Online Appendix for: Jacks of All Trades and Masters of One: Declining Search Frictions and Unequal Growth

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Online Appendix

A Related Literature

Our paper contributes to the literature on rising wage inequality between different groups of workers. The literature started by documenting the rise in the college premium (Katz and Murphy 1992). The canonical explanation for this phenomenon is that technological progress is biased in favor of skilled workers either by fiat (see, e.g., Katz and Murphy 1992 and Card and DiNardo 2002) or because capital equipment is complementary to skilled labor (Krusell et al. 2000). More recently, the literature has switched its focus from the college premium to the rise in wage inequality between routine and non-routine workers (Autor and Dorn 2013). The standard explanation for this phenomenon is again a version of the skilled-biased technical change hypothesis, in which automation erodes the wages of routine workers (see, e.g., Autor and Dorn 2013, Acemoglu and Restrepo 2018, Adao et al. 2020, Ray and Mookherjee 2020). Our paper provides a complementary explanation based on the view that improvements in the search technology have different effects on routine and non-routine workers.

Our paper also contributes to the literature on search frictions and wage inequality. Generally, this literature is focused on measuring the contribution of search frictions to the dispersion of wages among observationally similar workers (see, e.g., Albrecht and Axel 1984, Burdett and Mortensen 1998, Bontemps, Robin and Van Den Berg 2000, Postel-Vinay and Robin 2002, Bagger et al. 2014, Lise and Postel-Vinay 2018, Gregory 2020, Morchio and Moser 2020). In contrast, our paper is focused on understanding the effect of declining search frictions on wage inequality between different groups of workers.

Our paper is part of a broader research effort aimed at understanding the macro consequences of declining search frictions. Martellini and Menzio (2020) identify conditions under which there exists a BGP where unemployment, vacancies and workers' transition rates remain constant over time in the face of declining search frictions. They show that, in such a BGP, declining search frictions contribute to economic growth by allowing workers to find jobs that suit them better. Brugemann, Gautier and Tyros (2020) study the effect of a one-time decline in search frictions on the firm's choice between technologies requiring general or specialized skills. In the context of the product market, Menzio (2020) identifies conditions under which there exists a BGP where price dispersion for similar goods does not vanish as search frictions decline. He shows that, in such a BGP, declining search frictions lead to economic growth by allowing firms to design products that are more specialized. Our paper contributes to this line of research by showing that declining search frictions may have different rates of return for different agents in the economy depending on their degree of specialization.

B Occupation Crosswalk and Routineness

Our occupational scheme is based on the variable occ1990dd developed by David Dorn. This variable can be matched to the three-digit occupational codes for Census 1980-2000 and for the 2005 ACS. The 330 consistent occupations included in occ1990dd are mainly obtained by aggregating occupations that cover the same types of jobs in different years. Further details can be found on David Dorn's website https:// www.ddorn.net/ data/ Dorn_Thesis_Appendix.pdf. IPUMS provides an occupational crosswalk that links the 2015 ACS to the 2005 ACS, allowing us to adopt the consistent measure occ1990dd in 2015 as well (see https:// usa.ipums.org/ usa/ volii/ occ_acs.shtml and Ruggles et al.). Overall, we are able to compute wage dispersion and wage growth for 316 consistently defined occupations. We also use the occ1990dd scheme to harmonize the occupation codes in the CPS, since the CPS uses the same codes as the closest Census survey (see the crosswalk https:// cps.ipums.org/ cps-action/ variables/ OCC#codes_section and Flood et. al 2020).

The routine content of each occupation is obtained using the 1977 Dictionary of Occupational Titles (DOT). The DOT information on more than 12000 detailed occupations is matched to the three-digit 1970 Census occupation codes. It is then further matched to later Census surveys using a subsample of respondents to the 1980 Census whose occupation information was coded using both the 1970 and the 1980 schemes. See https://www.ddorn.net/ data/ Dorn_Thesis_Appendix.pdf for futher details.

