1 Literature

- Duranton and Puga (2020): elasticity of productivity with respect to density 0.04
- Phimister (2005) women have higher urban premia in UK.
- de la Roca and Puga (2017) they find the opposite for Spain (0.02 vs 0.05).

2 Ideas put forward by the literature

Explanations for the gender gap

- Gender-biased technological change (Black and Spitz-Oener, 2010).
- Differences in commuting patterns and transportation (Black et al., 2014; Liu and Su, 2020).
- Differences on job flexibility (Goldin, 2014).
- Structural change (Olivetti and Petrongolo, 2014, 2016)
- Changes in selection patterns (Mulligan and Rubinstein, 2008)

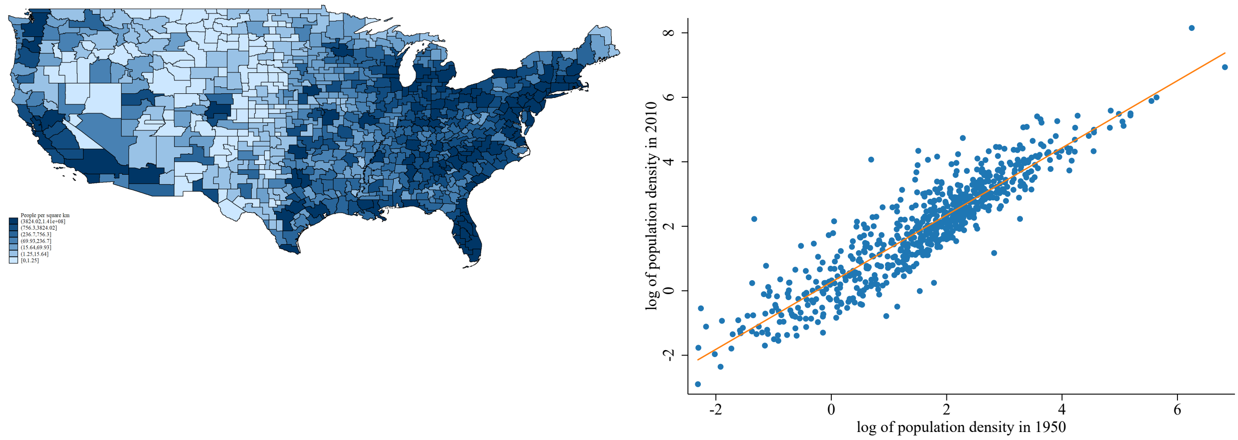
3 Data notes

3.1 Putting density in perspective

Spacial distribution where are the densest CZ? See panel a of Figure 1

Figure 1: The geography of population density and its persistence

(a) Population density in 2020 (b) Density in 2020 vs 1950



Note: Figure restricts to czones with population densities above 1 person per km^2 Figure generated on 1 Dec 2020 at 18:57:04. Figure generated using the dofile 2_analysis/code_files/create_gender_gap_maps.do.

Persistence: panel b of figure 1 shows that density is highly persistent. The slope coefficient from the regression in the figure is 1.04.

Summary statistics selected summary statistics for the 625 CZ in my sample are shown in table 1.

What are the densest CZ? Table 2 shows examples of CZ at different points of the density distribution. Whenever available, the table lists the main city in the CZ.

3.2 Residualization procedure

Throughout this document I explore the relationship between average wages (gender wage gap) and CZ population density. I am also interested in how this relationship has changed over time.

To discard the possibility that the observed relationships arise because of simple changes in the population composition, I compute average wages net of individuals' characteristics.

Procedure

1. I regress log of the individuals' wages on individual characteristics separately by year, including a gender $\times$ CZ fixed effect. Models are estimated separately for each census year.

$$w_{igrt} = X_{irt}\gamma_t + \lambda^g_{rt}$$

2. $\hat{\lambda}_{grt}$ is my estimate of CZ wages, net of individual characteristics.

3. I compute the CZ-specific gender gap as:

$$gap_{rt} = \hat{\lambda}^m_{rt} - \hat{\lambda}^f_{rt}$$

Throughout the document, the control variables X_{irt} come into for different sets:

- **Basic controls:** age dummies, race dummies, and foreign born dummy.
- **Human capital:** basic controls + 4-level education dummies.
- **Industry controls:** human capital controls + $\approx$ 150 industry fixed effects.
- **Full controls:** industry controls + occupation fixed effects.

Table 1: Selected summary statics for CZ, 2020

	count	p10	p25	p50	p75	p90
log of population density	625	.6182053	1.489836	2.357417	3.144841	4.051244
wage_raw_gap	625	.1288653	.1587546	.1871793	.2173289	.2517551

Table 2: Examples of CZ at different percentiles of population density in 2020

Percentile	(1) Main city	(2) State	(3) log of population density	(4) Population density	(5) Total population
1	undefined	Texas	-.43	.65	7577
1	undefined	South Dakota	-.49	.61	1424
5	undefined	Texas	.16	1.18	4933
5	undefined	South Dakota	.14	1.16	10137
10	undefined	Kansas	.62	1.86	16528
10	undefined	Nebraska	.61	1.84	5473
25	undefined	Wyoming	1.49	4.44	55507
25	undefined	California	1.49	4.43	78207
50	undefined	Missouri	2.36	10.56	84805
50	undefined	Illinois	2.36	10.56	72896
75	undefined	West Virginia	3.14	23.22	180731
75	undefined	Pennsylvania	3.14	23.14	198774
90	undefined	North Carolina	4.05	57.47	253676
90	Youngstown OH	Ohio	4.03	56.53	386753
95	Fort Worth TX	Texas	4.46	86.08	1340106
95	Reading PA	Pennsylvania	4.43	84.09	652241
99	Baltimore MD	Maryland	5.49	241.41	1476239
99	Philadelphia PA	Pennsylvania	5.44	229.79	3178354
100	Miami FL	Florida	8.15	3462.06	2550814
100	New York City NY	New York	6.93	1027.16	6829386

Note: figure restricts to czones with population densities above 1 person per km^2

4 Basic findings

4.1 Densest CZ have experienced faster decline in the gender wage gap

Consider the regression

$$gap_{r2020} - gap_{r1970} = \alpha + \beta \ln(density)_{r1970}$$

where $gap_r = w_r^{male} - w_r^{female}$, where w stands for average log-wage in the commuting zone.

Table 3 shows the estimates of β for different average wage measures. All the estimates are significant and negative $\implies$ densest CZ experienced a significantly larger reductions in the gender wage gap.

Several observations

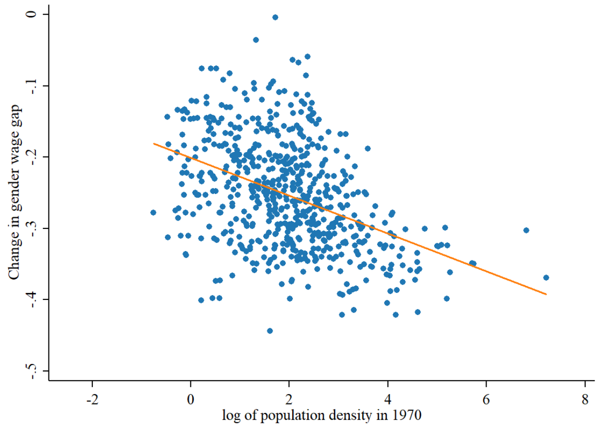
- **Density measure:** Duranton and Puga (2020) argue that total population is more linked to the "experienced" density in a labor market than the "naive" population density. Table 3 shows that the gradient is virtually unchanged when using: "naive" CZ population density, or total CZ population.
- **Magnitude of the coefficient:** The gradient is large under multiple benchmarks. Let's focus on interpreting the gradient for the raw wage gap on population density.
  - **Standardized effect** an increase of 1 s.d. in population density (1.18) $\implies$ a change of -.4 s.d. in the gender wage gap. A model with just just population density accounts for 17% of the variation 1970-2020 gender gap change.
  - **IC gap:** a CZ in the 25 percentile had an expected decline in the gap of 23 log points. In contrast, a CZ in the 75 percentile experienced a 27 log-point decline $\implies$ a decrease that is 17% larger.
  - **IC gap relative to the mean:** the 4 log-point gap is equivalent to 15.6% of the decline in the gender gap for *the average CZ*.

Table 3: Gender wage gap vs density

	Raw gap	**Net of basic controls**	**Net of human capital controls**
l_czone_density_70	-0.026***	-0.027***	-0.022***
	(0.002)	(0.002)	(0.002)
l_czone_pop_70	-0.025***	-0.025***	-0.023***
	(0.002)	(0.002)	(0.002)

Note: changes based on unweighted estimated elasticities. Sample restricted to full-time year-round workers. Table generated on 30 Nov 2020 at 11:17:18. Table generated with do file 2_analysis/code_files/write_regression_coefplots.do

Figure 2: Change in gender wage gap, 1970-2020



Note: figure restricts to CZ with more than 1 people per km^2. Figure generated on 30 Nov 2020 at 11:17:17. Figure generated using the dofile 2_analysis/code_files/write_regression_coefplots.do.

4.2 The relationship between density and gender gap went from positive to negative during 1970-2020

In figure 4 I show estimates of β_t in the regression:

$$gap_{rt} = \alpha_t + \beta_t \ln(density)_{rt}$$

Several remarks

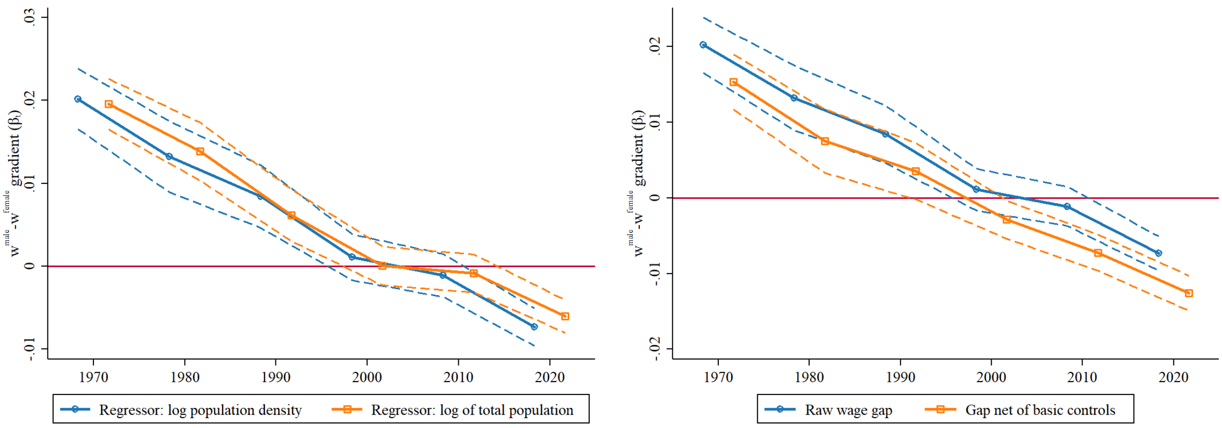
- The density gradient declined gradually over the period. It went from positive in 1970 to negative in the 2020.
- The gradient declines roughly in 2.7 log-points, which roughly corresponds to the coefficient found in in the previous section.
- The inversion of the gradient is robust to controlling for basic individual characteristics.

The cross-sectional gradient in perspective:

- **Implied IC gap**:
  - 1970: 2.8 log-points $\implies$ .4 s.d. increase in gender gap. This is also equivalent to an increase of 7% in the gender wage gap.
  - 2020: 1.16 log-points $\implies$ .3 s.d. increase in gender gap. This is also equivalent to an increase of 6% in the gender gap. If I account for differences in the age distribution of the population, then this difference becomes 2 log-points. Again, this is roughly equivalent to .2 s.d. in the adjusted wage gap.
- **In international perspective:**

Figure 3: Coefficient on population density β_t

(a) Alternative density measures (b) Alternative gender gap measures



Note: figure restricts to CZ with more than 1 people per km^2. Bars show 90% confidence intervals. Standard errors clustered at the CZ level. Figure generated on 30 Nov 2020 at 11:17:20. Figure generated using the dofile 2_analysis/code_files/write_regression_coefplots.do.

