The Structural Sources of Racial Inequality: Heterogeneous Labor Supply Elasticities and Wage Markdowns

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We provide novel estimates of heterogeneity in labor supply elasticities among different groups of U.S. workers, using survey and administrative datasets. Our survey results use the Federal Reserve's SHED for 2021 to 2024, which asked workers how they would respond to hypothetical wage cuts. Our administrative results use QWI separation data on restaurant workers from 2001 to 2019. Elasticities are greater among white workers than black or Hispanic workers, among men than among women and vary little with age, education and household income. Building on Amior and Manning (2021), we then examine the wage implications of heterogeneous labor supply elasticities. Our baseline model contains only one type of worker– all workers are equally productive, are paid the same entry-level wage and have the same labor supply elasticity. Our model retains identical productivity and wage rates for different worker groups, but allows their labor supply elasticities to differ. Compared to our baseline, the less elastic labor supply of some groups results in greater wage markdowns for all workers; these become even larger when the labor supply is more heterogeneous.

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1 Introduction

Since Manning (2003), labor economists have increasingly studied search and matching frictions in labor markets (Kline, HLE 2025). Most studies find substantial frictions, indicating the presence of employer power to mark down wages (Sokolova and Sorenson, 2020). More recently, researchers have also studied firm-level labor supply elasticities using discrete choice experiments on workers' willingness to switch jobs if faced with a wage cut. Prominent examples include studies of job switching in Denmark, Germany and New Zealand.[1]

Meanwhile, economists have also continued to study racial inequality, which persists in U.S. labor markets despite the 1964 Civil Rights Act banning pure wage and employment discrimination and subsequent enforcement efforts. Although early audit studies found considerable racial inequality in employer responses to applications for entry-level positions, recent studies (Kline et al. (2024)) find that racial inequality is small for entry level positions. Moreover, racial wage inequality increases over labor market careers. This literature suggests that more limited job mobility options might play a larger role in perpetuating racial inequality than has been previously understood.

This paper contributes to all three of these research strands. We estimate differences in labor supply elasticities among sociodemographic groups of U.S. workers, explore why they might differ by race and consider their implications for wage markdowns. Our empirical analysis begins with data from the Federal Reserve Board's Survey of Household Economic Decision-making. Since 2021, SHED has randomly asked employed respondents how likely they were to look for another job if their pay remained the same or if it was reduced by 1, 5 or 10 percent. These questions capture workers' probabilities of leaving their jobs if their wages were reduced.[2]

We first estimate job quitting probabilities using a logit regression in which the reference group consists of non-Hispanic whites with a zero wage cut. When the SHED vignettes posit that wages would remain the same, the likelihood of leaving one's current employer is smaller for lower-wage workers, consistent with well-known higher turnover rates among lower wage workers. When the vignettes posit pay cuts, black workers, Hispanic workers, female and older (45 +) workers indicate they are less likely than the reference group to search for other jobs.[3] We then use the job quitting probabilities to estimate labor supply elasticities.

We use Quarterly Workforce Indicators (QWI) data on separation rates and leverage state-level minimum wage variation to estimate separation elasticities by race/ethnicity, gender, education and age. We find lower labor supply elasticities among black and Hispanic workers than among non-Hispanic white workers. We then discuss some of the mechanisms that rationalize lower black

[1]Caldwell and Harmon (2019) and Malchow-Møller et al. (2012) use Danish data. Caldwell and Danieli (2024),Jaeger et al. (2024) and Caldwell et al. (2025) use German data. Townsend and Allan (2024) uses New Zealand data.

[2]To our knowledge, ours is the first paper to use these SHED questions.

[3]Our SHED results are consistent with our calculations of white and black workers' reservation wages, reported in the labor market module of the FRBNY's Survey of Consumer Expectations:$19.23 and $15, respectively.

labor mobility.

Finally, we use our estimated labor supply elasticities to calibrate a model of imperfect competition in the labor market when different groups of workers have different supply elasticities (Amior and Manning, 2020). To keep the analysis focused on essentials, we consider here only two groups of workers, black and white. black and white workers are are employed in similar entry-level jobs and equally productive. Employers pay them the same wage, consistent with the 1964 Civil Rights Act. However, during their careers black workers face a series of obstacles that limit their access to better-paying employers; they therefor have have fewer outside options than otherwise similar white workers.

Importantly, the model shows that black workers' greater constraints in moving to different employers reduces not only their own pay, but also the pay of white workers. The magnitude of the wage markdown depends on the difference between the two labor supply elasticities and the proportion of black workers in the labor force. However, policies to improve racial equality may also benefit white workers.

1.1 Related literature

Job switching rates. A number of recent papers have estimated workers' job switching rates in other countries. Using Danish data, Caldwell and Harmon (2019) found that workers' switching rates are limited by their knowledge of outside options.[4] Caldwell and Danieli (2024) estimates that differences in outside options explain 20 percent of gender pay gaps in Germany, while Jaeger et al. (2024) found that German workers' beliefs about their outside options are one-tenth as large as estimates implied by actual job switching behavior. Caldwell et al. (2025) estimates that job switching costs among German workers range between 9 and 18 percent of annual pay. Using changes in immigrant worker visa policies in New Zealand, Townsend and Allan (2024) finds that such job restrictions reduce immigrants' pay as much as 20 percent. These papers suggest that job search and matching costs may be greater than economists have previously estimated.

We extend this research with U.S. data, where wage inequality and job flows are both considerably greater than elsewhere. Indeed, using the New York Fed's Survey of Consumer Expectations, Guo (2025) finds much smaller differences between perceived and observed outside options in the U.S.

Group differences in separation rates. Wursten and Reich (2023) and Naidu and Carr (2022) examine racial differences in job mobility using, respectively, the QWI and the SIPP. Two previous studies examine differences in reservation wages among employed workers. Hofler and Murphy (1994) use 1983 CPS data and a multivariate regression design. They find that reservation wages of homeowners exceeds those of renters by about 20 percent. Faberman et al. (2017) find that female workers place much more weights on non-wage amenities. Neither study reports results by race.

Labor supply elasticities. Manning (2021) and Sokolova and Sorenson (2020) review estimates

[4]Malchow-Møller et al. (2012) also used Danish data.

of labor supply elasticities to the firm. Hirsch et al. (2022) estimates recruitment elasticities in Germany. Caldwell and Oehlsen (2023) estimate differences in labor supply elasticities by gender. Gerard et al. (2021) finds racial differences in labor supply elasticity in Brazil.

Racial differences in job mobility. Our paper also connects with a small number of previous studies of racial differences in reservation wages. These studies generally examine unemployed workers, while we examine employed workers. Using a sample of unemployed New Jersey workers during the Great Recession, Fryer et al. (2013) found that reservation wages were 7 percent lower among black workers.[5] We use two different datasets to estimate racial differences in job leaving probabilities and labor supply elasticities among employed workers– and we explore their implications for wage markdowns among both black and white workers.

Wage markdowns. Naidu et al. (2025) examine the wage markdown effects among in a specific context: when incarcerated and free workers are employed in the same Alabama auto parts supply plants and are paid identical wages. Our model builds on theirs in a more general context.

Our paper makes three main contributions: a) We use SHED and QWI data to estimate labor supply elasticities for a variety of sociodemographic groups; b) We provide a model of imperfect competition in a labor market with differing labor supply elasticities between two groups of workers; and c) Using that model, we show that a lower labor supply elasticity among black workers substantially increases wage markdowns among both black and white workers.

Section 2 presents our estimates of job quitting probabilities by sociodemographic group. We present our separation rate and labor supply elasticity estimates in Section 3. Section 4 discusses how fewer job mobility optio s lead to lower labor supply elasticities among black workers. In Section 5 we present our wage determination model with differing group labor supply elasticities and calibrate the model using our estimated black and white labor supply elasticities to estimate substantial wage markdowns for each group. Section 6 concludes.

2 Labor supply elasticity estimates using discrete choice experiments

In this section we introduce the SHED data, discuss descriptive statistics, present our estimation method and discuss our results.

2.1 SHED data

Since 2013 the Federal Reserve Board has annually surveyed a sample of U.S. households, with the goal of learning about the distribution of households' financial well-being. The Survey of Household Economics and Decision-making (SHED) asks respondents about their access to credit,

[5] Krueger and Mueller (2016), using a sample of unemployed Ohio workers in 2018-19, find that reservation wages, relative to their previous wage, are about five percent higher among black workers than among white workers, echoing a much earlier finding by Holzer (1986). This counter-intuitive result makes sense if black workers place greater weights on non-wage amenities.

financial behavior, savings, retirement, education, student loans and their sociodemographic characteristics. The sample represents U.S. adults age 18 and older.[6]

SHED added a module in 2021 that asked employed workers their likelihood of looking for another job if their pay remained the same, or if their pay was reduced by one, five or ten percent. These choices were randomized among the sampled population.[7] As far as we can ascertain, the responses to these questions have not been utilized in any previous research studies.

These hypothetical vignettes, also known as discrete choice experiments (DCEs), do not reveal how respondents would actually respond to wage cuts. However, a review of DCEs in a variety of contexts by Mas (2025) finds that the responses closely match actual behavior. And as we will show below, our results using the SHED vignette data match up reasonably well with our results on job separations using the Quarterly Workforce Indicators' administrative data.

A more serious challenge concerns the representativeness of responses to questions about leaving one's current job, especially in 2021 and 2022, when the labor market was still recovering from the Covid-19 shocks. The Atlanta Fed's Wage Growth Tracker shows that job moving rates– and the return to moving to new jobs– rose steadily during 2021, peaked in 2023, declined in 2023 and then returned to historical levels in 2024. These changes were greater among black workers than among white workers.[8] Moreover, Şahin and Tasci (2022) have shown that these unusually high rates resulted not from the very tight labor market, but from one-time events– a pent-up desire to change jobs during Covid and the financial cushions provided to workers by the Paycheck Protection Act.