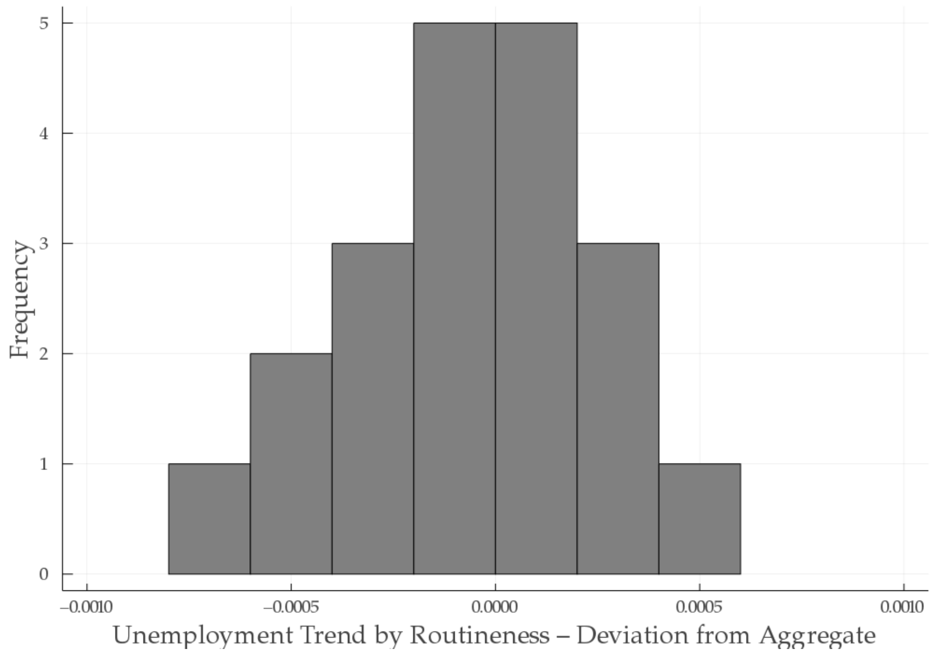


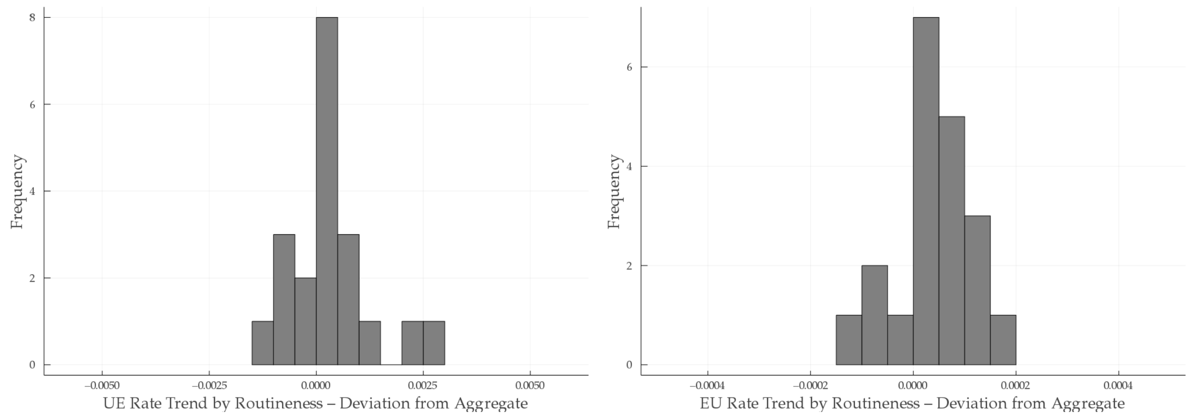
Figure 2: Distribution of Unemployment Trends by Occupation

C Occupation Unemployment, UE and EU Rates

We can compute the unemployment, UE and EU rates at the occupation level only starting in 1983. We define an occupation by its 3-digit code, and use the crosswalk developed by David Dorn to maintain a consistent definition of occupation over time. We find that the low-frequency dynamics of unemployment, UE and EU rates at the occupation level are similar to the low-frequency dynamics of unemployment, UE and EU rates at the aggregate level.

