The Unexpected Compression: Competition, wages and inequality during the U.S. recovery

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(based on joint work with David Autor and Annie McGrew)

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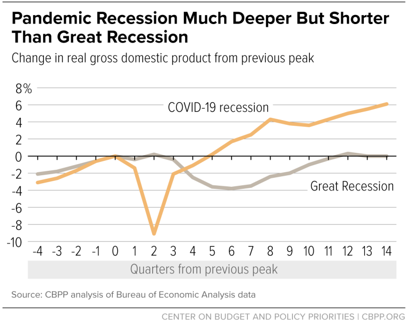
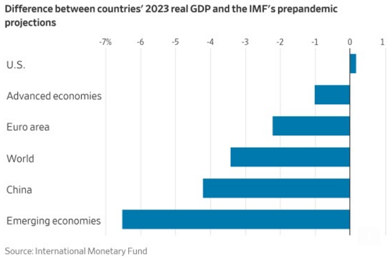
Recession, relief, and recovery

- The pandemic downturn was met with a strong fiscal response in the U.S.
  - CARES ACT, American Rescue Plan
- The pandemic downturn recovery has been much faster than previous downturns, especially the Great Recession
  - GDP recovery surprisingly strong
- Combination of pandemic-related disruptions, along with strong fiscal support $\rightarrow$ once-in-a-generation tight labor market.

1. What did historically tight labor market mean for wages, inequality, and inflation?
2. What was the role of labor market competition?



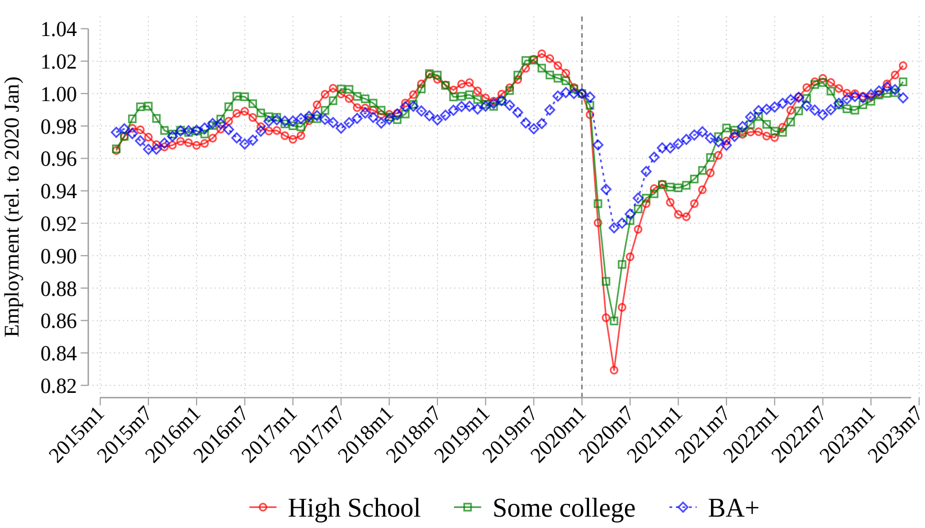


Plan of Attack

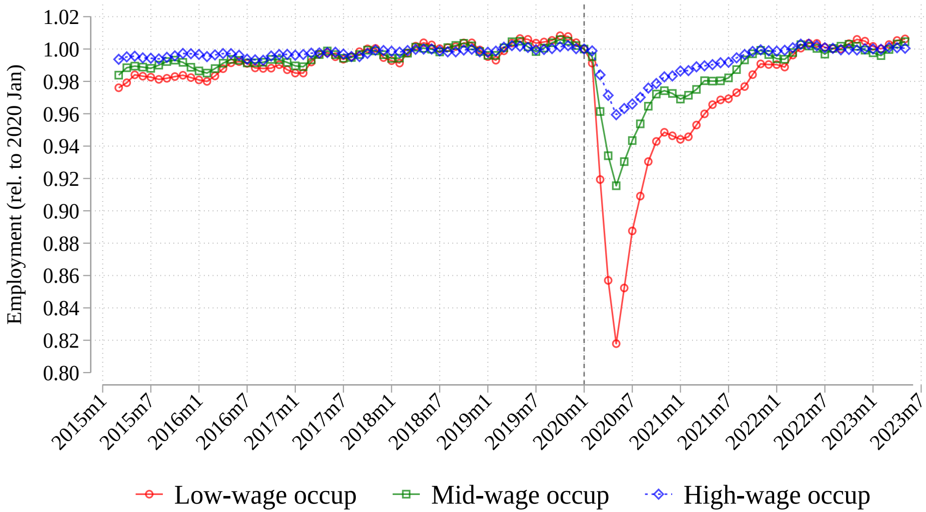
- Some unexpected facts: A sharp reversal in inequality, driven by rising wages among low-paid workers
- A simple conceptual framework: Changes in *demand* versus changes in *competition*
- Evidence on changes in demand vs. changes in competition
  1. Rising job-to-job transition rates
  2. Labor market tightness and wage growth
  3. Who is quitting? The role of low pay
  4. Decomposing wage growth into movers and stayers
- Wage growth and price growth: What's the connection?
- Conclusion

Jobs Rebound: Participation rates have largely rebounded – and Emp/Pop has risen by even more than labor force participation

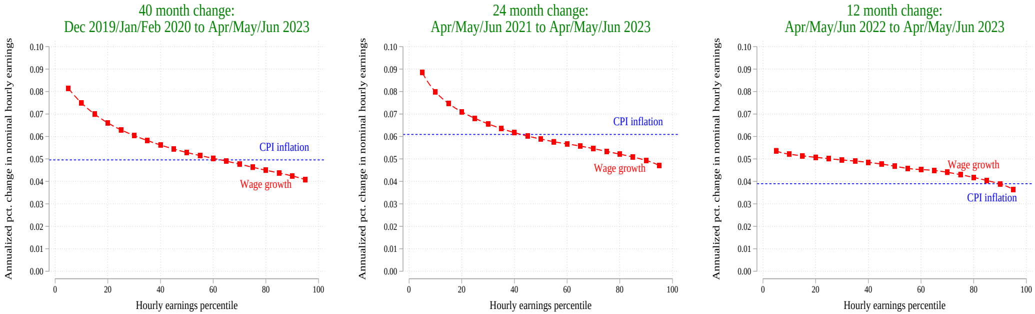
Education: Employment losses were much larger for non-college workers – but the rebound was also proportionately larger (2015-2023)



Occupations: Analogous pattern for low-, mid-, and high-wage occupations

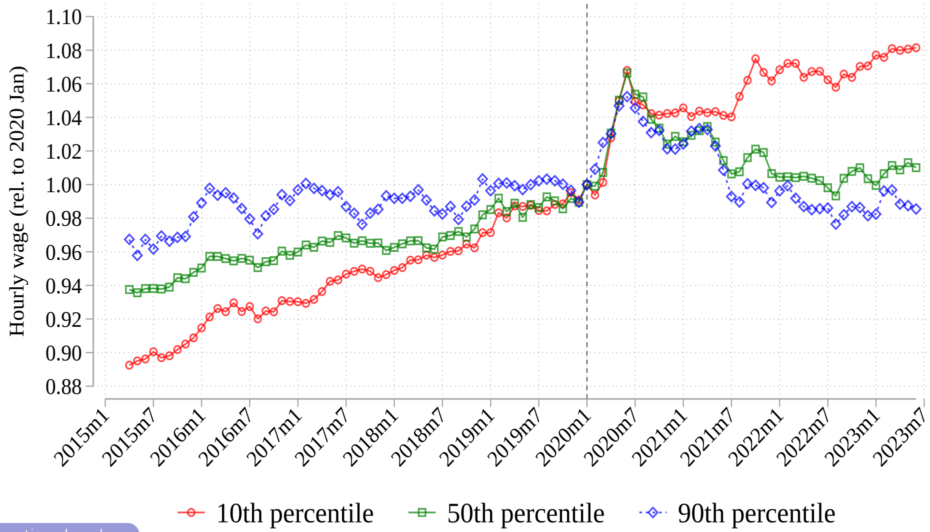


Substantial wage growth in bottom of wage distribution —
Inflation offset nominal gains above median until recently



Wage inequality: Real wage trends by quantiles

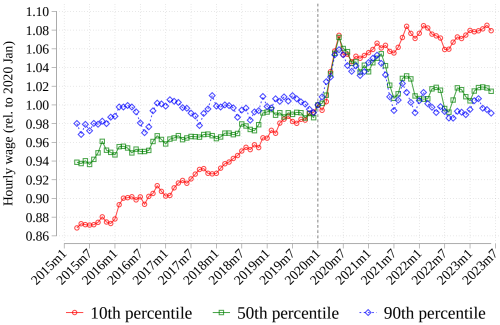
P10 growth > P50 growth > P90 growth



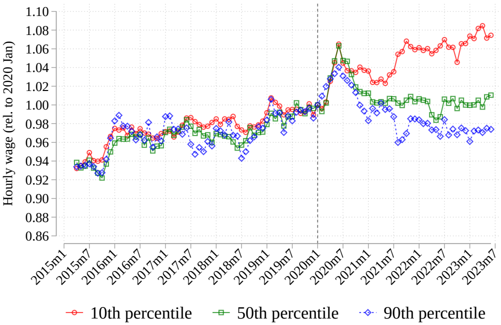
▸ Excluding tipped workers

Pre-pandemic wage compression was underway between 2015 and 2020 — But primarily in states that were raising their minimum wages

State minimum wage

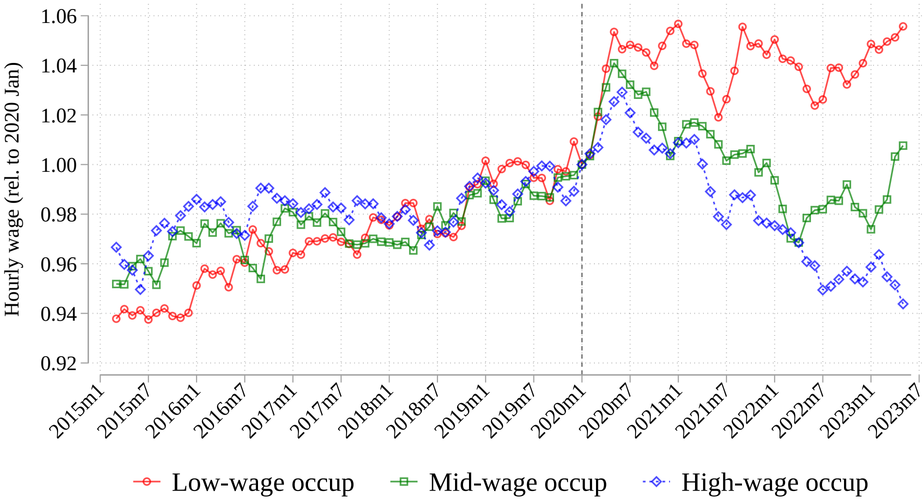


No state minimum wage



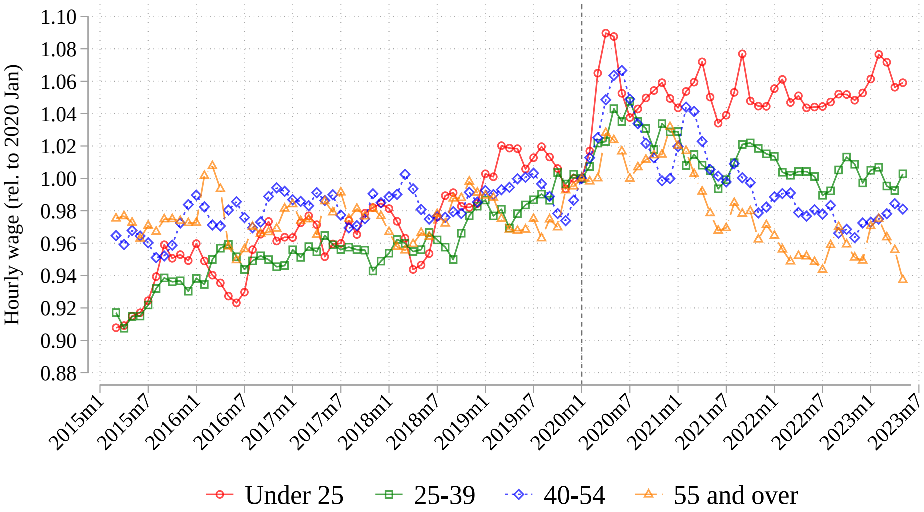
▸ Figure: Role of state min p10, p50, p90
▸ Figure: Role of state min 50-10 ratio

Occupational inequality: Real wage growth fastest in lowest-paid 3^{rd} of occs



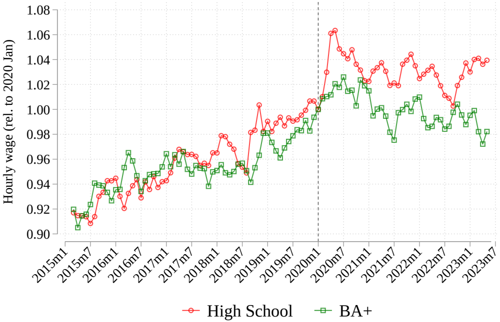
▸ Wage trends: routine v. non-routine tasks

