Gender Differences in Sorting on Wages and Risk

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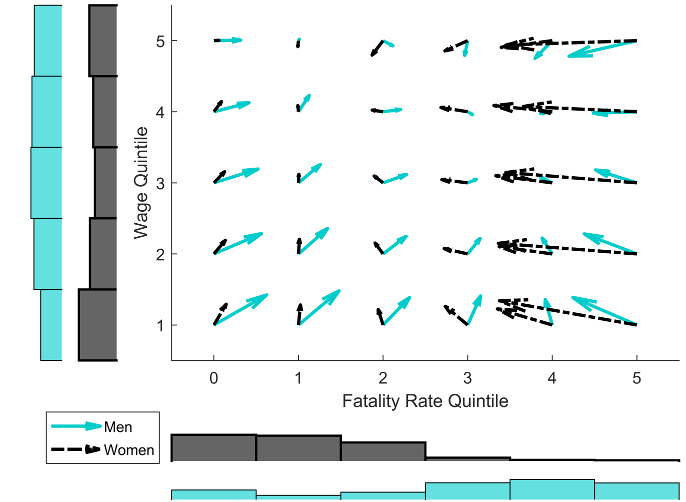
Overview

- Gender skills gaps have largely closed in recent decades, but wage gaps and workplace segregation have remained
  - Wage gaps and segregation pervasive at every level—occupations, industries, and establishments [Bayard et al. (2003); Card et al. (2016); Cortes and Pan (2017); Goldin et al. (2017)]
- Question: why have gender differences in labor market sorting not converged along with skills gap?
- We study whether risk, and gender differences in risk preferences, contribute to gender gap in labor market sorting

Figure 1: Job-to-Job Transition Gradient Field: Physical Risk

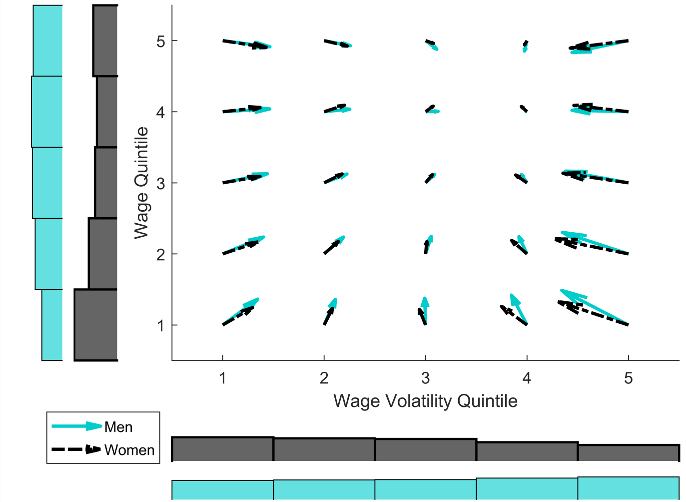


Overview

What can explain the gender divergence in job sorting patterns?

1. Spurious pattern driven by many correlated job characteristics for which men and women have different preferences
   - Large literature in psychology and economics show women are more financially risk averse [Bertrand (2011)]
     - Experimental evidence suggests preferences predictive of actual differences in job sorting [Wiswall and Zafar (2003)]
   - Small literature on physical risk preferences: DeLeire and Levy (2004) find gender gap in preferences for physical risk explains about 1/4 of occupational segregation
   - Compare job sorting on the basis of physical vs financial risk—do we see similar patterns?

Figure 2: Job-to-Job Transition Gradient Field: Financial Risk



Why do women and men sort so differently on safety?

2. Large literatures showing women are compensated less per unit of risk, and that women have stronger preferences for safety [Hersch (1998); Viscusi and Aldy (2003); DeLeire and Levy (2004); Blau and Kahn (2016)]
    - If these are both true, sorting patterns may be utility maximizing given prices
    - Difficult to reconcile:
        - Wrong-sided: hedonic wage theory suggests compensating differentials determined by preferences of marginal worker [Rosen 1974]
        - Substitutability: if male and female labor is substitutable, then men and women share the same marginal worker
    - We replicate gender gap in compensating wage differentials, and show that it is explained by measurement error and limitations in modeling non-random job assignment

Why do women and men sort so differently on safety?

3. Within-establishment gender differences in average rents paid to men and women
    - Card, Cardoso, and Kline (2016) show women earn only 90% of the establishment wage premium earned by men
    - If establishment sorting is a primary channel of within-worker wage growth, this may dampen relative incentives of women to sort on pay versus amenities

    - In Brazil, within-establishment gender difference in rents explains only 0.7 pp of gender gap
    - Holding fixed establishment assignment, if women were paid male rents their wages would actually *decrease* by 1.6 pp

Why do women and men sort so differently on safety?

3. Can these patterns by explained by gender differences in assignment to establishments?
   - Could occur due to differences in job consideration sets or discriminatory establishments

   - Potentially—we show that there is substantial segregation of men and women across occupations and establishments
   - Gender segregation is strongly correlated with occupational safety
   - Establishment segregation compounds differences in earnings growth from job mobility

Implications of Sorting Patterns

- Direct effect of compensating wage differential on gender wage gap is small: 1 pp
- However, sorting on safety leads to gender segregation across establishments
- Women disproportionately end up in establishments that pay all workers low rents
  - Women over-represented in firms that pay higher rents to women than men
  - Men over-represented in firms that pay higher rents to men than women
  - Within-firm gender gap in rents is dominated by across-firm difference in average rents
- This establishment sorting, which is strongly correlated with safety, can explain 1/3 of the entire (unconditional) gender wage gap in Brazil

Data and empirical setting

Empirical Setting

- Longitudinal matched employer-employee data from Brazil: 2003-2010
    - Covers all formal-sector jobs (50 million per year, 430 million job-years)
    - Purpose of the data is to administer the *Abono Salarial*, a constitutionally-mandated annual bonus equal to one month's earnings
- Job characteristics: earnings, contracted hours, occupation, date of hire, date of separation, cause of separation (including death on the job)
- Worker characteristics: age, education, race, gender
- Establishment characteristics: industry, number of workers, location

Fatality Rates

- We calculate fatality rates using the cause of separation data
- Preferred measure is three-year moving average fatality rate by gender by 2-digit industry by 3-digit occupation cell
  - 22,880 gender industry-occupation cells compared to 720 in BLS data
  - Scale measure to equal deaths per 100,000 full-time equivalent job-years
- Gender-Ind-Occ measure is dramatically different than previous measures (Gender-Ind, Gender-Occ)
  - 91% of variation is within industry; 89% of variation is within occupation
  - Very different Ind-Occ interaction effects than for men
  - Women 38% safer than men *within* Ind-Occ cells

Analysis Sample

- Workers ages 23-65
- Full-time (30 hrs) dominant job in each calendar year
- Exclude singleton firms, government and temporary jobs
- Exclude industry-occupation cells with fewer than 10,000 full-time full-year equivalent workers
- Winsorize wage distribution at 1st and 99th percentiles