We compute a linear time-trend for the unemployment rate of each occupation. Similarly, we compute a linear time-trend for the aggregate unemployment rate. We then compute the difference between the one-year change in the unemployment rate of each occupation implied by its time-trend and the one-year change in the aggregate unemployment rate implied by its time-trend. We group occupations into 20 bins by increasing degree of routineness, following the classification of Autor and Dorn (2013). Figure 2 plots the histogram of residual one-year changes in the unemployment rate for the 20 occupation groups. Figure 2 shows that nearly all occupation groups have an average yearly change in the unemployment rate that is within ± 0.0005 of the average yearly change in the aggregate unemployment rate. That is, for nearly all occupation groups, the average yearly change in the unemployment rate is within ± 0.05 percentage points from the average yearly change in the aggregate unemployment rate. If the aggregate unemployment rate is 0, it takes more than 20 years for the unemployment rate of an occupation group to go from, say, 10% to either 9 or 11%.

We carry out the same exercise for the UE and EU rates and find, again, that the time-trends at the occupational level are close to the time-trends at the aggregate level. Figure

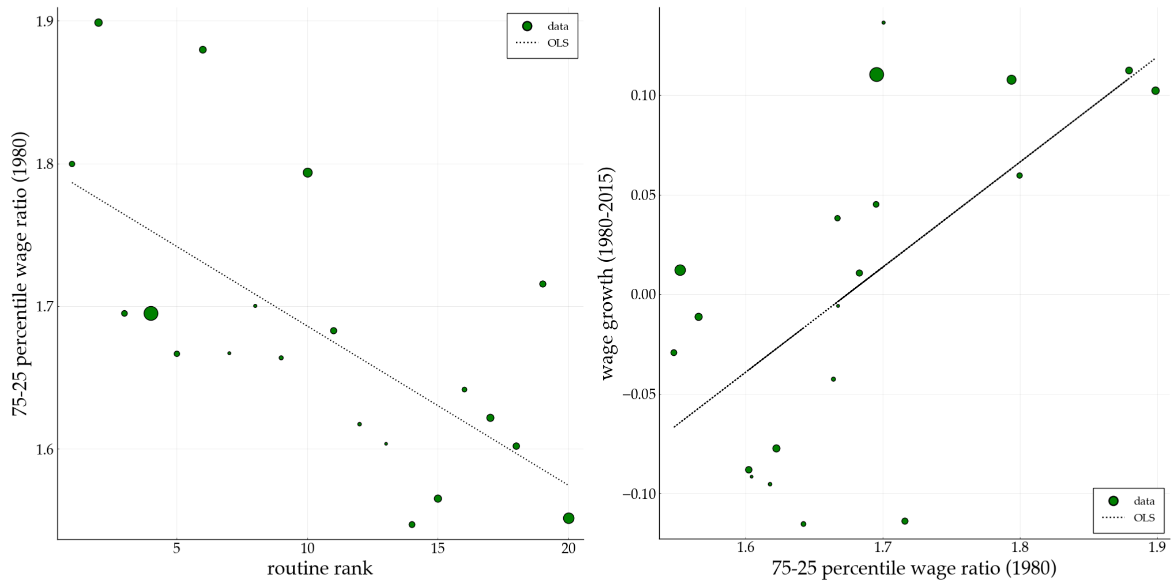


(a) Distribution of UE trends (b) Distribution of EU trends

Figure 3: Distribution of UE and EU Trends by Occupation

