The Effect of Working from Home on the Agglomeration Economies of Cities: Evidence from Advertised Wages

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U.S. Productivity Growth: Looking Ahead

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[1]The views expressed here are those of the authors and do not necessarily represent the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

Introduction

- **Agglomeration economies**:
  - Spatial clustering of economic activities:
    cost-saving advantages and productivity benefits.
  - Higher productivity in large cities.
  - Key mechanism: Interpersonal interactions.
    - Knowledge spillovers
    - Relationships and networks

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    cost-saving advantages and productivity benefits.
  - Higher productivity in large cities.
  - Key mechanism: Interpersonal interactions.
    - Knowledge spillovers
    - Relationships and networks
- Massive adoption of **working from home (WFH)**:
  - Reduced workplace interactions.
  - Weakened agglomeration economies?

Outline

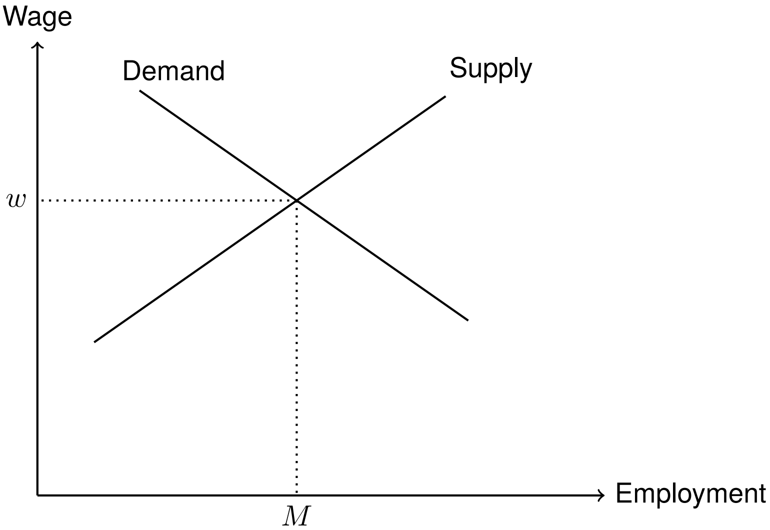
1. **Conceptual framework**
2. Data and empirical evidence
   - Test model predictions
   - Gelbach decomposition by skill
3. Conclusion

Conceptual Framework

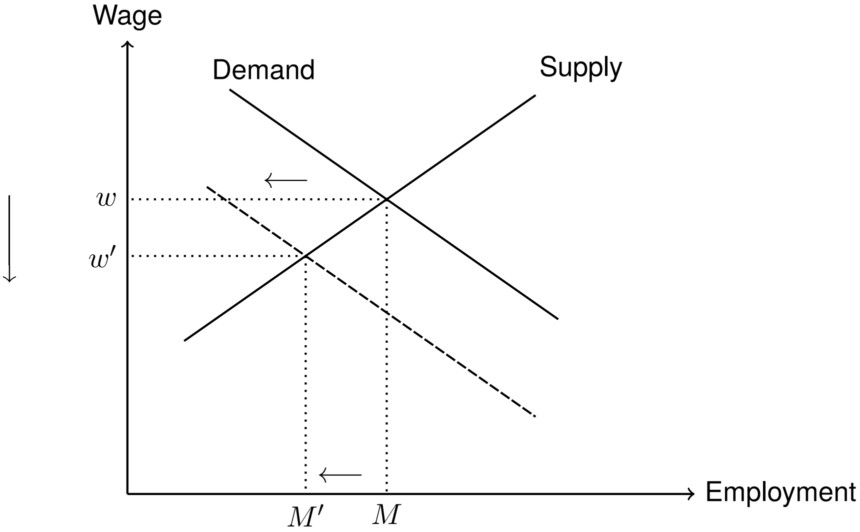
- Two-city model:
  - Large city: agglomeration effect.
  - Small city.
- Before WFH: Work and residential locations are **bundled**.
  - Large city enjoys productivity spillovers from workers' physical concentration.
  - Constrained by limited housing supply.
- After the prevalence of WFH: Work and residential locations are **decoupled**.
  - Demand force: Large city may lose agglomeration effect due to $\downarrow$ onsite workers.
  - Supply force: Gain access to a larger labor pool due to $\uparrow$ remote workers.

Model Setting

Labor Market in the Large City



Labor Market in the Large City



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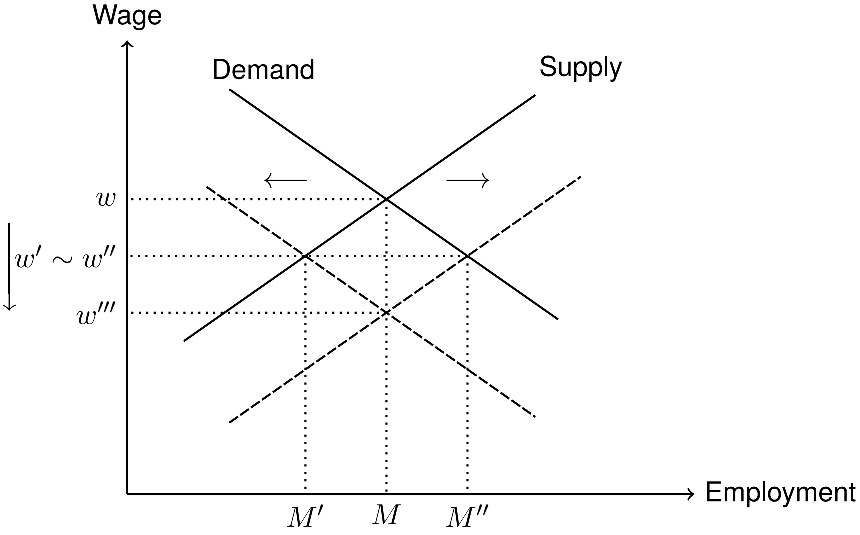