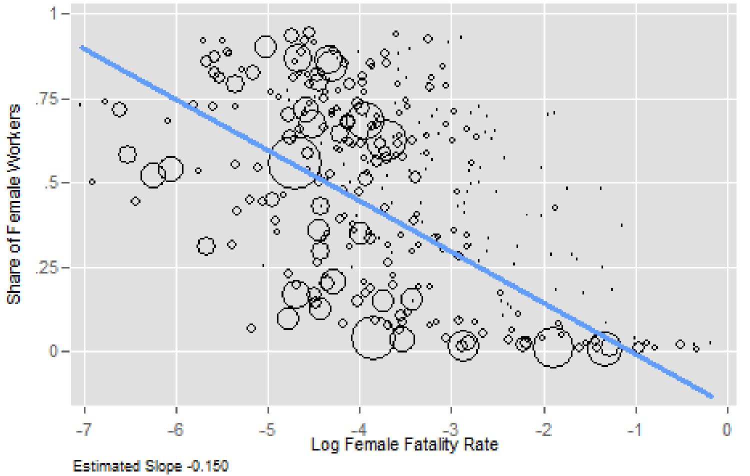
Summary statistics and stylized facts

Summary Statistics

	Full Population		Attached Dominant Jobs	
	Women	Men	Women	Men
Age	35.83	35.46	38.36	38.64
Race White	0.57	0.56	0.69	0.64
Less than High School	0.32	0.53	0.38	0.58
High School	0.41	0.33	0.40	0.33
Some College	0.05	0.03	0.06	0.03
College or More	0.21	0.10	0.16	0.07
Contracted Weekly Hours	39.46	42.03	42.05	43.04
Log Hourly Wage	1.33	1.42	1.44	1.61
Total Experience (Years)	18.35	18.98	22.12	23.43
Job Tenure (Months)	62.36	51.69	89.56	82.93
Pooled Fatality Rate (per 100,000)	0.02	0.07	0.02	0.08
Gender-Specific Fatality Rate	0.01	0.08	0.01	0.08
Zero Fatality Rate	0.26	0.15	0.35	0.12
N	134,361,238	194,907,785	11,419,266	22,234,188

Women Are Disproportionately Represented in Safer Jobs

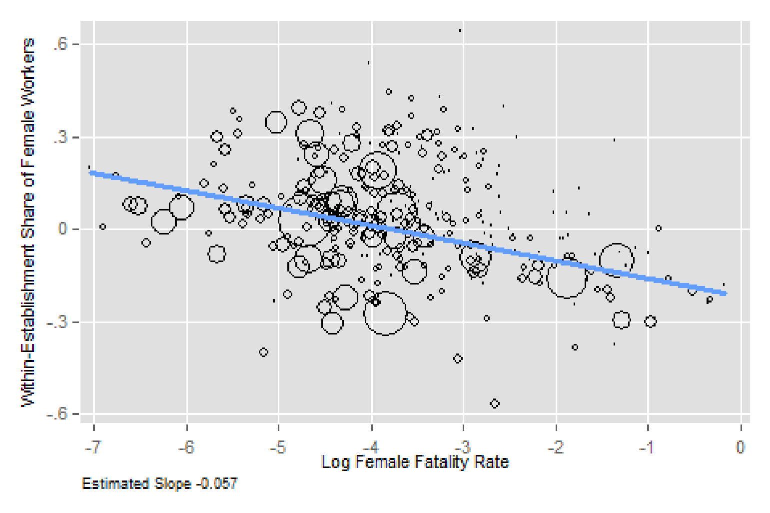
Figure 3: Share of Female Workers by Log Fatality Rate



- Doubling fatality rate associated with 15% reduction in female employment share

This is Also True Within Establishments

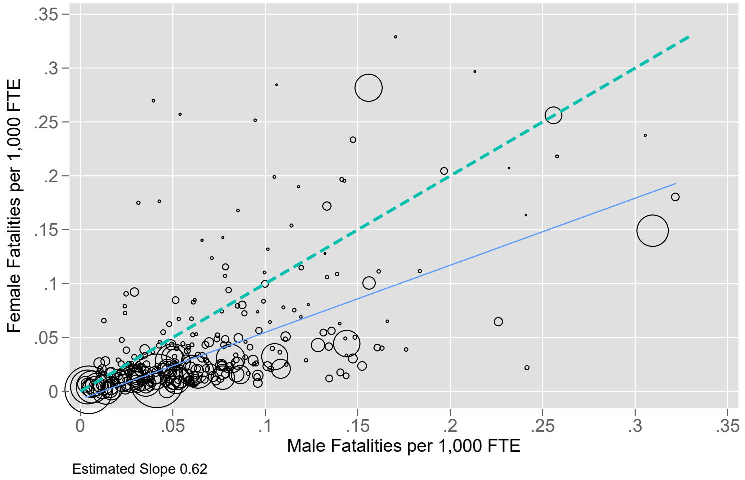
Figure 4: Share of Female Workers by Log Fatality Rate



- Within establishments, female employment share is higher in safer occupations

Women Are Safer than Men Within Similar Jobs

Figure 5: Female vs Male Fatality Rates by Industry-Occupation



- Average female fatality rate is 38% lower than male rate within industry-occupation

Can sorting patterns be explained by compensating wage differentials?

Descriptive Baseline Estimates

- We begin by evaluating gender differences in compensating wage differentials for safety:

$$\ln w_{it} = x_{it}\beta + \gamma^g a_{c(i,t),t} + \theta_i + \varepsilon_{it}$$

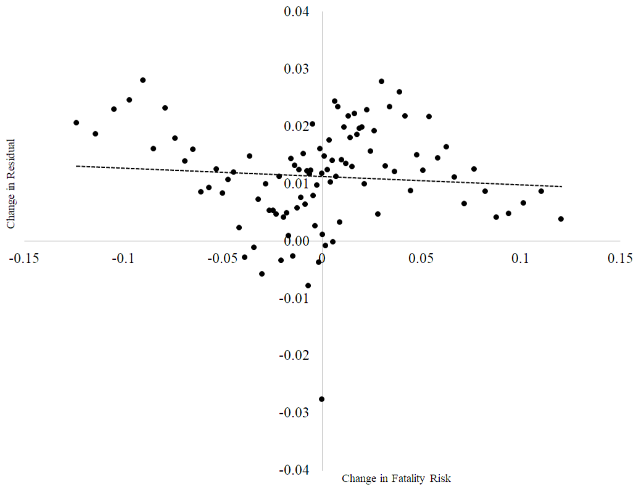
- X includes a cubic in experience interacted with race, establishment size effects, tenure, state effects, year effects, 1-digit industry effects, and 1-digit occupation effects
- $a_{c(i,t),t}$ is the gender-specific fatality rate in ind-occ cell c in which worker i is employed in year t
- γ^g is gender-specific coefficient
- θ_i fixed worker effect

Estimates

Table 1: Compensating Wage Differentials for Full-Time Prime-Age Men

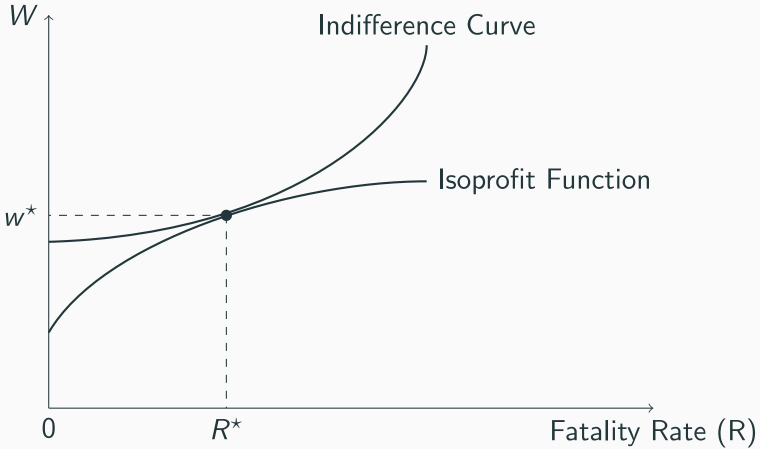
	Dependent Variable: ln(*Wage*)	
	Pooled	Worker Effects
Fatality Rate	0.284	0.122
	(0.013)	(0.005)
Fatality Rate*Male	0.111	0.010
	(0.013)	(0.005)
N	22,241,909	22,241,909
R^2	0.462	0.955

Figure 6: Worker Effects Model: Average Job-to-Job $\Delta\epsilon_{it}$ by $\Delta R_{c(i,t)}$