3(a) plots the histogram of residual one-year changes in the UE rate for the 20 occupation groups. For nearly all occupation groups, the average yearly change in the UE rate is within ± 0.0025 of the average yearly change in the aggregate UE rate. That is, they are within ± 0.25 percentage points from the average yearly change in the aggregate UE rate (which is around 30%). Figure 3(b) plots the histogram of residual one-year changes in the EU rate for the 20 occupation groups. For nearly all occupation groups, the average yearly change in the EU rate is within ± 0.0002 of the average yearly change in the aggregate UE rate. That is, they are within ± 0.02 percentage points from the average yearly change in the aggregate EU rate (which is around 2.5%).

It is worth point out that the period over which we can carry out the analysis of unemployment at the occupation level is somewhat special. The period between 1983 and 2019 happens to features a low-frequency decline in both the aggregate UE and EU rates. The preceding period (between 1946 and 1983) happens to feature the opposite low-frequency change: an increase in the aggregate UE and EU rates. For this reason, we presented our results on occupation-specific unemployment, UE and EU rates as time-trend deviations from the aggregate unemployment, UE and EU rates.



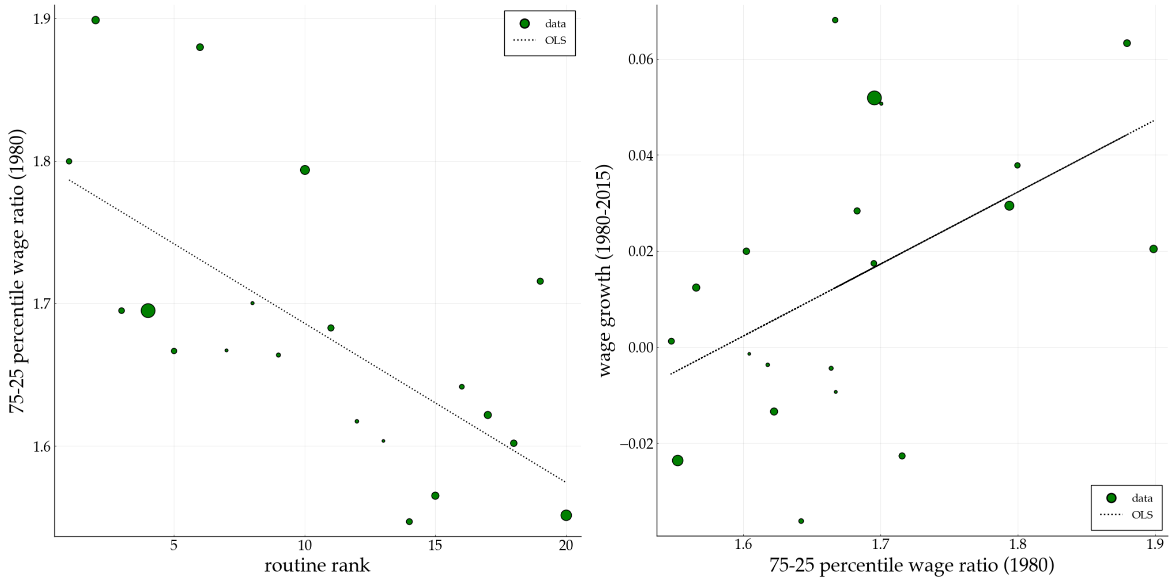
(a) Routineness and Residual Wage Dispersion (b) Residual Wage Dispersion and Growth

