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

Samuel Dodini
(Norwegian School of Economics)

Michael Lovenheim
(Cornell University and NBER)

Alexander Willén
(Norwegian School of Economics)

January 2022

Abstract

Concurrent with the precipitous decline in private sector unionization over the past half century, there has been a substantial 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 first document that for both men and women, private sector unionized jobs became higher-skilled by requiring more non-routine, cognitive skills and fewer manual or routine skills. We then show that union, non-union skill differences have polarized, with unionized worker occupations becoming relatively more intensive in non-routine, cognitive skills and in manual/routine skills. These changes have been more pronounced for women than for men. Next, we decompose these skill 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 entry and exit. Most of the skill changes we document are driven by the second two forces. In the third part of the analysis, we estimate union wage premiums that account for the changing skill mix. We find that accounting for skills has a small effect on the union wage premium and that the premium remains high at over 20% for both men and women. Finally, we show how this evidence can be reconciled with a model of skill-biased technological change that explicitly accounts for the institutional framework surrounding collective bargaining.

---

[1] Michael Lovenheim: Department of Economics, Cornell University, Ithaca, NY 14850. Email: mfl55@cornell.edu. Samuel Dodini: Department of Economics, Norwegian School of Economics, 5045 Bergen. Email: snd46@cornell.edu. Alexander Willén: Department of Economics, Norwegian School of Economics, 5045 Bergen, Norway. Email: alexander.willen@nhh.no.

We are grateful to Daron Acemoglu and Lars Lefgren as well as seminar participants at the University of Albany, Brigham Young University and Wilfrid Laurier University for helpful comments and suggestions. This project was partially funded by the Research Council of Norway through its Centers of Excellence Scheme, FAIR project no. 262675.

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 just over 6% in 2020. Parallel with the sharp drop in private sector unionization, the skill composition of the US workforce has shifted towards higher-skilled jobs that are less manual and routine and more cognitive/analytical (Autor, Katz, and Kearney 2006; Autor, Levy, and Murnane 2003). In this paper, we study the interaction of these two trends to understand how the skill content of private sector union coverage has changed, why these changes have occurred, and what the resulting effects is on both the union wage premium and the return to skill in unionized jobs. While a sizable literature has documented and analyzed the decline in private sector unionization and the trend in the union wage premium (e.g., Card, Lemieux, and Riddell 2020; Acemoglu and Autor 2011; Card 2001), there has been little focus on understanding how (and why) the nature of private sector union coverage has changed and what the implications of these changes are for the union wage premium and the return to skill that workers experience.

This paper sheds new light on these questions using a task-based approach, which was first introduced by Autor, Levy, and Murnane (2003). We are the first to apply these insights to the analysis of labor unions. 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 and, for the first time in the literature, show how the skill composition of workers covered by private sector unions has changed. We focus on two main categories that aggregate the skills analyzed in the seminal work of Autor, Levy, and Murnane (2003): "non-routine, cognitive" and "routine or manual."[2] Throughout our analysis we focus on private sector workers, as the dramatic reduction in unionization over the past decades has been driven entirely by the private sector (Card, Lemieux, and Riddell 2020).

The first part of the paper presents descriptive trends in the skill composition of the unionized and non-unionized workforce, overall and by gender. These trends provide new insight

[2] The "non-routine, cognitive" skill group is an additive combination of non-routine, cognitive/analytical and non-routine, cognitive/interpersonal. The "routine or manual" skill group is an additive combination of routine, cognitive; routine, manual; and non-routine, manual." We aggregate across groups to ease exposition, since results across skill categories within each of our groupings are similar. We present disaggregated results in the Online Appendix. Note that these two measures comprise different dimensions of skills that do not necessarily move mechanically with one another.

into how the overall decline in unionization interacts with changes in skill demand to alter the types of workers who are union members. Next, we conduct a decomposition that seeks to explain why skills of unionized jobs have changed over time. We decompose the changes into three parts: (1) changes in skills within an occupation, (2) changes in worker concentration across existing occupations, and (3) changes to the occupational mix from both entry and exit over time. Finally, we examine how changes to the skill mix of unionized and non-unionized occupations affect the measured union wage premium. Our paper is the first to explicitly consider how changes in skills affect this parameter. We do so by interacting union membership with each skill measure in a wage regression. The results not only reveal how unions influence the return to specific skills but also allow us to calculate the implied union wage premium that incorporates changes in the union-specific return to skill.

We focus on two broad types of skills: "non-routine, cognitive" and "routine or manual." These represent separate skill domains that allow us to paint a comprehensive picture of how unionized job coverage of different types of skills have changed over time. Consistent with broader patterns of skill-biased technological change (SBTC), our descriptive analysis shows that there were large increases in the non-routine, cognitive skills of unionized jobs between 1973 and 2017. In addition, there were large declines in routine or manual skills of unionized occupations. This skill upgrading is consistent with the findings in Farber et al. (2021), who show evidence of increased educational attainment of private sector unionized workers over this period. The patterns we document are evident even after controlling for worker characteristics (including education). Our results therefore are not simply a reflection of shifts in the types of workers who sort into unionized professions.

We further present evidence of increased *polarization* of skills across union and non-union workers. First, we find that the differences in non-routine, cognitive skill between union and non-union worker occupations declined, with unionized workers exhibiting faster growth than their non-unionized counterparts. Second, the gap in routine or manual skill demand increased: union workers are relatively more likely to be working in occupations that require these skills than non-union workers over time. These patterns provide evidence that the gap in more advanced cognitive skills between union and non-union occupations has narrowed or been eliminated, while the decline in manual/routinized skills has been less dramatic in the union relative to the non-union sector. Indeed, the demand for manual/routine skills is increasingly concentrated in unionized professions. The result is that unionized jobs have experienced increased relative skill demand both in terms of cognitive, analytic and routine/manual skills.

Because of the large differences in occupational sorting by men and women combined with historical differences in private sector union coverage, we focus on gender-specific estimates throughout the paper. Among men, we find similar but muted patterns relative to the pooled estimates. Changes in cognitive, analytical skill coverage of unionized workers are larger among women: the skill gap is completely eliminated by 2017. Routine and manual skills of unionized jobs also decline substantially, but they do so similarly across union and non-union sectors. While the gender-specific patterns in skill coverage by union and non-union workers generally align, the changes are much more pronounced among women.

We next decompose the gender-specific changes in skills among union and non-union workers to examine the role of within-occupation changes in skills, changes due to the share of workers in each existing occupation, and changes to the mix of occupations through entry and exit. Among men, changes to the worker share of occupations and entry/exit are individually important and explain 83% of the change in non-routine, cognitive skill coverage of unionized work. Hence, the increased concentration of these skills among unionized workers can be explained by shifts in unionized labor towards occupations that require these skills as well as the introduction of new occupations that are skill-intensive along these dimensions and the destruction of occupations that are not. Within-occupation changes in skill requirements only explain 17% of the increase in non-routine, cognitive skills among unionized workers. For routine or manual skills, changes in worker shares across occupations and changes to entry/exit of occupations explain more than the total overall decline. These patterns are balanced with an increase within occupations of the need for routine or manual skill.

Among women, 93% of the change in coverage of non-routine, cognitive skills can be explained by worker sorting across occupations and occupation entry/exit. All three explanations contribute to the large declines we document in routine or manual skill demand.

In order to help explain our results, we present a simple Roy model that extends the model of Acemoglu, Aghion, and Violante (2001) to include three new features. First, we allow unions to adjust wages for the average skill level of workers in a given bargaining unit. This feature of collective bargaining leads to the prediction that increases in the returns to skill will have only a minor effect on workers' incentives to switch from a unionized to a non-unionized firm. As average wages increase in both sectors, only workers who experience an increase in the idiosyncratic component of their skill that is large enough to overcome search frictions will find it optimal to switch. Second, our model incorporates the cost of unionizing, which has increased substantially since the 1980s due to changes in the political environment and reductions in worker protections. Third, we include the cost of de-unionizing through a union decertification election. We present evidence from National Labor Relations Board (NLRB) union certifications and decertifications over time that are consistent with these costs being large.

The model highlights that skill-biased technological change is unlikely to cause the patterns we document through changes in the return to skill. Rather, SBTC shifts the demand for workers across occupations and leads to occupation creation and destruction. Workers shift towards higher-skilled occupations that are less likely to be unionized, and the new high-skilled occupations that enter are less likely to have workers that seek to unionize. Occupations that exit also are more heavily unionized. Increases in the cost of a successful unionization drive keep these previously non-unionized professions from becoming unionized. Hence, we argue that one component of the decline in unionization reflects changes in the occupation mix, entry of non-unionizing occupations that tend to be higher-skill, and exit of more unionized occupations that tend to be lower-skill, combined with the high cost of unionizing. This explanation stands in contrast to the more traditional argument that unionization declined because the return to skill increased, which reduced the return to unionizing. That only a small number of bargaining units decertify provides additional supporting evidence for our preferred interpretation of the results.

Our explanation for changes in the relative skill coverage of unionized jobs assumes that unions are able to respond to changes in the return to average skill in the bargaining unit. Combined with changes in the skill coverage of unionized relative to non-unionized jobs, this has potentially important implications for the union wage premium. We next examine how the return to average skill in occupations varies across union and non-union workers over time and how accounting directly for occupation-specific skills affects the union wage premium.

Among both men and women, there is a sizable return to non-routine, cognitive skill in the unionized sector that is lower than the return in the non-union sector. This gap has been reduced substantially over time, such that the return to non-routine, cognitive skill is similar between the union and non-union sectors by the end of our analysis period. For men, the return to routine/manual skills is higher among unionized workers, and the gap has grown since the

1990s. Women in unionized jobs experienced lower relative returns to routine/manual skills until the mid-1990s, at which point the gap was eliminated and then reversed. These changes have been most pronounced among professions in the top quartile of each skill category.

Finally, we estimate union wage premia ignoring skill measures, including skill measures as controls, and including interactions between skills and union status. Despite the large changes in skill coverage and the returns to skill that we present, accounting for skills in these models has little impact on the estimates. Our results are consistent with prior research in showing a stable union wage premium over most of this time period of between 0.2 and 0.3 log points (Card, Lemieux, and Riddell 2020; Farber et al. 2021).

This paper makes several important contributions to the literature. First, we provide novel evidence on how the task content of unionized workers have 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. 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. Farber et al. (2021) also do not decompose the changes in the educational attainment of unionized workers, which provides important insight into why the task content of unionized jobs has changed.

Second, we present novel evidence that unionized workers experience a large return to skill that has grown over time relative to the non-union sector. We show the first evidence that unions use their bargaining power to increase the return to average skill in an occupation, which is consistent with unions negotiating to increase the wages of the median worker in a bargaining unit. Furthermore, our results provide new evidence on the stability of the union premium over time and the effect of accounting directly for occupational skill demand in these models.

Third, our results help reconcile an unresolved puzzle in the literature: unionized workers have become more high-skilled (Farber et al. 2021), but models of skill-biased technological change predict that high-skilled workers will become less unionized over time because they are the beneficiaries of wage dispersion (Acemoglu, Aghion, and Violante 2001). Our results show that these two arguments are not at odds. Unions cover more high-skilled workers over time because labor demand has risen disproportionally among higher-skilled professions. These professions do not “de-unionize,” but heavily-unionized professions with lower-skilled workers 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.

Fourth, our paper contributes to a growing literature that examines changes in the skill composition of the workforce. In their seminal paper, 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, which we argue allows us to break new ground in understanding the implications for workers of the decline in private sector unionization.

The rest of this paper is organized as follows: Section 2 provides a literature review focusing on what is known about changes to private sector unionization and the union wage premium. Section 3 provides a detailed discussion on the data we use in the analysis. Section 4 presents trends in skill coverage of private sector union jobs as well as the decomposition of those changes into cross-occupation shifts, within-occupation changes, and changes in the composition of occupations themselves. The estimation of union wage premiums that account for the skill content of jobs is presented in Section 5. Section 6 provides a discussion and conclusion.

