendency to stay within that sector is also more pronounced among female workers. Table 4 details the correlation between average home and market wages for both women and men. Home annual wages constructed for women surpass those for men, aligning with existing literature indicating a positive gender gap in the home sector (Albanesi and Olivetti, 2009). In Figure 1, displays trends in home wages, indicating that this gender gap has persisted over the years.

4.2 Parameters of the Model

The baseline model is calibrated to the 2005 U.S. economy. Notation *zero* denotes values in 2005, marking the economy's starting point. As the aggregate production function has a Cobb-Douglas form, θ represents the cost share of labor in gross output of that sector. The U.S. Bureau of Labor Statistics (BLS) provides the cost share of labor by industry. The initial distribution of labor, L_0, is derived from CPS March supplement for 2005, which was used in the flow derivation in previous section. Initial distribution of energy input and gross output levels by industry, Y_0, are obtained from the Bureau of Economic Analysis's tables.

Calibration of technology parameter, A, is done by calculation of production function for the baseline year. Following expression will provide A.[27]

$$A_0^j = Y_0^j (1/L_0^j)^{\theta_0^j} (1/E_0^j)^{1-\theta_0^j}$$

Elasticity of substitution between education and gender groups are calibrated with values in the literature, and these parameters can be considered as model-free parameters. I calibrate elasticity between high- and low-educated workers (σ_1) 1.42 as a common value in literature, following Katz and Murphy (1992).

Elasticity of substitution between female and male workers may vary across sectors and education groups. Female and male workers are less substitutuable in low-educated group compared to high-educated (Acemoglu et al., 2004), while substitution in goods sector 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). There is more evidence for more conservative estimates

[27] Values of gross output, employment level, and energy input are normalized.

within the range of 1 to 1.4 (De Giorgi et al., 2015). This paper uses lower bound for low-educated workers in carbon-intensive sectors, while upper bound is taken for all education levels in for non-carbon sectors, and and high-educated workers in carbon sectors.[28]

Using the elasticity of substitution parameter and the First Order Conditions (FOC) for wages derived in Appendix A.1, it is possible to determine the share of specific labor in production, $\alpha_1^j, \alpha_2^j, \alpha_3^j$. Right hand side of the equation 9 can be observed in data, given elasticity of substitution ($\hat{\sigma}$), values for α_2^j can be calculated.[29]

$$ln(\alpha_2^j/(1-\alpha_2^j)) = ln(w_{fl0}^j/w_{ml0}^j) + (1/\hat{\sigma})ln(L_{fl0}^j/L_{ml0}^j) \tag{9}$$

Since home goods are considered perfect substitute for particular market services (Ngai and Petrongolo, 2017), Y_0 for the non-market sector is targeted to match with services such that represents perfect substitution for home production.[30] Calibration of λ_i, the home sector productivity of the labor, is driven by the home sector wages. As explained section 4.1.2, I calculated potential wages for home sector for each type, and ratio of wages will provide the efficiency of the labor according to 7. Initial total labor employed in home sector is matched CPS 2005 non-employed population and normalized.

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

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. Table 5 shows all parameters of the baseline model.

[28] This assumption follows Olivetti and Petrongolo (2014)'s argument of good sectors considered as "brawn", while service sector is considered as "brain", which reflect the elasticity of substitution between female and male workers.

[29] Equation 9 shows calculation of α_2 which represents the share of low-educated female and male workers in production. Similarly, low-and high-educated aggregates are used for α_1, and for α_3 high-educated female and male worker aggregates are used.

[30] Following Aguiar et al. (2012), I consider food away from home, alcohol away from home, vehicle maintenance, taking care of adults, personal services, household operations.

5 Results

5.1 Moving Costs Across Sectors

I estimate average moving costs across sectors for female and male workers by applying data to Equation 8 with a common time discount parameter.[31] This estimation does not differentiate sectors but considers the average moving costs resulting from any direction of gross flows.