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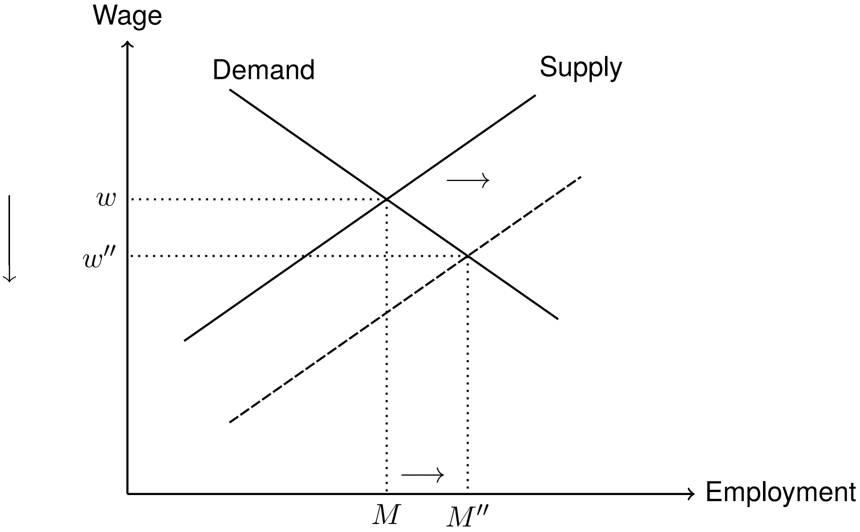

Predictions: Weakened Agglomeration Economies

- Empirical predictions:
  1. Decrease in the **urban wage premium** among occupations with high WFH adoption.
  2. Large cities lose payroll employment to smaller cities.
- COVID-19 pandemic as an empirical setting: $\uparrow$ WFH for various occupations/ industries.

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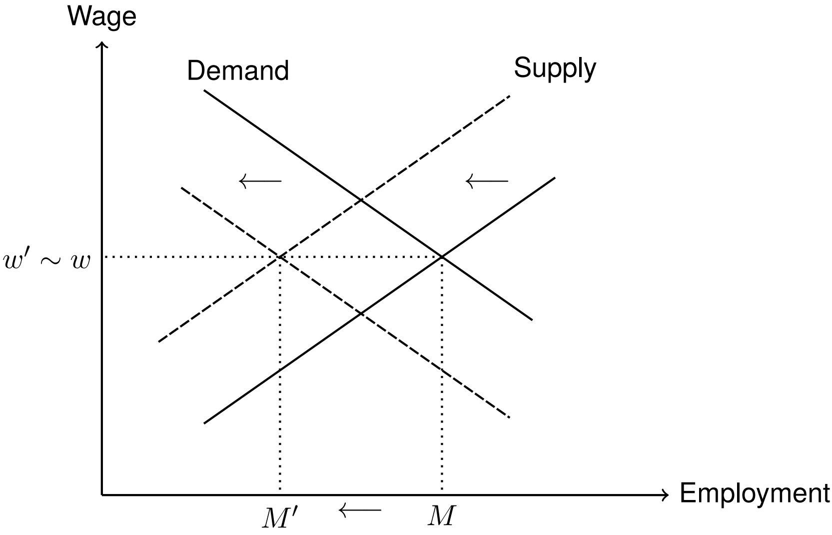
- COVID-19 pandemic as an empirical setting: $\uparrow$ WFH for various occupations/ industries.
- Comparison group: occupations with low WFH adoption?
  - Migration away from large cities.

COVID-Era Predictions: Occupations with Low WFH Adoption in Large Cities



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Data

- Burning Glass Technologies (Lightcast now): 2018–May 2023.
  Representativeness
  - Jobs posted on online job boards.
  - Wage, date, geography (county), NAICS, SOC, etc.
  - Detailed skill requirements.
- Quarterly Census of Employment and Wages (QCEW): Number of jobs by industry based on firms' locations.
  Industry Share Validation with QCEW
- Measuring WFH prevalence:
  - Original texts of job postings: WFH-compatible or not.
    Procedures Validations
  - High/ moderate/ low WFH adoption: changes in the share of WFH-compatible jobs. Examples
  - Robustness: American Community Survey (ACS) and O*NET; American Time Use Survey (ATUS).

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Changes in the Urban Wage Premium By WFH Adoption

$$
\begin{aligned}
\ln(w_{ikjt}) = {} & \alpha_0 \ln M_{kj} + \alpha_1 \ln M_{kj} \times Mod_k + \alpha_2 \ln M_{kj} \times High_k \\
& + \alpha_3 \ln M_{kj} \times Post_t + \alpha_4 \ln M_{kj} \times Mod_k \times Post_t \\
& + \alpha_5 \ln M_{kj} \times High_k \times Post_t \\
& + \alpha_6 Post_t + \alpha_7 Mod_k + \alpha_8 High_k + \alpha_9 Post_t \times Mod_k \\
& + \alpha_{10} Post_t \times High_k + \mathbf{X}_{ikjt}\mathbf{\Theta} + \varepsilon_{ikjt}.
\end{aligned}
$$

- w_{ikjt}: posted wage by job i, in occupation k, MSA j, and at time (month-year) t;
- M_{kj}: initial employment size;
- $Post_t$: after March 2020;
- Mod_k: occupations with moderate WFH adoption;
- $High_k$: occupations with high WFH adoption.

Regression Results

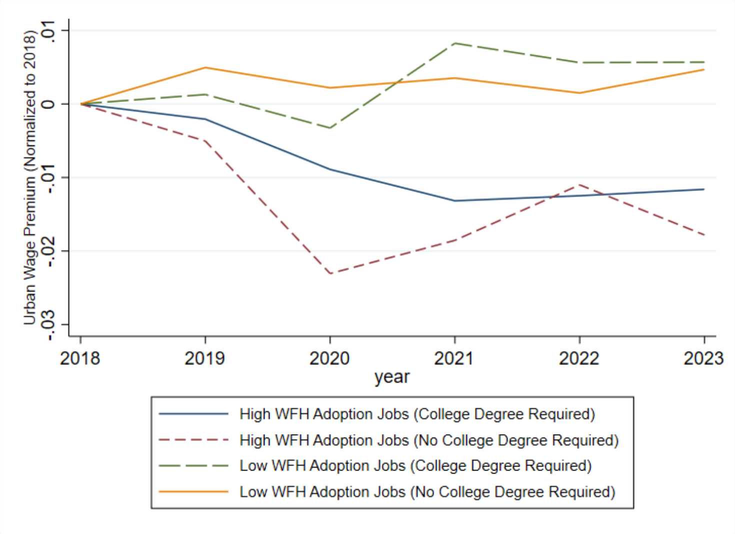
	Log Posted Hourly Wages			
	(1)	(2)	(3)	(4)
Log M	0.0169***	0.0175***	0.0244***	0.0186***
	(0.00405)	(0.00400)	(0.00409)	(0.00428)
Log M $\times$ Moderate WFH	0.0193***	0.0141***		0.0209***
	(0.00165)	(0.00132)		(0.00165)
Log M $\times$ High WFH	0.0267***	0.0223***	0.0262***	0.0282***
	(0.00316)	(0.00254)	(0.00377)	(0.00323)
Log M $\times$ Post	0.00176	0.00068	-0.00261***	0.00255***
	(0.00108)	(0.0011)	(0.00087)	(0.00116)
Log M $\times$ Moderate WFH $\times$ Post	**-0.00944*** **	-0.00628***		-0.0103***
	(0.00075)	(0.00066)		(0.000756)
Log M $\times$ High WFH $\times$ Post	**-0.0123*** **	-0.0127***	-0.00834***	-0.0130***
	(0.00157)	(0.00136)	(0.00179)	(0.00159)
Controls: Job characteristics	X	X	X	X
Controls: Skill Requirements		X		
Specification	Baseline	Baseline	Alt. High WFH Def.	Heckman Correction
Observations	7,316,072	5,996,752	7,316,072	20,434,736