  - The US is the 6th country with the highest gender gap within the the OECD. Moving from a 10th percentile CZ to a 90th in 2020 $\implies$ decline of 3 log-points in the gender gap. This is roughly equivalent to moving from the US to Germany $\approx$ erasing 50% of the gap between the US and the average for OECD countries see this data.
  - **Tangential remark on gender sd:** there is as much variation in the gender gap within the US (2020), as there is in the across countries in the OECD.

- **In terms of the urban wage premium?**
  - **In 2020**: the urban wage premium for men was of 4.4 log points. For women was 5.2 log-points $\implies$ 18% larger premium for women. Adjusting wages for age / race $\implies$ premium for women was 25% larger than for men.
  - **Change across time:** since the peak in 1990, male's premium declined by 3.84 log-points 47% (41% when adjusting by age / race). By comparison, women's premium declined by 2.25 log points. This a decline of 30% (26% when adjusted by age / race) $\implies$ this is a big difference in the evolution of men's and women's fortunes. Women's decline in the premium is just 58% of men's decline in the premium.

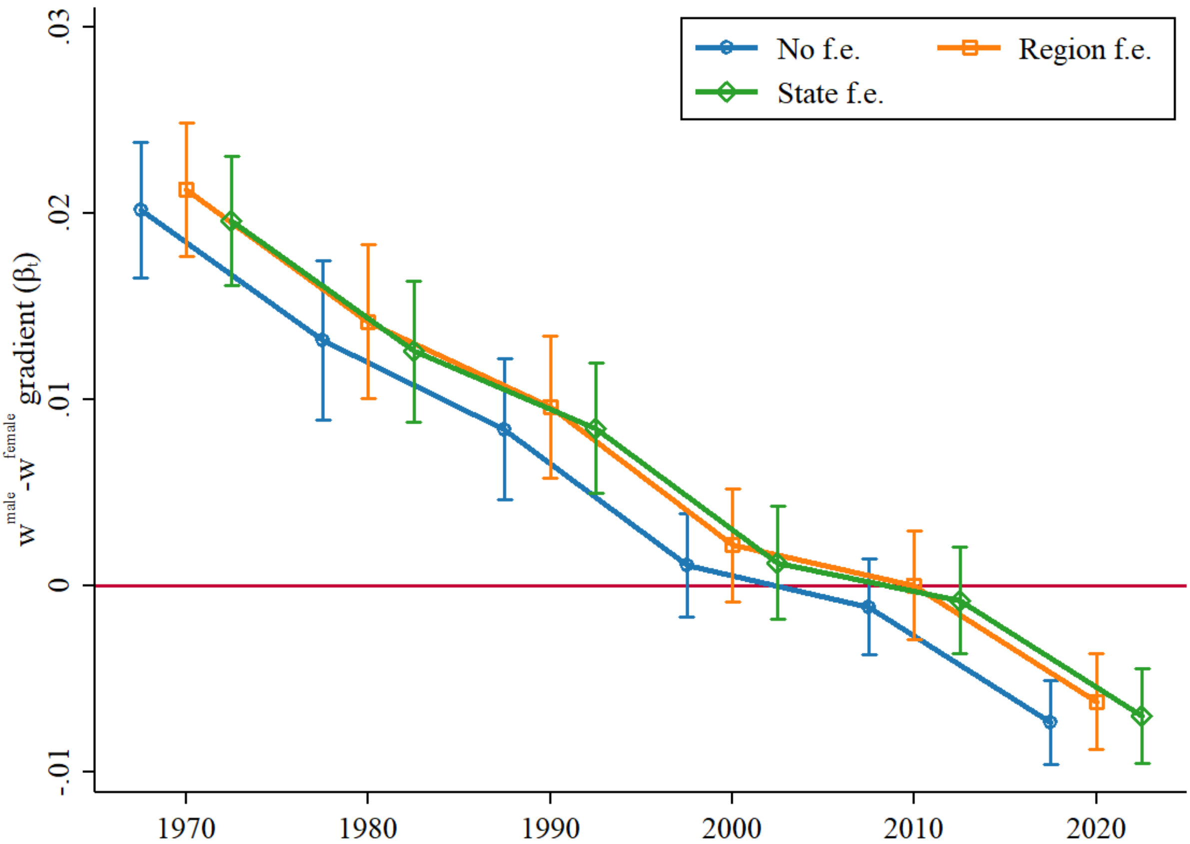
My conclusion here, is that the observed coefficients on density are big relative to the overall within-country variation in the gender gap, even though the IC seems modest.

4.3 Further checks

4.3.1 Is the density gradient just capturing cross-region variation?

No. The gradient and it drift is robust to controlling for region and state fixed effects!

Figure 4: Density gradient is robust to adding region and state fixed-effects



Note: figure restricts to CZ with more than 1 people per km^2. Bars show 90% confidence intervals. Standard errors clustered at the CZ level. Figure generated on 30 Nov 2020 at 11:17:20. Figure generated using the dofile 2_analysis/code_files/write_regression_coefplots.do.

4.3.2 The drift in the gradient is not driven just by small / rural CZ

One concern with the results in the previous sections is that they might be driven by very small CZ, which are relatively unpopulated and which have little bearing in the overall US labor market. To study whether this is a concern I also compute gradients for "big" CZ. I define big CZ as those which had a population density of at least 2.5 people per km^2 in 1950. These 175 CZs had a median population of 316k people and accounted for around 74% of the US population in all the years I am considering.

Figure 5 shows that this is not the case. There I compare the gradients for all CZ vs those I get when I limit estimation to big CZ only. Two features stand out:

1. The gradient *also arises for the* the largest CZ.

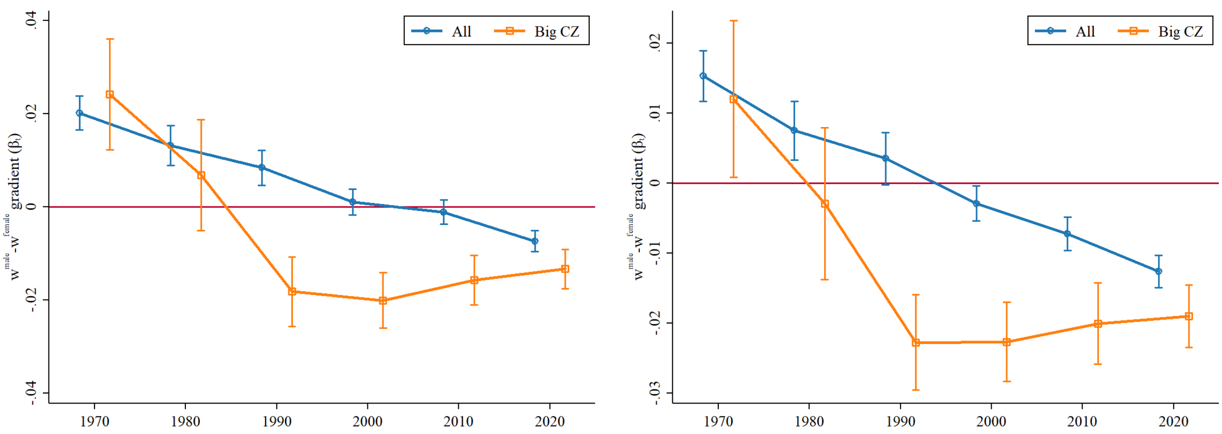
2. Big CZ also feature a decline in the gender-gap gradient. However, this decline is concentrated on the 1970-1990 period. From then on, the gradient remains negative and roughly constant. Panel (b) shows that the picture remains unchanged if I adjust wages for age / race.

Takeway from this exercise:

The gender gap gradient is not driven just by small CZ. Big CZ feature a more striking pattern of gradient decline during 1970-1990. Smaller CZ do drive the gradual decline from 1990 onward.

Figure 5: Density gradient is robust to adding region and state fixed-effects

(a) Raw wages (b) Net of age/race



Note: figure restricts to CZ with more than 1 people per km^2. Bars show 90% confidence intervals. Big CZ are defined as those having a density of at least 2 people per square km in 1950. Standard errors clustered at the CZ level. Figure generated on 30 Nov 2020 at 11:17:22. Figure generated using the dofile 2_analysis/code_files/write_regression_coefplots.do.

4.3.3 Is this about gender?

Given the facts shown above, a natural question to ask is whether this is really about gender? In other words, do I see similar patterns when, for instance, I examine race? To test this I perform a similar exercise for the black-white gap. I run the regression,

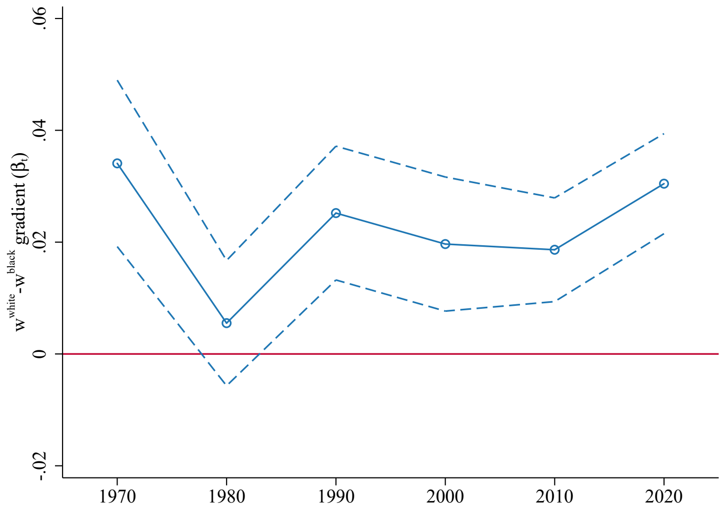
$$w_{rt}^{white} - w_{rt}^{black} = \alpha_t + \beta_t \ln(density)_{rt}$$

Figure 6 shows the estimated β_t. The decline in the gradient does not appear in race. In fact, with the exception of 1990, there is little change in the gradient over the whole period.

Takeaway

There is something distinct between the interaction of gender and population density

Figure 6: Coefficient on population density β_t



Note: figure restricts to CZ with more than 1 people per km^2. Bars show 90% confidence intervals. Standard errors clustered at the CZ level. The figure restricts to year-round full time men workers. Figure generated on 30 Nov 2020 at 11:17:27. Figure generated using the dofile 2_analysis/code_files/write_regression_coefplots.do.

5 Questions inspired by these facts?

- Why has the decline in the urban premium has been less severe for women over the period?
- What explains the inversion in the gender gap - density gradient?
- Do women benefit more from moving to a city today?

5.1 Incipient answers

5.1.1 Do women benefit more from cities?

Fixing ideas To fix ideas let's consider the following model for wages, where g indexes gender and r indexes region:

$$w^g_{iert} = \alpha_t + \delta_{et} + \gamma^g_{ert} + \varepsilon_{it}$$

For the sake of the argument, suppose e indexes education. Here δ_e represents the economy-wide return to having education e, while γ represents the region-specific return to education. Then, the average wage in a commuting zone is given by,

$$w^g_{rt} = \alpha_t + \sum_e s^g_{ert}\delta_{et} + \sum_e s_{ert}\gamma_{ert} + u_{rt}$$

To fix ideas, let us impose the strong assumption that $\gamma_{ert} = \omega^g_t \ln(density)_{rt} + \nu_{rt}$ the above equation reduces to:

$$w^g_{rt} = \alpha_t + \sum_e s^g_{ert}\delta_{et} + \omega^g_t \ln(density)_{rt} + v_{rt}$$

By running the regression:

$$w_{rt}^{g} = \alpha + \beta_t^g \ln(density)_{rt}$$

we have that:

$$plim(\beta_t^g) = \omega_t^g + \frac{cov(\sum_e s_{ert}^g \delta_{et}, \ln(density)_{rt})}{var(\ln(density)_{rt})}$$

therefore β_t^g has two components

- ω_t^g = gender-specific urban wage premium.
- A term reflecting bias due to heterogeneous composition of the population across labor markets. For example, if high-wage groups are more likely to locate in cites $\Longrightarrow$ β_t^g overestimates the gains from moving to a city.

