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THE CHANGING SKILL CONTENT OF PRIVATE SECTOR UNION COVERAGE

Samuel Dodini
Michael F. Lovenheim
Alexander Willén

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ABSTRACT

Concurrent with the precipitous 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, using data from the Current Population Survey combined with occupation-specific task requirements from the Dictionary of Occupational Titles and the Occupational Information Network. We partition skills into four groups based on two dimensions of task requirements: non-routine cognitive, non-routine manual, routine cognitive, and routine manual. 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 for both groups but also relatively more routine skills. We decompose these skill 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 skill 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 explicitly accounts for the institutional framework surrounding collective bargaining.

Samuel Dodini
Department of Economics
Norwegian School of Economics
Helleveien 30
5045 Bergen
Norway
samuel.dodini@nhh.no

Michael F. Lovenheim
Brooks School of Public Policy
ILR School, and Department of Economics
Cornell University
271 Ives Hall
Ithaca, NY 14853
and NBER
mfl55@cornell.edu

Alexander Willén
Department of Economics
Norwegian School of Economics
Helleveien 30
5045 Bergen
Norway
alexander.willen@nhh.no

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 (Autor, Levy, and Murnane 2003).

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). These data allow us to track the skill composition of occupations over time to show how the task content of private sector unionized jobs has changed. 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. We show that unionized professions increased substantially in their coverage of non-routine cognitive skills, from -0.591 standard deviation units in 1973 to -0.041 in 2017. This shift was accompanied by a convergence between union and non-union jobs, with the skills gap declining by 0.1 standard deviations (or 35.5%). We do not observe similar patterns for non-routine manual skills: coverage of these tasks does not change over time in either union or non-union jobs. Routine cognitive and routine manual skill coverage decline overall in the union sector but increase relative to the non-union sector. Taken together, these results show that unionized professions have experienced a growth in skill requirements relative to non-unionized jobs along the dimensions we consider.

Our data allow us to examine these trends by gender as well, which is important because of large differences in occupation sorting between men and women. Among men, coverage of non-routine cognitive skills increased by 0.44 standard deviations, and the gap with non-union jobs decreased by 0.126 standard deviations. There are at most minor changes overall or relative to non-union jobs for the other three skill dimensions for men.

Women experienced even larger changes than men: non-routine, cognitive skills increased by 0.830 standard deviations among unionized workers, and the gap with non-union workers declined by 0.212 standard deviations. For the other three skill categories, skill intensity declined among unionized workers. However, the declines were smaller in unionized relative to non-unionized jobs, leading to increases in skill coverage relative to non-unionized jobs. Hence, the relative skill coverage increased among women for all of the types of job tasks we consider.

Next, we conduct a decomposition that seeks to explain why the skills of unionized jobs have changed. 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. For men, changes to worker share and occupational composition have led to increased non-routine cognitive skill intensity and decreased intensity of the other three skill groups. Within-occupation changes for the latter three skill categories have moved in the opposite direction, which has led to modest overall changes. No such offsetting shifts are evidence for non-routine cognitive skills, which is why there has been a large increase in the intensity of this skill. Among women, non-routine, cognitive skill increases are driven mostly by changes in worker shares across occupations and by occupational entry/exit. All three explanations are relevant for explaining the decline in the other three skill dimensions.

Several aspects of our results are at odds with existing models of unionization under skill-biased technological change (e.g., Acemoglu, Aghion, and Violante 2001). These models incorporate insights from the Roy Model to explain declining unionization under SBTC: unions compress wages and reduce the return to skill, and thus when SBTC increases the return to skill outside of unionization, higher-skilled workers will not want to unionize. There are several implications of this type of model that are at odds with the data. First, our results from the initial part of the paper demonstrate that unionized jobs have become higher skilled along several dimensions. Second, the SBTC models assume that unions will reduce the return to skill. In contrast, we use data from the CPS to show evidence that the return to all four skills in unionized jobs has increased or remained constant over the period of our analysis. Third, SBTC models predict that the returns to unionization should decline as there will be reduced rents from high-skilled workers to be distributed to lower-skilled workers. Card, Lemieux, and Riddell (2020) and Farber et al. (2021) find that the union wage premium has remained stable over time at between 0.2 to 0.3 log points. We reproduce this result in our data and show that it holds when one also controls for occupation and the task content of jobs.

Finally, we propose a model that can reconcile SBTC with these empirical patterns. Our model accounts for the fact that bargaining is done by firm- and occupation-specific units that are likely to be quite homogenous. These bargaining units can negotiate for pay increases that reflect the market-wide return to skills covered by their occupations. Our model also includes changing costs of unionization and de-unionization, which we show have been substantial using data from the National Labor Relations Board. We argue that the pattern of results we document is unlikely to be caused by reductions in the desire of workers to unionize because of skill-biased technological change but rather due to increased costs of unionization combined with SBTC-driven shifts in the composition of employment.

This paper makes several contributions to the literature. First, we provide novel evidence of how the task content of unionized workers has changed over time and how these changes compare to non-unionized 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.[2] Our results align with theirs but provide a more comprehensive picture of how the specific skill coverage of unionized workers has changed and how these changes compare to non-unionized workers. Indeed, our results and conclusions hold even after controlling for worker educational attainment. We additionally contribute to the literature by decomposing the changes in task content that we document, 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: unionized workers have become more highly educated and thus higher skilled (Farber et al. 2021), but models of skill-biased technological change (SBTC) 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

[2] Farber et al. (2021) also examine union wage premiums over time and find stable estimates of 0.2 log points over their sample period. Card, Lemieux, and Riddell (2020) estimate union wage premiums over several decades using CPS data and find that the male and female wage premiums remained quite stable from 1973 to 2015 at about 0.2 log points. These union premiums align with earlier work (e.g., Freeman and Medoff (1984)).

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 unionized 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.[3] We are the first to use this framework and these data to examine the skill content of union versus non-union jobs. This allows us to break new ground in understanding the implications for workers of the decline in private sector unionization.

2. The Decline in Private Sector Unionization

Private sector unionization has declined precipitously since the 1970s, from 25% in 1973 to 6% in 2022. The drop in private sector unionization was particularly pronounced among men, from 30% to 8%, while for women the decline was more modest, from 14% to 5%. The decline was largest in the early 1970s-mid 1980s, and thereafter there has been a more gradual but persistent decrease. 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%.[4] 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

[3] See Acemoglu and Autor (2011) for a review of this literature.
[4] Source: http://www.unionstats.com/.

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. When there is SBTC, unionization declines for two reasons: 1) the outside option of incumbent higher-skilled workers increases and 2) new workers obtain more education to take advantage of higher wages and then sort into non-unionized firms. The underlying assumption of this model is that unions compress the wage structure, which makes unionized jobs increasingly less attractive for high-skilled workers.[5] 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 of skill 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: skill-biased technological change alters the composition of the economy, which is reflected by changes to the demand for different 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.[6]

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[5] 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.

[6] DiNardo, Fortin, and Lemieux (1996) include three occupation categories in their decompositions of changes to the distribution of wages as part of the controls for worker composition. Because their paper is focused on how changes to unionization affect the distribution of wages, they do not isolate the effect of secular occupation shifts nor do they examine how such changes impact the types of jobs covered by private sector unions.

3. Data

Data on worker characteristics and wages come from the Current Population Survey (CPS) May supplement for the years 1973-1981 and from the Current Population Survey Outgoing Rotation Group (ORG) sample for the years 1983-2017.[7] While the ORG survey replaced the May CPS as the primary data source for wage and employment information beginning in 1979, the May CPS continued to ask union membership questions through the early 1980s. The ORG surveys began asking union membership questions only 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 the CPS that year.

Our analysis sample is restricted to private sector workers with positive earnings who are not self-employed. We measure hourly wages directly for those paid hourly; for workers not paid hourly, we calculate hourly wages by dividing usual weekly earnings by weekly hours worked. Consistent with prior literature, 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). We also correct for inconsistencies in the CPS in questions about educational attainment before and after 1992 and create a time-consistent measure of years of schooling (Card 2001; Card, Lemieux, and Riddell 2020).[8] We standardize wage values to 2016 dollars using the Personal Consumption Expenditure index. Finally, like prior work (Card 1996; Card, Lemieux, and Riddell 2020), we drop workers whose wage calculations rely on allocated earnings data. Omitting these workers is important because the allocated earnings in the ORG supplement are based on a "hot deck" procedure, and union status was not a factor used in this procedure (Bollinger and Hirsch 2006; Kaplan and Schulhofer-Wohl 2012). Estimates of the union wage premium, therefore, have been shown to be biased when relying on allocated data (Hirsch and Schumacher 2004).[9]

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

[7] We rely on the CPS ORG extracts maintained by NBER: https://www.nber.org/data/morg.html.

[8] There was a change in the way educational attainment was coded between the 1991 and 1992 surveys. We recode post-1992 values to their pre-1992 years of schooling counterparts for consistency.

[9] Dropping those with allocated earnings reduces our total sample size of men by just under 25% and our sample of women by 20%. These are in line with the allocation rates of 26.5% for union workers and 25.7% for nonunion workers reported in Hirsch and Shumacher (2004), which covered 1996-2001.

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.[10]

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 managed by the US Department of Labor. 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 measures of occupational task requirements follow the insights of Autor, Levy, and Murnane (2003). 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 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

[10] 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.

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.

We follow Autor, Levy, and Murnane (2003) in how we measure each skill, which is shown in Online Appendix Table A-1. Non-routine cognitive tasks are a combination of non-routine cognitive analytical and non-routine cognitive interpersonal.[11] The former is measured by "GED – math" in the DOT and by "math" ability in O*NET, while the latter is measured by "Direction, control, planning" in the DOT and by "organizing, planning, and prioritizing work" in O*NET. For non-routine manual skills, "eye, hand, and foot coordination" in the DOT corresponds to our constructed index in O*NET which is the average of "gross body equilibrium" and "spatial orientation." The DOT measure of routine, cognitive tasks, "set limits, tolerance, or standards," corresponds to a combined index in the O*NET that captures the average of "controlling machines and processes," "drafting, laying out, and specifying technical devices, parts, and equipment," and "troubleshooting." Finally, our measure of routine, manual work, "finger dexterity," is a simple conceptualization that is common across the DOT and O*NET data. Within 1990 occupations, we interpolate trends over non-survey years to capture long-run changes in these relative skills over time.

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.

To address different scales in the DOT and O*NET datasets, 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 (i.e., gender, industry, etc.). In other words, our measures are capturing

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

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, however, which is less sensitive to this issue because it is based on a fixed scale. For more details on the construction of our occupational skill measures, see Appendix B.

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 Table 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.

Table 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 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 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 below 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.

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 unionized and non-unionized 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) to facilitate mapping of changes in skills of unionized work with changes in private sector union membership.

Panel A shows patterns for non-routine, cognitive skills. The coverage of this skill among unionized 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 large 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 unionized workers is coming predominantly from a substantial reduction in the union coverage of jobs that are low in this skill measure. The time pattern of this reduction matches the change in overall union coverage very closely.

It is instructive to compare the changes in skill coverage among unionized workers to those among non-unionized workers to determine whether the changes we document are economy-wide or are more localized to unionized employment. Panel A of Figure 1 shows this comparison for non-routine, cognitive tasks.. There is a convergence 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). Thus, not only are unionized workers increasingly in jobs that require high levels of non-routine, cognitive skills, the skill increases they experience are large relative to the non-unionized 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 trends over time for non-routine, manual skills. The patterns differ starkly from those in Panel A, showing little change over time for both the union and non-union groups. In both sectors, this skill becomes slightly less important, from 0.447 and -0.107 in 1973 among unionized and non-unionized jobs, respectively, to 0.313 and -0.185 in 2017. The difference between union and non-union coverage changes negligibly as well. Figure 2, Panel B shows that there is a decline in the unionization rate of professions with both high and low task ratings along this dimension, with a larger relative decline among occupations with a high non-routine manual task requirement. As we show below, this is balanced by within-occupation increases in non-routine manual task intensity, which counteracts the declines shown in Figure 2. Taken together, 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 skills rather than those that require more manual skills.

Next, we turn to routine skill coverage, examining routine, cognitive skills in Panel C and routine, manual 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 type. 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 is also experienced in the non-union sector, although the gap also increases somewhat from 0.323 to 0.449. Combined with the results in Panel A, there is a clear increase in coverage of cognitive tasks in unionized relative to non-unionized 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. The main result is that 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 unionized versus non-unionized jobs along the dimensions we consider. Non-routine cognitive skill coverage grows in overall levels for unionized occupations as well as relative to non-union occupations. For both manual and cognitive dimensions of routine skill, levels decline in both sectors but more so among non-union jobs. There is little change in levels or relative terms for non-routine manual skills. Unionized workers thus are increasingly working in jobs that require higher levels of non-routine cognitive skills and in jobs that require relatively more non-routine cognitive and non-routine manual skills.

Prior research has not addressed this changing skill content of unionized and non-unionized work, although there is evidence that the educational attainment of unionized workers has increased (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 very similar to the raw estimates shown in Figure 1. The one exception is that the residualized patterns exhibit a small increase in non-routine manual skill coverage among unionized occupations. Online Appendix Figure A-1 thus highlights that our findings are not driven by changes to worker composition and that there is independent information in the skill measures we employ relative to the estimates in Farber et al. (2021) that focus on educational attainment. The changes in the skills required by union jobs, therefore, have changed even more starkly than was documented in Farber et al. (2021), which only can be uncovered by examining the task coverage of occupations.