Young v. old inequality: Wage growth fastest for youngest workers, <40, <25

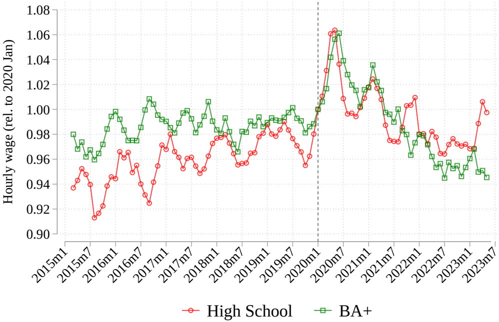


Educational inequality: High school workers < age 40 have steepest wage gains

HS vs. BA+ Under 40



HS vs. BA+ Age 40+

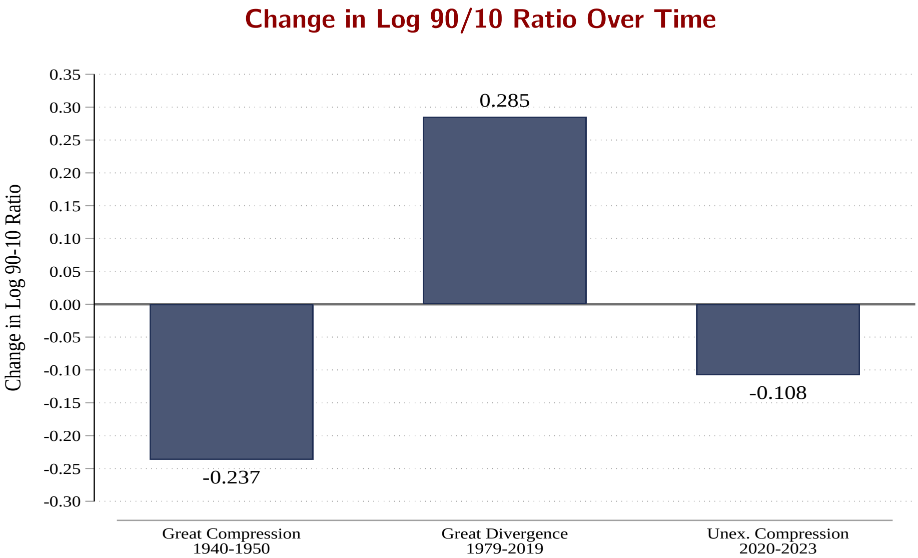


▸ Wage trends: Non-BA vs. BA, by age

Additional wage trends

- **By race**
  - Fig: Wage trends by race
- **By sex**
  - Fig: Wage trends by sex
- **By education and state minimum wage status**
  - Fig: Wage trends by education and state minwage status
- **By education groups**
  - Fig: Wage trends by 3-category education
  - Fig: Wage trends by 5-category education

Unexpected compression in historical perspective



The Great Reshuffle Rise in quit rates concentrated in low-wage sectors

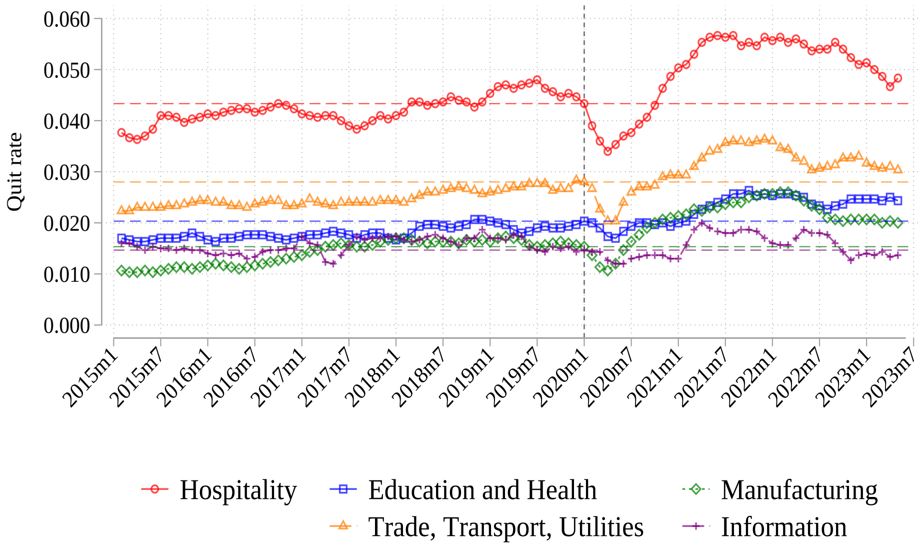
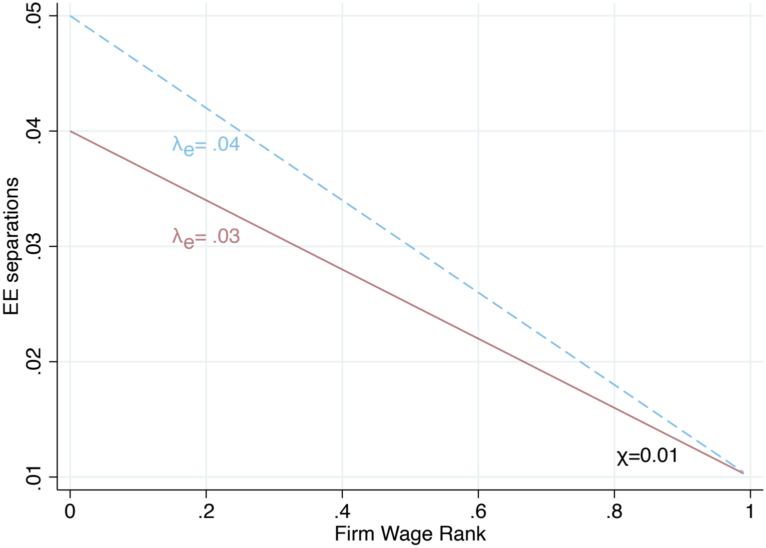


Fig: Overall quits

Critical question: Why did the quit rate rise so much, and what impact did it have on inequality?

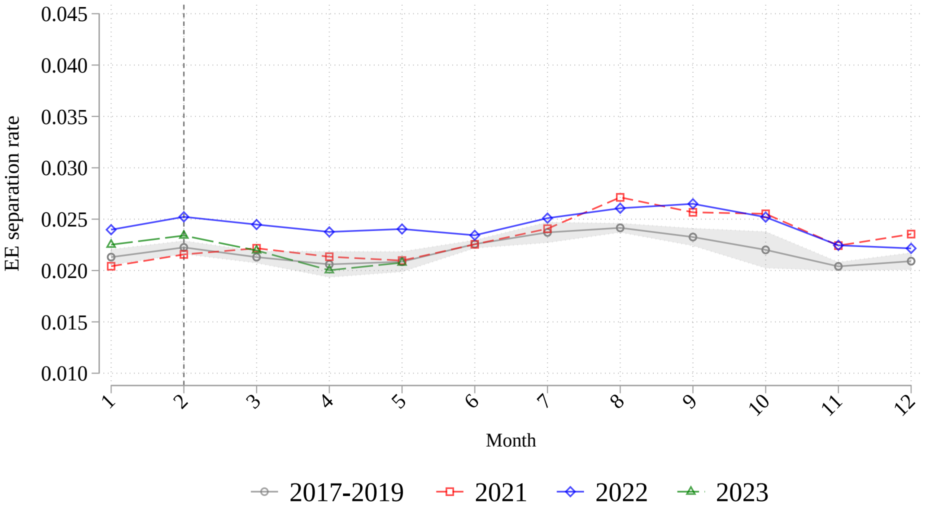
- Pandemic-related concerns including reduced employer attachment and increased 'footlooseness, as well as increased savings during the pandemic, and word of mouth.
- Theoretical explanation deriving from canonical job ladder model Burdett, Mortensen '98
  - Tighter labor market—either through greater vacancies (demand) or reduced labor supply—leads to higher rate of job offer arrival
  - Key mechanism: quits (or EE separations) rise most at worst-paying jobs, as workers move up the job ladder
  - Increase in "quit elasticity"—key proximate measure of labor market power
  - Raises wages most strongly at the bottom of pay distribution
  - Reallocates work away from low-productivity

Rise in job contact rate (tightness) causes larger jump in job-to-job separations at low wage rank firms

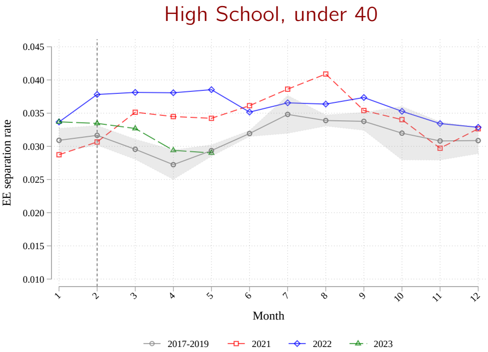


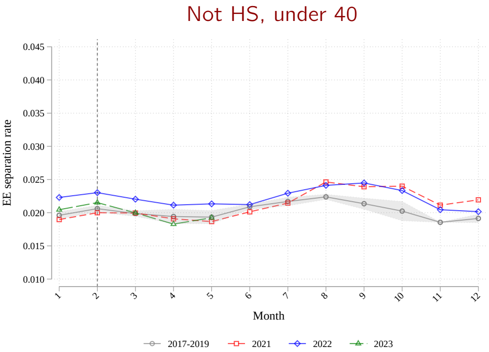
Overall monthly employment-to-employment (EE) separation rates:

Approximately 6% above pre-pandemic levels

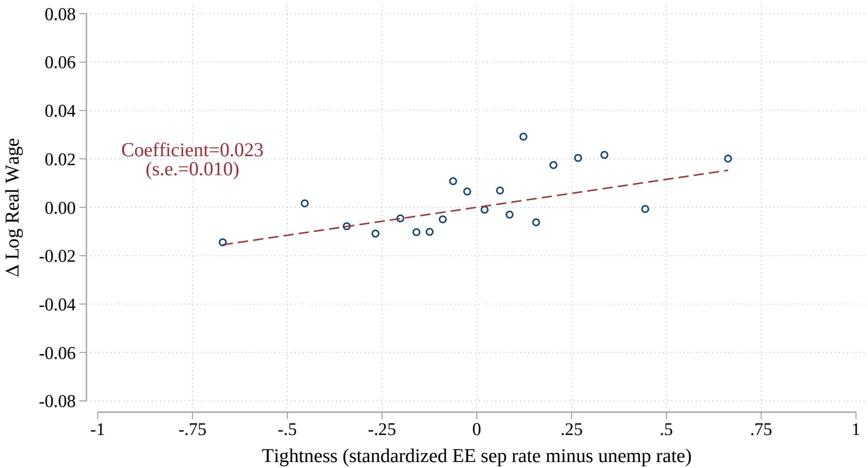


Rising transition rates driven by young, high school-educated workers





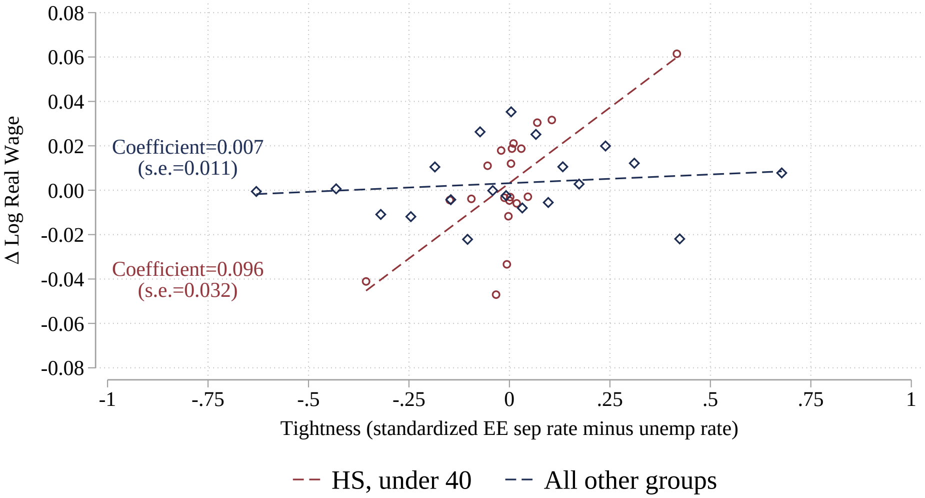
State-level wage-Phillips curve: Wages rising faster in tighter markets



Estimating equation: $\ln W_{iskt_k} = \beta \left(\text{Tightness}_{skt_{k=0}} \times \mathbb{1}\left[t_k = 1\right]\right) + X_i^{'}\gamma_k + \alpha_{kt_k} + \delta_{sk} + e_{iskt_k}$