Table 6 shows moving costs in terms of normalized average annual wages. In the first column, female workers need to forgo 2.24 times the average wages to switch industries among market sectors, while male workers need to give up 1.6 times the wages. Both estimations are statistically significant, indicating that moving costs are not negligible and are more pronounced for women. If flows are fully responsive to wage differentials, other non-monetary factors would have a limited role in moving decisions across market sectors, resulting in a low η estimate. I find that η is small, 0.68, indicating that flows across market sectors are highly responsive to wage differentials.[32]

As a second step, I estimate the moving costs between home and any market sectors. In Table 6, second column shows cost of switching between market and non-market (home) sectors. Leaving the market sectors is equally costly for both genders, and it is more costly than switching across market sectors. Both men and women need to give up approximately four times of their annual wages to for any move between home and market sectors. Non-monetary importance is 3.3 which is higher than non-monetary importance in decision moving across market sectors.

Results are intuitive, as moving market sectors might be driven by wage differentials and better economic opportunities, and moves related to the home might be driven by non-monetary factors like family-related reasons or employer-initiated separations. Compared to transitioning between market sectors, decisions involving home incur higher costs, suggesting reentering the labor market involves greater barriers than remaining in the market but switch-

[31] I dropped the education groups because female data for some sectors have too little observation for different education groups which would not allow me to credible estimate mobility cost.

[32] Underlying assumption is both female and male workers have the same non-monetary constraints in moving decisions. However, this may not hold in many cases. I also estimate η by using only female and only male data. Counterfactual Scenarios section provides detailed explanation for varying non-monetary value for female and male workers. Since the estimation of η was similar for both samples, I assume non-monetary importance is the same for everyone for the main model.

ing to a different sector. I find higher mobility costs for female workers, which is consistent with research on displacement costs (Jacobson et al., 1993; Illing et al., 2021; Ivandić and Lassen, 2023) and mobility costs (Dix-Carneiro, 2014; Ashournia, 2018).

5.2 Simulation: An Energy Tax

To understand the role of mobility costs in an environmental regulation setting, I estimate the model and impose a tax on energy input. I assume the price of energy input increases 15% at year 5, and worker can respond to this shock by changing their sector with estimated costs in **Section 5.1**.[33] Other prices are determined endogenously inside the model.

I study female and male workers' discounted lifetime utilities, 30 years following the tax, to account for possible welfare effects in the long run. Table 7 shows long-run percentage changes for each type of worker for each sector. Relative changes in welfare are more substantial for female workers relative to male workers for all education groups and sectors.[34] Workers who remain in carbon-intensive sectors are affected by the tax, while those in non-carbon sectors may face spillover effects, as workers from carbon-intensive sectors can move to non-carbon sectors. Workers would bear the cost of moving, which would reflect their change in discounted lifetime utilities. The biggest relative decline in welfare is experienced by high-educated female workers across all sectors.

The biggest declines happen in home-sector individuals for all education levels, both men and women. Moving from and to home imposes higher costs on workers; in case of an energy tax in which the hiring rate might decline, these costs can create additional barriers to entry into the labor market. Differences between men and women in the home sector are relatively small, as opposed to differences in market sectors, potentially indicating the role of similar moving costs in the home sector. Compared to transitioning between market sectors, decisions involving moves related to the home incur higher costs, suggesting reentering the labor market involves greater barriers than remaining in the market but switching to a different sector.

[33] This paper takes energy tax as exogenously given. In carbon tax arguments, the most common pricing is 50$ per metric tonne of carbon dioxide (Metcalf, 2019), while this would translate to differential increases for fossil fuels prices, ranging from 14% to 207% (Metcalf et al., 2008). This paper considers the most conservative estimation for the main analysis.

[34] One limitation of the model is having the 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

I use a common time discount parameter from the literature to estimate moving costs in **Section 5.1**. Intuitively, as β gets low, moving costs should be smaller since individuals discount less future benefits of the new sector. I estimate costs with different time discount parameters from the literature to assess the sensitivity of the estimates to the choice of time discount. Table 8 depicts the findings for two different future discounting parameters. The estimated cost is lower with low β for both men and women. When the discount parameter is 0.97, female workers need to give up 3.55 times the average wages while male workers pay 2.26 times the wages. In all specifications, women have relatively higher moving costs than men.

In the model, η aims to capture the relative effects of non-monetary factors, such as preference for a specific job, non-wage benefits, and location attributes, on moving decisions. Women and men behave differently in the labor market, and it is expected that non-wage factors will affect their choices differently. Thus, I estimate moving costs using female-only and male-only samples, allowing non-monetary factors (variance of idiosyncratic shocks) to be independently estimated for each sample. Table 9 shows average moving cost and importance of non-monetary for each separate sample and relative results with different time discount values. While he importance of non-monetary factors is similar for both samples with different time discount values, it is slightly higher for female workers.

