The Changing Skill Content of Private Sector Union Coverage[1]

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Abstract

Concurrent with the decline in private sector unionization over the past half century, there has been a shift in the type of work covered by unions. We take a skill-based approach to studying this shift. For both men and women, private sector unionized jobs have changed to require more non-routine, cognitive skills and for women, less routine/manual skills. Union, non-union skill differences have grown, with unionized jobs requiring relatively more non-routine cognitive skill and relatively more routine manual and routine cognitive skills. We decompose these changes into (1) changes in skills within an occupation, (2) changes in worker concentration across existing occupations, and (3) changes to the occupational mix from entry and exit. Most of the changes we document are driven by the second two forces. Finally, we discuss how this evidence can be reconciled with a model of skill-biased technological change that directly accounts for the institutional framework surrounding collective bargaining.

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Concurrent with the decline in private sector unionization over the past half century, there has been a shift in the type of work covered by unions. We take a skill-based approach to studying this shift. For both men and women, private sector unionized jobs have changed to require more non-routine, cognitive skills and for women, less routine/manual skills. Union, non-union skill differences have grown, with unionized jobs requiring relatively more non-routine cognitive skill and relatively more routine manual and routine cognitive skills. We decompose these changes into (1) changes in skills within an occupation, (2) changes in worker concentration across existing occupations, and (3) changes to the occupational mix from entry and exit. Most of the changes we document are driven by the second two forces. Finally, we discuss how this evidence can be reconciled with a model of skill-biased technological change that directly accounts for the institutional framework surrounding collective bargaining.

1. Introduction

One of the most dramatic trends in the US labor market over the past 50 years is the large decline in private sector union coverage, from 25% in 1973 to 6% in 2022. Parallel with the sharp drop in private sector unionization, the skill composition of the US workforce has shifted toward jobs that are less manual and routine and more cognitive (Autor, Katz, and Kearney 2006; Autor, Levy, and Murnane 2003). We study the interaction of these two trends to understand how the skill content of private sector union coverage has changed and why these changes have occurred using a task-based approach.

We combine data from the Current Population Survey (CPS) from 1973 through 2017 with data on occupational skills from the Dictionary of Occupational Titles (DoT) and the Occupational Information Network (O*NET). We partition tasks into four groups: routine manual, routine cognitive, non-routine manual, and non-routine cognitive. Our focus on these tasks is motivated by the historically-strong union coverage among heavily routine and manual occupations combined with shifts in the US economy over the past half century toward occupations that require more cognitive and non-routine skills.

The first part of the paper presents descriptive trends in the skill composition of the unionized and non-unionized workforce. Next, we conduct a decomposition that explains why the skills of unionized jobs have changed over time. We decompose the changes into three parts: (1) changes in skills within an occupation, (2) changes in worker concentration across existing occupations, and (3) changes to the occupational mix from both entry and exit over time. Finally, we discuss the theoretical implications of our results within the context of a Roy model that allows unions to adjust wages for the average skill level of workers in a given bargaining unit and accounts for changing costs of unionization and de-unionization. We argue that our results are unlikely to be driven by reductions in the desire of workers to unionize because of skill-biased technological change (SBTC).

This paper makes several contributions to the literature. First, we provide novel evidence of how the task content of union workers has changed over time and how these changes compare to non-union workers. The most related analysis is Farber et al. (2021), who use Gallup Poll data back to the mid-1930s and show that union density is inversely proportional to worker educational attainment. Our results align with theirs but provide a more comprehensive picture of how the specific skill coverage of union workers has changed and how these changes compare to non-union workers. Indeed, our results and conclusions hold even after controlling for worker educational attainment. We additionally contribute to the literature by decomposing changes in task content, which provides new insight into why the skills covered by unionized jobs have changed.

Second, our results help reconcile an unresolved puzzle in the literature: union workers have become more highly-educated and higher skilled (Farber et al. 2021), but models of skill-biased technological change indicate that union membership should shift away from occupations that experience more wage dispersion toward those that experience less. Existing models of SBTC (e.g., Acemoglu, Aghion, and Violante 2001) predict that we should see the largest declines in unionization among professions that employ more non-routine, cognitive skills (where wage dispersion is high) toward those that use more manual and routine skills (where wage dispersion is lower). In contrast, we show that unionization has declined more in occupations that require less non-routine, cognitive skills and more routine and manual skills. We argue that these trends can be reconciled with a modified model of SBTC. Unions cover more jobs that are non-routine, cognitive intensive over time because labor demand has risen disproportionally in these professions. Heavily-unionized professions that rely on manual and routine tasks for which the labor market value has declined over time become smaller and/or disappear. Hence, SBTC can explain the reductions in unionization and the changes in skill coverage of union workers, but it operates through changes to the occupation mix rather than through changes to the return to skill.

Third, our paper contributes to a growing literature that examines changes in the skill composition of the workforce. Autor, Levy, and Murnane (2003) conducted the first such analysis to examine how computerization affects the skill content of different occupations. Since then, much work has been done that has taken a “task-based” approach to understanding changes in labor markets (Acemoglu and Autor 2011). We are the first to use this framework and these data to examine the skill content of union versus non-union jobs.

2. The Decline in Private Sector Unionization

Private sector unionization has declined precipitously since the 1970s, with an overall decrease from 25% in 1973 to 6% in 2022, a decline among men from 30% to 8%, and a decline among women of 14% to 5%. The reduction in unionization is isolated to the private sector: in the public sector unionization rates increased over the same time period, from 23% to more than 33%.[1] The fact that public sector coverage is higher reflects the fact that states (rather than the National Labor Relations Board (NLRB)) set public sector bargaining laws and most states have laws conducive to unionization (Frandsen 2016).

There currently is little understanding of *why* private sector unionization rates have declined so dramatically. One of the most prominent arguments is that the decline is driven by skill-biased technological change. Acemoglu, Aghion, and Violante (2001) provide a prominent example of a model linking declining unionization with SBTC. Their model is based on the idea that unions transfer wages from high-skilled to low-skilled labor, thereby compressing wages and making unionized jobs less attractive for high-skilled workers. Furthermore, as higher-skilled workers exit unionization, there are fewer rents to redistribute to lower-skilled workers, and the union premium declines.

This model predicts that SBTC will lead to a reduction in union coverage by those with skills highly valued in the labor market. Farber et al. (2021) show evidence to the contrary, demonstrating that the educational attainment of private sector union members has grown substantially over time while the union premium is unchanged. However, they do not propose a theoretical model that is consistent with their findings.

Farber et al. (2021) focus on educational attainment as their worker skill measure. This is a noisy measure because worker skill is multi-dimensional. Our task-based approach, which focuses on four dimensions of the demand for specific skills, allows us to examine in more detail how the composition of union jobs has changed over time. We highlight a second dimension of SBTC that has received little prior attention in the union literature: SBTC alters the demand for existing occupations and the entry/exit of occupations. Farber and Western (2001) show that the change in employment rates between the union and non-union sectors can explain all of the private sector unionization decline between 1973 and 1998. They do not examine changes in which types of occupations or workers are covered by unions, however. We show that sorting across occupations as well as entry/exit of occupations are of first-order importance when seeking to understand the change in the skill coverage of union jobs.

3. Data

Data on worker characteristics and wages come from the Current Population Survey

[1] Source: http://www.unionstats.com/.

(CPS) May supplement for 1973-1981 and from the CPS Outgoing Rotation Group (ORG) sample for 1983-2017. The May CPS asked union membership questions through the early 1980s, while the ORG surveys began asking union membership questions in 1983. Consistent with prior work, we focus on union membership status (Card 2001; Card, Lemieux, and Riddell 2020). We omit 1982 from our analysis because the question on union membership was not asked in that year.

Our analysis sample is restricted to private sector workers with positive earnings who are not self-employed. Hourly wages are measured directly for those paid hourly; for other workers we calculate hourly wages by dividing usual weekly earnings by weekly hours worked. We correct for changes in top-coded earnings over ORG surveys by multiplying these earnings by a factor of 1.5 (Autor, Katz, and Kearney 2008; Autor, Manning, and Smith 2016; Hirsch and Schumacher 2004) and drop workers whose wage calculations rely on allocated earnings data (Card 1996; Card, Lemieux, and Riddell 2020). We also correct for inconsistencies in questions about educational attainment before and after 1992 to create a time-consistent measure of years of schooling (Card 2001; Card, Lemieux, and Riddell 2020). Wages are adjusted to 2016 dollars using the Personal Consumption Expenditure index.

To identify the relevant skills and tasks of each occupation, we use metrics of occupation characteristics in the 1977 and 1991 editions of the Dictionary of Occupation Titles (DOT) survey as well as the 2004 and 2017 editions of the Occupational Information Network (O*NET) survey. Appendix B contains more details on the construction of our occupational skill measures and our analysis dataset.

Given the historical importance of routine tasks in unionized occupations, we first split tasks into routine versus non-routine. We then further examine the role of manual and cognitive task requirements of occupations because of the large shift in the US economy away from manual and toward cognitive tasks (Autor, Levy, and Murnane 2003). We thus focus on four dimensions of occupational skill requirements: non-routine cognitive, non-routine manual, routine cognitive, and routine manual.

A core impediment to using the O*NET and DOT data is that the skill measures differ in the two datasets. We construct harmonized skill measures across these datasets by matching information in the DOT to the 2004 and 2017 O*NET data. This procedure involves locating a direct match or constructing an index across similar measures if a direct match cannot be found. We convert O*NET skill ratings into a single index by taking the mean across each measure.

To address different scales in DOT and O*NET, we standardize each measure to be mean zero with a standard deviation of one in each year across 1990 occupations. This standardization is done across occupations in each year, where each occupation is one observation. This implicitly weights each occupation equally. Hence, shifts in occupation shares will not mechanically change the standardized measure. This is important because decomposing changes in relative occupational task coverage by unions into within-occupation shifts and cross-occupation employment shifts is one goal of this study. This standardization process means that our measures should be interpreted as changes in *relative* skill content over time within sectors and across groups. In other words, our measures are capturing relative changes in skill content over time net of any macroeconomic absolute changes in skills.

One concern with this approach is that these macroeconomic shifts could be large, thus obscuring important changes to the skill content of union coverage. We show that our results are robust to using the percentile rank of the occupation in each skill measure over time, which is less sensitive to this issue because it is based on a fixed scale. However, even the percentile measure will not fully capture aggregate changes to the skill distribution. The task measures we use do not permit one to employ a fixed baseline that would address this problem, since the measures change over time. Aggregate changes to skill demand should not affect our comparison across union and non-union occupations. However, normalizing by year will not allow us to incorporate the macroeconomic shifts towards non-routine and cognitive tasks and away from manual and routine tasks that occurred over our period of study. As a result, one should consider the large changes we document as lower bounds on the changes in task demand in the union and non-union sectors.

In total, our analysis sample consists of 3.4 million workers during the 1973-2017 period. Summary statistics for the analysis sample are shown in Appendix Table A-1. Workers who are members of a union are older, slightly less educated, make about 0.2 log points more per hour, and have wages that are less dispersed, relative to the average non-union worker. Importantly, union workers are in occupations that require significantly less non-routine cognitive skill and more of the other three skill categories. Appendix B and Dodini, Lovenheim, and Willen (2023) contain additional descriptive evidence on task distributions and unionization rates.

4. Trends in Skill Coverage by Union Status

4.1. Overall Trends for Private Sector Workers

Figure 1 presents trends in each normalized skill measure for union and non-union private sector workers by year from 1973 to 2017. Each panel shows means of a specific skill by year and union status (left y-axis) as well as the trend in the overall private-sector unionization rate (right y-axis).

Panel A shows that the coverage of non-routine, cognitive skills among union workers increased substantially, from -0.591 in 1973 to -0.041 in 2017. This 0.550 standard deviation increase is most pronounced during the 1990-2005 period. As overall unionization rates declined, unions increasingly covered occupations that had higher skill requirements along this dimension. This can be seen most prominently in Figure 2, where we split the sample into occupations in the top and bottom quartile of each skill measure in 1991 and show trends in union coverage for each group. Panel A of Figure 2 demonstrates that the increase in non-routine, cognitive skills is coming from a decline in union coverage in jobs with low levels of this skill. The union coverage in the bottom quartile declines from 34% in 1973 to 8% in 2017. The reduction in unionization among high non-routine, cognitive jobs is much smaller, from 8% in 1973 to 5% in 2017. Hence, the increase in this skill concentration among union workers is coming predominantly from a substantial reduction in the union coverage of jobs that are low in this skill measure.

It is instructive to compare the changes in skill coverage among union workers to those among non-union workers to determine whether the changes we document are economy-wide or are more localized to unionized employment. Panel A of Figure 1 shows that there is a convergence in non-routine, cognitive tasks between the union and non-union sectors. Non-union jobs have higher levels of this skill requirement throughout our time period, but the gap declines over time from 0.283 in 1973 to 0.182 in 2017 (a 0.10 standard deviation decline, or a 35.5% reduction). Not only are union workers increasingly in jobs that require high levels of non-routine, cognitive skills, the skill increases they experience are large relative to the non-union sector. These general trends match those in Atalay et al. (2020) for the overall labor market despite using different datasets and occupation definitions.

Panel B of Figure 1 shows starkly different patterns for non-routine, manual skills. In both sectors, this skill becomes slightly less important, from 0.447 and -0.107 in 1973 among union and non-union jobs, respectively, to 0.313 and -0.185 in 2017. The difference between union and non-union coverage changes negligibly. Panels A and B of Figure 1 demonstrate that the increased intensity of non-routine skills in unionized jobs is localized to occupations that require more cognitive rather than manual skills.

Next, we examine routine, cognitive skills in Panel C and routine, manual skills in Panel D of Figure 1. Routine cognitive skill coverage declines substantially among unionized occupations, from 0.404 in 1973 to 0.080 in 2017. Panel C of Figure 2 shows that this decline is driven by a large reduction in unionization rates among professions that are highly-intensive in this task. Routine cognitive coverage among non-union jobs also declines, from 0.081 in 1973 to -0.369 in 2017. Much of the reduction in this skill coverage among unionized jobs thus also is experienced in the non-union sector, although the gap also increases from 0.323 to 0.449. Combined with the results in Panel A, there is a clear increase in coverage of cognitive tasks in union relative to non-union jobs. With non-routine cognitive tasks, this relative increase comes from larger growth in task intensity, while for non-routine cognitive tasks it comes from a smaller decline. Over time, unionized professions have experienced a faster acceleration in cognitive skill demands relative to non-unionized jobs.

We examine trends in routine, manual skill coverage in Panel D of Figure 1. In the 1970s, union and non-union jobs required the same amount of this skill. Beginning in the 1990s, non-union jobs required less routine, manual tasks while this task requirement among unionized professions remained constant. As a result, there is a union-non-union gap of 0.294 by 2017. Panel D of Figure 2 shows a similar decline in the unionization rate among professions that have high and low coverage of this skill dimension, which is why the routine manual coverage remains similar over time.

Overall, the evidence from Figures 1 and 2 points to a relative growth in skill requirements of union versus non-union jobs. Prior research has not addressed this changing skill content of union and non-union work, although there is evidence that the educational attainment of union workers has increased over time (Farber et al. 2021). To ensure that our results do not simply reflect a change in the educational or demographic composition of the unionized workforce, we residualize the skill measures with respect to worker age, race/ethnicity, gender, and educational attainment. Online Appendix Figure A-1 shows that the resulting patterns are similar to the raw estimates presented in Figure 1. The one exception is that the residualized patterns exhibit a small increase in non-routine manual skill coverage among unionized occupations. The changes in the skills required by union jobs, therefore, have changed even more starkly than was documented in Farber et al. (2021).

A potential concern with the estimates in Figures 1 and 2 is that we normalize the skill measures using the annual mean and standard deviation in order to make comparisons across

DOT and O*NET. This scaling decision could obscure large aggregate changes in the task requirements of jobs. In Online Appendix Figure A-2, we show that the patterns and conclusions are very similar if we instead use the percentile rank of each skill.

4.2. Trends for Private Sector Workers by Gender

Because of large differences in union coverage and occupational sorting by gender, we examine changes in the skill content of unionized jobs separately for men and women. Figure 3 shows trends in standardized skill measures by gender and union status for non-routine, cognitive and non-routine, manual task measures. Among unionized men, there has been a sizable increase in non-routine, cognitive skill requirements of their jobs of 0.422 standard deviations, from -0.567 to -0.145. This increase is considerably larger than the increase among non-union workers of 0.296.[2] The gap between union and non-union skills hence declined by 0.126 standard deviations. As with the overall estimates, the trends for non-routine manual skills among men are flat in both sectors.

Changes for women are larger than among men, which highlights the importance of examining this under-analyzed group in the union literature. Non-routine, cognitive skills increase by 0.830 standard deviations among union workers, while the change among non-union workers is 0.618. The pre-existing gap for this task across union and non-union workers thus declined by 0.212. For non-routine manual skills, there are modest declines of about 0.17 standard deviations experienced in both union and non-union jobs. As a result, the union-non-union differences change little.

Figure 4 shows patterns for the two types of routine skills. Among men, there is little long-run change in skill coverage in either sector. Together with Figure 3, these results show that men have experienced increasing intensity of non-routine cognitive skills with little change in the other three skill categories. In contrast, routine cognitive and routine manual skill intensity decline substantially for women; the aggregate reductions in these task requirements shown in Figure 1 are driven predominantly by occupations that disproportionately employ women. Furthermore, the relative increases in routine cognitive and routine manual task content of union relative to non-union jobs largely reflects trends among women. Because of these gender differences, we examine men and women separately in the remainder of the paper.

[2] Online Appendix Figures A-3 and A-4 present trends in the union vs non-union gap in each occupational skill for men and women, respectively, to facilitate comparisons across union and non-union workers.

4.3. Decomposition of Skill Changes

The results discussed above show that the skill composition of occupations covered by unions has changed considerably over time: why has unionized work changed in this way? As a first step in addressing this question, we decompose the change in each task type over time into three parts: (1) the part due to changes in the union worker share in existing occupations, (2) the part due to changes in skill requirements within existing occupations, and (3) the part due to entry/exit of occupations. This decomposition yields new insight into the causes of changes to private sector unionization that cannot be identified without a task-based approach.

Let S_{kt} be the standardized skill measure of occupation k in year t, and ω_{kt}^{u} be the share of all union workers in that occupation and year ($\omega_{kt}^{u} = \frac{L_{kt}^{u}}{\sum_k L_{kt}^{u}}$, where L_{kt}^{u} is the number of union workers in the occupation and year). Define τ_{2017} as the share of union labor in occupations in 2017 that span 1973-2017 and τ_{1973} as share of union labor in occupations in 1973 that span 1973-2017. It is helpful to partition occupations (K) into three groups:

- K_1 – occupations that exist in both 1973 and 2017
- K_2 – occupations that exist in 1973 but not in 2017
- K_3 – occupations that exist in 2017 but not in 1973.