Motivating model selection:
Graphical overview

Graphical Overview: Rosen Pricing Function



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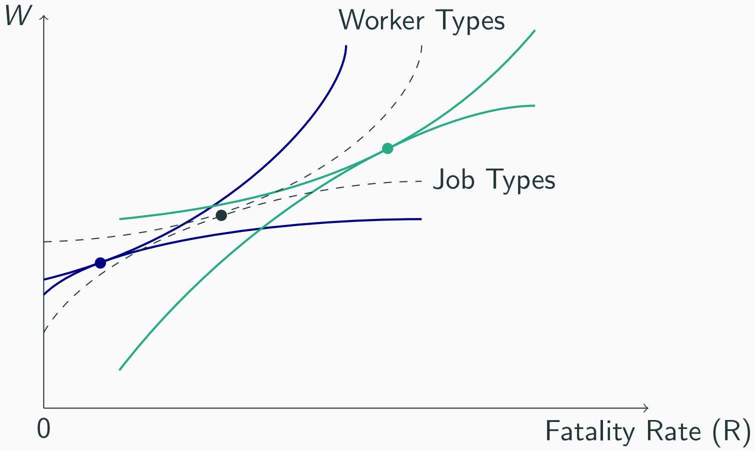

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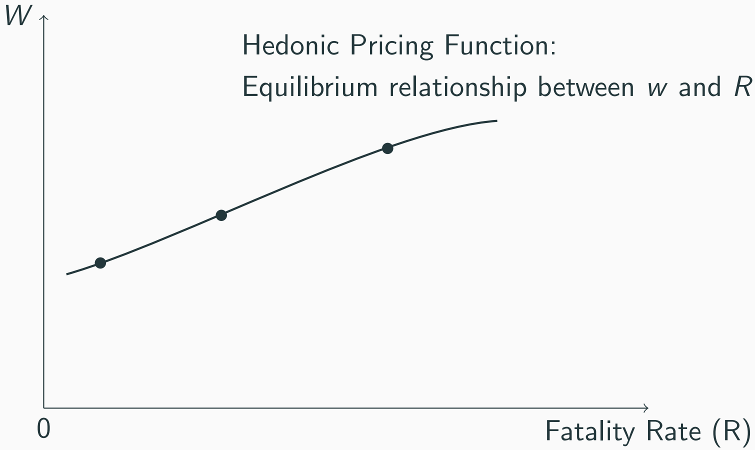
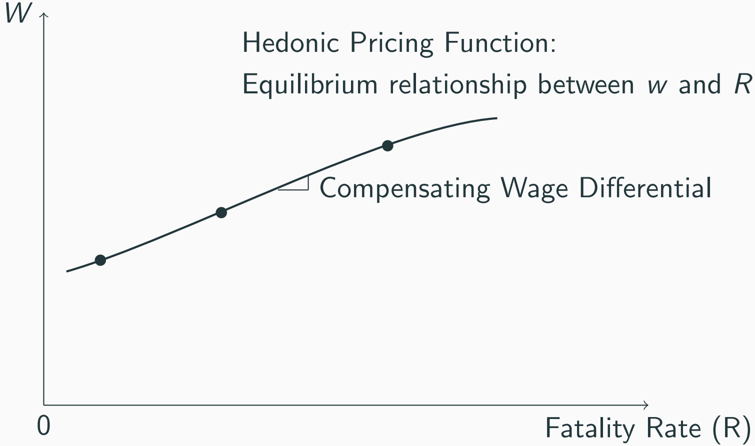


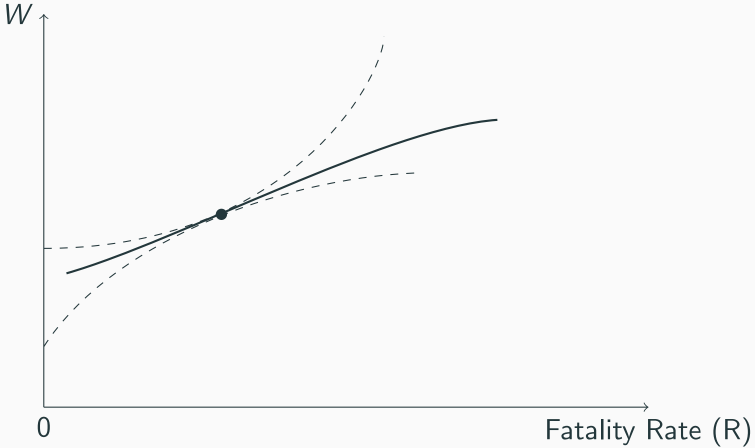
Graphical Overview: Rosen Pricing Function



$\ln w_{it} = X_{it}\beta + \gamma R_{it} + \varepsilon_{it}$ estimated in hundreds of studies in labor economics

The ability bias puzzle

Graphical Overview: Ability Bias



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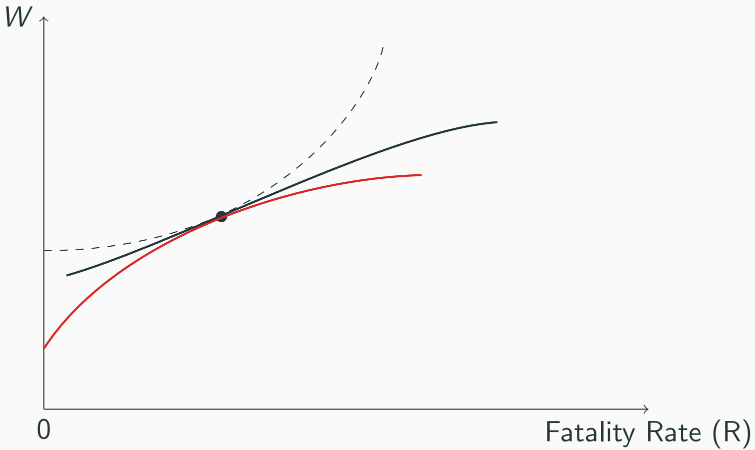

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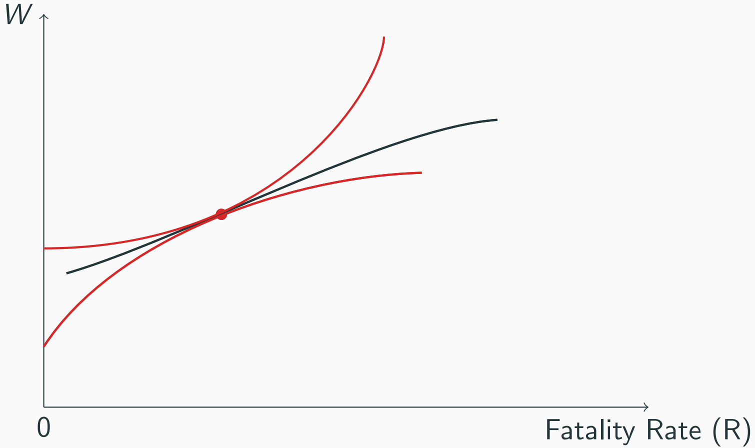
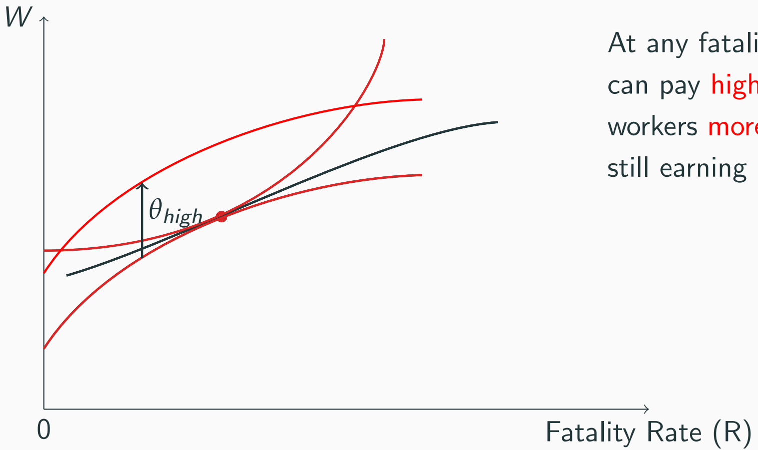
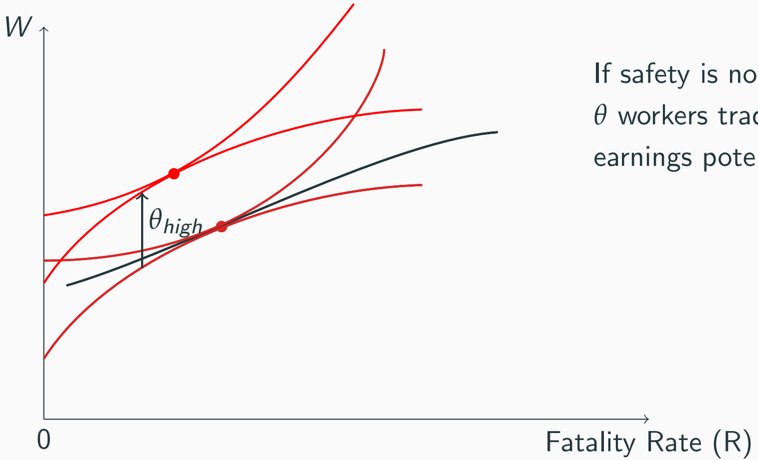