▸ Specification

State-level wage-Phillips curve steeper for high school $<$ 40 v. everyone else



Specification   Table: WPC by age & education

Many additional wage-Phillips results and cuts of the data

- **By wage quartile**

  ▸ Figure: WPC Quartiles ▸ Table: WPC by quartiles

- **By age and education**

  ▸ Table: WPC by age & education

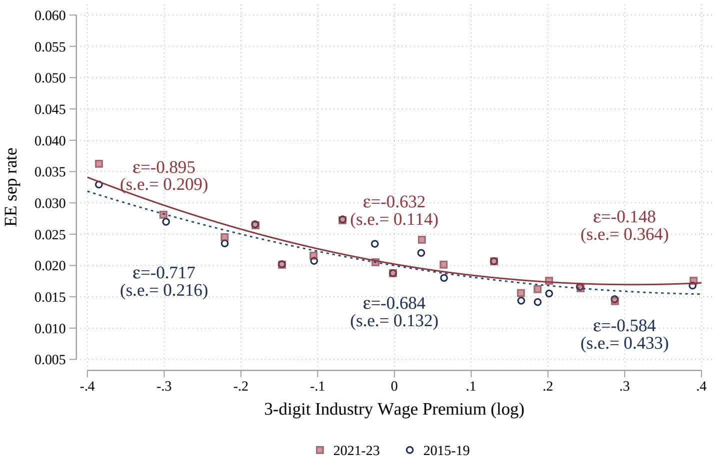
- **With many sets of controls**

  ▸ Table: WPC - trim 15^{th} percentile ▸ Table: WPC - pooled estimates

- **Historical estimates**

  ▸ Figure: WPC - estimates over time

The aggregate wage-separation elasticity has not changed much — Pooling all education levels

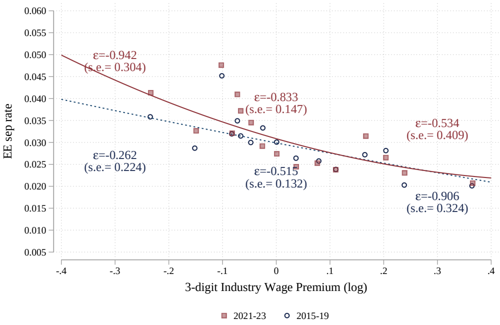


Estimating equation: $\text{EEsep}_{it} = a + \beta_1 \ln \tilde{w}_{j(i),t-1} + \beta_2 \ln \tilde{w}^2_{j(i),t-1} + X'_{it}\gamma + e_{it}$

Specification | Table: Overall elasticities

The wage-separation elasticity has gotten steeper
Among high school workers < age 40

High School, Age < 40



Everyone but HS, under 40

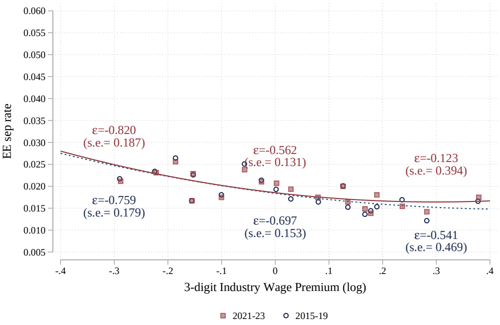
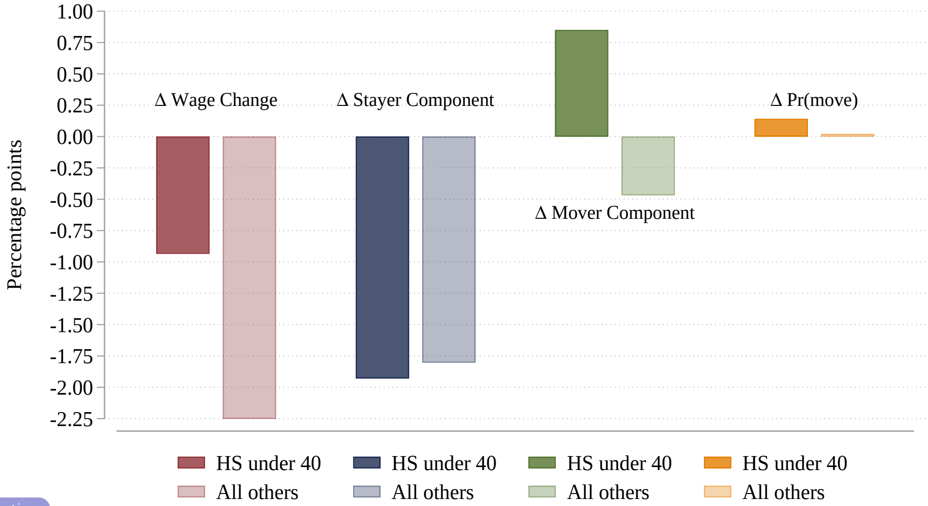


Table: HS elasticities | Figure: BA+ elasticities | Figure: Elasticities over time | Reallocation: Bottom half | Reallocation: Bottom quartile | Reallocation: Hospitality

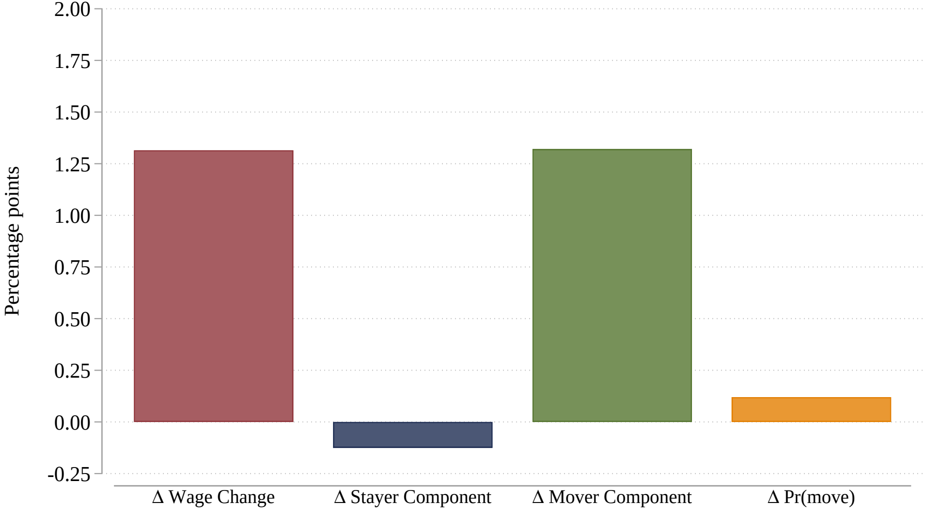
Decomposing contributions of switching vs. staying to total wage change
Contrasting post-pandemic to pre-pandemic



Specification

Decomposing difference in wage change: HS $<$ 40 vs. all others

Contrasting post-pandemic to pre-pandemic, HS $<$ 40 vs. all others



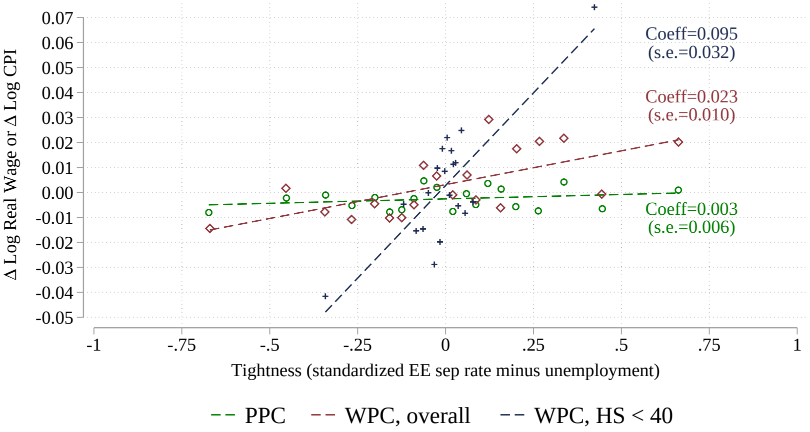
▸ Table

Labor market tightness, inflation, and real wages: Key questions

How much does tightness contribute to inflation?

How much does inflation erode the beneficial effects of tightness on wages?

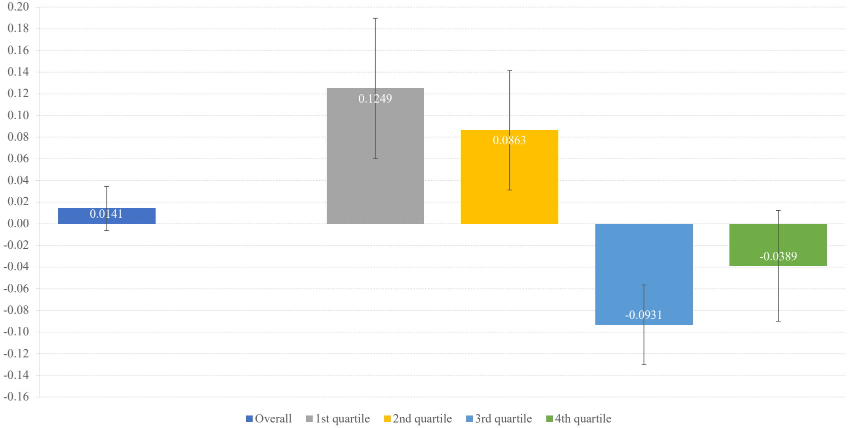
Wage Phillips Curves vs. Price Phillips Curve



Estimating equation: $\ln P_{ir(s)kt_k} = \beta \left(\text{Tightness}_{r(s)kt_{k=0}} \times \mathbb{1}\left[t_k = 1\right] \right) + X_i^{'} \gamma_k + \alpha_{kt_k} + \delta_{kt_k} + e_{ir(s)kt_k}$

▸ Specification ▸ Table: WPC vs PPC ▸ Table: WPC vs PPC periodized

Real Wage Phillips Curve – by Wage Quartile



▸ Table: Real WPC by Quartile ▸ Table: Real WPC by education ▸ Figure: Inflation inequality (Jaravel)

Labor market tightness, inflation, and real wages: Summary

1. Labor market tightness had greater impact on <u>mean</u> local wages than prices
2. Estimates imply that labor market tightness (and wage growth) contributed little to post-pandemic inflation
    - About 13% of 4.9 percent rise btwn 2021 – 2023q2 ▸ Figure
3. Tightness associated with **real wage growth** among bottom two quartiles of workers, young high school and some-college workers
4. But what about <u>inflation inequality</u>: Are low-wage workers subject to disproportionate inflation? Jaravel '22

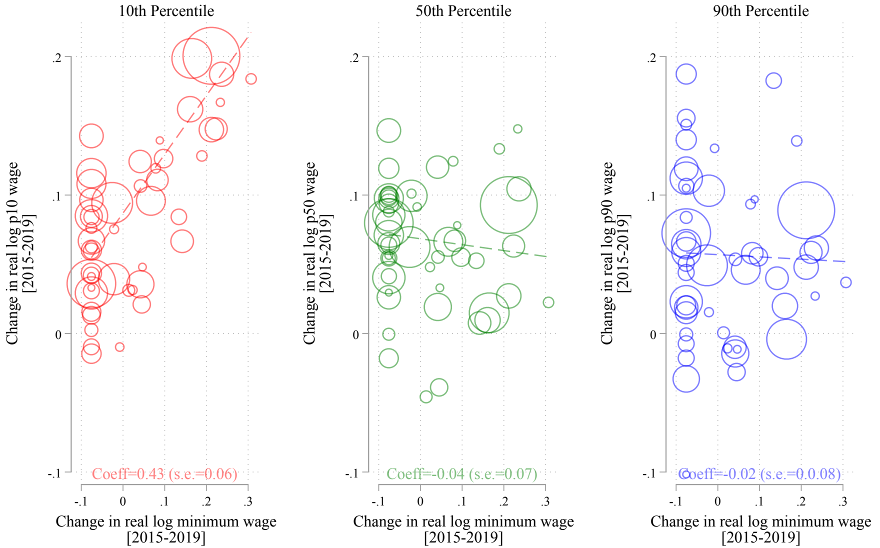
Conclusions

1. For first time in four decades, wage inequality falling, due to rising lower tail
2. Despite inflation, *real wages rising* among young HS grads, 1st-2nd quartile workers
3. Driven by 'tight' labor markets—but what does this mean in practice?
   - The *simplest explanation* is that labor markets are operating on a higher point on the labor demand curve
   - Evidence indicates this explanation *too simple*: Competition has intensified
4. Distinction is critical: Rising competition means higher wages that better reflect productivity *and* higher aggregate productivity — a double dividend

Thank you

Appendix slides

Aside: Role of state minimum wage laws in wage compression, 2015–2019



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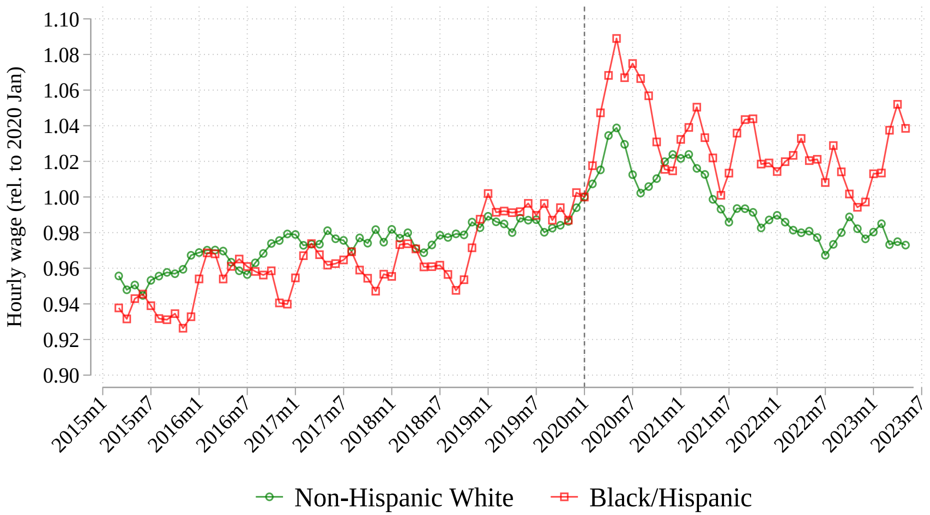
Aside: Role of state minimum wage laws in wage compression, 2015–2019