Additional Controls | QCEW Weekly Earnings | Within-MSA Cross-County Effects

Robustness Checks: Alternative Mechanisms

- Larger cities' disproportionate adoption of WFH.
  Onsite vs. Remote Jobs/ Workers
  - Different wages between onsite and remote workers: compensating wage differential.
- Reduced compensating differentials: Amenity of less commuting. ACS Commuting
  - The reduction in commute time due to WFH adoption is likely to be larger for workers who live in neighborhoods with longer commute time pre-pandemic.

Urban Wage Premium by Year



High WFH Adoption | Lower WFH Adoption | UWP by Education Req | UWP with Respect to MSA Emp | UWP Validation with ACS | UWP Validation with ACS by Occupation

Employment Growth by Local Employment Size

$$
\begin{aligned}
\Delta \ln Emp_{kjt} = & \sum_{t=2019,2022} a_1^t \ln M_{kjt}^0 \times Low_k \\
& + \sum_{t=2019,2022} a_2^t \ln M_{kjt}^0 \times Mod_k \\
& + \sum_{t=2019,2022} a_3^t \ln M_{kjt}^0 \times High_k + \eta_{kt} + \theta_j + e_{kjt},
\end{aligned}
$$

- $\Delta \ln Emp_{kjt}$ over 2017–2019 vs. 2020–2022;
- M_{kjt}^0: initial employment size;
- Low: industries with low WFH adoption;
- Mod: industries with moderate WFH adoption;
- $High$: industries with high WFH adoption.

Employment Growth by Local Employment Size

	Changes in Log Number of Jobs	
	(1)	(2)
Log M $\times$ 2017–2019 $\times$ Low WFH	-0.0265**	
	(0.0105)	
Log M $\times$ 2020–2022 $\times$ Low WFH	-0.0550***	
	(0.00696)	
Log M $\times$ 2017–2019 $\times$ Moderate WFH	-0.00741*	
	(0.00382)	
Log M $\times$ 2020–2022 $\times$ Moderate WFH	-0.0250***	
	(0.00470)	
Log M $\times$ 2017–2019 $\times$ High WFH	-0.00433	
	(0.0129)	
Log M $\times$ 2020–2022 $\times$ High WFH	**-0.0373***	
	(0.0196)	
Log M $\times$ 2017–2019 $\times$ Other Ind		-0.0218***
		(0.00808)
Log M $\times$ 2020–2022 $\times$ Other Ind		-0.0457***
		(0.00571)
Log M $\times$ 2017–2019 $\times$ Fin./Info./Prof.		-0.00512
		(0.00690)
Log M $\times$ 2020–2022 $\times$ Fin./Info./Prof.		-0.0314***
		(0.00753)
Observations	97,015	97,015

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Spatial Analysis of Skill Demand

- Urban wage premium by skill:
  - Before WFH: More interactions in large cities $\rightarrow$ **Interpersonal** skills command higher wage return in large cities.
  - If WFH diminishes interactions $\rightarrow$ Wage premium of interpersonal skills in large cities $\downarrow$.
  - Gelbach decomposition: *Which* skills saw large drops in their wage premiums? Gelbach Decomposition

Gelbach Decomposition Results

2020		2021		2022–2023	
Skill	π	Skill	π	Skill	π
Marketing and Public Relations	13.5%	Customer and Client Support	33.3%	Communications	22.5%
Business Management	11.0%	Finance	23.5%	Information Technology	22.2%
Information Technology	10.1%	Marketing and Public Relations	23.2%	Customer and Client Support	21.4%
Physical Abilities	5.2%	Building Relationship	17.5%	Building Relationship	16.1%
Finance	4.5%	Business Management	13.7%	Administration	15.9%
Building Relationship	4.1%	Communications	11.9%	Marketing and Public Relations	14.1%
Maintenance, Repair, and Installation	3.5%	Maintenance, Repair, and Installation	9.1%	Business Management	11.6%
Engineering	1.3%	Administration	8.1%	Maintenance, Repair, and Installation	6.6%
Agriculture	1.2%	Physical Abilities	3.4%	Physical Abilities	4.6%
Creativity	1.0%	Decision Making	1.0%	Human Resources	3.1%
Environment	0.7%	Leadership	0.6%	Creativity	2.9%
Education and Training	0.5%	Education and Training	0.5%	Engineering	2.3%
Manufacturing and Production	0.4%	Environment	0.5%	Decision Making	2.2%
Design	0.4%	Design	0.4%	Personal Care and Services	2.1%
Public Safety and National Security	0.4%	Personal Care and Services	0.4%	Education and Training	1.8%
Legal	0.1%	Public Safety and National Security	0.2%	Media and Writing	0.8%
Economics, Policy, and Social Studies	0.1%	Economics, Policy, and Social Studies	0.1%	Design	0.6%
Health Care	0.0%	Legal	0.0%	Public Safety and National Security	0.5%
Decision Making	0.0%	Energy and Utilities	-0.1%	Agriculture	0.2%
Energy and Utilities	0.0%	Agriculture	-0.1%	Economics, Policy, and Social Studies	0.1%
Personal Care and Services	-0.1%	Creativity	-0.1%	Energy and Utilities	0.0%
Human Resources	-0.1%	Engineering	-0.2%	Manufacturing and Production	0.0%
Media and Writing	-0.2%	Manufacturing and Production	-0.4%	Legal	-0.2%
Planning	-0.3%	Media and Writing	-0.8%	Organizational Skills	-0.3%
Architecture and Construction	-0.8%	Architecture and Construction	-1.2%	Architecture and Construction	-0.4%
Leadership	-2.5%	Analysis	-1.2%	Environment	-0.5%
Industry Knowledge	-2.5%	Health Care	-2.1%	Finance	-0.6%
Administration	-6.4%	Industry Knowledge	-4.3%	Leadership	-1.7%
Communications	-8.5%	Planning	-4.6%	Health Care	-6.2%
Analysis	-10.6%	Human Resources	-6.2%	Planning	-7.2%
Organizational Skills	-14.7%	Organizational Skills	-19.2%	Analysis	-10.3%
Customer and Client Support	-21.5%	Information Technology	-24.7%	Industry Knowledge	-11.2%