Graphical Overview: Ability Bias



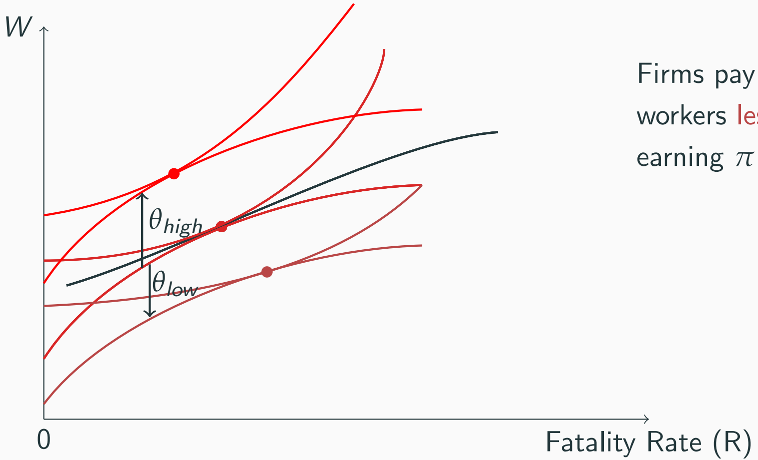
At any fatality rate, firms can pay high ability workers more while still earning $\pi = 0$

Graphical Overview: Ability Bias



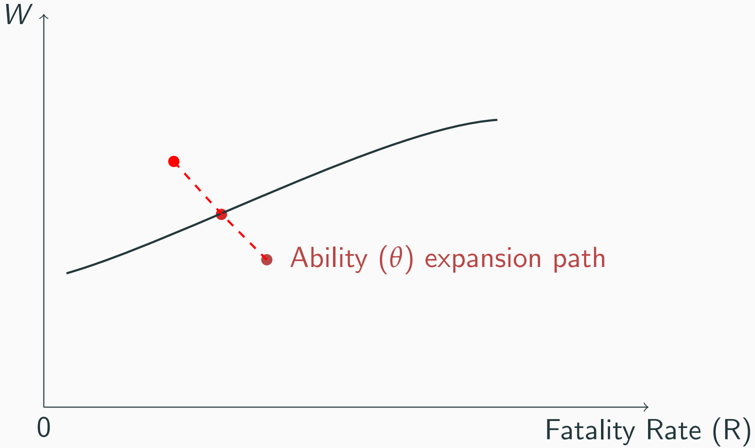
If safety is normal, high θ workers trade greater earnings potential for safety

Graphical Overview: Ability Bias



Firms pay low ability workers less when earning $\pi = 0$

Graphical Overview: Ability Bias



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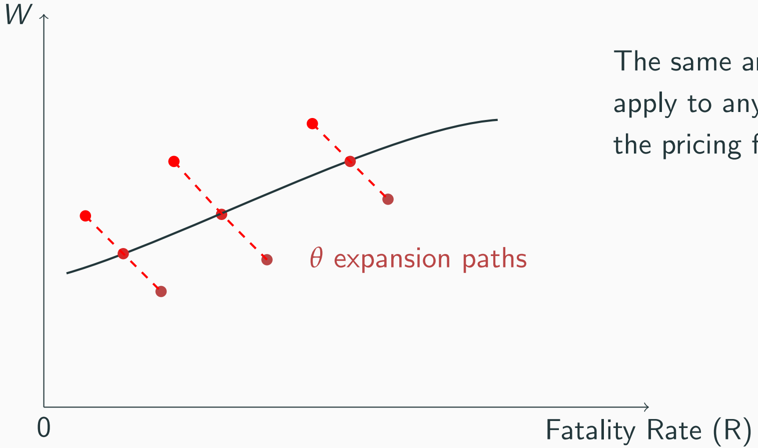
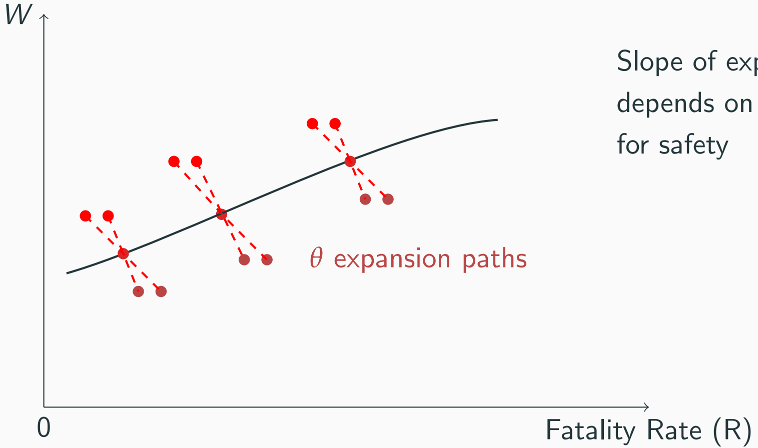


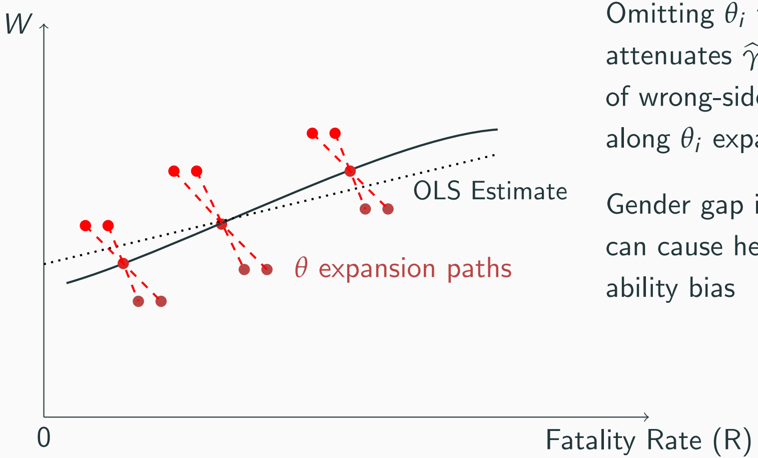
The same argument can apply to any point along the pricing function