Estimations with different time discount parameters and separate samples conclude with similar results to the main analysis. The main result, indicating that women experience relatively higher mobility costs than men, is not sensitive to the choice of time discount parameter or the assumption of a common non-monetary factor.

Simulation with Same Moving Costs

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

Table 10 shows results when female workers' mobility costs are equal to male workers and provides a comparison with the main results. The difference in changes in welfare between high-educated females and males diminishes, as low-educated women still experience slightly greater losses compared to low-educated men, although the difference is less than 1%. Results suggest mobility costs drive long-run differences in welfare, implying substantial mobility costs have significant long-run distributional consequences. Findings suggest any policy targets women, and their transition to green employment may have the potential to alleviate the long-run welfare gap.

6 Local Labor Markets

6.1 Coal-fired Power Plants and American Community Survey

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, wind, hydroelectric, solar), generator nameplate capacity in megawatts (MW), the power plant that generator is part of, and which utility owns the power plant.[35] In particular, EIA-860 contains information about the generator's status, whether active or retired. For active generators, whether there is a planned retirement, while for retired generators, which date the generator got retired. It is not legally binding to report a planned retirement date, but there is a specific question considering the 5-year window for retirement is in survey.[36]

To understand local labor market responses to anticipation of closure, I aggregate the generator-level data to obtain plant-level data. I sum across the generator nameplate capacity to obtain plant-level and planned retired capacity for the year. EIA-860 survey provides detailed information on the location of the plant-level data, including state, county, and zip code. It is expected that multiple plants will serve one local market, or one plant can be at the intersection of multiple local markets. Thus, I match the zip code of the power plants to ACS's PUMAs by using existing weights in the crosswalk prepared by the University of Missouri.[37] I build a coal-fired power plant data by PUMA showing total capacity, if there is a retirement,

[35] Nameplate capacity is the highest value the generator can produce 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.

[36] 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 a 5-year retirement window.

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

when did the first retirement happen when is the last retirement, when maximum capacity got retired, operational capacity.[38]

Table 11 details the number of generators per PUMA, the total coal-fired capacity in each PUMA, the active plants in 2019, and the projected retirements and the corresponding PUMAs affected by these retirements over the next 20 years. In 2019, the active capacity of coal-powered plants stood at 243,956 MW distributed across 631 generators. An estimated 51,930 MW among the active capacity is anticipated to retire in the 45 years following 2019.[39]

I spatially link PUMA coal-power plant data to yearly ACS from 2010 to 2019, which provides employment status, gender, age, education level, industry, wages, occupation, and marital status of individuals. I follow the same classification as the first part of the paper: agriculture, mining, utilities, construction, and transportation are considered carbon-intensive sectors, while the remaining as non-carbon sectors. The sample consists of workers whose age is between 25 to 65; college graduates are considered as high-educated workers.[40] As shown in Table 12, PUMAs with an anticipated coal-fired power plant and always active coal-fired power plants were similar in 2010.

Figure 2 illustrates the female-to-male earning ratio in local markets with coal-fired power plants compared to PUMAs without these plants. As anticipated, the female-to-male earning ratio is higher in carbon-intensive sectors and lower in non-carbon sectors. However, in communities with coal-fired power plants, these ratios are lower than the national averages. While this descriptive graph might be driven by many factors that are out of the scope of this paper, it potentially suggests initial conditions in local markets with coal-fired power plants might differ for women, aligning with existing literature on market structure and gendered effects (Baum and Benshaul-Tolonen, 2021; Petrongolo and Ronchi, 2020). Figure 3 shows tha map

[38] There can be multiple retirements in a PUMA and this study I consider 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 influence of coal-power plants 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 be retired in 2020. To assign the status of PUMA in these situations, I have created when the first generator retired in PUMA and when the highest capacity retired in PUMA. If they were at the same time, anticipation effects only occurred between the planned and retired date if there is a 3-5 year effect, creating an anticipation effect in the community.

[39] This paper does not consider the period between 2019 to 2023 since the effect of COVID-19 might confound the analysis.