The responses to the SHED vignettes might therefore reflect higher than usual propensities to leave jobs, especially so for black workers. Our results here may thus understate constraints on job mobility among all workers and the effects of racial inequality in mobility on wage markdowns.

2.2 Descriptive statistics

In this section we present descriptive statistics for the SHED sample and then summarize the probabilities that workers in different groups will look for another job and/or leave their current job if their pay is cut. We assess differences in the probability of searching for another jobs among sociodemographic groups for a given wage cut, using searching probabilities at constant pay as the reference point.

The SHED sample for 2021 to 2024 includes 28,787 employed workers. In Table **??**, we present

[6]The SHED survey is administered by Ipsos, a private consumer research firm, using KnowledgePanel, a nationally representative probability-based online panel. Ipsos has selected survey respondents for KnowledgePanel since 2009, based on address-based sampling (ABS). SHED respondents were then selected from this panel.

[7]The question of interest (D36B): How likely would you be to actively look for another job or leave your job if your employer (kept your pay the same for a year / decreased your pay by 1 percent / decreased your pay by 5 percent / decreased your pay by 10 percent)? (SHED added the 1 percent option in 2022). The response options were: "Very likely," "Somewhat likely," "Not that likely." "Not at all likely."

[8]`fred.stlouisfed.org`. We observe a similar annual pattern in the SHED data, as Table **??** shows.

the weighted shares of observations by demographic characteristics. Among all employed workers, 61 percent are non-Hispanic white, 12 percent are black, 17 percent are Hispanic (non-black), 6 percent are Asian, and less than 3 percent report no or more than two races. These numbers are similar to those reported by the BLS Labor Force Statistics from the Current Population Survey 2023.[9]

The validity of the demographic characteristics is important for our research design. Reassuringly, characteristics such as household income, gender, education, and age are all close to the reports in public data for all employed workers. This similarity suggests the SHED data are representative of the U.S. labor force. Controlling for characteristics that are correlated with race or ethnicity and with job searching probabilities assures that we capture the differences by race (ethnicity) and other factors.

To obtain valid estimates of elasticities, it is crucial that the size of the wage cut is assigned randomly to each respondent. To assess if the assignment is random, we regress the question each respondent faced on their demographic characteristics. The results are presented in Table A1. Column 1 pools all respondents together, examining the correlation between the question a respondent faced and their demographic characteristics. Columns 2-5 explore each wage cut separately, examining if certain groups are more likely to face a certain wage cut in the question.

Most coefficients in Table A1 are insignificant, indicating that the questions are not correlated with demographic characteristics. In column 1, none of the coefficients are significant. The resulting adjusted R-squared is close to zero, suggesting that characteristics of respondents do not explain what question they face. Similarly, most coefficients are not statistically significant in columns 2 to 5. Each column has an adjusted R-squared close to zero.[10]

2.3 Estimation

We estimate differences in quit elasticities, using the SHED survey question we described above. Our main specification is as follows:

$$Switching_i = \alpha + \sum \lambda_r D_r + \theta log(1-w_i) + \sum_r \beta_r D_r log(1-w_i) + \gamma X_i + \varepsilon_i. \qquad (1)$$

In this equation, the outcome, $Switching_i$, is a fraction representing a reported probability of a respondent i to search for another job. $Switching_i = 1$ if respondent answered *very likely*, 0.75 if *somewhat likely*; 0.5 if *not that likely*; and 0 if *not at all likely*.[11] D_r is a set of mutually exclusive indicators for the groups of interest. For example, for race and ethnicity, we include four indicators: Asian, black, Hispanic, and (non-Hispanic) white.[12] We also estimate this equation, including

[9] `https://www.bls.gov/cps/data/aa2023/cpsaat11.htm`

[10] A few coefficients are significant in column (3), indicating that Asian, Hispanic and other ethnicity or race workers are more likely to face a one percent wage cut in the question. This is likely a result of the absence of one percent as an option in 2021.

[11] We also perform analyses with alternative definitions of the outcome as robustness checks.

[12] The omitted (reference) category is *non-Hispanic white* workers.

indicators for gender, educational attainment, age, and household income.

$log(1-w_i)$ is the natural logarithm of 1 minus the wage cut posed to the respondent in the survey (0, 0.01, 0.05, or 0.1). We interact group indicators and $log(1-w_i)$ to estimate the probability of looking for another job by race in response to a percent wage cut, relative to the reference group. β_r denotes the relative response for a given group, r. To further isolate the effects of each characteristic, we include a set of control variables, X_i. These controls include all available demographic data, omitting the groups of interest, and industry and occupation data. Additionally, we estimate elasticities for food workers only as a closer comparison to QWI results presented later in the paper.

Importantly, the outcome in the specification above is a fractional variable capturing the probabilities of an event occurring. Thus, we estimate the equation above using *fractional logistic regression* (*fractional logit*). Unlike the linear probability model (OLS with a binary outcome), logit does not assume a linear probability function. Logit is more robust to extreme values and produces predicted probabilities within the [0,1] range (see Hosmer Jr et al. (2013) for a detailed discussion). We then transform coefficients to elasticities, $\eta_r = \beta_r P_r(1-P_r)$, where P_r is an average predicted propensity of switching a job by group r. We report estimated elasticities in tables.

The resulting elasticities are close in interpretation to quit elasticities. Thus, to translate them to labor supply elasticities, we use Manning (2003) equation: $\eta = -2 * \eta_q$. That is, in steady state, labor supply elasticity is equal to minus two times quit elasticity. We refer to estimated elasticities as our main results and discuss them below.

2.4 Results

We present results in Figures 1 and 2. Each panel in both figures depict estimated labor supply elasticities using various specifications and for all groups of interest. Blue circles refer to the baseline specification, red squares refer to the specification with controls, while green triangles refer to the specification with controls and interactions. Vertical lines depict 95% confidence intervals.

Race and ethnicity Panel (a) of Figure 1, displays results by race and ethnicity. Notably, for each group, the baseline estimates are close to those with controls and to those with controls and interactions. This pattern suggests that unconditional elasticities are similar to ones conditioned on other demographic characteristics. For Asian workers, the labor supply elasticity estimate is around 4.5, although with a wide confidence interval. The estimate for black workers is 4, with confidence intervals ranging between 3 and 5. The Hispanic elasticity, is around 4.5, with confidence intervals ranging from 3.5 to 5. Finally, the white elasticity is 6, with confidence intervals from 5.5 to 6.5.

As can be seen from the above, white workers exhibit a higher labor supply elasticity than do black and Hispanic workers. For each respective specification, estimates are statistically different between black and white workers and Hispanic and white workers. These results suggest that employers possess greater wage-setting power over black and Hispanic workers than over white workers.

Gender In Panel (b) of Figure 1, we assess heterogeneity in labor supply elasticities by gender. These results suggest that female workers have slightly higher elasticities than their male counterparts (5.5 vs. 5). However, the two groups' elasticities are statistically indistinguishable from one other. This finding is consistent with Caldwell and Danieli (2024), who show that the gig-economy specific labor supply elasticity is similar between the two genders, but contrary to Hirsch et al. (2022), who find lower labor supply elasticities for women in Germany.

Education, age, and income Panel (a) of Figure 2 implies that labor supply elasticity increases slightly with higher levels of educational attainment. Interestingly, the highest educated group has lower elasticity than some less educated workers. However, the estimates are statistically indistinguishable, even between the least and the most educated groups. Similarly, Panel (b) of Figure 2 suggests that labor supply elasticities increase with age. The youngest group has an elasticity of 4. By contrast, workers of ages 55-64 and 65+ have elasticities of 5.5 and 6, respectively. Finally, Panel (c) of Figure 2 suggests that the labor supply of workers with higher household income is more elastic than that of those with lower income.

Restaurant industry For all demographic groups, the respective elasticity for workers in the restaurant industry is slightly lower than the average elasticity across all industries. This indicates that employers in the restaurant industry might possess a higher monopsonistic power than average. This is expected, as the industry has previously been documented to exhibit monopsonistic power.

Robustness In Figures A1 and A2 we show alternative estimates with SHED data. Instead of treating the outcome variable as a fractional variable, we define it as a binary outcome and use logit. Figure A1 shows results when *very likely* and *somewhat likely* responses are treated as an indication of switching the job. In Figure A1, only *very likely* to switch are defined as switching jobs. Both figures reveal very similar relative elasticities across all characteristics. white workers have significantly higher elasticities than black and Hispanic workers. There are no significant gender differences in elasticities. Though each model produces much higher magnitudes of elasticities compared to our preferred specification.

3 Labor supply elasticity estimates using minimum wage variation

In this section, we present estimates of labor supply elasticity for by race, gender, education level, and age. Manning (2003) showed that in equilibrium, the elasticity of labor supply equals twice (the negative of) the separation rate elasticity. We use state minimum wages as exogenous variation and QWI data to estimate the effects on earnings and separation rates. These in turn provide us with the separation rate elasticity and thereby the elasticity of labor supply.

3.1 Data

We use the Census Bureau's Quarterly Workforce Indicators (QWI) to estimate restaurant industry separation rates. The QWI provides separation rates for all workers and for workers by race and ethnicity, allowing us to obtain estimates by group of interest. Since the exogenous variation comes from minimum wage changes, we focus on the industry that is most affected by minimum wages: NAICS code 7225, Restaurants and Other Eating Places. As previous studies have shown, the restaurant industry has the highest share of workers earning near or at the minimum wage and a high share of labor costs in operating costs. The QWI data are assembled from employer-employee matched data collected by the Census Bureau and other government surveys.