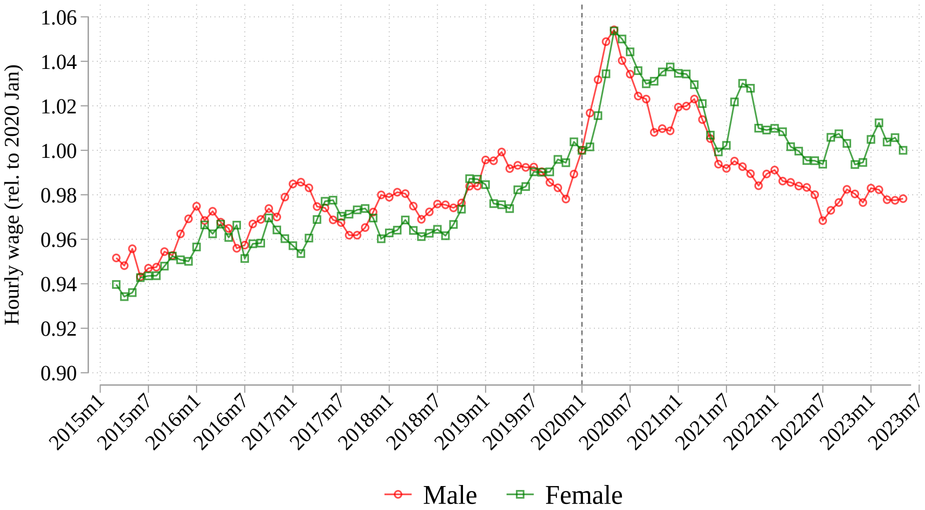
Back

Racial/ethnic inequality: Notable fall in Black/Hispanic wage deficit



Slide: Additional wage trends

Gender inequality: Slight change in gender wage gap

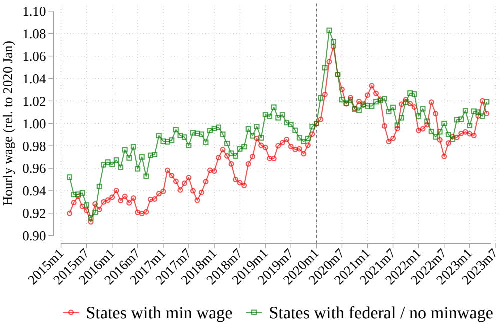


◂ Slide: Additional wage trends

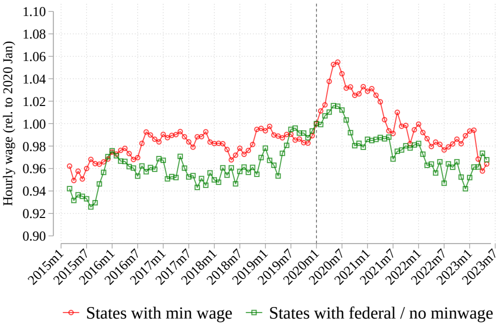
Wage gains for High school vs. BA+ workers by state minimum wage status

State minimum wages compressing HS wages pre- but not post-pandemic

High school workers

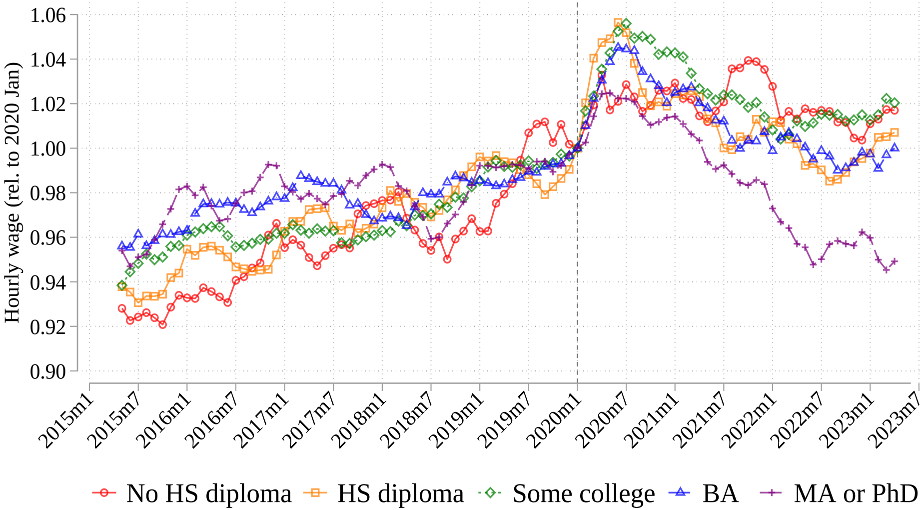


BA+ workers



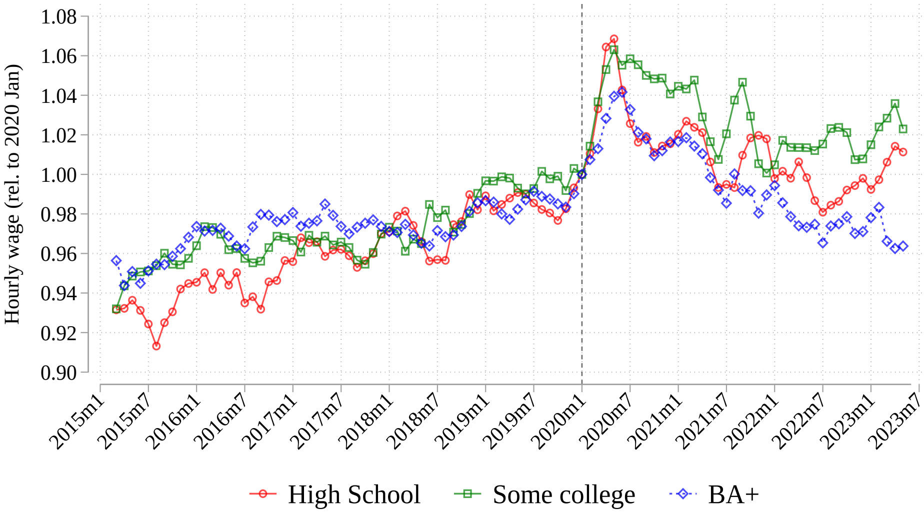
Slide: Additional wage trends

Remarkable overtaking of wage growth among less educated workers, 2015-2023



Slide: Additional wage trends

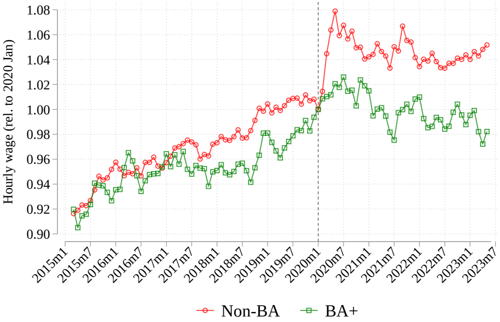
Remarkable overtaking of wage growth among Non-college-educated workers, 2015-2023



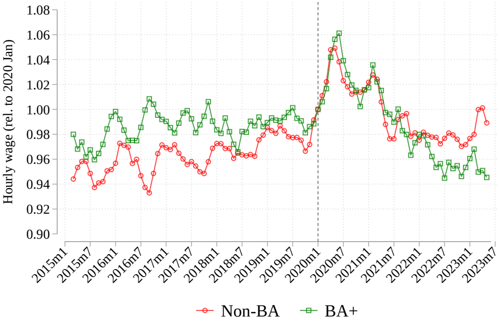
◂ Slide: Additional wage trends

Steepest wage gains found among non-college grads under age 40, 2015-2023

Non-BA vs. BA Under 40



Non-BA vs. BA Age 40+



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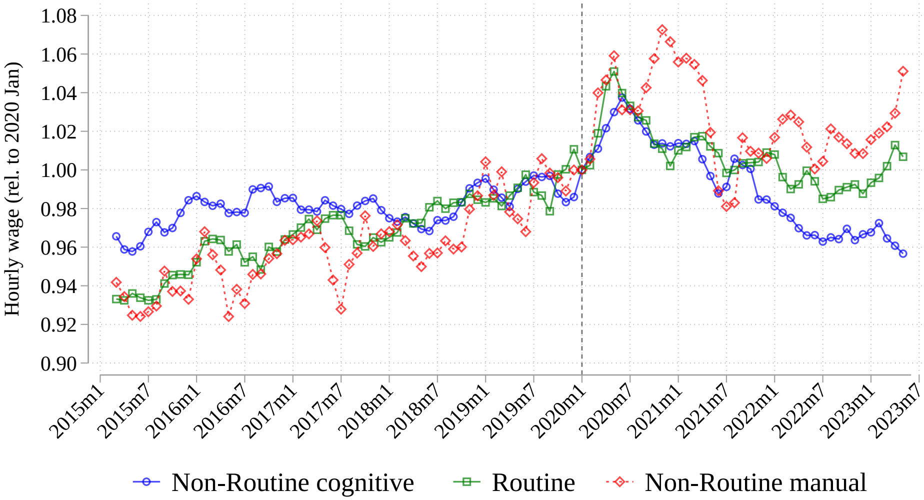
Routine v. non-routine cognitive v. non-routine manual occupations

Wage growth fastest in ‘less-skilled’ occupations (2015-2023)



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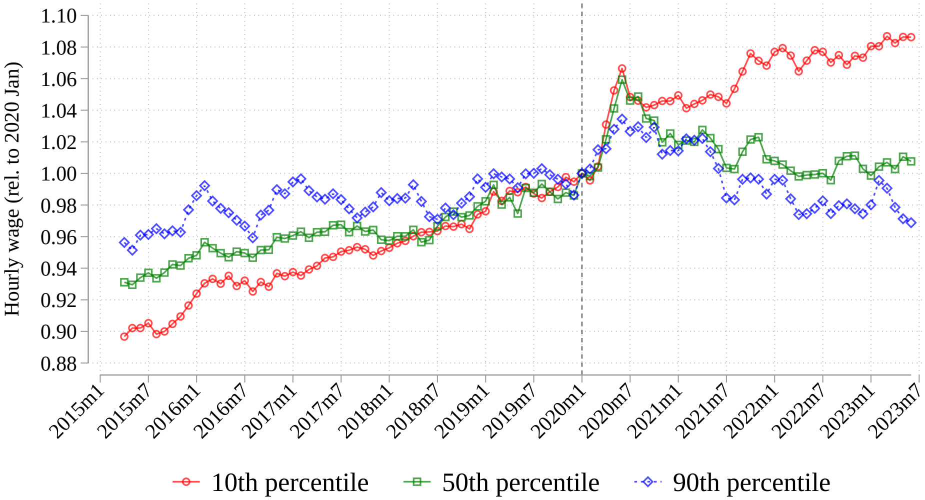
Wage growth at bottom of the wage distribution

Excluding workers not earnings tips, overtime, commissions



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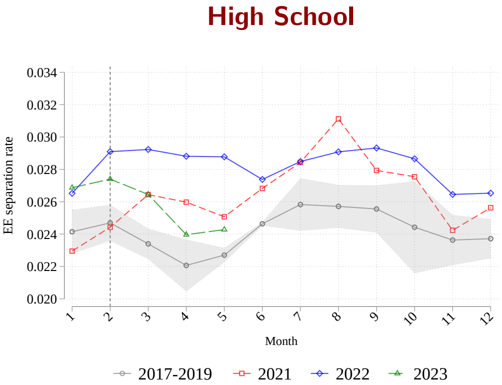
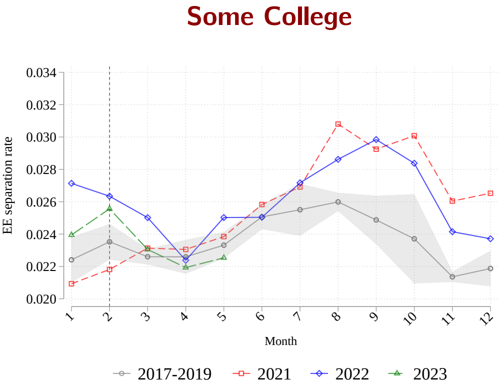
Job-to-job transitions: non-BA workers