I will impose another strong assumption. Let $\frac{cov(\sum_e s_{ert}\delta_{et}, \ln(density))}{var(\ln(density)_{rt})} = \chi_t^g$.

Then, abusing a bit of notation, we have

$$\beta_t^g = \omega_t^g + \chi_t^g$$

This simple model suggests a procedure to decompose the density gradient into the selection / urban premium components.

1. β_t^g is obtained from a simple regression of average *raw wages* on population density.
2. Under the assumption of $\gamma_{ert} = \omega_t^g \ln(density)_{rt}$ an individual's wage is reduced to:

   $$w_{iert}^g = \alpha_t + \delta_{et} + \gamma_{rt}^g + \varepsilon_i$$

   which is just a regression of individual's wages on education fixed-effects, and a gender$\times$CZ fixed effects. In this case γ_{rt}^g gives an estimate of $\omega_t^g \ln(density)_{rt}$.
3. From there, it is straightforward to obtain an estimate of the urban wage premium, just estimate the regression:

   $$\gamma_{rt}^g = \eta_t + \omega_t^g ln(density)_{rt} + \nu_{rt}$$

4. The selection component is obtained out of the difference between the estimates in part 1 and 3.

Some remarks:

- In the discussion above I am assuming that the urban wage premium is the same for education groups $\gamma_{er}^g = \omega_t^g \ln(density)_{rt}$. If the premium were education-specific then,

  $$w_{rt}^g = \alpha_t + \sum_e s_{ert}^g \delta_{et} + \sum_e s_{ert}\omega_{et}^g \ln(density)_{ert} + u_{rt}$$

  which would introduce heterogeneity in the density gradient across commuting zones. One can easily explore whether this is an issue by estimating ω^g by education group (this is feasible only when there is a limited number of education groups).

Results

Premium today: in the table below I show the decomposition described above under different sets of controls.

Density premium by gender, 2020

Men	Raw	Basic	Human capital	Industry	Industry and occupation
Men					
Adjusted premium	0.044	0.049	0.035	0.032	0.025
Selection component		-0.005	0.015	0.003	0.007
% explained		-0.118	0.296	0.083	0.210
Women					
Adjusted premium	0.052	0.062	0.049	0.045	0.039
Selection component		-0.010	0.014	0.004	0.006
% explained		-0.202	0.218	0.082	0.124
Wage gap					
Adjusted premium	-0.007	-0.013	-0.014	-0.013	-0.014
Differences in selection		0.005	0.001	-0.001	0.001
% explained		-0.703	-0.087	0.080	-0.095

Interpretation notes:

- From left to right, each column adds a new set of regressors controls. Thus the interpretation of the selection component in, say the human capital column, is how much of the density gradient is accounted by the human capital controls, over an above the basic set of controls. As a result, the % explained column is computed relative to the adjusted premium in the basic column.
- A negative selection component $\implies$ denser cities have higher shares of low wage groups.
- A positive component $\implies$ denser cities have lower shares of low income groups.

What does stand out?

- Women's premium is always larger than men's.
- Selection component of basic (age, rage, foreign born dummies) is always negative (city's population is blacker and younger, which tend to be associated with a lower income). *Selection on basic demographics* is twice as important for women than for men.
- Selection on education, industry, occupation is very similar for both genders.
- **Overall message:** even after accounting for this rich set of characteristics, women's premium is positive and bigger than men. Cities appear to draw more women from low-wage groups $\implies$ accounting for different demographic composition actually *increases* women's relative density premium.

Premium over time The table below shows the decomposition of the density gradient for three selected years.
What does stand out?

- In 1970, city women were more likely to come from low education groups. This had reversed by 2020.
- 1970-1990: Accounting for industry of employment eliminates the gender gap in the urban premium. Even though both genders are employed in higher pay industries in cities, men are more likely to do so $\implies$ most of density premium can be explained by gender segregation across industries.
- Note however, that industry and occupation does not erase the gap in the urban premium across genders in 2020. Even after accounting for industry and employment, the women's premium is 56% larger than men's.
- The table also makes clear the pattern already noted by [cite autor here]. There's a precipitous decline in men's urban wage premium. If we concentrated in the last column, between 1990 and 2020 men's premium declines by 61%. What is remarkable, is that women's premium is relatively more resilient, declining by 40% over the same period.
- Without adjusting for industry and occupation men's decline in the premium was so strong that it went from being *above* women's, to being below it.

The attached coefficient plots basically paint the same picture. They also suggests that the reversal of fortunes happened during the 1990s. From then on, there is a gradual expansion of the gender gap in the premium.

Some interpretation caveats

- In the discussion above I am interpreting $\hat{\omega}_t^m - \hat{\omega}_t^f$ as evidence of differneces genders in the urban wage premium. This interpretation might not be correct. For example, suppose that urban wage premium differs by education level, but not across genders. That is:

  $$\gamma_{ert}^m = \gamma_{ert}^f = \omega_{et} \ln(density)_{er}$$

  note that in this case:

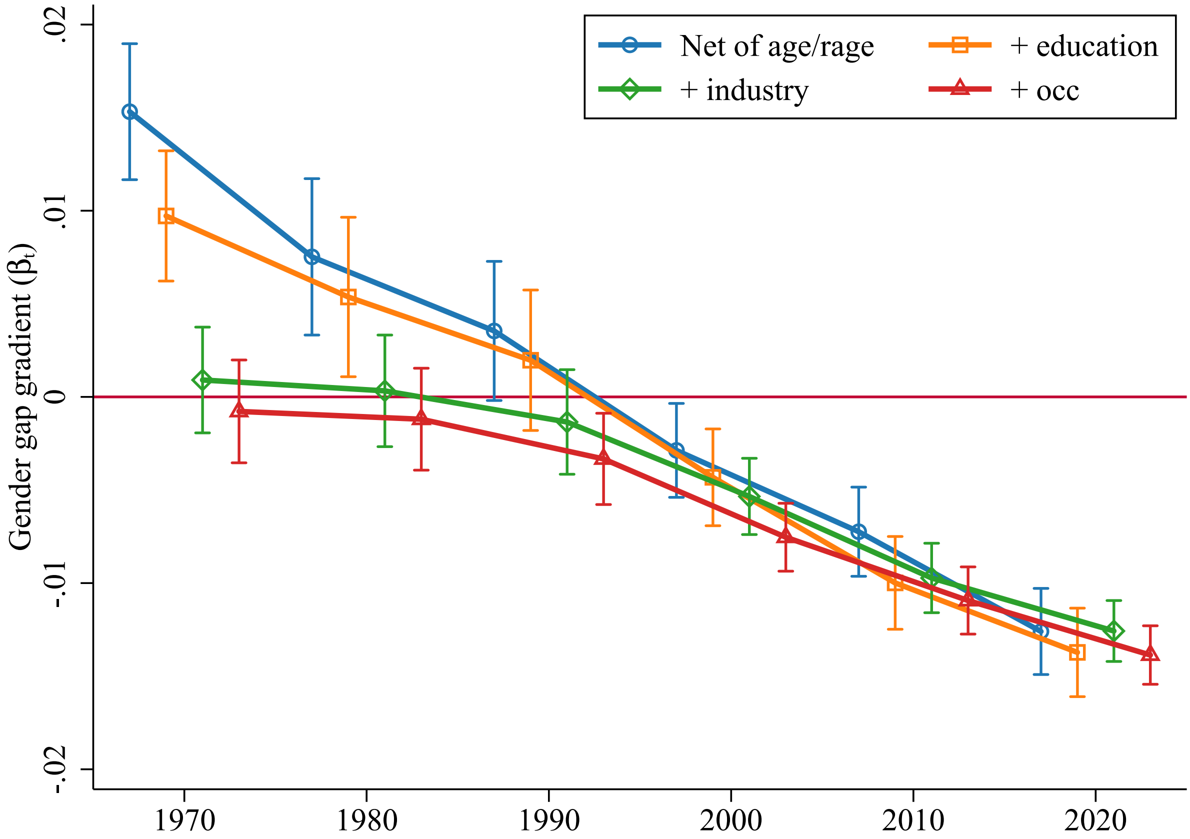
  $$w_{rt}^m - w_{rt}^f = \alpha_t^m - \alpha_t^f + \sum_e \delta_e (s_{ert}^m - s_{ert}^f) + \sum_e \omega_{et} (s_{ert}^m - s_{ert}^f) \ln(density)_{rt} + u_{rt}$$

  Under this scenario the gradient on density is given by:

  $$\sum_e \omega_{et} (s_{ert}^m - s_{ert}^f)$$

  The expression above will likely be negative if:

Figure 7: Coefficient on population density β_t controlling for worker characteristics



Note: figure restricts to CZ with more than 1 people per km^2. The regressions are done on data aggregated at the CZ level. Bars show 90% robust confidence intervals. Standard errors clustered at the CZ level. Figure generated on 30 Nov 2020 at 11:17:23. Figure generated using the dofile 2_analysis/code_files/write_regression_coefplots.do.

- Women concentrate more heavily in high urban wage premium groups.

If we now focus on the drift down of the premium, men's advantage will decline if:

- The premium for men-heavy groups is declining over time.
- Or women are increasingly concentrating in high urban premium groups.

Note that this model also suggests' a quick way to discard this possibility. Note that the within-group gender wage wage is given by:

$$w^m_{ert} - w^f_{ert} = \alpha^m_t - \alpha^f_t + u_{rt}$$

thus there shouldn't be a within-group gender-gap gradient on density. Given the increase in women's educational attainment since the 1970 education is a natural target to apply this test.

The discussion above takes the proposed model too seriously, but it gives an useful intuition. If the drift in the gender-gap premium is driven by differences in group premia + changes in the the composition of the labor force across genders, then these issues should be less prevalent when I compute the regressions by group.