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 datasets. 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 now 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 0.422 standard deviation increase is considerably larger than the increase in this skill category among non-unionized workers (0.296).[12] 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 unionized workers, while the change among non-unionized 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 the occupations disproportionately employing 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.

4.3. Decomposition of Skill Changes

The results discussed above show that the skill composition of occupations and workers

[12] Online Appendix Figure A-3 presents trends in the union vs non-union gap in each occupational skill for men to facilitate comparisons across union and non-union workers. Online Appendix Figure A-4 presents the same information for women.

covered by unions has changed considerably over time. Unionized work has shifted to include more non-routine, cognitive skills and less routine manual and routine cognitive skills. However, for all skill types, intensity among unionized professions has grown relative to non-unionized professions. This has led to unionized jobs becoming more highly skilled along a number of dimensions. These results raise a central question: why has unionized work changed in this way?

As a first step in addressing this question, we decompose the change in each skill coverage over time into three parts: (1) the part due to changes in the unionized worker share in existing occupations, (2) the part due to changes in skill requirements within existing occupations, and (3) the part due to entry and exit of occupations themselves. This decomposition yields new insight into the causes of changes to private sector unionization that cannot be identified without taking 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 unionized workers in that occupation and year ($\omega_{kt}^{u} = \frac{L_k^u}{\sum_k L_k^u}$, where L_k^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, $\tau_{2017} = \frac{\sum_{k_1} L_{k_1}^u}{\sum_{k_1} L_{k_1}^u + \sum_{k_3} L_{k_3}^u}$ and $\tau_{1973} = \frac{\sum_{k_1} L_{k_1}^u}{\sum_{k_1} L_{k_1}^u + \sum_{k_2} L_{k_2}^u}$. The average relative skill level of skill S among unionized workers can then be written as follows:

$$\bar{S}_{2017}^{u} = \left(\sum_{k_1} S_{k_1 2017}^{u} * \omega_{k_1 2017}^{u}\right) * \tau_{2017} + \left(\sum_{k_3} S_{k_3 2017}^{u} * \omega_{k_3 2017}^{u}\right) * (1 - \tau_{2017}) \qquad (1)$$

$$\bar{S}_{1973}^{u} = \left(\sum_{k_1} S_{k_1 1973}^{u} * \omega_{k_1 1973}^{u}\right) * \tau_{1973} + \left(\sum_{k_2} S_{k_2 1973}^{u} * \omega_{k_2 1973}^{u}\right) * (1 - \tau_{1973}) \qquad (2)$$

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

$$
\begin{aligned}
\bar{S}^u_{2017} - \bar{S}^u_{1973} &= \tau_{2017} * \left\{ \sum_{k_1} S^u_{k_1 2017} * \left(\omega^u_{k_1 2017} - \omega^u_{k_1 1973}\right) + \sum_{k_1} \omega^u_{k_1 1973} * \left(S^u_{k_1 2017} - S^u_{k_1 1973}\right) \right\} \\
&+ \left(\sum_{k_1} S^u_{k_1 1973} * \omega^u_{k_1 1973} \right) * \left(\tau_{2017} - \tau_{1973}\right) + \left(\sum_{k_3} S^u_{k_3 2017} * \omega^u_{k_3 2017} \right) \\
&* \left(1 - \tau_{2017}\right) + \left(\sum_{k_2} S^u_{k_2 1973} * \omega^u_{k_2 1973} \right) * \left(1 - \tau_{1973}\right) \qquad (3)
\end{aligned}
$$

The first term in 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. This part of the decomposition shows us how much of the observed change in skills among unionized workers during this period is due only to changes in the concentration of workers across existing occupations. That is, it shows us how union coverage of skill *S* in 2017 would have changed if unionized workers were distributed across existing occupations as in 1973. Note that this decomposition only includes unionized 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 in curly brackets in equation (3) shows the change in skill *S* due to shifts in skill requirements within occupations. This part of the decomposition shows how much of the change in each skill is due to changes in the occupation itself. If unionized occupations are changing skill requirements differently than non-unionized occupations, it could drive some of the relative changes we present in Section 4.1. An alternative interpretation of the second term in equation (3) is that it shows what the average skill requirement would have been in 2017 had the skill requirements of occupations been the same as in 1973.

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 many 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 in 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 at all in the 1990s (1950s).[13]

The results of this decomposition are shown in Table 5. Panel A presents results for men and Panel B shows results for women. 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 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.

For the other three skill categories, a similar pattern emerges: 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 5 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.[14]

Online Appendix Tables A-2 and A-3 show decompositions for changes in skill coverage

[13] While it would be of great value to understand the determinant of when a label is added or dropped, we are not aware of any study that examines this question.

[14] It is important to 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. We therefore do not believe that the decomposition results showing the skill mix change is coming from occupation are mechanical. 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.

from 1973-1990 and 1990-2017, respectively.[15] This sub-period analysis is informative because the rise of computers and information technology such as the Internet occurred largely after 1990. Despite some interesting sub-period differences, in general, the results align across periods and reinforce the conclusions from Table 5.

Panel B of Tables 5, A-2, and A-3 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. Women generally move in the same direction, and all contribute to the aggregate change. The sub-period analyses show a similar pattern in Appendix Tables A-2 and A-3.

Finally, to study the sources of the changes in union-non-union skill differences, Online Appendix Table A-4 shows similar decompositions for non-unionized workers. Interestingly, the decompositions show key differences between the sources of 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 occupation 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

[15] Note that the sub-period decompositions do not sum to the overall decomposition estimates because we allow the set of occupations that exist throughout the analysis period and that enter/exit to be different across the two sub-periods.

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 much less routinized over time. This change has been more dramatic in the non-union sector.[16]

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-5 show decompositions that are residual to these worker characteristics.[17] Although some of the magnitudes change, a similar story emerges that highlights the role of changes in worker share and entry/exit of occupations for non-routine cognitive skills among men. For women, the estimates are similar to those in Table 5. The conclusions drawn from the baseline decompositions in Table 5 thus are robust to accounting for worker composition and educational attainment. This further demonstrates 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-5 show decompositions that are residualized with respect to major 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 industrial composition does not play a large role in explaining 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 skill-biased technological change (SBTC),[18] since the return to skill in the labor market has coincided with the large reduction in private sector unionization. There are notably few models

[16] The non-unionized sector acts as a relatively strong measure of overall trends. Within-occupation shifts are relatively more important outside the unionized sector in terms of explaining changes, in part because compositional changes are less pronounced. This is consistent with Atalay et al. (2020), who also show that within-occupation changes are relatively more important.

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

[18] 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.

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.[19] 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, unionized jobs have become higher skilled along several dimensions. Specifically, there has been a large increase in the intensity of non-routine cognitive skills in unionized jobs, even relative to non-union jobs. In addition, unionized professions have become more skill intensive with respect to routine skills relative to non-union professions. These patterns align with those in Farber et al. (2021), who show that unionized workers have become more educated over time, and are clearly at odds with the predictions of SBTC-based models.

Second, these models assume that unions reduce the returns to skill. This assumption has not been examined empirically in prior research; Figures 5 and 6 present the first such estimates in the literature for men and women, respectively. The solid and dashed lines show the same changes in each skill presented in Figures 3 and 4 and discussed in Section 4.2. The open circles and squares show coefficients on the skill measure and the skill measure interacted with union status, respectively, derived from the following wage regression:

$$Ln(w)_{ict} = \beta_0 + \beta_1 Union_{ic} + \sum_{j=1}^{4} \phi^j S_{ct}^j + \sum_{j=1}^{4} \tau^j S_{ct}^j * Union_{ic} + \gamma X_i + \phi_t + \theta_c + \epsilon_{it}. \quad (4)$$

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, ϕ_t are year fixed effects, θ_c are occupation fixed effects, and S_{ct}^j are the four standardized skill measures. The circles in Figures 5 and 6 are the ϕ^j and τ^j from equation (4).

[19] 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.

The interpretation of these parameters is the return to a standard deviation in each skill level for union and non-union workers.

For non-routine cognitive skills in Panel A of Figures 5 and 6, 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 returns largely disappears. The value of this skill is high in the labor market and is growing over recent decades; the growth among unionized workers is larger than the growth among non-unionized workers. That the 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.[20]

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.[21] That unionized 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-6 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

[20] To explore this in more detail, we use the NLSY79 to examine the return to AFQT conditional on the skill content of workers' occupation and year fixed effects, separately for union and non-union members. The results from this exercise are provided in Appendix Figure A-5. The results demonstrate that 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 and supports the notion that skill-biased technological change has not necessarily reduced the incentive for skilled workers to unionize. The relatively higher gap at the bottom of the AFQT distribution also is consistent with wage compression within the unionized sector.

[21] 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 results show that the skill returns within unions are not exclusively driven by the production sector, suggesting that automation in itself cannot explain our results.

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 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

The contradiction between theoretical predictions from SBTC models and empirical results leads to an important question of what type of model can produce the patterns we document. 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.[22] This is an important distinction from prior models of union behavior because with homogenous bargaining units, skill-biased technological change, or any increase in the return to skill, will not necessarily reduce the incentive to unionize. Unions may reduce the within-occupation variance in wages, but they can do so without reducing (or even increasing) the cross-occupation variance. 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 market power, higher-skilled workers should want to unionize into relatively homogenous bargaining units because the union can better extract monopsony rents from the firm than can any single employee (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. In the top panel that shows certification elections, it is clear that unions continue to win elections. Although there was a sharp decline in the prevalence of elections after 1982 due to policies of the Reagan administration that made it more difficult to organize, new certification elections were still common at over 3,000 per year. Furthermore, the fraction of new certification elections won each year has remained relatively constant over time. The bottom panel shows similar tabulations for decertification elections. Decertification

[22] 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.

elections are much rarer, and only about 100 bargaining units win such elections each year. Figure 7 shows clearly that the inflow of newly-unionized bargaining units is an order of magnitude larger than the outflow of workers who no longer collectively bargain.[23] 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. We collapse the industries into three aggregate groups: Manufacturing, Services, and "Other." The number of elections in manufacturing drops sharply in the early 1980s during the Reagan administration. The decline in new certification elections won in services is more modest, such that the year-to-year number of elections is larger in the service sector than in the manufacturing sector by the early 1990s. In a similar vein, the share of certification elections won in manufacturing falls gradually over time, from about 50% to 40%, while the share of elections won in the services industry increases over time from about 55% to 65%. The number of decertification elections actually declines in services and manufacturing; however, the likelihood of winning such an election increases modestly. Taken together, Figure A-9 shows that the net reduction in unionization is more pronounced in manufacturing, which has the lowest 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 professions that require skills with high returns in the broader labor market. These patterns also are consistent with Figure 2.

It is instructive to further explore the empirical relevance of predictions from existing models as they relate to certification and decertification elections. Prior 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. To explore this set of hypotheses, Appendix Figure A-10 shows the number of total certification elections (Panel A), the share of certification elections won (Panel B), the total number of decertification elections (Panel C), the share of decertification elections won (Panel D), and the net change in union coverage (Panel E), by non-routine cognitive skill level based on industry-

[23] 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 even among non-unionized 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.

level skill means in each year in the CPS. The data generally do not align with the predictions of prior models, with the small caveat of a weak, negative correlation with total certifications for non-routine cognitive skills. However, these slopes are not strong and are primarily driven by a small number of outliers. Rather, the figures show that 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 unionized 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 despite changes in political administrations (Kleiner 2001; Farber and Western 2001; McCartin 2006).[24] As a result, the barriers to collective bargaining entry for new occupations are high, which likely dissuades many of these 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 skill-biased technological change 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.[25] Each occupation has a skill requirement, S_o that does not vary across unionized and non-unionized firms. Hence, unionized and non-unionized jobs within the same occupation do not differ in terms of the skills needed to do those jobs but rather in the wage returns to those skills. Let skill S for worker i in occupation o be given by:

[24] 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.

[25] In practice, unions can cover multiple occupations within each bargaining unit. However, it is straightforward to negotiate salaries for different occupations within the same bargaining unit, so we simplify the setup by assuming bargaining units are firm and occupation specific.

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

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 further posit three sources of friction in the model. The first is job switching costs, $\bar{e}$ (e.g., firm-specific training or job search costs). Furthermore, there are costs of unionizing $(\bar{u})$ and de-unionizing $(\bar{d})$. The cost of unionization comes from the time, effort, and potential friction with one's employer that characterizes any organizing drive. They also include the frictions associated with negotiating the contract with the employer. De-unionization 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, which makes it costly to hold and win such an election. The large gap between decertification elections held and won shown in Figure 7 highlights the uncertainty associated with a decertification drive as well.

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 unionized 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:

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

The last equality of equation (8) comes from the assumption that in non-unionized environments, $\beta = \gamma$. Workers will switch from U to N when $W^N - \bar{e} \geq W^U$, where $\bar{e}$ is the cost of switching from a union to a non-union firm. Plugging in the terms from equations (9) and (10) and rearranging, we get the following incentive compatibility constraint:[26]

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

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 skill and differences in the return to 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 $\gamma^U > \gamma^B$ due to the existence of a non-zero union wage premium.