Graphical Overview: Ability Bias



Slope of expansion path depends on preferences for safety

Graphical Overview: Ability Bias



Omitting θ_i from model attenuates $\widehat{\gamma}$ because of wrong-sided variation along θ_i expansion paths

Gender gap in preferences can cause heterogeneous ability bias

Ability Bias

$$\ln w_{it} = x_{it}\beta + \gamma^g a_{c(i,t),t} + \theta_i + \varepsilon_{it}$$

- Latent θ_i likely negatively correlated with fatality rate a
- Potential solution—estimate within-worker model using panel data [Brown (1980); Garen (1988); Kniesner et al 2012]
- Puzzle:
  - Within-worker estimates indicate $\widehat{\gamma}_{\text{Cross-Sectional}} >> \widehat{\gamma}_{\text{Panel}}$

The role of firms in explaining the ability bias puzzle

Job Mobility and Wages:

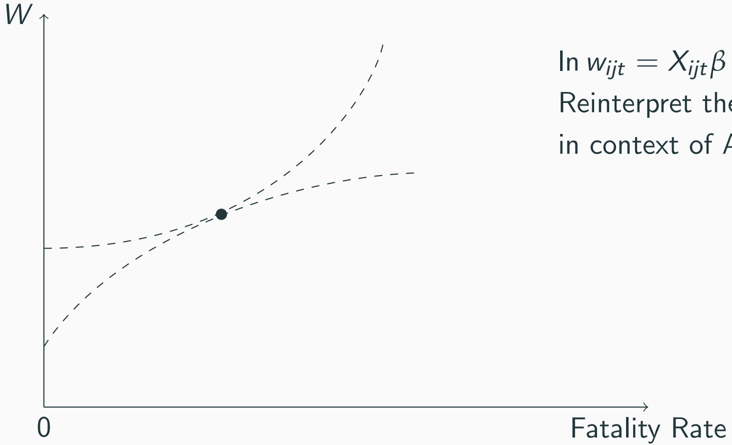
- Explanation: worker effects model cannot adequately capture within-worker wage process, largely driven by job mobility
- Why do workers move?
  1. Search frictions affect wage/amenity bundles
     [Hwang, Mortensen, Reed (1998); Lang and Majumdar (2004)]
  2. Workers get good/bad news about ability
     [Gibbons and Katz (1992)]
  3. Workers get good/bad news about match quality
     [Abowd, McKinney, Schmutte (2015)]
  4. Preference changes, potentially correlated with family structure
     [DeLeire and Levy (2004); Hotz et al. (WP)]

AKM and the Components of Earnings Structures

$$\ln w_{ijt} = X_{ijt}\beta + \theta_i + \psi_{J(i,t)} + \varepsilon_{ijt}$$

- Separate literature has studied the components of earnings
  [Abowd et al. (AKM 1999); Woodcock (2004); Card et al. (2013)]
- Across many countries worldwide, surprisingly similar wage patterns:
  - $\approx$ 40% of earnings variance explained by θ_i
  - $\approx$ 20-25% of earnings variance explained by $\psi_{J(i,t)}$
- Firm earnings effects $\psi_{J(i,t)}$ potentially consistent with search frictions, imperfect competition, efficiency wages, or unobserved firm-level amenities
- Evidence that $\psi_{J(i,t)}$, and therefore job mobility based on $\psi_{J(i,t)}$, differs by gender
  [Card et al. (2016)]

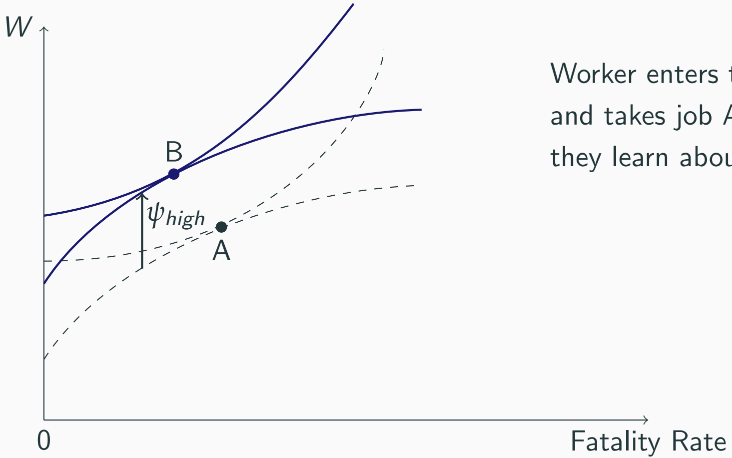
Explaining the Ability Bias Puzzle



$\ln w_{ijt} = X_{ijt}\beta + \theta_i + \psi_{J(i,t)} + \varepsilon_{ijt}$

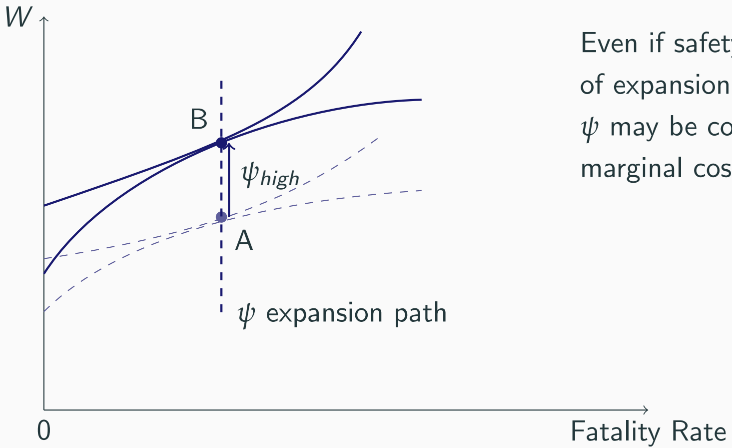
Reinterpret the wage process
in context of AKM wage model

Explaining the Ability Bias Puzzle



Worker enters the labor market and takes job A. After searching, they learn about job B and switch.

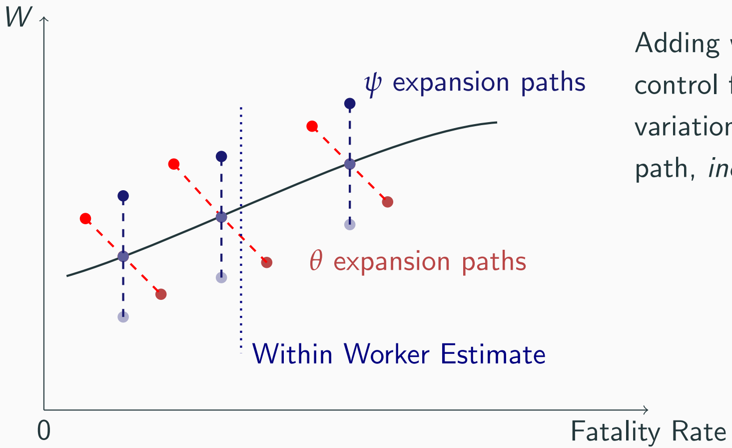
Explaining the Ability Bias Puzzle



Even if safety is normal, slope of expansion path ambiguous

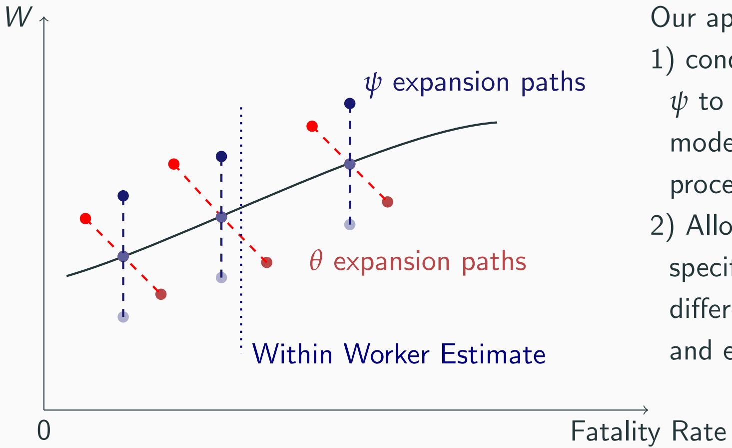
ψ may be correlated with marginal cost of safety