Urban wage premium over time

	Raw	Basic	Human capital	Industry	Industry and occupation
1970					
Men					
Adjusted premium	0.067	0.075	0.077	0.058	0.052
Selection component		-0.008	-0.003	0.020	0.006
		-0.120	-0.035	0.255	0.107
Women					
Adjusted premium	0.047	0.060	0.068	0.057	0.052
Selection component		-0.013	-0.008	0.011	0.005
		-0.277	-0.138	0.161	0.081
Wage gap					
Adjusted premium	0.020	0.015	0.010	0.001	-0.001
Differences in selection		0.005	0.006	0.009	0.002
% explained		0.243	0.366	0.907	1.778
1990					
Men					
Adjusted premium	0.083	0.088	0.084	0.072	0.064
Selection component		-0.005	0.015	0.003	0.007
		-0.063	0.165	0.035	0.093
Women					
Adjusted premium	0.074	0.085	0.082	0.073	0.067
Selection component		-0.011	0.003	0.008	0.006
		-0.144	0.038	0.103	0.083
Wage gap					
Adjusted premium	0.009	0.004	0.002	-0.001	-0.003
Differences in selection		0.005	0.002	0.003	0.002
% explained		0.576	0.472	1.684	-1.615
2020					
Men					
Adjusted premium	0.044	0.049	0.035	0.032	0.025
Selection component		-0.005	0.015	0.003	0.007
% explained		-0.118	0.296	0.083	0.210
Women					
Adjusted premium	0.052	0.062	0.049	0.045	0.039
Selection component		-0.010	0.014	0.004	0.006
% explained		-0.202	0.218	0.082	0.124
Wage gap					
Adjusted premium	-0.007	-0.013	-0.014	-0.013	-0.014
Differences in selection		0.005	0.001	-0.001	0.001
% explained		-0.703	-0.087	0.080	-0.095

5.2 Are the results above driven by different wage premium across educational groups?

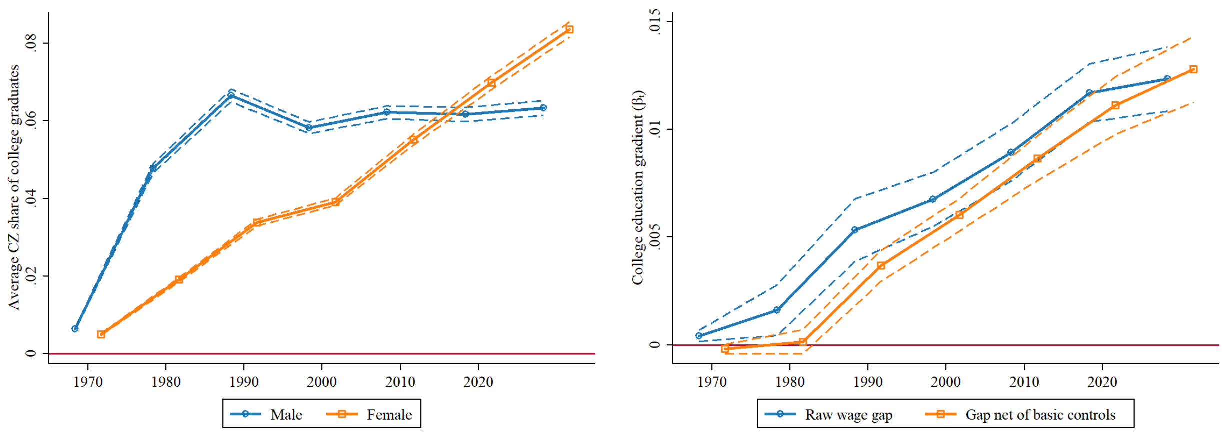
Short answer: no. But the drift in the gender-gap gradient is driven by workers without a bachelor degree.

Panel a in figure 8 shows that women educational attainment have increased dramatically relative to men. Panel b shows that it has increased more in the densest labor markets. If the urban wage premium of college graduates is larger than non-college graduates, then this trends could drive the patterns described in previous sections.

Figure 8: Educational attainment by gender

(a) Average share college graduates

(b) College share-density gradient



Note: figure restricts to CZ with more than 1 people per km^2. Bars show 90% confidence intervals. Standard errors clustered at the CZ level. Figure generated on 30 Nov 2020 at 11:17:24. Figure generated using the dofile 2_analysis/code_files/write_regression_coefplots.do.

In panel a of figure 9, I show estimates of β_{et} for the following regression model:

$$w^m_{ret} - w^f_{ret} = \alpha_{et} + \beta_{et} \ln(density)_{rt}$$

If all the variation is driven by changes in education-specific urban wage premium, then we should expect β_{et} to be zero in all years. This is not what the data shows. The gender-gap gradient is positive and mostly constant for college graduates. The decline in the gradient arises for non-college graduates only. Panel b shows that adjusting the gap for age and race does not change this finding (panel b).

Panels c and d show the density premiums by gender. There I plot the density slope in regressions of the form:

$$w^g_{ret} = \alpha^g_{et} + \beta^g_{et} \ln(density)_{rt}$$

- Women with a bachelor degree benefit *less* from cities than men. Moreover, panel (b) shows that there is no decline in the urban wage premium for college workers. This is consistent with the findings by [autor].

- The decline for non college workers happens in both genders. But again, women are less affected by this development $\implies$ *the reversal of fortunes is happening for college without a college education.*

Although education is an endogenous outcome, it is remarkable that the urban wage premium for college graduates is so constant for both genders over the whole period.

- Women's labor force participation and educational attainment has increased massively over the years. Moreover, their concentration in urban areas has also increased. If anything, a simple supply-demand framework would have suggested that the gender-gap premium should have decreased.

- This begs the question of whether the urban wage premium is smaller for college women. If so, what prevents them from reaping the same benefits as men from cities?

5.3 1970-1990

Figure 21 suggests that industry of employment accounts for both the (i) cross-sectional gender-gap gradient, and (ii) its decline during 1990-2020. Here I zoom in on the relationship between industrial structure, population density, and employment shares across genders.

5.3.1 What are the high pay industries?

Figure 10 shows two main facts:

- High pay industries are primarily manufacturing in 1970-2020.
- Over time, high-pay industries become more service-intensive.

5.3.2 Women are less likely to be employed in high pay industries

I include 147 industry classifications.

First I show that there are differences across gender in the likelihood of being employed in a high pay industry. For this I run the regression:

$$s_t^g = \alpha_t^g + \beta_t^g \lambda_{jt}$$

where s_t^g indicates the nation-wide employment share of gender g in industry j, and $\lambda_j t$ represents the industry fixed effect obtained in the first stage regressions.

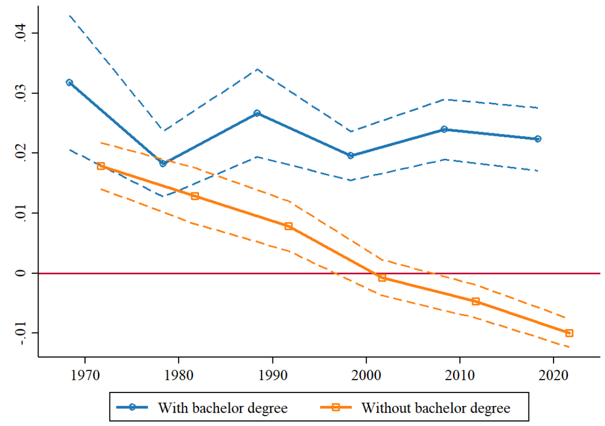
Figure 11 shows the estimated β^g for both genders.

Two features that stand out:

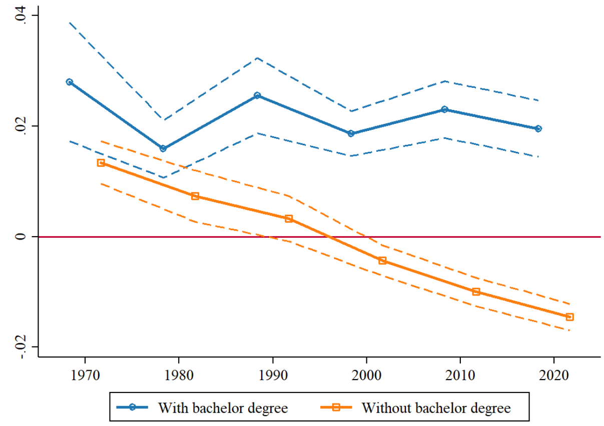
- On average women are less likely to be employed in the high wage industries. That said, estimates become much noisier from 1990 onward.

Figure 9: The density gradient by education level

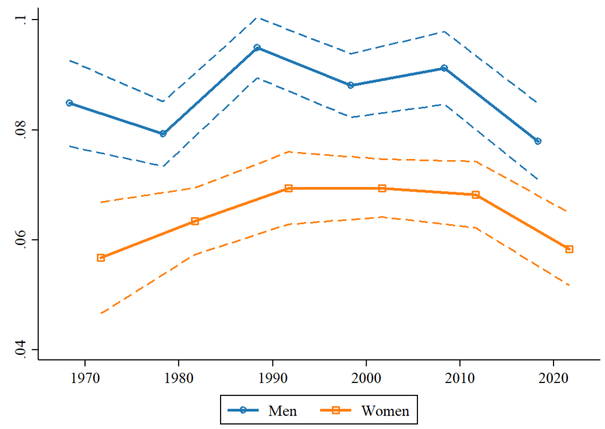
(a) Gender gap gradient



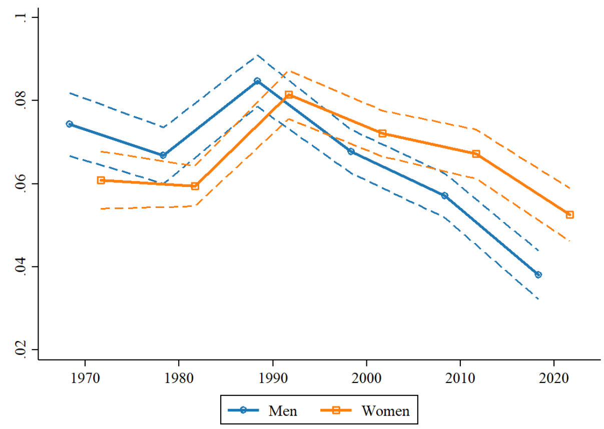
(b) Gender gap gradient, age and race adjusted



(c) Urban wage premium (age/race adjusted), with bachelor degree



(d) Urban wage premium (age/race adjusted), without bachelor degree



Note: figure restricts to CZ with more than 1 people per km^2. Dashed lines represent 90% confidence intervals. Figure generated on 30 Nov 2020 at 11:17:27. Figure generated using the dofile 2_analysis/code_files/write_regression_coefplots.do.

- There's a slight downward trend in men's likelihood of being employed in high-wage industries.

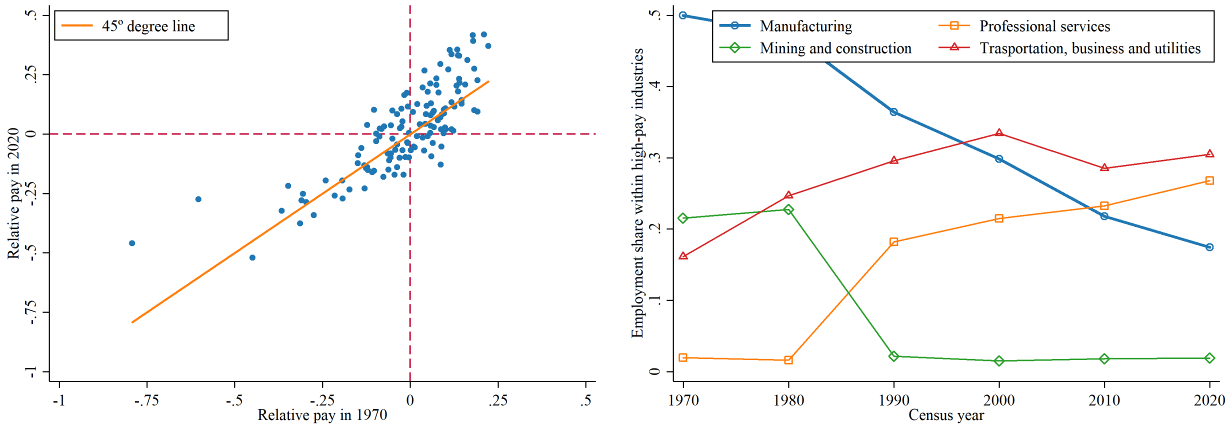
Panel a of figure 12 gives a more detailed description of the employment distributions by gender. Women in 1970 are primarily concentrated in low-pay industries, but over 1970 to 1990, they gained access to industries with better pay.

Men's evolution is also interesting. A comparison between panels (a) and (b) in 12 reveals two facts:

1. In 1970, men are highly concentrated in industries at the top of the pay distribution. Panel (a) also shows that there is persistence in this employment distribution. They continue to concentrated in industries that were high pay in 1970, even in 2020.