The predictions of this model align with the patterns described in Section 4.[27] First, consider what happens when β and γ increase by the same amount. 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 unionized workers are paid more on average than non-unionized workers in

[26] This model abstracts from job amenities for simplicity. If unions provide more amenities for all workers, this would effectively raise $\bar{e}$ and would reduce the likelihood of workers switching due to wage dispersion. Alternatively, unions could provide more job 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.
[27] There likely are other models that also produce these predictions, although none have been presented in prior work.

the same occupation means that the variance in individual skill must be quite large for a non-negligible subset of workers to find it worthwhile to switch to the non-union sector. 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 therefore not cause an unraveling of unionization.

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. This follows from the assumption that 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. We argue it is, therefore, unlikely that wage dispersion associated with SBTC is a core driver of reductions in the number of new certification elections. Rather, as discussed above, $\bar{u}$ has increased since the 1980s as the political environment has become more hostile to unions.

Finally, will SBTC lead unionized bargaining units to decertify? Following a similar argument as above, 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 5. 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 5 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.

A main assumption of our model is that unions are able to negotiate wages that reflect the returns to the average skill level in the bargaining unit. We show in Figures 5 and 6 that this is the case, which implies that changes to the return to skill will not have a large effect on unionization decisions. Put differently, 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 presents the first analysis of how the task content of unionized employment has changed over time. We combine data from the CPS from 1973-2017 with occupation-specific task requirements from the Dictionary of Occupational Titles and the Occupational Information Network. We first document that the skills covered by unionized workers have shifted 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 next 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 itself. 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. For the other three skill categories, men experience little overall change in task coverage because the within-occupation changes move in the opposite direction from the sizable shifts due to occupational changes and worker occupational sorting. These changes largely cancel one another out. Among women, the three components of the decompositions all contribute to the observed changes in the routine manual, routine cognitive, and non-routine manual content of unionized jobs.

Finally, we discuss that the evidence is at odds with three key predictions of prevailing models of skill-biased technological change (e.g., Acemoglu, Aghion, and Violante (2001)): 1) unions should be covering lower-skilled jobs over time, 2) unionized jobs should exhibit lower returns to skill, and 3) the union wage premium should be declining. We argue that these patterns in the data can be reconciled with SBTC using a simple Roy model that incorporates union flexibility in wage bargaining for different bargaining units as well as costs for both unionization and de-unionization. The model shows that changes to the returns to skills driven by SBTC are unlikely to affect unionization rates and the types of workers covered by unions 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 skill-biased technological change has caused large shifts in the types of skills covered by unionized worker occupations. These changes in private sector unions 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 unionized 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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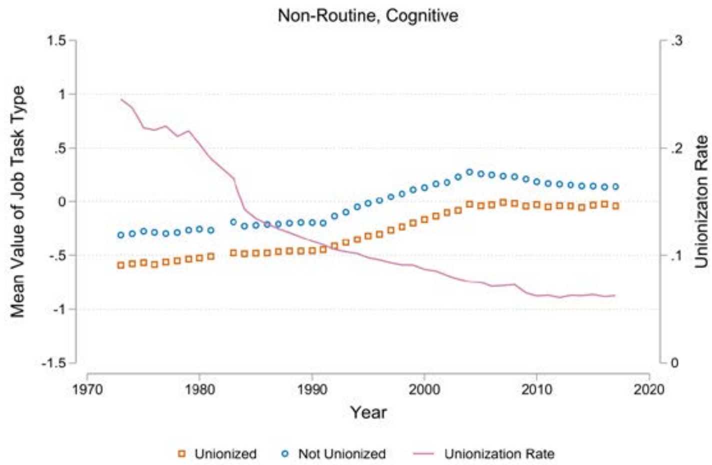
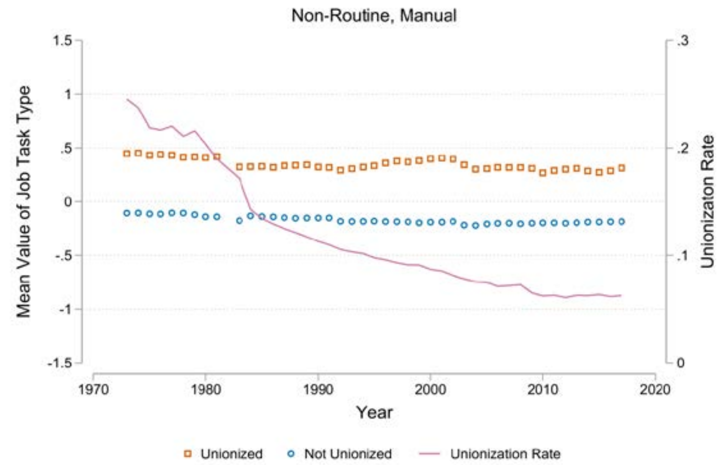
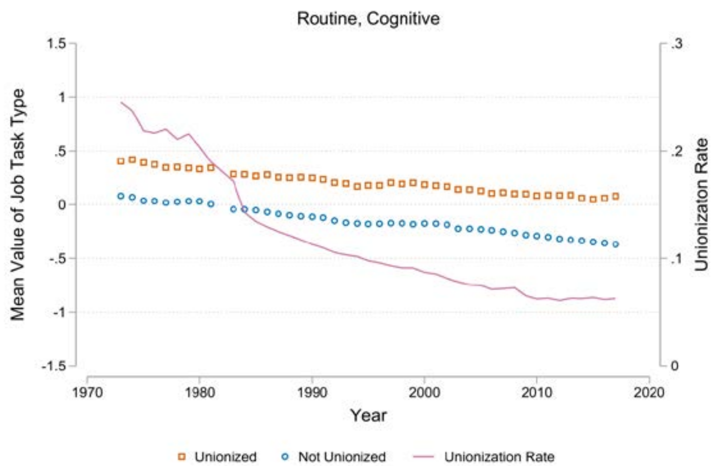
Figure 1: Trends in Occupational Skill Requirements by Union Status

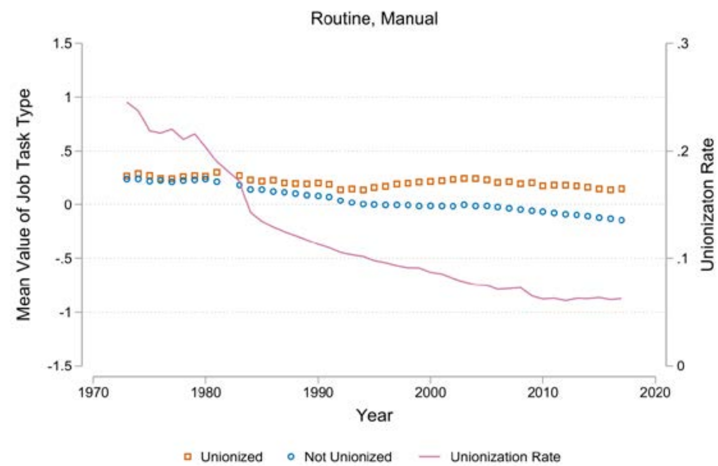
Panel A Panel B





Panel C Panel D

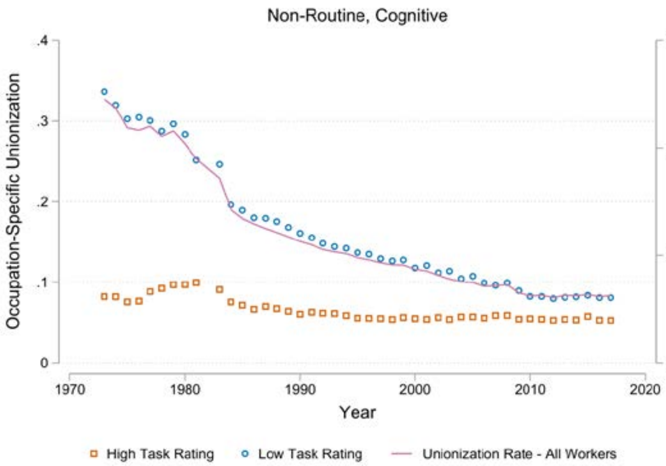




Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

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

Panel A



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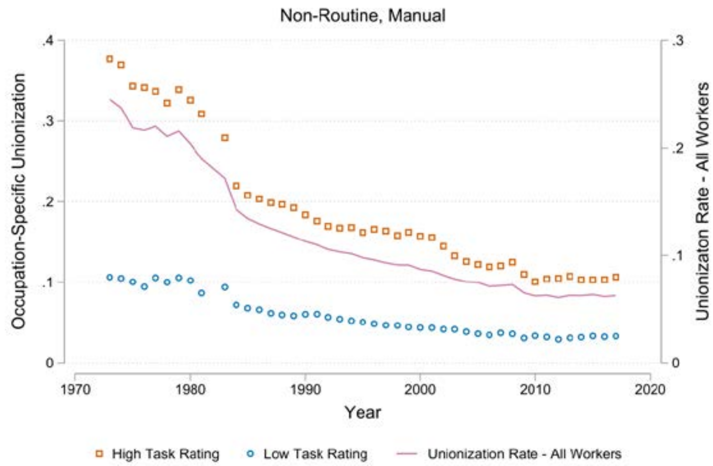

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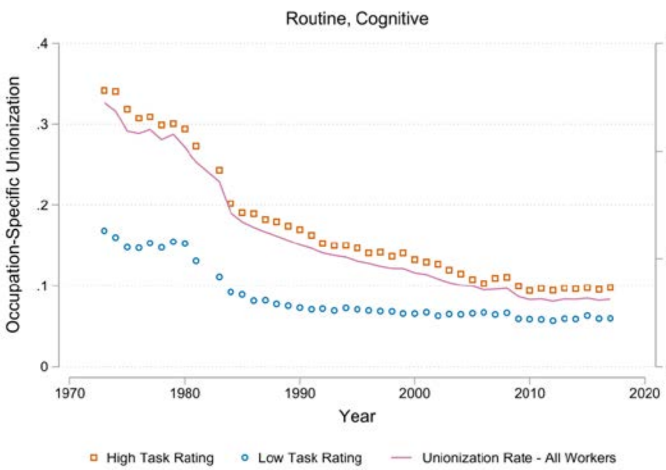

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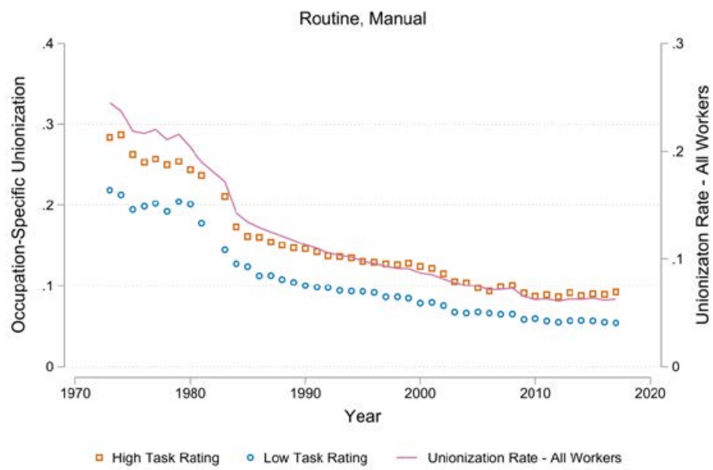
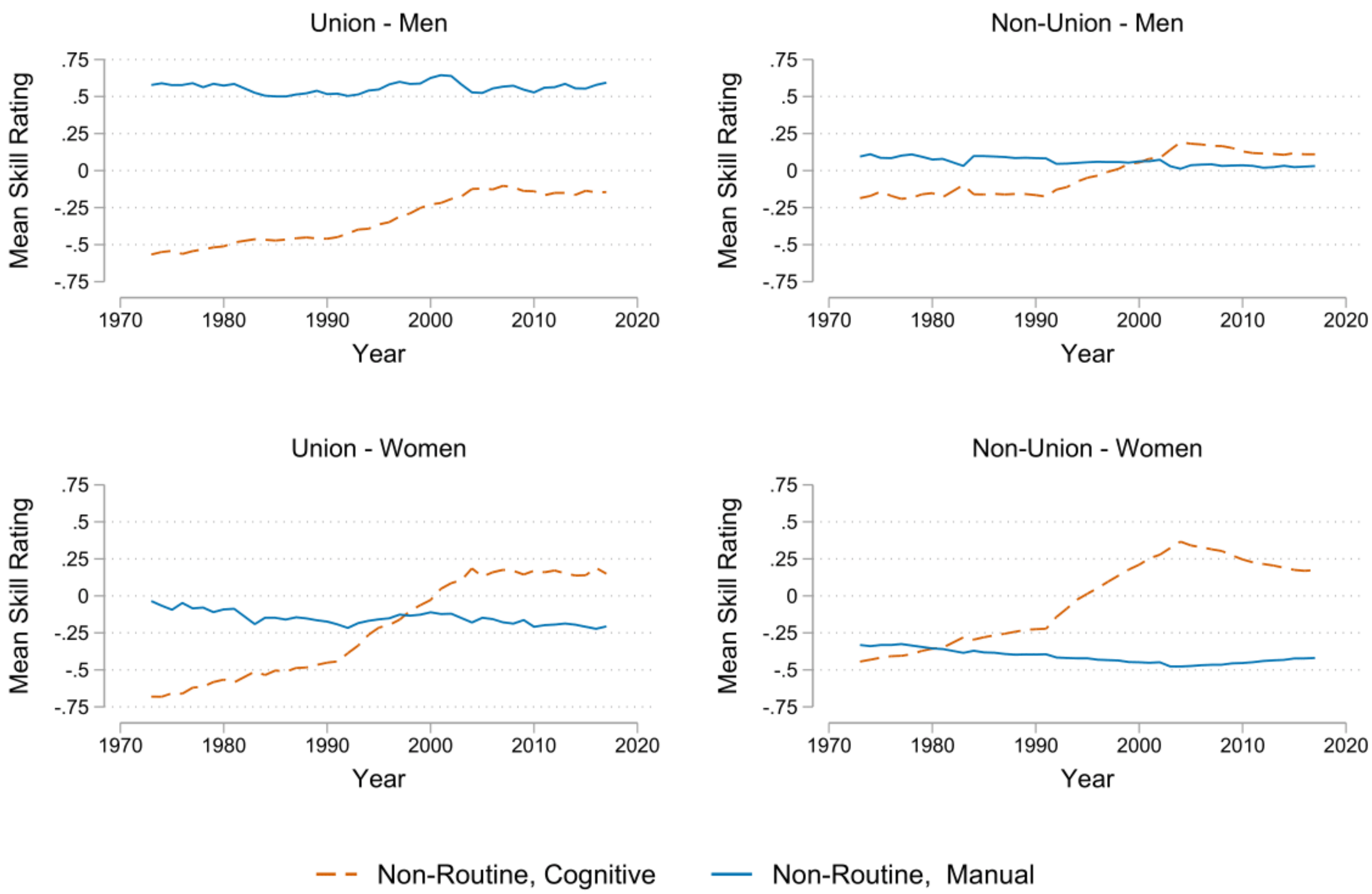