Figure 4: Residual Wage Dispersion and Growth by Routineness

D Wage Residuals

In order to control for differences in the composition of the workforce across different occupations, we compute log-wage residuals in 1980 from a Mincer regression of log-wages on a gender dummy, a race dummy (white/non-white), an education dummy, a 3-digit industry dummy and a quadratic polynomial of age. We compute the ratio of the 75^{th}-to-25^{th} percentile of the exponentiated log-wage residuals for every occupation. Then we average out the 75^{th}-to-25^{th} percentile ratio across all occupations within the same routineness bin. We find that, for all occupation groups, the 75^{th}-to-25^{th} percentile ratio of wage residuals is quite close to the 75^{th}-to-25^{th} percentile ratio of raw wages. For this reason, we still find a strong negative relationship between routineness and wage dispersion when we use residual wages rather than raw wages (Figures 4(a) and 5(a), which are the same figure). Specifically, the coefficient on routineness in an OLS regression of residual wage dispersion is -0.011 (standard error of 0.0029 and R^2 of 44%), while the coefficient on routineness in an OLS regression of raw wage dispersion is -0.014 (standard error of 0.0034 and R^2 of 48%). This finding is not surprising, as it is well-known that Mincer regressions do not account for much of the cross-sectional dispersion of wages in the data.

We also control for changes in the composition of the workforce within a particular occupation over time. We compute log-wage residuals in 2015 from the Mincer regression coefficients estimated on the 1980 data. We compute the wage growth in an occupation as the ratio between the exponentiated log-wage residuals in 2015 and in 1980. Then we average out the residual wage growth across all occupations within the same routineness bin. We find that the growth rate of residual wages is lower than the growth rate of raw wages for

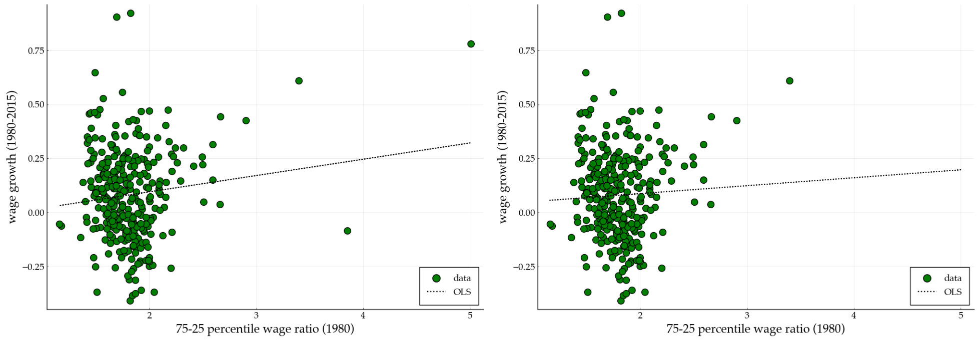


(a) Routineness and Residual Wage Dispersion (b) Residual Wage Dispersion and Growth

Figure 5: Residual Wage Dispersion and Growth by Routineness

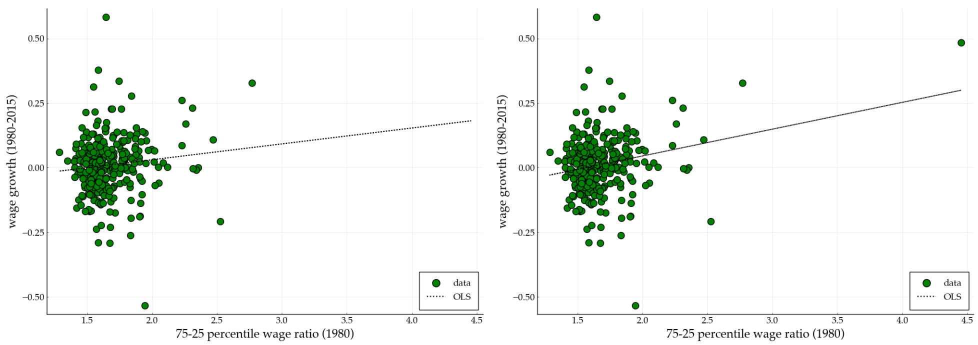
all occupation groups. We find, however, that the relationship between wage dispersion and wage growth is very similar using residual wages and raw wages (Figure 4(b)). Specifically, the coefficient on residual wage dispersion in an OLS regression of residual wage growth is 0.52 (standard error of 0.15 and R^2 of 38%). The coefficient on raw wage dispersion in an OLS regression of wage growth is 0.38 (standard error of 0.11 and R^2 of 39%).