Figure 10: Industries and relative pay

(a) Relative pay in 2020 vs 1970 (b) High-pay industries by industry-group



Note: figure restricts to CZ with more than 1 people per km^2. Figure generated on 30 Nov 2020 at 23:01:52.

2. However, panel (b) that the industry ranking has changed, so that from 1990 onward, men are not as concentrated in high-pay industries as panel (b) suggests $\implies$ men's jobs are in relative decline *at the national level*

In parallel, men stat the period with a high concentration in high-pay industries, but this concentration diffuses over time.

Panel b also shows that even though men are still disproportionately concentrated on industries that were highly-paid in 1970, they are no longer high pay by the end of the period.

All in all, this exercise suggests that women's employment distribution is becoming more like men's. But this happens in part by men being less likely to be employed in high-wage industries.

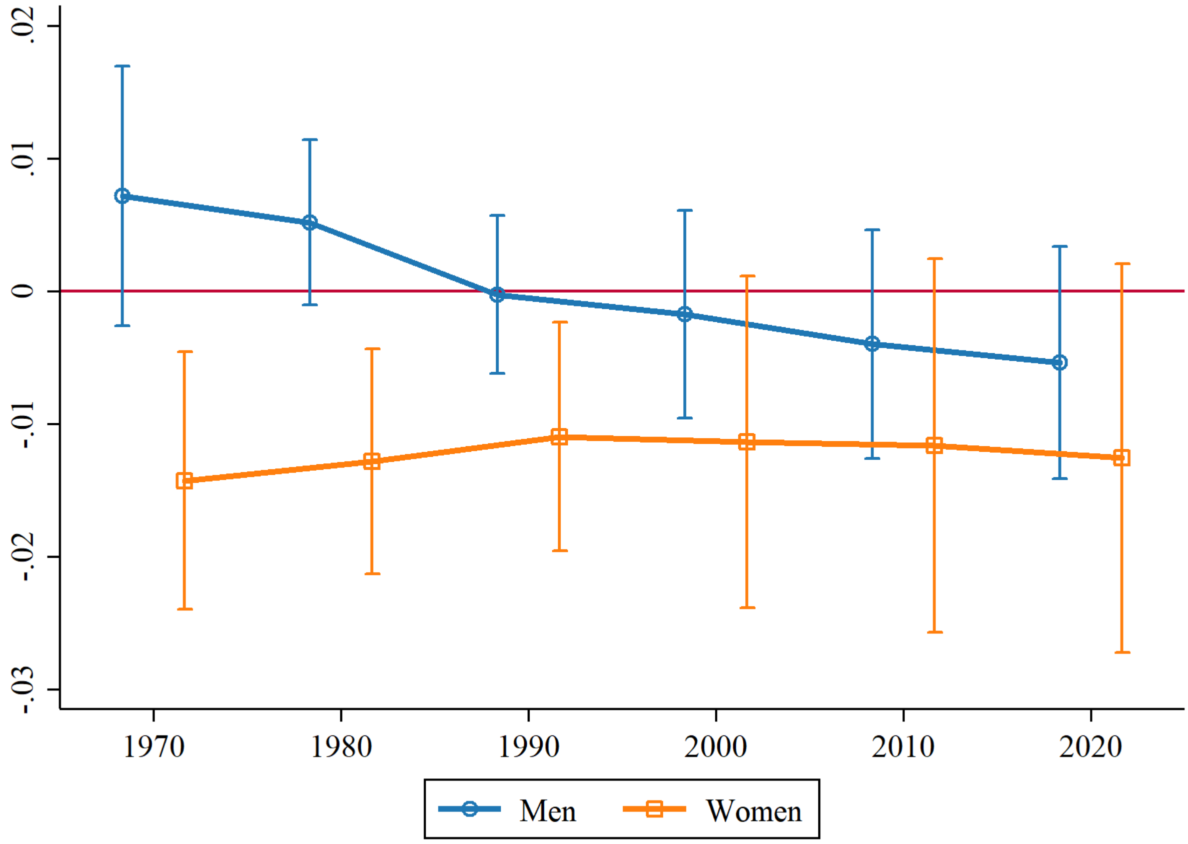
5.3.3 High pay industries are larger in denser cities

Figure 13 studies the relationship between high-pay industries and population density. To construct this figure, first I define an industry as being high-pay, it is in the top tercile of the national relative-pay rank. Rankings are computed separately for each year. Next I compute the CZ-level employment shares in high-pay industries.

- Panel (a) shows that dense cities are highly specialized in high-pay industries. However, this specialization decreases over time.
- Panel (b) shows a similar pattern as the scatterplots. There I plot the slope coefficient in the regression:

$$s_{rt}^{highpay} = \alpha_t + \beta \ln(density)_{rt}$$

Figure 11: Industry employment share by gender



Note: figure restricts to CZ with more than 1 people per km^2. Bars show 90% confidence intervals. Standard errors clustered at the CZ level. Figure generated on 30 Nov 2020 at 23:01:43.

the "fixed ranking" line computes the employment shares when the industry pay rank is fixed to 1970 values. The "variable ranking" allows the ranking to change over time. Either way, the message is the same: dense cities were highly specialized in high-pay-industries, but this specialization reduces over time.

Ten industries disappear over the sample period. Check what is happening to them

5.3.4 Can the industrial composition alone account for the gender-gap gradient?

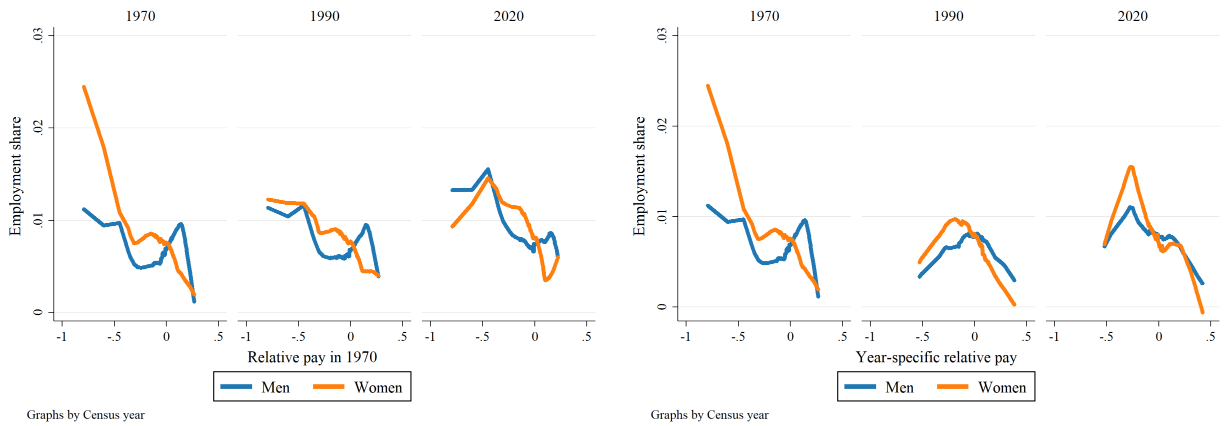
Yes, at least for the 1970-1990. To test this let's decompose the change in wages into a part that reflects only changes in the industrial employment distribution, and a second component that reflects only changes in average wages. Note that,

$$w^g_{rt} - w^g_{r1970} = \sum_j (s^g_{rjt} - s^g_{rj1970}) w^g_{rjt} + \sum_j s^g_{rj1970}(w^g_{rjt} - w^g_{rj1970})$$

- $\sum_j (s^g_{rjt} - s^g_{rj1970}) w^g_{rjt}$: captures only changes in the employment distribution over time.
- $\sum_j s^g_{rj1970}(w^g_{rjt} - w^g_{rj1970})$ captures only changes in the industrial average wages.

Figure 12: Industry employment distribution by gender

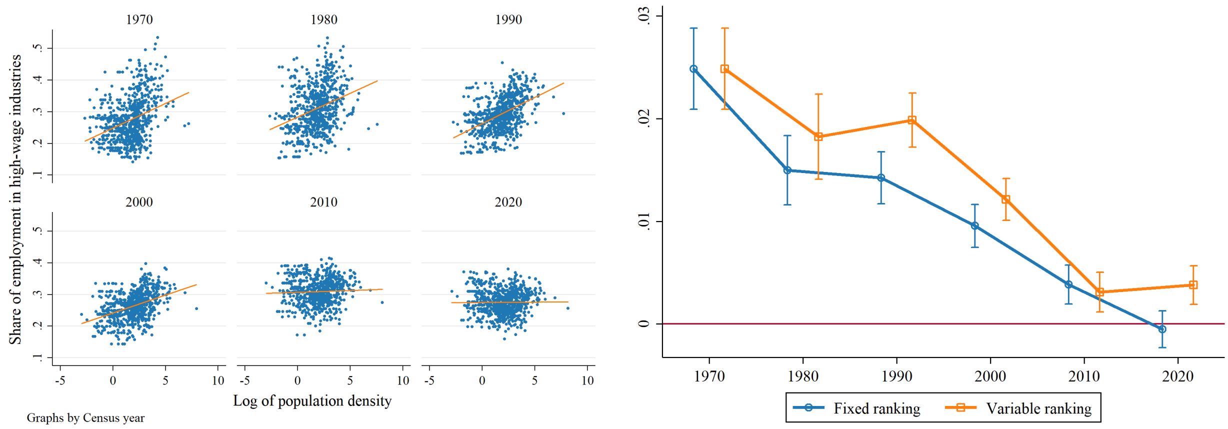
(a) Ranking fixed in 1970 (b) Varying the ranking



Note: figure restricts to CZ with more than 1 people per km^2. Figure generated on 30 Nov 2020 at 23:01:48.

Figure 13: High wage industries and population density

(a) Scatterplots by year (b) Density gradient



Note: figure restricts to CZ with more than 1 people per km^2. Figure generated on 30 Nov 2020 at 23:01:57.

Then if we consider the following two regressions:

$$\begin{aligned} w_{rt} &= \alpha_t + \beta_t \ln(density)_{rt} \\ \sum_j s^g_{rj1970} w^g_{rjt} &= \bar{\beta}_t + \bar{\beta}_t \ln(density)_{rt} \end{aligned}$$

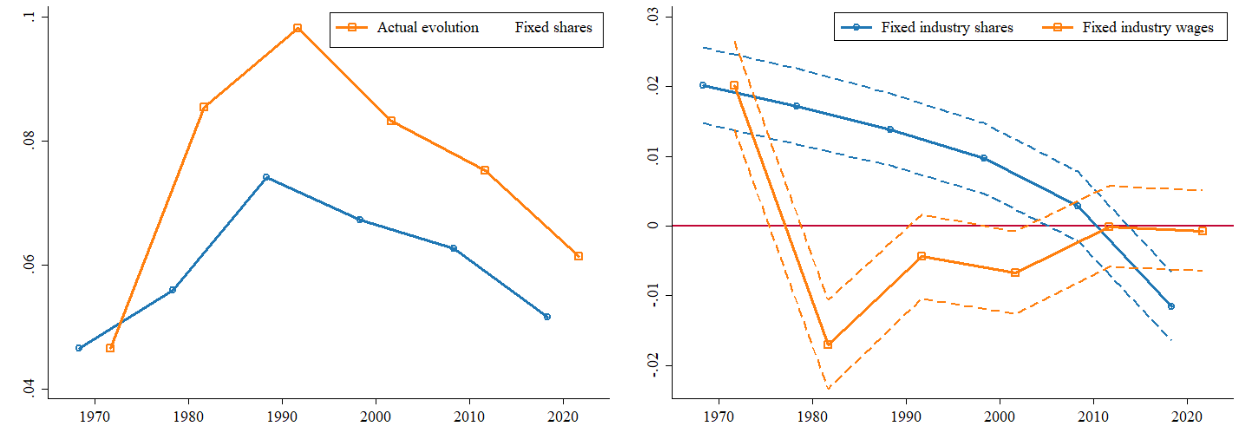
Then following the above decomposition we can readily interpret the density coefficients as follows:

- $\beta_t - \bar{\beta}_t$: change in the urban wage premium explained by changes in the industrial employment distribution.