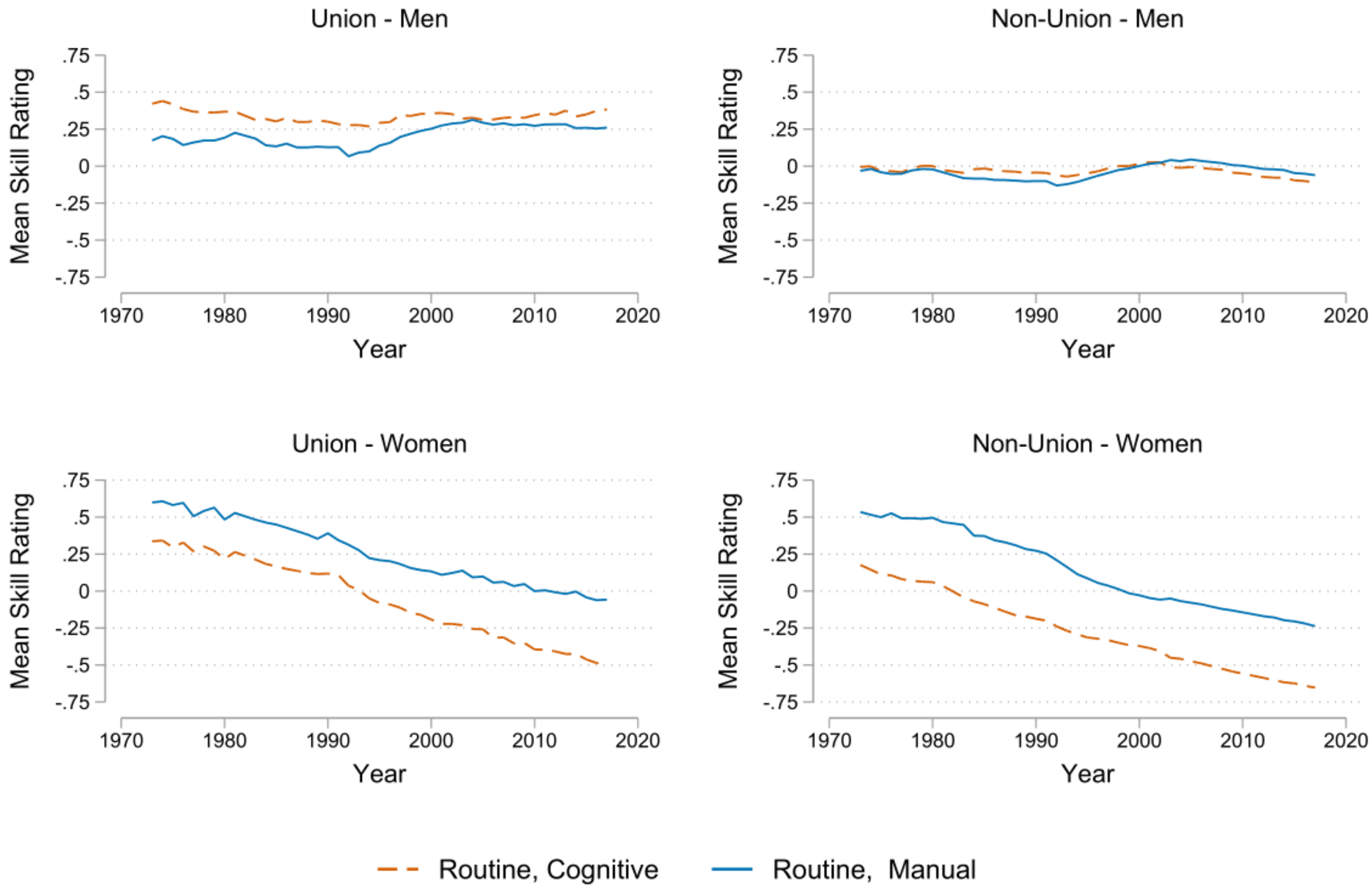
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

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.

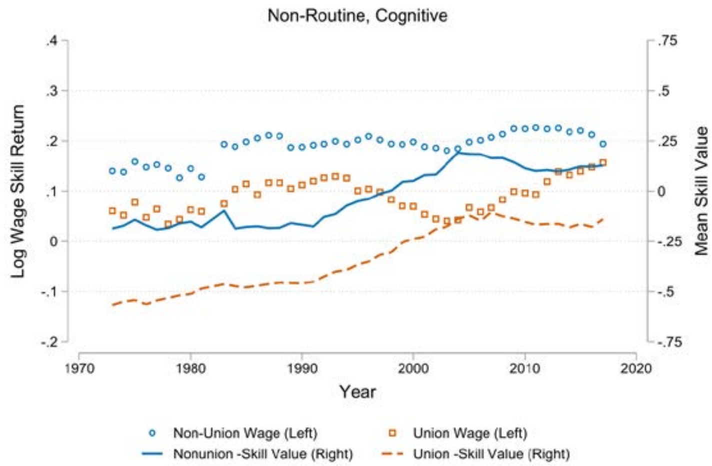
Figure 4: Trends in Occupational Skill Requirements by Union Status and Gender: Routine, Cognitive and Routine, Manual Skills



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



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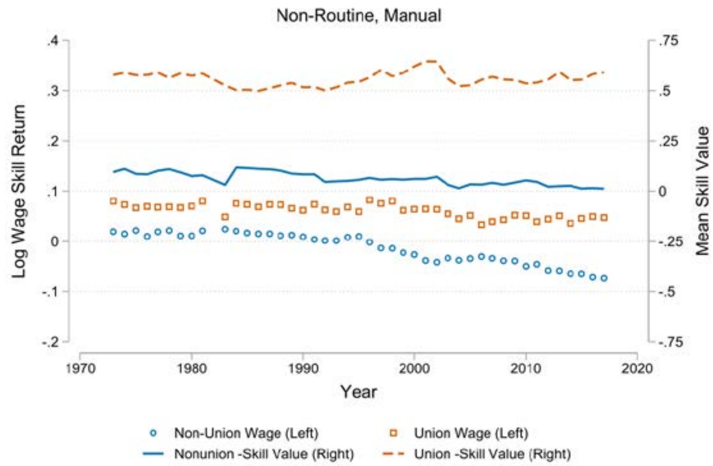

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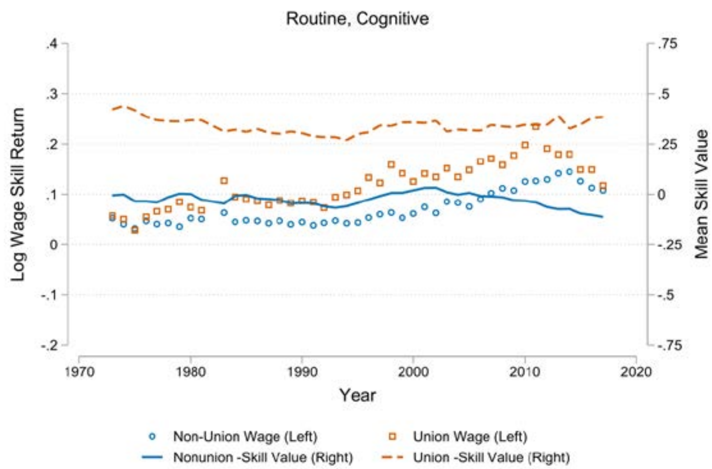
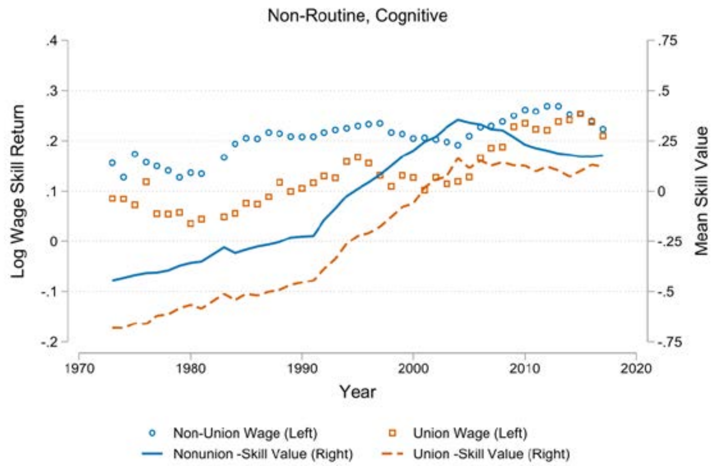


Panel D

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

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

Panel A



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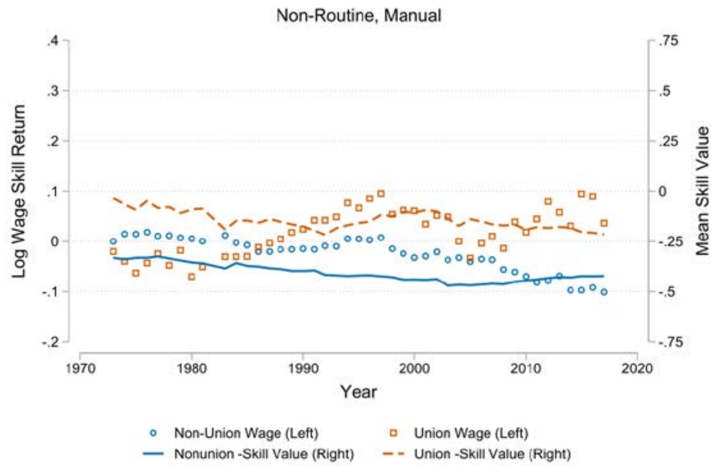
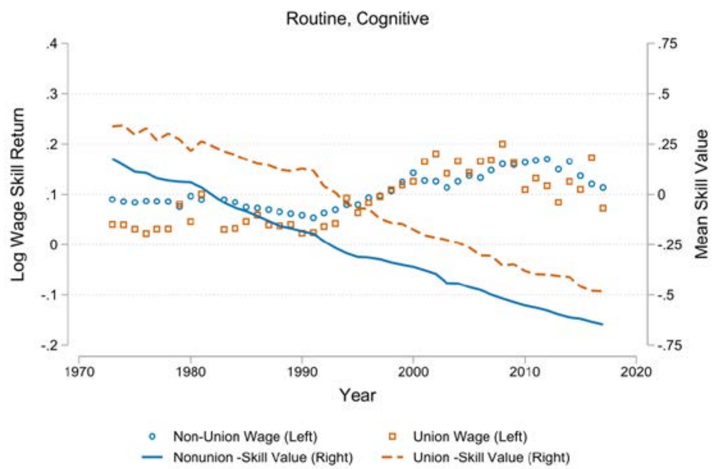
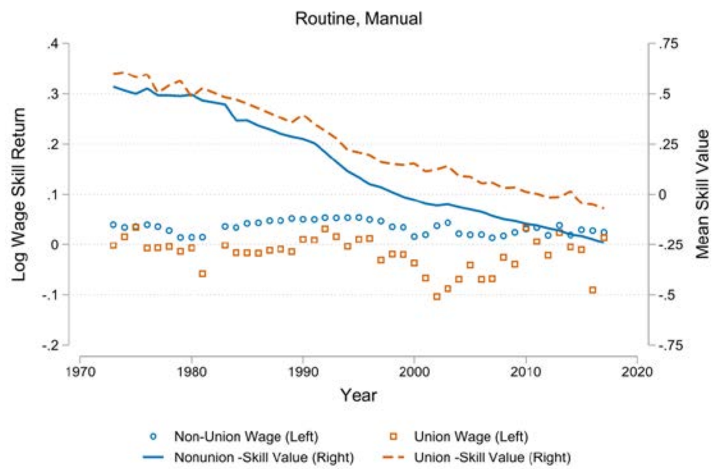