Skill Listing Frequency

	IT	Business	Building Relations	Communication	Customer Support	Marketing
	(1)	(2)	(3)	(4)	(5)	(6)
Log M	0.00717***	0.00523***	0.00574***	0.00901***	-0.00194	0.00711***
	(0.000999)	(0.00142)	(0.00141)	(0.00104)	(0.00160)	(0.000774)
Log M $\times$ 2020	-0.000173	-0.000408	0.00180***	-0.000823	0.00132***	-0.00178***
	(0.000648)	(0.000667)	(0.000578)	(0.000709)	(0.000453)	(0.000630)
Log M $\times$ 2021	0.00154*	-8.31e-05	0.000119	-0.00180**	-0.000143	-0.00205***
	(0.000806)	(0.000510)	(0.000519)	(0.000720)	(0.000654)	(0.000496)
Log M $\times$ 2022–2023	0.000136	-0.00118**	-0.00281***	-0.00143*	0.000188	-0.00221***
	(0.000773)	(0.000586)	(0.000747)	(0.000832)	(0.000580)	(0.000570)
Observations	1,792,510	1,792,510	1,792,510	1,792,510	1,792,510	1,792,510

Disproportionate decrease in demand for interpersonal skills by large-city jobs with high WFH adoption $\leftarrow$ Diminished interactions in large cities.

Conclusion

- WFH weakened agglomeration economies of large cities.
- The weakened agglomeration effect outweighs the labor supply reallocation channel over 2020–2023.
  - May be the reverse over the long run with hybrid models.
- Caveats:
  - Hybrid model.
  - Better remote technology: remote interactions $\rightarrow$ agglomeration effect.

Literature Contribution

- **The impact of WFH** on
  - Cities: Gupta et al. (2021), Liu and Su (2021), Ramani and Bloom (2021), Althoff et al. (2022), Delventhal et al. (2022), Li and Su (2022), Monte et al. (2023).
  - Productivity: Bloom et al. (2015), Barrero et al. (2021), Behren et al. (2021), Davis et al. (2021), Delventhal and Parkhomenko (2022), Emanuel and Harrington (2023), Emanuel et al. (2023).
- **Mechanisms of agglomeration economies**
  - Glaeser and Mare (2001), Rosenthal and Strange (2003), Duranton and Puga (2004), Combes et al. (2008), Moretti (2010), Bleakley and Lin (2012), D'Costa and Overman (2014), De La Roca and Puga (2017), Gaubert (2018), Eckert et al. (2022), Martellini (2022).

Model: Setting

- Production in two locations:
  - **High**-Density/**Large** City Location (H)
    - For production at H, workers can either work onsite (also living in H) or remotely (by living in L):

$$F_H(B_H, N_{HH}, N_{HL}) = B_H(N_{HH} + N_{HL})^{\gamma},$$

    - Local productivity spillover (agglomeration externality):

$$B_H(N_{HH}) = B_{0H}{N_{HH}}^{\theta},$$

  - **Low**-Density/**Small** City Location (L)
    - For production at L, workers must work and live in L:

$$F_L(B_L, N_{LL}) = B_L N_{LL}^{\gamma}.$$

- Housing markets: Rent responds to local housing demand.

$$r_H = \pi_{0H} + \pi_H \ln(N_{HH}).$$

$$r_L = \pi_{0L} + \pi_L \ln(N_{HL} + N_{LL}).$$

Model: Worker's Problem

- Worker's utility depends the work and residential location choices:

$$U_{HH} = w_H - \beta r_H,$$

$$U_{HL} = w_H - \beta r_L - \phi,$$

$$U_{LL} = w_L - \beta r_L.$$

- Assume non-corner solution:

$$\bar{U} = U_{HH} = U_{HL} = U_{LL}.$$

- Equilibrium: $N_{HH}, N_{HL}, N_{LL}, B_H, w_H, w_L, r_H, r_L$.
  - Impact of ϕ on all equilibrium objects.

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Model: Equilibrium Effect of WFH

- WFH's effect on the urban wage premium:

$$r_H - r_L = \frac{\phi}{\beta},$$

$$w_H - w_L = \phi.$$

  - WFH reduces the urban wage premium.
- WFH's effect on aggregate productivity:

$$\frac{\partial(F_H + F_L)}{\partial(-\phi)} = \underbrace{\theta B_{0H} N_{HH}^{\theta-1} \frac{\partial N_{HH}}{\partial(-\phi)} (N_{HH} + N_{HL})^{\gamma}}_{\substack{\text{Weakening of Agglomeration Economies} \\ < 0}} +$$

$$\underbrace{(W_H - W_L) \frac{\partial(N_{HH} + N_{HL})}{\partial(-\phi)}}_{\substack{\text{Reallocation of Labor from } L \text{ to } H \\ < 0 \text{ or } > 0}}$$