Under these definitions, $\tau_{2017} = \frac{\sum_{k\in K_1} L_k^u}{\sum_{k\in K_1} L_k^u + \sum_{k\in K_3} L_k^u}$ and $\tau_{1973} = \frac{\sum_{k\in K_1} L_k^u}{\sum_{k\in K_1} L_k^u + \sum_{k\in K_2} L_k^u}$. The average level of skill S among union workers then can be written as follows:

$$\bar{S}_{2017}^{u} = \left(\sum_{k\in K_1} S_{k,2017}^{u} * \omega_{k,2017}^{u} \right) * \tau_{2017} + \left(\sum_{k\in K_3} S_{k,2017}^{u} * \omega_{k,2017}^{u} \right) * (1 - \tau_{2017}) \quad (1)$$

$$\bar{S}_{1973}^{u} = \left(\sum_{k\in K_1} S_{k,1973}^{u} * \omega_{k,1973}^{u} \right) * \tau_{1973} + \left(\sum_{k\in K_2} S_{k,1973}^{u} * \omega_{k,1973}^{u} \right) * (1 - \tau_{1973}) \quad (2)$$

In Online Appendix C, we show that we can decompose the change in each skill among union workers into three constituent parts:

$$\bar{S}^u_{2017} - \bar{S}^u_{1973} = \tau_{2017} * \left\{ \sum_{k \in K_1} S^u_{k,2017} * \left(\omega^u_{k,2017} - \omega^u_{k,1973}\right) + \sum_{k \in K_1} \omega^u_{k,1973} * \left(S^u_{k,2017} - S^u_{k,1973}\right) \right\}$$
$$+ \left(\sum_{k \in K_1} S^u_{k,1973} * \omega^u_{k,1973} \right) * (\tau_{2017} - \tau_{1973}) + \left(\sum_{k \in K_2} S^u_{k,1973} * \omega^u_{k,1973} \right)$$
$$* (1 - \tau_{1973}) + \left(\sum_{k \in K_3} S^u_{k,2017} * \omega^u_{k,2017} \right) * (1 - \tau_{2017}) \quad (3)$$

The first of the two terms inside the curly brackets in equation (3) shows the change in skill coverage among union workers due to changes in worker sorting across existing occupations between 1973 and 2017. Note that this decomposition only includes union workers. If declining unionization affects all occupations equally, there will be no change in worker share. The worker share only will change if there are changes in worker concentration across unionized professions.

The second term inside the curly brackets in equation (3) shows the change in skill due to shifts in skill requirements within occupations. The last three terms in equation (3) show the effect of occupational entry and exit from the CPS on the skill content of unionized jobs. Entry and exit are important to consider, especially because we focus on a long time period over which there was much technological change. This led to the creation of many new occupations and the elimination of older, obsolete occupations. Since new occupations, particularly high-skilled ones, may be less likely to unionize, this part of the decomposition provides direct evidence of the role of skill-biased technological change in driving changes to the skill content of unionized jobs. This insight that entry/exit or compositional changes to occupational titles are important is echoed by Atalay et al. (2020), who show that approximately 40 (45) percent of the job titles that were most common in their SOC codes in the 1950s (1990s) did not exist in the 1990s (1950s).

The decomposition results are shown in Table 1. Panel A presents results for men and Panel B shows results for women.[3] In each panel, each column is a separate decomposition. We show the part of the change that is due to each component as well as the percent of the overall change due to each component in brackets. For example, non-routine, cognitive skills increased by 0.422 standard deviations among men between 1973 and 2017. The part due to changes

[3] Online Appendix Tables A-3 and A-4 show decompositions for changes in skill coverage from 1973-1990 and 1990-2017, respectively.

across existing occupations is 0.140 standard deviations, which is 33.30% of the total, while 0.208 standard deviations (49.39%) are due to changes in the occupational mix from entry and exit. Together, these two components explain 82.69% of the total change in this skill coverage. The remaining 17.31% is explained by within-occupation changes in skill requirements.

The other three skill categories exhibit a common pattern: there is a small overall change that obscures larger within-occupation shifts in the opposite direction of changes due to the entry/exit of occupations and worker shares. But for the fact that surviving unionized professions have increased in their intensity with respect to non-routine manual, routine manual, and routine cognitive skills, there would be large declines in these skill dimensions from occupational changes and worker occupational sorting.

The results in Panel A of Table 1 show that changes to worker share and occupational composition have acted to strongly increase non-routine cognitive skill intensity and decrease intensity of the other three skill groups. Within-occupation changes for the latter three skill categories have moved in the opposite direction, though, which has led to the modest overall shifts that we documented in Figures 3 and 4. For non-routine cognitive skills, there has been no offsetting shift within occupations, leading to a large increase in the intensity of this skill.[4]

Panel B of Tables 1, A-3, and A-4 show decomposition results for women. Non-routine, cognitive skill increases by 0.830 standard deviations, which, similar to men, is driven mostly by changes in worker shares across occupations and by occupational entry/exit. However, changes to worker share are relatively more important in explaining changes among women, while for men occupation entry/exit is more important. All three explanations are relevant for explaining the decline in the other three skill dimensions, except that changes due to worker share move against the aggregate shift for routine cognitive skill. Importantly, these results highlight that there is nothing mechanical that is causing within-occupation changes to move in the opposite direction from worker shares and occupation entry/exit among men. The three forces move in the same direction among women, all contributing to the aggregate change.

For comparison, Online Appendix Table A-5 shows similar decompositions for non-union workers. Interestingly, the decompositions show key differences between the sources of

[4] Note that a mechanical change driven by changes in occupational titles only would generate an effect on unionization if the new occupations are differentially (un)likely to be in a union. If occupations are substantively changing, leading to a change in the title, and if this shift accompanies a change in unionization, then this is part of the mechanism of interest. There should be nothing mechanical about occupation title changes and unionization of which we are aware.

changes in the union and non-union sectors. Among men, changes in worker share drive the relative difference in non-routine cognitive skills coverage across the union and non-union sectors. For non-union workers, worker sorting across occupations would lead to a *decline* in this skill intensity. This finding suggests that the changes to worker composition that drive much of the non-routine cognitive skill content of union occupations are localized to unionized jobs rather than being economy-wide. The changes for the other three skill types are smaller in the non-union sector than in the union sector, but the overall patterns are similar to one another.

The relative growth in non-routine, cognitive skills for unionized women is due to a much larger shift of workers across occupations. While non-union women experience more significant within-occupation shifts for this skill, it is not enough to make up for the smaller worker share component. For the two routine skills, the relatively larger decline in the non-union sector among women is driven by sizable within-occupation shifts. Notably, these shifts are not evident for men, suggesting that the occupations into which women sort have changed to become less routinized over time. This change has been more dramatic in the non-union sector.

As discussed in Section 4.1, our results and conclusions are robust to controlling for worker composition as measured by educational attainment, race/ethnicity, and age. The even columns of Online Appendix Table A-6 shows decompositions that are residual to these worker characteristics.[5] Although some of the magnitudes change, a similar story emerges. These results further demonstrate that there is independent information in the skill measures we employ relative to those in Farber et al. (2021).

The odd columns of Table A-6 show decompositions that are residualized with respect to industry groups. Given the role of worker occupational shares, it could be that our results largely reflect economy-wide industrial changes that are occurring over this time period. The results are similar to our baseline estimates, which suggests that broad changes to industrial composition do not explain our results.

5. Theoretical Implications

5.1. Predictions from SBTC Models

In this section, we discuss how our results from Section 4 align with theoretical predictions. Much of the discussion surrounding declining unionization in the US has focused on the role of

[5] We regress each standardized skill measure on educational attainment, race/ethnicity, and age indicators and take the residual. We then use these residualized skill requirements to conduct the decomposition in equation (3).

skill-biased technological change,[6] since the return to skill in the labor market has coincided with the large reduction in private sector unionization. There are few models of union behavior that focus on the role of SBTC. The most prominent one is presented in Acemoglu, Aghion, and Violante (2001), who set up a model in which unions transfer wages from high-skilled to low-skilled labor and thus compress the wage structure by reducing the return to skill. When there is SBTC, unionization declines for two reasons: 1) the outside option of incumbent higher-skilled workers increases and 2) new workers invest in more skill and then sort into non-unionized firms/jobs to obtain higher wages.[7] While this is a prominent example of this class of models, it incorporates more general insights from the Roy Model: if unions compress wages and reduce the return to skill, an outward shift in the return to skill from SBTC should lead to lower rates of unionization among higher-skilled workers.

There are three key implications of this type of model that are at odds with the data. First, as shown in Section 4, union jobs have become higher-skilled along several dimensions. Second, these models assume that unions reduce the returns to skill, which has not been examined empirically in prior research.[8] To investigate returns to skill by union status, we estimate the following regression:

$$Ln(w)_{ict} = \beta_0 + \beta_1 Union_{ic} + \sum_{j=1}^{4} \phi_t^j S_{ct}^j + \sum_{j=1}^{4} \pi_t^j S_{ct}^j * Union_{ic} + \gamma X_i + \zeta_t + \theta_c + \epsilon_{it}, \qquad (4)$$

where w_{it} is the wage of individual *i* in year *t* and occupation *c*, *Union* is an indicator variable equal to 1 if the worker is a member of (or is covered by) a union, X_i is a vector of observed characteristics, ζ_t are year fixed effects, θ_c are occupation fixed effects, and S_{ct}^j are the four standardized skill measures.

The open circles and squares in Figures 5 and 6 present the ϕ_t^j and ϕ_t^j+π_t^j estimates from equation (4) for men and women, respectively. The interpretation of these parameters is the return to a standard deviation in each skill level, and they are the first such estimates in the

[6] Skill-biased technological change encompasses a wide range of forces. We follow Violante (2008) in defining it as "…a shift in the production technology that favors skilled over unskilled labor…." The main implication is that SBTC leads to an increase in the returns to skill in the labor market.
[7] Acikgoz and Kaymak (2014) build on this model to show that SBTC will lead skilled workers to leave firms, which reduces the productivity of low-skilled workers. As a result, firms will be less willing to pay union rates for low-skilled workers, thereby further reducing unionization rates.
[8] Hirsch and Schumacher (1998) show that the union premium is similar across the worker skill distribution, which is closely related to but conceptually distinct from examining how unions affect the return to skill directly.

literature. We present these results alongside the trends in occupational skill requirements by union status, and together these results constitute a summary of the main empirical findings in this paper. For non-routine cognitive skills in Panel A, the return to skill among unionized jobs is high and stable through the 1990s and then increases for both men and women such that the returns gap between union and non-union workers largely disappears. The value of this skill is high in the labor market and is growing over recent decades; the growth among union workers is larger than the growth among non-union workers. That the coverage of and returns to this skill are high and have increased relative to the non-union sector over the past two decades is inconsistent with the predictions from models of SBTC and underscores the point that SBTC has not necessarily reduced the incentive for skilled workers to unionize.[9]

The returns to the other three skill measures are positive and similar for union and non-union workers. The return to cognitive manual skills in the unionized sector has increased modestly relative to the non-union sector, while the relative returns to both routine skills are similar across the union and non-union sectors.[10] That union workers experience a substantial return to skill that matches or in many cases exceeds the returns in the non-union sector is at odds with the predictions from SBTC models.

Third, SBTC models predict that the return to unionization should decline as the returns to skill in the non-unionized sector rise and the rents available for redistribution in the union sector decrease. In contrast, Card, Lemieux, and Riddell (2020) and Farber et al. (2021) show that the union wage premium has remained stable over time at between 0.2 to 0.3 log points. These estimates do not account for job skill requirements, however, which could change the results given the patterns of task changes we document. Online Appendix Table A-7 shows estimates of the union wage premium from versions of equation (4). We show estimates that exclude skill controls, that control for skills in levels, and that include $union * skill$ interactions as shown in equation (4). We also show how results change when we include occupation fixed effects. The union wage premium estimates change little with controls and over time, ranging

[9] We additionally use the NLSY79 to examine the return to AFQT conditional on the skill content of workers' occupation and year fixed effects, separately by union status. The results are provided in Appendix Figure A-5. Unions increase the return to AFQT across the AFQT distribution, with the exception of the very top. This suggests that cognitive returns are still higher in the unionized sector. The relatively higher gap at the bottom of the AFQT distribution also is consistent with wage compression within the unionized sector.

[10] To better understand the role of automation in explaining these results, we estimated the return to each skill type separately for production and non-production workers (using the BLS/SOC code definitions of production occupations). These results are shown in Appendix Figure A-6 for men and A-7 for women. The skill returns within unions are not exclusively driven by the production sector, suggesting that automation cannot explain our results.

from 0.2 to 0.3 log points. These results align with prior estimates and conflict with theoretical predictions that the union wage premium should decline over time due to SBTC.

5.2. A Reconciliation of Theoretical Predictions and Empirical Results

Three features of the unionized environment lend themselves to an extension of the Acemoglu, Aghion, and Violante (2001) model that we argue can explain our results. The first is the fact that negotiations are done by bargaining units, which can be quite homogenous.[11] This is an important distinction from prior models of union behavior because with homogenous bargaining units, skill-biased technological change will not necessarily reduce the incentive to unionize. If unions bargain by raising the wages of the median worker in the bargaining unit, increases in the skill requirements of unionized jobs should lead to higher pay. Indeed, if there is employer monopsony power, higher-skilled workers should want to unionize into relatively homogenous bargaining units because the union can better extract monopsony rents from the firm (Dodini, Salvanes, and Willen 2021).

Second, there are frictions associated with de-unionizing. Workers can vote to decertify a union and cease collective negotiations, but such decertification elections are rare. Figure 7 shows trends in certification and decertification elections from 1962-2009, which we obtained from publicly-available NLRB data.[12] The inflow of newly-unionized bargaining units is an order of magnitude larger than the outflow of workers who no longer collectively bargain.[13] Holding the distribution of workers across occupations fixed, Figure 7 shows that there would be a persistent increase in absolute private sector union coverage over time.

Appendix Figure A-9 provides information on the number of union elections and election success over time by industry group: Manufacturing, Services, and "Other." The figure shows that the net reduction in unionization is more pronounced in manufacturing, which has the lowest

[11] Online Appendix Figure A-8 shows the size of bargaining units over time from certification elections. Prior to 1998 the average bargaining unit was 65-70 employees, while after 1998 it dropped to under 40. Workers are likely to be homogenous in such small bargaining units.
[12] The data we use come from historical NLRB data created by Jean-Paul Ferguson (JPF), which can be downloaded from http://jpferguson.net. There are some small discrepancies between the JPF data and the now-digitalized annual NLRB reports in terms of the annual number of certifications and decertifications. However, the general patterns are similar and the conclusions we draw would not change if we were to scrape the original data. Also note that the NLRB reports do not provide us with sufficient subindustry detail to be able to conduct our analyses that link the certification and decertification elections to the O*NET data (Appendix Figures A-9 and A-10).
[13] Dickens and Leonard (1985) present similar evidence that decertification elections cannot explain the decline in private sector unionization prior to 1980. This evidence also is aligned with survey results in Kochan et al. (2019), who show that unions are popular among both union and non-union workers and that they remain a well-regarded form of exercising worker voice in the workplace. These findings underscore that many workers still want to be unionized and that decertification elections are likely to be challenging to win.

prevalence of non-routine cognitive skills and the highest prevalence of routine skills. This evidence is consistent with our model but not with models that predict lower levels of unionization in professions that require skills with high returns in the broader labor market.

Existing models suggest there will be more decertification elections among higher-skilled professions, fewer certification elections among these professions, and greater difficulty in winning these elections in higher-skilled jobs. Appendix Figure A-10 shows that the data generally do not align with these predictions: professions with high levels of non-routine cognitive task intensity are highly successful at certifying and are less likely to decertify. Ultimately, these dynamics mean that the overall relationship between non-routine, cognitive skills and the change in union coverage is flat. These novel findings are inconsistent with the existing model of SBTC and unionization, which predicts union workers should become less skilled over time.

The third feature of the union environment relevant to the interpretation of our results also is shown in Figure 7: the barriers to organization have increased over time, especially since the 1980s. President Reagan's fight against the air traffic controllers' union combined with changes to the composition of the NLRB to be more business-friendly led to a much less favorable unionization environment in which employers can more easily fight a unionization effort, and that effect appears to persist over the subsequent decades (Kleiner 2001; Farber and Western 2001; McCartin 2006).[14] The high barriers to collective bargaining entry for new occupations are likely to dissuade workers from engaging in organization efforts.

We present a Roy model that extends Acemoglu, Aghion, and Violante (2001) to account for these additional features. Our model illustrates how SBTC is consistent with relative increases in the coverage of skilled occupations and a lack of de-unionization. We model firms as collections of workers in different occupations, and each of these occupations can be unionized with its own bargaining unit. Each occupation has a skill requirement, S_o that does not vary by union status. Hence, unionized and non-unionized jobs only vary in the wage returns to skills. Let skill S for worker i in occupation o be given by:

$$S_{oi} = S_o + \eta_i \, , \tag{5}$$

[14] Two other contributing factors to the increasing barriers to organization were the Volker shock of high interest rates meant to break the power of unions to raise wages and the Reagan tax cuts that pushed down high-end marginal tax rates so that CEOs and investors had stronger incentives to bargain harder and more aggressively fight unions because they could keep more of any resulting profits.

where η_i is an individual-specific component of skill distributed $N(0, \sigma_o)$. That is, each occupation has a skill requirement, and workers on average have skills that match the skill requirement of the occupation in which they work. There also is idiosyncratic worker skill that is distributed symmetrically about the mean skill requirement. The variance of the worker-specific component of skill is given by σ_o and is assumed to be exogenously given but can differ across occupations.

Wages of individual *i* in occupation *o* and in firm *f* are determined by:

$$W_{ofi} = \gamma^{fo} S_o + \beta^{fo} \eta_i, \tag{6}$$

where γ shows the return to average skill and β is the return to individual idiosyncratic skill. The skill returns are bargaining unit (i.e., firm and occupation) specific. A non-unionized firm only cares about the worker's overall skill level, given by $S_0 + \eta_i$ and thus will set $\gamma = \beta$. Unions typically attempt to raise average pay but compress the wage structure. In the extreme, they will set $\beta = 0$ and will set a bargaining unit-specific wage of γS_o.

We posit three sources of friction in the model: job switching costs ($\bar{e}$) and the costs of unionizing ($\bar{u}$) and de-unionizing ($\bar{d}$). The cost of unionizing comes from the time, effort, and potential friction with one's employer that characterizes any organizing drive as well as the frictions associated with negotiating the contract. De-unionizing costs come from the fact that the decision to hold a decertification election is likely to be controversial and to take substantial time and effort on the part of organizers.

SBTC can be modeled by a change in the return to skill parameters (β and γ). For simplicity, we will consider what happens when β and γ change by the same amount. This is akin to a general increase in the return to skill. The first goal of the model is to characterize under what conditions skill-biased technological change will cause high-skilled union workers to leave unionized firms and join non-unionized firms. We hold occupation fixed, so we assume workers shift across firms but not occupations. Consider two firms, the first of which is unionized for occupation *o* (denoted *U*) while the second firm is not unionized for that occupation (denoted N). Wages in each firm are given by:

$$W^U = \gamma^{Uo} S_o + \beta^{Uo} \eta_i \tag{7}$$
$$W^N = \gamma^{No} S_o + \beta^{No} \eta_i = \beta^{No}(S_o + \eta_i) \tag{8}$$

The last equality of equation (8) comes from the assumption that in non-unionized environments,

$\beta = \gamma$.[15] Workers will switch from U to N when $W^N - \bar{e} \geq W^U$. Plugging in the terms from equations (5) and (6) and rearranging, we get the following incentive compatibility constraint:[16]

$$\bar{e} \leq S_o(\gamma^{No} - \gamma^{Uo}) + \eta_i(\beta^{No} - \beta^{Uo}) \tag{9}$$

Equation (9) highlights that a worker will not switch from a unionized to a non-unionized job if the switching cost is high relative to the net benefit of switching. In turn, the net benefit of switching is driven by differences in the return to average and idiosyncratic skill. If in the limit unions eliminate wage dispersion within the bargaining unit, equation (9) reduces to $\bar{e} \leq S_o(\gamma^{No} - \gamma^{Uo}) + \eta_i\beta^{No}$. In general, we expect $\beta^{No} > \beta^{Uo}$ because unions reduce within bargaining unit wage dispersion, while we expect $\gamma^{U_0} > \gamma^{N_0}$ due to the existence of a non-zero union wage premium.