2. Background

2.1. The Decline in Private Sector Unionization

Private sector unionization has declined precipitously since the 1970s, from approximately 25% in 1973 to 6% in 2017. The drop in private sector unionization was particularly pronounced among men, from 30% to 8% over this time period, while for women the decline was more modest, from 14% to 5%. The reduction in private sector union coverage was largest in the early 1970s-mid 1980s, and thereafter there has been a more gradual but persistent decrease. The decline in unionization is isolated to the private sector: in the public sector unionization rates actually increased over the same time period, from 23% in 1970 to 34% in 2017.[4] Private sector collective bargaining rules are set by the NLRB, while states set public

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

sector bargaining laws for non-Federal employees. The fact that public sector union coverage is so much higher reflects the fact that most states have worker-friendly union laws that have resulted in high and stable unionization rates for teachers, firefighters, and police officers (Frandsen 2016).

There currently is little understanding about *why* private sector unionization rates have declined so dramatically. One of the most prominent arguments is that the decline is driven by skill-biased technological change. Acemoglu, Aghion, and Violante (2001) present a model of unionization under SBTC that is predominantly 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 declines in unionization should be accompanied by a relative shift towards coverage of lower-skilled occupations.

While the Acemoglu, Aghion, and Violante (2001) model is compelling along a number of dimensions and provides clear predictions, there are several aspects of the collective bargaining environment that are not accounted for. Most importantly, the authors model collective bargaining as a *firm* level decision rather than as a *bargaining unit* level decision. Bargaining units are more narrowly defined than firms and either are occupation-specific or group similar occupations together. Large firms usually have multiple bargaining units, even if the bargaining units themselves all are represented by the same union. In such an environment, what matters most for workers is the skill variance within the bargaining unit. To take an extreme case, if all workers are identical within a bargaining unit, SBTC should not reduce the incentives to unionize because unions can negotiate wages for all employees that reflect the market value of their skill. If unions set wages based on the median skill of workers in the bargaining unit, increases in the return to skill driven by SBTC will not lead to much reduction in

[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.

unionization.

The Acemoglu, Aghion, and Violante (2001) model predicts that SBTC will lead to a reduction in high-skilled employees being covered by a union, which is at odds with existing evidence. Farber et al. (2021) construct a new dataset on union membership from Gallup Polls back to the 1930s that include questions on union membership. They combine these data with the CPS to generate the longest historical micro data series of its kind on union membership in the US, and they show that the educational attainment of private sector union members has grown substantially over time. Additionally, as union coverage declines, the union wage premium is unchanged, which contradicts the theoretical predictions of Acemoglu, Aghion, and Violante (2001). While Farber et al. (2021) document this inconsistency, they do not adduce a model that can resolve it. We address this puzzle directly in this paper.

Farber et al. (2021) focus on educational attainment as their worker skill measure. This is a noisy measure of skill, however, because skill is likely to be multi-dimensional. Our skill-based approach allows us to examine in more detail how the skill 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. Outside of Farber and Western, this aspect of SBTC has not been included in prior models or in prior empirical work, and 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] In sum, we argue that a task-based approach provides important new information on how workers have been affected by the decline in private sector unionization and points to some key revisions to the Acemoglu, Aghion, and Violante (2001) model that allow us to align theoretical predictions and empirical results.

[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.

2.2. Union Wage Premium

There is a rich literature studying the wage effect of unionization. Lewis (1986) and Freeman and Medoff (1984) provide early estimates from the heyday of private sector unions in the 1960s and 1970s.[7] These papers use micro data on workers and estimate regression models that rely on selection-on-observables methods for accounting for endogenous selection into unionization. A large set of studies has emerged since that time, using similar methods on updated data to estimate the union wage premium. Most recently, Card, Lemieux, and Riddell (2020) estimate union wage premiums over several decades using CPS data. They find that the male and female wage premiums remained quite stable from 1973 to 2015 at about 0.2 log points (22%). Farber et al. (2021) find similarly-stable estimates of 0.2 log points over this period. These estimates align closely with those in Freeman and Medoff (1984). Much research also has examined the effect of unions on inequality (e.g., DiNardo, Fortin, and Lemieux 1996; Card 2001; Firpo, Fortin and Lemieux 2018; Card, Lemieux, and Riddell 2020; Farber et al. 2021). These papers generally find that deunionization contributes importantly to wage inequality.

DiNardo and Lee (2004) take a different approach from the rest of the literature by estimating regression discontinuity models surrounding union representation elections. By comparing outcomes of elections in which the bargaining unit barely won to outcomes of elections in which the bargaining unit barely lost, they find no effect on wages. Importantly, this approach only identifies wage effects among unions that barely won an election, which might be a different effect from those that win more handily if vote share is related to underlying bargaining power.

While estimates of the union wage premium are relatively well established, none of the prior papers in the literature consider the skill content of the jobs covered by unions. With declining unionization and changes in the occupations covered by unions, it is surprising that the premium has remained constant over time. We are the first to directly embed job-based skill measures into the estimation of union wage premia, which are potentially important because as we show the task content of union jobs has changed considerably over time. Accounting for these factors allows us to more accurately identify the union wage premium for both men and women than has been possible in the prior literature.

[7] Blanchflower and Bryson (2004) provide an update of Freeman and Medoff (1984) and obtain similar results.

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.[8] 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 rather than union coverage to maintain comparability over time and across survey designs (Card 2001; Card, Lemieux, and Riddell 2020).[9] 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).[10] We standardize wage values to 2016 dollars using the Personal Consumption Expenditure (PCE) 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, which imputes missing wages based on a set of worker characteristics matched to workers with non-missing wage data (Hirsch and Schumacher 2004; Kaplan and Schulhofer-Wohl 2012). Because union status was not a factor used in this procedure, estimates of the union wage premium have been shown to be biased downward when relying on allocated data (Hirsch and

[8] We rely on the CPS ORG extracts maintained by NBER: https://www.nber.org/data/morg.html.
[9] In particular, the 1973-1976 CPS did not ask a union *coverage* question, but only asked a union *membership* question.
[10] There was a change in the way educational attainment was coded between the 1991 and 1992 surveys from highest grade completed to a measure of highest degree achieved. We recode post-1992 values to their pre-1992 years of schooling counterparts for consistency.

Schumacher 2004).[11]

To obtain a time consistent definition of the occupations, we crosswalk all Census occupation codes to their 1990 equivalent based primarily on the method proposed by Acemoglu and Autor (2011) and the harmonized occupation codes at the IPUMS USA repository (Ruggles, et al. 2019). We match the remaining occupations by hand using occupation descriptions available from the Census. Some occupations do not have a clear 1990 equivalent, either because the occupation no longer exists in meaningful numbers (e.g. telegraph operators), or because an occupation first enters the CPS in a later year. Our decomposition analysis accounts for these changes to occupation coverage in the data.[12] The use of consistent 1990 occupation codes prevents us from mischaracterizing code changes as entry/exit of different occupations.

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

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

[11]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.

[12] 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 qualitatively similar and our conclusions are unchanged when comparing other time periods that did not experience this reclassification.

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.

"GED – math" is the measure of non-routine, cognitive, analytical skill in DOT that corresponds to "math" ability in the O*NET data. "Direction, control, planning" in DOT corresponds to "organizing, planning, and prioritizing work" in O*NET and represents non-routine, cognitive, interpersonal skills. The DOT measure of routine, cognitive tasks, "set limits, tolerance, or standards," corresponds to a combined index in the O*NET that incorporates "controlling machines and processes," "drafting, laying out, and specifying technical devices, parts, and equipment," and "troubleshooting." As our measure of routine, manual work, "finger dexterity," is a simple conceptualization that is common across the DOT and O*NET data. Finally, for non-routine, manual skills, "eye, hand, and foot coordination" in the DOT corresponds to our constructed index in O*NET that combines "gross body equilibrium" and "spatial orientation." 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 weighting each occupation equally. Hence, shifts in occupation shares will not mechanically change the standardized measure. Appendix Table A-1 shows each DOT measure we use and its O*NET equivalent(s).

To reduce dimensionality and facilitate exposition, we collapse the skills categories into two groups: "non-routine, cognitive" is the sum of non-routine, cognitive/analytical and non-routine, cognitive/interpersonal, while "routine or manual" is the sum of routine, cognitive; routine, manual; and non-routine, manual. The descriptive patterns of the disaggregated skills within each of the aggregated groups are similar to one another, so we lose little information by aggregating. The Online Appendix presents our results using the more disaggregated skill categories. Note that these two 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 both skill types, which is why we do not combine these further into a single skill index. For example, an occupation may experience a change in the level of interpersonal collaboration required to perform the job, while changes in technology or other inputs may make day-to-day work in the occupation more routine.

In total, our analysis sample consists of 3.4 million workers during the 1973-2017 period. Summary statistics for our sample are shown separately for men and women and by union membership status in Table 1. Workers who are members of a union are older, slightly less educated, make about 0.2 to 0.3 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 are significantly more routine or manual in nature and that require less non-routine, cognitive skills than their non-union counterparts.

Table 2 presents the five largest unionized occupations in 1973 and in 2017 for men as well as their union membership rate and the skill level among the five skills we consider. In both 1973 and 2017, the five largest unionized occupations require substantial routine or manual skills and require less non-routine, cognitive skills. 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. Despite the fact that four out of the five occupations change, the occupations accounting for the largest share of unionized workers continue to be heavily routinized and manual.

Table 3 presents similar information for women. It is important to note that there is no overlap in either time period between the five largest unionized occupations for men and women. This finding supports examining men and women separately, because they sort into very different occupations. As with men, the largest unionized occupations 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 skill, 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 exercise 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 of Private Sector Union Workers

4.1. Trends in Skills of Private-Sector Unionized 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.

The top panel shows patterns for non-routine, cognitive skill.[13] 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.[14] The top panel of Figure 2 demonstrates that the increase in non-routine, cognitive skill 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 33.6% in 1973 to 8.1% in 2017. The reduction in unionization among high non-routine, cognitive jobs is much smaller, from 8.2% in 1973 to 5.3% in 2017. Hence, the increase in this skill concentration among unionized workers is coming predominantly from a substantial reduction in the union coverage of low-skilled jobs for this skill measure. As the figure demonstrates, the time pattern of this reduction matches the change in overall union coverage very closely. Figures 1 and 2 demonstrate that the non-routine, cognitive skill content of unionized jobs has grown substantially over time, which mostly is driven by reduced unionization of workers in occupations that have low non-routine, cognitive skill requirements.

[13] Online Appendix Figure A-4 shows patterns for the five disaggregated skill categories that comprise the two skill groups on which we focus.
[14] Online Appendix Figure A-5 shows these patterns for the five disaggregated skill groups.

Routine or manual skills among unionized jobs have declined markedly, as shown in the bottom panel of Figure 1. The overall change is 0.460 standard deviations, going from 0.503 in 1973 to 0.043 in 2017. These declines are mostly driven by routine, manual and routine, cognitive skills (See Online Appendix Figure A-4). Figure 2 shows that the decline in union coverage was most pronounced for occupations requiring high levels of this skill.

It is instructive to compare the changes in skill coverage among unionized workers to those among non-unionized workers. Figure 1 includes these comparisons. For non-routine, cognitive skills there is convergence between the union and non-union sectors. Non-union jobs have higher levels of this skill requirement, 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.

Unionized workers are in occupations that have more routine or manual skill requirements. This is expected, as private sector unions traditionally covered workers in more routinized and manual professions. As the demand for such work has declined, however, the routinized/manual skill gap between non-union and union workers has grown. The difference increased from -0.414 to -0.534 – a 29.1% increase from the initial difference.

Taken together, the evidence from Figure 1 points to increased stratification of skills across the union and non-union sectors. Unionized workers are increasingly working in jobs that require higher levels of non-routine, cognitive skills. This increase is occurring overall and relative to the non-union sector. However, relative to non-unionized workers, unionized workers also increasingly are working in occupations that require manual or routinized skills. The coverage of these skills has declined over time in both sectors, but it has done so more steeply for non-unionized workers. As a result, manual and routine skills coverage is increasingly concentrated in unionized professions.

Prior research has not addressed this changing skill content of unionized and non-unionized work, although there is evidence that educational attainment of unionized workers has increased (Farber et al. 2021). This raises the question of whether our results simply reflect a change in the composition of the unionized workforce. To address this question, we residualize the skill measures with respect to worker age, race/ethnicity, gender, and educational attainment. Online Appendix Figure A-6 shows that the resulting patterns are very similar to the raw estimates shown in Figure 1. These results highlight 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).