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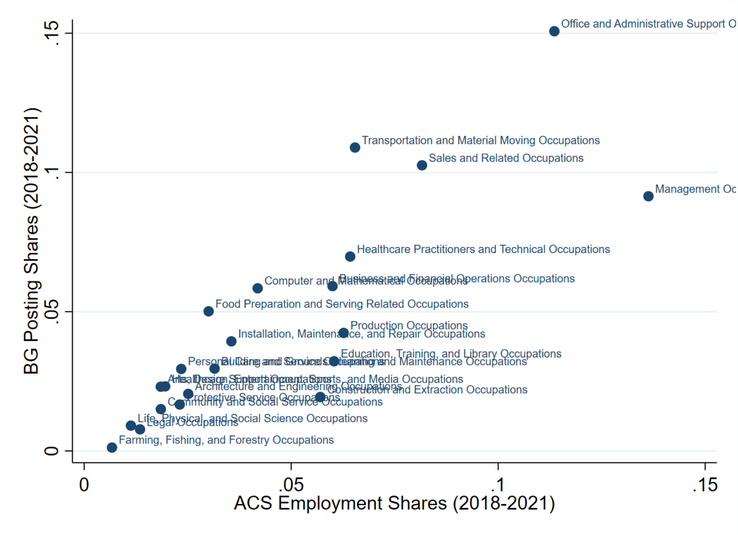
Appendix: Representativeness



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Appendix: Dictionary Approach for WFH Adoption Classification

- **Keywords for WFH:** "remote," "telework," "work from home," "work at home," "wfh," "home office," "virtual," "work anywhere," and "mobile office."
- **Negation:** "cannot," "couldn't," "don't," etc. within 20 characters preceding each keyword. Similarly, we look for "no" or "not" immediately following any keywords
- **Keywords for removal:** "fully onsite," "fully on-site," "attendance," "physical appearance," "physically," "show up on time," "in office," "in person," "requires onsite," "requires on-site," "require onsite," "require on-site," "onsite required," "on-site required," "onsite only," and "on-site only."

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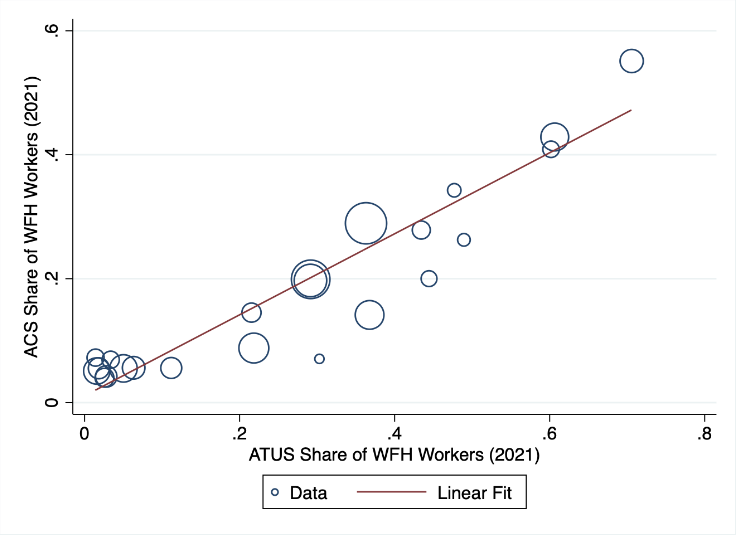
Appendix: ACS vs. ATUS



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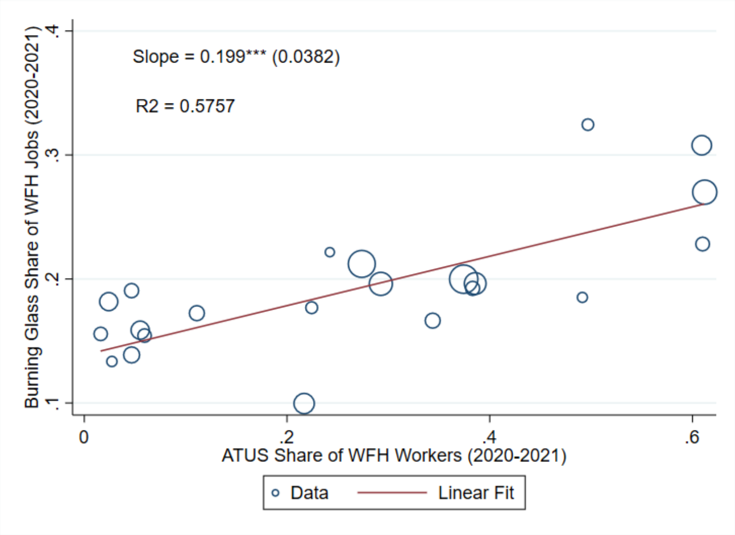
Appendix: Burning Glass vs. ATUS



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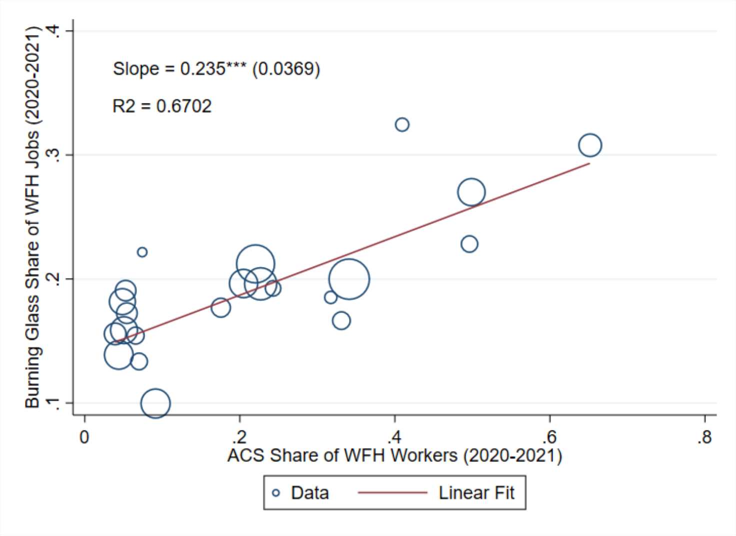
Appendix: Burning Glass vs. ACS



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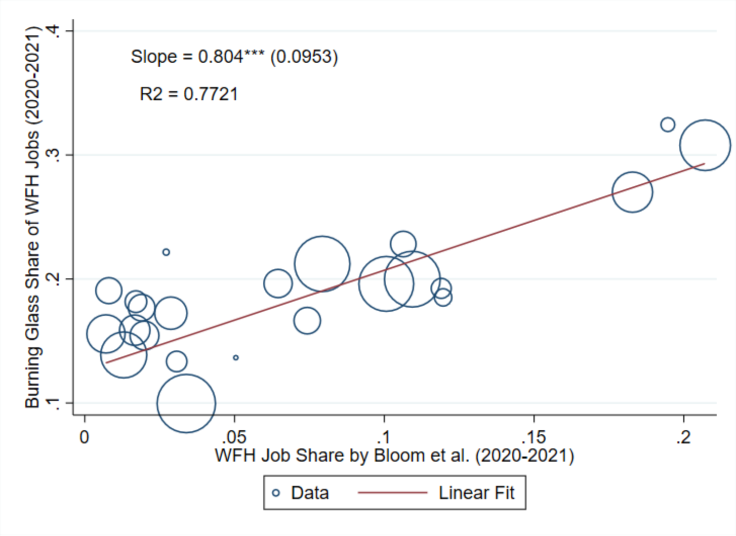
Appendix: Burning Glass vs. Bloom et al. (2022)