We also construct an alternative measure of residual wage growth, which not only controls for changes in the composition of the workforce in an occupation, but also for changes in the "price" of different components of a worker's human capital. Also using this alternative measure of residual wage growth, we find a positive relationship between residual wage dispersion and residual wage growth (Figure 5(b)). Specifically, the coefficient on residual wage dispersion in an OLS regression of residual wage growth is 0.15 (standard error of 0.06 and R^2 of 24%). The regression coefficient is lower because highly educated workers are more prevalent in non-routine occupations (that have higher wage dispersion) and the "price" of high education has risen between 1980 and 2015.



(a) All Occupations (b) No Outliers

Figure 6: Wage Dispersion and Growth by Occupation (Raw Wages)



(a) All Occupations (b) No Outliers

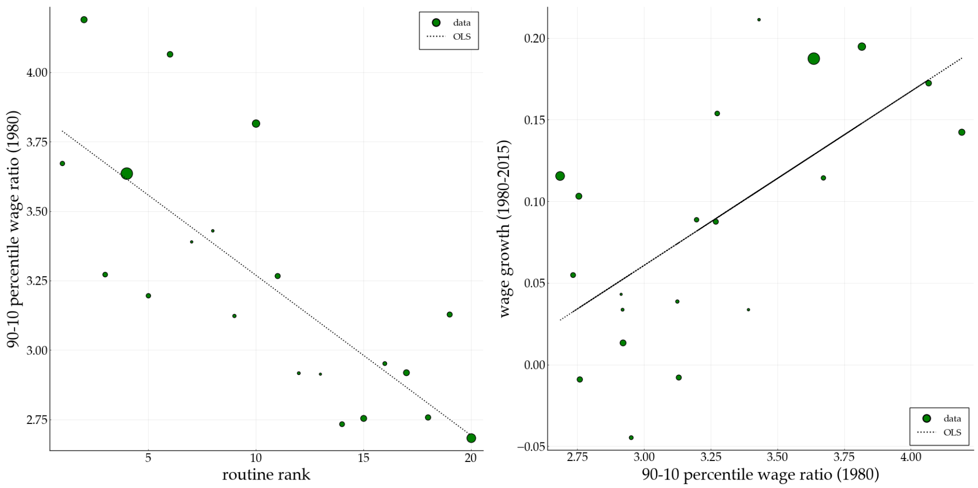
Figure 7: Wage Dispersion and Growth by Occupation (Residual Wages)

E Wage Dispersion and Growth for all Occupations

Figure 6(a) is the plot of wage dispersion and wage growth for all 3-digit occupations. The coefficient on wage dispersion from an OLS regression is 0.075 with a standard error of 0.035, which is significant at the 5% level. The R^2 of the OLS regression is 1.4%. Figure 6(b) eliminates outliers from the data. The coefficient on wage dispersion from an OLS regression becomes 0.036 with a standard error of 0.04, which is not statistically significant. The R^2 of the OLS regression becomes 0.2%.

Figure 7(a) is the plot of wage dispersion and wage growth for all 3-digit occupations, using the wage residuals constructed as in Appendix D. The coefficient on wage dispersion from an OLS regression is 0.10 with a standard error of 0.024, which is significant at the 1% level. The R^2 of the OLS regression is 5.5%. Figure 7(b) eliminates outliers from the data. The coefficient on wage dispersion from an OLS regression is 0.06 with a standard error of 0.03, which is significant at the 5% level. The R^2 of the OLS regression is 1.2%.

F 90-10 Percentile Ratio



(a) Routineness and Wage Dispersion (b) Wage Dispersion and Growth

Figure 8: 90-10 Percentile Ratio and Growth by Routineness