Because of large differences in union coverage and occupational sorting by gender, we now turn to an examination of changes in skill content of unionized jobs separately for men and women. Figure 3 shows trends in standardized skill measures by gender and union status.[15] 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 is much larger than the increase in this skill category among non-unionized workers (0.296).[16] The gap between union and non-union skills hence declined by 0.125 standard deviations. The manual or routine skill measure declined among unionized men by 0.182 standard deviations. This was smaller than the 0.257 standard deviation decline among non-unionized men, resulting in an increase in this skill difference of 0.076 standard deviations among unionized relative to non-unionized men. As with the overall pattern, there is clear increased stratification of skills across male union and non-union worker occupations, with relative increases in both skill groups.

Changes for women are larger than among men, which highlights the importance of examining this under-analyzed group in the private sector union literature.[17] 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 skills gaps across union and non-union workers thus declined by 0.212 standard deviations. The decline in routine or manual skill requirements of unionized jobs was particularly pronounced among women, dropping by 0.921 standard deviations. As Figure 3 shows, as of the early 2000s, unionized work among women required relatively more non-routine, cognitive skill than routine or manual skill. We do not observe a similar crossing among unionized men. The decline in routine or manual skill for unionized women was similar to what non-union female workers experienced, such that there was little relative change across sectors in routine or manual job requirements. Hence, the

[15] Online Appendix Figure A-7 presents analogous results for the five disaggregated skill groups, while Figure A-8 shows results using skills that have been residualized with respect to worker characteristics (age, educational attainment, and race/ethnicity).

[16] Online Appendix Figure A-1 presents trends in each occupational skill for men by union and non-union status on the same figure (identical to Figure 1) to facilitate comparisons across union and non-union workers. Online Appendix Figure A-2 presents the same information for women.

[17] With the exception of Card, Lemieux, and Riddell (2020), all of the prior literature on the private sector union wage premium focuses on men.

increase in manual/routine skills among unionized workers relative to non-unionized workers is concentrated among men.

Because of differences in how skill coverage of unionized and non-unionized workers varies by gender, driven in part by differences in how men and women sort into occupations, we examine men and women separately in the remainder of the paper. Pooled estimates are available from the authors upon request.

4.2. Decomposition of Skill Changes

The results discussed above show that the skill composition of occupations and workers covered by unions has changed considerably over time. Unionized work has shifted to include more non-routine, cognitive skills and less manual or routine skill. At the same time, there has been a polarization in skills across union and non-union workers. These results raise a central question: why has unionized work changed in this way?

As a first step in understanding why private sector unionization coverage has changed in the manner shown in Section 4.1, 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 occupation, (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 the private sector union decline 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 skill level of skill *S* among unionized workers can then be written as follows:

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

$$\bar{S}^u_{1973} = \left(\sum_{k_1} S^u_{k_1 1973} * \omega^u_{k_1 1973}\right) * \tau_{1973} + \left(\sum_{k_2} S^u_{k_2 1973} * \omega^u_{k_2 1973}\right) * (1 - \tau_{1973}) \quad (2)$$

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

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

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:

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

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

$$
\begin{aligned}
\bar{S}^u_{2017} - \bar{S}^u_{1973} = {} & \tau_{2017} * \left\{ \sum_{k_1} S^u_{k_1 2017} * \left(\omega^u_{k_1 2017} - \omega^u_{k_1 1973}\right) + \sum_{k_1} \omega^u_{k_1 1973} * \left(S^u_{k_1 2017} - S^u_{k_1 1973}\right) \right\} \\
& + \left(\sum_{k_1} S^u_{k_1 1973} * \omega^u_{k_1 1973} \right) * \left(\tau_{2017} - \tau_{1973}\right) + \left(\sum_{k_3} S^u_{k_3 2017} * \omega^u_{k_3 2017} \right) \\
& * \left(1 - \tau_{2017}\right) + \left(\sum_{k_2} S^u_{k_2 1973} * \omega^u_{k_2 1973} \right) * \left(1 - \tau_{1973}\right) \qquad (5)
\end{aligned}
$$

The first term in curly brackets in equation (5) shows the change in skill coverage among union workers due to changes in worker sorting across existing occupations between 2017 and 1973. This part of the decomposition shows us how much of the observed change in skills among unionized workers between 1973 and 2017 is due only to changes in the concentration of workers across existing occupations. That is, it shows us what union coverage of skill *S* in 2017 would have been 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 (5) 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 (5) is that it shows what the average skill level would have been in 2017 had the skill requirements of occupations been the same as in 1973.

The last three terms in equation (5) show the effect of occupational entry and exit 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 on the role of skill-biased technological change in driving changes in the skill content of unionized jobs.

Results of this decomposition are shown in Table 5.[18] 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 skill increased by 0.422 standard deviations among men between 1973 and 2017. The part due to changes across existing occupations is 0.141 standard deviations, which is 33.30% of the total, while 0.208 standard deviations (49.39%) is due to changes in the occupational mix from entry and exit. Together, these two components explain 82.69% of the total change in this skill coverage. The remaining 17.31% is explained by within-occupation changes in skill requirements.

The change due to worker share and due to entry/exit of occupations each explains over 100% of the total change in the coverage of routine or manual skills among men. The within-occupation change, however, moves in the opposite direction. But for the fact that unionized professions have become more manual and routine, the decline in routine or manual skills of unionized jobs would have declined even more. These findings highlight the importance of examining each of these forces separately to paint a more complete picture of how unionized work has changed over time. Taken together, the results in Panel A of Table 5 show that most of the changes to the skill composition of male unionized jobs are due to shifts in the composition of workers across existing occupations and occupation entry/exit.

Online Appendix Tables A-2 and A-3 shows decompositions for changes in skill coverage from 1973-1990 and 1990-2017, respectively.[19] This sub-period analysis is informative because the rise of computers and information technology such as the Internet occurred largely after 1990. The results in each sub-period generally align with overall decomposition estimates, with one notable difference: the within-occupation routine/manual skill change is negative and sizable in the early period and is positive in the later period. It also is the case that changes due to occupational entry/exit explain a relatively larger share of the non-routine, cognitive skill increase between 1973 and 1990, while changes in worker share across occupations is relatively

[18] Decompositions for each of the five disaggregated skill groups are presented in Online Appendix Table A-5. The results are similar to those in Table 5.
[19] 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.

more important in the later period.

Panel B of Tables 2, 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 is 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 routine or manual skill. The sub-period analyses show a similar pattern in Appendix Tables A-2 and A-3. While changes in skill coverage are larger post-1990 than pre-1990, the changes in each period are driven by shifts in workers across occupations and occupational entry/exit.

Sub-period decompositions in Online Appendix Tables A-2 and A-3 tell a somewhat similar story as the overall decompositions. In the early period, within-occupation changes are important for explaining the decline in routine or manual skill, while changes due to worker shares are less important. In the later period, occupation entry/exit has less explanatory power for both skill groups, and within-occupation shifts in skill requirements take on more importance. The sub-period decompositions continue to show the importance of worker shifts across occupations and occupation entry/exit, however they also suggest a somewhat larger role for within-occupation changes as well.

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 explain none of the increase in non-routine, cognitive skills, which suggests that this is a key source of the narrowing of the gap in this skill between union and non-union jobs. For routine or manual skill, there is little role for within-occupation changes and a more modest role for the other two categories. The non-routine, cognitive decomposition results are similar among women for union and non-union workers, while the results for routine or manual show a large role for within-occupation changes in explaining the decline in this skill requirement among non-unionized women.

4.3. A Model of Return to Skill and Unionization

The findings from Section 4.1 demonstrate that unionized jobs have become higher-skilled in terms of non-routine cognitive skills for both men and women. In addition, male unionized workers are in positions that require slightly more manual or routine skills, while unionized women are in occupations that require less routine or manual skills. Our decompositions in Section 4.2 demonstrate that changes in both workers' share across occupations and occupational entry/exit have produced large increases in non-routine, cognitive skill coverage and declines in manual and routine skill coverage for both genders. Within-occupation skill changes often obscure these broader patterns in manual or routine skill prevalence, however, especially for men.

As discussed above, these findings are inconsistent with the existing model of SBTC and unionization because it predicts unionized workers should become *less* skilled over time (Acemoglu, Aghion, and Violante 2001). This leads to an important question of what type of model can produce the patterns we document.[20]

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.[21] 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 to 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.

Second, there are large frictions associated with de-unionizing. Workers can vote to decertify a union and cease collective negotiations, but such decertification elections are rare. Figure 4 shows trends in certification and decertification elections from 1962-2009, which we

[20] Farber et al. (2021) also discuss the fact that their findings are in contradiction to the predictions from Acemoglu, Aghion, and Violante (2001), however they do not pose a different model that can explain their results.
[21] Online Appendix Figure A-3 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.

obtained from publicly-available National Labor Relations Board 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. Further, the fraction of new certification elections won each year has remained relatively constant throughout the time period considered. The bottom panel shows similar tabulations for decertification elections. Decertification elections are much rarer, and only about 100 bargaining units win such elections each year. Figure 4 shows clearly that the net inflow of newly-unionized bargaining units is an order of magnitude larger than the outflow of workers who no longer collectively bargain.[22] Holding the distribution of workers across occupations fixed, Figure 4 shows that there would be a persistent increase in absolute private sector union coverage over time.

Appendix Figure A-16 provides information on the number of union elections and election success over time by industry. We collapse the industries into three aggregate groups to facilitate interpretation of the results: Manufacturing, Services, and "Other." The figure shows that 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-16 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/manual skills. This evidence is consistent with our model but not with models that predict lower levels of unionization among higher-skilled professions. Notably, 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

[22] Dickens and Leonard (1985) present similar evidence that decertification elections cannot explain the decline in private sector unionization prior to 1980.

be more decertification elections among higher-skilled professions, fewer certification elections among these professions, and a greater difficulty in winning these elections in higher-skilled jobs. To explore this set of hypotheses, Appendix Figures A-14 and A-15 show 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 (Appendix Figure A-14) and routine/manual (Appendix Figure A-15). 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 non-routine cognitive professions are highly successful at certifying and continue to be, and the opposite is true for routine/manual. 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 for the interpretation of our results also is shown in Figure 4: 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 (Kleiner 2001; Farber and Western 2001). As a result, the barriers to collective bargaining entry for new occupations is high, which likely dissuades many of these workers from engaging in organization efforts.

We present a Roy model that is an extension of Acemoglu, Aghion, and Violante (2001) which accounts 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.[23] Each occupation has a skill

[23] 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.

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:

$$S_{oi} = S_o + \eta_i \; , \tag{6}$$

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:

$$W_{ofi} = \gamma^{fo} S_o + \beta^{fo} \eta_i, \tag{7}$$

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 frictions in the model. The first is job switching costs, $\bar{e}$. This cost can come from the existence of firm-specific training costs or from 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 4 highlights the uncertainty associated with a decertification drive as well.

Skill-biased technological change 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:

$$W^U = \gamma^{Uo} S_o + \beta^{Uo} \eta_i \tag{8}$$

$$W^N = \gamma^{No} S_o + \beta^{No} \eta_i = \beta^{No}(S_o + \eta_i) \tag{9}$$

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

$$\bar{e} \leq S_o(\gamma^{No} - \gamma^{Uo}) + \eta_i(\beta^{No} - \beta^{Uo}) \tag{10}$$

Equation (10) 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 (10) 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 Sections 4.1 and 4.2.[24] 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 have any effect on firm (and thus union) choice.

The prior literature on unions indicates a sizable union wage premium on the order of 0.2 log points. That is, $\gamma^{Uo}$is about 20% higher than γ^{No}. That unionized workers are paid more on

[24] There likely are other models that also produce these predictions, although none have been presented in prior work. Our goal is to provide a simple Roy Model framework to understand the patterns we present in the data. We do not argue that this is the only model that aligns with our results. A more thorough theoretical analysis is an important area for further research.

average than are non-unionized workers in 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 to a non-unionized firm. As long as the skill variance is not very large within each occupation, SBTC itself will 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 therefore is 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 to the one presented 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 6. 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 6 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. As long as unions can negotiate wages such that the return to this average skill is similar to what non-union workers experience, 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 drive unionization decisions. Whether unions generate a return to average skill and the resulting effect of these skill returns combined with changes in the skill coverage of unions has not been documented in prior research. We now turn to such an analysis to provide new evidence on these questions.