- $\bar{\beta}_t - \beta_{1970}$: change in the urban wage premium that is explained by the evolution of industrial average wages.

Figure 14: Coefficient on population density β_t

(a) Fixed employment shares　　(b) Fixed employment shares vs fixed wages



Note: figure restricts to CZ with more than people per km^2. Bars show 90% confidence intervals. Standard errors clustered at the CZ level. Figure generated on 2 Dec 2020 at 13:48:43.

Taking the model presented in the previous Following the wage model presented in previous sections, the industry fixed effects account for the density gradient as long as there are differences by gender in the employment distributions by gender. As a quick check, consider the regression:

$$gap_{rt} = \alpha_t + \beta_t \ln(density)_{rt} + \chi_t(s_{rt}^{highpay,m} - s_{rt}^{highpay,f}) + \delta_t s_{rt}^{highpay,m} sh$$

where $s_{rt}^{highpay,g}$ is the employment share in high-pay industries for gender g. Panels (a) and (b) of figure 15 show the coefficient on density in the above regression. Two facts stand out:

1. Most of the cross-sectional correlation between density and the gender gap during the period 1970-1990 is accounted for the share of employment in high-pay industries.

2. Adding these additional regressors also accounts for *change in the gradient over this period.*

5.3.5 Is this about decline of these industries, or women's access to these coveted jobs?

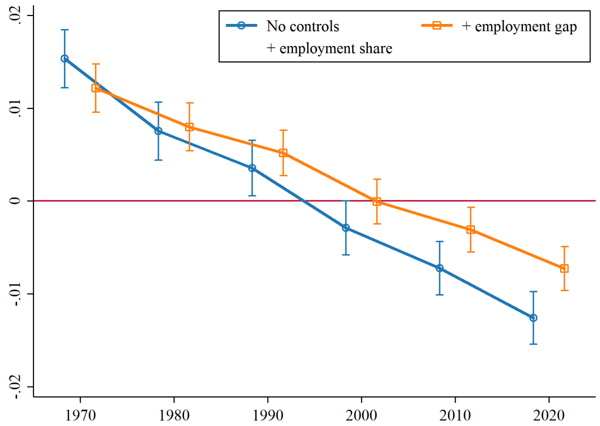
Consider the following regression:

$$gap_{rt} = \alpha_t + \beta_t \ln(density)_{rt} + \chi_t s_{rt}^{highpay} + \delta_t male\_share_{rt}^{highpay,f}$$

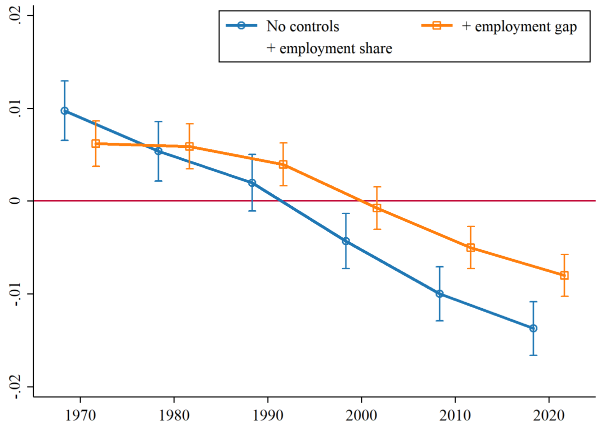
The idea here is to distinguish between two possible stories:

Figure 15: High wage industries by gender

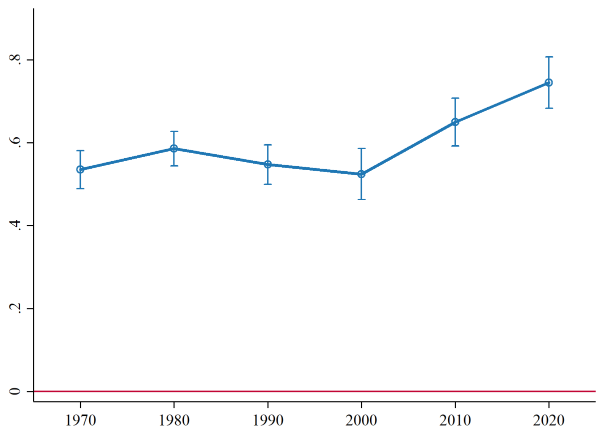
(a) Net-of race/age gender gap and high-wage industry share



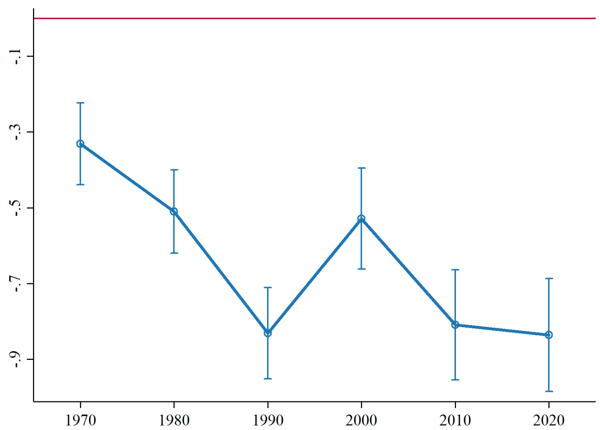
(b) Net-of-education gap and high-wage industry share



(c) Men's high-wage industry employment, men



(d) Women's high-wage industry employment



Note: figure restricts to CZ with more than 1 people per km^2. Figure generated on 30 Nov 2020 at 18:49:34.

- **Decline of high pay industries:** men in cities are heavily concentrated in industries that in urban decline.
- **Women access to better employment:** women in cities are initially excluded from high-pay jobs. Over time, they are able to access to these high-pay, which looks like a gain relative to men.

5.3.6 High pay industries are mostly manufacturing industries. Is 1970-1990 this about manufacturing?

No. Suppose the story at work here is:

- Manufacturing is concentrated in cities.

- Manufacturing is heavily male and high-pay.
- Over time, women get access to these coveted jobs.

Then, this could be captured in the regression,

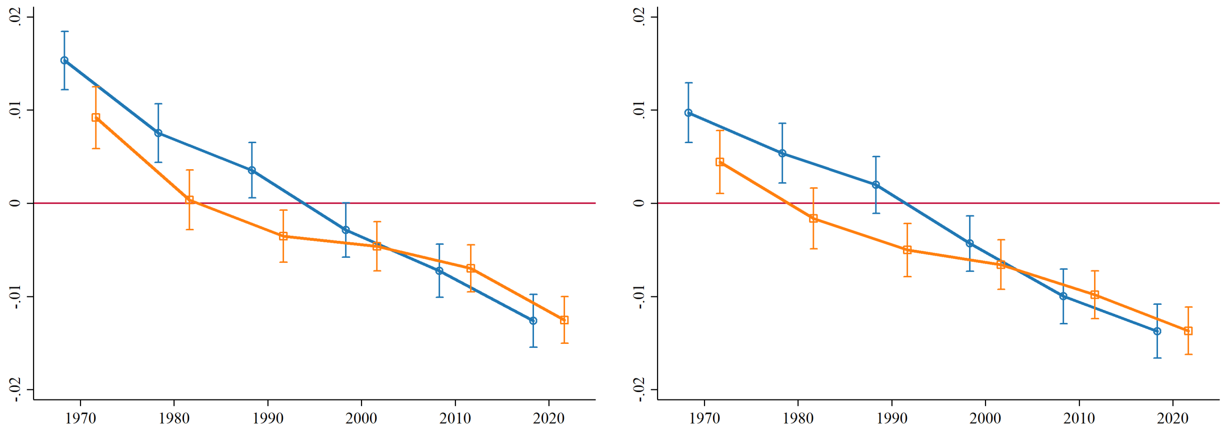
$$gap_{rt} = \alpha_t + \beta_t \ln(density)_{rt} + \chi_t s_{rt}^{manufacturing}$$

where we should expect the density gradient to disappear during 1970-1990. This is not what figure shows 16. Thus the point has to be more subtle.

Figure 16: High wage industries by gender

(a) Net-of race/age gender gap and high-wage industry share

(b) Net-of-education gap and high-wage industry share



Note: figure restricts to CZ with more than 1 people per km^2. Figure generated on 30 Nov 2020 at 18:49:36.

5.3.7 What is different about the high-pay industries?

5.3.8 Why doesn't industry account for the drift after 1990?

Following evidence presented in 13 the gradient on high-pay industries essentially disappears $\implies$ CZ-industry specialization stops driving the gradient.

It would also be hart to argue that gender differences across

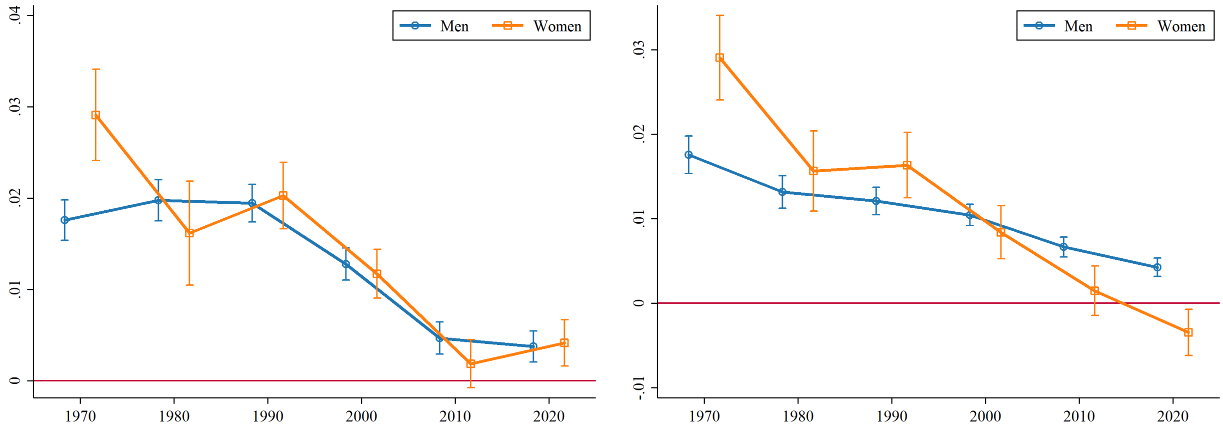
5.3.9 Taking stock:

Explaining the positive gradient during 1970-1990

- High-pay industries were heavily concentrated in dense commuting zones.
- These high pay industries (mostly manufacturing) where heavily male.
- The two above facts $\implies$ women were less likely to have high pay in densest cities $\implies$ positive gender-gap gradient over 1970-1990.

Figure 17: High wage industries by gender

(a) Variable industry ranking (b) Industry ranking fixed at 1970



Note: figure restricts to CZ with more than 1 people per km^2. Figure generated on 30 Nov 2020 at 23:02:04.

- Over time, high-pay industries become more service intensive. Services more female-friendly industries $\implies$ there's little difference in the employment distribution

- Moreover, industries (such as manufacturing) are in fast decline in the densest labor markets.

So, overall I think that 1970-1990 can be explained by decline in manufacturing. Whatever is happening from 1990 cannot be explained by manufacturing decline. Gradient in manufacturing is likely flat by the end of the period.

[next step=> what happens if I just control for the share of manufacturing in the aggregate level regression]

[structural transformation was larger in denser cities $\implies$ change towards female driven industries]

[Story after the 1990s appear to be more complicated]

6 Descriptive analysis

6.1 Basic facts and trends

- Most CZ are relative small. 40% of CZ account for 85% of the of the total population in almost all years.