We use quarterly county-level data, which are available for various demographic characteristics. In our main results, we use the years 2001-2019. This period includes balanced data for counties from 45 states and yields 28 minimum wage events. For robustness, we present results with data starting in 2004. This sample includes 48 states[13] and 24 events. To avoid contamination of the estimates by Covid-era effects, we end the analysis period in 2019. We also deseasonalize the data, assuming state-specific seasonal trends. Importantly, a sample of counties for which QWI data is available for each quarter varies based on the group considered. Thus, geographies and events vary between regressions for each group. To address this issue and ensure the validity of our results, we supplement each estimate with an equivalent estimate that uses only counties balanced in time across all demographic groups considered.

3.2 Methodology

To estimate the effects of minimum wages on separation rates and earnings[14], we follow the difference-in-difference method developed by Cengiz et al. (2019), which accommodates staggered changes changes in minimum wages. Moreover, since some states are *late adopters*, they can be used both as control and treated states at different points in time. Hence, as the recent difference-in-differences literature suggests, a classic two-way fixed effect model is not appropriate for estimating the average treatment effect.

Dube et al. (2024), who further refined the implementation of dynamic difference-in-differences methods, show that state-level minimum wage variation is appropriate for estimating the effects of state-wide minimum wage policies. We apply their methods with appropriate adjustments to accommodate the specific characteristics of QWI data.

These characteristics concern variation in the size of black and Hispanic populations at the the county level, and that quarterly county-level restaurant employment can be small for some worker

[13]Excluded states are Washington, DC, which we exclude from analyses, and Massachusetts, which only joined QWI in 2010

[14]The QWI reports average weekly earnings per quarter, raising the possibility that changes in weekly hours might affect our estimates. However, previous studies of minimum wage effects on restaurant worker earnings does not detect changes in hours.

groups in less-populated counties. To protect data confidentiality, the QWI suppresses data for counties with low black employment counts. This suppression can bias estimated effects when using county-level data. To account for such bias we additionally perform estimation only for counties for which data is available in each quarter for all groups. We weight the average treatment effects by the working-age population of a respective group to obtain a representative average effect.

We obtain separation elasticity to earnings by using an instrumental variable approach combined with the DID specification. Specifically we regress separation rate on earnings instrumented by minimum wage events. We then obtain labor supply elasticities using Manning (2003).

3.3 Results

In Figures 3 to 4, we present our results from the QWI event studies by race, sex, education level, and age. Blue circles represent point estimates using entire sample of counties, while green triangles present results using counties balanced across groups. Vertical lines indicate corresponding 95% confidence intervals. The left-most estimate in panel (a) of Figure 3 depicts results for all workers in the restaurant industry (NAICS 7225). This estimate suggests a positive labor supply elasticity of 2.90. This estimate is close to the mean elasticity reported in the meta-analysis performed by Sokolova and Sorenson (2020). The underlying earnings and separation effects are reported in the first column of Table A2. The earnings effect of 0.035 is slightly higher than the range of estimates in Dube et al. (2024) (0.020 to 0.033). This is expected given a more recent period considered in our study. The separation rate decreases with higher minimum wages–the estimated effect is -0.051. Using counties balanced across all demographic groups yields a similar labor supply elasticity of 3.07, and the underlying earnings and separation effects are comparable.

In panel (a) of Figure 3, we show labor supply elasticity estimates by race and ethnicity. For black workers, the estimates suggest an elasticity of 2.19. Hispanic workers are estimated to have a smaller elasticity of 0.588 statistically indistiguishable from zero. By contrast, white workers' elasticity is higher at 3.11. Moving to results with a sample balanced between groups, results are similar and suggest even higher differences between black and white workers. Black workers are estimated to have a 2.14 labor supply elasticity, while white workers have an elasticity of 3.522. A formal t-test for equivalence of coefficients is rejected at 5% significance level in Hispanic-white comparisons (F-stat is 6.66 with a P-value of 0.014). However, we fail to reject the equivalence of black-white comparisons (F-stat is 1.26 with a P-value of 0.269), likely due to the elasticity for black workers being estimated less precisely.

Additional results in Tables A3 and A4 show results using alternate periods and using states available in QWI for the corresponding period. Tables A3 uses 2003-2019, includes 48 states and 23 underlying events. Table A4 uses 2004-2019, includes 49 states and 19 underlying events. Both sets of analyses produce labor supply elasticity estimates lower than the preferred specification. However, the relative elasticities are consistent with white workers having the highest elasticity, black workers having a lower elasticity, and Hispanic workers having the lowest elasticity statistically indistinguishable from zero.

Overall, these results suggest that black and Hispanic workers' labor supply elasticities are lower than those of white workers. Compared to SHED estimates, all elasticities are smaller in magnitude. Moreover, an estimate of 2.90 for all workers is close to the average estimate using separation rates of 3.05 reported in Sokolova and Sorenson (2020), Table 1. While our estimates by group are higher for white workers and lower for black and Hispanic workers. Thus, our findings may shed light on the wide range of elasticity estimates reported in the prior literature.

Comparing by gender in panel (b) of Figure 3, we find that male workers have very close elasticities to the female–3 and 2.8, respectively. This is similar to results using SHED survey data presented above, but is different from findings from recent literature. In addition, panels (a) and (b) of Figure 4 present estimates by educational attainment and age. They are weakly suggestive of elasticity staying the same with the level of education and increasing with age. Note, however, that the restaurant industry is dominated by young and lower-educated workers, making assessment of differences by education and age difficult.

3.4 Comparing SHED and QWI elasticities

Both results in Sections 2 and 3 indicate higher labor supply elasticities for white workers than for black and Hispanic workers. However, magnitudes differ substantially based on the data and method used. Our preferred estimates for the restaurant industry using SHED survey data are 3.5, 4, and 5.5 for black, Hispanic, and white workers, respectively. Using QWI data and minimum wages as a natural experiment produces corresponding elasticities of 2.2, 0.6, and 3.1. Elasticities for black and white workers are approximately 40 percent lower with the latter method. Additionally, Hispanics' elasticity is even more different.[15] This pattern may be explained by three main factors.

First and most importantly, estimates differ conceptually. While survey-based results measure labor supply elasticity of workers to a firm, QWI results measure industry-wide elasticity of all workers. A potential explanation for the elasticity of a firm being higher is that changing a firm within an industry is easier than changing industry due to an industry-wide shock.

Second, we estimate the intention of workers to search for a new job. This intention is related to but not the same as actually searching for another job. And many employed workers who search for a new job end up staying with their current employer. [16]

Third, we estimate the response to wage cuts as opposed to wage increases. The behavioral economics literature suggests that workers are more likely to react to a wage cut than to a wage increase

[15] Note that QWI estimates for Hispanic workers are not statistically significant.

[16] Stevenson, 2009; Faberman et al. (2022) In both papers, the context for the surveys differs considerably from SHED's. Hence, we do not pay much attention to their results about the frequency of on-the-job search. But the finding that many searches do not result in a job separation remains valid and motivates treating our SHED estimates as upper bounds.

of the same magnitude. This pattern implies a potential asymmetry in labor supply elasticity with regard to wage cuts versus wage increases. Thus, we treat our SHED estimates as an upper bound of the labor supply elasticities.

4 Black and Hispanic workers have fewer job mobility options

In the Becker (1957) model of employer discrimination, white employers will hire black workers only if they can pay them less than equivalent white workers. The outcome: firms hire both black and white workers and black workers are paid less than white workers. In the Becker (1957) model of employee discrimination, white workers prefer not to work with black workers, leading employers to pay black and white workers the same wage, but hiring only all white or all black workforces. These models possessed some intuitive basis during the Jim Crow era, when black workers were paid lower wages and workplaces were highly segregated by race.[17]

However, the 1964 Civil Rights Act and its subsequent enforcement banned wage discrimination and eliminated the most egregious forms of racial discrimination in pay and employment, particularly in the South (Freeman et al., 1973). A 1971 Supreme Court decision (Griggs v. Duke Power) established that disparate racial employment patterns were also illegal, even if employers had not intentionally discriminated against black workers.

Today, as Figure A.3 shows, black and white workers are paid the same wage for similar entry-level jobs. Moreover, most large employers respond similarly to black and white applicants for entry-level jobs.[18] Our labor market model thus presumes that black and white workers are paid the same wage and that employers hire black workers in proportion to their numbers in local pools of labor.

This assumption does not imply that all black workers receive the same pay as all white workers. Indeed, job ladders differ for black and white workers. As the longitudinal data in Figure A.3 shows, beginning at the age of 22, age-earnings profiles become flatter for black high school graduates than for white high school graduates. Over their working careers, black workers continue to face numerous other dimensions of racial inequality. A partial list includes: persistent racial residential segregation that can reduce the number of jobs available in a given radius from black workers' residences–and that importantly affect local school quality; racial differences in savings, wealth and home ownership rates, which affect reservation wages; differences in non-wage treatment by managers, supervisors, co-workers and customers, which require black workers to search for more jobs than white workers would; lower unemployment insurance replacement rates in states with larger concentrations of black workers, and smaller networks of friends, relatives and co-workers

[17](Wright, 1986). As late as the 1960s, black workers were often shunted into less desirable jobs in the same workplace (Foote et al., 2003).

[18]Kline et al. (2024) sent over 83,000 fictitious employment applications for over 10,000 entry-level job openings at 108 Fortune 500 companies. Applications with black names received 23 fewer callbacks per 1,000 applications than white applicants. Earlier studies and studies among smaller firms, found only marginally greater differences.

who can refer blacks workers to job openings.[19] Moreover, these forms of inequality may reinforce each other, making overall inequality greater than the sum of the individual parts.