5. Private Sector Union Wage Premium

5.1. Empirical Approach

What effect has the changes to union skill coverage had on the union wage premium? Several recent papers show that the returns to unionization have remained stable over the past 40 years (Farber et al. 2021; Card, Lemieux, and Riddell 2020). This is a surprising finding, especially in light of the above analysis which demonstrates that the skills covered by unionized workers have changed considerably. Most importantly, they have changed relative to non-union workers. In this section, we examine the implications of these changes for the union wage premium.

The traditional model used to estimate the wage returns to unionization is a simple log-linear regression model that relies on selection-on-observables (Freeman and Medoff 1984):

$$Ln(w)_{it} = \beta_0 + \beta_1 Union_i + \gamma X_i + \phi_t + \epsilon_{it}, \tag{11}$$

where $w_{it}$is the wage of individual *i* in year *t*, *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, and ϕ_t are year fixed effects. These models are usually estimated using repeated cross-section micro data, such as the CPS, which contains only sparse worker observables such as age, race, gender, and educational attainment.

We estimate expanded versions of equation (11) in which we directly account for skills in two different ways. First, we simply control for each skill level in each occupation (c) and year: S_{ct}. Specifically, we estimate models of the following form:

$$Ln(w)_{ict} = \beta_0 + \beta_1 Union_{ic} + \sum_{j=1}^{2} \phi^j S_{ct}^j + \gamma X_i + \phi_t + \theta_c + \epsilon_{it}, \tag{12}$$

In equation (12), the S_{ct}^j terms act as controls for skill, essentially treating skills as a previously-unobserved confounder in equation (11). We also include in equation (12) occupation fixed effects. These fixed effects are rarely included in union wage regressions, but if workers sort into occupations based on unobserved aspects of productivity, occupation effects and union effects can be confounded. Furthermore, occupation fixed effects capture much of the variation in job skills that could be important if there is measurement error in the skill measures we use or if there are other dimensions of skill that we cannot capture with our data. To facilitate comparisons with prior work, we show estimates both with and without occupation fixed effects. Standard errors are clustered at the occupation level throughout the analysis.

In equation (12), the union wage premium, β_1, is *net* of the skills included in each occupation. These skills may be an important component of the union wage premium, however. In our final model, we include skill-union interactions that incorporate this effect in the estimated union wage premium:

$$Ln(w)_{ict} = \beta_0 + \beta_1 Union_{ic} + \sum_{j=1}^{2} \phi^j S_{ct}^j + \sum_{j=1}^{2} \tau^j S_{ct}^j * Union_{ic} + \gamma X_i + \phi_t + \theta_c + \epsilon_{it}. \tag{13}$$

The union wage premium in equation (13) is given by $\beta_1 + \sum_{j=1}^{2} \tau^j \bar{S}$. This summation term incorporates any differential returns to each skill that is granted to unionized workers that does not apply to non-unionized workers. Standard errors are calculated using the Delta Method.

5.2. Results

Figure 5 presents estimates of the union wage premium for our three models by year. Panel (a) presents results for men while panel (b) shows estimates for women. All of these estimates include occupation fixed effects. Aligned with the findings in Farber et al. (2021) and Card, Lemieux, and Riddell (2020), we find that the union wage premium has remained relatively stable over time when one compares the early 70s to 2017. However, there is evidence for men and women that the union wage premium has fallen since its peak in the mid-1980s: the union wage premium from the "basic" model declines by about 11 percentage points for both men and women from 1985 to 2017.

For men, we find that failing to account for skills has led to an understatement of the union wage premium of about 2 percentage points up until the early 2000s, after which the bias from ignoring skills is positive but is very small. The result of this difference is that the fall in the union wage premium since the mid-1980s is larger, at about 15 percentage points. Accounting for skills has a negligible effect on the wage premium among women, with the wage-inclusive estimates falling within 1 percentage point of the more traditional model estimate in most years. Interestingly, across genders, the models that control for job skill and that include skills in the union wage premium estimate are nearly identical. Hence, the specific way in which we control for job skill requirements does not matter.[25]

Table 6 presents estimates for select years in each decade as well as standard errors. For men, the traditional estimates without fixed effects or skill controls shows a union wage premium of between 24 and 35 percent. Once we include skill controls, the estimates increase by 4-6 percentage points prior to the 2000s and thereafter are slightly lower than the skill-exclusive estimates. Hence, ignoring occupational fixed effects and incorporating skills into the regression shows a stronger pattern of declining wage returns to unionization. When we control for occupation fixed effects, the estimates become somewhat larger and exhibit a similar time pattern. As with the estimates in Figure 5, these results indicate that the union wage premium is still high but has declined since the early 2000s.

Panel B shows results for women. Similar to the results for men, the inclusion of occupation fixed effects increases the estimates, but the difference is much smaller, at 1-2 percentage points. Adding in skill measures further increases the wage premium, which in all models declines by about 11-13 percentage points from the peak in 1985. The results and conclusions are unchanged when controlling for occupation fixed effects.

The effect of accounting for the skills of unionized jobs on the union wage premium depends both on changes in the skills covered by unionized jobs over time as well as changes in the returns to those skills across the union and non-union sectors. As discussed in Section 4.3, the ability of unions to alter the return to average skill has important implications for the role of technological change in driving declines in unionization rates. Figure 6 presents the first

[25] Online Appendix Figure A-9 shows union wage premium estimates that incorporate the five disaggregated skill groups. The estimates for men are nearly identical to those in Figure 5, while for women the skill-inclusive union wage premium is slightly higher in all years than the skill-exclusive premium. Union premium estimates for select years in each decade are shown in Online Appendix Table A-6.

estimates in the literature on how these different components of the union wage premium are changing over time for men.[26] The solid and dashed lines shows the same changes in each skill presented in Online Appendix Figure A-1 and discussed in Section 4.1. The open circles and squares show the coefficients on the skill measure and the skill measure interacted with union, respectively, in the wage regression. 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 skill, the return to skill among unionized jobs declines in the 1990s both in an absolute terms and relative to the return in non-union jobs. Beginning in the early 2000s, the returns to this skill increase substantially, and by the end of our sample period union and non-union workers experience similar return to non-routine, cognitive skill.
That the returns to this skill is high and has increased relative to the non-union sector over the past two decades underscores the point that skill-biased technological change has not necessarily reduced the incentive for skilled workers to unionize.[27]

The bottom panel of Figure 6 shows similar estimates for routine or manual skill. The return to these skills are positive and similar for union and non-union workers until the 1990s, at which point the returns drop for non-unionized relative to unionized workers. As a result, by the mid-2000s the return to manual/routine skill is substantially higher in the union sector.[28]

Figure 7 allows for non-linearity in the returns to skill by allowing the returns to vary by quartile of the non-routine, cognitive skill level. The top panel shows estimates for non-unionized workers, while the bottom panel shows results for unionized workers. There is a clear non-linearity in both sectors, with the returns to skill being highest among the highest skill quartile jobs. The non-linearity is strongest in the unionized sector, where the returns to skill are

[26] Online Appendix Figures A-10 and A-11 show the returns to skill estimates for each of the five disaggregated skill groups among men and women, respectively.

[27] 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-17. 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 increasing in the unionized sector, and supports the notion that skill-biased technological change has not necessarily reduced the incentive for skilled workers to unionize.

[28] To better understand the role of automation in explaining these results, we estimated the return to non-routine, cognitive skills and routine or manual skills separately for production and non-production workers (using the BLS/SOC code definitions of production occupations). These results are shown in Appendix Figure A-12 for men and A-13 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.

almost entirely concentrated in the fourth quartile. These results suggest that changes in the return to skill have had different effects across different unionized professions. The gains from increasing return to non-routine, cognitive skills in the economy have flowed towards the higher-skilled professions, even in the unionized sector. This has important implications for inequality that is a ripe area for future work.

Estimates of the return to skill for women are presented in Figure 8. For both skill groups, unionized women experienced lower returns to skill than their non-union counterparts early in the sample. Beginning in the 1990s for routine/manual skills and in the early 2000s for non-routine, cognitive skills, the returns converged across sectors. Currently, unionized and non-unionized women experience a similar return to both skills. Figure 9 explores whether these returns to skill are linear with skill. As with men, the returns are highest for the fourth skill quartile, and the non-linearity is strongest among unionized workers.

That unionized workers experience a substantial return to skill that has grown over time in both absolute terms and relative to the non-union sector is at odds with the predictions from prior models for how SBTC should affect unionization. Those models assert that unionization reduces the return to skill and leads high-skilled workers to opt out of unionization. Instead, the results are consistent with a model in which there are frictions in both unionization and de-unionization as well as a shift in workers and occupations towards the non-unionized sectors. These shifts in workers and occupations are in turn being driven by SBTC, which alters the industrial mix of the economy. The unionization frictions are sufficient to keep these new occupations or the growing non-unionized jobs from unionizing at high rates, even though the financial return to doing so is high. It is the combination of SBTC and these unionization frictions that generate the patterns we show in the data.

6. Discussion and Conclusion

This paper presents the first analysis of how the skills covered by unionized employment have changed over time and how these changes affect the union wage premium. 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 towards more non-routine, cognitive skills and less routine skills. These changes are evident overall and separately for men and women, though the shifts are larger for women than for men. Relative to non-union workers, we document an increased polarization of skills: union, non-union skill gaps decline for non-routine, cognitive skill, while relative skills gaps increase for routine or manual skills.

We next decompose the changes in skill coverage we document 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 skills we document for men. For women, we additionally find some role for within-occupation changes in skill requirements. Finally, we show how accounting for these skill changes affect the estimated union skill premia. For both men and women, we first document a substantial decline of about 11 percentage points in the union wage premium since 1985. The bias from excluding skill measures is small; skill-inclusive premia are larger in the early part of the sample and then converge. The decline in the union wage premium is larger when we account for skills among men, while for women the decline is the same magnitude. We also present the first evidence in the literature that unions generate a high return to skill that has grown in absolute terms and relative to the non-union sector.

We argue that increasing skill coverage among unionized jobs 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 return to skill 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. Our results are consistent with this assumption. Rather, SBTC shifts workers to previously non-unionized professions and creates new professions that are not unionized. The high cost of engaging in a unionization drive we argue 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. Over time, unionized employment has moved away from manual and routine jobs and towards more non-routine and cognitive 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. 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.

References

[1] Acemoglu, Daron, Philippe Aghion, and Giovanni L. Violante. 2001. "Deunionization, Technical Change and Inequality." In *Carnegie-Rochester Conference Series on Public Policy* 55: 229–264. Elsevier.

[2] Acemoglu, Daron and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics* 4: 1043–1171. Elsevier.

[3] Autor, David, Lawrence F. Katz, and Melissa Kearney. 2006. "Measuring and Interpreting Trends in Economic Inequality." *AEA Papers and Proceedings* 96: 189–194.

[4] Autor, David, Alan Manning, and Christopher L Smith. 2016. "The Contribution of the Minimum Wage to US Wage Inequality over Three Decades: A Reassessment." *American Economic Journal: Applied Economics* 8(1): 58–99.

[5] Autor, David, Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in US Wage Inequality: Revising the Revisionists." *The Review of Economics and Statistics* 90(2): 300–323.

[6] Autor, David, Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics* 118(4): 1279–1333.

[7] Blanchflower, David G. and Alex Bryson. 2004. "What Effect do Unions Have on Wages Now and Would Freeman and Medoff Be Surprised?" *Journal of Labor Research* 25(3): 383–414.

[8] Card, David. 1996. "The Effect of Unions on the Structure of Wages: A Longitudinal Analysis." *Econometrica* 64(4): 957–979.

[9] Card, David. 2001. "The Effect of Unions on Wage Inequality in the US Labor Market." *Industrial and Labor Relations Review* 54(2): 296–315.

[10] Card, David, Thomas Lemieux, and W. Craig Riddell. 2020. "Unions and Wage Inequality: The Roles of Gender, Skill and Public Sector Employment." *Canadian Journal of Economics* 53(1): 140-173.