[40] PUMAs identifiers from 2010 to 2012 follow 2000 Census boundaries, while from 2012 to 2019 follow 2010 Census boundaries. I use crosswalk provided by IPUMS between 2000 to 2010 Census boundaries, and obtain a unified 2010 PUMA identifier between 2010 to 2019.

of local labor markets (as PUMAs) considered in this study with capacities.

6.2 Research Design with Coal-fired Power Plants

Characterized by substantial coal dependence and transition into a low-carbon economy in the last decade, local labor markets with coal-fired power plants can provide a setting that shows how new regulations would interact with initial gender segragation in the local market. It is often the case that the EIA announces plant retirements years before closure, as the EIA-860 survey provides data on planned retirement for a generator.[41] Survey includes whether there is a planned retirement in the next 5 years while reporting to EIA is not legally binding.[42] Davis et al. (2021) analyze news, announcements, and actual retirements in the last decade and find the median time between announcements and retirement was 3 years. Coal-fired power plant closures are not a one-time shock to the local labor market, and I study whether there is a differential gendered effect in the anticipation of closures.

A local labor market with a coal-fired power plant can differ from other markets, such as service sector-dominated ones. I restrict the sample to only areas with active or retired coal-fired power plants and study the anticipation of closure. Local markets with electric generators with different sources are not included in the model.[43] The capacity of the coal-fired power plant can significantly impact the employment levels and the labor market's dependence on coal-related jobs.[44]

To account for capacity effects, I consider 3 thresholds for the capacity; the first specification considers all capacities, while the second one considers only when capacities are greater than 250 MW, and the third one considers when it is greater than 1000 MW.[45]

I start specify the following:

$$ln(workers_{pt}) = \beta_1 \left[Anticipation_{pt} \times Ever\ Retired_p\right] + \mathbf{X}'_{pt}\gamma + \mu_s + \theta_t + \epsilon_{pt} \tag{10}$$

[41] For example, the 2019 EIA-860 survey shows which coal power plants will get retired in 2058, 2040, or during the 2020s.

[42] Recent changes in the EIA-860 survey made this timeline 10 years.

[43] Local labor markets without power plants would inherently differ from those with power plants. Markets reliant on wind or solar generators are expected to exhibit different dynamics compared to coal-dependent markets.

[44] https://cnee.colostate.edu/wp-content/uploads/2021/08/Supporting-the-Nations-Coal-Workers-report.pdf For example, if the name plate capacity is less than 250 MW, it is associated with the employment of 50 workers on average, while for more than 1000 MW is associated with 200 workers.

[45] 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.

The dependent variable is the 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-fired power plant retirements would directly impact carbon-intensive industries, I estimate Equation 10 for carbon and non-carbon sectors separately. Anticipation is a binary variable equal to 1 if the retirement decision is listed in EIA-860, which is 5 years before the actual retirement. I include a second specification; according to the literature, anticipation becomes anticipation before 3 years of retirement. Ever retired is also a binary variable, which is equal to 1 if PUMA has a power plant that has retired at some point in the last decade.

PUMA level controls, percentage of whites, the percentage living in urban areas, average income, percentage of college graduates, percentage married, and average age are included in X_{pt}. Year fixed effects are included to account for 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.

The identification assumption is that the labor composition of carbon and non-carbon sectors with active coal-power plants PUMAs would be the same with PUMAs experiencing a retirement except for the anticipation of retirement coal-power plant in 5 (or 3) years. However, unobservable characteristics of PUMAs, ϵ_{pt}, might correlated with retirement decisions. I provide a snapshot of the PUMAs characteristics in 2010 if they were different before these retirement decisions. In addition, Davis et al. (2021) find retirement decisions are not related to local labor market conditions but rather driven by national factors (natural gas prices, renewable portfolios) or plant-specific factors. In addition, EIA documents retirements between 2009 to 2019 were driven by stringent mercury regulations and plant age.[46] Watson et al. (2023) also argues it is driven by the increasing cost of production rather than local effects.