5 Wage markdowns with group differences in labor supply elasticities

In this section we first discuss the setup of our model with black and white workers. We then examine wage markdowns with one type of worker and then with two types of workers

5.1 A model with black and white workers

We build our model from Naidu et al. (2025), which in turn draws on the model in Naidu et al. (2016); see also Amior and Manning (2021).[20] Firms hire both white and black workers and face upward-sloping labor supply schedules. white and black workers are equally productive and are paid the same wage for similar work, but black workers have fewer outside options; that is, their labor supply schedules are steeper. The position and slope of a firm's labor supply schedule depends on the steepness of the white and black labor supply schedules and the proportion of each in the firm's pool of potential workers.

In this model, when employers can hire from a pool of workers who are willing to accept jobs at very low wages, the pay and employment of other workers fall. To quantify these effects, we focus on the labor supply elasticities of the two types of workers, black workers and white workers. Our underlying assumption is that black workers have fewer outside options than white workers.

Model assumes two types of workers: white and black, both types are equally productive. The firm chooses a single wage level, w, for all employees, both white and black.[21] s denotes the number of black workers and $1-s$ denotes the number of white workers. The employer's (inverse) labor supply function maps a wage offer w to a quantity of workers who will take the job. black workers' labor supply is $L^B(w) = Cw^{\varepsilon}$; white workers' labor supply is $L^W(w) = Aw^{\eta}$. ε and η express the responsiveness of each group's labor supply to wage offers.

Assuming, black workers have fewer alternative job options than white workers, their labor supply is less responsive to the offered wage: η is greater than ε. Adding the white and black employment levels together, the overall labor supply facing an employer with access to s black workers is:

$$L(W) = (1-s)L^W(w) + sL^B(w) \tag{2}$$

[19] Many of these dimensions of racial inequality are documented in Zhang (2023); Skandalis et al. (2022); Dube et al. (2022); Wursten and Reich (2023)

[20] This model differs from Joan Robinson's pioneering model of a discriminating monopsonist. Robinson's monopsony model was designed to show why wages of women were lower than the wages of similarly-skilled men. As we explained above, this approach is not appropriate for the contemporary U.S. In contrast to Robinson, in our model there are no wage differences between the two groups.

[21] Pay discrimination by race was banned by Title VII of the 1964 Civil Rights Act, which also created an enforcement arm, the Equal Employment Oppotunity Commission.

Panel (a) of Figure 5 shows a simplified model set up for two cases. First case is described by black labor supply, S_1^B. In that case elasticities between white and black workers are the same and the only difference is the lower population of black workers. Scenario 2, categorized by black labor supply S_2^B represents the case when elasticity of black workers is lower than elasticity of white workers.

We next derive implied wage markdowns for two cases: when elasticities are equal (i.e., one type of worker) and when one of the groups has a lower labor supply elasticity. Both cases are shown in panel (b) of Figure 5 and discussed in detail below.

5.2 Wage markdowns with one type of worker

The profit maximizing wage (w_W) and number of employees (L_W) satisfies this equation:

$$\frac{F'(L_W) - w_W}{w_W} = \frac{1}{\eta}$$

where $F'(L_W)$ denotes the marginal product of labor. The left side of this expression equals the wage markdown, the gap between the wage and the value of what a worker produces.

The share of the marginal product that a worker is paid is given by

$$\mu_1 = \frac{\eta}{1+\eta} \tag{3}$$

In Figure 1, the white-only labor supply curve $\left(S^W\right)$ shows the combination of wages and employment levels that white workers alone would make available to the employer. A profit-maximizing employer would choose wage w_W and employment level L_W.

5.3 Wage markdowns with two types of workers

In this case, the firm can also hire black workers, with the labor supply curve $L^W(w)$ described earlier, in addition to $L^B(w)$. The total labor supply curve is given by Equation 1 and the profit-maximizing wage (w_{W+B}) and number of employees (L_{W+B}) would satisfy:

$$\frac{F'(L_{W+B}) - w_{W+B}}{w_{W+B}} = \frac{1}{s\varepsilon + (1-s)\eta} \tag{4}$$

Since black workers have a less elastic supply, the total labor supply curve steepens. Since there are additional workers, the total labor supply curve shifts rightward. In Figure 1, this new total labor supply curve is S^{W+B}.

The share of the marginal product that a worker keeps is now

$$\mu_2 = \frac{s\varepsilon + (1-s)\eta}{1 + s\varepsilon + (1-s)\eta} \tag{5}$$

Since $\eta > \varepsilon$, the above expression is decreasing in s and in $\eta - \varepsilon$. That is, the wage markdown increases with a higher share of disadvantaged workers and with the higher difference in elasticities between groups.

Graphically, panel (b) of Figure 5 shows profit-maximizing wage and employment for monopsonists for two scenarios: (1) when elasticities are the same between the two groups, S_1^{W+B}, and (2) when the elasticity of black workers is lower, S_2^{W+B}. As can be seen, the equilibrium for the second case has a lower wage and employment. Since productivity between groups is the same, it implies a higher markdown than in the case with equal elasticities.

Additionally, the model can be extended to a finite number of groups of workers $i = 1, 2, ..., N$ with corresponding labor supply elasticities η_i. In such case, the share of the marginal product that a worker keeps is

$$\mu_N = \frac{\sum_{i=1}^{N} s_i \times \eta_i}{1 + \sum_{i=1}^{N} s_i \times \eta_i} \tag{6}$$

5.4 Wage markdown estimates

Next, we calculate the wage markdowns predicted by the model using the estimated elasticities we presented in Sections 2 and 3.

According to BLS data for 2023, 13 percent of the labor force is black, 18 percent is Hispanic (non-black),59 percent are non-Hispanic whites, 7 percent are Asian, and 3 percent are of other races and ethnicities. In our our calculations below, we rescale our estimates to account for the population share for which we do not estimate elasticities (3 percent for SHED data and 10 percent for QWI data).

Our estimated labor supply elasticities from the SHED data are 4.62, 4.16, 4.34, and 5.89 for Asian, black, Hispanic, and white workers, respectively. Combining these labor supplies yields an overall elasticity of $\eta = 5.28$, which implies a markdown of $1 - \mu_2 = 1 - \frac{5.28}{1+5.28} = 0.16$. If, instead, all workers had an elasticity of 5.89 (that of whites), the markdown would be $1 - \mu_1 = 1 - \frac{5.89}{1+5.89} = 0.15$. These numbers suggest an increase of 1 percentage point (6.7 percent) in the fraction of the marginal product kept as monopsonistic rents.

Turning to the QWI results, elasticities are 2.19, 0.59, and 3.52 for black, Hispanic, and white workers, respectively. Rescaling populations and combining labor supplies yields an elasticity of $\eta^N = 2.742$. The implied markdown is $1 - \mu_2 = 0.27$. In the case of a single group with an elasticity of 3.52, the markdown is $\mu_1 = 0.22$. The 5 percentage point increase in markdown is non-trivial, suggesting that monopsonistic markdowns increase by 23 percent due to differences in elasticities between demographic groups.

The above estimates use the national average for the share of black and Hispanic populations: 13 percent and 18 percent, respectively. However, wage markdowns depend on the proportion of minority workers in *local* labor markets. Assuming that labor supply elasticities for each group of workers are similar among metropolitan statistical areas (MSAs), we report below examples of markdowns in a few large MSAs.

In the New York–Newark–Jersey City, NY-NJ-PA MSA, the black and Hispanic population accounts for around 16 and 25 percent of the total population, respectively, resulting in a markdown of 0.14 or a 16.7 percent increase from our benchmark with one type of worker. The markdowns are substantially higher for MSAs with higher minority population shares. In the Los Angeles-Long Beach-Anaheim MSA, the Hispanic population share is around 45 percent, the black population share is 6 percent, and the white share is 28 percent. These shares imply a wage markdown of 0.19– 58.3 percent higher than the benchmark of 0.12.

Moreover, local labor markets tend to be much smaller than MSAs (Bartik, 2024), especially for black workers, who are disproportionately concentrated in central cities. The City of Atlanta, for example is 47 percent black, compared to 36 percent of the Atlanta MSA. The monopsonistic markdown in Atlanta due to racial inequality would then be 0.16, which is 33.3 percent higher than the benchmark with one type of worker. Black shares of central city populations are especially high in the South, where half of all black workers reside and where surveys suggest that racial prejudice is higher than nationwide. The wage markdowns that result from racial inequality are consequently likely to be even greater in these local labor markets. In summary, in local labor markets, racial differences in job mobility generate substantial wage markdowns for black and white workers.

6 Conclusions

Using the Federal Reserve's Survey of Household Economic Decision-making, we find that hypothetical wage cuts would generate lower job switching probabilities among Asian, black, and Hispanic workers than among white workers. Our analysis of separation rates using Quarterly Workforce Indicator data on restaurant workers reveals similar racial differences between black, Hispanic and white labor supply elasticities. These elasticities are consistent with previous studies of employer power to reduce wages.

We apply our labor supply elasticity estimates to a simple monopsony model with several types of workers and compare the results to a model with just one type of worker. After taking racial differences in job mobility into account and using our one type of worker model as a baseline, we obtain even greater wage markdowns for both black and white workers. These results imply that policies that reduce racial inequality– such as minimum wages or unemployment insurance reform– benefit white and black workers.