[11] Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." *The Quarterly Journal of Economics* 132(4): 1593–1640.

[12] DiNardo, John, Nicole M. Fortin, and Thomas Lemieux. 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach." *Econometrica* 64(5): 1001-1044.

[13] Farber, Henry S., Daniel Herbst, Ilyana Kuziemko, and Suresh Naidu. 2021. "Unions and Inequality over the Twentieth Century: New Evidence from Survey Data." *Quarterly Journal of Economics* 136(3): 1325-1385.

[14] Farber, Henry S. and Bruce Western. 2001. "Accounting for the Decline of Unions in the Private Sector, 1973–1998." *Journal of Labor Research* 22(3): 459–485.

[15] Firpo, Sergio, Nicole Fortin, and Thomas Lemieux. 2016. "Decomposing Wage Distributions using Recentered Influence Function Regressions." *Econometrica* 6(2): 28.

[16] Fortin, Nicole and Thomas Lemieux. 2016. "Inequality and Changes in Task Prices: Within and Between Occupation Effects." In *Inequality: Causes and Consequences; Research in Labor Economics*, volume 43, pages 195–226. Emerald Group Publishing Limited.

[17] Frandsen, Brigham R. 2016. "The Effects of Collective Bargaining Rights on Public Employee Compensation: Evidence from Teachers, Firefighters, and Police." *Industrial and Labor Relations Review* 69(1): 84–112.

[18] Freeman, Richard B. and James L. Medoff. 1984. "What Do Unions Do?" *Industrial and Labor Relations Review* 38(2): 244.

[19] Hirsch, Barry T. and Edward J. Schumacher. 2004. "Match Bias in Wage Gap Estimates Due to Earnings Imputation." *Journal of Labor Economics* 22(3): 689–722.

[20] Kaplan, Greg and Sam Schulhofer-Wohl. 2012. "Interstate Migration has Fallen Less Than You Think: Consequences of Hot Deck Imputation in the Current Population Survey." *Demography* 49(3): 1061–1074.

[21] Kleiner, Morris M. 2001. "Intensity of Management Resistance: Understanding the Decline of Unionization in the Private Sector." *Journal of Labor Research* 22(3): 519–540.

[22] Lewis, H. Gregg. 1986. "Union Relative Wage Effects." In *Handbook of Labor Economics* 2: 1139–1181.

[23] Ruggles, Steven, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. IPUMS USA: Version 9.0 [dataset]. Minneapolis, MN: IPUMS, 10:D010, 2019.

Table 1: Summary Statistics, Private Sector Workers, 1973-2017

Panel A: Men				
	Union		Non-Union	
Variable	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
Routine or Manual Skill	0.427	0.886	-0.059	0.884
Non-Hispanic White(%)	74.4		70.9	
Non-Hispanic Black(%)	10.8		8.4	
Non-Hispanic Other(%)	3.3		5.1	
Hispanic(%)	11.5		15.7	
N	251,540		1,510,836	

Panel B: Women				
	Union		Non-Union	
Variable	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
Routine or Manual Skill	-0.022	0.794	-0.337	0.761
Non-Hispanic White(%)	65.9		73.5	
Non-Hispanic Black(%)	16.7		10.3	
Non-Hispanic Other(%)	5.7		4.9	
Hispanic(%)	11.7		11.2	
N	109,754		1,566,716	

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**

	Occ. Share of Union Employment	% Occ in Union	Non-Routine, Cognitive	Routine or Manual
1973				
Machine operators, n.e.c.	8.85	57.77	-0.66	1.37
Truck, delivery, and tractor drivers	8.8	46.54	-0.88	-0.54
Heavy equipment and farm equipment mech	3.34	50.66	-0.44	1.16
Assemblers of electrical equipment	3.28	62.99	-0.97	0.40
Welders and metal cutters	2.88	63.69	-0.39	0.92
2017				
Truck, delivery, and tractor drivers	8.24	11.70	-0.36	0.75
Electricians	4.86	31.01	0.10	1.36
Laborers outside construction	4	12.18	-0.99	0.36
Construction laborers	3.25	9.54	-0.89	0.86
Carpenters	3.14	16.09	0.10	1.31

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

	Occ. Share of Union Employment	% Occ in Union	Non-Routine, Cognitive	Routine or Manual
1973				
Textile sewing machine operators	10.48	36.15	-1.03	1.77
Machine operators, n.e.c.	10.18	43.07	-0.66	1.37
Assemblers of electrical equipment	8.36	41.63	-0.97	0.40
Cashiers	6.90	25.94	-0.58	1.00
Packers, fillers, and wrappers	6.04	43.62	-1.07	-0.34
2017				
Registered nurses	13.95	13.73	1.15	-0.25
Nursing aides, orderlies, and attendants	6.94	7.16	-0.13	-0.12
Primary school teachers	4.34	18.41	0.99	-1.43
Cashiers	4.05	4.21	-1.31	-1.02
Customer service reps, investigators and adjusters, except insurance	2.67	4.07	0.26	-1.32

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 women. 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	Unionization Rate 1973	Unionization Rate 2017	Occupation 2017	Unionization Rate 1973	Unionization Rate 2017
Actors, directors, producers	1.00	0.13	Railroad conductors & yardmasters	0.89	0.71
Railroad conductors & 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: Routine or Manual

Occupation 1973	Unionization Rate 1973	Unionization Rate 2017	Occupation 2017	Unionization Rate 1973	Unionization Rate 2017
Explosives workers	1.00	0.33	Locomotive operators (engineers and firemen)	1.00	0.60
Millwrights	0.81	0.48	Locomotive operators (engineers and firemen)	1.00	0.60
Structural Metal Workers	0.80	0.44	Elevator installers/repairers	N/A	0.58
Telecom/Line Installers & Repairers	0.77	0.29	Millwrights	0.81	0.48
Lay-out Workers	0.75	N/A	Structural metal workers	0.80	0.44
Patternmakers and Model Makers	0.74	0.74	Other plant & system operators	Reclassified	0.38

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. "Rec" refers to an occupation that was reclassified between 1973 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	
	Skill Type	:
Change Category	Non-Routine Cognitive	Routine or Manual
Total Change	0.422	-0.182
Change due to Worker Share	0.141	-0.203
	[33.30%]	[111.63%]
Change due to Intra-Occ. Skills	0.073	0.223
	[17.31%]	[-122.90%]
Change due to Occupation Entry/Exit	0.208	-0.202
	[49.39%]	[111.27%]
	Panel B: Women	
	Skill Type	:
Change Category	Non-Routine Cognitive	Routine or Manual
Total Change	0.830	-0.921
Change due to Worker Share	0.492	-0.219
	[59.24%]	[23.79%]
Change due to Intra-Occ. Skills	0.052	-0.368
	[6.26%]	[39.92%]
Change due to Occupation Entry/Exit	0.286	-0.334
	[34.50%]	[36.29%]

Authors' estimation of equation (5) in the text. 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 6: Union Wage Premium Estimates by Decade

Panel A: Men

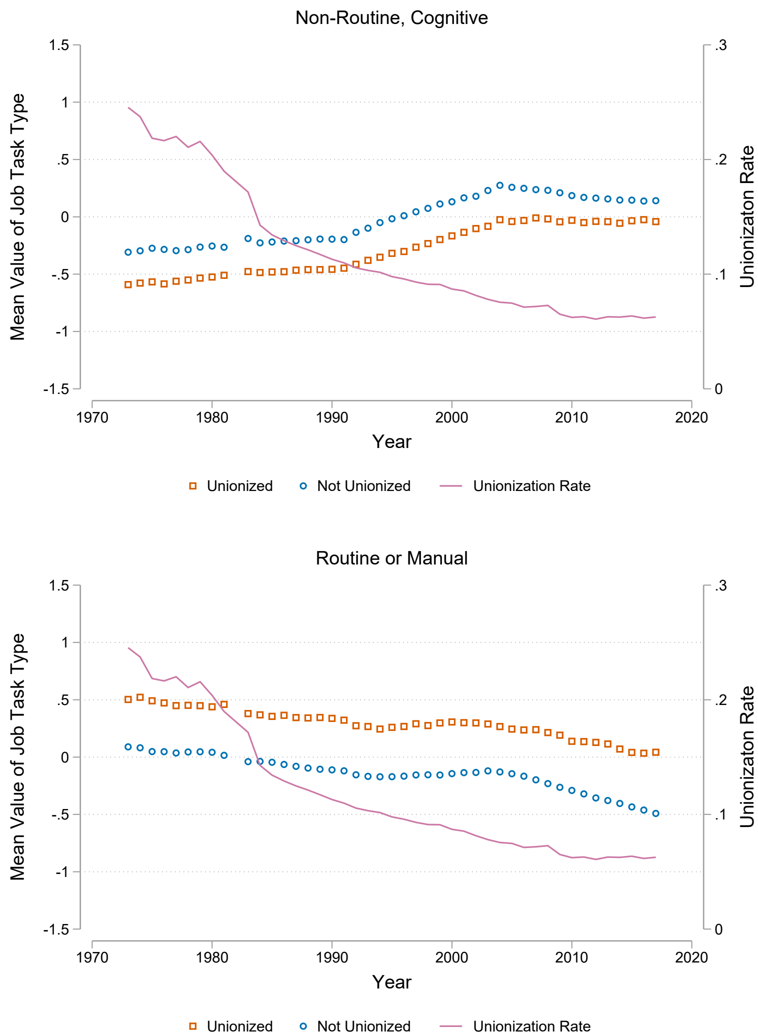
Year	Basic Model (i)	Skill Controls (ii)	Skill Interactions (iii)	Basic Model (iv)	Skill Controls (v)	Skill Interactions (vi)
1975	0.224***	0.281***	0.281***	0.301***	0.314***	0.313***
	(0.026)	(0.027)	(0.025)	(0.019)	(.020)	(0.019)
1985	0.301***	0.354***	0.354***	0.360***	0.383***	0.382***
	(0.026)	(0.021)	(0.023)	(0.017)	(0.015)	(0.014)
1995	0.228***	0.281***	0.281***	0.282***	0.307***	0.305***
	(0.028)	(0.019)	(0.018)	(0.018)	(0.015)	(0.012)
2005	0.243***	0.236***	0.236***	0.296***	0.289***	0.284***
	(0.028)	(0.025)	(0.021)	(0.019)	(0.019)	(0.014)
2015	0.219***	0.215***	0.215***	0.271***	0.265***	0.259***
	(0.035)	(0.027)	(0.024)	(0.023)	(0.022)	(0.023)
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***	0.266***	0.266***	0.280***	0.281***	0.287***
	(0.030)	(0.031)	(0.025)	(0.026)	(0.027)	(0.028)
1985	0.292***	0.311***	0.311***	0.317***	0.321***	0.325***
	(0.027)	(0.031)	(0.025)	(0.022)	(0.022)	(0.017)
1995	0.219***	0.245***	0.245***	0.238***	0.250***	0.253***
	(0.025)	(0.023)	(0.022)	(0.015)	(0.016)	(0.018)
2005	0.218***	0.220***	0.220***	0.221***	0.224***	0.225***
	(0.040)	(0.033)	(0.038)	(0.018)	(0.018)	(0.023)
2015	0.219***	0.217***	0.217***	0.216***	0.217***	0.217***
	(0.049)	(0.028)	(0.026)	(0.021)	(0.020)	(0.024)
Occupation FE	No	No	No	Yes	Yes	Yes