- CZ at the very top have lost population share. "Mid"-tier cities are the ones with the fastest population growth.

- Overall, the US has experienced manufacturing decline. But decline has been much faster in the top 30% CZ (see here).

6.2 The gender gap

- Wage gap is decreasing everywhere. But decline is faster in densest CZ.
- There is a clear inversion of the gender-gap density gradient.
- This inversion is also present if I focus attention to the top 248 CZ. [see this graph].
-

6.3 LFP

- Employment to population ratio has always had an U pattern for men. The U pattern has exacerbated over the years. Decline in middle places has been faster. This is in line with the Ely Lecture (see here)
- For women, densest places offered more employment at the start. Over time, they have become more like men. U pattern seems to be intriguing (see here)
- What about the absolute values:
  - For men, the story if one of decline in LFP. With faster decline in the middle of the distribution. See here
  - For women, the story is one of faster progress at the tails of the distribution. here

7 Main findings

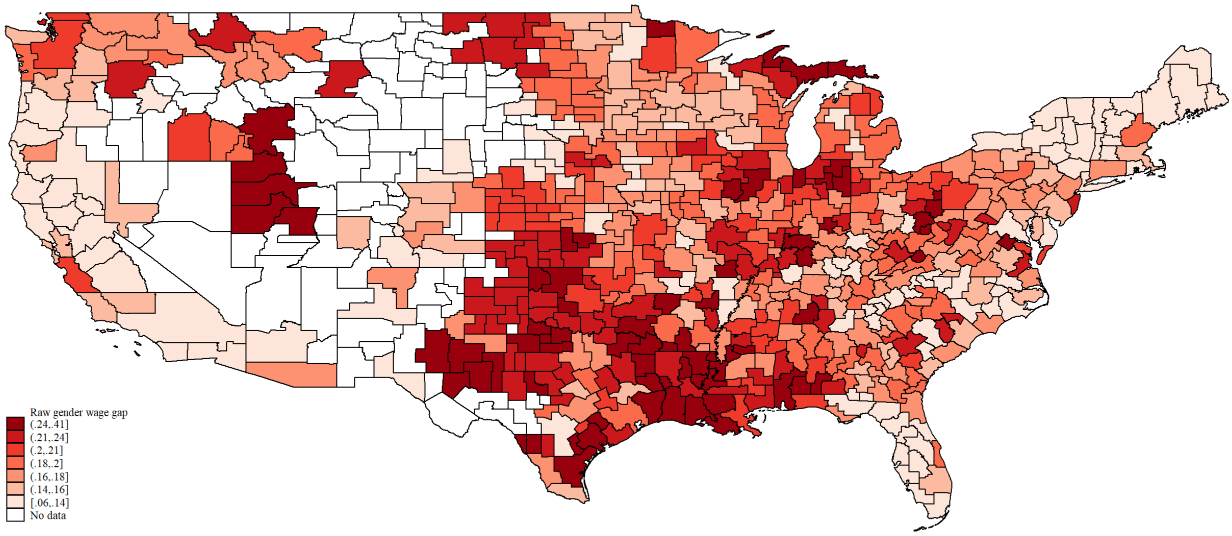
Fact 1: there are substantial differences in the level of the gender gap across CZ Figure 18 illustrates variation of the gender gap across US CZ in 2020. The figure restricts to CZ with population densities above 1 person per square kilometer in 1950. In 2020, men had an unconditional average wage 19 (se 5) log-points larger than women's. The map however, shows that there are wide variations from this average across CZ. Men's wage advantage is below 14 log-points in the Northeast and most of the West Coast, while it is above 24 log-points in the parts of the South West. The standard deviation in gender-wage gap across the 625 CZ shaded in the graph is of 5 log-points, which represents 26% of the average national gap.

[make an argument here that these differences are economically significant]

Fact 2: there are substantial differences in the evolution of the gender gap across CZ

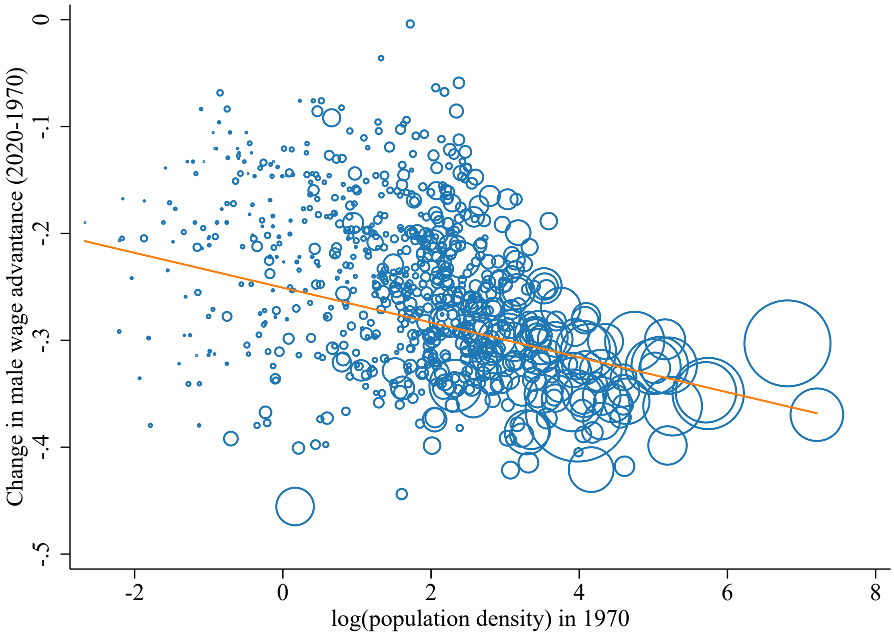
- Take two CZ as an example and show the evolution of the gender gap in these two places.
- Then show statistics on the change of the gender gap across places.

Figure 18: The gender gap in the US in 2020



Note: darker colors denote higher relative wages for men. Figure restricts to czones with population densities above 1 person per km^2 and full-time year-round workers.

Figure 19: Change in male wage advantage in US CZ



Fact 3: the gender gap has decreased the most in the densest CZ [add residualization at the individual level]

Fact 4: the relationship between population density and the gender gap has inverted over the period [write regression I am writing here]

[graph of cross-sectional slope goes here]

8 Robustness of facts 3 and 4

8.1 Composition of the sample

- Results are robust to including all male and female workers.
- Results are also results for controlling for basic demographics

8.2 Weighting of regressions

Both facts are robust to alternative weighting mechanisms. Weighting only changes the timing of the decline in the population density gradient.

- This happens because decline of the gap happens first in denser places and then it decelerates.
- Places at medium levels of density speed the decline from 1990 on. This would explain the difference between between weighted and unweighted estimates.

8.3 Alternative measures of density

- Results are robust to using population as a measure of density.

9 Possible explanations

9.1 Causes for the gender gap in the literature

9.2 Increased sorting

- Regressions above do not control for observable characteristics.
- If women with stronger ability sort themselves:
  - Increasingly in denser cities.
  - This sorting is stronger than men.
- This would generate faster decrease of the gender gap in denser places.

Suppose wages are determine as follows:

$$y_{igr} = X_{igr}\gamma + \varepsilon_{igr}$$

taking averages by gender at the CZ level we have:

$$\bar{y}_{gr} = \bar{X}_{gr}\gamma + \bar{\varepsilon}_{gr}$$

therefore:

$$\bar{y}_{mr} - \bar{y}_{fr} = (\bar{X}_{mr} - \bar{X}_{fr})\gamma + \bar{\varepsilon}_{mr} - \bar{\varepsilon}_{fr}$$

so by running the regression:

$$\bar{y}_{mr} - \bar{y}_{fr} = \beta \log(density)_r + \bar{\varepsilon}_{mr} - \bar{\varepsilon}_{fr}$$

β would be reflecting the correlation between CZ population density and the average gap between male and female characteristics. This omitted variable problem is easily resolved by running the regression:

$$\bar{y}_{mr} - \bar{y}_{fr} = (\bar{X}_{mr} - \bar{X}_{fr})\gamma + \beta \log(density)_r + \bar{\varepsilon}_{mr} - \bar{\varepsilon}_{fr} \tag{1}$$

Things to have in mind

- These regressions impose the same return to observable characteristics for men and women in all CZ. Differential returns across CZ will go into the residual.

Procedure

Aggregate level data I run the regression

$$\bar{y}_{mr} - \bar{y}_{fr} = \alpha_t + (\bar{X}_{mr} - \bar{X}_{fr})\gamma_t + \beta_t \log(density)_r + u_{rt}$$

where I allow the return to observable characteristics to vary by year. The main interest is looking at the resulting evolution of β_t.

Individual level data This just allows for a more flexible variation on the returns of age birth place. Here the estimation is done in two steps:

1. Estimate the regression:

$$y_{igr} = X_{igr}\gamma + \lambda_{gr} + \varepsilon_{igr} \tag{2}$$

2. Compute CZ-adjusted wage gap:

$$\tau_r = \lambda_{mr} - \lambda_{fr}$$

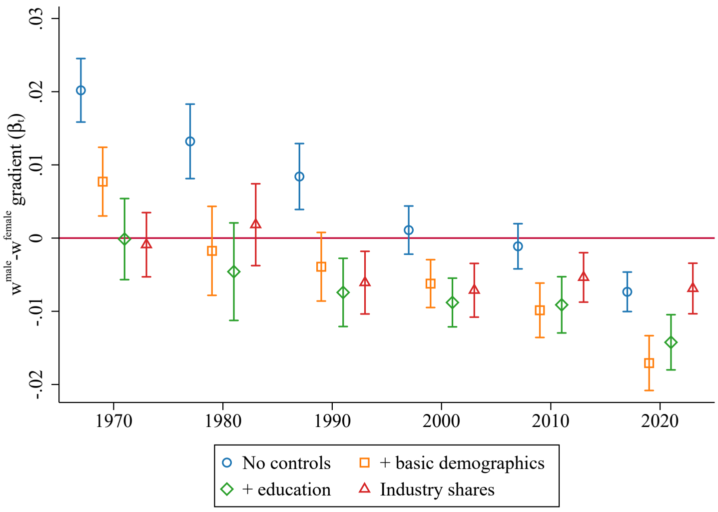
3. Run the regression:

$$\tau_r = \alpha_t + \beta_t \log(density)_r$$

I prefer this method as it exploits the individual level data in a richer way.

Results Overall individual level characteristics have limited value in accounting for the cross-sectional gradient and time-variation. Industry-level dummies are much more successful in accounting for the 1970-1990 period.

Figure 20: Coefficient on population density β_t controlling for worker characteristics



Note: figure restricts to CZ with more than 1 people per km^2. The regressions are done on data aggregated at the CZ level. Bars show 95% robust confidence intervals. Standard errors clustered at the CZ level.

9.3 Changes in CZ industrial structure

Figure 4 suggests that changes in the CZ industrial structure can go a long way in accounting for the cross-sectional variation. Here I do several exercises to explore this possibility.

9.3.1 Some national level facts

Women are initially concentrated in low-pay industries See here => regions specialized on these high-pay industries will show a higher gender gap.