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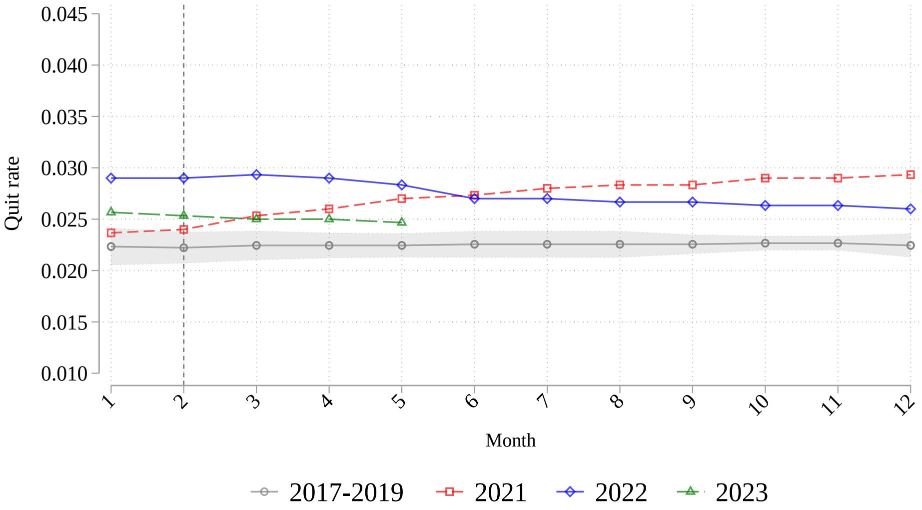
Rising monthly quit rates:

Approximately 20% above pre-pandemic levels



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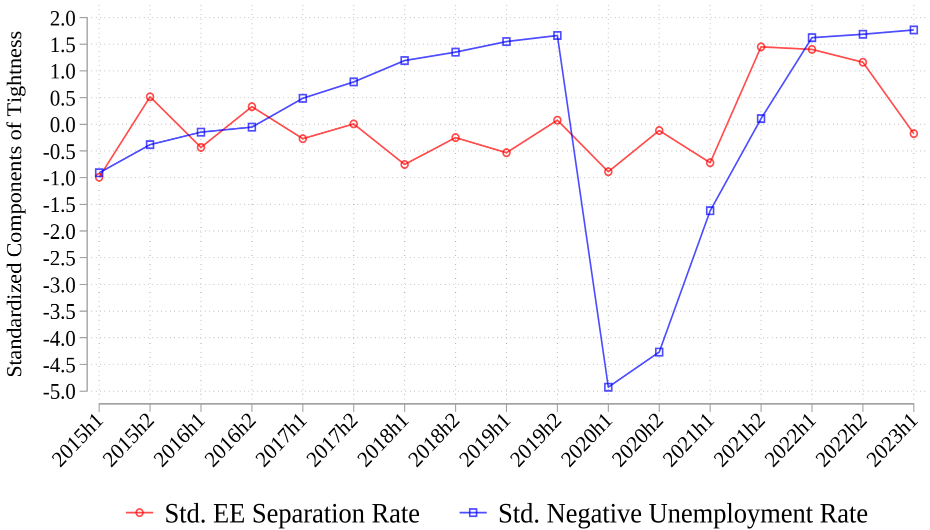
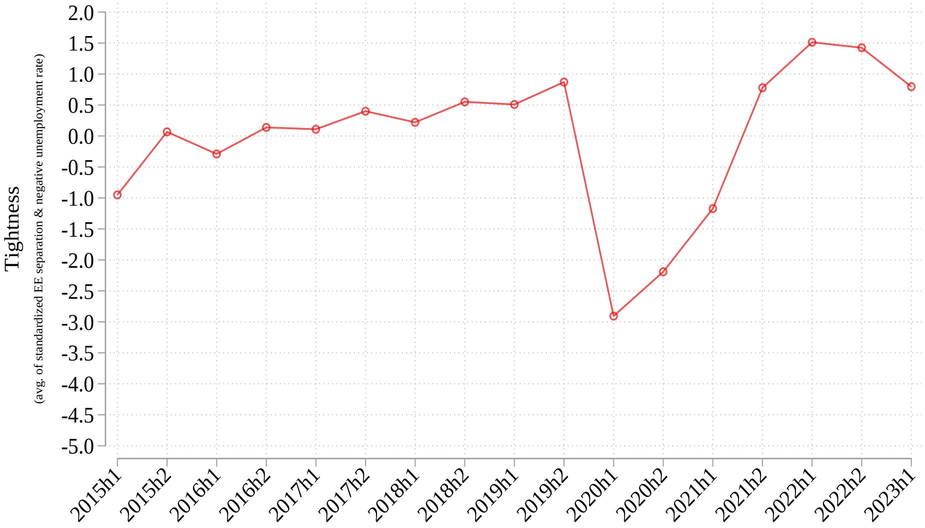
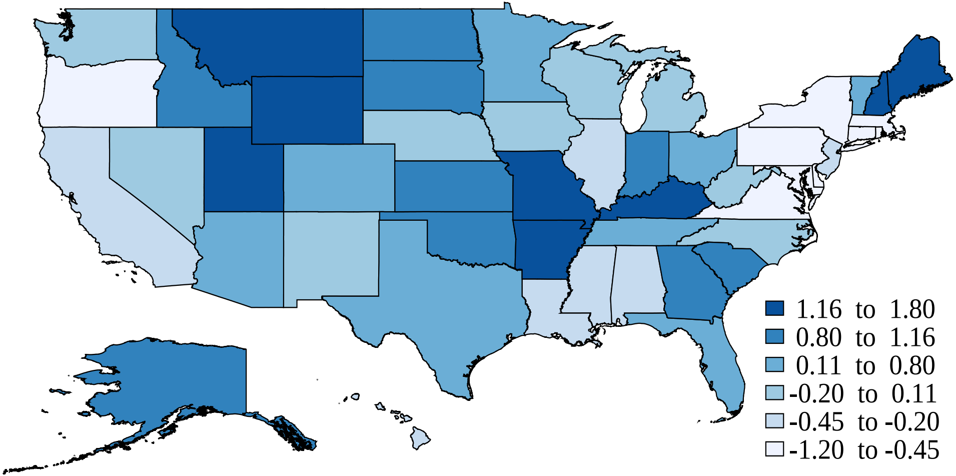
Components of tightness measure: EE separations and (-) unemployment



Composite tightness measure: Sharp increase in tightness post-pandemic



Cross-state variation in tightness (2021 - 2023)



Tightness and wage growth: Wage-Phillips curves

- Measuring labor market tightness: two ingredients
  1. Unemployment rate
  2. Job-to-job separation rate

- Tightness combines standardized EE-Sep and Unemp

$$\text{Tightness}_{st} = 0.5 \times \text{STD}(\text{Job-to-job separation rate}_{st}) - 0.5 \times \text{STD}(\text{Unemp}_{st})$$

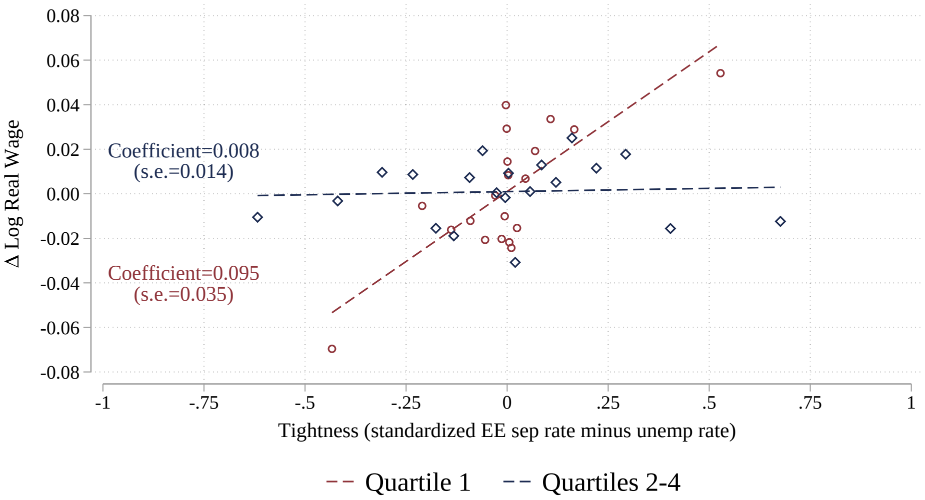
- Estimating equation: Annualized quarterly $\Delta \ln W$ between 2021q1 and 2023q2

$$\ln W_{iskt_k} = \beta \left(\text{Tightness}_{skt_{k=0}} \times \mathbb{1}\left[t_k = 1\right]\right) + X_i^{'}\gamma_k + \alpha_{kt_k} + \delta_{sk} + e_{iskt_k}$$

  - Tightness is measured at the state (s) and quarter level (kt_k)
  - Wages from person-level microdata (i) with SE's clustered at state level
  - Controls: Education, age group, sex, race, sector (manuf, finance, business svcs, prof svcs), state Covid death rate

Figure: Overall Figure: Age/Educ

State-level wage-Phillips curve especially steep for bottom quartile



◂ Back ▸ Table: WPC by quartiles

Nominal Wage Phillips Curve – by Wage Quartile

	(1)	(2)	(3)	(4)	(5)
Overall	0.0315**	0.0244**	0.0260**	0.0231**	0.0231**
	(0.0136)	(0.0118)	(0.0103)	(0.0097)	(0.0097)
Within wage quartiles					
1st Quartile	0.1269***	0.1271***	0.1220***	0.1216***	0.1216***
	(0.0387)	(0.0384)	(0.0378)	(0.0378)	(0.0378)
2nd Quartile	0.0958***	0.0967***	0.0945***	0.0930***	0.0930***
	(0.0309)	(0.0306)	(0.0293)	(0.0290)	(0.0290)
3rd Quartile	-0.0737***	-0.0743***	-0.0705***	-0.0713***	-0.0713***
	(0.0201)	(0.0201)	(0.0200)	(0.0199)	(0.0199)
4th Quartile	-0.0163	-0.0192	-0.0168	-0.0157	-0.0157
	(0.0283)	(0.0282)	(0.0271)	(0.0268)	(0.0268)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Dependent variable is log wage. All specifications include state and period FE. Controls include age group, sex, race, education, industry (finance, manuf, business svcs, prof svcs), and state COVID death rates. Standard errors in parentheses, clustered at state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

◂ Fig: WPC Quartile 1 ◂ Slide: additional WPC findings

Nominal Wage Phillips Curve – by Age and Education

	(1)	(2)	(3)	(4)	(5)
High School, under 40	0.0928***	0.1146***	0.1057***	0.0953***	0.0953***
	(0.0354)	(0.0347)	(0.0340)	(0.0321)	(0.0321)
High School, 40+	0.1298**	0.1215**	0.1153**	0.1084**	0.1084**
	(0.0539)	(0.0518)	(0.0524)	(0.0506)	(0.0506)
Some College, under 40	0.1027***	0.0772***	0.0756***	0.0642**	0.0642**
	(0.0340)	(0.0273)	(0.0263)	(0.0252)	(0.0252)
Some College, 40+	0.0181	0.0099	0.0036	-0.0059	-0.0059
	(0.0293)	(0.0289)	(0.0274)	(0.0265)	(0.0265)
BA+, under 40	-0.0706**	-0.0720**	-0.0599**	-0.0471	-0.0471
	(0.0314)	(0.0314)	(0.0301)	(0.0303)	(0.0303)
BA+, 40+	-0.0281	-0.0351	-0.0385	-0.0386	-0.0386
	(0.0304)	(0.0318)	(0.0297)	(0.0301)	(0.0301)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Dependent variable is log wage. All specifications include state and period FE. Controls include age group, sex, race, education, industry (finance, manuf, business svcs, prof svcs), and state COVID death rates. Standard errors in parentheses, clustered at state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

◂ Fig: WPC HS under 40 vs. everyone ◂ Slide: additional WPC findings

Nominal Wage Phillips Curve – trimming bottom 15^{th} percentile

	(1)	(2)	(3)	(4)	(5)
Overall	0.0348***	0.0298***	0.0284***	0.0265***	0.0265***
	(0.0125)	(0.0114)	(0.0095)	(0.0091)	(0.0091)
1st Quartile	0.2057***	0.2048***	0.1936***	0.1930***	0.1930***
	(0.0308)	(0.0310)	(0.0283)	(0.0283)	(0.0283)
High School, under 40	0.1562***	0.1766***	0.1678***	0.1597***	0.1597***
	(0.0399)	(0.0394)	(0.0362)	(0.0349)	(0.0349)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Dependent variable is log wage. Observations trimmed to those above the 15th wage percentile at the state, period level. All specifications include state and period FE. Controls include age group, sex, race, education, industry (finance, manuf, business svcs, prof svcs), and state COVID death rates. Standard errors in parentheses, clustered at state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Slide: additional WPC findings

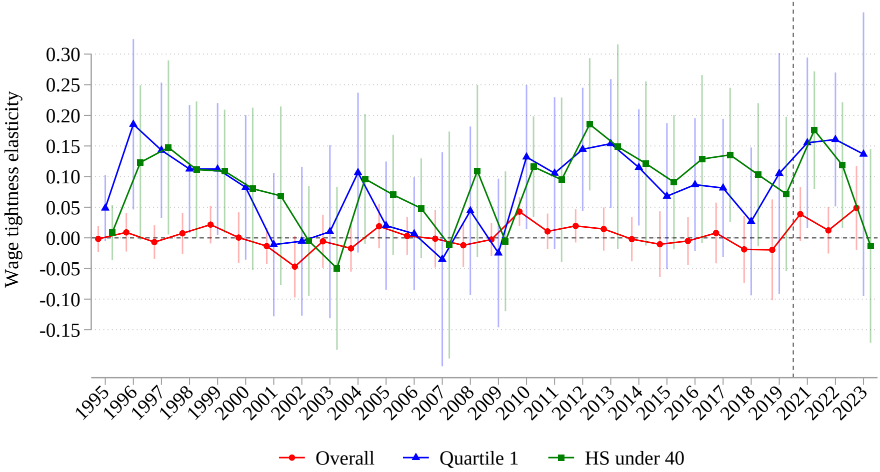
Nominal Wage Phillips Curve – pooled estimates