The predictions of this model align with the patterns described in Section 4. First, consider what happens when β and γ increase by the same amount in the overall economy. The net return to occupational skill S_o does not change across firms, but non-union sector workers experience an increase relative to their unionized counterparts because $\beta^{No} > \beta^{Uo}$. If the variance of η is small relative to the cost of switching jobs, few workers are induced to switch to the non-union sector even though that sector becomes more attractive. With perfectly homogenous workers within occupations, changes in the return to skill will not affect firm (and thus union) choice.

The union wage literature suggests a premium on the order of 0.2 log points, such that $\gamma^{Uo} = 1.2\gamma^{No}$. That union workers are paid more on average than non-union workers in the same occupation means that only those with idiosyncratic skill levels sufficiently high to overcome the 20% average wage difference *and* the switching costs will want to switch. As long as the skill variance is not very large within each occupation, SBTC itself will not cause an

[15] For simplicity, this is a partial equilibrium model of unionization and wages. See Taschereau-Dumouchel (2020) for a general equilibrium model that provides a microfoundation for these wage parameters. His model does not include unionization frictions, and it predicts that higher-skilled workers will not vote to unionize because they do not benefit from the redistribution of worker surplus. This is at odds with the main findings of our paper.

[16] This model abstracts from job amenities. If unions provide more amenities for all workers, this would effectively raise $\bar{e}$ and reduce the likelihood of workers switching due to wage dispersion. Alternatively, unions could provide more amenities for higher-skilled workers, which would be akin to γ^{Uo} being larger. Non-union jobs could provide better amenities for those with more idiosyncratic skill, which would lead to a higher β^{No}. Hence, depending on how job amenities are distributed with respect to worker skill, they could increase or decrease the incentive to unionize (see for example Dodini et al. 2023). Alternatively, if compensating differentials reduce wages based on how workers value them at the margin, then one can reinterpret the wages in the model as being inclusive of the value of job amenities.

unraveling of unionization. This result is not driven by our partial equilibrium setting: general equilibrium models in which workers endogenously elect to be in a union (e.g., Taschereau-Dumouchel 2020; Dinlersoz and Greenwood 2014) also predict that workers will unionize when there is a large wage return relative to the within-bargaining-unit variance in productivity.

We can conduct a similar exercise to show the conditions under which a non-unionized firm will unionize. Workers in a non-union firm will vote to unionize when their wage will increase in the union relative to the non-union environment sufficiently to offset any unionization costs. Assuming that workers are paid their marginal product or that unions are able to successfully extract monopsony rents from firms, increases in the return to skill for the median worker in a firm and occupation will be reflected in γ (since η is mean zero). Hence, with a non-zero cost of unionization ($\bar{u} > 0$), increases in the return to skill from SBTC will not alter the incentive for the median worker to unionize. It therefore is unlikely that wage dispersion associated with SBTC is a core driver of reductions in the number of new certification elections. Rather, $\bar{u}$ increased beginning in the 1980s as the political environment became more hostile to unions.

Finally, as long as unions pay the median worker in a bargaining unit at least her marginal product, and if the cost of decertification ($\bar{d}$) is non-zero, increasing returns to skill will not cause the median worker to vote for decertification. Our simple model thus can explain why decertifications are not rising substantially despite large reductions in the unionization rate.

This model underscores that changes in the returns to skill from SBTC are unlikely to cause the changing skill patterns we document. Rather, SBTC shifted the US industrial base away from manual and routine jobs to jobs that require non-routine, cognitive skills (Autor, Levy, and Murnane 2003; Deming 2017). The latter occupations have lower unionization rates; the shift to less-unionized occupations is reflected in the "change due to worker share" component of the decomposition results in Table 1. Furthermore, many highly-unionized occupations that were prominent in the 1970s no longer exist, and many new occupations have arisen that tend to require advanced skills. The "Change due to Occupation Entry/Exit" estimates in Table 1 argue for a central role of this mechanism as well. In both cases, our model indicates that the new or pre-existing non-unionized occupations do not unionize because the costs of unionization have risen over time.

We argue that it is the return to average skill rather than the dispersion of skills in a firm-occupation that drives unionization decisions. SBTC likely has been a core driver of changes in unionization rates in the private sector, but it is through changing the sorting of workers across occupations and changing the mix of occupations combined with increased difficulty of engaging in new unionization drives rather than through reducing the incentive for high-skilled workers to unionize.

6. Discussion and Conclusion

This paper documents that the skills covered by union workers have shifted over time toward more non-routine, cognitive skills and less routine skills. Relative to non-union jobs, unionized occupations have increased in terms of their non-routine cognitive, routine manual, and routine cognitive intensities. The changes in non-routine cognitive skill coverage are evident for both men and women, while the changes in routine cognitive and routine manual skills are driven predominantly by women.

We decompose these changes in skill into the part due to shifts in workers across occupations, the part due to within-occupation skill changes, and the part due to changes in the occupation mix. Changes to worker concentration across occupations combined with changes in occupation entry/exit are responsible for the majority of the changes in non-routine cognitive skills among both men and women.

Finally, we discuss that the evidence is at odds with key predictions of prevailing models of SBTC (e.g., Acemoglu, Aghion, and Violante (2001)). We argue that the data can be reconciled with SBTC using a Roy model that incorporates union flexibility in wage bargaining for different bargaining units as well as costs for both unionizing and de-unionizing. The model shows that changes to the returns to skills driven by SBTC are unlikely to affect unionization rates as long as unions can negotiate wages that reflect the average skill level of workers in a bargaining unit. Rather than causing unionization to decline, SBTC shifts workers to previously non-unionized professions and leads to the creation of new professions that are not unionized. The high cost of engaging in a unionization drive is a likely reason why these new and growing professions do not unionize.

Taken together, we show that SBTC has caused large shifts in the types of skills covered by unionized occupations. These changes highlight that the reduction in overall private sector unionization has been accompanied by a change in the type of worker who is unionized. Hence, unions are potentially serving a different role in the labor market today than they did 50 years ago because of the change in the skill composition of the workers covered. These changes are likely to intensify as the US economy continues to evolve away from manufacturing and toward service-intensive sectors as well as with the creation of new types of jobs through the growth of "gig" occupations and the knowledge economy. Indeed, a recent ruling by the National Labor Relations Board makes it easier for independent contractor "gig" workers to unionize, which could have large effects on the types of workers who engage in unionization drives. These jobs cover much different tasks and are organized differently than canonical union professions in the US, which underscores that the types of jobs covered by private sector unions will continue to evolve alongside the US economy and labor relations regulations. Additional work examining how these changes to private sector union coverage affect workers and the operation of higher-skilled labor markets can shed more light on the implications of these changes for both workers and employers.

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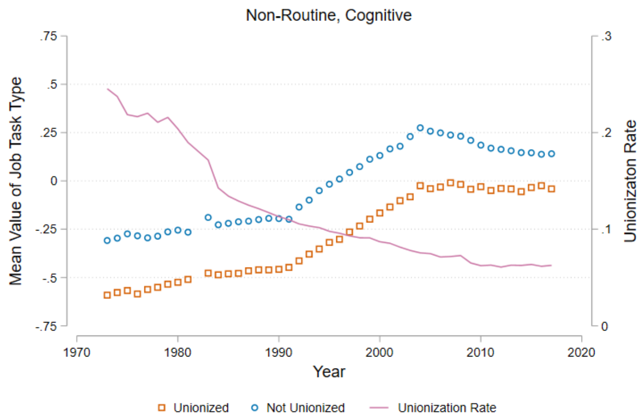
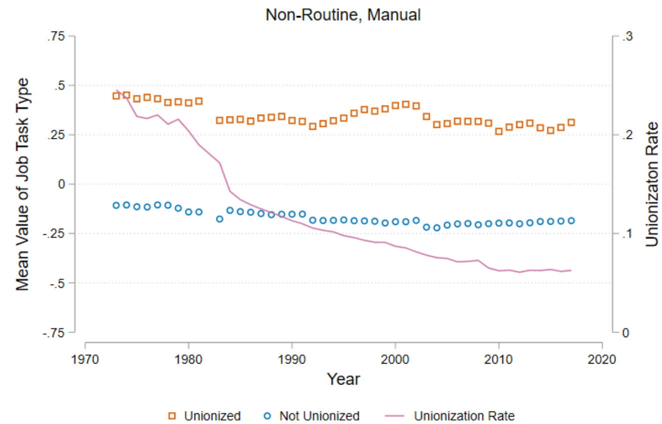
Figure 1: Trends in Occupational Skill Requirements by Union Status

Panel A



Panel B



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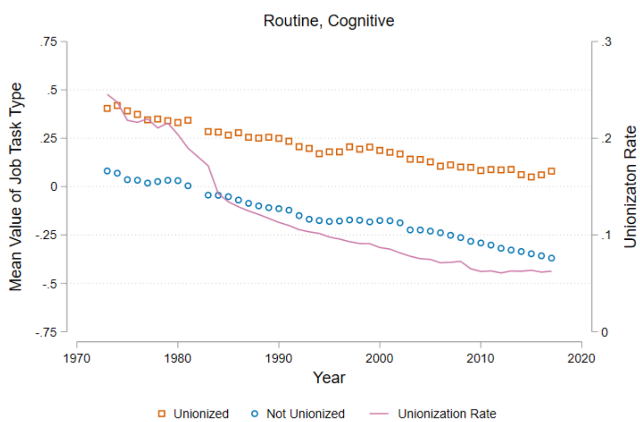
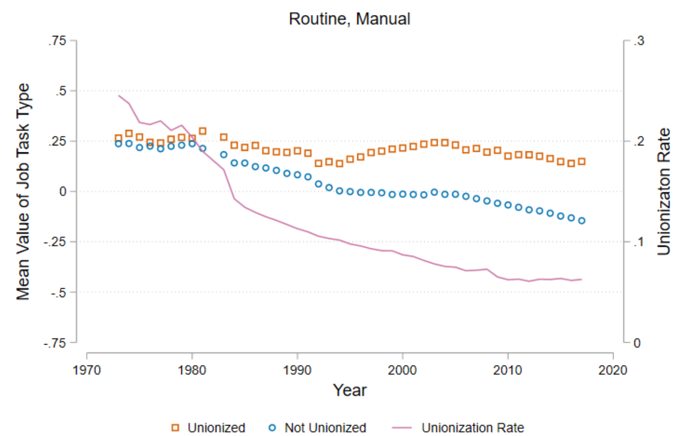


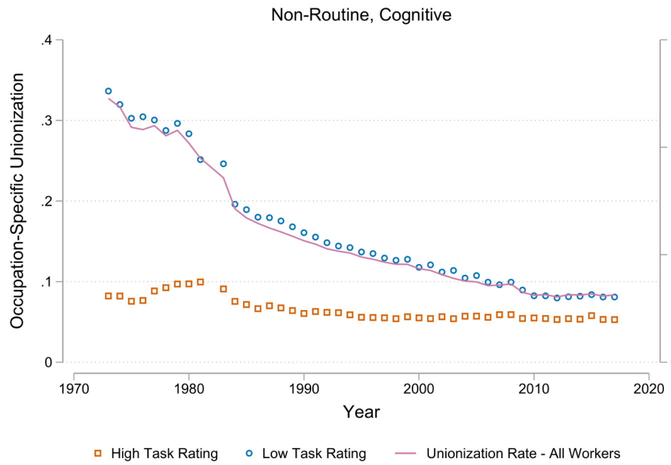
Panel D



Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure 2: Trends in Occupational Skill Requirements Among Unionized Occupations by Top and Bottom Quartile of Skill Level

Panel A



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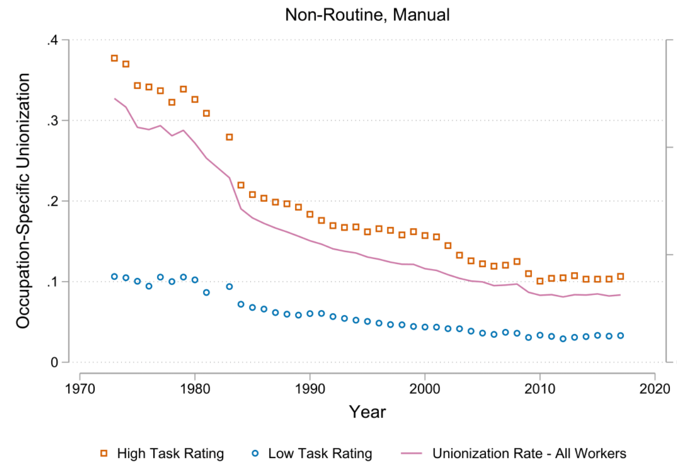

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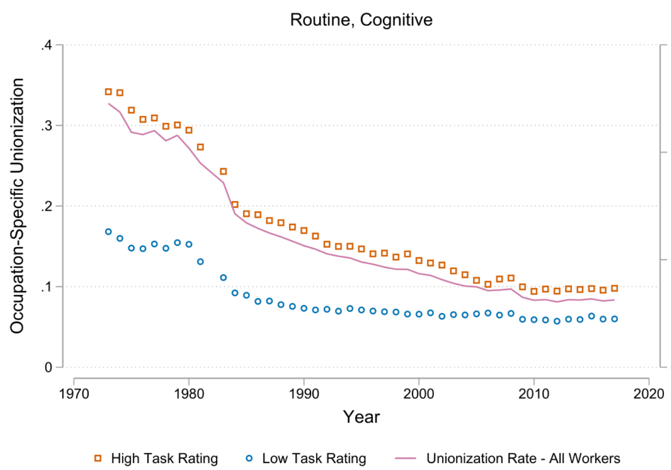

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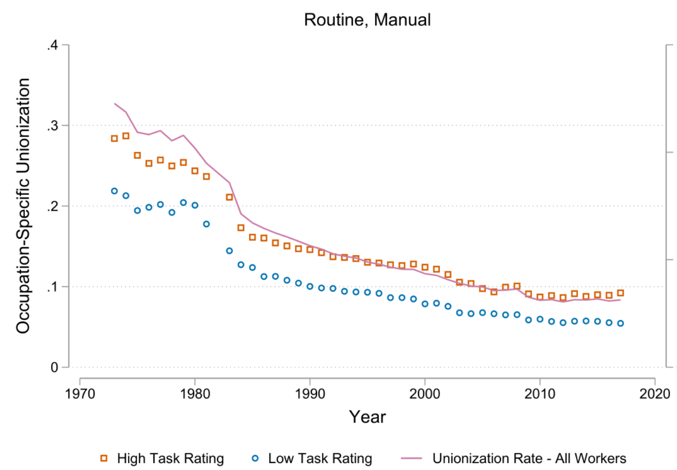
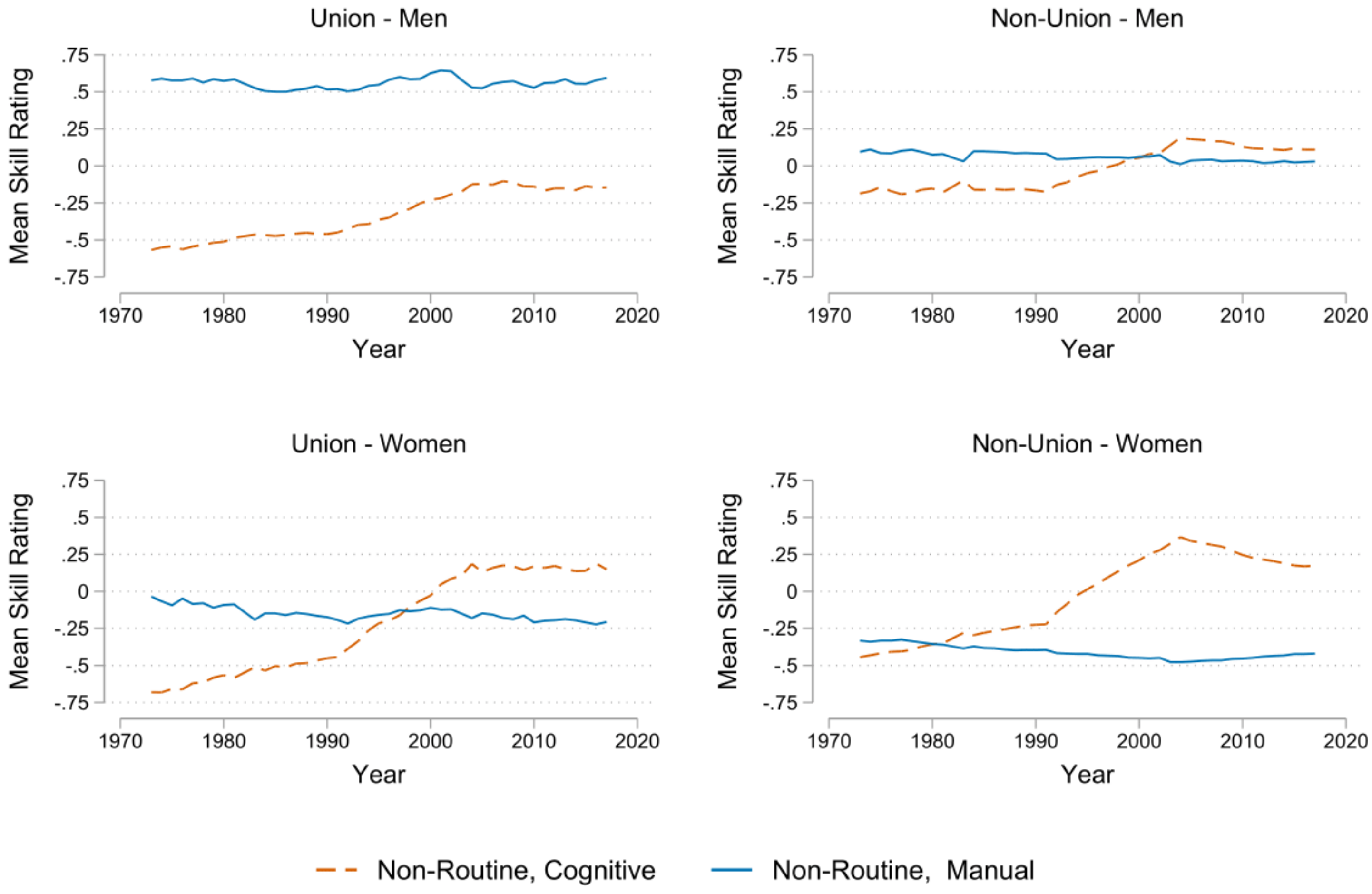