Panel C



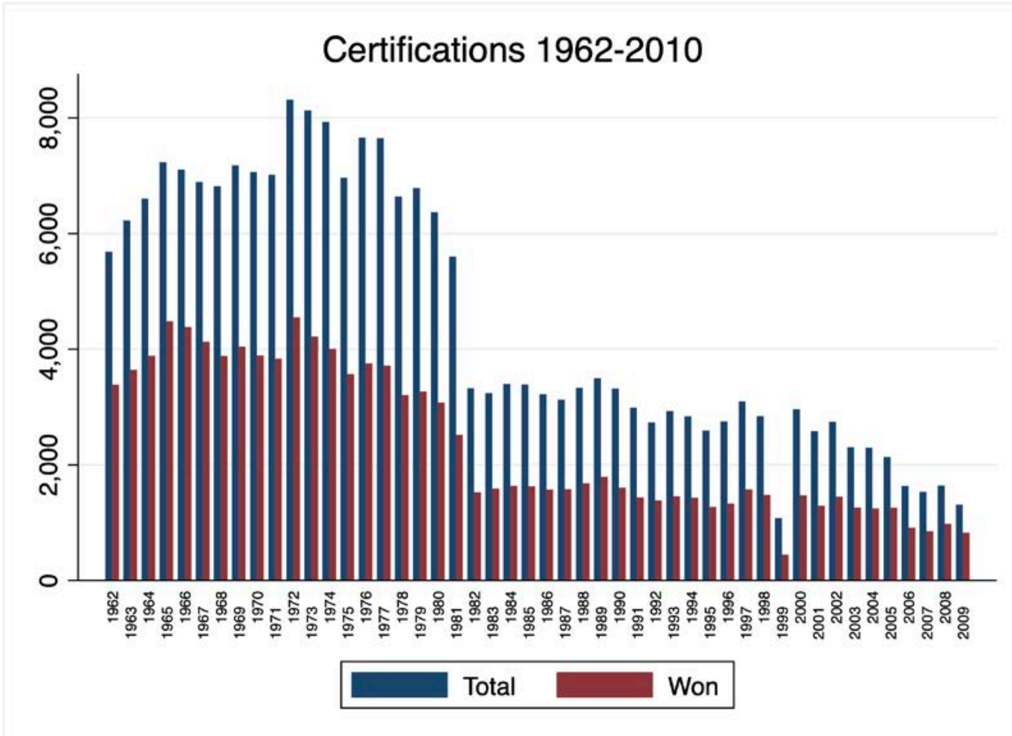
Panel D



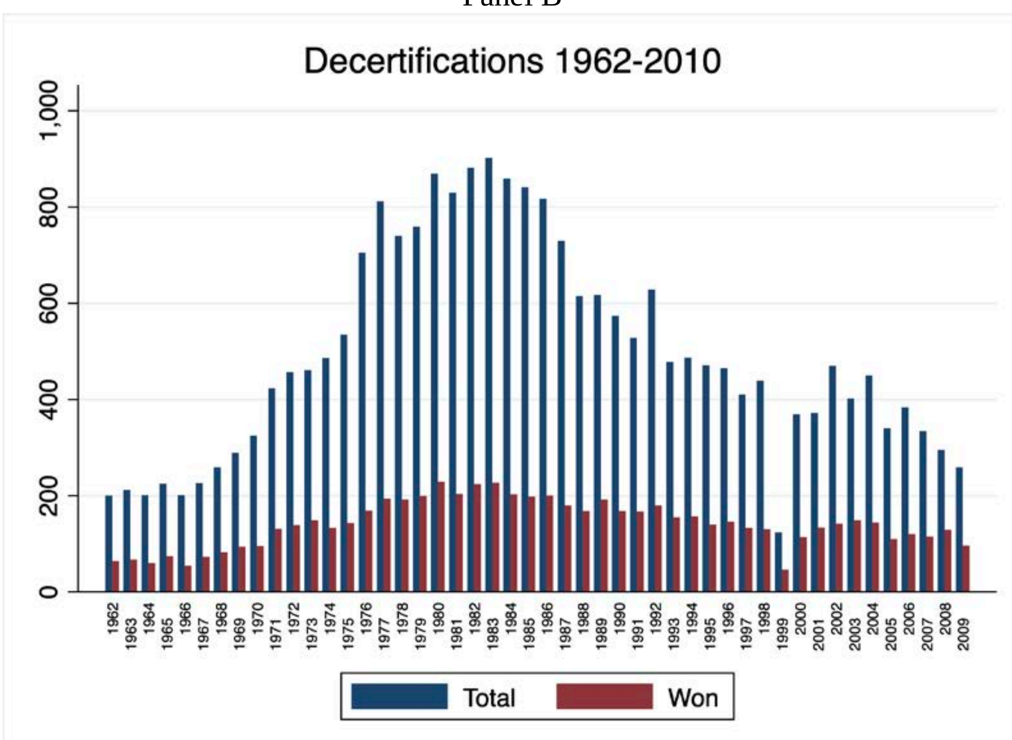
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure 7: Certification and Decertification Elections, 1962-2009

Panel A



Panel B



Source: Authors' tabulations from National Labor Relations Board Data.

Tables

Table 1. 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 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 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 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.

Table 5: 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

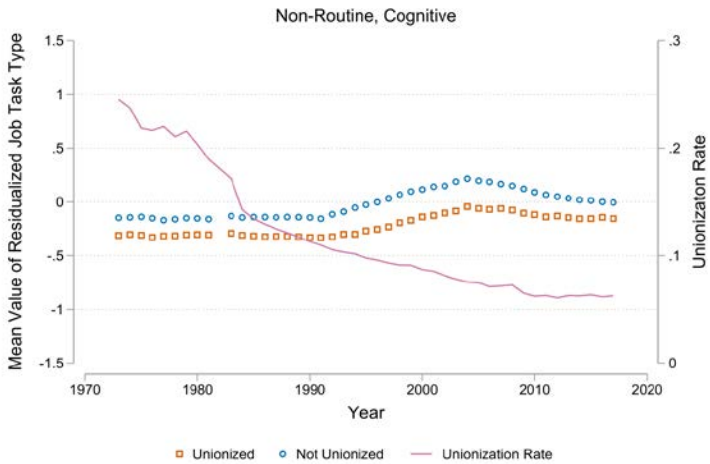
Change Category	Skill Type: Non-Routine, Cognitive	Non-Routine, Manual	Routine, Cognitive	Routine, Manual
Total Change	0.830	-0.139	-0.219	-0.208
Change Due to Worker Share	0.492	-0.068	0.046	-0.014
	[59.24%]	[49.35%]	[-20.84%]	[6.75%]
Change Due to Intra-Occ Skill Changes	0.052	-0.056	-0.155	-0.076
	[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 below. All skill measures are in standard deviation units.

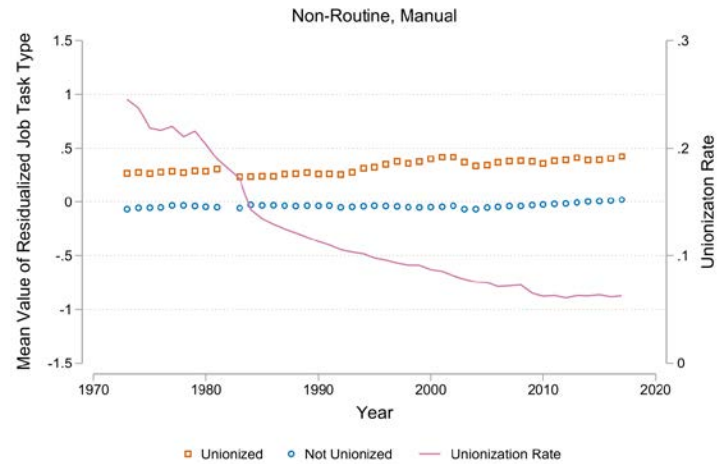
Appendix A: Additional Figures and Tables

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

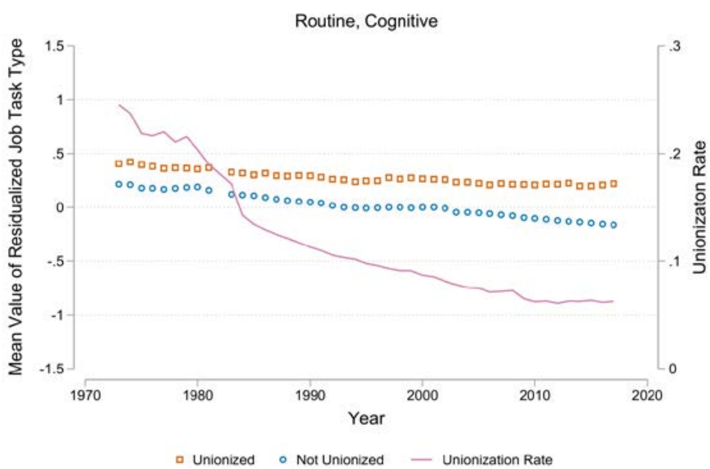
Panel A



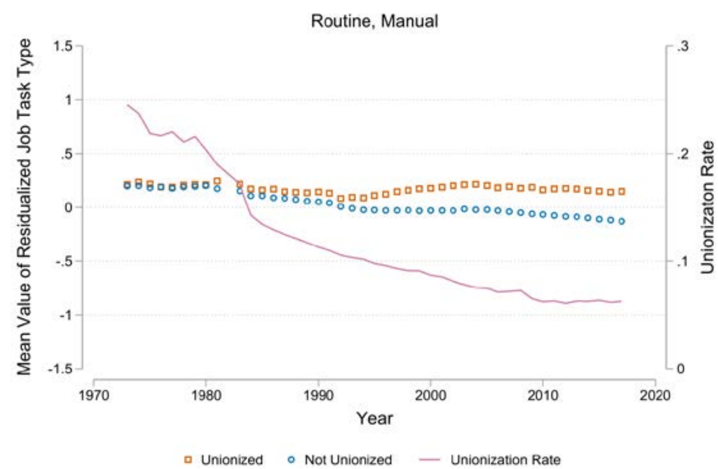
Panel B



Panel C



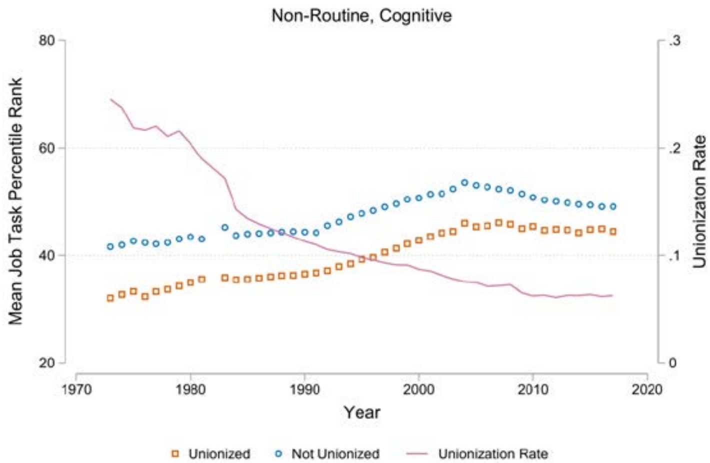
Panel D



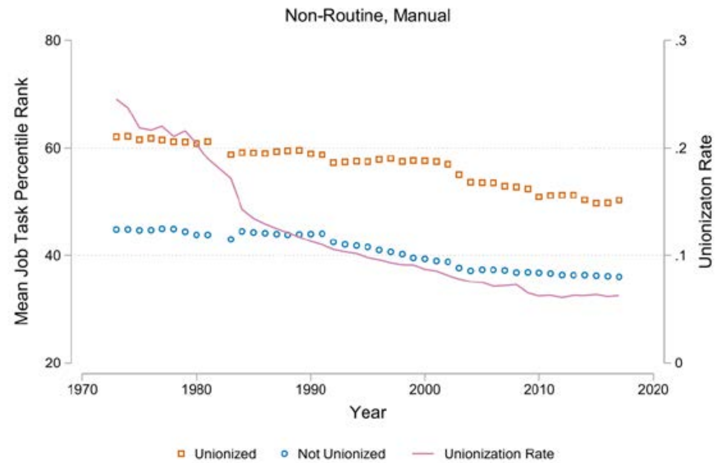
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.
Notes: Outcomes are first residualized using a regression of each skill type on worker age, race/ethnicity, gender, and educational attainment.