	(1)	(2)	(3)
A. Overall			
2015-2019	-0.0149	-0.0152	-0.0090
	(0.0148)	(0.0138)	(0.0105)
2021-2023	0.0291*	0.0218	0.0224**
	(0.0153)	(0.0135)	(0.0108)
B. 1st Quartile			
2015-2019	0.0476	0.0495	0.0475
	(0.0325)	(0.0324)	(0.0322)
2021-2023	0.1236***	0.1233***	0.1186***
	(0.0402)	(0.0400)	(0.0390)
C. High School, under 40			
2015-2019	0.0505*	0.0769***	0.0737**
	(0.0290)	(0.0293)	(0.0297)
2021-2023	0.0819**	0.0967***	0.0793**
	(0.0374)	(0.0367)	(0.0343)
Controls:			
Age		X	X
Demographics			X
Sector			X
Covid Death Rate			X

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

◂ Slide: additional WPC findings

Wage growth over time - Higher wage growth in times of higher tightness



Slide: additional WPC findings

Wage-separation elasticity as a measure of labor market competition

- Quit elasticity is a key measure of labor market power
  - Responsiveness of job-to-job (EE) separations to wages Manning 2021; Bassier et al. 2022
- Using CPS, can estimate quits in 12 months following first wage observation
- Estimating equations
  1. Using own-wage variation, $w_{i,t-1}$

$$\text{EEsep}_{it} = a + \beta_1 \ln w_{i,t-1} + \beta_2 \ln w_{i,t-1}^2 + X_{it}^{'}\gamma + e_{it}$$

  2. Using industry wage premiums, $\tilde{w}_{j(i),t-1}$

$$\text{EEsep}_{it} = a + \beta_1 \ln \tilde{w}_{j(i),t-1} + \beta_2 \ln \tilde{w}_{j(i),t-1}^2 + X_{it}^{'}\gamma + e_{it}$$

- Details
  - Own-wage controls: age, educ, gender, race, ethnicity, citizenship, state, metro area
  - Estimate both linear and quadratic fits, standard errors clustered at state level
  - $\ln \tilde{w}_j$: Wage regression on sex, education, age, age^2, age^3, race, ethnicity, citizenship, metro area, industry FE's ($t = 2015 - 19$)

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Overall Employment-to-Employment Separation Elasticity
Estimates at Different Values of Industry Wage Premiums

	IWP = -0.3	IWP = 0	IWP = 0.3
2015-19	-0.7166***	-0.6837***	-0.5842
	(0.2160)	(0.1322)	(0.4331)
2021-23	-0.8954***	-0.6318***	-0.1483
	(0.2086)	(0.1135)	(0.3643)
Difference	-0.1788	0.0518	0.4360
	(0.2999)	(0.1741)	(0.5653)

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

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Employment-to-Employment Separation Elasticity
Estimates at Different Values of Industry Wage Premiums - HS workers

	IWP = -0.3	IWP = 0	IWP = 0.3
High School Educated, Under 40 Years Old			
2015-19	-0.2621	-0.5151***	-0.9064***
	(0.2238)	(0.1321)	(0.3245)
2021-23	-0.9415***	-0.8328***	-0.5335
	(0.3040)	(0.1472)	(0.4086)
Difference	-0.6794*	-0.3177	0.3729
	(0.3770)	(0.1975)	(0.5211)
High School Educated, 40 Years and Older			
2015-19	-0.6779**	-0.4596**	-0.1232
	(0.3449)	(0.1968)	(0.2803)
2021-23	-0.7198**	-0.5070***	-0.1617
	(0.3491)	(0.1929)	(0.3838)
Difference	-0.0419	-0.0474	-0.0384
	(0.4902)	(0.2752)	(0.4746)

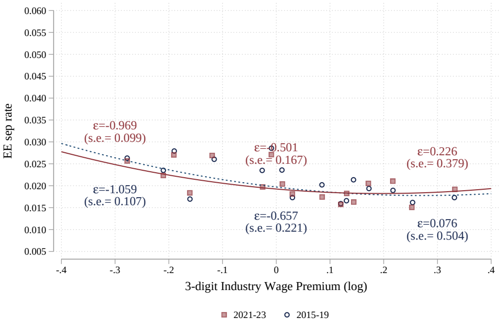
Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

◂ Figure: HS elasticities

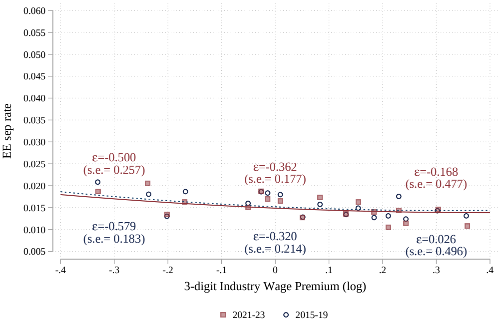
Separation elasticity – little change for highly educated workers

Workers with a bachelor's degree or more by age

BA+, under 40



BA+, 40+



◂ Fig: HS elasticities ▸ Table: BA+ elasticities

Employment-to-Employment Separation Elasticity
Estimates at Different Values of Industry Wage Premiums - BA+ workers

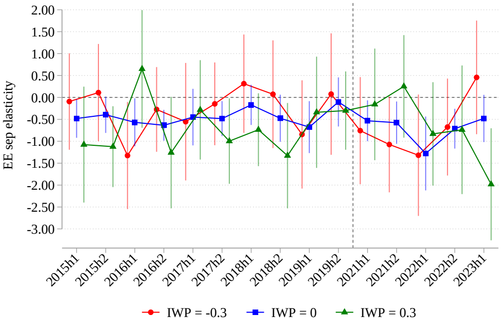
	IWP = -0.3	IWP = 0	IWP = 0.3
Bachelor's Degree or Higher, Under 40 Years Old			
2015-19	-1.0592***	-0.6572***	0.0757
	(0.1070)	(0.2211)	(0.5041)
2021-23	-0.9687***	-0.5013***	0.2256
	(0.0992)	(0.1666)	(0.3795)
Difference	0.0905	0.1559	0.1500
	(0.1457)	(0.2766)	(0.6303)
Bachelor's Degree or Higher, 40 Years and Older			
2015-19	-0.5790***	-0.3196	0.0264
	(0.1833)	(0.2135)	(0.4964)
2021-23	-0.4998*	-0.3624**	-0.1682
	(0.2569)	(0.1767)	(0.4774)
Difference	0.0792	-0.0428	-0.1946
	(0.3152)	(0.2769)	(0.6878)

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

◂ Fig: HS elasticities ◂ Fig: BA+ elasticities

Wage separation elasticities peak in early 2022 - for young, high school workers

High School, Age < 40



All others

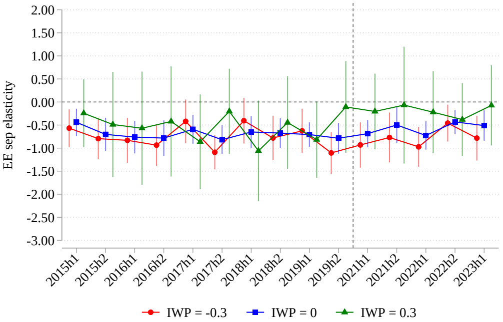
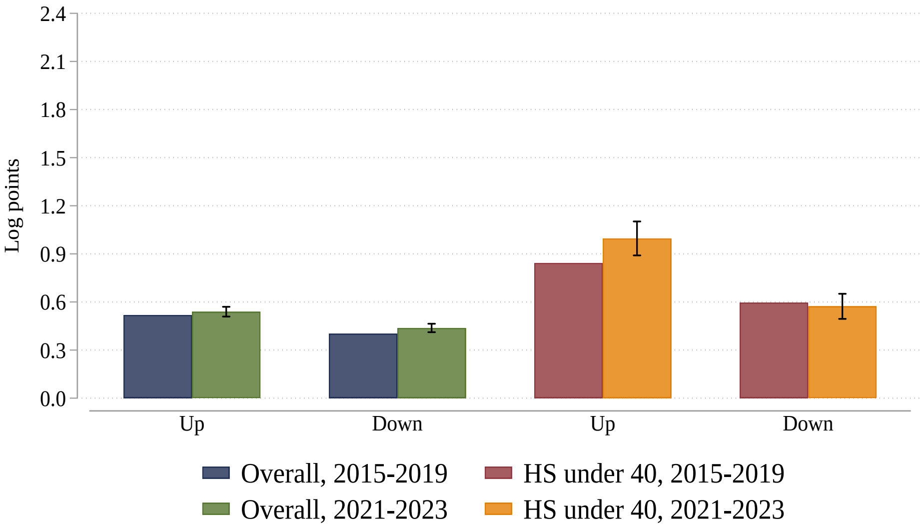


Fig: HS elasticities

More mobility out of bottom-half of wage distribution among HS<40 workers

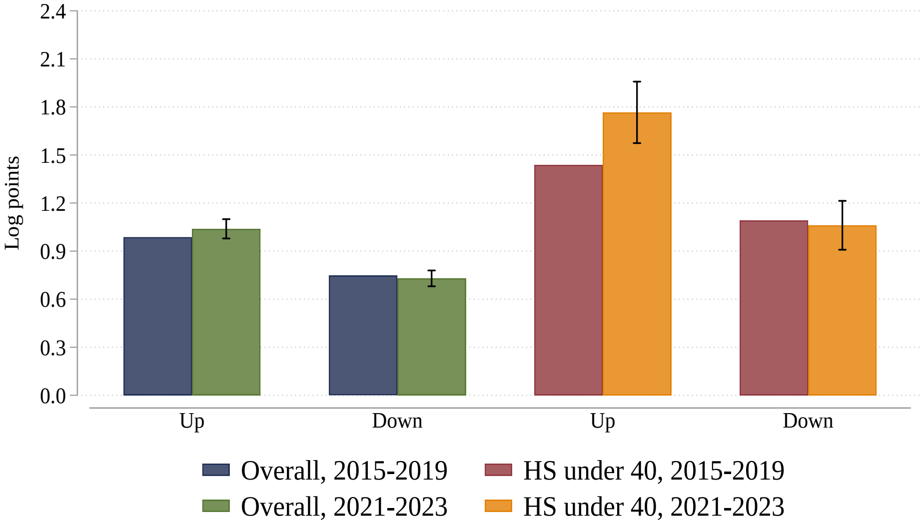
Using industry wage premia to proxy wage levels



Back Table: Top & bottom flows Figure: Top & bottom flows over time

More mobility out of bottom-quartile of wage dist'n among HS<40 workers

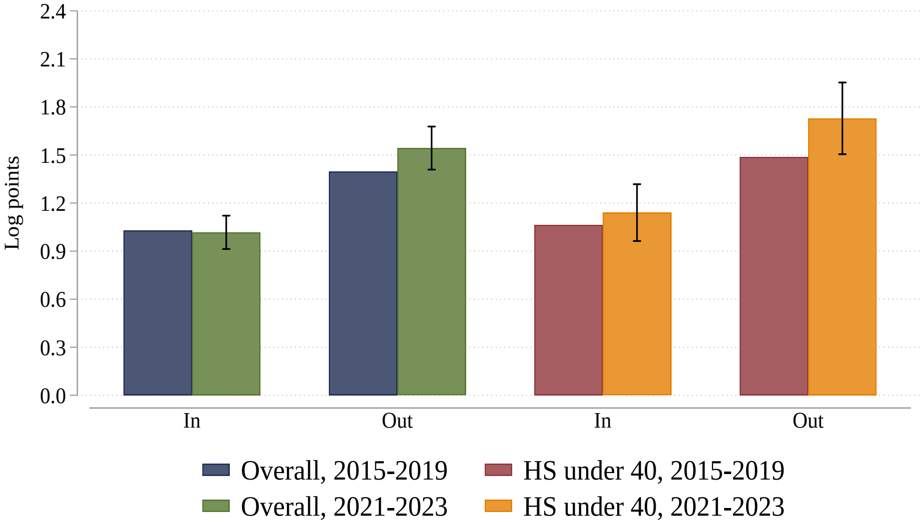
Using industry wage premia to proxy wage levels



Back | Table: Bottom quartile flows | Figure: Bottom quartile flows over time

Sharp rise in net mobility out of the Hospitality sector, esp. among HS < 40

Hospitality is the canonical low-wage, low-stability job sector



Back Table: Hospitality flows Figure: Hospitality flows over time

Movement between top half and bottom half of the 3-digit industry wage premia distribution