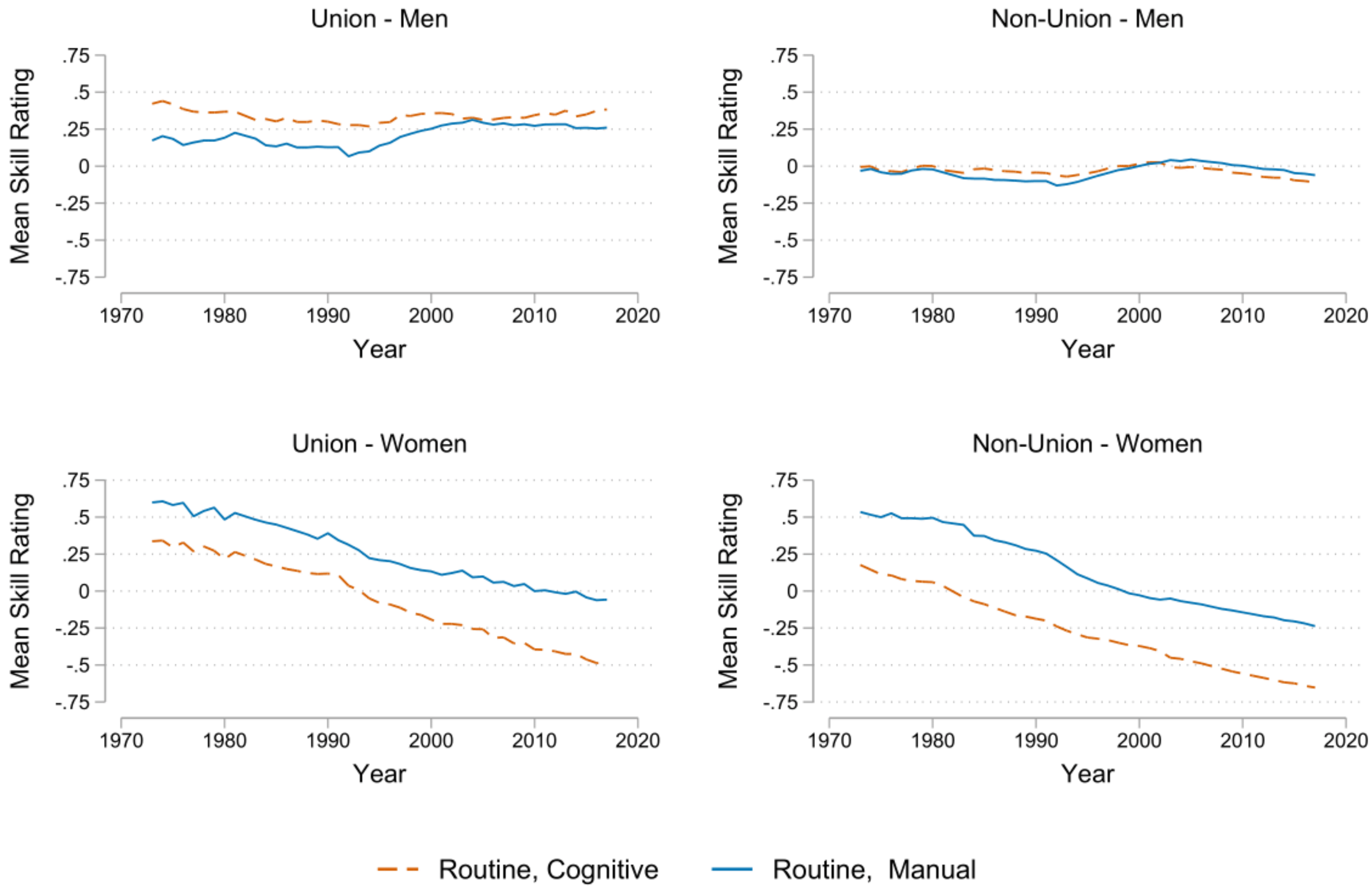
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure 3: Trends in Occupational Skill Requirements by Union Status and Gender: Non-Routine, Cognitive and Non-Routine, Manual Skills



Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

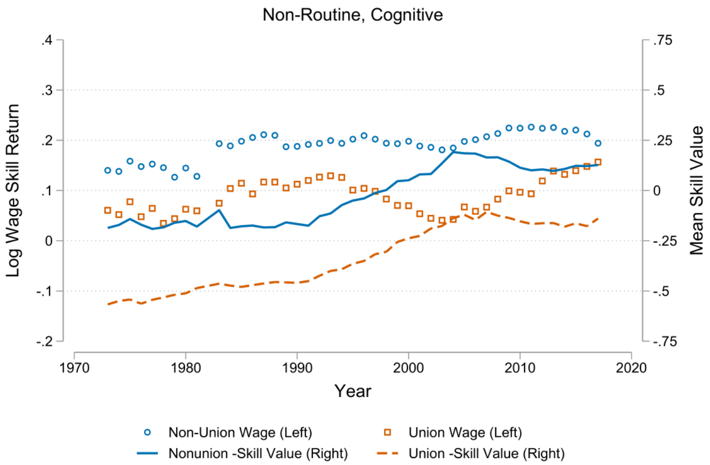
Figure 4: Trends in Occupational Skill Requirements by Union Status and Gender: Routine, Cognitive and Routine, Manual Skills



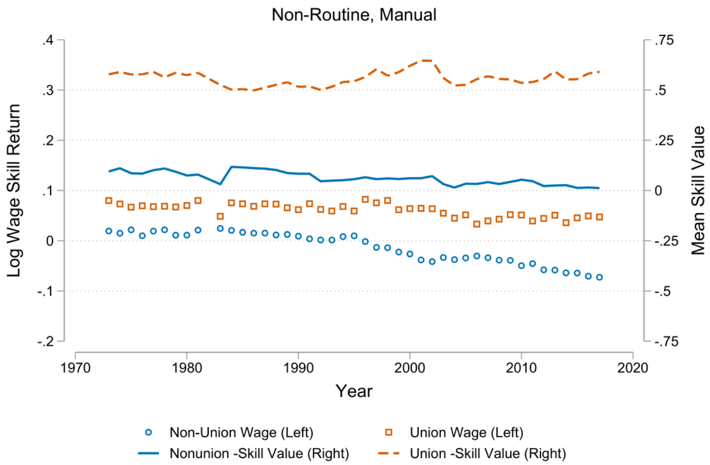
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure 5: Trends in the Return to Job Skills by Union Status – Men

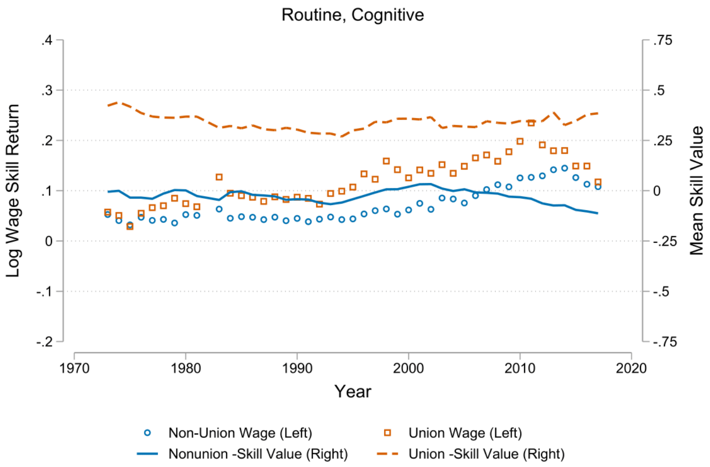
Panel A



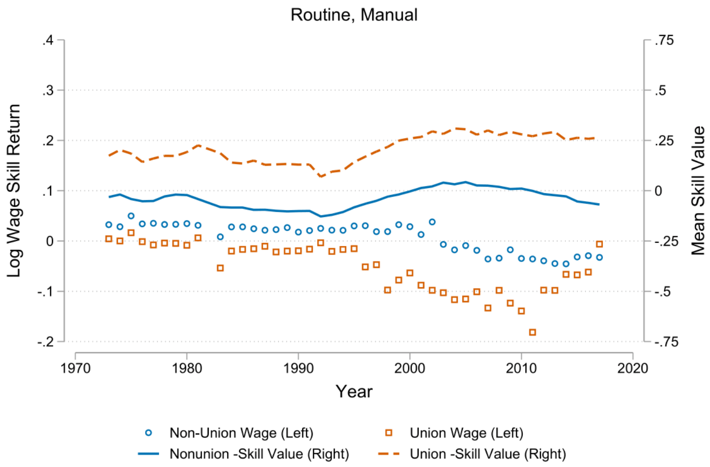
Panel B



Panel C



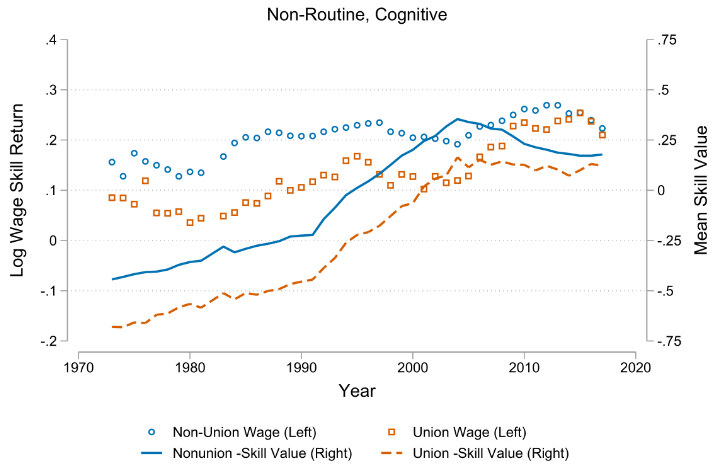
Panel D



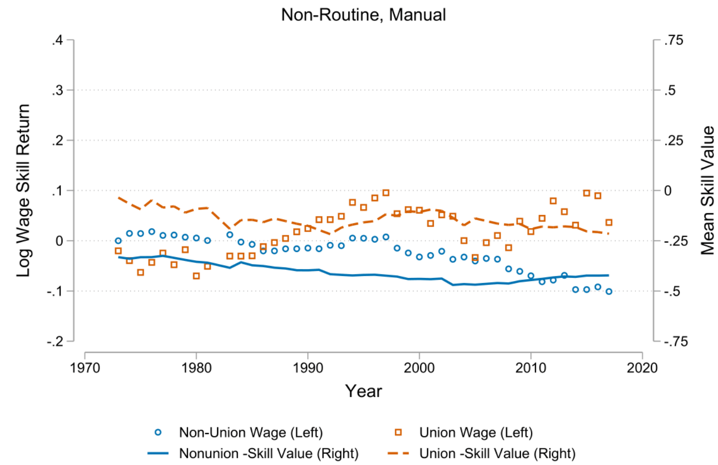
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure 6: Trends in the Return to Job Skills by Union Status – Women

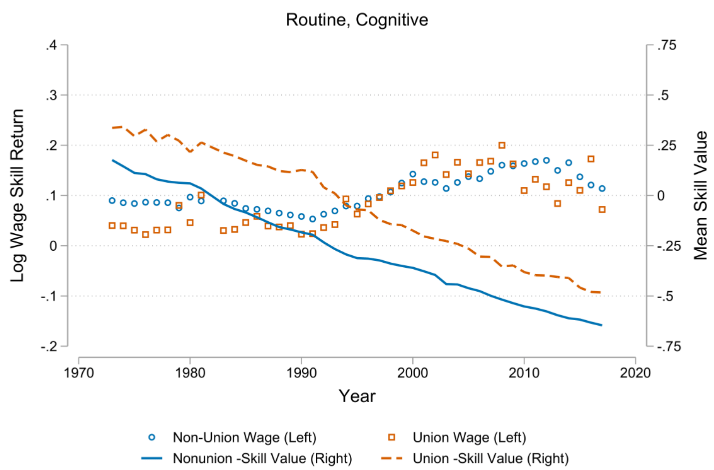
Panel A



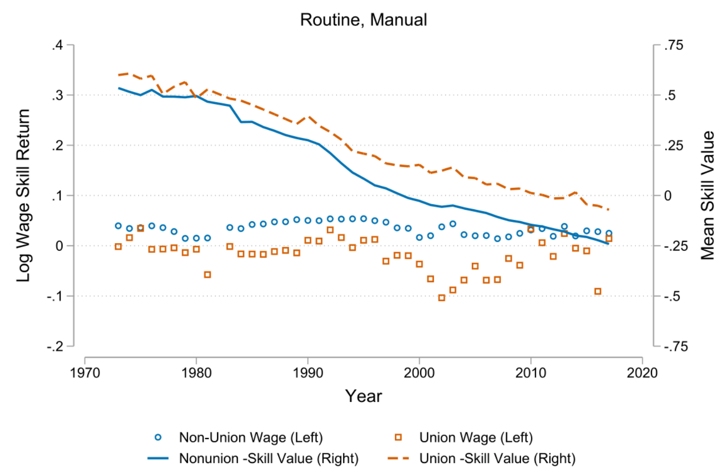
Panel B



Panel C



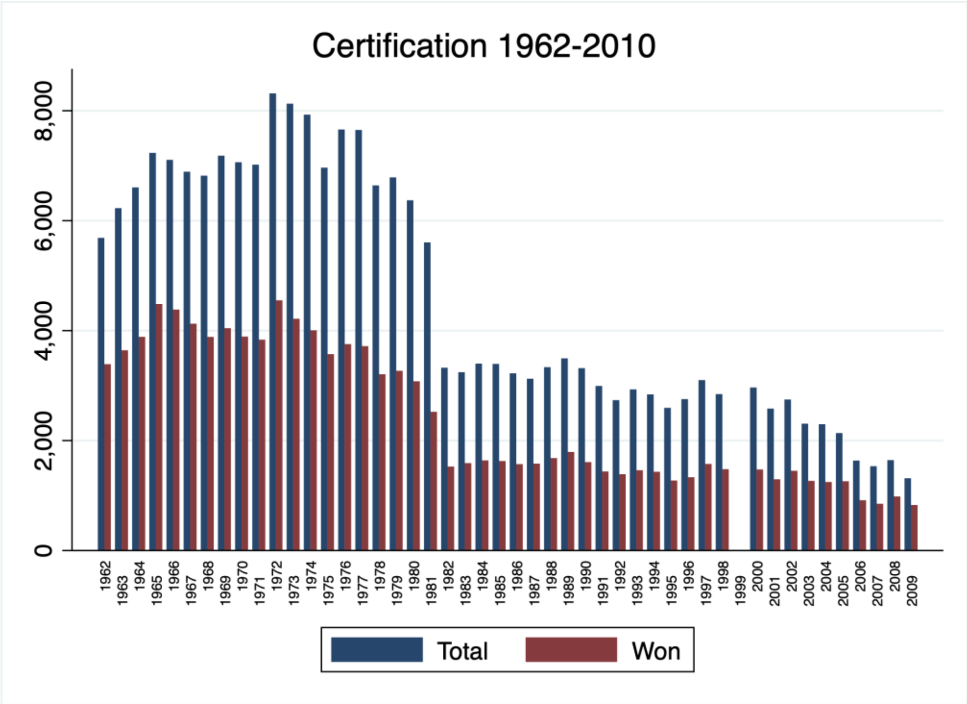
Panel D



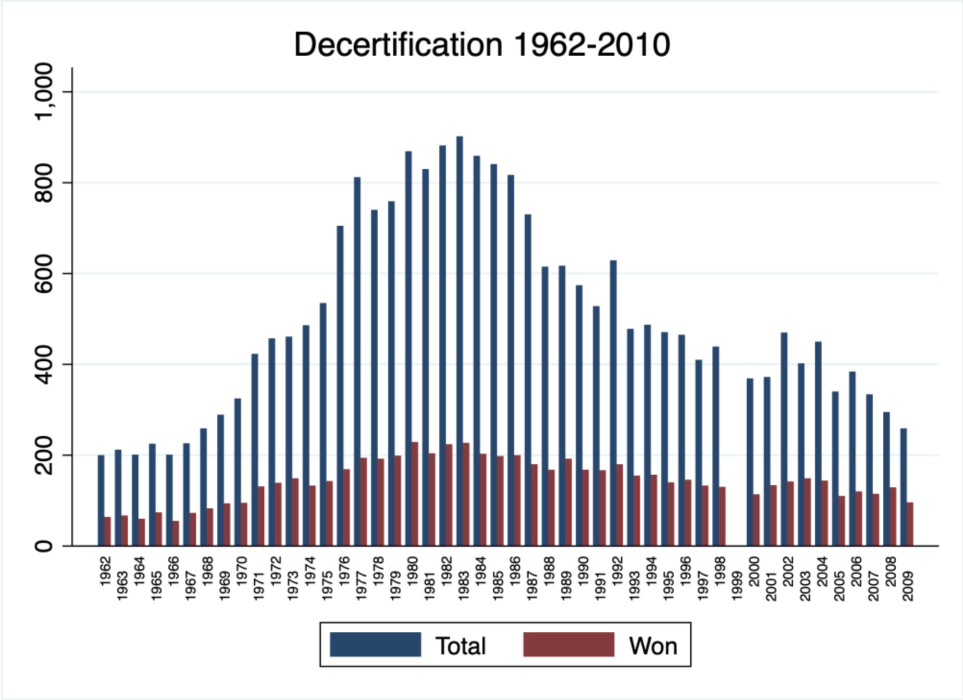
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure 7: Certification and Decertification Elections, 1962-2009

Panel A



Panel B



Source: Authors' tabulations from historical NLRB time series data that Jean-Paul Ferguson (JPF) created from archived NLRB data documents held by the AFL-CIO in Washington D.C.. All data can be downloaded from Jean-Paul Ferguson's website: http://jpferguson.net.

Notes: Data for 1999 has been omitted by the authors because this represents a transition year with partial coverage in the JPF data. This omission has no effect on the conclusion we draw from these data.

Table 1: Decomposition of Changes in Skill Content of Unionized Occupations, 1973-2017

Panel A: Men

Change Category	Skill Type Non-Routine, Cognitive	Non-Routine, Manual	Routine, Cognitive	Routine, Manual
Total Change	0.422	0.016	-0.039	0.087
Change Due to Worker Share	0.140	-0.149	-0.179	-0.144
	[33.3%]	[-952.49%]	[462.69%]	[-166.32%]
Change Due to Intra-Occ Skill Changes	0.073	0.227	0.292	0.343
	[17.31%]	[1455.44%]	[-753.26%]	[395.67%]
Change due to Occupation Entry/Exit	0.208	-0.063	-0.151	-0.112
	[49.39%]	[-402.95%]	[390.58%]	[-129.35%]

Panel B: Women

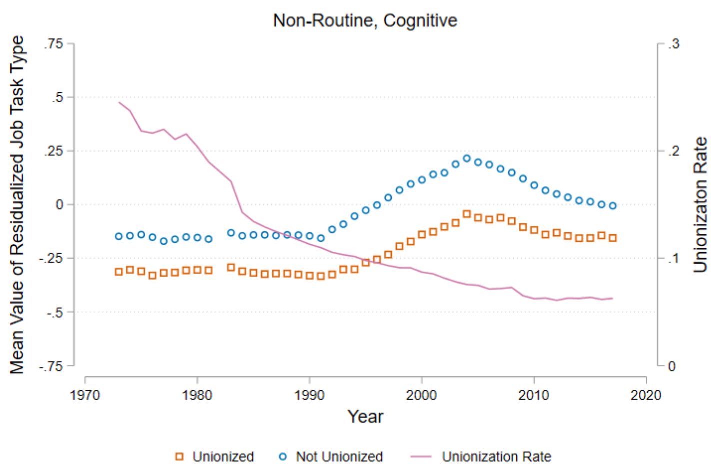
Change Category	Skill Type Non-Routine, Cognitive	Non-Routine, Manual	Routine, Cognitive	Routine, Manual
Total Change	0.830	-0.139	-0.219	-0.208
Change Due to Worker Share	0.492	-0.068	0.046	-0.014
	[59.24%]	[49.35%]	[-20.84%]	[6.75%]
Change Due to Intra-Occ Skill Changes	0.052	-0.056	-0.155	-0.076
	[6.26%]	[40.71%]	[70.88%]	[36.38%]
Change due to Occupation Entry/Exit	0.286	-0.014	-0.109	-0.118
	[34.5%]	[9.94%]	[49.96%]	[56.87%]

Source: Authors' estimation of equation (3) in the text.
Notes: The sum of the three change categories equals the total change by definition. The contribution of each category to the overall change is shown, with the percent effect in brackets. All skill measures are in standard deviation units.