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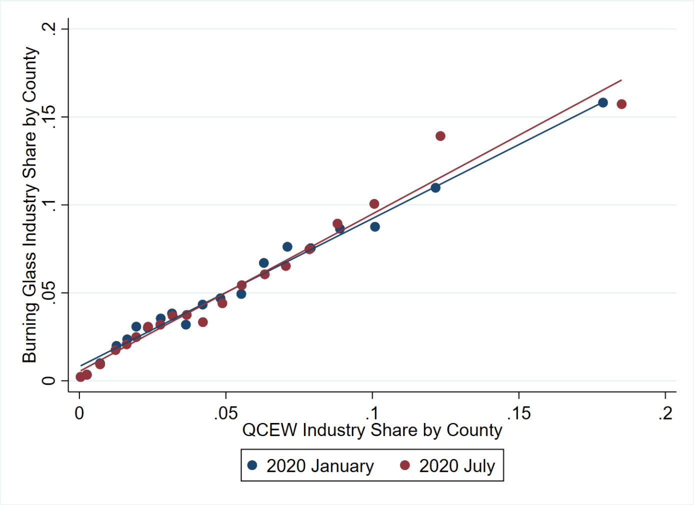
Appendix: Industry Share in QCEW vs. Burning Glass



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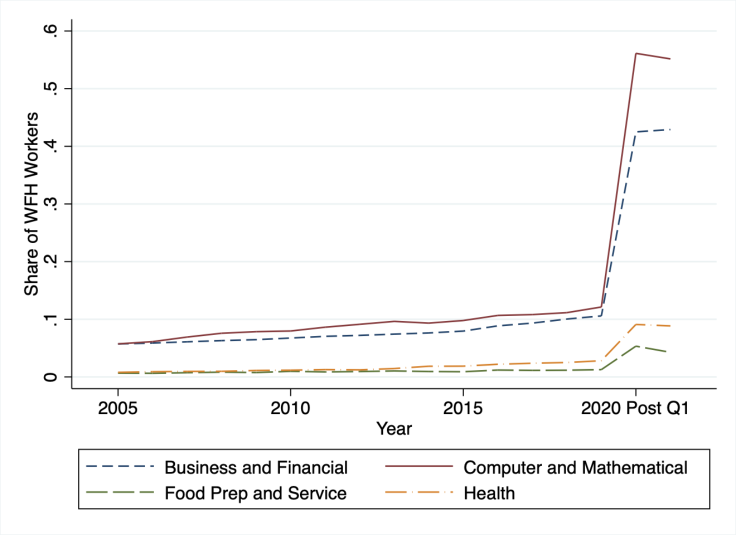
Share WFH across Occupation (ACS)



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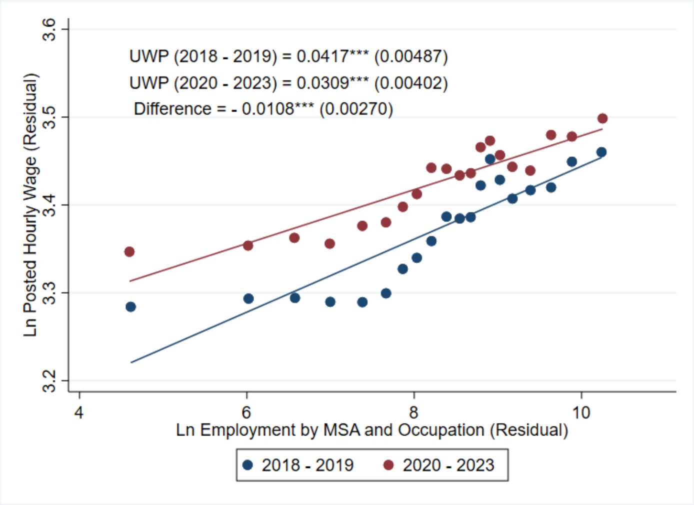
Appendix: UWP in High-WFH Occupations



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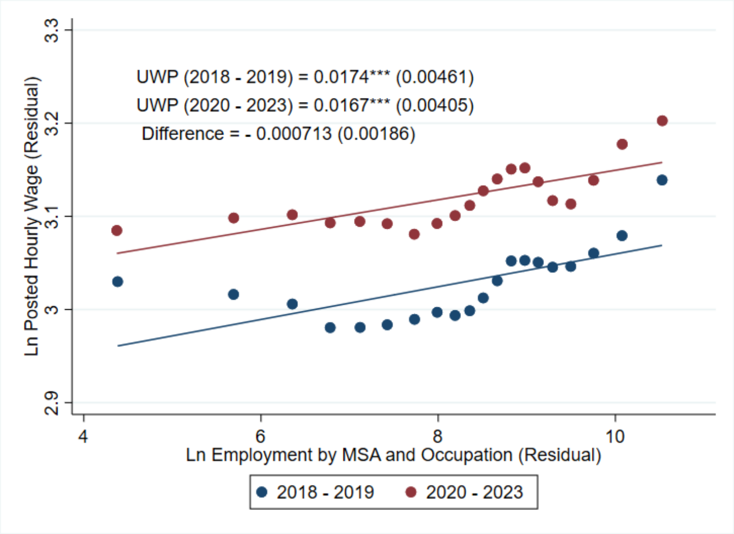
Appendix: UWP in Low-/Moderate-WFH Occupations