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

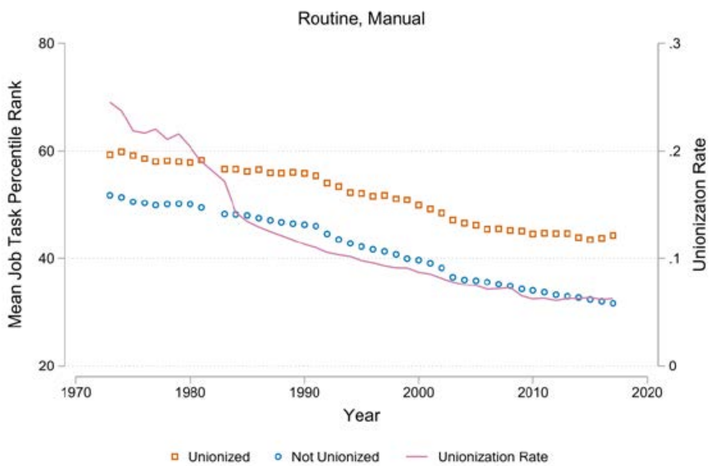
Panel A



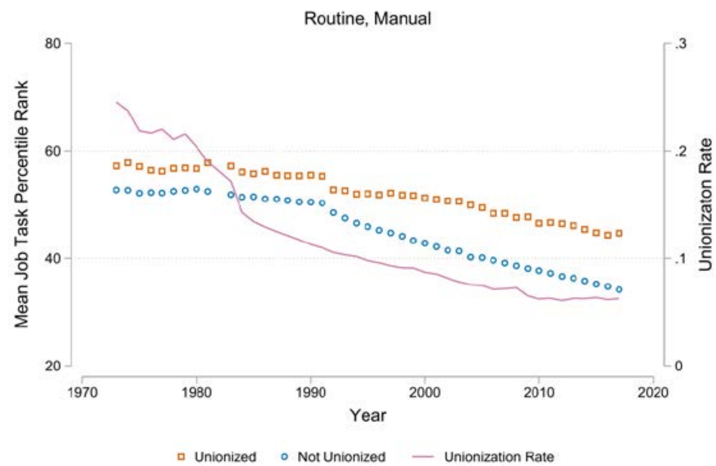
Panel B



Panel C



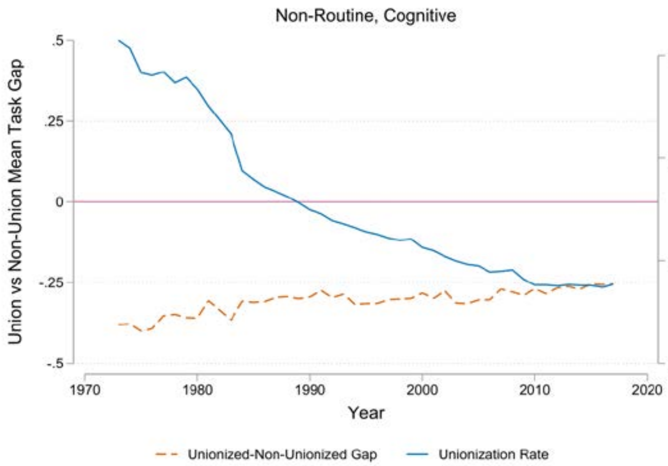
Panel D



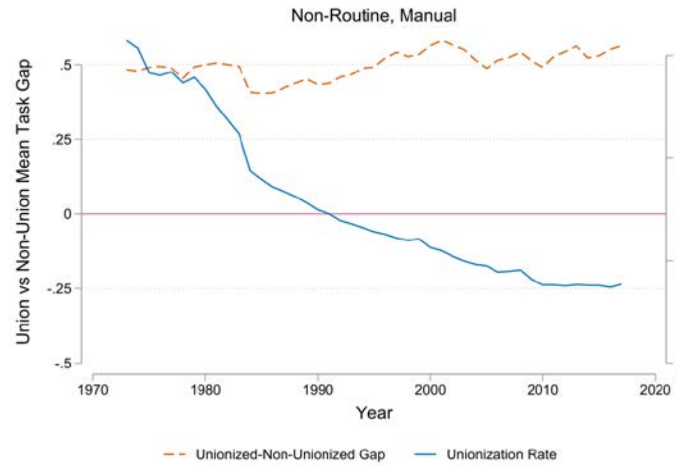
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.
Notes: Instead of normalizing each skill value, we instead assign each occupation a percentile rank in each of the measured years. The figure then plots the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

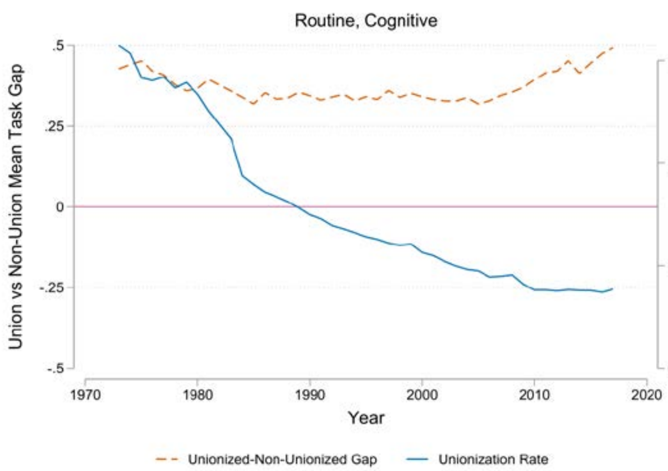
Panel A



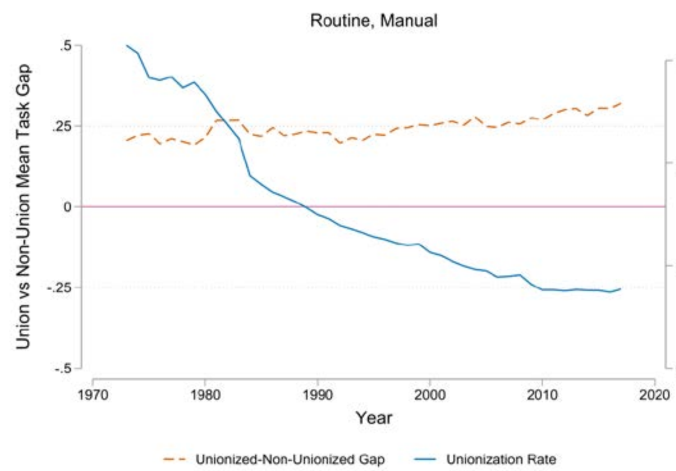
Panel B



Panel C



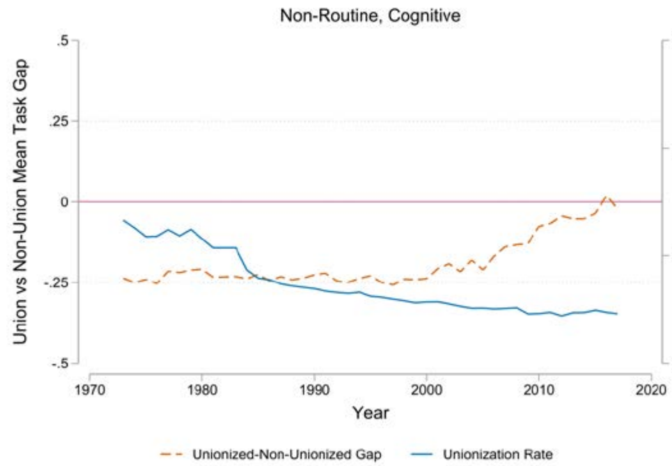
Panel D



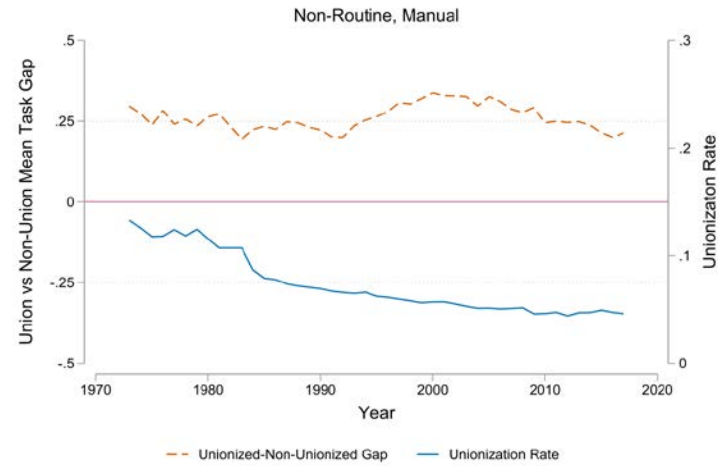
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

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

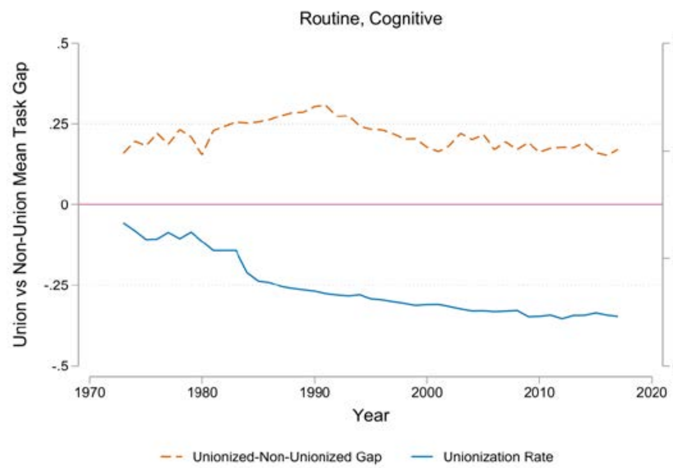
Panel A



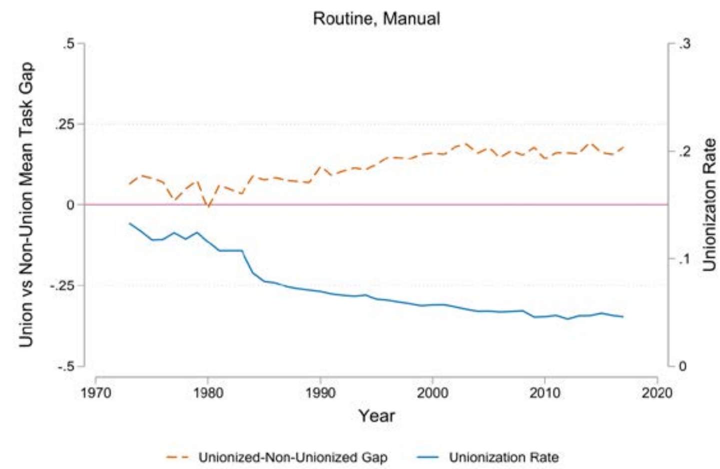
Panel B



Panel C

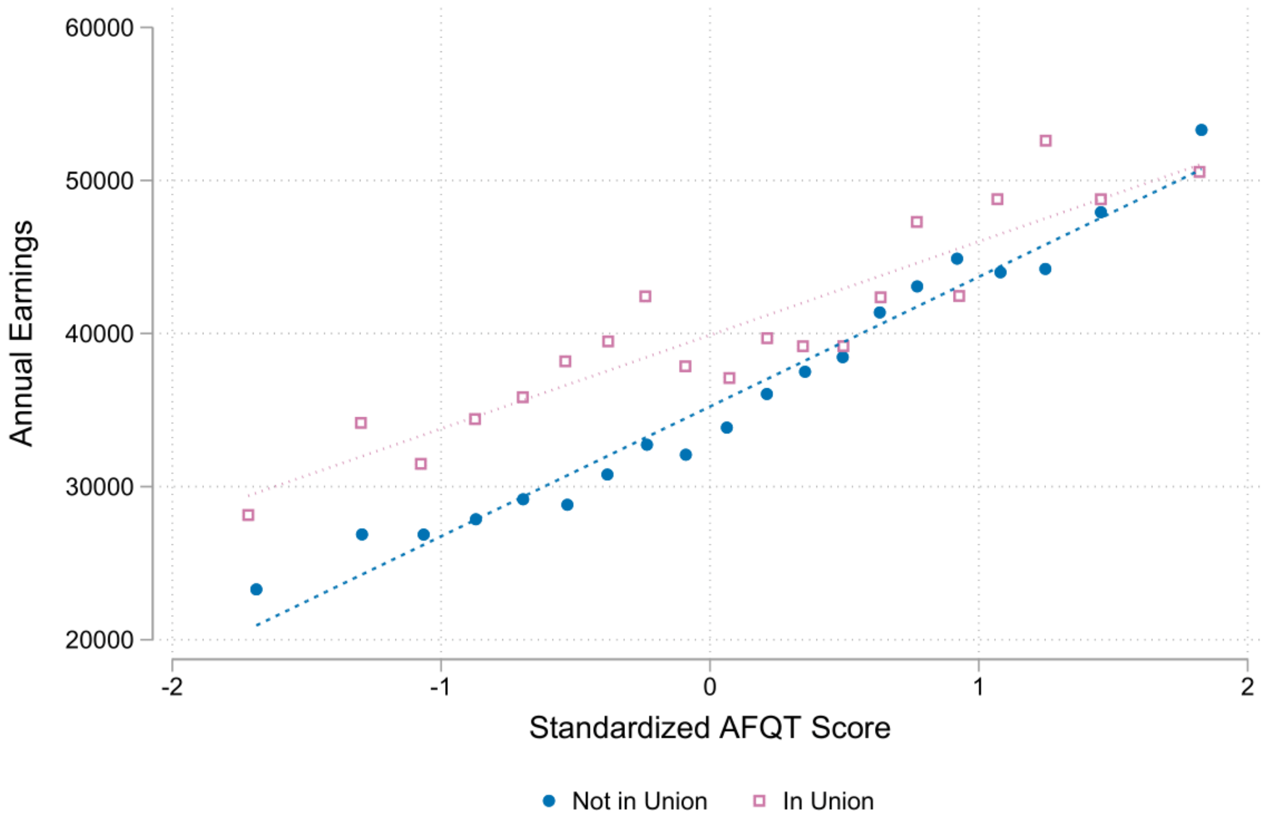


Panel D



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

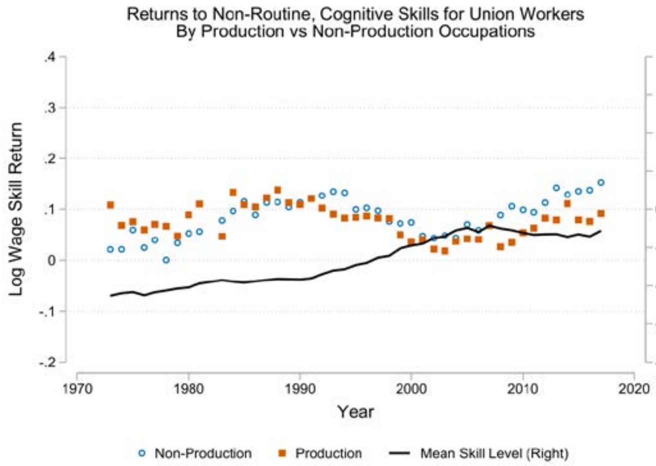
Figure A-5: AQFT and earnings by union status controlling for cognitive skills of occupation and year fixed effects



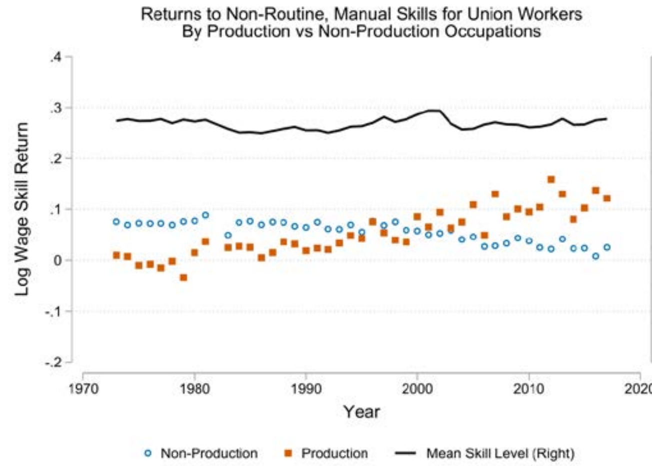
Source: Authors' tabulations using data from NLSY79.
Notes: Figure shows binned averages of annual earnings after conditioning on fixed effects for year and controlling for the cognitive skill level of the occupation.