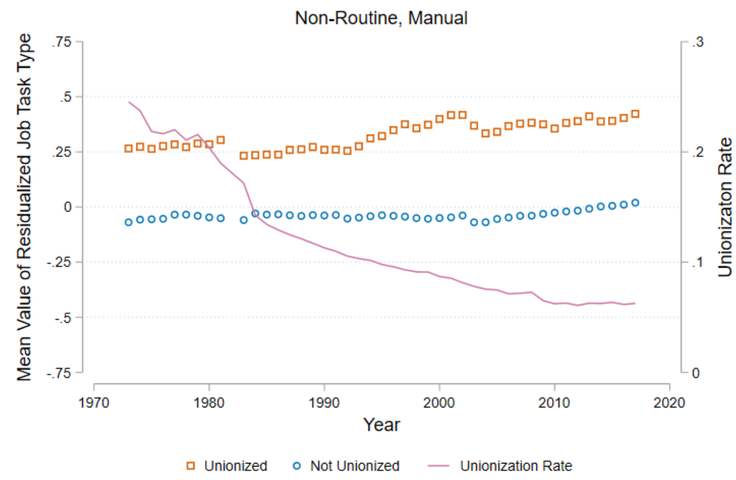
Appendix A: Additional Figures and Tables

Figure A-1: Trends in Residualized Occupational Skill Requirements by Union Status and Skill Measure

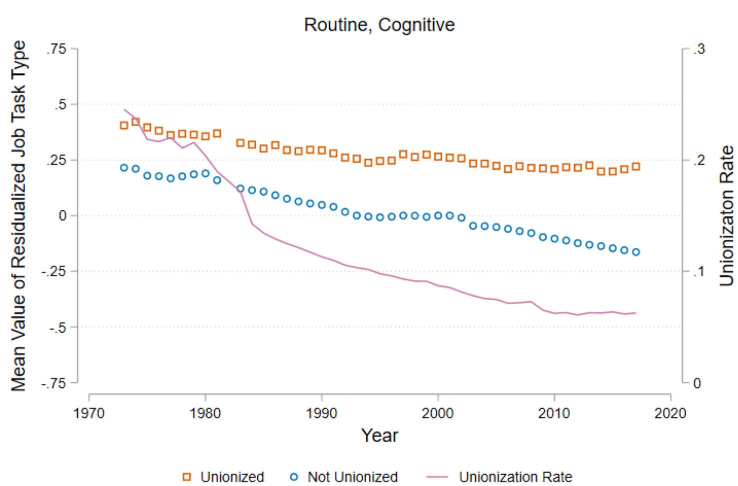
Panel A



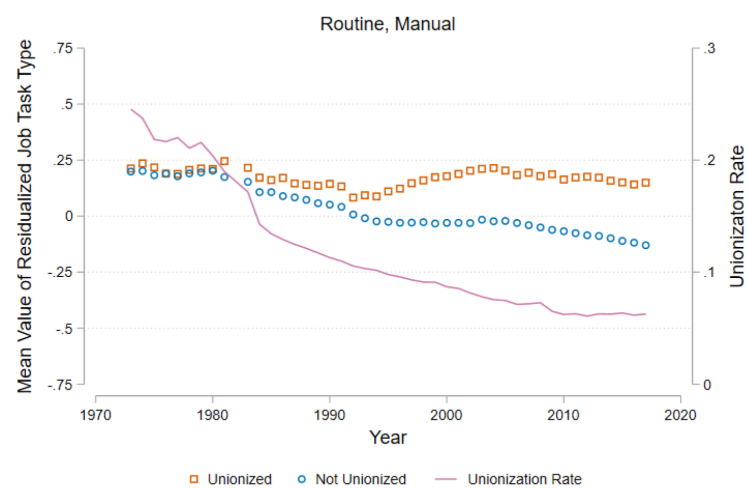
Panel B



Panel C



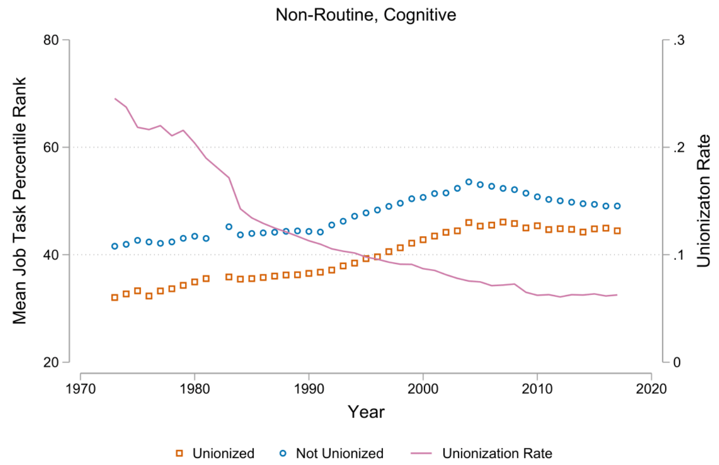
Panel D



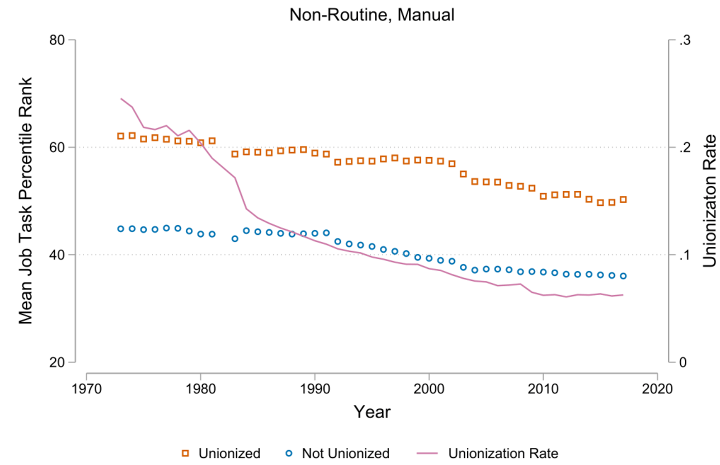
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.
Notes: Outcomes are first residualized using a regression of each skill type on worker age, race/ethnicity, gender, and educational attainment.

Figure A-2: Trends in Occupational Skill Requirements by Union Status - Percentile Ranks

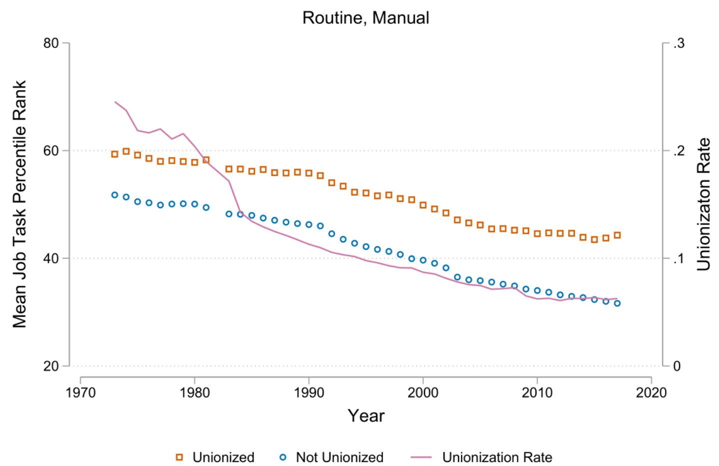
Panel A



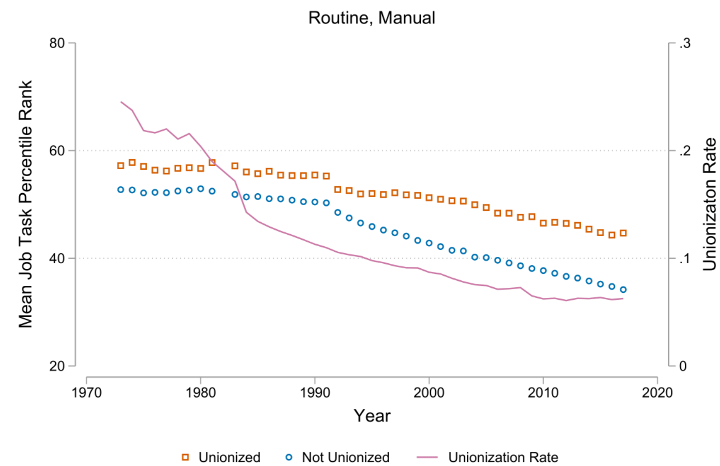
Panel B



Panel C



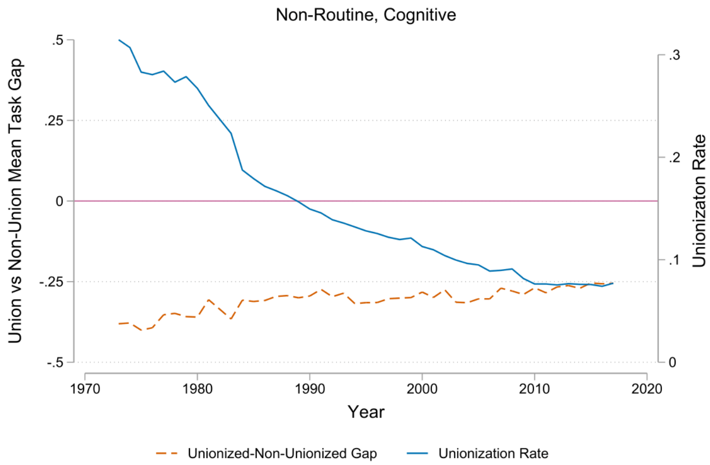
Panel D



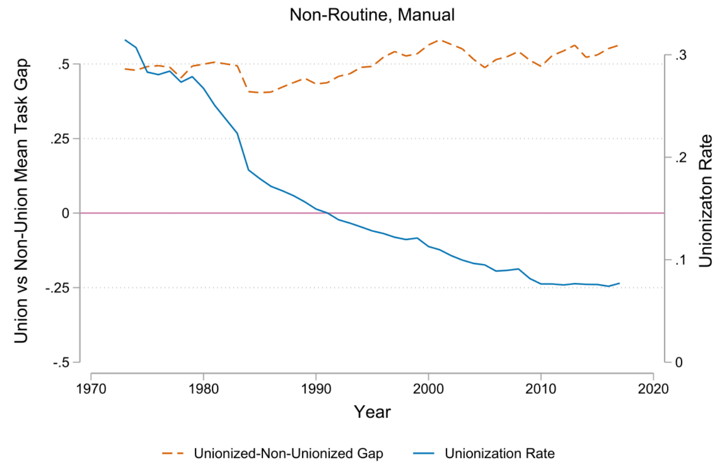
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.
Notes: Instead of normalizing each skill value, we instead assign each occupation a percentile rank in each of the measured years. The figure then plots the average in the CPS of the percentile rank of each worker's occupation across the unionized and non-unionized sectors.

Figure A-3: Trends in Union vs Non-Union Skill Gaps - Men

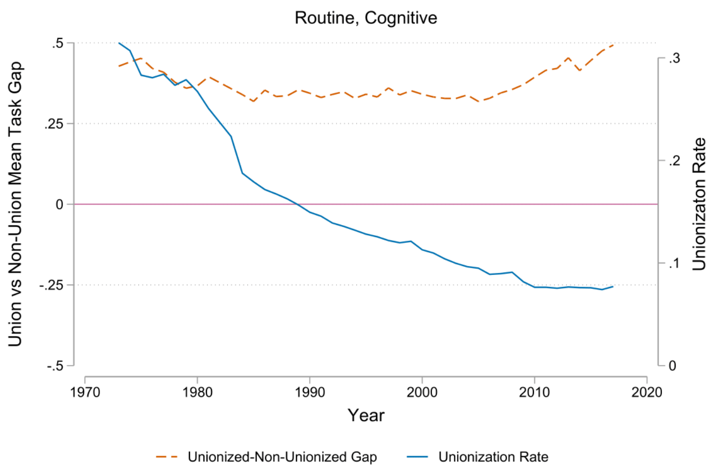
Panel A



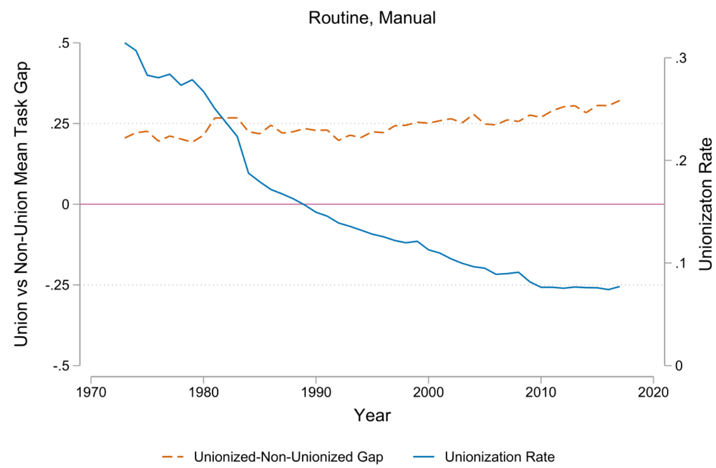
Panel B



Panel C



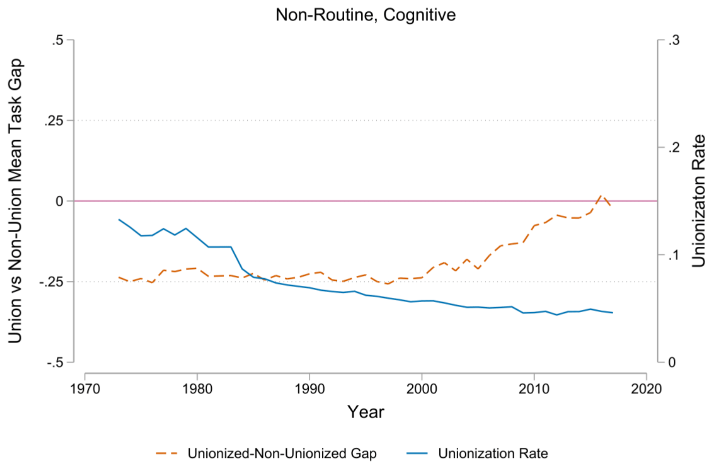
Panel D



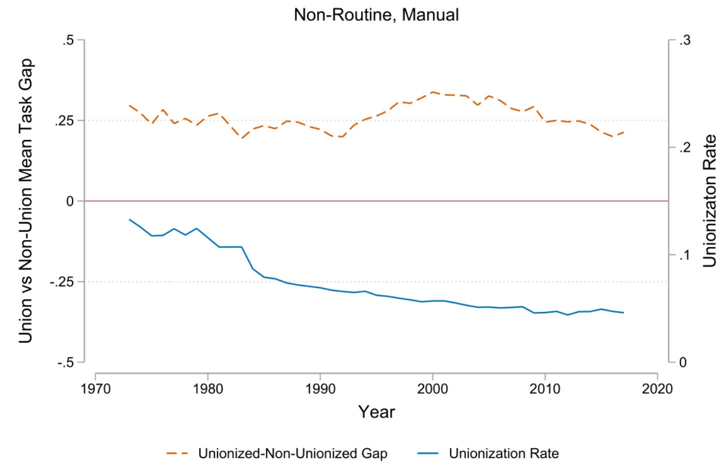
Source: Authors’ calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure A-4: Trends in Union vs Non-Union Skill Gaps - Women

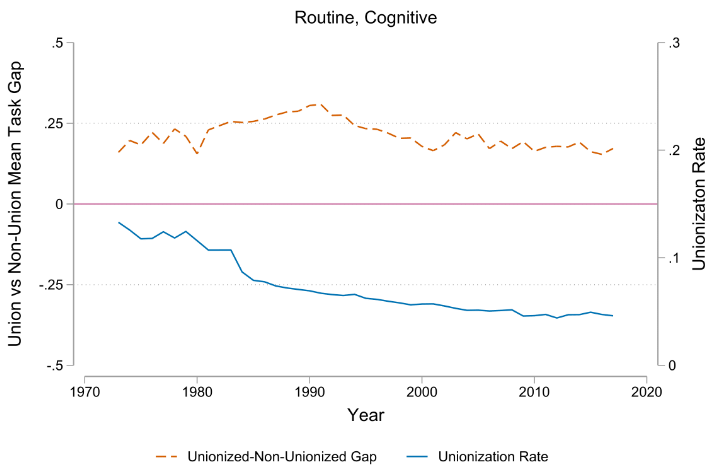
Panel A



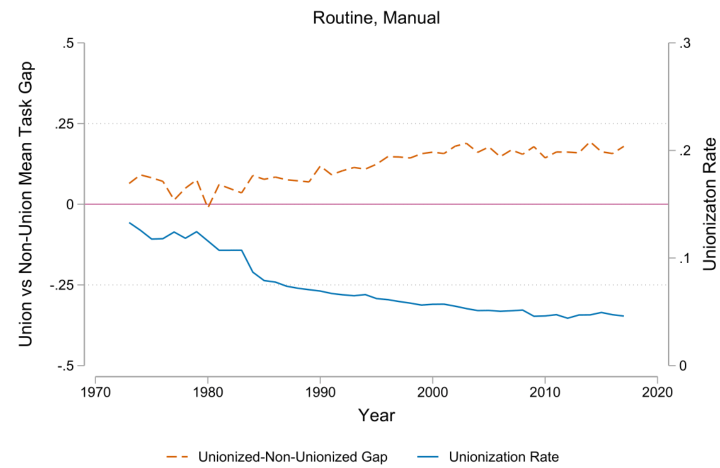
Panel B



Panel C

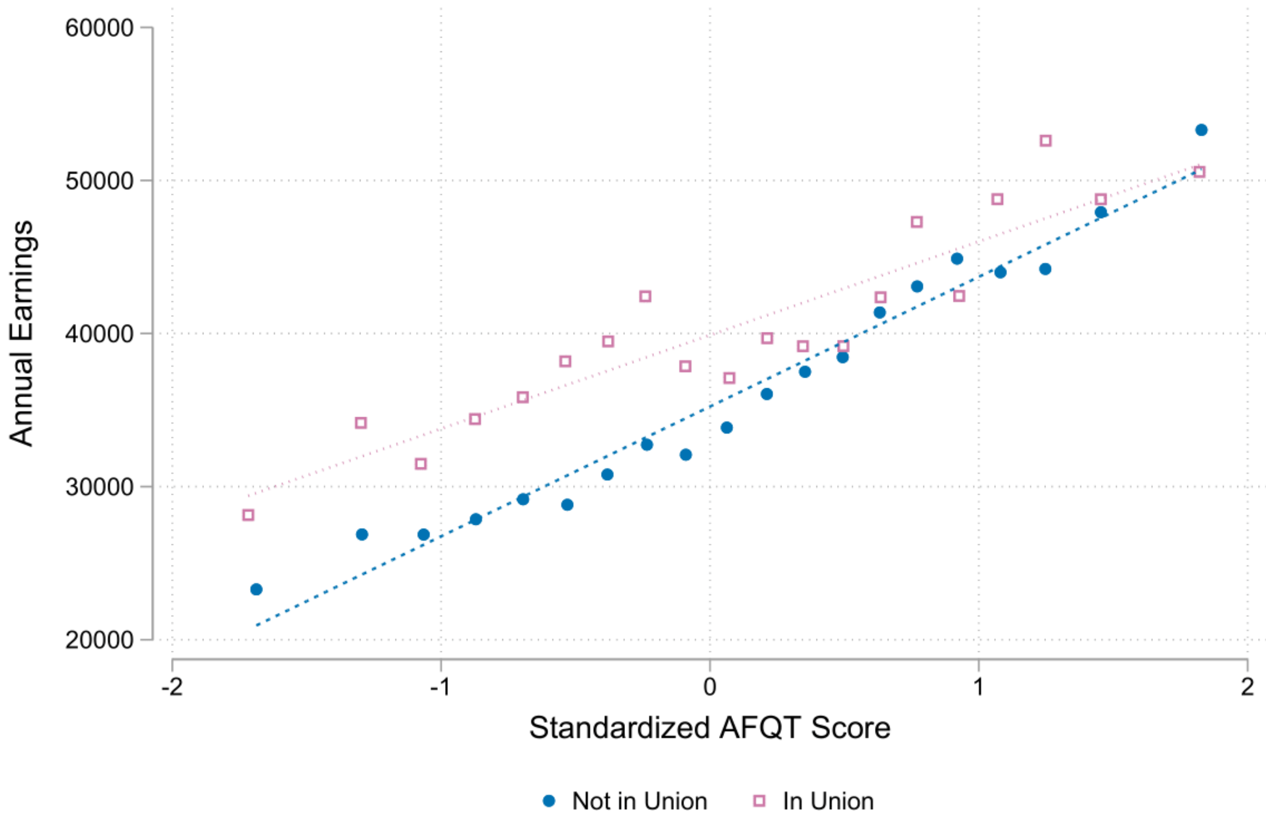


Panel D



Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

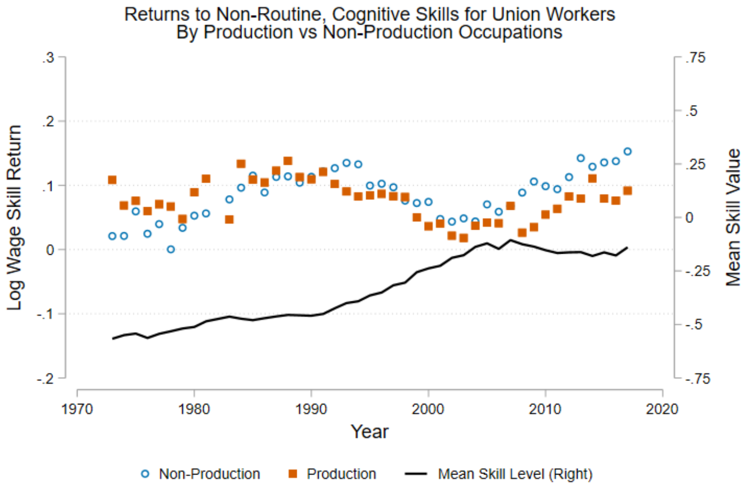
Figure A-5: AQFT and earnings by union status controlling for cognitive skills of occupation and year fixed effects