As PUMA-level analysis provides insight into changes in the composition of the workers across sectors, an individual-level analysis could show worker-level heterogeneity in adjustments to anticipation of coal plant closure. I start specifying the following equation:

[46] `https://www.eia.gov/todayinenergy/detail.php?id=44636` identification assumption would be violated if high maintenance cost plants are concentrated in one area rather than distributed randomly. As generator age is correlated with high maintenance costs, I will include a robustness check with generator age.

$$Y_{ipt} = \beta_1 \left[Anticipation_{ipt} \times EverRetired_{ip}\right] + \mathbf{X}'_{ipt}\gamma + \mu_s + \theta_t + \epsilon_{ipt} \tag{11}$$

The dependent variable equal to 1 is worker i in PUMA p at the t is unemployed or employed in the carbon-intensive sector. Individual level controls like age, marital status, race, and living in urban areas are included, and anticipation is similar to Equation 10. 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 for each capacity threshold. The dependent variable is binary, and including fixed effects can create additional problems with logistic and probit estimations. So, I use a linear probability model with fixed effects following Greene (2004).

Anticipations regarding power plant retirement can affect other labor market outcomes. Workers can adjust at an intensive margin by potentially reducing their working hours. To assess the occurrence of such adjustments and their extent, I estimate Equation 11, with the dependent variable, Y_{ipt} equal to the number of hours worked per week by worker i in PUMA p at time t and wages.

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 retirement, adjustments in the local labor market would start.[47] As mentioned in the research design part, total capacity in PUMA might indicate different labor markets, so I consider 3 different sub-samples in terms of capacities. Table 13 shows results for all specifications and sub-groups.

The first specification considers all capacities; while neither the total number of workers nor female and male workers respond to being enlisted in the EIA-860 form, female workers tend to leave the sectors, and female representation in the carbon sectors decreases by 7% due to anticipation of retirement in the next 3 years. This effect gets stronger for the places with higher capacities; it doubles in PUMAs with more than 250 MW capacity and almost

[47] I exclude the post-retirement period since that period will be more related to mass layoffs and displacement of workers. Appendix A.4 provides an analysis of post-period effects.

triples and becomes 22% for the PUMAs with more capacity than 1000 MW. 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 on male workers; 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 logarithms has many benefits, dealing with skewness in the data percentage change may mask the possible movements of male workers. I estimate the same analysis with the number of workers instead of the logarithm of the workers. Table 14 shows results for the level of workers. As a coal-power plant in the PUMA enlisted in EIA-860 data, on average 13 male workers leave carbon-intensive sectors in these PUMAs in anticipation of retirement. While almost the same number of men leave the carbon-intensive sector by anticipation of retirement in 3 years, female workers also leave these sectors. All outflows happen in carbon-intensive sectors, while men and women respond at different times and magnitudes.

Previous analysis changes in the composition of the carbon sector employment in anticipated PUMA. To understand individual responses and allow for additional breakdown of the data by the educational group, I study whether the likelihood of being employed in carbon-intensive sectors is changing by anticipation. As seen in Table 15 low-educated female workers are less likely to be employed in carbon sectors in all-capacity and higher-capacity PUMAs in anticipation of retirement, which is 3 years before the actual closure. In contrast, anticipation does not affect the likelihood of being employed in carbon-intensive sectors among high-educated female workers.[48]

Is one group more likely to be unemployed compared to another group? I study the likelihood of being unemployed for each group and each capacity specification in Table 16. High-educated female workers 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, implying anticipation does not increase the likelihood of unemployment for male workers and low-educated female workers. The finding suggests that low-educated female workers leave carbon-intensive sectors but end up in non-

[48] Walker (2013) offers insights into the characteristics of leavers and stayers in the context of displacement due to environmental regulation.

carbon sectors, while high-educated female workers are more likely to become unemployed. In PUMAs capacities greater than 1000 MW, unemployment effects disappear, which means that when carbon sectors can absorb possible layoffs, there is no anticipation effect on unemployment. High-educated female workers might have high reservation wages, which makes them leave carbon sectors and spend some time job searching, while the results in low-educated female workers state 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 experience a reduction in hours worked per week in anticipation of retirement; while there is no significant effect on female workers' hours, high-educated male workers only in high-capacity markets increase their time in the labor market. Findings suggest that female workers in carbon-intensive sectors disproportionately affected by the anticipation of power plant closure.