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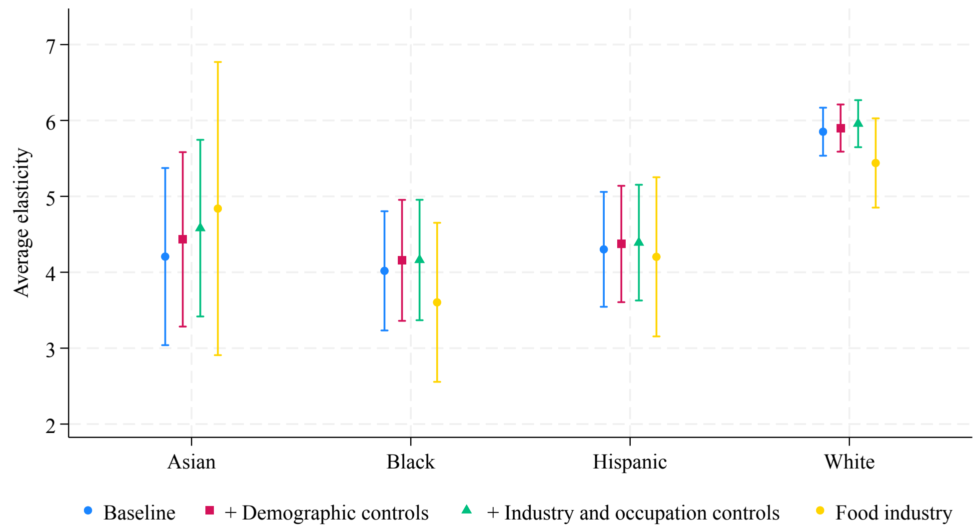
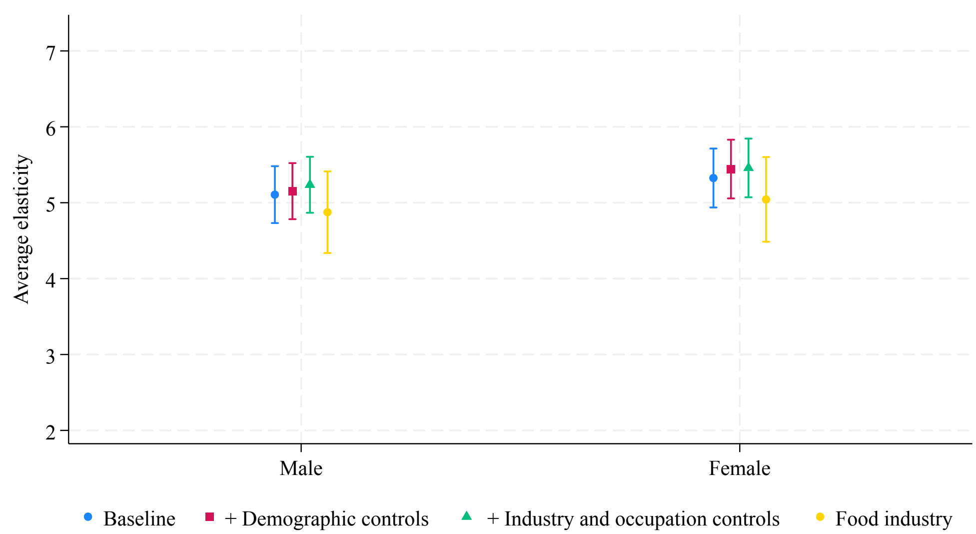
Figures and tables

Figure 1: Labor supply elasticity estimates using SHED data

(a) By race and ethnicity



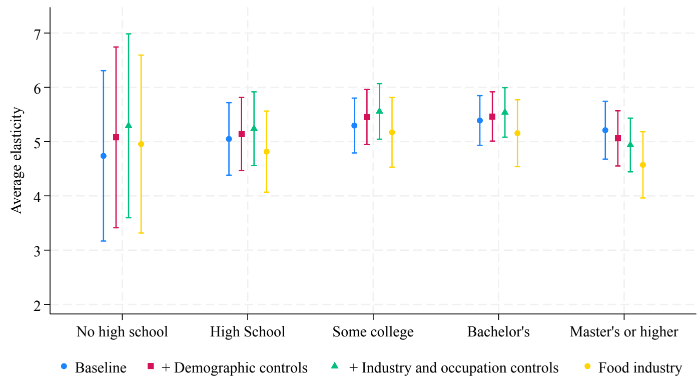
(b) By gender



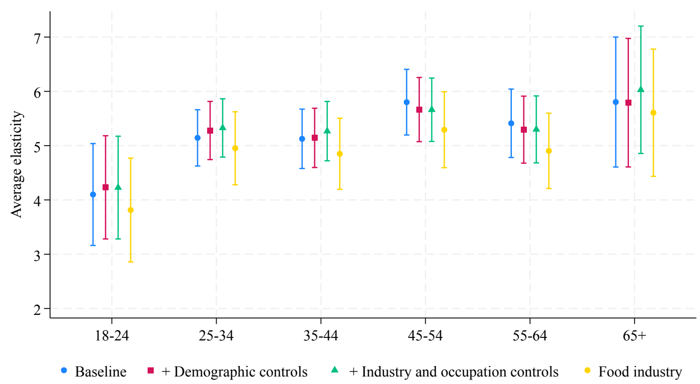
Note: The figure depicts labor supply elasticity estimates obtained using SHED survey data and logit specification described in Equation 1. Circles show estimates for a specification without any controls, squares show estimates with controls, and triangles show estimates with controls and interactions between independent variables and controls. Each regression has 27,787 observations. Lines show 95 percent confidence intervals. Panel (a) presents results by race and ethnicity. Asian and black workers can be of any ethnicity; Hispanic workers excludes Hispanics who are black; white workers are non-Hispanic. Panel (b) presents results by gender.

Figure 2: Labor supply elasticity estimates using SHED data

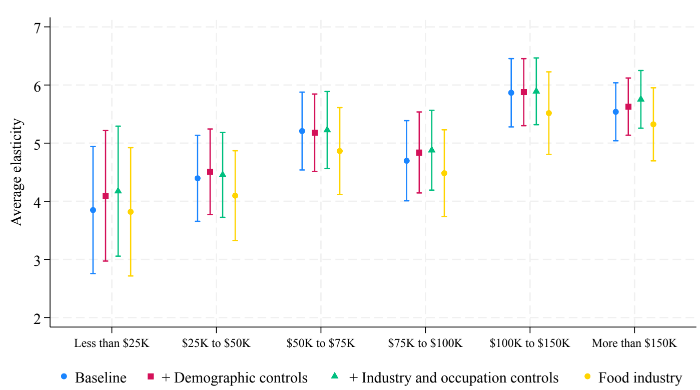
(a) By educational attainment



(b) By age group



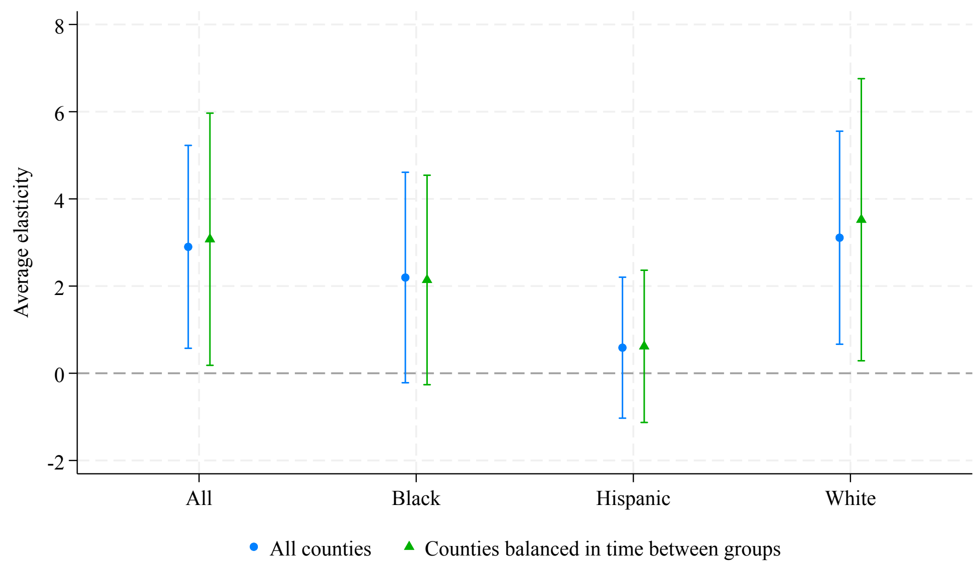
(c) By household income



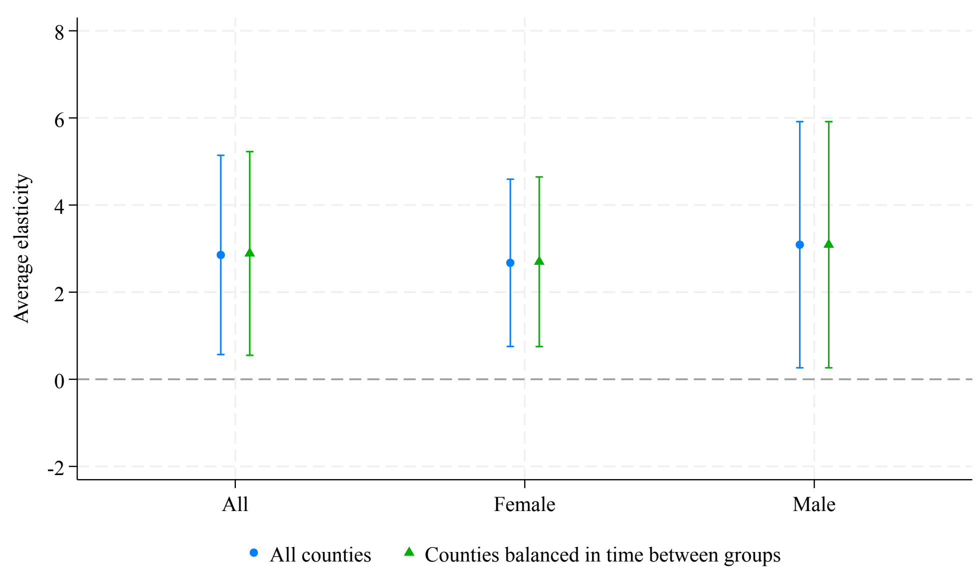
Note: The figure depicts labor supply elasticity estimates obtained using SHED survey data and logit specification described in Equation 1. Circles show estimates for a specification without any controls; squares show estimates with controls; triangles show estimates with controls and interactions between independent variables and controls. Each regression has 28,787 observations. Lines show 95 percent confidence intervals. Panel (a) presents results by highest educational attainment. Panel (b) presents results by age group. Panel (c) presents results by household income.