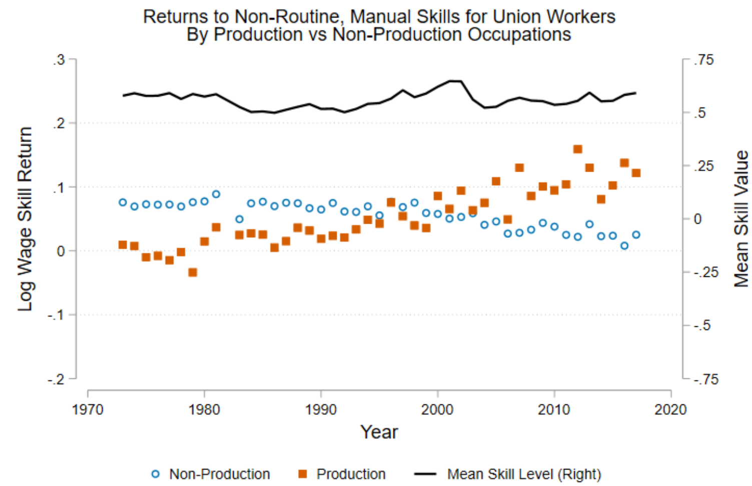
Source: Authors' tabulations using data from NLSY79.
Notes: Figure shows binned averages of annual earnings after conditioning on fixed effects for year and controlling for the cognitive skill level of the occupation.

Figure A-6: Trends in the Return to Job Skills by Union Status, Production versus Non-production Workers – Men

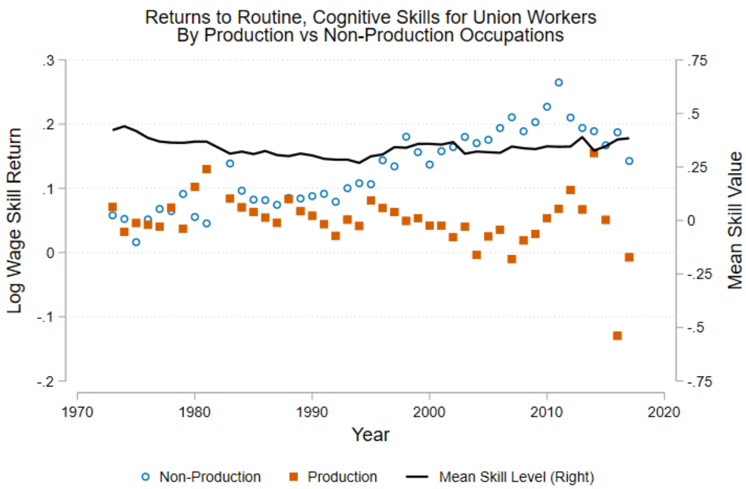
Panel A



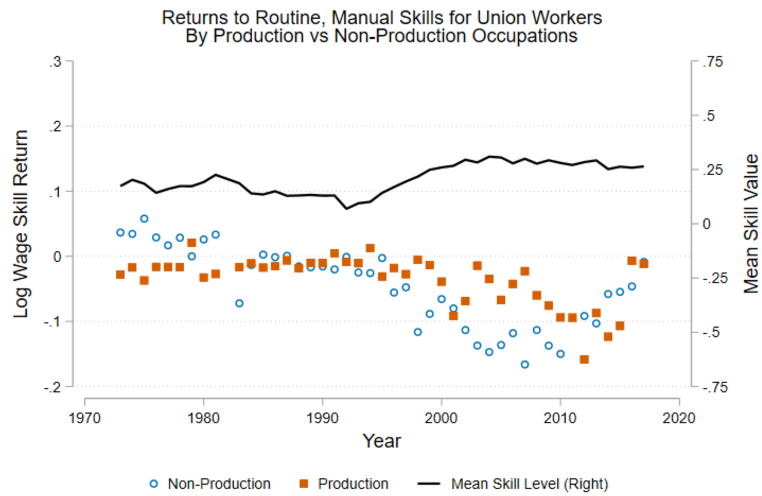
Panel B



Panel C



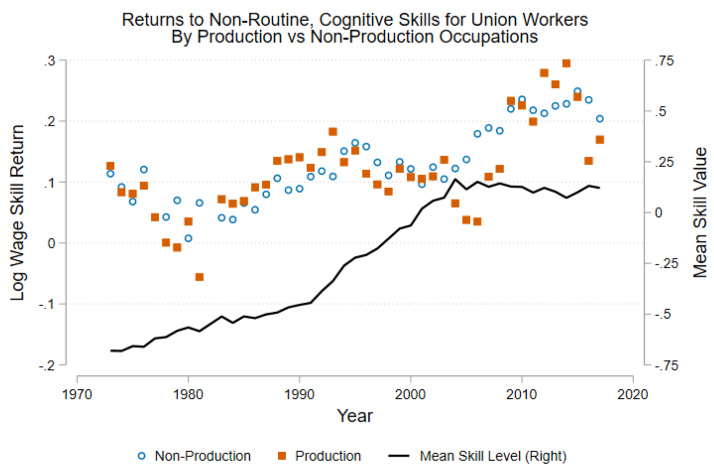
Panel D



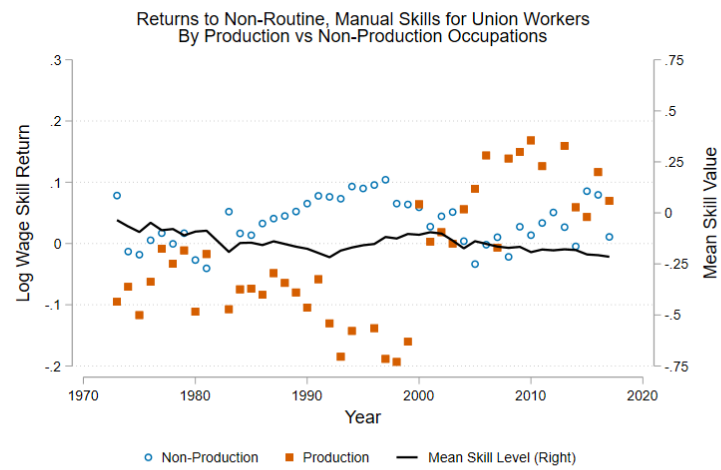
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.
Notes: Production definitions come from the Bureau of Labor Statistics.

Figure A-7: Trends in the Return to Job Skills by Union Status, Production versus Non-production Workers – Women

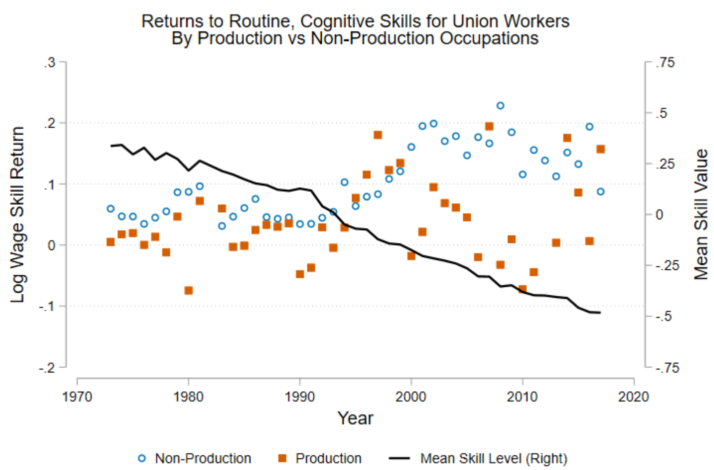
Panel A



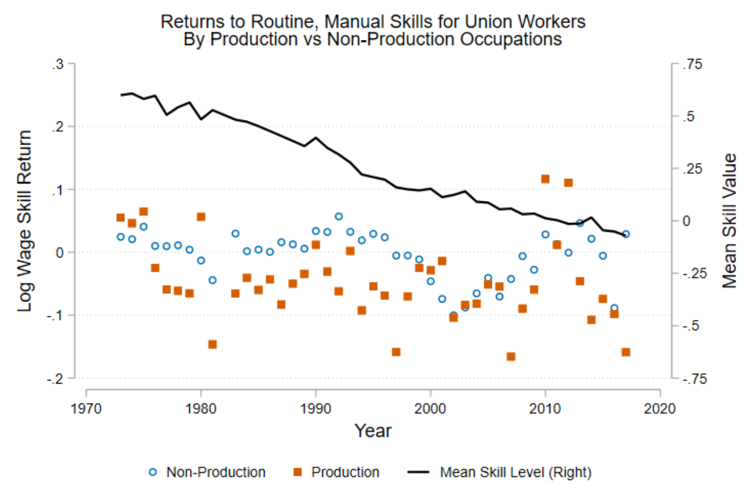
Panel B



Panel C

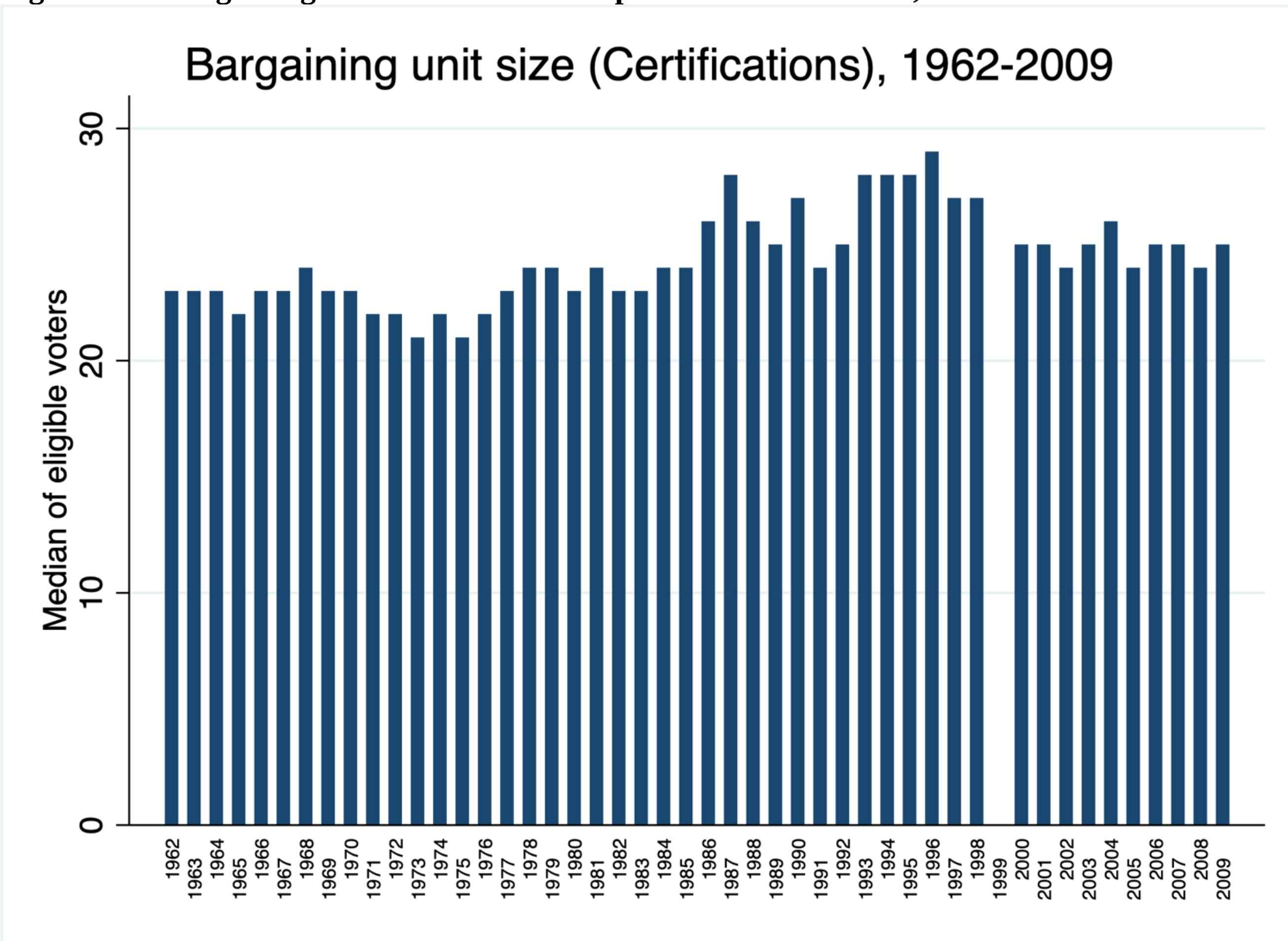


Panel D



Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.
Notes: Production definitions come from the Bureau of Labor Statistics.

Figure A-8: Bargaining Unit Size in Union Representation Elections, 1962-2009

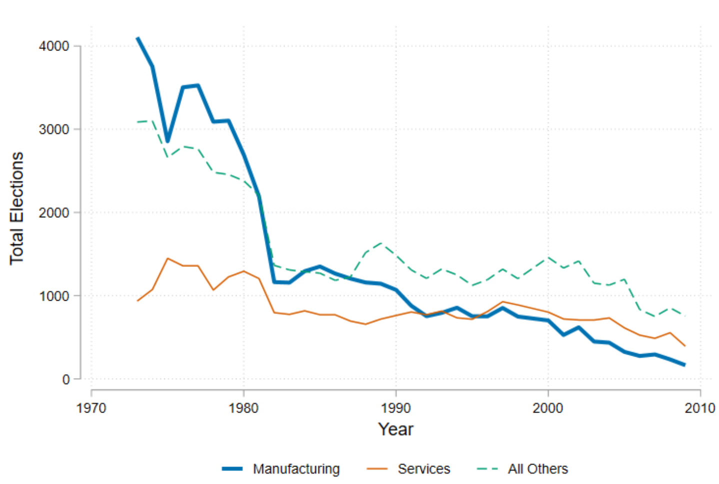


Source: Authors' tabulations from historical NLRB time series data that Jean-Paul Ferguson (JPF) created from archived NLRB data documents held by the AFL-CIO in Washington D.C.. All data can be downloaded from Jean-Paul Ferguson's website: http://jpferguson.net.

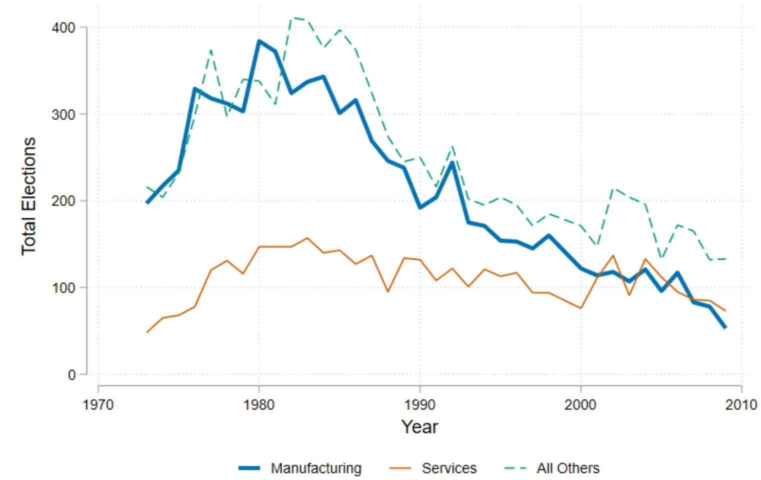
Notes: Data for 1999 has been omitted by the authors because this represents a transition year with partial coverage in the JPF data. This omission has no effect on the conclusion we draw from these data.

Figure A-9: Union elections and election success over time by industry

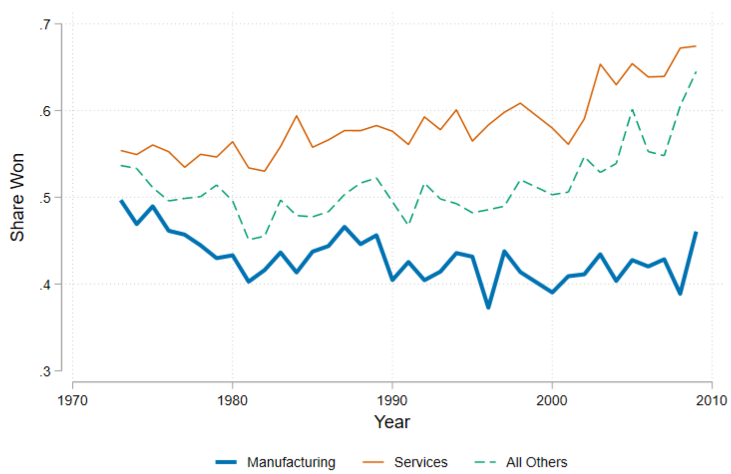
Panel A: Total Certification Elections



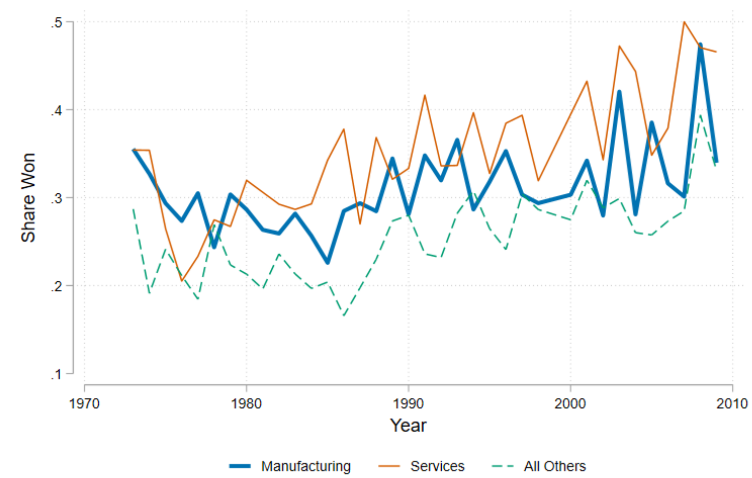
Panel B: Total Decertification Elections



Panel C: Share of Certifications Won



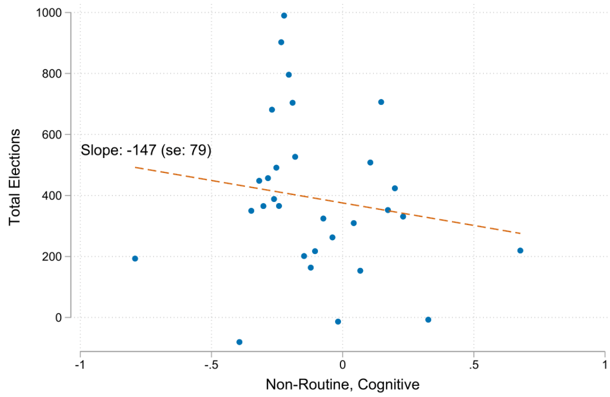
Panel D: Share of Decertifications Won



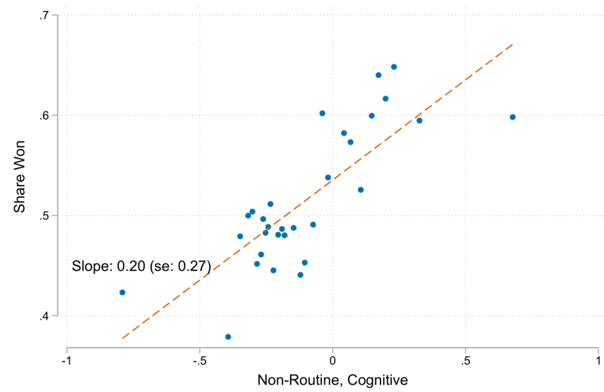
Source: Authors' tabulations from historical NLRB time series data that Jean-Paul Ferguson (JPF) created from archived NLRB data documents held by the AFL-CIO in Washington D.C. (aggregated to major industry groups). All data can be downloaded from Jean-Paul Ferguson's website: http://jpferguson.net.
Notes: Data for 1999 has been omitted by the authors because this represents a transition year with partial coverage in the JPF data. This omission has no effect on the conclusion we draw from these data.