Explaining the Ability Bias Puzzle



Adding worker effects may control for ability, but leaves only variation along ψ expansion path, *increasing* total bias

Explaining the Ability Bias Puzzle



Our approach:

1) condition on both θ and ψ to account for ability while modeling within-worker wage process
2) Allow $\psi^{g}_{J(i,t)}$ to be gender specific to account for differences in job-mobility and establishment rents

Wage Decomposition Model

- We estimate a two-step variant of AKM model

$$w_{it} = x_{it}\beta^{g} + \tilde{\gamma}^{g} a_{c(i,t),t} + \Phi_{i,M(i,t)} + \epsilon_{it}$$

$$w_{it} - x_{it}\widehat{\beta^{g}} = \pi^{g} z_{it} + \gamma^{g} a_{c(i,t),t} + \theta_{i} + \psi^{g}_{J(i,t)} + \varepsilon_{it}$$

- $\Phi_{i,M(i,t)}$ worker-establishment-occupation match effects
- $\psi^{g}_{J(i,t)}$ gender-specific establishment effects
- Identifies gender-specific CWDs (γ^{f}, γ^{m}) using across-job variation
- Allows job mobility choices to be correlated with unobserved worker and gender-specific establishment characteristics

Wage Decomposition Model

$$w_{it} = x_{it}\beta^g + \tilde{\gamma}^g a_{c(i,t),t} + \Phi_{i,M(i,t)} + \epsilon_{it}$$

$$w_{it} - x_{it}\widehat{\beta^g} = \pi^g z_{it} + \gamma^g a_{c(i,t),t} + \theta_i + \psi^g_{J(i,t)} + \varepsilon_{it}$$

- Why not use $\widehat{\tilde{\gamma}^g}$?
  - Only 3% of variation in fatality rates occurs within jobs, very small changes may not be salient, and wages may not adjust quickly
  - Objective is to use across-job variation in R, while correcting for potential endogeneity associated with job changes

Identification of $\psi^g_{J(i,t)}$

$$w_{it} = x_{it}\beta^g + \tilde{\gamma}^g a_{c(i,t),t} + \Phi_{i,M(i,t)} + \epsilon_{it}$$
$$w_{it} - x_{it}\widehat{\beta^g} = \pi^g z_{it} + \gamma^g a_{c(i,t),t} + \theta_i + \psi^g_{J(i,t)} + \varepsilon_{it}$$

- Normalization required to interpret $\psi^g_{J(i,t)}$
  - Each disconnected subset has mean zero $\psi_{J(i,t)}$, cannot compare levels without common reference point
  - (Almost) never observe the same worker transitioning for receiving male $\psi^m_{J(i,t)}$ to receiving female $\psi^f_{J(i,t)}$
  - Normalization: assume that in lowest paying industries there are no rents paid to men or women [Card et al. (2016)]
- Normalized $\psi^g_{J(i,t)}$ only identified in the intersection of the connected job mobility networks of male and female workers

Summary Statistics

	Full Population		Attached Dominant Jobs		Dual Connected Set	
	Women	Men	Women	Men	Women	Men
Age	35.83	35.46	38.36	38.64	38.20	38.37
Race White	0.57	0.56	0.69	0.64	0.68	0.63
Less than High School	0.32	0.53	0.38	0.58	0.36	0.52
High School	0.41	0.33	0.40	0.33	0.39	0.36
Some College	0.05	0.03	0.06	0.03	0.06	0.04
College or More	0.21	0.10	0.16	0.07	0.18	0.09
Contracted Weekly Hours	39.46	42.03	42.05	43.04	41.63	42.79
Log Hourly Wage	1.33	1.42	1.44	1.61	1.54	1.72
Total Experience (Years)	18.35	18.98	22.12	23.43	21.80	22.89
Job Tenure (Months)	62.36	51.69	89.56	82.93	90.91	84.66
Pooled Fatality Rate (per 100,000)	0.02	0.07	0.02	0.08	0.02	0.07
Gender-Specific Fatality Rate	0.01	0.08	0.01	0.08	0.01	0.08
Zero Fatality Rate	0.26	0.15	0.35	0.12	0.37	0.13
N	134,361,238	194,907,785	11,419,266	22,234,188	8,193,244	14,567,312

Can Differences in CWDs Explain Sorting Patterns?

	Fatality Rate Industry*Occupation		Fatality Rate Gender*Industry*Occupation		
	(1) Men	(2) Women	(3) Men	(4) Women	(5) Both
Fatality Rate	0.233*	0.161*	0.174*	0.174*	0.174*
	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)
Fatality Rate*Female					0.001
					(0.005)
VSL (million reais)	3.41	2.06	2.55	2.23	2.43
	[3.34, 3.47]	[1.94, 2.18]	[2.49, 2.60]	[2.11, 2.35]	[2.33, 2.54]
N	13,985,793	8,131,646	13,985,793	8,131,646	22,117,439
R-Sq	0.959	0.970	0.959	0.970	0.971

Can Differences in CWDs Explain Sorting Patterns?

- Summary:
  - Previous evidence suggested women earn smaller CWDs (and therefore have lower VSLs)
  - We show this is a result of model specification error and measurement error
  - There is precisely zero gender gap in CWDs in our empirical context
- Answer: No, CWDs for safety cannot explain sorting patterns
- NB: this says nothing about the importance of preferences, only implicit market prices

Can sorting patterns be explained by gender differences in $\psi^{g}_{J(i,t)}$?

OME Decomposition Estimates

Variance Components	Women		Men	
	Component	Variance Share	Component	Variance Share
SD of Log Wages	0.74	100%	0.69	100%
SD Worker Effects	0.59	63%	0.54	60%
SD Estab-Gender Effects	0.31	17%	0.28	16%
SD of $X\beta$	0.11	2%	0.13	4%
SD Residual	0.13	3%	0.14	4%
Cov (θ, ψ^g)	0.03	6%	0.04	8%
Cov $(\theta, X\beta)$	0.00	1%	–0.00	0%
Cov $(\psi^g, X\beta)$	0.00	0%	0.00	0%

- Women have larger wage variance, in large part because of establishment assignment ψ^g
- Similar assortative matching on θ and ψ^g

Decomposing Establishment Treatment from Assignment

- To what extent do women sort differently in the $\psi^{g}_{J(i,t)}$ dimension because establishments pay different wage premia to women relative to men?
- To answer this question, need to compare levels of $\psi^{f}_{J(i,t)}$ and $\psi^{m}_{J(i,t)}$, but these are estimated on disconnected sets, so comparison requires a normalization
  - We normalize the average $\psi^{f}_{J(i,t)} = 0$ and $\psi^{m}_{J(i,t)} = 0$ in the five lowest industries

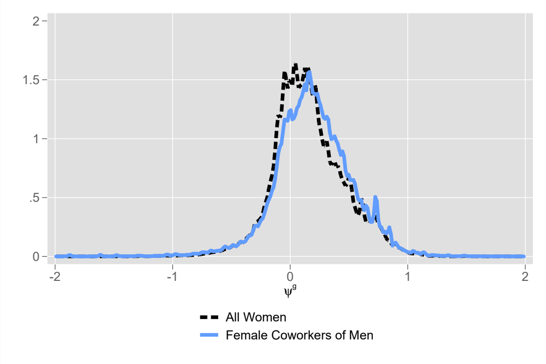
Normalized Female vs Male $\widehat{\psi_{J(i,t)}}$