Figure 3: Labor supply elasticity estimates using QWI data and minimum wage variation

(a) By race and ethnicity



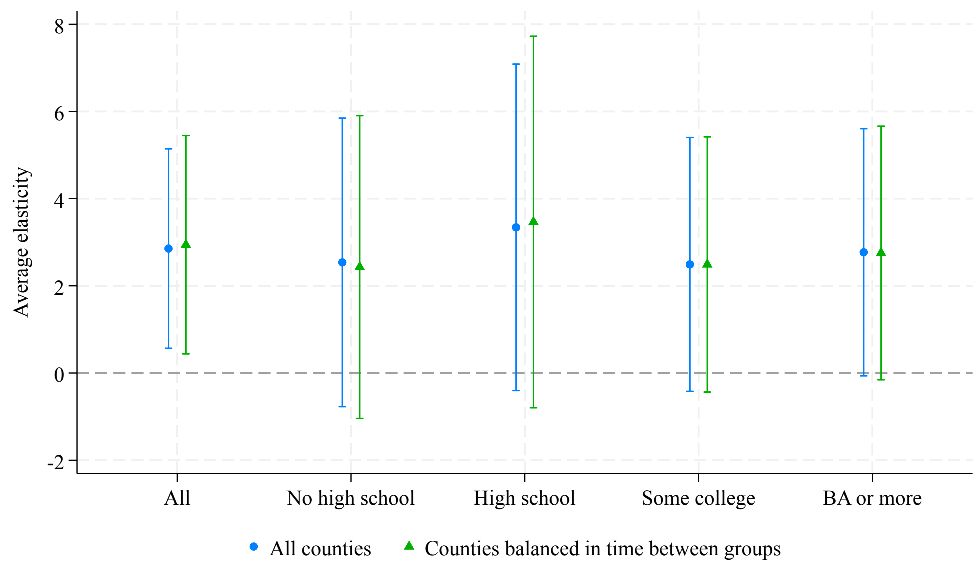
(b) By gender



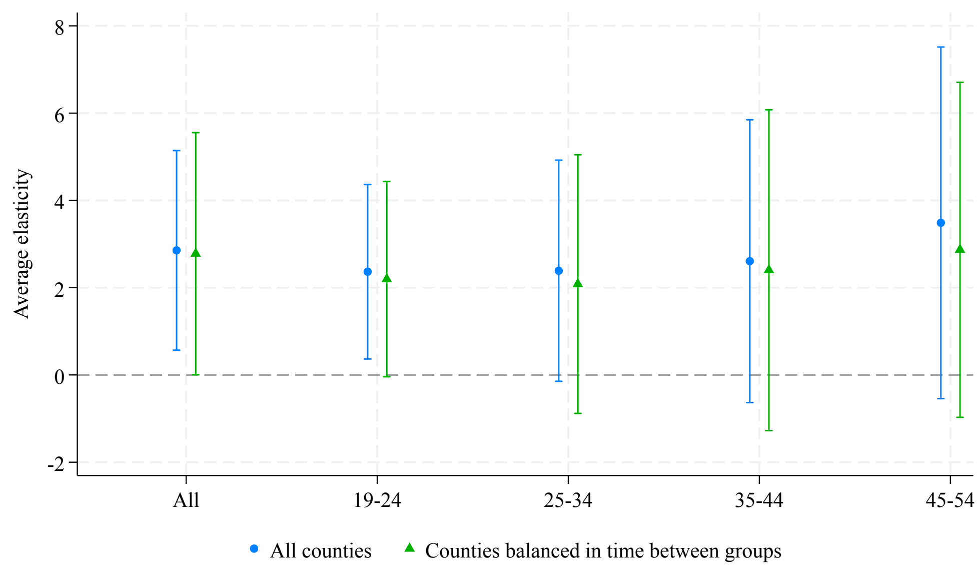
Note: The figure depicts labor supply elasticity estimates obtained using QWI data, state minimum wages, and difference-in-differences event-study. Circles show point estimates while lines show 95 percent confidence intervals. Panel (a) presents results by race and ethnicity. Black workers can be of any ethnicity, Hispanic workers excludes non-black workers, and white workers are non-Hispanic only. Panel (b) presents results by gender.

Figure 4: Labor supply elasticity estimates using QWI data and minimum wage variation

(a) By educational attainment



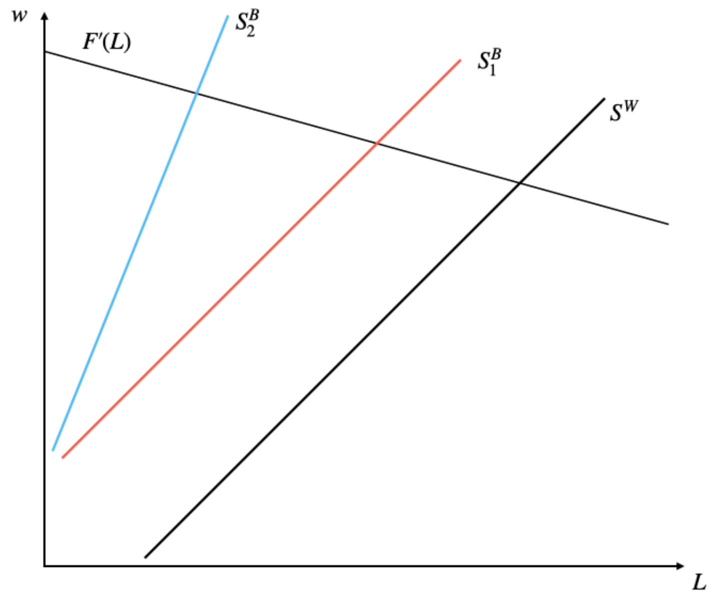
(b) By age group



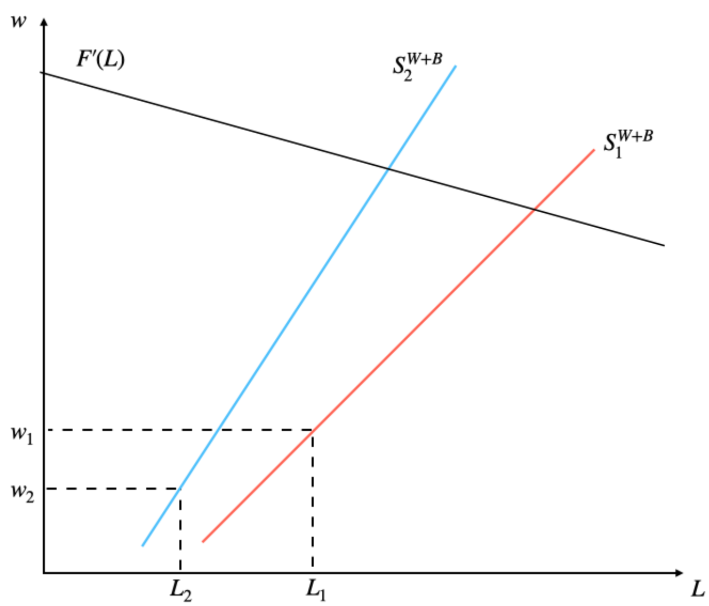
Note: The figure depicts labor supply elasticity estimates obtained using QWI data, state minimum wages, and difference-in-differences event-study. Circles show point estimates while lines show 95 percent confidence intervals. Panel (a) presents results by highest educational attainment. Panel (b) presents results by age group. Includes only estimates with a strong first stage.

Figure 5: Wage and employment levels with two types of workers

(a) Labor supply and monopsony



(b) Combined labor supply



Note: The figure depicts a simplified version of the model outlined in the paper. Panel (a) shows a monopsonistic labor market with two groups of workers: W and B. S^W represents the labor supply of group W, while S^B represents labor supply of group B. Further, S_1^B represents the case where labor supply elasticities are equal between two groups, while S_2^B represents a scenario where group B has a lower elasticity. Panel B shows result of combining two groups for both cases: S_1^{W+B} for when elasticities are equal, and S_2^{W+B} when elasticities are different between groups. Graph suggests that wages and employment are lower when difference in elasticities exist.