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

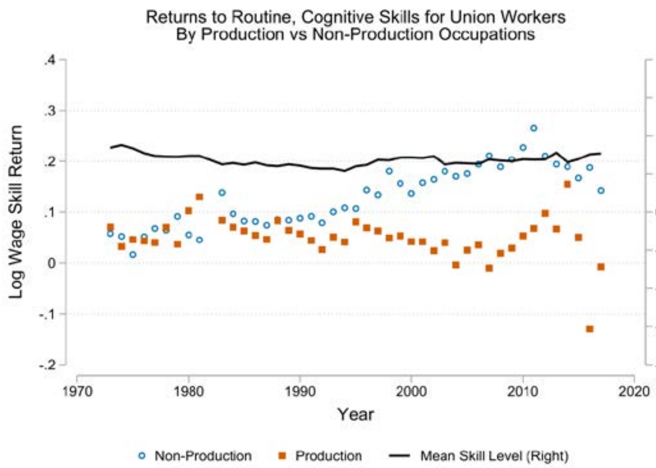
Panel A



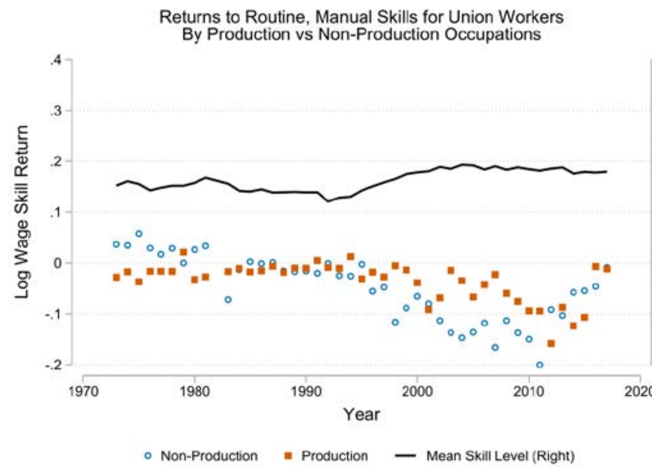
Panel B



Panel C



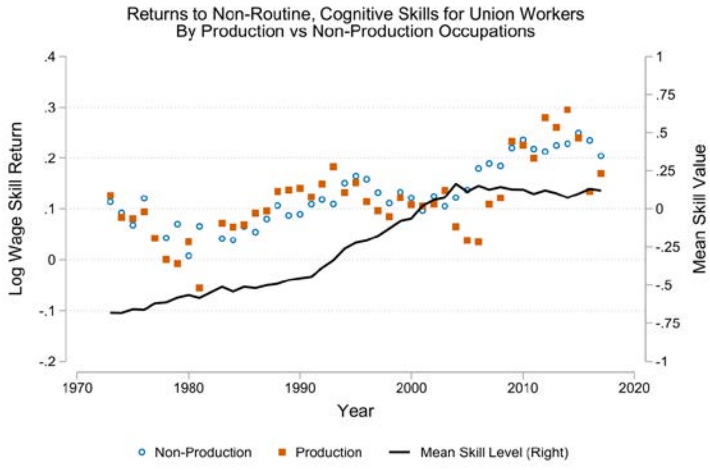
Panel D



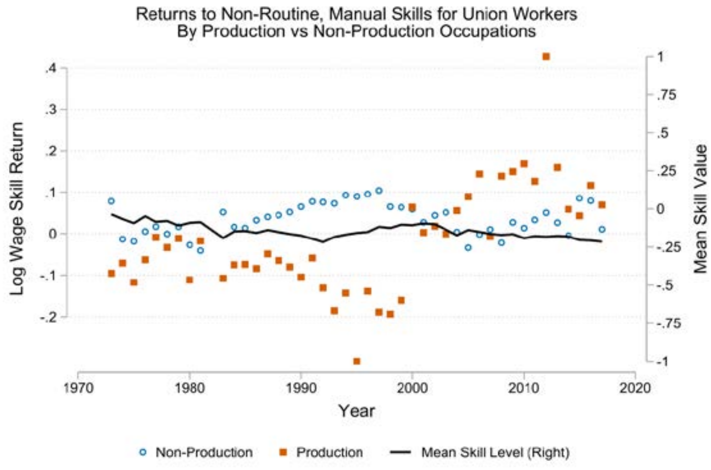
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.
Notes: Production definitions come from the Bureau of Labor Statistics.

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

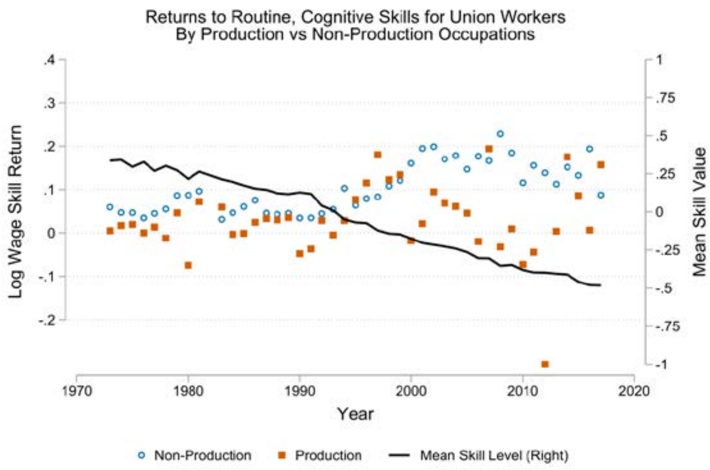
Panel A



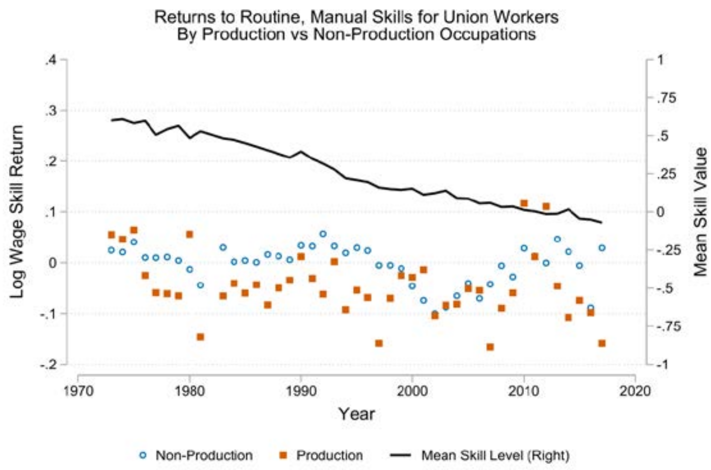
Panel B



Panel C

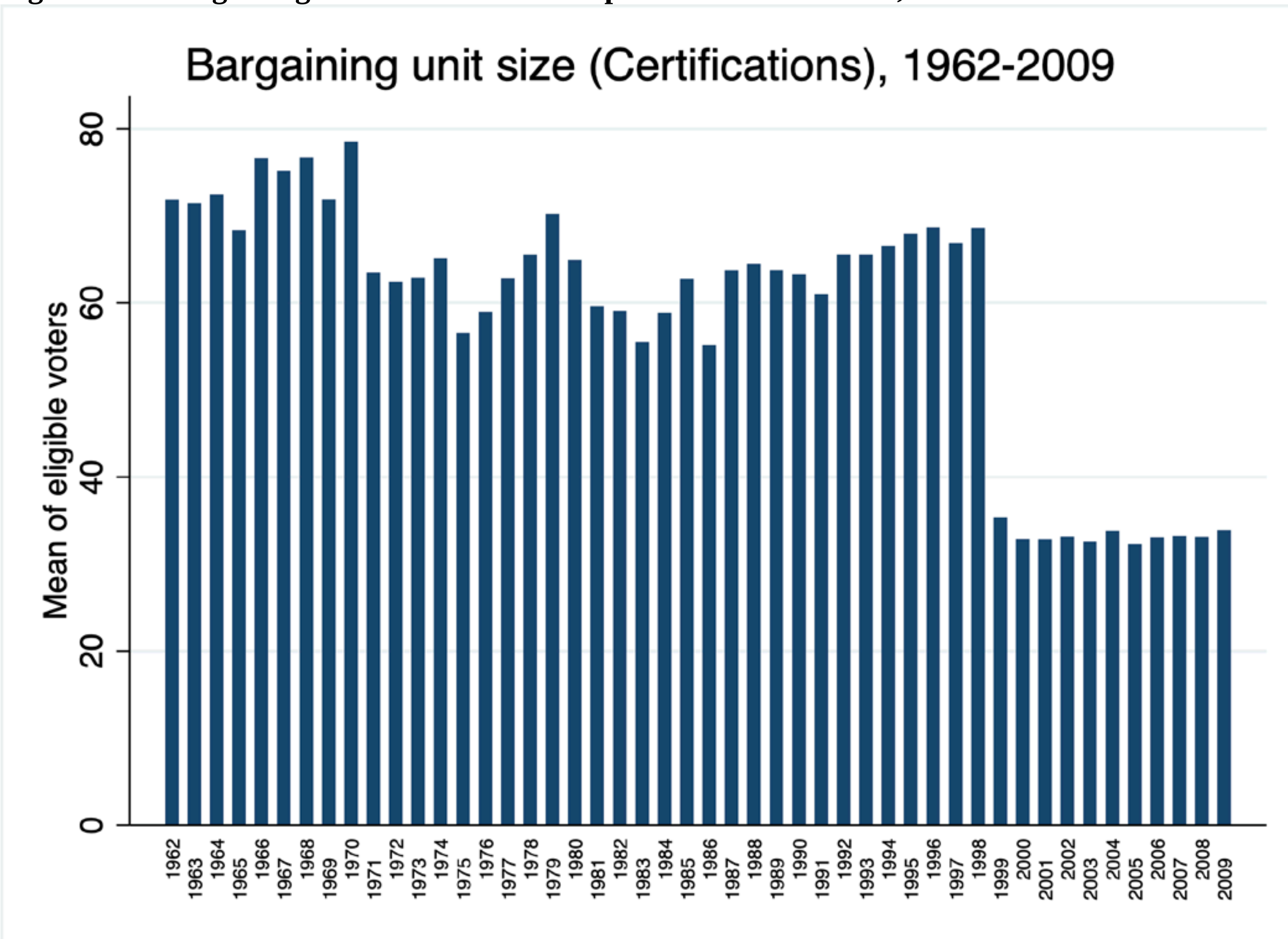


Panel D



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.