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 extent to which 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 higher costs than intersectoral moves. As mobility costs have significant long-run distributional consequences, policies that reduce such barriers for women can reduce and 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 cannot differentiate between whether the employer or employee initiates these separations. Future work with longitudinal data and 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 highlight the significance of recognizing this gender dimension, emphasizing that mobility costs can give rise to disparities in the transition to a green economy. 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
Agriculture, Mining	0.814	0.056	0.033	0.096
	0.794	0.014	0.024	0.168
Construction, Utilities, Transportation	0.010	0.867	0.033	0.090
	0.005	0.775	0.025	0.195
Manufacturing	0.010	0.043	0.837	0.109
	0.004	0.010	0.846	0.140
Trade, Service	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 sector in which non-employed are employed.

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.

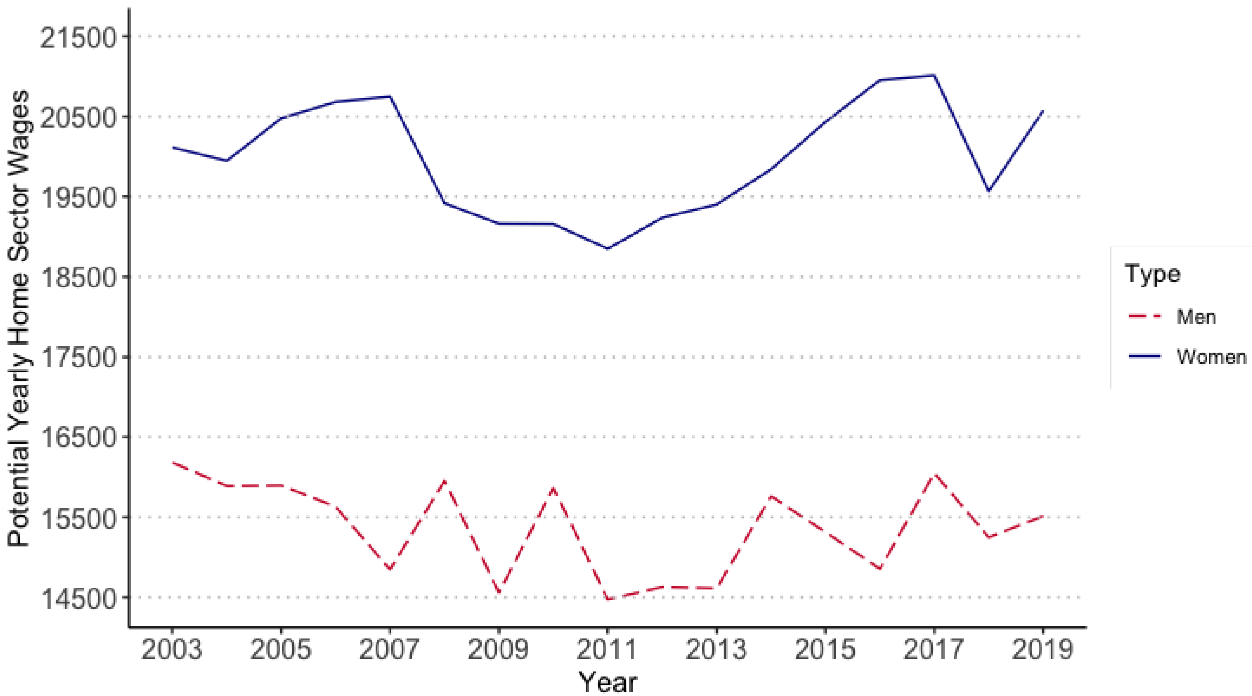

Figure 1: Trends in Potential Constructed-*Home* Wages for Non-Employed

Table 5: Model Parameters

	Carbon Sectors		Non-Carbon Sectors		Home	Source
	Model Specific Matched Parameters					
	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		In Text
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