Appendix A

Table A1: Randomness of wage cut in SHED survey

	(1) Pooled	(2) No wage cut	(3) One percent	(4) Five percent	(5) Ten percent
Asian	-0.093	-0.003	0.019*	-0.010	-0.006
	(0.112)	(0.013)	(0.011)	(0.012)	(0.012)
Black	0.039	-0.000	0.005	-0.016*	0.011
	(0.077)	(0.009)	(0.007)	(0.008)	(0.009)
Hispanic	0.025	-0.014*	0.015**	-0.004	0.003
	(0.072)	(0.008)	(0.007)	(0.008)	(0.008)
Other	-0.120	-0.016	0.036***	-0.008	-0.012
	(0.120)	(0.013)	(0.013)	(0.013)	(0.013)
Female	0.005	-0.003	0.004	-0.002	0.001
	(0.048)	(0.005)	(0.005)	(0.005)	(0.005)
No high school	0.125	-0.004	-0.004	-0.010	0.018
	(0.139)	(0.015)	(0.013)	(0.015)	(0.015)
High school	0.090	-0.011	0.000	0.005	0.007
	(0.076)	(0.008)	(0.007)	(0.008)	(0.008)
Some college	0.057	-0.008	-0.002	0.008	0.002
	(0.066)	(0.007)	(0.006)	(0.007)	(0.007)
Master's degree or higher	-0.001	-0.005	0.003	0.005	-0.003
	(0.068)	(0.008)	(0.007)	(0.008)	(0.008)
18-24	-0.071	0.014	-0.000	-0.014	-0.000
	(0.111)	(0.012)	(0.011)	(0.012)	(0.012)
25-34	-0.035	0.011	-0.008	0.001	-0.003
	(0.076)	(0.008)	(0.008)	(0.008)	(0.008)
35-44	0.106	-0.002	-0.011	0.003	0.010
	(0.074)	(0.008)	(0.007)	(0.008)	(0.008)
55-64	0.001	0.007	-0.004	-0.008	0.004
	(0.074)	(0.008)	(0.007)	(0.008)	(0.008)
65+	-0.000	0.002	-0.002	-0.002	0.001
	(0.090)	(0.010)	(0.009)	(0.010)	(0.010)
Less than $25K	-0.079	0.011	0.000	-0.006	-0.005
	(0.113)	(0.013)	(0.011)	(0.012)	(0.012)
$25K to $50K	0.038	-0.013	0.004	0.012	-0.003
	(0.091)	(0.010)	(0.009)	(0.010)	(0.010)
$50K to $75K	0.024	-0.009	-0.001	0.015	-0.005
	(0.088)	(0.010)	(0.008)	(0.010)	(0.010)
$100K to $150K	-0.027	-0.003	0.006	0.002	-0.004
	(0.081)	(0.009)	(0.008)	(0.009)	(0.009)
More than $150K	0.097	-0.030***	0.012	0.020**	-0.001
	(0.080)	(0.009)	(0.008)	(0.009)	(0.009)
Observations	28,787	28,787	28,787	28,787	28,787
R-squared	0.001	0.001	0.001	0.001	0.000
Adj. R-squared	-0.000	0.000	0.000	0.000	-0.000

Note: Black workers are of any ethnicity; Hispanic workers are non-black. Robust standard errors in parentheses. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Separation elasticity by race using minimum wage events and QWI data 2001-2019

	(1) All	(2) Black	(3) Hispanic	(4) White
A. All counties				
Log earnings	0.035***	0.034***	0.042***	0.033***
	(0.008)	(0.009)	(0.012)	(0.007)
Log separation rate	-0.051***	-0.038*	-0.012	-0.052***
	(0.015)	(0.019)	(0.014)	(0.016)
Separation elasticity	-1.450**	-1.098*	-0.294	-1.555**
	(0.574)	(0.595)	(0.399)	(0.602)
N	54,982	29,759	26,678	52,356
# of Events	28	28	28	28
B. Counties balanced between groups				
Log earnings	0.032***	0.034***	0.041***	0.030***
	(0.009)	(0.009)	(0.012)	(0.007)
Log separation rate	-0.049***	-0.036*	-0.013	-0.052***
	(0.016)	(0.019)	(0.015)	(0.017)
Separation elasticity	-1.537**	-1.070*	-0.309	-1.761**
	(0.713)	(0.592)	(0.430)	(0.798)
N	20,953	20,953	20,953	20,953
# of Events	28	28	28	28

Notes: Estimated using the event study specification described in Dube et al. (2024) using Quarterly Workforce Indicators and Census data. Panel A includes the entire sample, while Panel B includes the counties observed for all groups in all quarters from 2001 to 2019. Events include state, and exclude federal, minimum wage increases from 2001 to 2019. Note, a given minimum increase counts as a single event regardless of how many post-periods we average over. Outcomes include log separation rates, log average earnings, and separation rate elasticities for the restaurant industry (NAICS 7225). Separation elasticity is the IV estimate from regressing log separation rate on log earnings instrumented by the event dummy. Estimates are weighted by county population of a given group, where white refers to non-Hispanic whites. Standard errors, reported in parentheses, are clustered at the state level. Stars indicate statistical significance as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Separation elasticity by race using minimum wage events and QWI data 2003-2019

	(1) All	(2) Black	(3) Hispanic	(4) White
A. All counties				
Log earnings	0.042***	0.048***	0.055***	0.038***
	(0.009)	(0.008)	(0.013)	(0.007)
Log separation rate	-0.047***	-0.035	-0.013	-0.044***
	(0.012)	(0.023)	(0.014)	(0.012)
Separation elasticity	-1.127***	-0.720	-0.238	-1.151***
	(0.375)	(0.456)	(0.297)	(0.377)
N	51,900	28,651	24,919	49,647
# of Events	23	23	23	23
B. Counties balanced between groups				
Log earnings	0.040***	0.048***	0.053***	0.034***
	(0.010)	(0.009)	(0.013)	(0.007)
Log separation rate	-0.045***	-0.034	-0.016	-0.041***
	(0.013)	(0.023)	(0.014)	(0.013)
Separation elasticity	-1.125**	-0.701	-0.294	-1.198**
	(0.459)	(0.465)	(0.306)	(0.499)
N	19,965	19,965	19,965	19,965
# of Events	23	23	23	23

Notes: Estimated using the event study specification described in Dube et al. (2024) using Quarterly Workforce Indicators and Census data. Panel A includes the entire sample, while Panel B includes the counties observed for all groups in all quarters from 2003 to 2019. Events include state, and exclude federal, minimum wage increases from 2003 to 2019. Note, a given minimum increase counts as a single event regardless of how many post-periods we average over. Outcomes include log separation rates, log average earnings, and separation rate elasticities for the restaurant industry (NAICS 7225). Separation elasticity is the IV estimate from regressing log separation rate on log earnings instrumented by the event dummy. Estimates are weighted by county population of a given group, where white refers to non-Hispanic whites. Standard errors, reported in parentheses, are clustered at the state level. Stars indicate statistical significance as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

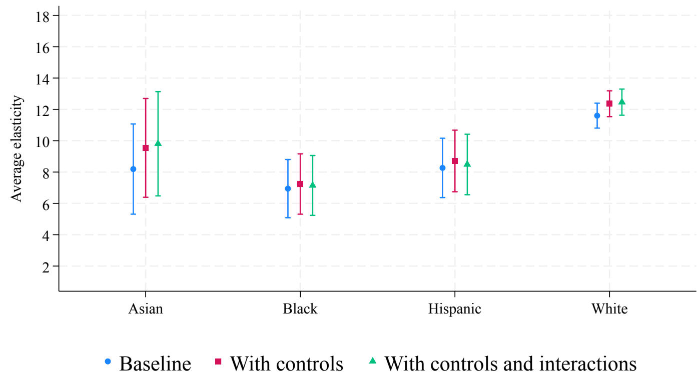
Table A4: Separation elasticity by race using minimum wage events and QWI data 2004-2019

	(1) All	(2) Black	(3) Hispanic	(4) White
A. All counties				
Log earnings	0.050***	0.057***	0.060***	0.047***
	(0.010)	(0.011)	(0.013)	(0.008)
Log separation rate	-0.044**	-0.043*	-0.013	-0.039**
	(0.017)	(0.024)	(0.016)	(0.017)
Separation elasticity	-0.877**	-0.750	-0.216	-0.822*
	(0.411)	(0.463)	(0.301)	(0.422)
N	49,448	28,254	23,714	47,290
# of Events	19	19	19	19
B. Counties balanced between groups				
Log earnings	0.046***	0.057***	0.058***	0.041***
	(0.011)	(0.011)	(0.013)	(0.009)
Log separation rate	-0.043**	-0.043*	-0.016	-0.038**
	(0.018)	(0.024)	(0.015)	(0.018)
Separation elasticity	-0.936*	-0.751	-0.273	-0.912*
	(0.487)	(0.474)	(0.309)	(0.522)
N	19,181	19,181	19,181	19,181
# of Events	19	19	19	19

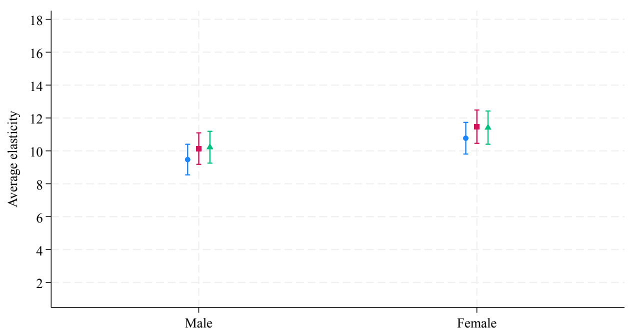
Notes: Estimated using the event study specification described in Dube et al. (2024) using Quarterly Workforce Indicators and Census data. Panel A includes the entire sample, while Panel B includes the counties observed for all groups in all quarters from 2004 to 2019. Events include state, and exclude federal, minimum wage increases from 2004 to 2019. Note, a given minimum increase counts as a single event regardless of how many post-periods we average over. Outcomes include log separation rates, log average earnings, and separation rate elasticities for the restaurant industry (NAICS 7225). Separation elasticity is the IV estimate from regressing log separation rate on log earnings instrumented by the event dummy. Estimates are weighted by county population of a given group, where white refers to non-Hispanic whites. Standard errors, reported in parentheses, are clustered at the state level. Stars indicate statistical significance as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Labor supply elasticity estimates using SHED data and binary job-switching definition