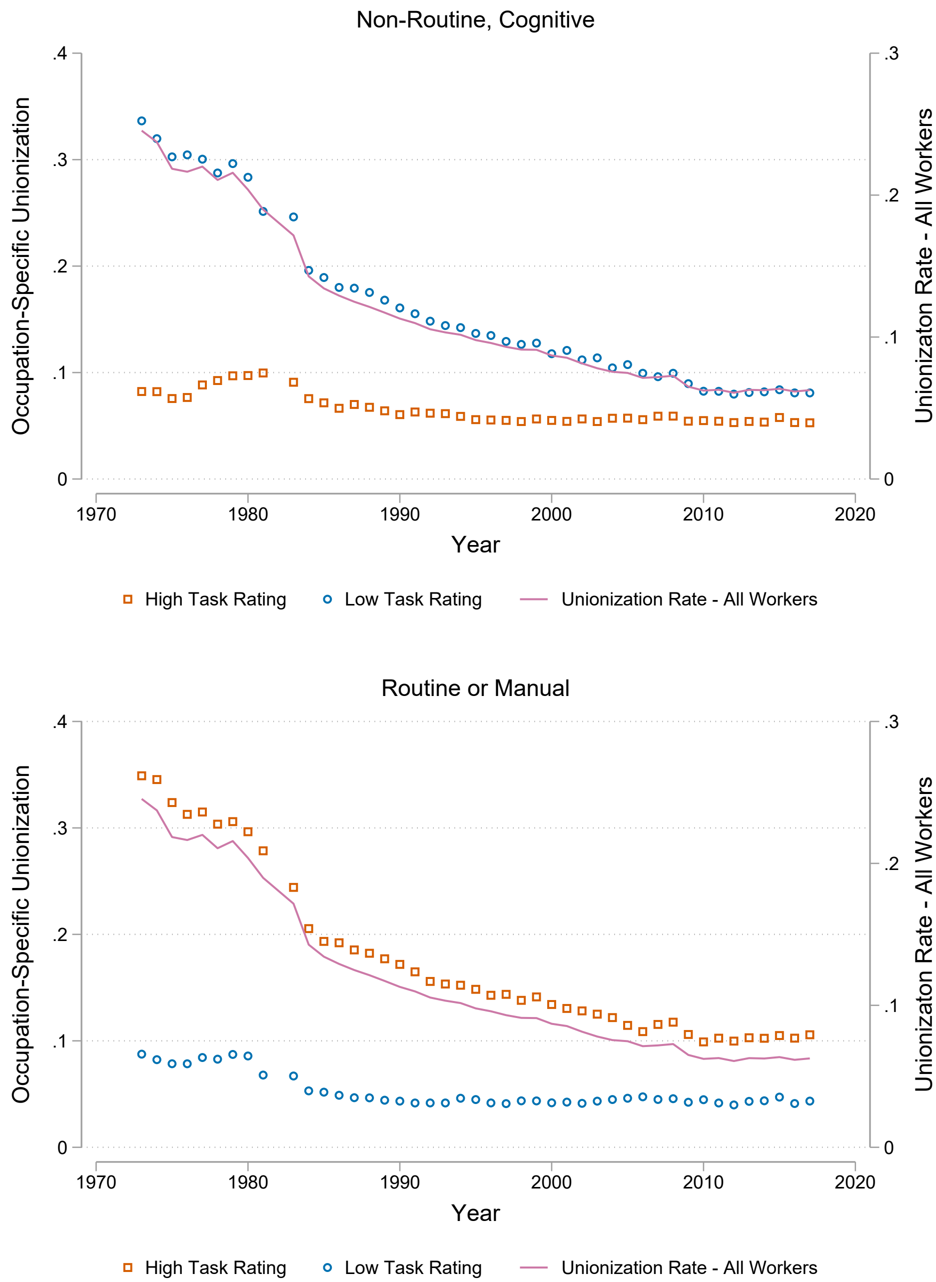
Notes: Authors' estimation of equation (1) as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET. Only results for selected years are shown: full estimates are presented in Figure 5. All estimates include controls for education, race, and age. 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.

Figure 1: Trends in Occupational Skill Requirements by Union Status



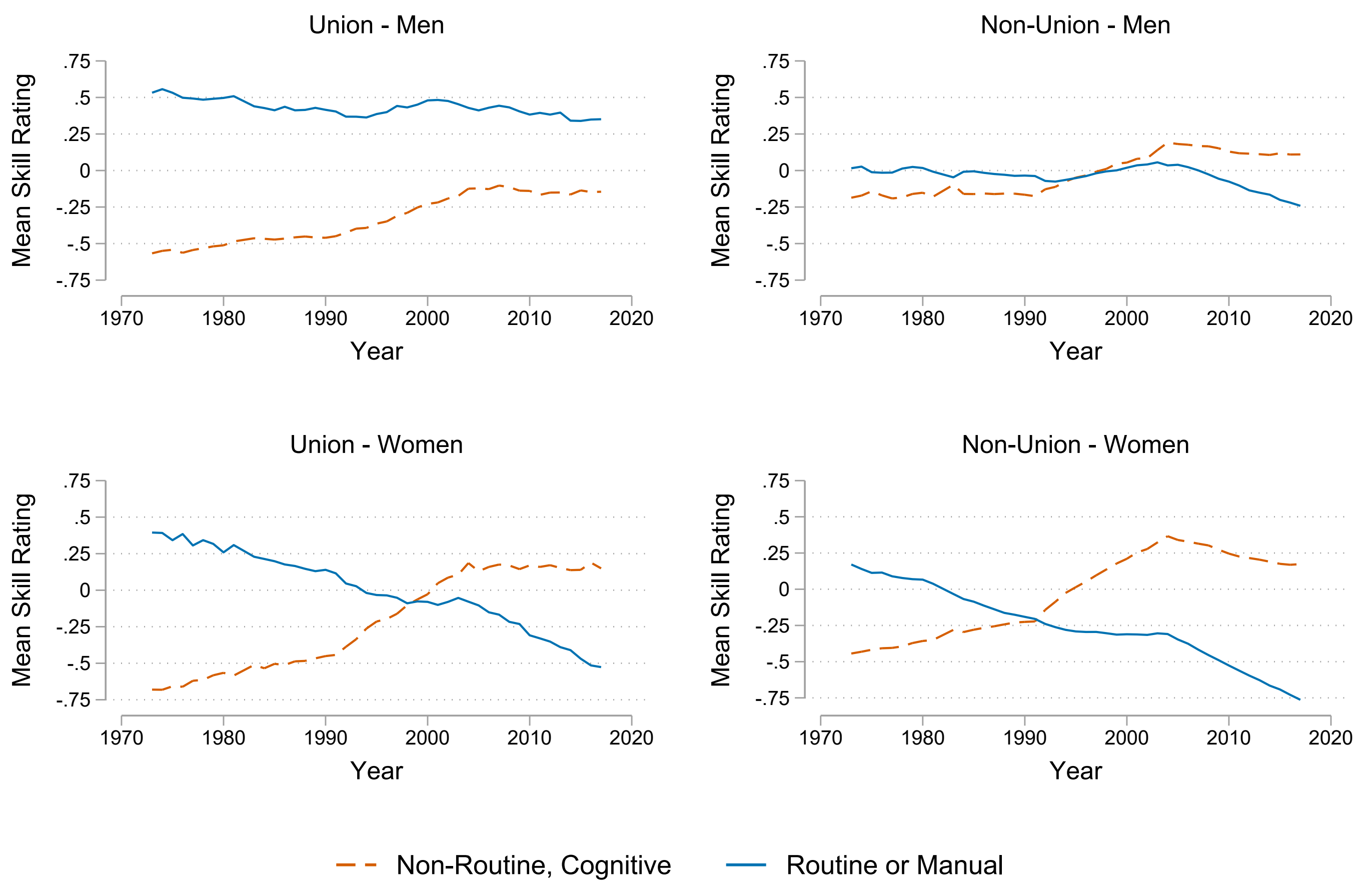
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

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



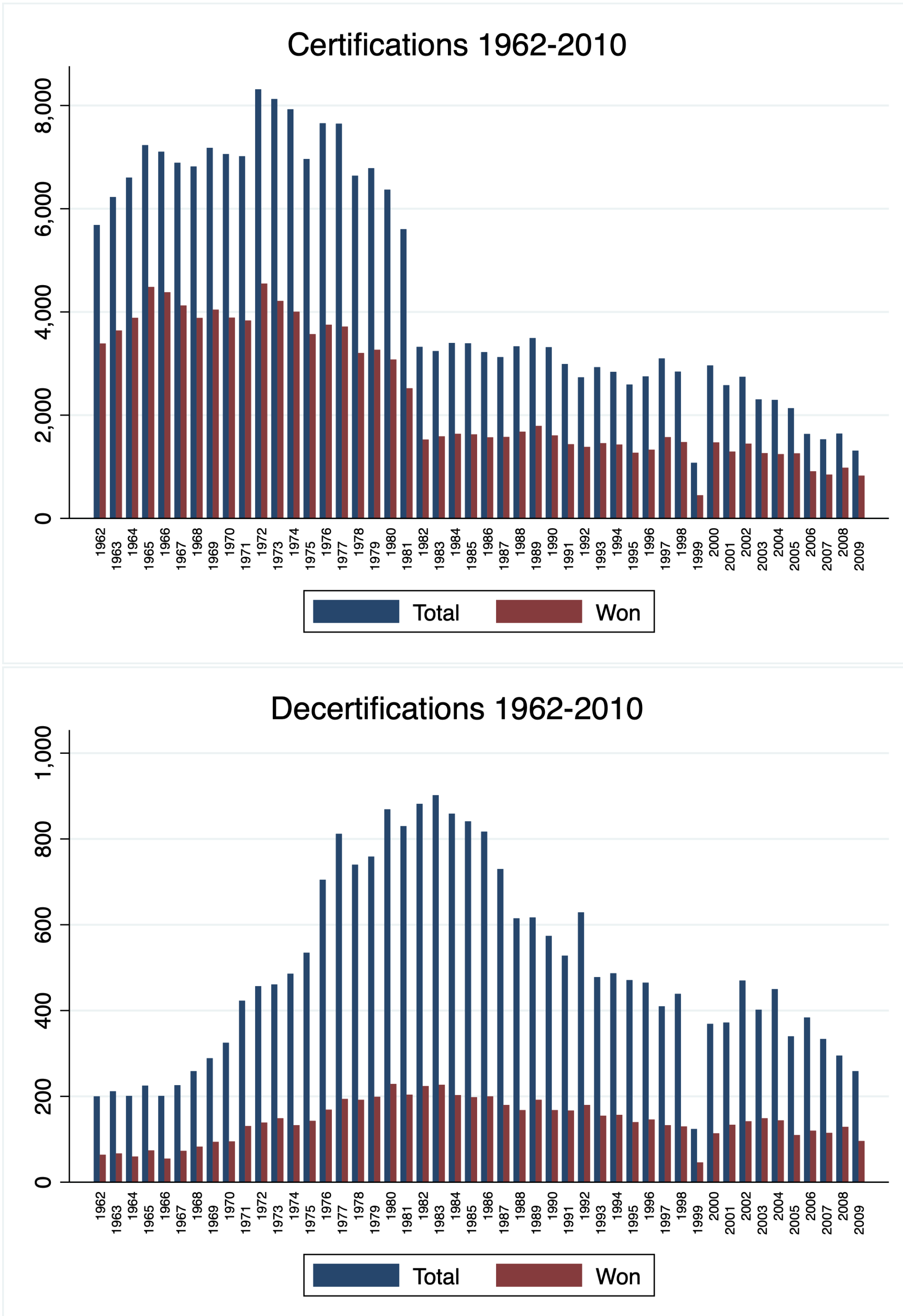
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure 3: Trends in Occupational Skill Requirements by Union Status and Gender



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

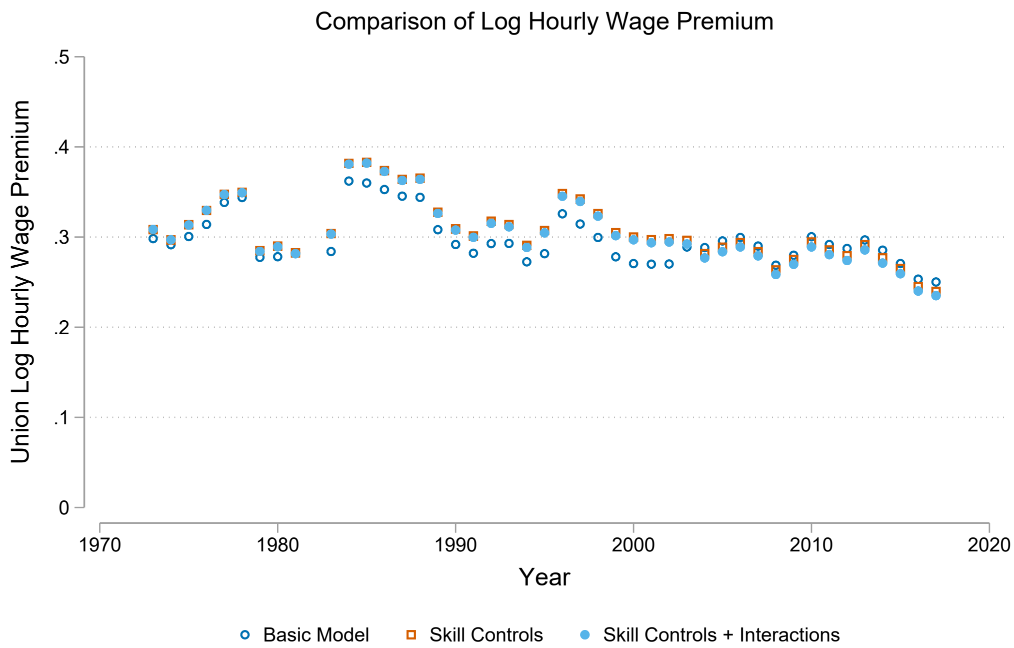
Figure 4: Certification and Decertification Elections, 1962-2009