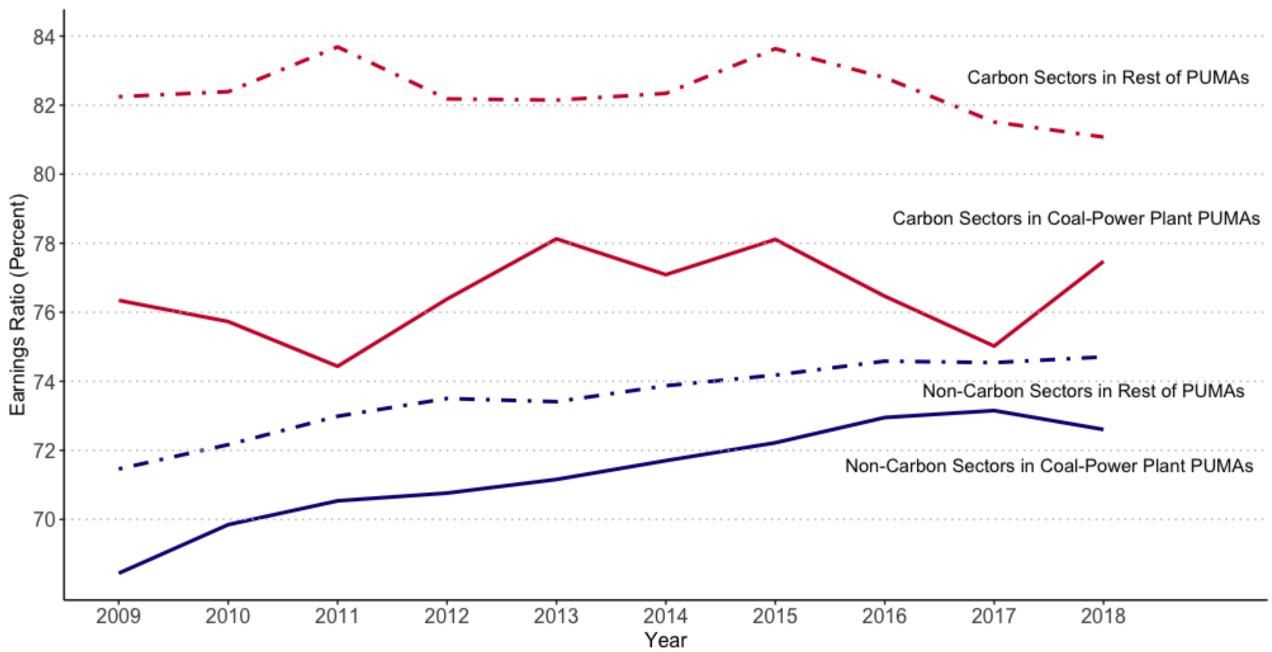

Figure 2: Female-to-Male Earnings Ratio Trends in Coal-Fired Power Plant PUMAs and Rest of other PUMAs

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.