OME Estimated Components of Wage Gap

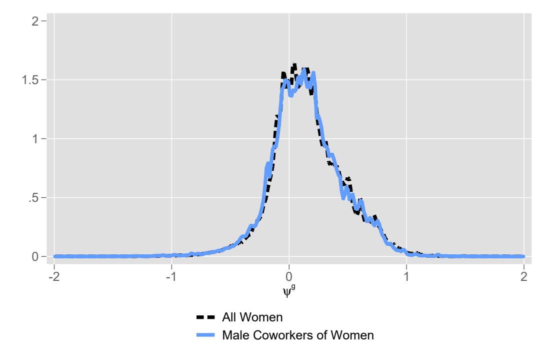
	Women	Men	Gender Gap	Share
Log Wage	1.544	1.727	0.183	100%
First Stage Controls (Exp. and Year)	0.670	0.652	–0.018	-10%
Occupation Effects	0.030	0.004	–0.027	-15%
Person-Specific Component	–0.109	0.063	0.172	94%
Establishment Assignment	0.160	0.211	0.051	28%
Within-Estab. Gender Gap	0.001	–0.000	0.001	1%

*Remainder of gap is from differences in timing of assignment to jobs

Decomposing Effects of Establishment Assignment and Treatment Conditional on Establishment



(a) Treatment



(b) Assignment

Job Assignment and Establishment Wage Effects

	All Jobs	Jobs Held by Women	Jobs Held by Men
Normalized Female Establishment Effect	0.184	0.161	0.197
Normalized Male Establishment Effect	0.190	0.153	0.212
Female Fatality Rate	0.014	0.011	0.016
Male Fatality Rate	0.056	0.034	0.068
N	21,813,701	8,050,994	13,762,707

Impacts of establishment-level gender segregation

Two-Dimensional Sorting Framework

- A very simple framework for characterizing 2-dimensional sorting patterns (Lindenlaub and Postel-Vinay, 2017)
- Consider jobs that differ in attributes $\mathbf{y} = (y_\psi, y_a)$
- Workers have vector of skills or characteristics $\mathbf{x} = (\theta, g)$
- Surplus of a job match $\sigma(\mathbf{x}, \mathbf{y})$ can depend on interactions between $\mathbf{x}$ and $\mathbf{y}$
- Frictional search, workers move when $\sigma(\mathbf{x}, \mathbf{y}^d) > \sigma(\mathbf{x}, \mathbf{y}^o)$

Two-Dimensional Sorting Framework

- Conditional probability of moving to a job with attributes $\mathbf{y}$ is $Pr\left[\mathbf{y}|\mathbf{y^o},\mathbf{x}\right]$
- Without any additional structure, can full characterize job sorting in this model by gradient vectors:

$$\{\mathbb{E}[\Delta\psi|\mathbf{y^o},\mathbf{x}],\mathbb{E}[\Delta a|\mathbf{y^o},\mathbf{x}]\}$$

- Gradient vectors characterize how systematic patterns of job changes shift the marginal distributions of job attributes (y_ψ, y_a)
- We empirically estimate the field of these gradient vectors

Female Job-to-Job Transition Gradient Field

Figure 8: Average Gradients of Job Changes by Decile of Origin $\psi^{g}_{J(i,t)}$ and a

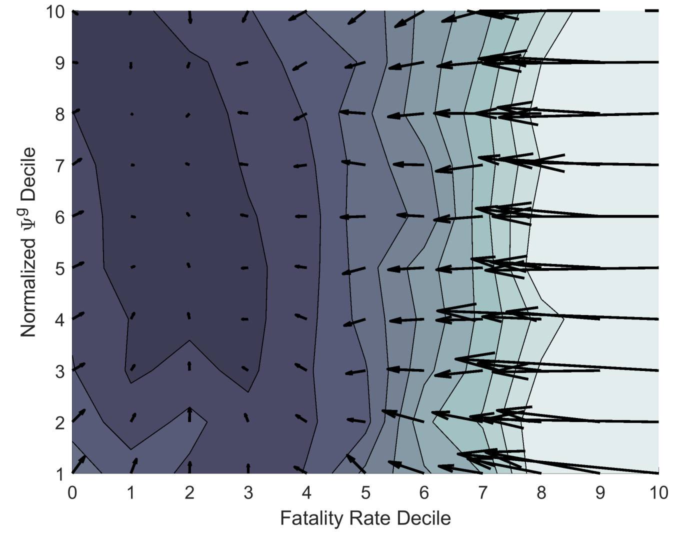
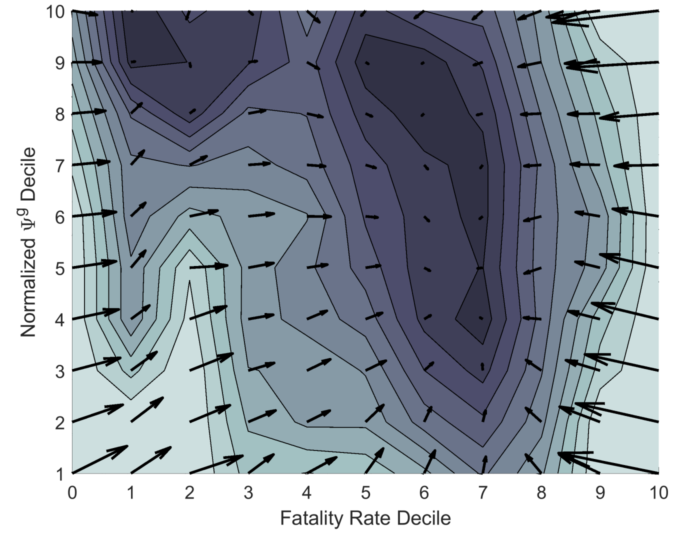
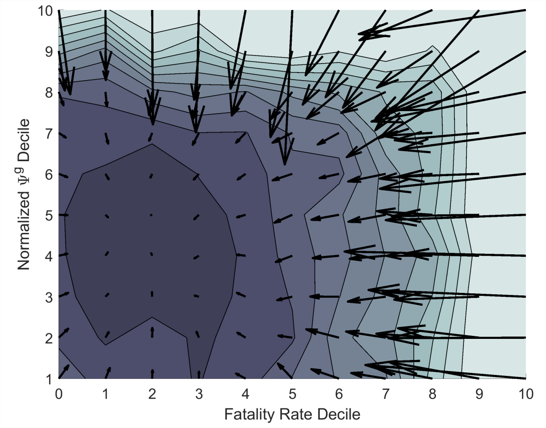


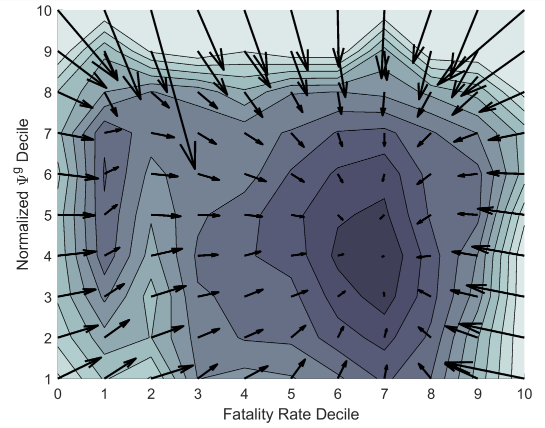
Figure 9: Average Gradients of Job Changes by Decile of Origin $\psi^g_{J(i,t)}$ and a