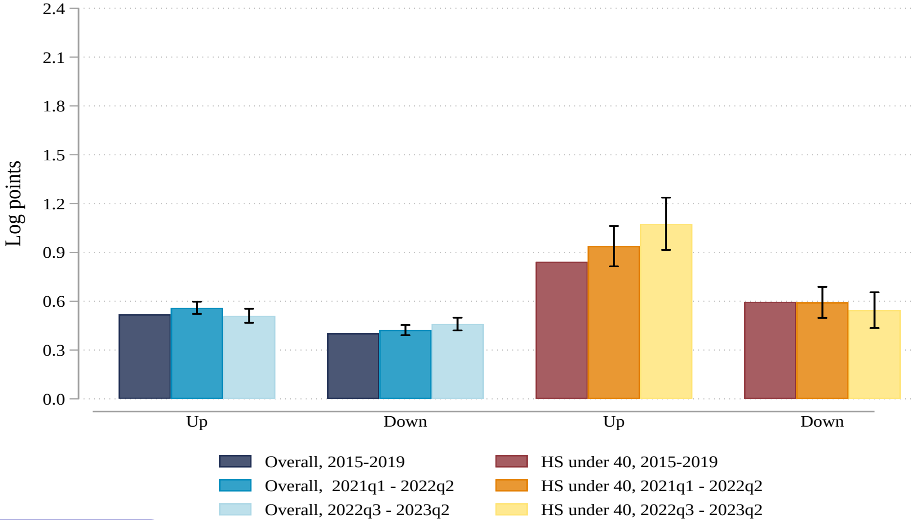
	(1) 2015-2019	(2) 2021-2023	(3) Difference
A. Exit rate from bottom half of IWP			
Overall	0.00519***	0.00539***	0.00020
	(0.00008)	(0.00013)	(0.00016)
HS, under 40	0.00843***	0.00996***	0.00153***
	(0.00026)	(0.00047)	(0.00054)
B. Exit rate from top half of IWP			
Overall	0.00403***	0.00438***	0.00035***
	(0.00007)	(0.00011)	(0.00013)
HS, under 40	0.00596***	0.00573***	-0.00024
	(0.00022)	(0.00033)	(0.00040)
C. Net exit rate from bottom half of IWP			
Overall	0.00116***	0.00101***	-0.00015
	(0.00010)	(0.00017)	(0.00020)
HS, under 40	0.00247***	0.00424***	0.00177***
	(0.00034)	(0.00057)	(0.00066)

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

◂ Fig: Top & Bottom flows

Mobility in and out of the bottom half of wage distribution

Over various periods



◂ Figure: Top & bottom flows

Movement in and out of the bottom quartile of the 3-digit industry wage premia distribution

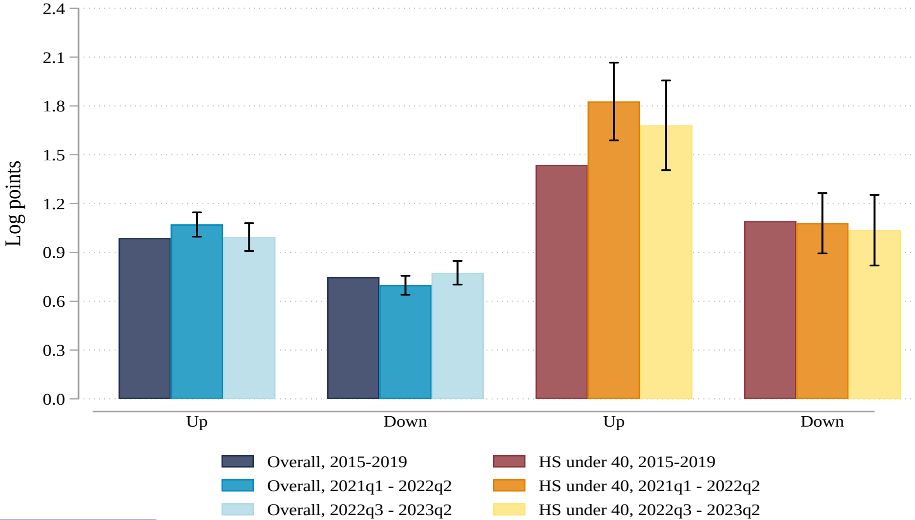
	(1) 2015-2019	(2) 2021-2023	(3) Difference
A. Exit rate from the bottom quartile of IWP			
Overall	0.00987***	0.01039***	0.00052*
	(0.00016)	(0.00027)	(0.00031)
HS, under 40	0.01438***	0.01766***	0.00328***
	(0.00047)	(0.00086)	(0.00098)
B. Exit rate from the top three quartiles of IWP			
Overall	0.00747***	0.00730***	-0.00018
	(0.00014)	(0.00021)	(0.00025)
HS, under 40	0.01091***	0.01061***	-0.00030
	(0.00043)	(0.00065)	(0.00078)
C. Net exit rate from bottom quartile of IWP			
Overall	0.00240***	0.00309***	0.00069*
	(0.00020)	(0.00033)	(0.00039)
HS, under 40	0.00347***	0.00705***	0.00358***
	(0.00062)	(0.00106)	(0.00123)

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Figure: Bottom quartile Flows

Mobility in and out of the bottom quartile of wage distribution

Over various periods



◂ Figure: Bottom quartile flows

Movement in and out of hospitality industry

	(1) 2015-2019	(2) 2021-2023	(3) Difference
A. Exit rate from Hospitality sector			
Overall	0.01397***	0.01543***	0.00146**
	(0.00034)	(0.00060)	(0.00069)
HS, under 40	0.01488***	0.01729***	0.00241**
	(0.00057)	(0.00099)	(0.00114)
B. Exit rate from non-Hospitality sector			
Overall	0.01029***	0.01017***	-0.00012
	(0.00029)	(0.00045)	(0.00053)
HS, under 40	0.01064***	0.01140***	0.00077
	(0.00048)	(0.00077)	(0.00090)
C. Net exit rate from Hospitality sector			
Overall	0.00368***	0.00526***	0.00158*
	(0.00043)	(0.00072)	(0.00084)
HS, under 40	0.00424***	0.00588***	0.00164
	(0.00073)	(0.00123)	(0.00143)

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

◂ Figure: Hospitality Flows

Movement in and out of the Hospitality sector

Over various periods

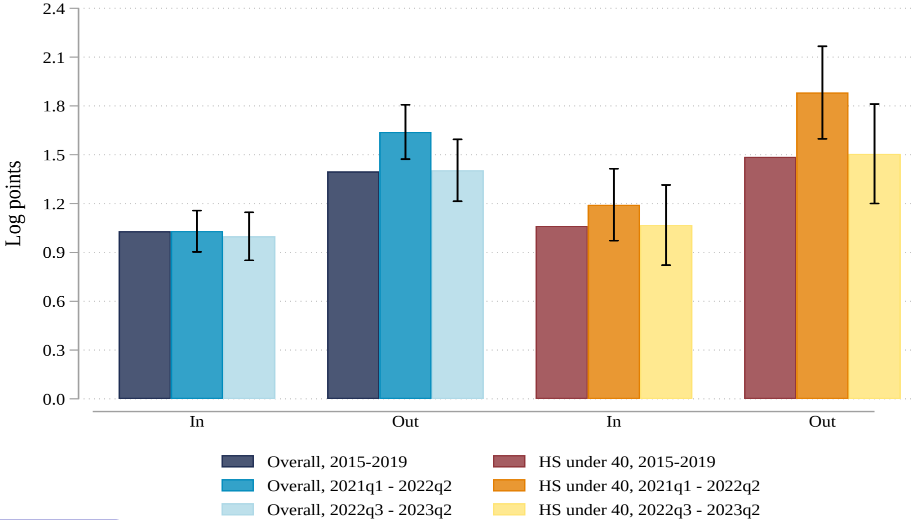


Figure: Hospitality flows

Oaxaca decomposition: Wage growth contributions of movers vs stayers

- **Mean wage change for demographic group in time t**
  - $\Delta \bar{w}_t = \Delta w_t^M \delta_t + \Delta w_t^S (1 - \delta_t)$ is wage change for demographic group in time t
  - Δw_t^M is wage change among job-movers,
  - Δw_t^S is wage change among job-stayers
  - $\delta_t = Pr(\Delta J_{12,t} = 1)$ is the move rate
- **Decomposing change in wage growth between two periods, $\Delta \bar{w}_1 - \Delta \bar{w}_0$**

$$= \underbrace{\left(\Delta w_1^M - \Delta w_0^M\right)\delta_0}_{\textit{Movers}} + \underbrace{\left(\Delta w_1^S - \Delta w_0^S\right)(1-\delta_0)}_{\textit{Stayers}} + \underbrace{(\delta_1 - \delta_0)\left(\Delta w_1^M - \Delta w_1^S\right)}_{\textit{Move rate}}.$$

Back

Decomposition of the Change in Annual Wage Growth
2021−23 vs. 2015−19

	High School under 40		All others	
	2015-2019	2021-2023	2015-2019	2021-2023
A. Job Change and Industry Change Rates				
Pr(Measured movers = 1)	7.64	8.42	5.37	5.57
Pr(Mover in past 3 qtrs)	21.21	23.20	15.27	15.79
Pr(Mover in past year)	27.23	29.66	19.82	20.48
Pr(Stayer in past year)	72.77	70.34	80.18	79.52
B. Mean Log Wage Changes by Switcher Status				
E(Wage change)	4.63	3.69	3.46	1.20
E(Wage change — Job move)	4.67	7.80	6.25	3.88
E(Wage change — No job move)	4.61	1.96	2.77	0.52
C. Decomposition of Wage Change: 2021-23 v. 2015-19				
Contribution of ind-movers		0.85		-0.47
Contribution of ind-stayers		-1.93		-1.80
Contribution of move rate		0.14		0.02
Total		-0.94		-2.25

Back

Labor market tightness, inflation, and real wages

- Estimating equations: $\Delta \ln P$ and $\Delta \ln W$ between 2021q1 and 2023q2

$$\ln P_{ir(s)kt_k} = \beta \left(\text{Tightness}_{r(s)kt_{k=0}} \times \mathbb{1}\left[t_k = 1\right] \right) + X_i^{'} \gamma_k + \alpha_{kt_k} + \delta_{kt_k} + e_{ir(s)kt_k}$$

$$\ln W_{ir(s)kt_k} = \beta \left(\text{Tightness}_{r(s)kt_{k=0}} \times \mathbb{1}\left[t_k = 1\right] \right) + X_i^{'} \gamma_k + \alpha_{kt_k} + \delta_{kt_k} + e_{ir(s)kt_k}$$

  - Fit to person-level wage data with state-clustered SEs

- Form regional price indices as follows
  - For workers in 21 metro areas, use Bureau of Labor Statistics (BLS) metro price index
  - For workers in other metro areas, use average of state metros
  - For workers in states with no metro price index, use BLS regional price index

Back

Wage Phillips Curve (Nominal) vs. Price Phillips Curve

	(1)	(2)	(3)	(4)	(5)
A. Price Phillips Curve - Coefficient on Tightness					
Tightness	0.0031	0.0030	0.0030	0.0028	0.0028
	(0.0064)	(0.0064)	(0.0064)	(0.0063)	(0.0063)
B. Wage Phillips Curve - Coefficient on Tightness					
Overall	0.0315**	0.0244**	0.0260**	0.0231**	0.0231**
	(0.0136)	(0.0118)	(0.0103)	(0.0097)	(0.0097)
1st Quartile	0.1269***	0.1271***	0.1220***	0.1216***	0.1216***
	(0.0387)	(0.0384)	(0.0378)	(0.0378)	(0.0378)
High School, under 40	0.0928***	0.1146***	0.1057***	0.0953***	0.0953***
	(0.0354)	(0.0347)	(0.0340)	(0.0321)	(0.0321)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Dependent variables are log wage and log CPI. All specifications include state and period FE. Controls include age group, sex, race, education, industry (finance, manuf, business svcs, prof svcs), and state COVID death rates. Standard errors in parentheses, clustered at state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

◂ Back ▸ Table: PPC estimates

Wage- and Price-Phillips Curve : Over Different Periods and Components

	(1) Tightness	(2) Std. 1-Unemp	(3) Std. EE Sep	(4) 1-Unemp	(5) EE Sep
A. Δ Log CPI (excluding energy)					
2018-2019	-0.0093*	-0.0033**	-0.0057	-0.5665**	-1.3873
	(0.0051)	(0.0016)	(0.0040)	(0.2670)	(0.9649)
2021q1−2022*q*2	0.0079***	0.0042***	0.0013	0.7170***	0.3237
	(0.0029)	(0.0011)	(0.0028)	(0.1905)	(0.6675)
2022q3−2023*q*2	-0.0087	-0.0020	-0.0058	-0.3301	-1.4026
	(0.0060)	(0.0058)	(0.0047)	(0.9885)	(1.1384)
B. Δ Log real wage					
2018-2019	-0.0025	-0.0006	-0.0018	-0.1085	-0.4395
	(0.0091)	(0.0038)	(0.0083)	(0.6410)	(2.0054)
2021q1−2022*q*2	0.0093*	0.0039	0.0050	0.6683	1.2219
	(0.0053)	(0.0028)	(0.0102)	(0.4678)	(2.4689)
2022q3−2023*q*2	0.0217*	0.0069	0.0122	1.1636	2.9572
	(0.0127)	(0.0073)	(0.0087)	(1.2408)	(2.1124)