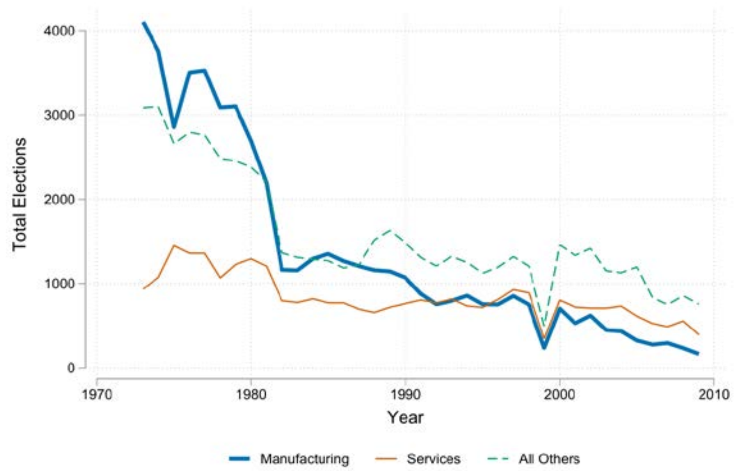
Figure A-7: Bargaining Unit Size in Union Representation Elections, 1962-2009



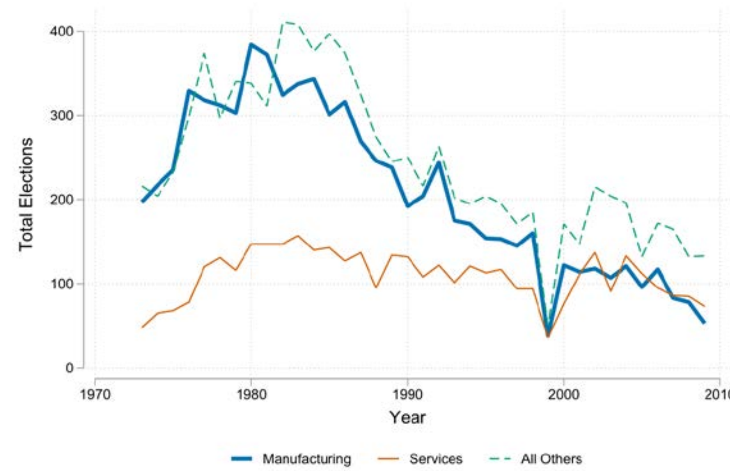
Source: Authors' tabulations from National Labor Relations Board Data.

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

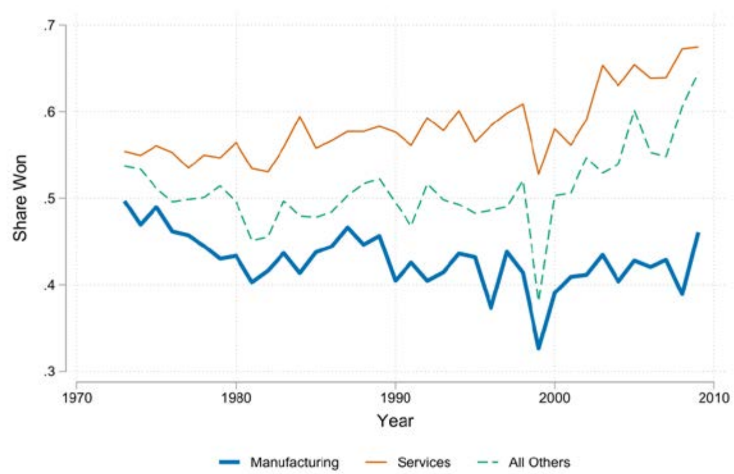
Panel A: Total Certification Elections



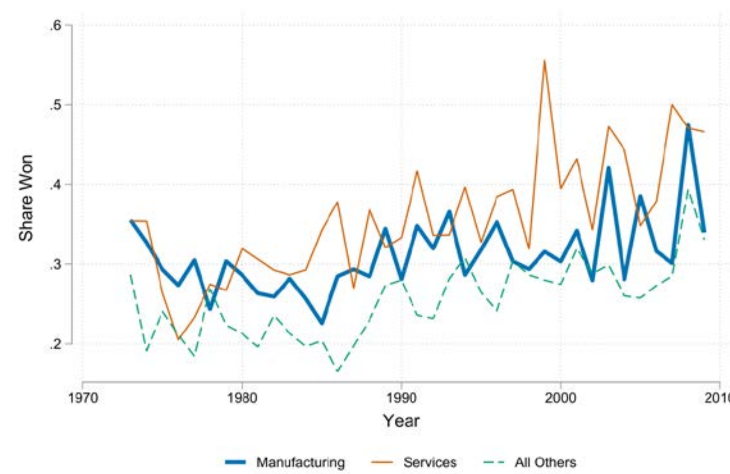
Panel B: Total Decertification Elections



Panel C: Share of Certifications Won



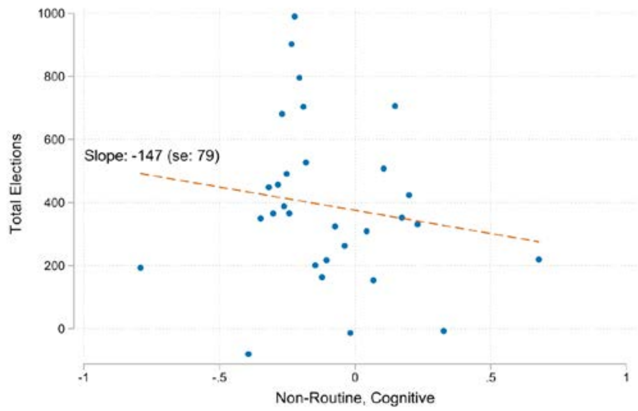
Panel D: Share of Decertifications Won



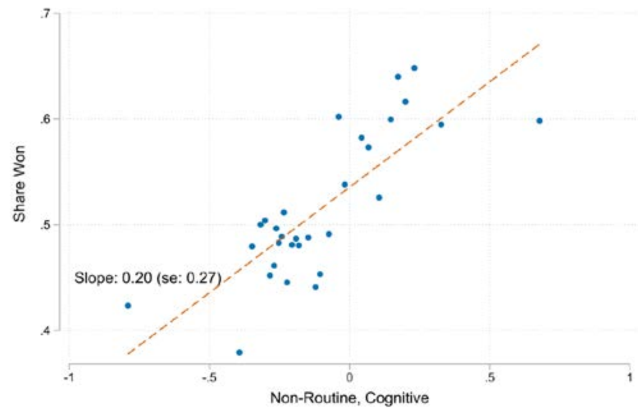
Source: Authors' tabulations from National Labor Relations Board Data aggregated to major industry groups.

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

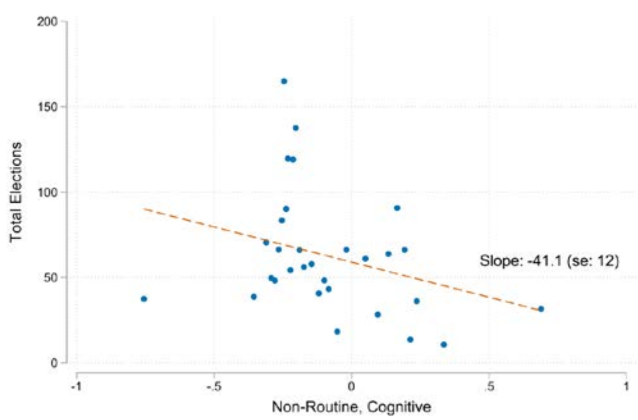
Panel A: Total Certification Elections



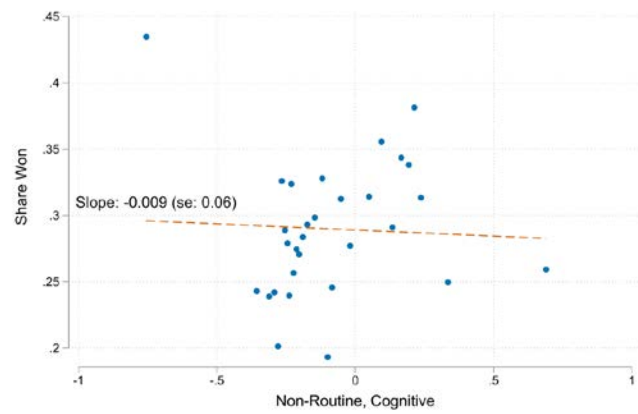
Panel B: Share of Certifications Won



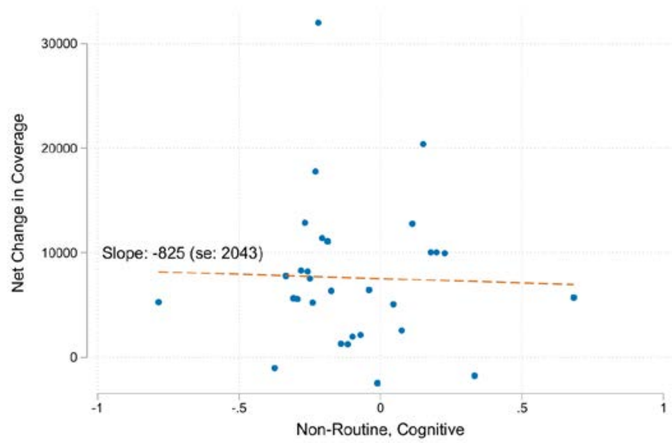
Panel C: Total Decertification Elections



Panel D: Share of Decertifications Won



Panel E: Net Change in Coverage



Source: Authors' tabulations from National Labor Relations Board Data.
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: 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-3: 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-4: 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-5: 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-6: Union Wage Premium Estimates by Decade

Panel A: Men

Year	Basic Model (i)	Skill Controls (ii)	Skill Interactions (iii)	Basic Model (iv)	Skill Controls (v)	Skill Interactions (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

Year	Basic Model (i)	Skill Controls (ii)	Skill Interactions (iii)	Basic Model (iv)	Skill Controls (v)	Skill Interactions (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

Skill Definitions from the DOT and O*NET

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.

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 interpersonal; routine manual; routine cognitive; and non-routine manual. 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 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-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)

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 ($\omega_{kt}^{u} = \frac{L_k^u}{\sum_k L_k^u}$, where L_k^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, $\tau_{2017} = \frac{\sum_{k_1} L_{k_1}^u}{\sum_{k_1} L_{k_1}^u + \sum_{k_3} L_{k_3}^u}$ and $\tau_{1973} = \frac{\sum_{k_1} L_{k_1}^u}{\sum_{k_1} L_{k_1}^u + \sum_{k_2} L_{k_2}^u}$. The average relative skill level of skill S among unionized workers can then be written as follows:

$$\bar{S}_{2017}^{u} = \left(\sum_{k_1} S_{k_1 2017}^{u} * \omega_{k_1 2017}^{u}\right) * \tau_{2017} + \left(\sum_{k_3} S_{k_3 2017}^{u} * \omega_{k_3 2017}^{u}\right) * (1 - \tau_{2017}) \qquad (1)$$

$$\bar{S}_{1973}^{u} = \left(\sum_{k_1} S_{k_1 1973}^{u} * \omega_{k_1 1973}^{u}\right) * \tau_{1973} + \left(\sum_{k_2} S_{k_2 1973}^{u} * \omega_{k_2 1973}^{u}\right) * (1 - \tau_{1973}) \qquad (2)$$

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

$$\begin{aligned}
\bar{S}_{2017}^{u} - \bar{S}_{1973}^{u} &= \left(\sum_{k_1} S_{k_1 2017}^{u} * \omega_{k_1 2017}^{u}\right) * \tau_{2017} + \left(\sum_{k_3} S_{k_3 2017}^{u} * \omega_{k_3 2017}^{u}\right) * (1 - \tau_{2017}) \\
&\quad - \left\{\left(\sum_{k_1} S_{k_1 1973}^{u} * \omega_{k_1 1973}^{u}\right) * \tau_{1973} + \left(\sum_{k_2} S_{k_2 1973}^{u} * \omega_{k_2 1973}^{u}\right) * (1 - \tau_{1973})\right\} \\
&= \tau_{2017} * \left\{\left(\sum_{k_1} S_{k_1 2017}^{u} * \omega_{k_1 2017}^{u}\right) - \left(\sum_{k_1} S_{k_1 1973}^{u} * \omega_{k_1 1973}^{u}\right)\right\} + \left(\sum_{k_1} S_{k_1 1973}^{u} * \omega_{k_1 1973}^{u}\right) \\
&\quad * (\tau_{2017} - \tau_{1973}) + \left(\sum_{k_3} S_{k_3 2017}^{u} * \omega_{k_3 2017}^{u}\right) * (1 - \tau_{2017}) + \left(\sum_{k_2} S_{k_2 1973}^{u} * \omega_{k_2 1973}^{u}\right) \\
&\quad * (1 - \tau_{1973}). \qquad (3)
\end{aligned}$$

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

$$\left(\sum_{k_1} S^u_{k_1 2017} * \omega^u_{k_1 2017}\right) + \left(\sum_{k_1} S^u_{k_1 2017} * \omega^u_{k_1 1973}\right) - \left(\sum_{k_1} S^u_{k_1 2017} * \omega^u_{k_1 1973}\right) - \left(\sum_{k_1} S^u_{k_1 1973} * \omega^u_{k_1 1973}\right)$$

$$= \sum_{k_1} S^u_{k_1 2017} * \left(\omega^u_{k_1 2017} - \omega^u_{k_1 1973}\right) + \sum_{k_1} \omega^u_{k_1 1973} * \left(S^u_{k_1 2017} - S^u_{k_1 1973}\right) \qquad (4)$$

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

$$\bar{S}^u_{2017} - \bar{S}^u_{1973} = \tau_{2017} * \left\{\sum_{k_1} S^u_{k_1 2017} * \left(\omega^u_{k_1 2017} - \omega^u_{k_1 1973}\right) + \sum_{k_1} \omega^u_{k_1 1973} * \left(S^u_{k_1 2017} - S^u_{k_1 1973}\right)\right\}$$

$$+ \left(\sum_{k_1} S^u_{k_1 1973} * \omega^u_{k_1 1973}\right) * (\tau_{2017} - \tau_{1973}) + \left(\sum_{k_3} S^u_{k_3 2017} * \omega^u_{k_3 2017}\right) * (1 - \tau_{2017})$$

$$+ \left(\sum_{k_2} S^u_{k_2 1973} * \omega^u_{k_2 1973}\right) * (1 - \tau_{1973}) \qquad (5)$$