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

Figure 5: Trends in the Union Wage Premium

(a) Men



(b) Women

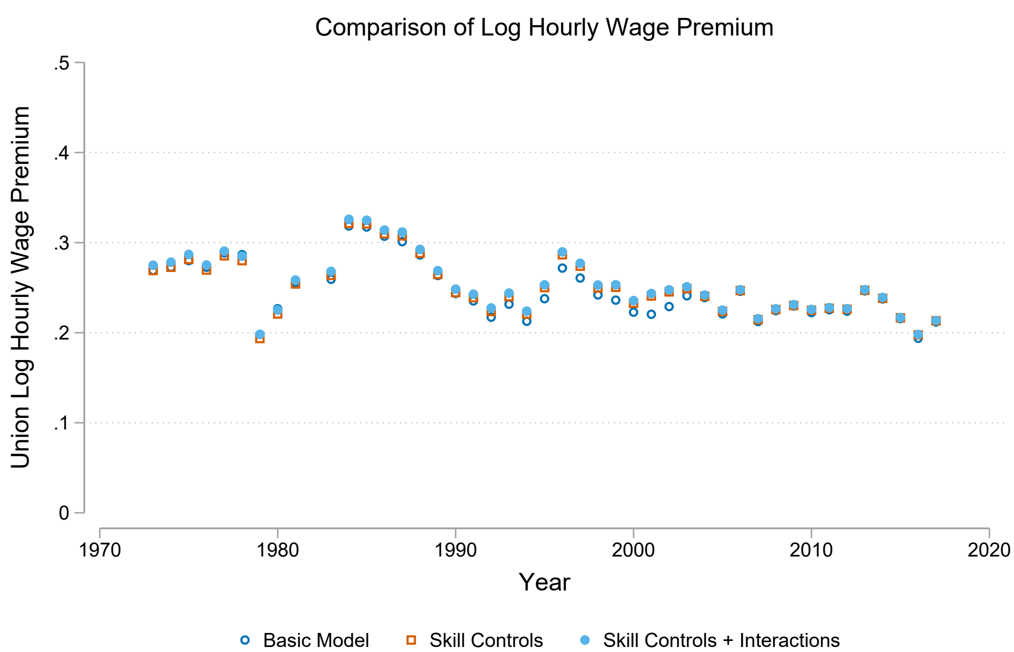
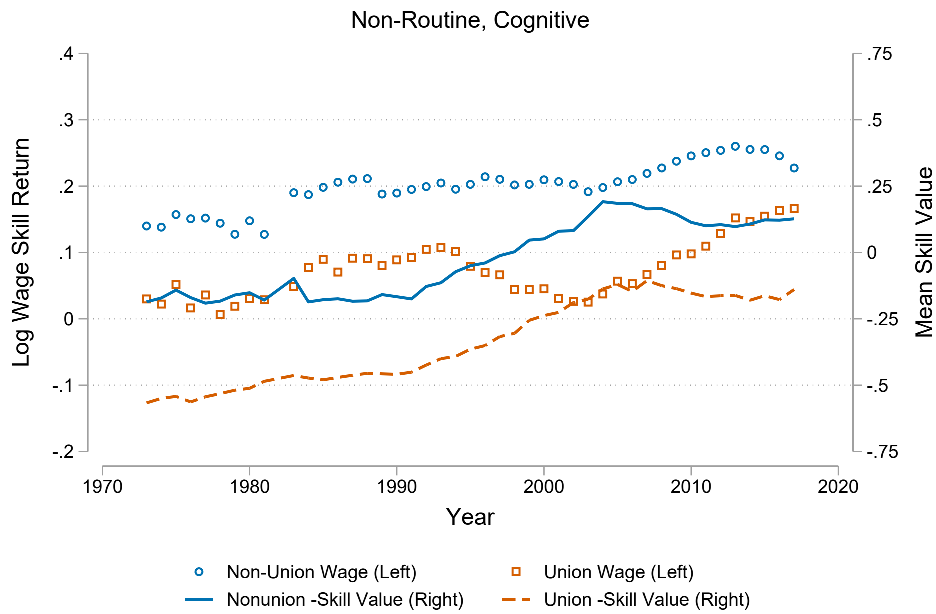
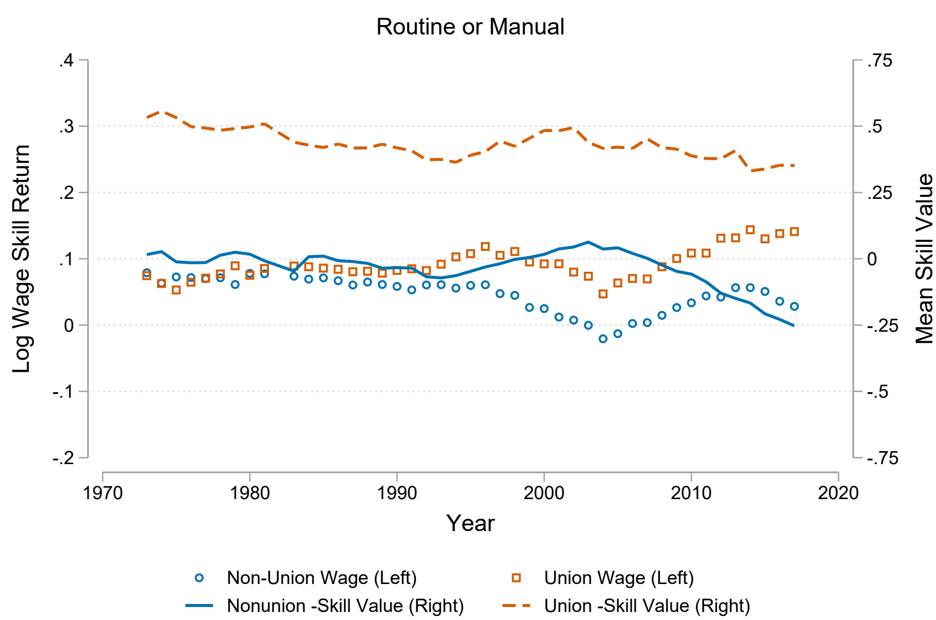


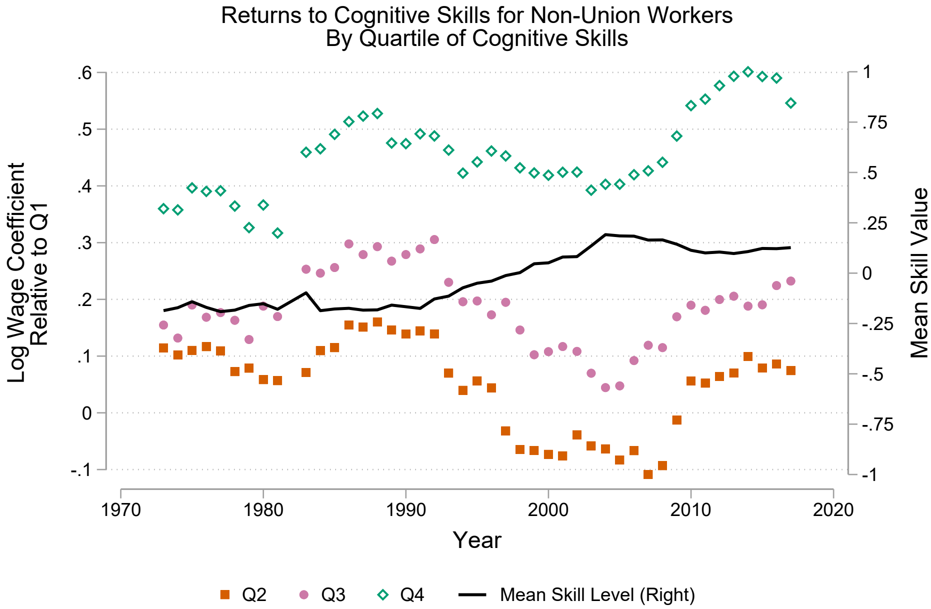
Figure 6: Trends in the Return to Job Skills by Union Status - Men