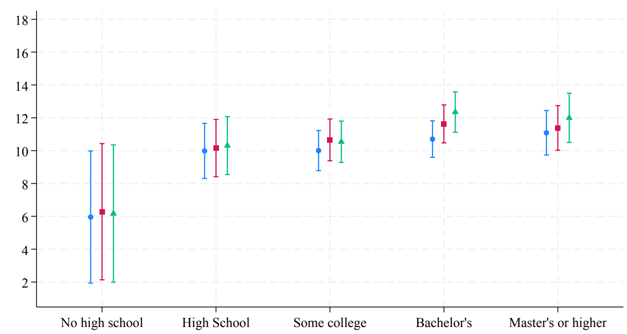
(a) By race and ethnicity



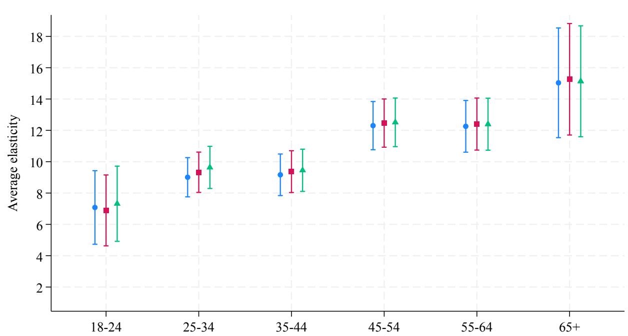
(b) By gender



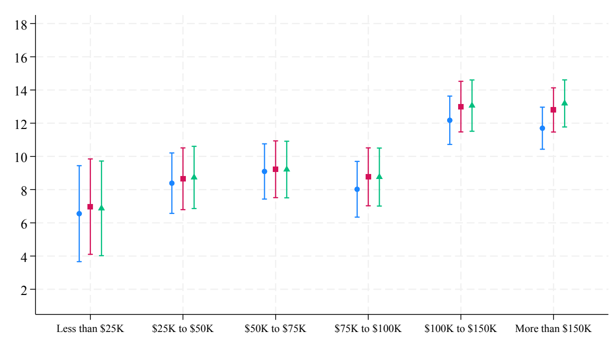
(c) By educational attainment



(d) By age group



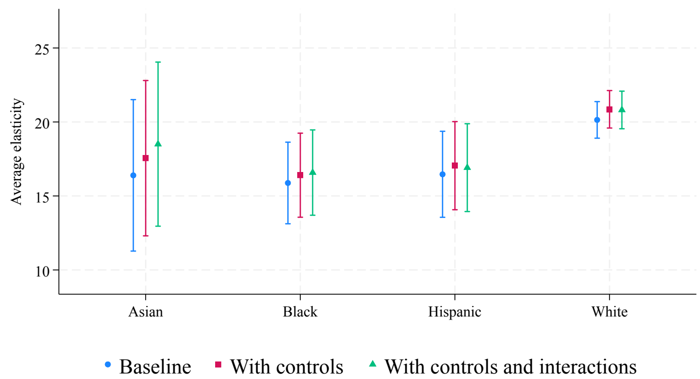
(e) By household income



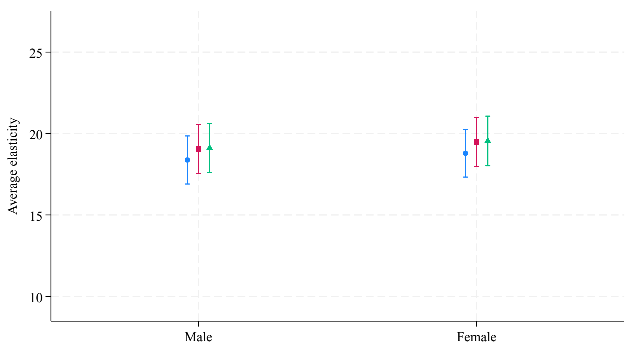
Note: The figure depicts labor supply elasticity estimates obtained using SHED survey data and logit specification described in Equation 1. Circles show estimates for a specification without any controls; squares show estimates with controls; triangles show estimates with controls and interactions between independent variables and controls. Number of observations in each regression is 28,787. Lines show 95% confidence intervals. Panel (a) presents results by race and eyhnicity. Where asian referss to workers of asian race and any ethnicity, black refers to workers of black race and any ethnicity; Hispanic refers to Hispanic workers of non-Black race, and white referes to white workers of non-Hispanic ethnicity. Panel (b) presents results by gender. Panel (c) presents results by highest educational attainment. Panel (d) presents results by age group. Panel (e) presents results by household income.

Figure A2: Labor supply elasticity estimates using SHED data and only the most likely to look for other jobs

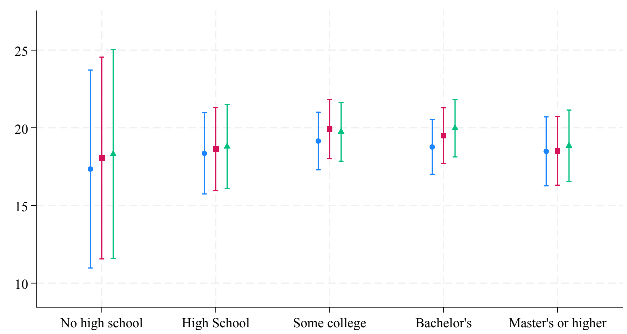
(a) By race and ethnicity



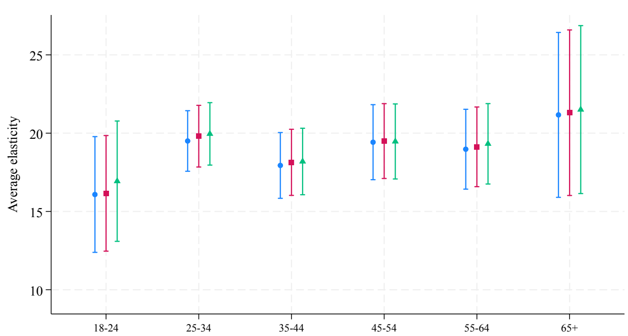
(b) By gender



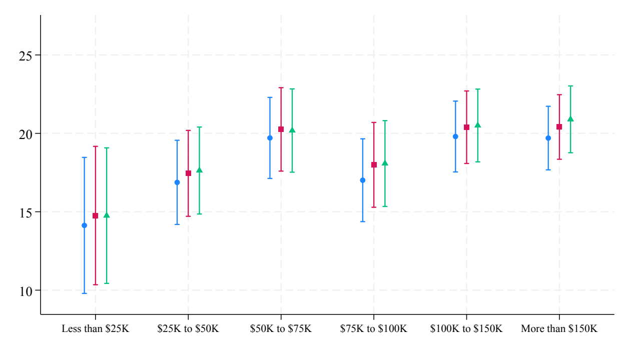
(c) By educational attainment



(d) By age group



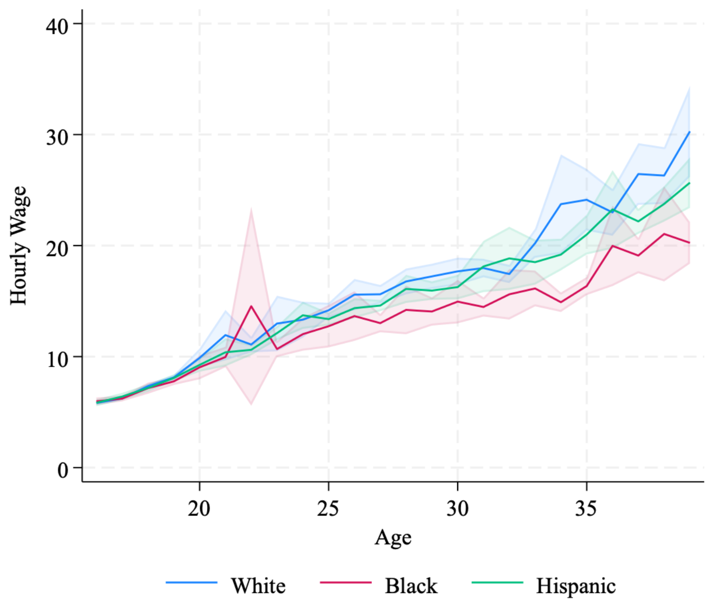
(e) By household income



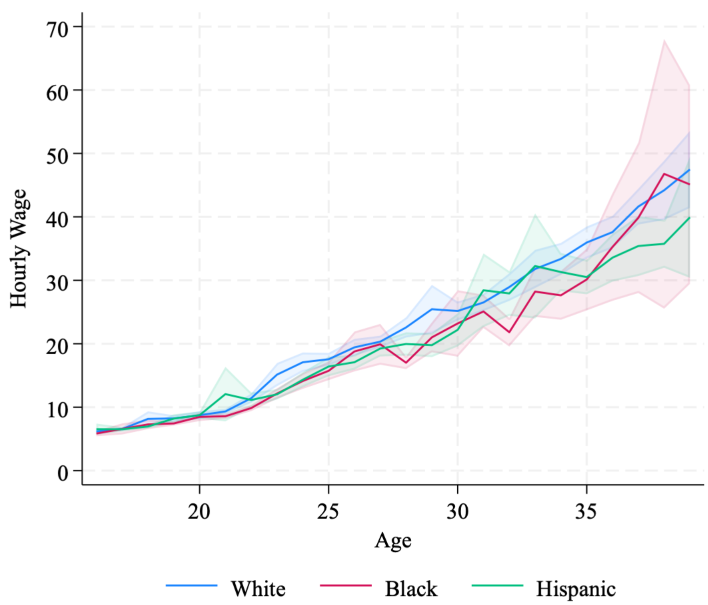
Note: The figure depicts labor supply elasticity estimates obtained using SHED survey data and logit specification described in Equation 1. Circles show estimates for a specification without any controls; squares show estimates with controls; triangles show estimates with controls and interactions between independent variables and controls. Number of observations in each regression is 28,787. Lines show 95 percent confidence intervals. Panel (a) presents results by race and ethnicity. Asian and black workers are of any ethnicity, Hispanic workers exclude black workers, and white workers are non-Hispanic. Panel (b) presents results by gender. Panel (c) presents results by highest educational attainment. Panel (d) presents results by age group. Panel (e) presents results by household income.

Figure A3: Average hourly wages by age, race, ethnicity and education

(a) High School Degree



(b) Bachelor's Degree



Notes: These graphs plot average hourly wages and 95% confidence intervals using NLSY97 data, a longitudinal dataset that follows teens in 1997 to roughly the age of 40 in 2021. Hourly wages are imputed as the midpoint for reported wage bin and 1.5 times the top-code. Bachelor's degree includes all graduates of four-year programs. White workers excludes Hispanic workers.