Dependent variables are log wage and log CPI. Tightness and components standardized relative to 2018-2019. All specifications include state and period FE. Controls include age group, sex, race, education, industry (finance, manuf, business svcs, prof svcs), and state COVID death rates. Standard errors in parentheses, clustered at state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

◂ Back ▸ Table: PPC estimates

Price Phillips Curve

Various Specifications of Regression of Log CPI on Measures of Tightness

	(1)	(2)	(3)	(4)	(5)
A. Independent vars: Standardized measures of tightness					
Tightness	0.0031	0.0030	0.0030	0.0028	0.0028
	(0.0064)	(0.0064)	(0.0064)	(0.0063)	(0.0063)
Std. 1-Unemp	0.0071**	0.0071**	0.0070**	0.0069**	0.0069**
	(0.0032)	(0.0032)	(0.0032)	(0.0031)	(0.0031)
Std. EE Sep	-0.0023	-0.0023	-0.0022	-0.0023	-0.0023
	(0.0039)	(0.0039)	(0.0038)	(0.0038)	(0.0038)
B. Independent vars: Components of tightness					
1-Unemp	0.5223**	0.5197**	0.5142**	0.5051**	0.5051**
	(0.2377)	(0.2375)	(0.2325)	(0.2304)	(0.2304)
EE Sep	-0.4561	-0.4653	-0.4536	-0.4663	-0.4663
	(0.7822)	(0.7806)	(0.7653)	(0.7608)	(0.7608)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Dependent variable is Log CPI. All specifications include state and period FE. Controls include age group, sex, race, education, industry (finance, manuf, business svcs, prof svcs), and state COVID death rates. Standard errors in parentheses, clustered at state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

◂ Table: WPC v. PPC ◂ Table: WPC v. PPC periodized

Real Wage Phillips Curve – by Wage Quartile

	(1)	(2)	(3)	(4)	(5)
Overall	0.0189	0.0130	0.0161	0.0141	0.0141
	(0.0126)	(0.0111)	(0.0111)	(0.0104)	(0.0104)
Within wage quartiles					
1st Quartile	0.1299***	0.1309***	0.1252***	0.1249***	0.1249***
	(0.0342)	(0.0340)	(0.0332)	(0.0331)	(0.0331)
2nd Quartile	0.0883***	0.0893***	0.0873***	0.0863***	0.0863***
	(0.0301)	(0.0296)	(0.0283)	(0.0281)	(0.0281)
3rd Quartile	-0.0959***	-0.0970***	-0.0923***	-0.0931***	-0.0931***
	(0.0192)	(0.0191)	(0.0186)	(0.0187)	(0.0187)
4th Quartile	-0.0398	-0.0428	-0.0402	-0.0389	-0.0389
	(0.0273)	(0.0273)	(0.0263)	(0.0261)	(0.0261)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Dependent variable is log wage. Wages deflated using metro level CPI when available, census division level otherwise. All specifications include state and period FE. Controls include age group, sex, race, education, industry (finance, manuf, business svcs, prof svcs), and state COVID death rates. Standard errors in parentheses, clustered at state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Back   Table: Real WPC by education

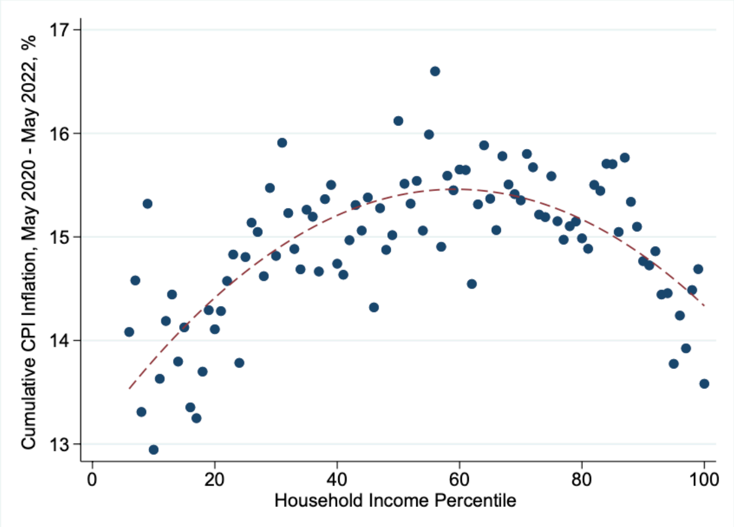
Real Wage Phillips Curve – by Age and Education

	(1)	(2)	(3)	(4)	(5)
High School, under 40	0.0889**	0.1117***	0.1048***	0.0958***	0.0958***
	(0.0373)	(0.0366)	(0.0355)	(0.0336)	(0.0336)
High School, 40+	0.1325**	0.1250**	0.1167**	0.1115**	0.1115**
	(0.0584)	(0.0564)	(0.0561)	(0.0547)	(0.0547)
Some College, under 40	0.0850**	0.0627**	0.0610**	0.0486*	0.0486*
	(0.0347)	(0.0276)	(0.0273)	(0.0257)	(0.0257)
Some College, 40+	0.0070	-0.0004	-0.0037	-0.0113	-0.0113
	(0.0308)	(0.0302)	(0.0290)	(0.0277)	(0.0277)
BA+, under 40	-0.0850***	-0.0860***	-0.0728**	-0.0599*	-0.0599*
	(0.0330)	(0.0330)	(0.0321)	(0.0325)	(0.0325)
BA+, 40+	-0.0537*	-0.0604**	-0.0618**	-0.0602**	-0.0602**
	(0.0274)	(0.0289)	(0.0269)	(0.0275)	(0.0275)
Controls:					
Age		X	X	X	X
Demographics			X	X	X
Sector				X	X
Covid Death Rate					X

Dependent variable is log wage. Wages deflated using metro-level CPI when available, census division-level otherwise. All specifications include state and period FE. Controls include age group, sex, race, education, industry (finance, manuf, business svcs, prof svcs), and state COVID death rates. Standard errors in parentheses, clustered at state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

◂ Back ◂ Table: real WPC overall and by quartiles

Inflation Inequality by Income Percentile



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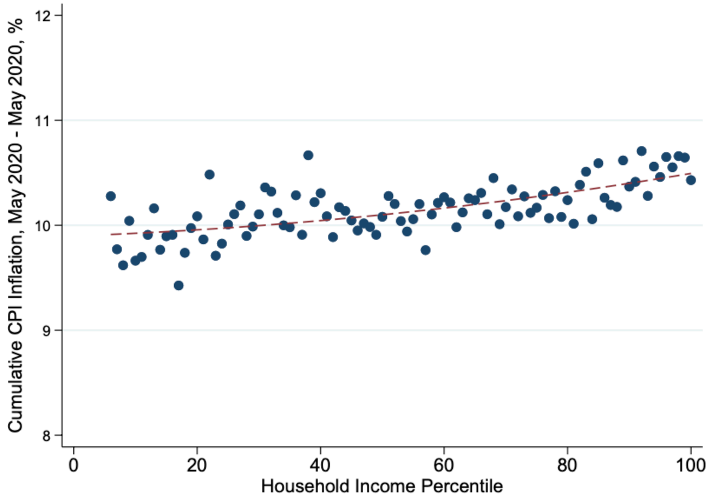
Source: Jaravel '22

Inflation Inequality by Income Percentile: Excluding Gas & Vehicles



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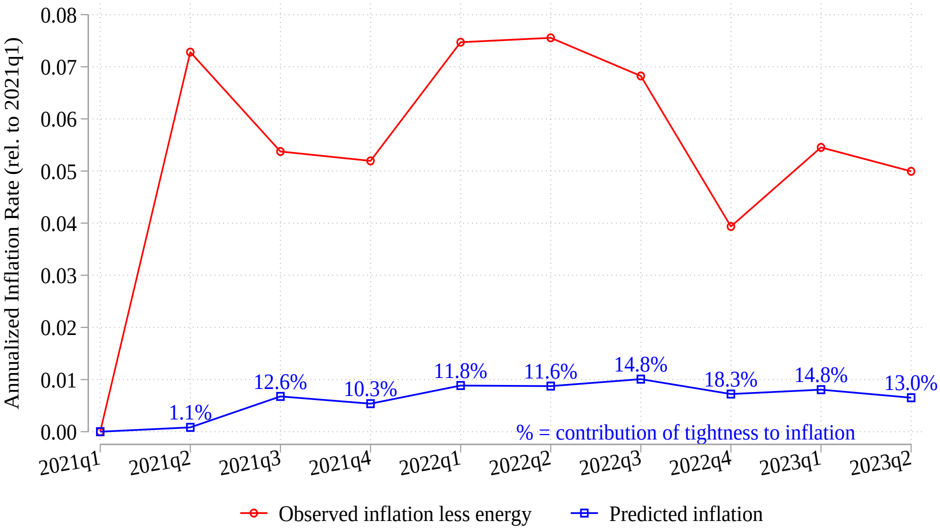
Source: Jaravel '22

Contribution of Tightness to Inflation



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Why competition causes wage compression (static model)

- Consider firm's revenue function as $Y = p_j \ln(l_j)$
- Profit maximization yields:

$$w_j^* = \frac{\epsilon^L}{1+\epsilon^L} \times \frac{p_j}{l_j}$$

- Given two firms $j \in \{H, L\}$ where $p_H > p_L$, equilibrium relative wages are:

$$\frac{w_L}{w_H} = \frac{l_H}{l_L} \cdot \frac{p_L}{p_H} \Longrightarrow \frac{w_L^*}{w_H^*} = \left(\frac{p_L}{p_H}\right)^{\frac{1}{\epsilon^L+1}} \tag{1}$$

- Taking logs and differentiating (1) with respect to ϵ^L yields:

$$\frac{\partial\left(\ln(w_L^*) - \ln(w_H^*)\right)}{\partial \epsilon^L} = \frac{\ln(p_H) - \ln(p_L)}{(\epsilon^L+1)^2} > 0.$$

- Derivative is positive $\rightarrow$ Rising competition compresses the wage distribution

Why competition reallocates labor towards more productive firms (static model)

- Rearrange equation (1) to obtain relative employment at high- and low-productivity firms:

$$\frac{l_L^*}{l_H^*} = \left(\frac{p_L}{p_H}\right)^{\frac{\epsilon^L}{\epsilon^L+1}} \tag{2}$$

Why competition reallocates labor towards more productive firms (static model)

- Rearrange equation (1) to obtain relative employment at high- and low-productivity firms:

$$\frac{l_L^*}{l_H^*} = \left(\frac{p_L}{p_H}\right)^{\frac{\epsilon^L}{\epsilon^L+1}} \tag{2}$$

- Taking logs and differentiating (2) with respect to ϵ^L yields:

$$\frac{\partial\left(\ln(l_L^*) - \ln\left(l_H^*\right)\right)}{\partial\epsilon^L} = \frac{\ln\left(p_L\right) - \ln\left(p_H\right)}{\left(\epsilon^L + 1\right)^2} < 0$$

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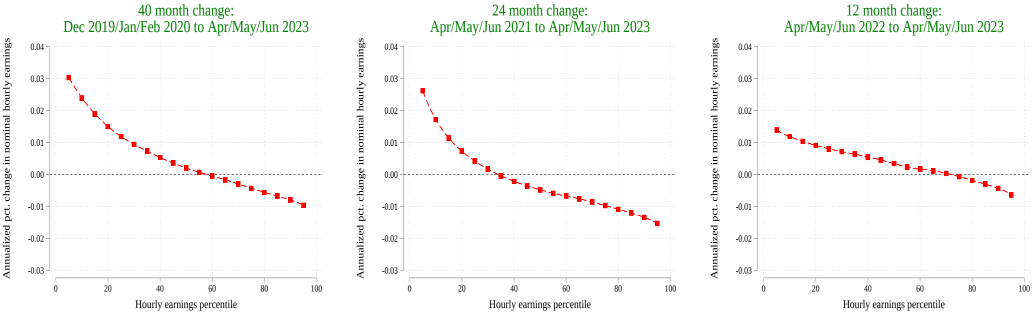
- Derivative is negative $\rightarrow$ Rising competition reallocates labor from low- to high-productivity firms

Regionally adjusted real wage growth

Inflation only marginally higher in regions where nominal wage growth is greater



Inferring wage changes among job movers

- Observed wage change among job movers
  $\Delta w_t^M = E\left[\Delta w | \Delta J_3 = 1\right] = 0.078$

- Probability of a job change last year given no job change last quarter

$$\begin{aligned}\Pr\left[\Delta J_{12} = 1 | \Delta J_3 = 0\right] &= 1 - \left(1 - \Pr\left(\Delta J_3 = 1\right)\right)^3 \\ &= 1 - 0.916^3 = 0.232\end{aligned}$$

- Probability of moving in the last year is then:

$$\begin{aligned}\Pr[\Delta J_{12} = 1] &= Pr[\Delta J_3 = 1] + (1 - Pr[\Delta J_3 = 1]) * \Pr\left[\Delta J_{12} = 1 | \Delta J_3 = 0\right] \\ &= .084 + .916 * .232\end{aligned}$$

- Use overall wage change, $\Delta \bar{w}_t = 0.037$, and wage $\Delta w_t^M = 0.078$ among job-movers to infer Δw_t^S among job stayers