Job-to-Job Transition Gradient Fields: Low Wage Women and Men

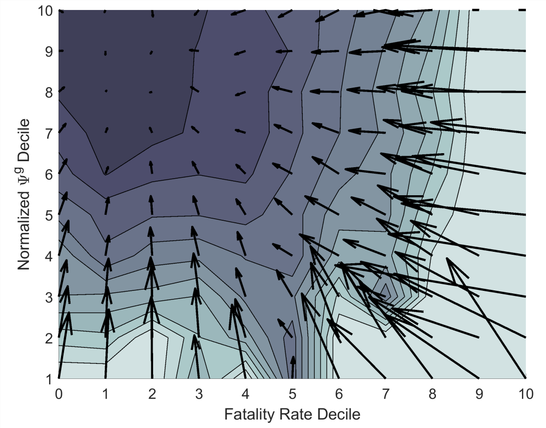


(a) Low Wage Women

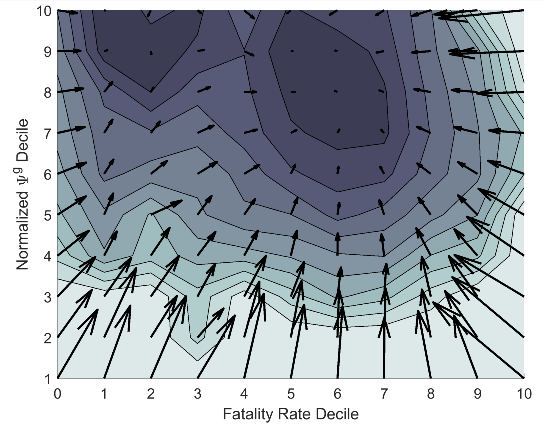


(b) Low Wage Men

Job-to-Job Transition Gradient Fields: High Wage Women and Men



(a) High Wage Women



(b) High Wage Men

Interpretation Caveats

- One concern is that establishments differ in safety, and workers may sort based on this establishment-specific component
  - Difficult to directly model because fatalities are very rare, more than 99% of establishments have zero fatalities
  - Inherent tradeoff between precision and measurement error
  - We fail to reject any difference in average fatality rates in establishment-occupation cells in which the female share is above vs below the industry-occupation average
- These analyses cannot isolate underlying cause of sorting patterns
  - Mechanisms that explains ψ itself are poorly understood, but most explanations involve labor market frictions
  - If (unmodeled) frictions differ by gender then sorting on ψ may not reflect differences in preferences or productivity

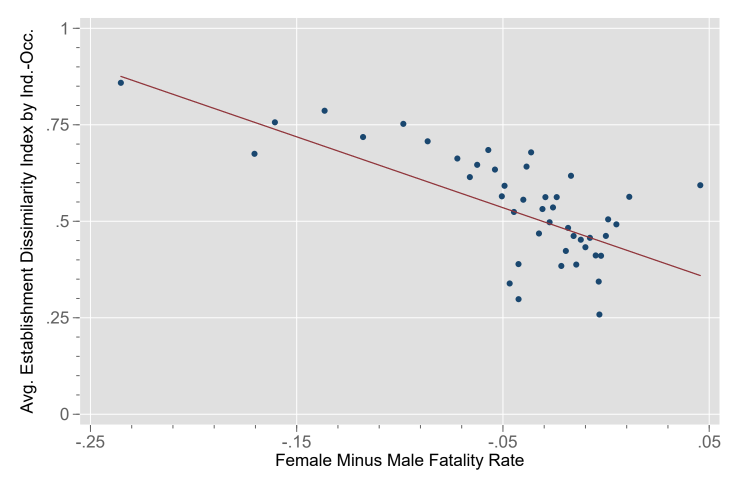
Establishment Segregation

- To what extent does sorting on safety contribute to gender gap in establishment assignment?
- Construct industry-occupation dissimilarity index:

$$D = \frac{1}{2} \sum_{\ell=1}^{K} \left| \frac{f_\ell}{F} - \frac{m_\ell}{M} \right|$$

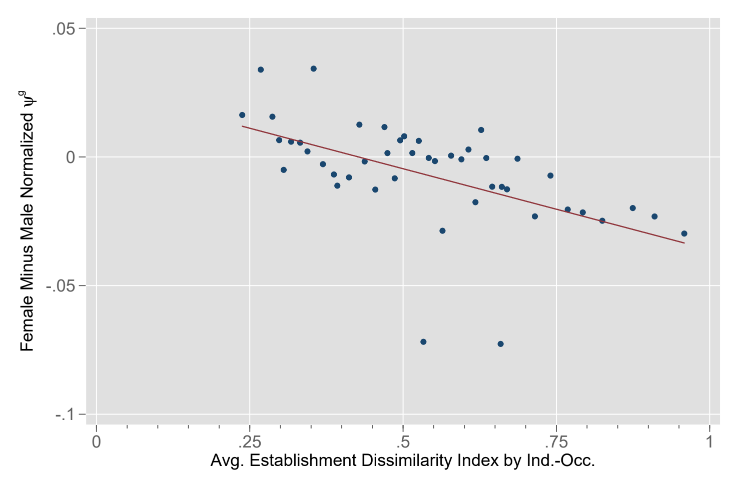
  - K: number of establishments in industry-occupation cell
  - F, M: number of women (men) employed in cell
  - f_ℓ, m_ℓ: number of women (men) in cell employed in establishment ℓ
- Interpretation: D measures share of workers who would have to be re-assigned to make establishment-occupation gender share match the industry-occupation gender share

Establishment Segregation vs Safety



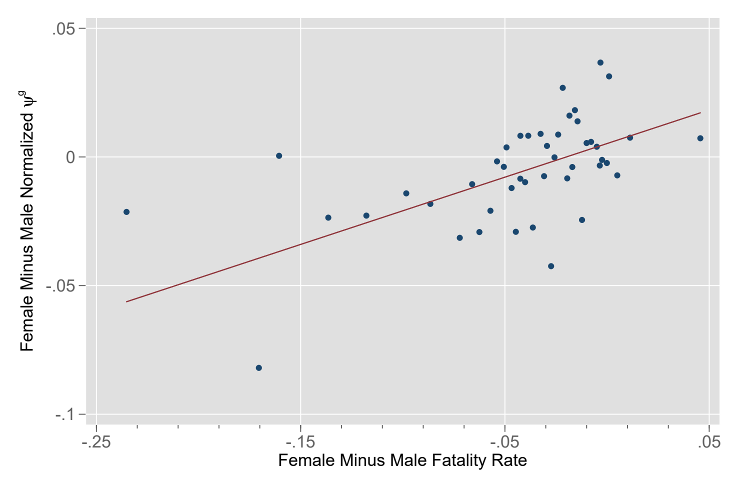
- Much stronger establishment segregation in industry-occupations in which women are safer than men
- Suggestive that safety gap may not be driven by task assignment

ψ vs Establishment Segregation



- Safety-driven segregation leads women to be over-represented in low-wage establishments

ψ vs Safety



- Connecting these two patterns shows that safety gap is strongly related to establishment pay
- Implies 1 SD increase in safety associated with 1.8 pp gender wage gap (10% of entire raw wage gap in Brazil)

Conclusion

- Revisit labor market sorting in two-dimensional framework: wages versus safety
- Show that safety plays strikingly large role in understanding job dynamics
  - Roughly as salient in explaining job mobility as sorting on firm-level compensation
  - Similar patterns do not exist for financial risk, despite clear gender gap in risk preferences
- In contrast to prior studies, no gender difference in compensating differentials for safety
- Large indirect effects of safety on wages caused by altering the distribution of establishment assignment for women
  - Segregation of men and women across establishments is strongly correlated with safety patterns
  - This establishment assignment channel explains 1/3 of the overall gender wage gap
- Suggests occupational safety regulations may be an overlooked policy tool for affecting wage disparities