Figure A-10: Relationship between union elections, election success, and cognitive skills

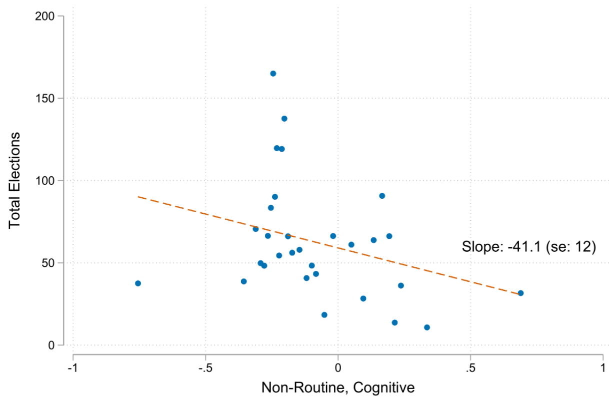
Panel A: Total Certification Elections



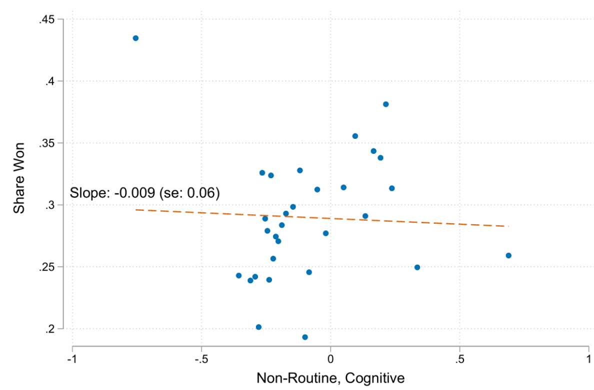
Panel B: Share of Certifications Won



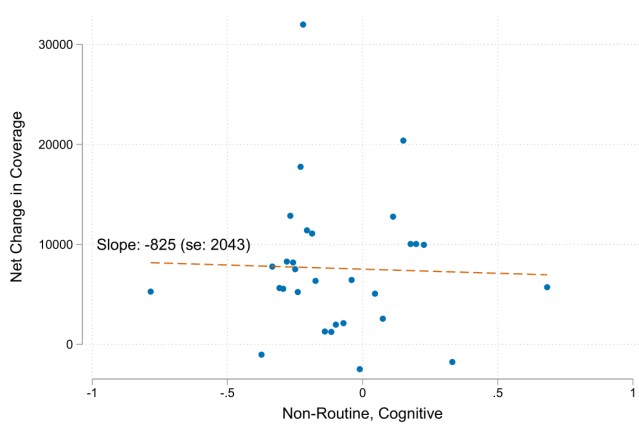
Panel C: Total Decertification Elections



Panel D: Share of Decertifications Won



Panel E: Net Change in Coverage



Source: Authors' tabulations from historical NLRB time series data that Jean-Paul Ferguson (JPF) created from archived NLRB data documents held by the AFL-CIO in Washington D.C.. All data can be downloaded from Jean-Paul Ferguson's website: http://jpferguson.net.
Notes: Skill levels are aggregated to major industry groups' mean cognitive skills in each year in the CPS.

Table A-1: Specific Skills Used to Construct Occupational Skill Measures in DOT and O*NET

Skill Type	DOT Measure (1977, 1991)	O*NET Equivalent(s) (2004, 2017)
Non-Routine, Cognitive/Analytical	General educational development (GED) math	Mathematics (ability)
Non-Routine, Cognitive/Interpersonal	Direction, control, planning	Organizing, planning, and prioritizing work
Non-Routine, Manual	Eye, hand, foot coordination	Gross body equilibrium, Spatial orientation
Routine, Cognitive	Set limits, tolerance, or standards	Controlling machines and processes; Drafting, laying out, and specifying technical devices, parts, and equipment; Troubleshooting
Routine, Manual	Finger dexterity	Finger dexterity
Non-Routine, Cognitive	An additive combination of Non-Routine, Cognitive/Analytical and Non-Routine, Cognitive/Interpersonal	

Table A-2. Summary Statistics, Private Sector Workers, 1973-2017

Panel A: Men

	Union		Non-Union	
	Mean	SD	Mean	SD
Log Hourly Wage	3.06	0.43	2.81	0.65
Age	40.3	11.5	35.9	12.2
Years of Education	12.27	2.32	13.06	3.00
Non-Routine, Cognitive Skill	-0.353	0.672	0.044	0.944
Non-Routine, Manual Skill	0.549	0.985	0.025	0.925
Routine, Cognitive Skill	0.333	0.900	-0.035	0.881
Routine, Manual Skill	0.192	0.794	-0.044	0.762
Race/Ethnicity	Percent		Percent	
Non-Hispanic White	74.4		70.9	
Non-Hispanic Black	10.8		8.4	
NH All Others	3.3		5.1	
Hispanic	11.5		15.7	
N	251,540		1,510,836	

Panel B: Women

	Union		Non-Union	
	Mean	SD	Mean	SD
Log Hourly Wage	2.81	0.51	2.59	0.60
Age	40.1	11.8	36.5	12.5
Years of Education	12.86	2.66	13.20	2.54
Non-Routine, Cognitive Skill	-0.210	0.765	0.077	0.847
Non-Routine, Manual Skill	-0.155	0.700	-0.433	0.614
Routine, Cognitive Skill	-0.078	0.819	-0.356	0.776
Routine, Manual Skill	0.232	0.799	0.051	0.895
Race/Ethnicity	Percent		Percent	
Non-Hispanic White	65.9		73.5	
Non-Hispanic Black	16.7		10.3	
NH All Others	5.7		4.9	
Hispanic	11.7		11.2	
N	109,754		1,566,716	

Source: Authors' tabulations as described in the text from the 1973-2017 CPS, the Dictionary of Occupational Titles (DoT), and the Occupational Information Network (O*NET).

Table A-3: Decomposition of Changes in Skill Content of Unionized Occupations, 1973-1990

Panel A: Men

Change Category	Skill Type Non-Routine, Cognitive	Non-Routine, Manual	Routine, Cognitive	Routine, Manual
Total Change	0.107	-0.062	-0.122	-0.046
Change Due to Worker Share	0.040	0.000	-0.013	-0.031
	[37.15%]	[0%]	[10.66%]	[67.39%]
Change Due to Intra-Occ Skill Changes	0.003	-0.010	-0.104	-0.005
	[3.19%]	[16.13%]	[85.25%]	[10.87%]
Change due to Occupation Entry/Exit	0.064	-0.052	-0.004	-0.010
	[59.66%]	[83.87%]	[3.28%]	[21.74%]

Panel B: Women

Change Category	Skill Type Non-Routine, Cognitive	Non-Routine, Manual	Routine, Cognitive	Routine, Manual
Total Change	0.229	-0.139	-0.219	-0.208
Change Due to Worker Share	0.126	-0.068	0.046	-0.014
	[55.12%]	[48.92%]	[-21%]	[6.73%]
Change Due to Intra-Occ Skill Changes	0.005	-0.056	-0.155	-0.076
	[2.01%]	[40.29%]	[70.78%]	[36.54%]
Change due to Occupation Entry/Exit	0.098	-0.014	-0.109	-0.118
	[42.83%]	[10.07%]	[49.77%]	[56.73%]

Source: Authors' estimation of equation (3) in the text.
Notes: The sum of the three change categories equals the total change by definition. The contribution of each category to the overall change is shown, with the percent effect in brackets below. All skill measures are in standard deviation units.

Table A-4: Decomposition of Changes in Skill Content of Unionized Occupations, 1990-2017

Panel A: Men

Change Category	Skill Type Non-Routine, Cognitive	Non-Routine, Manual	Routine, Cognitive	Routine, Manual
Total Change	0.315	0.077	0.083	0.133
Change Due to Worker Share	0.165	-0.159	-0.160	-0.128
	[52.38%]	[-206.49%]	[-192.77%]	[-96.24%]
Change Due to Intra-Occ Skill Changes	0.068	0.268	0.323	0.391
	[21.57%]	[348.05%]	[389.16%]	[293.98%]
Change due to Occupation Entry/Exit	0.082	-0.032	-0.080	-0.130
	[26.05%]	[-41.56%]	[-96.39%]	[-97.74%]

Panel B: Women

Change Category	Skill Type Non-Routine, Cognitive	Non-Routine, Manual	Routine, Cognitive	Routine, Manual
Total Change	0.600	-0.032	-0.598	-0.449
Change Due to Worker Share	0.367	-0.102	-0.191	-0.148
	[61.18%]	[318.75%]	[31.94%]	[32.96%]
Change Due to Intra-Occ Skill Changes	0.159	0.084	-0.379	-0.256
	[26.45%]	[-262.5%]	[63.38%]	[57.02%]
Change due to Occupation Entry/Exit	0.074	-0.014	-0.028	-0.045
	[12.39%]	[43.75%]	[4.68%]	[10.02%]

Source: Authors' estimation of equation (3) in the text.
Notes: The sum of the three change categories equals the total change by definition. The contribution of each category to the overall change is shown, with the percent effect in brackets below. All skill measures are in standard deviation units.

Table A-5: Decomposition of Changes in Skill Content of Non-Unionized Occupations, 1973-2017

Panel A: Men

Change Category	Skill Type Non-Routine, Cognitive	Non-Routine, Manual	Routine, Cognitive	Routine, Manual
Total Change	0.297	-0.065	-0.104	-0.029
Change Due to Worker Share	-0.019	-0.074	-0.073	-0.031
	[-6.24%]	[113.85%]	[70.19%]	[106.9%]
Change Due to Intra-Occ Skill Changes	0.077	0.093	0.070	0.094
	[25.94%]	[-143.08%]	[-67.31%]	[-324.14%]
Change due to Occupation Entry/Exit	0.238	-0.083	-0.102	-0.093
	[80.27%]	[127.69%]	[98.08%]	[320.69%]

Panel B: Women

Change Category	Skill Type Non-Routine, Cognitive	Non-Routine, Manual	Routine, Cognitive	Routine, Manual
Total Change	0.618	-0.088	-0.829	-0.772
Change Due to Worker Share	0.185	0.033	0.027	-0.005
	[29.91%]	[-37.5%]	[-3.26%]	[0.65%]
Change Due to Intra-Occ Skill Changes	0.186	-0.053	-0.749	-0.646
	[30.07%]	[60.23%]	[90.35%]	[83.68%]
Change due to Occupation Entry/Exit	0.247	-0.068	-0.108	-0.120
	[40.03%]	[77.27%]	[13.03%]	[15.54%]

Source: Authors' estimation of equation (3) in the text.
Notes: The sum of the three change categories equals the total change by definition. The contribution of each category to the overall change is shown, with the percent effect in brackets below. All skill measures are in standard deviation units.

Table A-6: Residualized Decompositions, 1973-2017

Panel A: Men

	Non-Routine, Cognitive		**Non-Routine, Manual**		**Routine, Cognitive**		**Routine, Manual**	
Skill Type:	Industry	Composition	Industry	Composition	Industry	Composition	Industry	Composition
	1	2	3	4	5	6	7	8
Total Change	0.376	0.102	-0.026	0.200	0.101	0.030	0.161	0.125
Change Due to Worker Share	0.116	0.101	-0.145	-0.125	-0.147	-0.168	-0.131	-0.132
Change Due to Intra-Occ Skill Changes	0.061	-0.127	0.191	0.343	0.351	0.332	0.376	0.357
Net Effect of Occupation Entry/Exit/Persistence in CPS	0.199	0.128	-0.072	-0.018	-0.103	-0.134	-0.084	-0.100

Panel B: Women

	Non-Routine, Cognitive		**Non-Routine, Manual**		**Routine, Cognitive**		**Routine, Manual**	
Skill Type	Industry	Composition	Industry	Composition	Industry	Composition	Industry	Composition
	1	2	3	4	5	6	7	8
Total Change	0.703	0.321	-0.034	0.120	-0.501	-0.694	-0.522	-0.562
Change Due to Worker Share	0.434	0.317	-0.026	0.005	-0.083	-0.203	-0.076	-0.100
Change Due to Intra-Occ Skill Changes	0.031	-0.103	0.028	0.099	-0.262	-0.254	-0.250	-0.244
Net Effect of Occupation Entry/Exit/Persistence in CPS	0.238	0.107	-0.036	0.015	-0.156	-0.236	-0.196	-0.218

Source: Authors' estimation of equation (3) in the text.

Notes: The sum of the three change categories equals the total change by definition. The contribution of each category to the overall change is shown, with the percent effect in brackets below. All skill measures are in standard deviation units. Odd columns are the decompositions after having first residualized the same on fixed effects for major industry group. The even columns are the decompositions after having first residualized on worker educational attainment, race/ethnicity, and age.

Table A-7: Union Wage Premium Estimates by Decade

Panel A: Men						
	Basic Model	Skill Controls	Skill Interactions	Basic Model	Skill Controls	Skill Interactions
Year	(i)	(ii)	(iii)	(iv)	(v)	(vi)
1975	0.224***	0.281***	0.281***	0.301***	0.314***	0.315***
	(0.026)	(0.028)	(0.024)	(0.019)	(0.021)	(0.017)
1985	0.301***	0.354***	0.354***	0.360***	0.383***	0.384***
	(0.026)	(0.021)	(0.022)	(0.017)	(0.015)	(0.015)
1995	0.228***	0.281***	0.281***	0.282***	0.308***	0.307***
	(0.028)	(0.019)	(0.017)	(0.018)	(0.015)	(0.012)
2005	0.243***	0.236***	0.236***	0.296***	0.289***	0.286***
	(0.028)	(0.023)	(0.019)	(0.019)	(0.019)	(0.014)
2015	0.219***	0.215***	0.215***	0.271***	0.265***	0.262***
	(0.035)	(0.026)	(0.023)	(0.023)	(0.022)	(0.022)
Occupation FE	No	No	No	Yes	Yes	Yes

Panel B: Women						
	Basic Model	Skill Controls	Skill Interactions	Basic Model	Skill Controls	Skill Interactions
Year	(i)	(ii)	(iii)	(iv)	(v)	(vi)
1975	0.253***	0.265***	0.265***	0.280***	0.285***	0.291***
	(0.030)	(0.029)	(0.023)	(0.026)	(0.028)	(0.029)
1985	0.292***	0.311***	0.311***	0.317***	0.324***	0.330***
	(0.027)	(0.030)	(0.022)	(0.022)	(0.023)	(0.015)
1995	0.219***	0.245***	0.245***	0.238***	0.253***	0.258***
	(0.025)	(0.023)	(0.02)	(0.015)	(0.016)	(0.017)
2005	0.218***	0.220***	0.220***	0.221***	0.227***	0.230***
	(0.040)	(0.031)	(0.04)	(0.018)	(0.018)	(0.020)
2015	0.219***	0.217***	0.217***	0.216***	0.220***	0.222***
	(0.049)	(0.027)	(0.024)	(0.021)	(0.021)	(0.022)
Occupation FE	No	No	No	Yes	Yes	Yes

Source: Authors' estimation of equation (4) as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Notes: Only results for selected years are shown. All estimates include controls for education, race, and age. Standard errors clustered at the occupation level are in parentheses: *** indicates significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level.

Appendix B – Data

To identify the relevant skills and tasks of each occupation, we use the metrics of occupation characteristics in the 1977 and 1991 editions of the Dictionary of Occupation Titles (DOT) survey as well as the 2004 and 2017 editions of the Occupational Information Network (O*NET) survey. Both surveys are fielded by the US Department of Labor. The DOT data are based on 1990 Census occupation codes and come from Autor, Levy, and Murnane (2003). The O*NET data are collected at the Standard Occupational Classification (SOC) code level, which is a designation that is finer than Census occupation codes. Following Acemoglu and Autor (2011), we create a weighted average of each skill rating in 1990 Census occupation code equivalents. This is done by weighting the O*NET data in each SOC code by total employment from the BLS Occupational Employment Statistics (OES) data for 2003-2017.

To obtain a time-consistent definition of occupations, we crosswalk all Census occupation codes to their 1990 equivalent based primarily on the method proposed by Acemoglu and Autor (2011) and the harmonized occupation codes at the IPUMS USA repository (Ruggles, et al. 2019). We match the remaining occupations by hand using occupation descriptions available from the Census. Some occupations do not have a clear 1990 equivalent, either because the occupation no longer exists in meaningful numbers (e.g., telegraph operators), or because an occupation first enters the CPS in a later year. Our decomposition analysis accounts for these changes to occupation coverage in the data.[1]

In each survey year, workers and occupation-specific experts are asked about the knowledge, skills, abilities, and tasks associated with each occupation. The DOT data are based on 1990 Census occupation codes and come from Autor, Levy, and Murnane (2003). The O*NET data are collected at the Standard Occupational Classification (SOC) code level, which is a designation that is finer than Census occupation codes. Following Acemoglu and Autor (2011), we create a weighted average of each skill rating in 1990 Census occupation code equivalents. This is done by weighting the O*NET data in each SOC code by total employment from the BLS Occupational Employment Statistics (OES) data for 2003-2017.

Our main measures of occupational skill are aligned with those in Autor, Levy, and Murnane (2003). We begin with five skill measures: non-routine, cognitive analytical; non-routine, cognitive

[1] In 1983, the CPS incorporated 1980 Census occupation codes, which expanded the set of occupations assigned a separate code relative to the 1970 definitions. While this change mechanically increases the share of skill changes attributed to entry/exit when including pre-1983 years, our results are similar and our conclusions are unchanged when comparing other time periods that did not experience this reclassification.

interpersonal; routine manual; routine cognitive; and non-routine manual. We then create a measure of non-routine cognitive tasks that are a combination of non-routine cognitive analytical and non-routine cognitive interpersonal.[2] This leaves us with four task groups. We emphasize that these measures comprise different dimensions of skills that do not move mechanically with one another. It, therefore, is possible for an occupation to require more or less of all task types relative to other occupations, which is why we do not combine these further into a single skill index.