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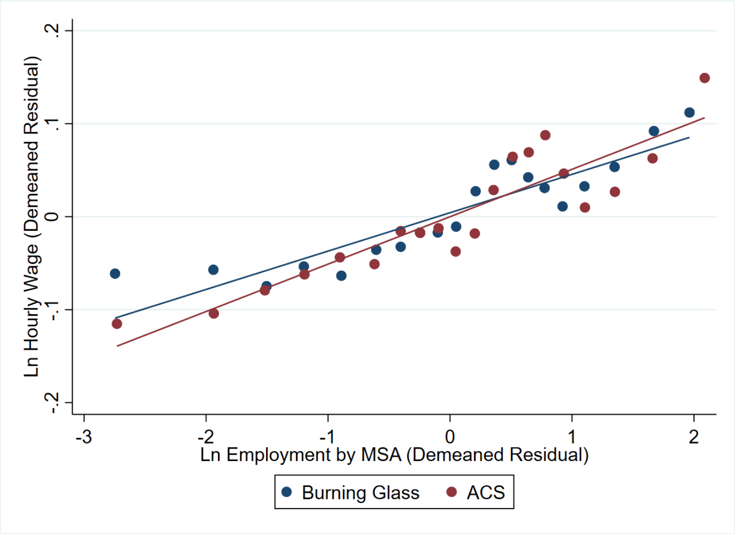
Appendix: UWP in 2019 ACS



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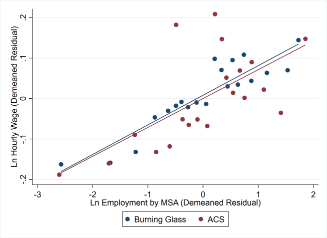
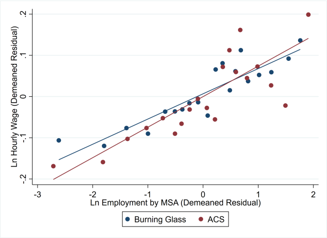
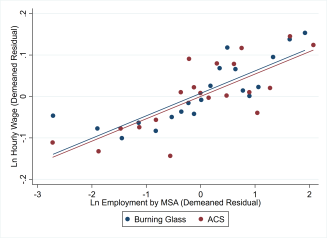
Appendix: UWP in 2019 ACS



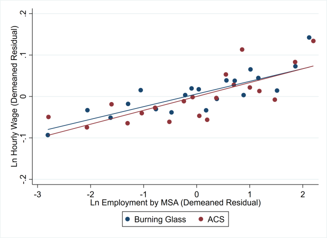
(a) Computer & Math



(b) Business and Finance



(c) Food Services



(d) Health

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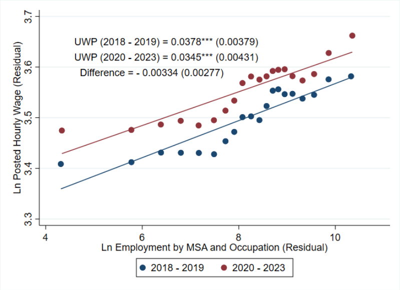
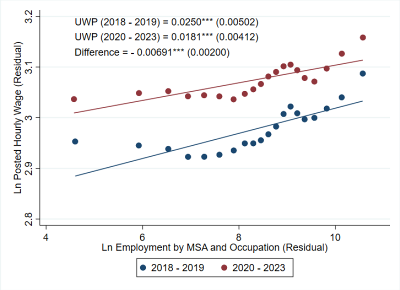
Appendix: UWP by Education



(a) College Required



(b) No College Required

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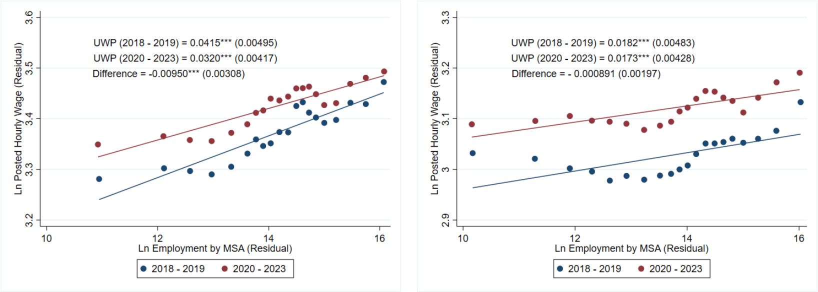
Appendix: UWP with MSA-level Employment



(a) High-WFH

(b) Low- and Moderate-WFH

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Changes in the Urban Wage Premium: Additional Controls

	Log Posted Hourly Wages			
	(1)	(2)	(3)	(4)
Log M	0.0275***	0.0204***	0.0169***	0.0175***
	(0.00842)	(0.00658)	(0.00405)	(0.00340)
Log M $\times$ Moderate WFH	0.0122***	0.00844***	0.0193***	0.0141***
	(0.00129)	(0.00114)	(0.00165)	(0.00132)
Log M $\times$ High WFH	0.0130***	0.0108***	0.0267***	0.0223***
	(0.00234)	(0.00210)	(0.00316)	(0.00254)
Log M $\times$ Post	0.00238	0.00277	0.00176	0.000676
	(0.00480)	(0.00379)	(0.00108)	(0.00108)
Log M $\times$ Moderate WFH $\times$ Post	-0.00538***	-0.00363***	-0.00944***	-0.00629***
	(0.000818)	(0.000678)	(0.000753)	(0.000658)
Log M $\times$ High WFH $\times$ Post	-0.00267*	-0.00513***	-0.0123***	-0.0127***
	(0.00160)	(0.00124)	(0.00157)	(0.00136)
Controls: Job Characteristics	X	X	X	X
Controls: MSA FE $\times$ Post, Occ $\times$ Post	X	X		
Controls: Skill Requirements		X		X
WFH Def Based on	SOC Occ.	SOC Occ.	NAICS Ind.	NAICS Ind.
Observations	7,316,061	5,996,739	7,316,072	5,996,752

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Changes in the Urban Wage Premium: Average Weekly Earnings from QCEW

	Log Average Weekly Earnings	
	(1)	(2)
Log M $\times$ Post	0.00277***	
	(0.000798)	
Log M $\times$ 2020		0.00242**
		(0.000958)
Log M $\times$ 2021		0.00200***
		(0.000728)
Log M $\times$ 2022		0.00528***
		(0.00130)
Log M $\times$ Moderate WFH $\times$ Post	-0.00399***	
	(0.000783)	
Log M $\times$ High WFH $\times$ Post	-0.0185***	
	(0.00273)	
Log M $\times$ Moderate WFH $\times$ 2020		0.00194
		(0.00163)
Log M $\times$ Moderate WFH $\times$ 2021		-0.00127
		(0.000878)
Log M $\times$ Moderate WFH $\times$ 2022		-0.00936***
		(0.00130)
Log M $\times$ High WFH $\times$ 2020		-0.00861***
		(0.00258)
Log M $\times$ High WFH $\times$ 2021		-0.00732
		(0.00585)
Log M $\times$ High WFH $\times$ 2022		-0.0290***
		(0.00303)
Observations	1,921,245	1,921,245