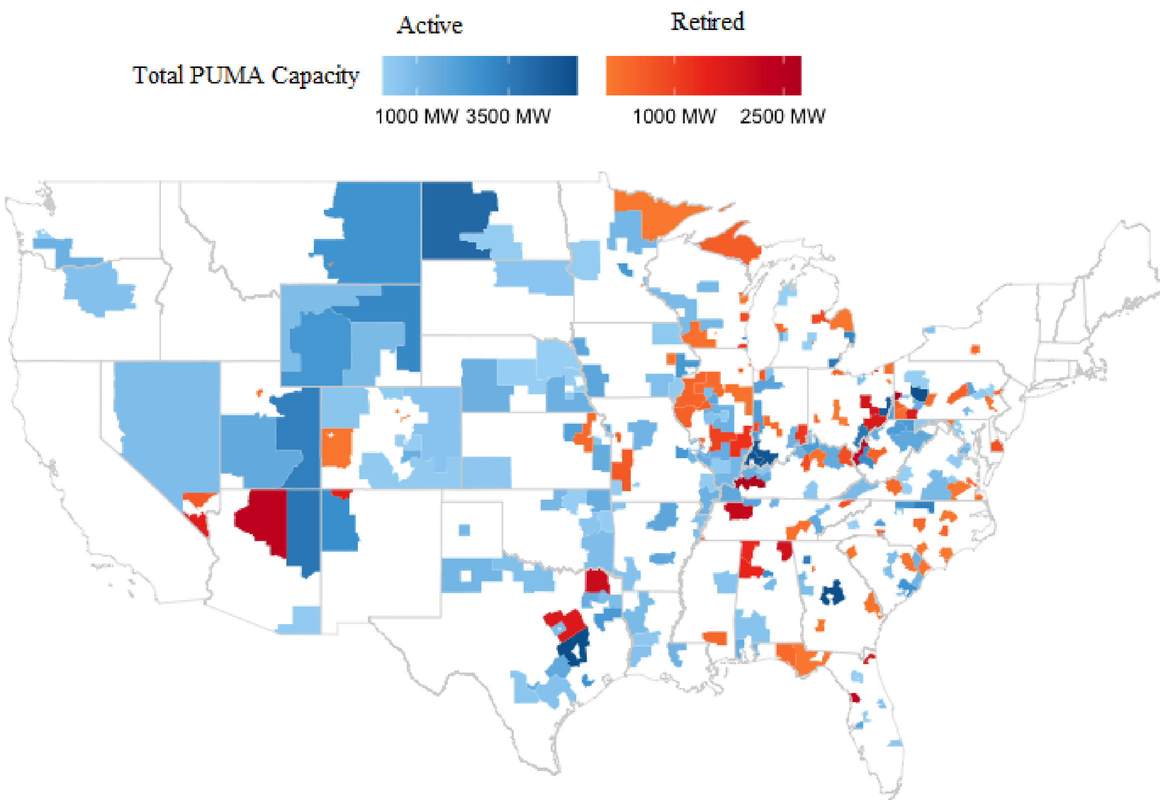

Figure 3: ACS PUMAs with Coal-fired Power Plants

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: * $p<0.05$; ** $p<0.01$; *** $p<0.001$.

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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 n:

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

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.

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

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:

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

Factoring out ϵ^k_i 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 $V_i^j - V_i^j = 0$

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

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

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

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.[49] 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 4 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.

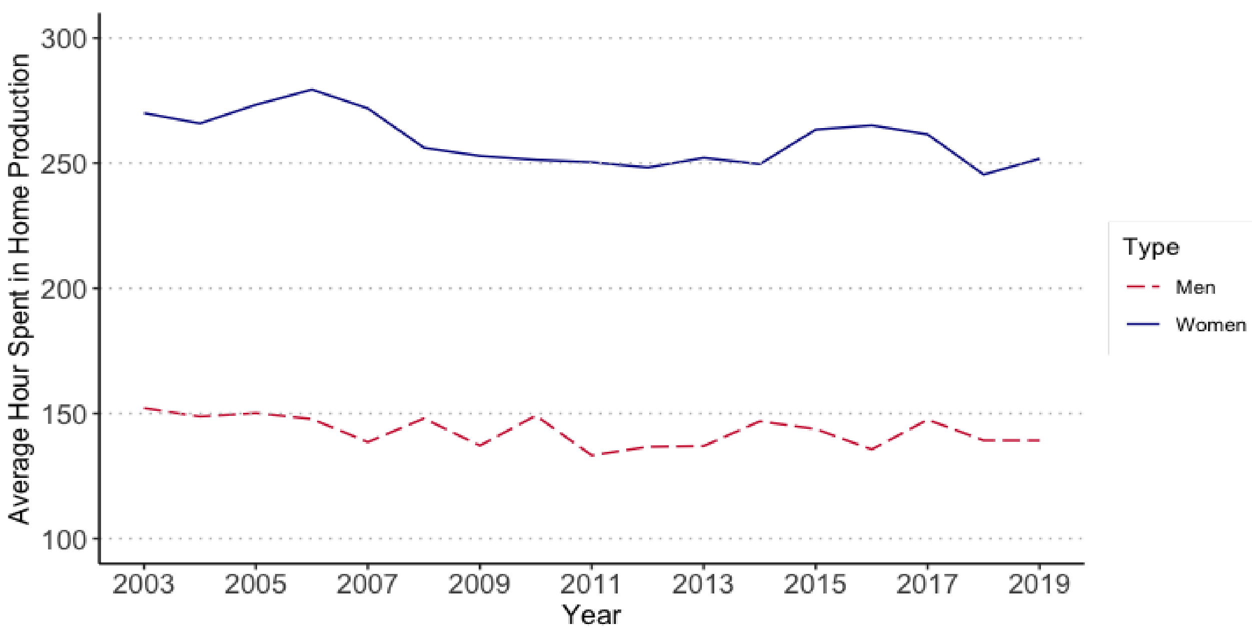

Figure 4: Yearly Time Spent in Home Production for Non-Employed Women and Men

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 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.

[49] 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.

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

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 1. As expected home sector can be considered as a sector in which women have a comparative advantage compared to men.

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.

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

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.