A core impediment to using the O*NET and DOT data is that the skill measures are different in the two datasets. We construct harmonized skill measures across the two datasets by matching information in the DOT data to the 2004 and 2017 O*NET data. This procedure involves locating a direct match or constructing an index across similar measures if a direct match cannot be found. We convert O*NET skill ratings into a single index by taking the mean across each measure. Appendix Table A-1 shows each DOT measure we use and its O*NET equivalent(s) that we use as inputs into these indices.

In the DOT and Autor, Levy, and Murnane (2003), "GED – math" is the measure of "non-routine, cognitive analytical" skills. We use the mathematics ability measure in the O*NET dataset to match the DOT measure. We employ this measure because it has the highest cross-sectional correlation with the DOT measure in 2004 among all other relevant factors that mention "mathematics" in the O*NET. The measure "Direction, control, planning" in the DOT is the ALM index for routine, cognitive, interpersonal skills. The O*NET equivalent we find is "organizing, planning, and prioritizing work."

The DOT and ALM measure of routine, cognitive tasks comes from the measure for "set limits, tolerance, or standards," which has no clear equivalent in the O*NET. We align this to a combined index in the O*NET that is the mean value of "controlling machines and processes," "drafting, laying out, and specifying technical devices, parts, and equipment," and "troubleshooting" within each occupation. The correlation between the DOT measure is highest for this combination of O*NET values than any one of these candidate components by itself.

The ALM measure of routine, manual work, "finger dexterity," is identical in description across the DOT and O*NET data, so we take these similarities as given. Finally, for non-routine, manual skills, ALM assign the value of "eye, hand, and foot coordination" in the DOT. Because there is no direct

[2] We combine non-routine cognitive interpersonal and non-routine cognitive analytical because the result for these two skills categories are very similar.

equivalent in the O*NET, we create a joint index that is the mean value of “gross body equilibrium” and “spatial orientation” within each occupation. Like the case of routine, cognitive skills, the combination of these measures is more highly correlated with the DOT index than either of these components by themselves.

To reduce dimensionality and facilitate exposition, we collapse the skills categories into two groups: “non-routine, cognitive” and “routine or manual.” Our measure of “non-routine, cognitive” skills the sum of non-routine, cognitive/analytical and non-routine, cognitive/interpersonal measures, while “routine or manual” is the sum of routine, cognitive; routine, manual; and non-routine, manual measures. The components of each of these measures follow similar descriptive paths, so we lose little by aggregating them, though we do present disaggregated results in the Online Appendix.

ALM generate index scales based on a 0-10 basis using the DOT. In their data collection phase, the DOT survey and the O*NET survey also present respondents with a different response scale, making direct comparability of absolute changes difficult. To address these different scales, we standardize each final measure to be mean zero with a standard deviation of one in each year across 1990 occupations. This standardization is done across occupations in each year, where each occupation is a single observation. This process implicitly weights each occupation equally regardless of employment levels in each occupation. This is crucial because one goal of this study is to decompose overall shifts in relative skills in the unionized sector into compositional changes via employment levels separately from within-occupation changes in relative skills.

Table B-1 contains details of the construction of each measure across each DOT/O*NET sample year, including the level of summation and standardization, which is marked in square brackets. To capture changes in relative skills over time, we linearly interpolate each skill measure within occupations between each sample year. Our within-occupations trends, therefore, are identified based on these points. The overall trends in the average relative skill measure for workers in the economy will therefore be a function of 1) changes within each occupation in the DOT/O*NET measure, and 2) changes in the composition of employment in the economy.

Table B-2 presents the five occupations that account for the most unionized employment in 1973 and in 2017 for men as well as their union membership rate and the skill level among the four task types we consider. In both 1973 and 2017, four of the five occupations (outside of truck, delivery, and tractor drivers) require substantial routine manual and routine cognitive skills. All five occupations have high non-routine manual skill requirements, especially in 2017, while none of them require much non-routine, cognitive skill. Unionization rates are very high in these professions in 1973, at between 47% and 64%. By 2017, the unionized share of even the most unionized occupations was far lower. However, the occupations accounting for the largest share of unionized workers continue to be heavily routinized and/or manual.

Table B-3 presents similar information for women. It is important to note that there is no overlap in the five occupations that account for the most unionized employment for men and women in either 1973 or 2017. This finding supports examining men and women separately because they sort into very different occupations. The five occupations that account for the most unionized employment in 1973 are quite different from those in 2017, and there is a large decline in the unionization rate across all occupations listed. The most substantive difference between men and women is in the skill requirements of unionized professions over time: in 1973 the professions contributing most to the overall unionization rate are heavily routinized and manual, but particularly among women, there is a substantial shift to jobs that require cognitive and non-routine skill (e.g., nursing and teaching) by 2017. We show below that this pattern is evident across a broader set of occupations.

Finally, we show the five occupations with the highest unionization rate among the top quartile of each skill category, separately for 1973 and 2017, in Table B-4. For each task category, there are substantial changes in which occupations are the most unionized over time. These differences are driven by some combination of changes in the number of unionized workers within occupations, changes in the occupation mix, and within occupation changes in skill requirements. Our decomposition in Section 5 is designed to shed light on the empirical relevance of each of these forces in driving the overall changes in the skill composition of union membership.

Table B-1: Details of the Construction of DOT/O*NET Skill Measures

	1977 (DOT)	1991 (DOT)	2004 (O*NET)	2017 (O*NET)
Non-Routine, Cognitive	[Math (GED) + Direction, Control, and Planning] ~ N(0,1)	[Math (GED) + Direction, Control, and Planning] ~ N(0,1)	[Math (Ability) + Organizing, Planning, and Prioritizing Work] ~ N(0,1)	[Math (Ability) + Organizing, Planning, and Prioritizing Work] ~ N(0,1)
Routine or Manual	[Set Limits, Tolerance, or Standards + Finger Dexterity + Eye, Hand, and Foot Coordination] ~ N(0,1)	[Set Limits, Tolerance, or Standards + Finger Dexterity + Eye, Hand, and Foot Coordination] ~ N(0,1)	[{(Controlling Machines and Processes + Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment + Troubleshooting)/3} + Finger Dexterity + {(Gross Body Equilibrium + Spatial Orientation)/2}] ~ N(0,1)	[{(Controlling Machines and Processes + Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment + Troubleshooting)/3} + Finger Dexterity + {(Gross Body Equilibrium + Spatial Orientation)/2}] ~ N(0,1)
Non-Routine, Cognitive, Analytical	[Math (GED)] ~ N(0,1)	[Math (GED)] ~ N(0,1)	[Math (Ability)] ~ N(0,1)	[Math (Ability)] ~ N(0,1)
Non-Routine, Cognitive, Interpersonal	[Direction, Control, and Planning] ~ N(0,1)	[Direction, Control, and Planning] ~ N(0,1)	[Organizing, Planning, and Prioritizing Work] ~ N(0,1)	[Organizing, Planning, and Prioritizing Work] ~ N(0,1)
Routine, Cognitive	[Set Limits, Tolerance, or Standards] ~ N(0,1)	[Set Limits, Tolerance, or Standards] ~ N(0,1)	[(Controlling Machines and Processes + Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment + Troubleshooting)/3] ~ N(0,1)	[(Controlling Machines and Processes + Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment + Troubleshooting)/3] ~ N(0,1)
Routine, Manual	[Finger Dexterity] ~ N(0,1)	[Finger Dexterity] ~ N(0,1)	[Finger Dexterity] ~ N(0,1)	[Finger Dexterity] ~ N(0,1)
Non-Routine, Manual	[Eye, Hand, and Foot Coordination] ~ N(0,1)	[Eye, Hand, and Foot Coordination] ~ N(0,1)	[(Gross Body Equilibrium + Spatial Orientation)/2] ~ N(0,1)	[(Gross Body Equilibrium + Spatial Orientation)/2] ~ N(0,1)

Table B-2: Skills and Unionization Rates of Occupations Accounting for Largest Share of Unionized Employment – Men

1973	**Occ. Share of Union Employment**	**% Occ In Union**	**Non-Routine, Cognitive**	**Non-Routine, Manual**	**Routine, Cognitive**	**Routine, Manual**
Machine operators, n.e.c.	8.85	57.77	-0.66	0.90	1.14	0.96
Truck, delivery, and tractor drivers	8.8	46.54	-0.88	2.28	-1.22	-1.05
Heavy equipment and farm equipment mech	3.34	50.66	-0.44	0.57	1.13	0.51
Assemblers of electrical equipment	3.28	62.99	-0.97	-0.50	0.57	0.46
Welders and metal cutters	2.88	63.69	-0.39	-0.44	1.17	0.59
2017	**Occ. Share of Union Employment**	**% Occ In Union**	**Non-Routine, Cognitive**	**Non-Routine, Manual**	**Routine, Cognitive**	**Routine, Manual**
Truck, delivery, and tractor drivers	8.24	11.70	-0.36	1.56	0.56	0.04
Electricians	4.86	31.01	0.10	1.55	1.14	0.94
Laborers outside construction	4	12.18	-0.99	0.46	0.37	0.46
Construction laborers	3.25	9.54	-0.89	1.09	0.78	0.56
Carpenters	3.14	16.09	0.10	1.74	1.12	0.61

Source: Authors’ tabulations as described in the text from the 1973-2017 CPS, the Dictionary of Occupational Titles (DoT), and the Occupational Information Network (O*NET).

Notes: The table shows the five occupations that account for the largest share of unionized employment (the Occ. Share of Union Employment) in 1973 and 2017 among men. Occupations are ordered by their share of the overall unionized worker population. All skill measures are in standard deviation units.

Table B-3: Skills and Unionization Rates of Occupations Accounting for Largest Share of Unionized Employment – Women

1973	Occ. Share of Union Employment	% Occ In Union	Non-Routine, Cognitive	Non-Routine, Manual	Routine, Cognitive	Routine, Manual
Textile sewing machine operators	10.48	36.15	-1.03	1.52	1.19	1.72
Machine operators, n.e.c.	10.18	43.07	-0.66	0.90	1.14	0.96
Assemblers of electrical equipment	8.36	41.63	-0.97	-0.50	0.57	0.46
Cashiers	6.9	25.94	-0.58	-0.87	0.95	2.11
Packers, fillers, and wrappers	6.04	43.62	-1.07	-0.09	-0.51	0.31
2017	Occ. Share of Union Employment	% Occ In Union	Non-Routine, Cognitive	Non-Routine, Manual	Routine, Cognitive	Routine, Manual
Registered nurses	13.95	13.73	1.15	-0.05	-0.33	0.35
Nursing aides, orderlies, and attendants	6.94	7.16	-0.13	0.29	-0.45	0.49
Primary school teachers	4.34	18.41	0.99	-0.83	-1.23	-0.81
Cashiers	4.05	4.21	-1.31	-0.52	-1.11	-0.19
Customer service reps, investigators and adjusters, except insurance	2.67	4.07	0.26	-0.93	-1.19	-0.43

Source: Authors' tabulations as described in the text from the 1973-2017 CPS, the Dictionary of Occupational Titles (DoT), and the Occupational Information Network (O*NET).

Notes: The table shows the five occupations that account for the largest share of unionized employment (the Occ. Share of Union Employment) in 1973 and 2017 among men. Occupations are ordered by their share of the overall unionized worker population. All skill measures are in standard deviation units.

Table B-4: Highest Unionization Rate Occupations Among the Top Quartile of Each Skill, 1973 and 2017

Panel A: Non-Routine, Cognitive

Occupation 1973	Union Rate 1973	Union Rate 2017	Occupation 2017	Union Rate 1973	Union Rate 2017
Actors, directors, producers	1.00	0.13	Railroad conductors and yardmasters	0.89	0.71
Railroad conductors and yardmasters	0.89	0.71	Airplane pilots and navigators	0.42	0.53
Sociology instructors	0.49	Reclassified	Primary school teachers	0.06	0.19
History instructors	0.36	Reclassified	Secondary school teachers	0.11	0.19
Math instructors	0.37	Reclassified	Supervisors of construction work	Reclassified	0.16

Panel B: Non-Routine, Manual

Occupation 1973	Union Rate 1973	Union Rate 2017	Occupation 2017	Union Rate 1973	Union Rate 2017
Explosives workers	1.00	0.33	Locomotive operators (engineers and firemen)	1.00	0.60
Locomotive operators (engineers and firemen)	1.00	0.60	Elevator installers and repairers	N/A	0.58
Railroad brake, coupler, and switch operators	0.95	N/A	Millwrights	0.81	0.48
Materials movers: stevedores and longshore workers	0.90	Reclassified	Meter readers	0.47	0.46
Railroad conductors and yardmasters	0.89	0.71	Structural metal workers	0.80	0.44

Panel C: Routine, Cognitive

Occupation 1973	Union Rate 1973	Union Rate 2017	Occupation 2017	Union Rate 1973	Union Rate 2017
Boilermakers	0.85	0.29	Locomotive operators (engineers and firemen)	1.00	0.60
Heat treating equipment operators	0.83	N/A	Cementing and gluing maching operators	N/A	0.59
Millwrights	0.81	0.48	Elevator installers and repairers	N/A	0.58
Telecom and line installers and repairers	0.77	0.29	Millwrights	0.81	0.48
Lay-out workers	0.75	N/A	Electric power installers and repairers	0.66	0.36

Panel D: Routine, Manual

Occupation 1973	Union Rate 1973	Union Rate 2017	Occupation 2017	Union Rate 1973	Union Rate 2017
Millwrights	0.81	0.48	Cementing and gluing maching operators	N/A	0.59

Telecom and line installers and repairers	0.77		0.29	Elevator installers and repairers	N/A		0.58
Lay-out workers	0.75	N/A		Motion picture projectionists		0.33	0.50
Patternmakers and model makers	0.74		0.74	Millwrights		0.81	0.48
Electric power installers and repairers	0.66		0.36	Structural metal workers		0.80	0.44

Source: Authors' tabulations using the 1973 and 2017 CPS combined with 1977 and 1991 editions of the Dictionary of Occupation Titles (DOT) survey and the 2004 and 2017 editions of the Occupational Information Network (O*NET) survey.
Notes: "Reclassified" refers to an occupation that was reclassified between1973 and 2017; "N/A" means there is no information on that occupation in that year.

Appendix C: Decomposition derivation

Let S_{kt} be the standardized skill measure of occupation k in year t, and ω_{kt}^{u} be the share of all unionized workers in that occupation and year ($\omega_{kt}^{u} = \frac{L_{kt}^{u}}{\sum_k L_{kt}^{u}}$, where L_{kt}^{u} is the number of unionized workers in the occupation and year). Define τ_{2017} as the share of unionized labor in occupations in 2017 that span 1973-2017 and τ_{1973} as share of unionized labor in occupations in 1973 that span 1973-2017. It is helpful to partition occupations (k) into three groups:

- K_1 – occupations that exist in both 1973 and 2017
- K_2 – occupations that exist in 1973 but not in 2017
- K_3 – occupations that exist in 2017 but not in 1973.

Under these definitions, $\tau_{2017} = \frac{\sum_{k\in K_1} L_k^u}{\sum_{k\in K_1} L_k^u + \sum_{k\in K_3} L_k^u}$ and $\tau_{1973} = \frac{\sum_{k\in K_1} L_k^u}{\sum_{k\in K_1} L_k^u + \sum_{k\in K_2} L_k^u}$. The average relative skill level of skill S among unionized workers can then be written as follows:

$$\bar{S}_{2017}^{u} = \left(\sum_{k\in K_1} S_{k,2017}^{u} * \omega_{k,2017}^{u}\right) * \tau_{2017} + \left(\sum_{k\in K_3} S_{k,2017}^{u} * \omega_{k,2017}^{u}\right) * (1-\tau_{2017}) \qquad (1)$$

$$\bar{S}_{1973}^{u} = \left(\sum_{k\in K_1} S_{k,1973}^{u} * \omega_{k,1973}^{u}\right) * \tau_{1973} + \left(\sum_{k\in, K_2} S_{k,1973}^{u} * \omega_{k,1973}^{u}\right) * (1-\tau_{1973}) \qquad (2)$$

We can decompose the change in each skill among unionized workers into the three constituent parts:

$$\begin{aligned}
\bar{S}_{2017}^{u} - \bar{S}_{1973}^{u} &= \left(\sum_{k\in K_1} S_{k,2017}^{u} * \omega_{k,2017}^{u}\right) * \tau_{2017} + \left(\sum_{k\in K_3} S_{k,2017}^{u} * \omega_{k,2017}^{u}\right) * (1-\tau_{2017}) \\
&\quad - \left\{\left(\sum_{k\in K_1} S_{k,1973}^{u} * \omega_{k,1973}^{u}\right) * \tau_{1973} + \left(\sum_{k\in K_2} S_{k,1973}^{u} * \omega_{k,1973}^{u}\right) * (1-\tau_{1973})\right\} \\
&= \tau_{2017} * \left\{\left(\sum_{k\in K_1} S_{k,2017}^{u} * \omega_{k,2017}^{u}\right) - \left(\sum_{k\in K_1} S_{k,1973}^{u} * \omega_{k,1973}^{u}\right)\right\} + \left(\sum_{k\in K_1} S_{k,1973}^{u} * \omega_{k,1973}^{u}\right) \\
&\quad * (\tau_{2017} - \tau_{1973}) + \left(\sum_{k\in K_3} S_{k,2017}^{u} * \omega_{k,2017}^{u}\right) * (1-\tau_{2017}) + \left(\sum_{k\in K_2} S_{k,1973}^{u} * \omega_{k,1973}^{u}\right) \\
&\quad * (1-\tau_{1973}). \qquad (3)
\end{aligned}$$

We can further decompose $\left(\sum_{K\in k_1} S^u_{k,2017} * \omega^u_{k,2017}\right) - \left(\sum_{K\in k_1} S^u_{k,1973} * \omega^u_{k,1973}\right)$ as follows:

$$\left(\sum_{k\in K_1} S^u_{k,2017} * \omega^u_{k,2017}\right) + \left(\sum_{k\in K_1} S^u_{k,2017} * \omega^u_{k,1973}\right) - \left(\sum_{k\in K_1} S^u_{k,2017} * \omega^u_{k,1973}\right) - \left(\sum_{k\in K_1} S^u_{k,1973} * \omega^u_{k,1973}\right)$$

$$= \sum_{k\in K_1} S^u_{k,2017} * \left(\omega^u_{k,2017} - \omega^u_{k,1973}\right) + \sum_{k\in K_1} \omega^u_{k,1973} * \left(S^u_{k,2017} - S^u_{k,1973}\right) \qquad (4)$$

Plugging (4) into (3) yields the full decomposition:

$$\bar{S}^u_{2017} - \bar{S}^u_{1973} = \tau_{2017} * \left\{\sum_{k\in K_1} S^u_{k,2017} * \left(\omega^u_{k,2017} - \omega^u_{k,1973}\right) + \sum_{k\in K_1} \omega^u_{k,1973} * \left(S^u_{k,2017} - S^u_{k,1973}\right)\right\}$$

$$+ \left(\sum_{k\in K_1} S^u_{k,1973} * \omega^u_{k,1973}\right) * (\tau_{2017} - \tau_{1973}) + \left(\sum_{k\in K_3} S^u_{k,2017} * \omega^u_{k,2017}\right) * (1 - \tau_{2017})$$

$$+ \left(\sum_{k\in K_2} S^u_{k,1973} * \omega^u_{k,1973}\right) * (1 - \tau_{1973}) \qquad (5)$$