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Changes in the Urban Wage Premium: Across Counties Within MSAs

	Log Posted Hourly Wages	
	(1)	(2)
Log M	0.0117***	0.00794***
	(0.00278)	(0.00174)
Log M $\times$ Moderate WFH	0.0192***	0.0170***
	(0.00196)	(0.00129)
Log M $\times$ High WFH	0.0268***	0.0290***
	(0.00353)	(0.00259)
Log M $\times$ Post	0.00454***	0.00156**
	(0.000672)	(0.000608)
Log M $\times$ Moderate WFH $\times$ Post	-0.0103***	-0.00654***
	(0.000775)	(0.000664)
Log M $\times$ High WFH $\times$ Post	-0.0118***	-0.0127***
	(0.00155)	(0.00122)
Controls: Job Characteristics	X	X
Controls: MSA $\times$ M / H WFH $\times$ Post		X
Measurement of M	Emp Size by Occ and County	Emp Size by Occ and County
Observations	7,429,678	7,315,951

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Changes in the Urban Wage Premium by Occupation's WFH Adoption Level and Jobs' WFH Compatibility

		Log Hourly Wages		
		(1)	(2)	(3)
Panel A: Burning Glass Data 2018–2023 (All Jobs)				
Log M	WFH Jobs	0.0312***	0.0409***	0.0233***
		(0.00484)	(0.00451)	(0.00425)
	Other Jobs	0.0426***	0.0345***	0.0180***
		(0.00438)	(0.00434)	(0.00411)
Log M $\times$ Post	WFH Jobs	-0.00595**	-0.0131***	-0.00668***
		(0.00269)	(0.00262)	(0.00232)
	Other Jobs	-0.0113***	-0.00725***	-0.00002
		(0.00212)	(0.00101)	(0.00121)
Controls: Job Characteristics		X	X	X
Sample		Occupations with High WFH Adoption	Occupations with Moderate WFH Adoption	Occupations with Low WFH Adoption
Observations		563,244	2,573,786	2,893,292
Panel B: ACS Data 2018–2021 (Onsite Workers Only)				
Log M		0.0796***	0.0620***	0.0371***
		(0.00900)	(0.00763)	(0.00696)
Log M $\times$ Post		-0.0123***	-0.0116***	-0.00595***
		(0.00283)	(0.00219)	(0.00151)
Controls: Worker Characteristics		X	X	X
Sample		Occupations with High WFH Adoption	Occupations with Moderate WFH Adoption	Occupations with Low WFH Adoption
Observations		315,494	1,044,938	1,140,382

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Changes in the Urban Wage Premium: Compensating Wage Differentials

	Log Hourly Wage		Commute Time	
	(1)	(2)	(3)	(4)
High WFH	0.355***	0.196***	0.249**	0.119
	(0.0170)	(0.0099)	(0.0987)	(0.1000)
High WFH $\times$ Post	-0.0135	0.0023	2.838***	3.671***
	(0.00948)	(0.00895)	(0.335)	(0.324)
Pre-Pandemic Commute	-0.00746***	-0.00344***	0.989***	0.985***
	(0.00114)	(0.00066)	(0.00438)	(0.00441)
Pre-Pandemic Commute $\times$ Post	-0.00052	-0.00036	-0.060***	-0.101***
	(0.00035)	(0.00030)	(0.0138)	(0.0124)
High WFH $\times$ Pre-Pandemic Commute	0.00693***	0.00348***	-0.00398	-0.00554
	(0.00064)	(0.00036)	(0.00366)	(0.00366)
Hig -WFH $\times$ Pre-Pandemic Commute $\times$ Post	0.00059*	0.00064**	-0.370***	-0.351***
	(0.00033)	(0.00031)	(0.0124)	(0.0120)
Controls: Year FE $\times$ MSA FE	Yes	Yes	Yes	Yes
Controls: Year FE $\times$ Worker Characteristics	No	Yes	No	Yes
Observations	7,471,296	7,471,296	7,313,590	7,313,590

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Gelbach Decomposition of UWP (1/2)

- Baseline equation for changes in UWP for high-WFH jobs:

$$\ln(w_{ikjt}) = \gamma_0 \ln M_{kj} + \gamma_1 Post_t + \gamma_2 \ln M_{kj} \times Post_t + \mathbf{X}_{ikjt}\mathbf{\Psi} + \epsilon_{ikjt}.$$

  - γ_2: decline in the urban wage premium.

- How much γ_2 would diminish once we add skills in the equation? ($\gamma_2 \rightarrow \tilde{\gamma}_2$)

$$\begin{aligned}\ln(w_{ikjt}) = {} & \tilde{\gamma}_0 \ln M_{kj} + \tilde{\gamma}_1 Post_t + \tilde{\gamma}_2 \ln M_{kj} \times Post_t + \mathbf{X}_{ikjt}\tilde{\mathbf{\Psi}} \\ & + \sum_s \beta_0^s \ln M_{kj} \times Skill_i^s + \sum_s \beta_1^s Post_t \times Skill_i^s \\ & + \sum_s \beta_2^s \ln M_{kj} \times Post_t \times Skill_i^s + \tilde{\epsilon}_{ikjt}.\end{aligned}$$

- Which skills account for γ_2, quantitatively?

Gelbach Decomposition of UWP (2/2)

- Take one covariate at a time:

$$\ln M_{kj} \times Post_t \times Skill_i^s = \Gamma_0^s \ln M_{kj} + \Gamma_1^s Post_t \\ + \Gamma_2^s \ln M_{kj} \times Post_t + \mathbf{X}_{ikjt}\mathbf{\Gamma}_{\boldsymbol{x}} + \eta_{ikjt}.$$

  - Γ_2^s: How much the covariate co-varies with main variable of interest.

- Gelbach decomposition:

$$\hat{\pi}^s = \frac{\hat{\Gamma}_2^s \cdot \hat{\beta}_2^s}{\hat{\gamma}_2},$$

where $\hat{\pi}^s$ is the fraction of $\hat{\gamma}_2$ that can be attributed to $\hat{\beta}_2^s$.

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