Getting a workable definition of a high-wage 70s industry A high wage industry is one that has a high worker-adjusted average pay in 1970. To be more precise, using individual level data in 1970 I run:

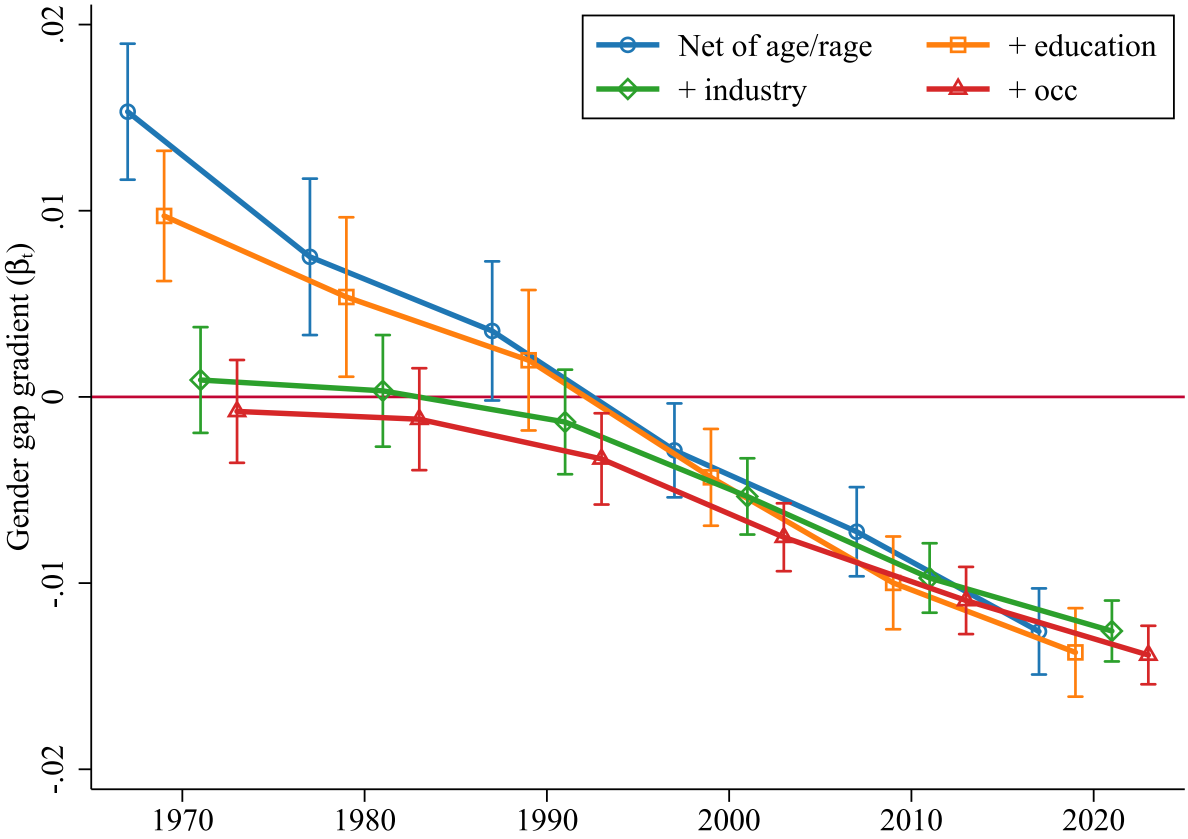
$$y_i = X_i\beta + \lambda_s \tag{3}$$

where s denotes the industry. I define an industry as having high-pay if they are in the top quartile of the λ_s distribution. When computing the quartiles, industries are weighted by employment share so that in 1970 each quartile accounts for 25% of the national level.

High pay industries were disproportionately concentrated in denser places in 1970 (graph)

High pay industries are in decline at the national level (graph) decline at the national level starts in 1990

Figure 21: Coefficient on population density β_t controlling for worker characteristics



Note: figure restricts to CZ with more than 1 people per km^2. The regressions are done on data aggregated at the CZ level. Bars show 90% robust confidence intervals. Standard errors clustered at the CZ level. Figure generated on 30 Nov 2020 at 11:17:23. Figure generated using the dofile 2_analysis/code_files/write_regression_coefplots.do.

High pay industries belong mainly to manufacturing (log file) the rest are mostly oil or utilities.

Employment share in highly paid industries accounts for most cross-sectional gradient on density during 1970-90 (graph) it also accounts for the time variation from 1970-90s. There's still something going on from 90 to 20

What can be happening:

- High wage industries are in decline in denser places... then the decline decline in male advantage comes from employment reallocation.
- It can be that at the start of the period, women are getting better access these industries. *I think for the 90's this seems to be the case.*

These industries continue to be highly paid industries See here

Denser CZ are more specialized in 70s high pay industries See here

70s high-pay industries decline disproportionately more in denser places

Women here

10 When would the national level fixed-effects account for the cross-sectional variation?

Suppose the wage profile of individuals is determined as follows:

$$w_{ir} = \lambda_e \tag{4}$$

where λ_e is a national-level fixed effects. Then,

$$\bar{w}_r^g = \sum_e \lambda_e s_r^g \tag{5}$$

then the gender gap in a given commuting zone is given by,

$$\bar{w}_r^m - \bar{w}_r^f = \sum_e^g \lambda_e^g (s_r^m - s_r^f) \tag{6}$$

suppose that:

$$s_r^g = \alpha_e^g + \beta_e^g \log(density)_r \tag{7}$$

then gender gap equation becomes,

$$\bar{w}_r^m - \bar{w}_r^f = \sum_e \lambda_e (\alpha_e^m - \alpha_e^f) + \sum_e \lambda_e (\beta_e^m - \beta_e^f) \log(density)_r \tag{8}$$

It follows that $\sum_e \beta_e^g = 1$. This follows from the identity below holding for all CZ:

$$1 = \sum_e s_{er}^g = \sum_e \alpha_e^g + (\sum_e \beta_e^g) \log(density)_r \tag{9}$$

So a negative coefficient in density requires:

$$\sum_e \lambda_e (\beta_e^m - \beta_e^f) < 0 \tag{10}$$

Which roughly requires that have a higher gradient on density in employment in "high-pay" groups relative to men.

Now suppose that the wage profile is given by:

$$w_{ir} = \lambda_e^g \tag{11}$$

then,

$$
\begin{aligned}
\bar{w}_r^m - \bar{w}_r^f &= \sum_e \lambda_e^m s_{er}^m - \lambda_e^f s_{er}^f && (12) \\
&= \sum_e (\lambda_e^m - \lambda_e^f) s_{er}^m + \lambda_e^f (s_{er}^m - s_{er}^f) && (13)
\end{aligned}
$$

thus it would have to be that the employment structure of the densest CZ is concentrated in those groups that experience the largest gender gap decline at the national level.

A On weighting

Here the basic question I want to answer is, can I have a good answer as to why I am not weighting.

Suppose wages are determined according to the model:

$$w_{ir}^g = \beta X_{ir}^g + \varepsilon_{ir}^g \tag{14}$$

where $\varepsilon_{ir}^g = \gamma_r^g + u_{ir}$ where γ_r^g and u_{ir} are independent.

$$
\begin{aligned}
\bar{w}_r^m - \bar{w}_r^f &= \beta(X_r^m - X_r^f) + \bar{\varepsilon}_r^m - \bar{\varepsilon}_r^f \\
&= \beta(X_r^m - X_r^f) + v_r
\end{aligned}
$$

note that if we assume that $var(\gamma_r^g) = \sigma_\gamma^2$ and $var(u_{ir}) = \sigma_u^2$.

$$
\begin{aligned}
var(v_r) &= var(\bar{\varepsilon}_r^m) + var(\bar{\varepsilon}_r^f) - cov(\bar{\varepsilon}_r^m, \bar{\varepsilon}_r^f) \\
&= 2\sigma_\gamma^2 + \sigma_u^2 \left(\tfrac{1}{N_m} + \tfrac{1}{N_f} \right)
\end{aligned}
$$

so, in the end I can test whether heteroskedasticity is a problem by running the regression (15) by OLS, extract the residuals and then run the regression:

$$\hat{u}_r = \alpha + \beta \left(\frac{1}{N_m} + \frac{1}{N_f} \right)$$

The results from this exercise give little justification for weighting the regressions. See this log-file.

B On the interpretation of the coefficients

The main findings come from regressions of the form:

$$\ln\left(w^{male} - w^{female}\right) = \alpha_t + \beta_t \ln(pop\_density)_{rt} + \epsilon_{rt}$$

without giving any causal interpretation to the coefficients, what is the interpretation of β_t?

B.1 Mathematical interpretation

First note that:

$$\beta_t = \frac{\partial \ln \left(w^{male} / w^{female} \right)}{\partial \ln pop\_density_{rt}}$$

thus β_t can be interpreted as the elasticity of the male wage advantage with respect to population density. Table 4 shows the estimated elasticities.

Table 4: Elasticities of male wage advantage to population density

Regression specification	**1970**	**1980**	**1990**	**2000**	**2010**	**2020**
Unweighted OLS	0.046***	0.030***	0.019***	0.003	-0.003	-0.017***
	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)
Weighted by population	0.034**	0.007	-0.019*	-0.026**	-0.024***	-0.026***
	(0.013)	(0.013)	(0.008)	(0.008)	(0.006)	(0.005)
Observations	625	625	625	625	625	625

Note: Robust standard errors in parenthesis. Sample restricts to full-time year-round workers.. Table generated on 14 Aug 2020 at 15:39:24.

B.2 Economic interpretation

My basic results show that this elasticity:

- Has continually declined since the 1970s.
- It went from positive in 1970, to negative by 2020.

These elasticities are big and economically significant. Tables and 6 shows two ways of putting these numbers into perspective. Table 5 shows that moving form a CZ with a population density in the 25th percentile, to one in the 75th percentile translates into an increase of 4 p.p. in the male wage advantage in 1970. However, this same movement is associated with a decrease of 1.5 p.p. in the male advantage in 2020. These movements are equivalent to:

- A change of ∼10% relative to the average male advantage in each respective year.
- If we translate these figures to dollar amounts using as reference the annual wage income of the average full-time female worker, moving from the 25th to the 75th percentile in population density translates into $1.1 k relative gain for men in 1970, but a $0.6k relative loss in 2020.

Additionally, table 6 shows the estimated elasticities when I transform both the wage gaps and the CZ population density. If we focus on the unweighted OLS estimates, an increase of 1 sd in the log of population density is associated with 0.3 sd in the male wage advantage in 1970, but with a 0.2 sd deviations decrease in 2020.

Table 5: Male advantange changes implied by estimated elasticities

p.p. change in male advantage	**1970**	**1980**	**1990**	**2000**	**2010**	**2020**
Average male advantage	0.44	0.41	0.33	0.26	0.20	0.19
p75-p25	0.04	0.03	0.02	0.00	-0.00	-0.01
Relative male gain ($ USD)	1,116	793	534	73	-80	-559
p85-p15	0.08	0.05	0.03	0.00	-0.00	-0.02
Relative male gain ($ USD)	1,898	1,313	877	122	-134	-910
p90-p10	0.09	0.06	0.04	0.00	-0.00	-0.03
Relative male gain ($ USD)	2,379	1,644	1,088	153	-167	-1,159

Note: changes based on unweighted estimated elasticities in table 4. Sample restricted to full-time year-round workers. I compute the dollar figures using the wage of the average full-time year-round woman in my sample, assuming she worked 40 hrs a week during 40 weeks. All figures are in 2018 dollars. Table generated on 14 Aug 2020 at 18:35:47. Table generated with do file 2_analysis/code_files/create_IC_table.do

Table 6: β_t on standardized data

Regression specification	**1970**	**1980**	**1990**	**2000**	**2010**	**2020**
Unweighted OLS	0.330***	0.205***	0.176***	0.029	-0.030	-0.192***
	(0.036)	(0.040)	(0.048)	(0.044)	(0.042)	(0.036)
Weighted by population	0.244**	0.047	-0.173*	-0.301**	-0.283***	-0.300***
	(0.089)	(0.089)	(0.076)	(0.091)	(0.074)	(0.057)
Observations	625	625	625	625	625	625

Note: Robust standard errors in parenthesis. Sample restricts to full-time year-round workers.. Table generated on 14 Aug 2020 at 16:48:21.

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