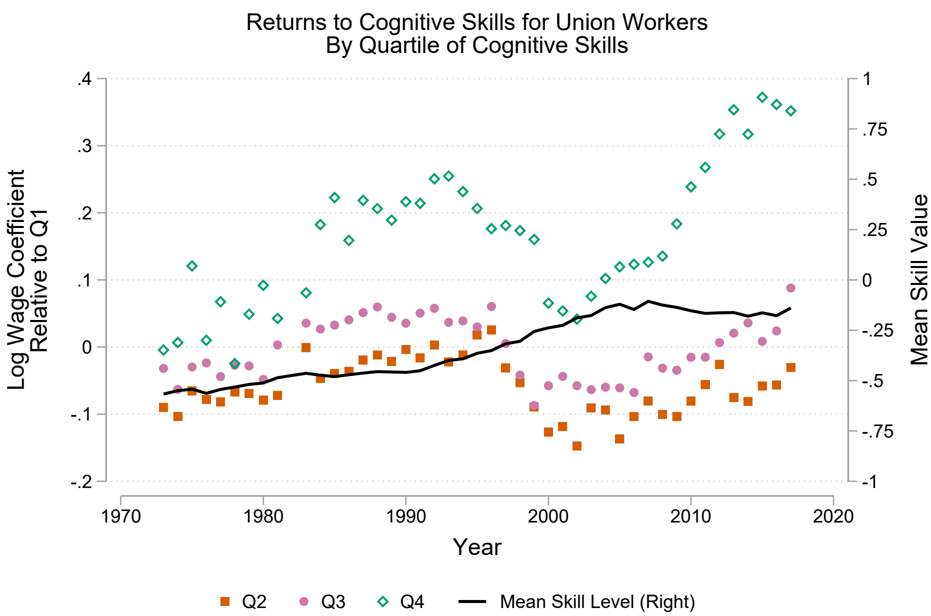




Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

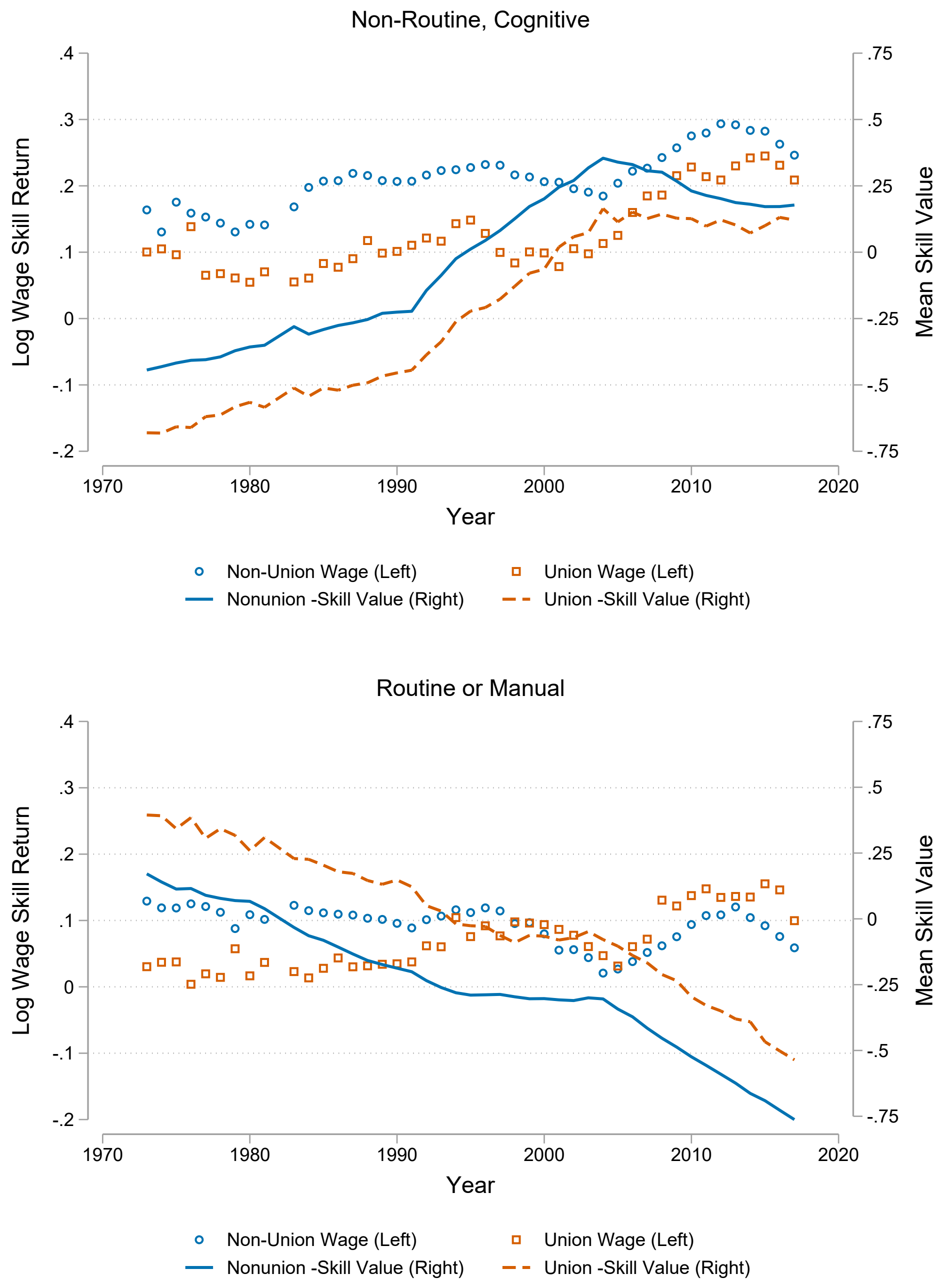
Figure 7: Trends in the Return to Job Skills by Union Status and Quartile - Men





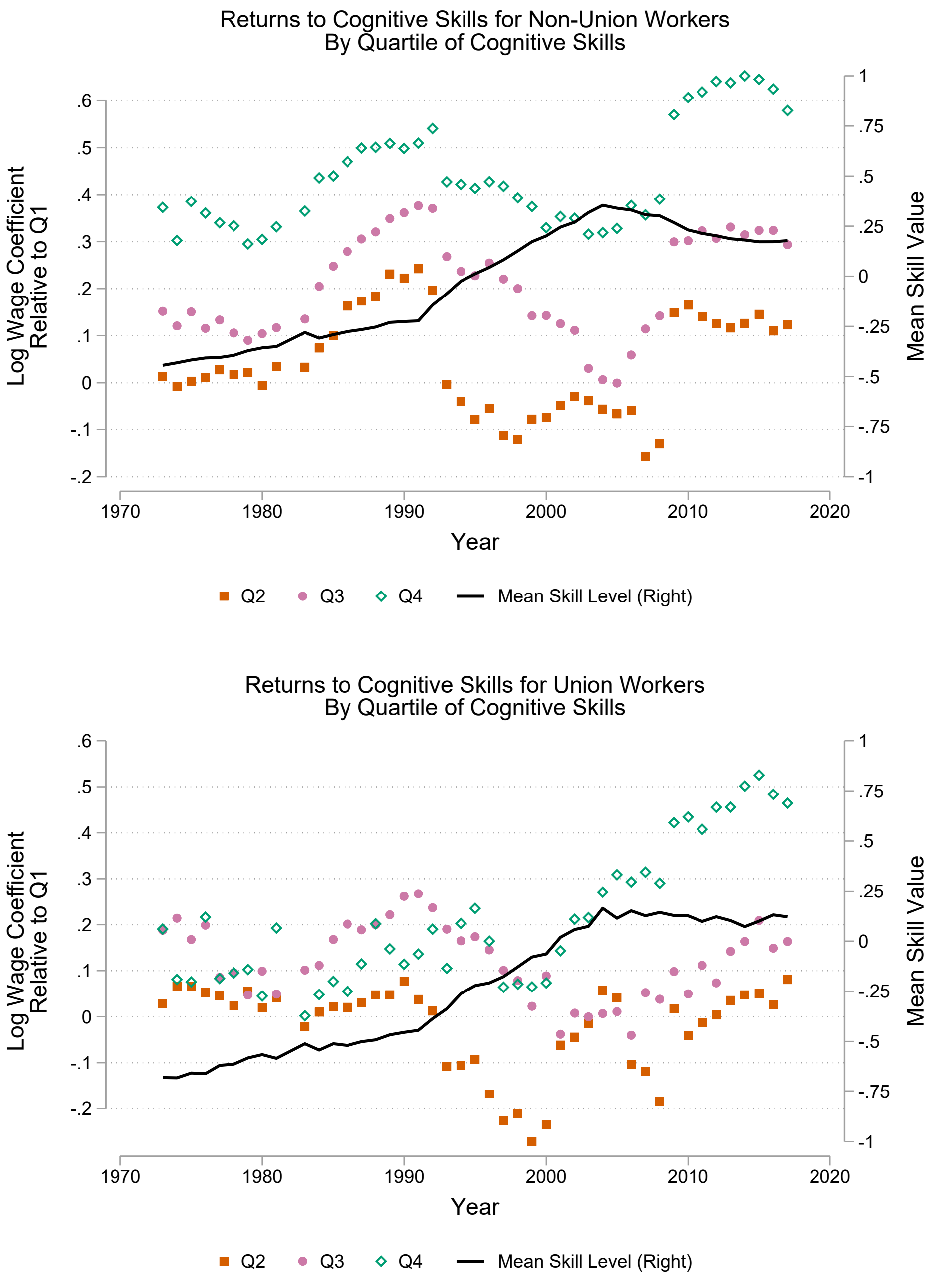
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure 8: Trends in the Return to Job Skills by Union Status - Women



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

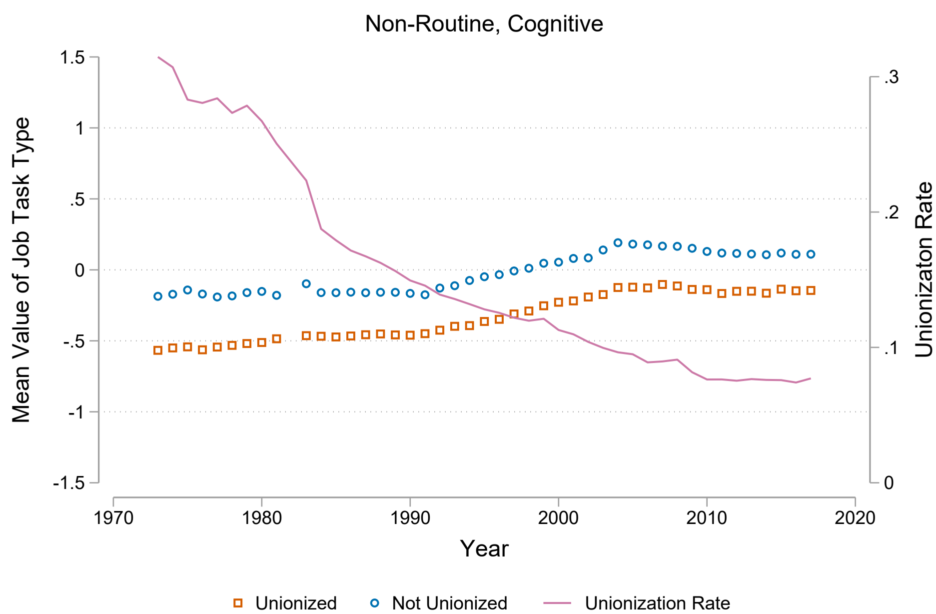
Figure 9: Trends in the Return to Job Skills by Union Status and Quartile - Women

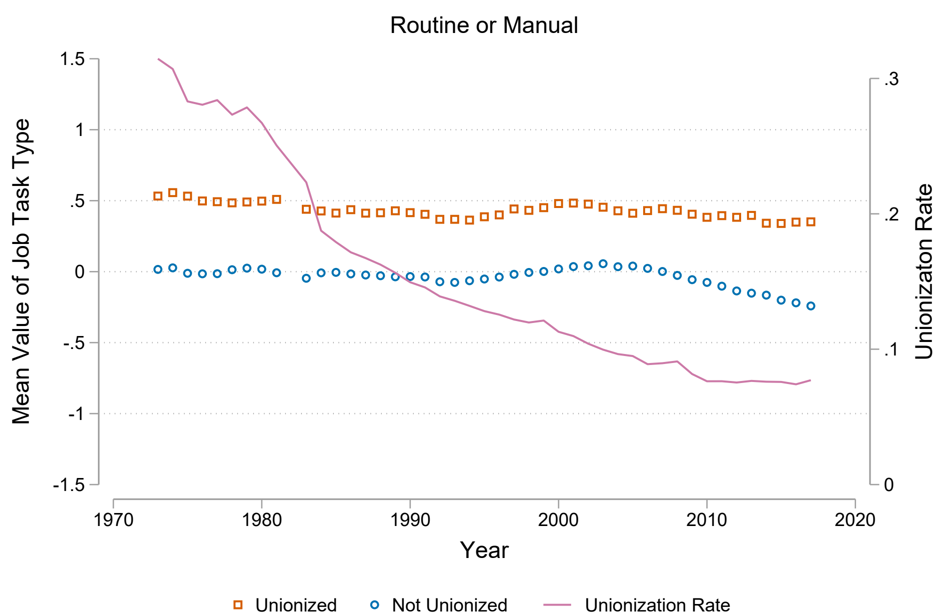


Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Online Appendix: Not for Publication

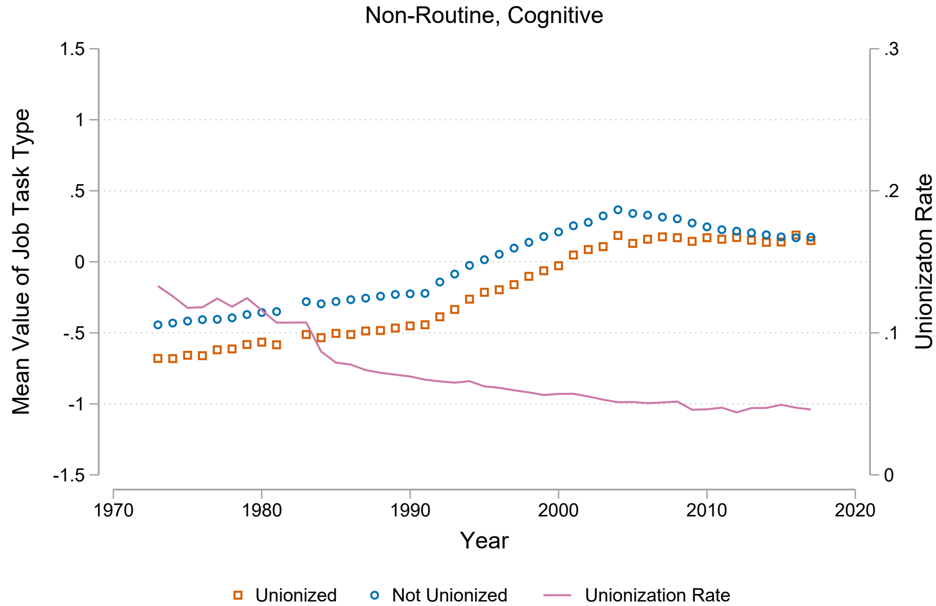
Figure A-1: Trends in Occupational Skill Requirements by Union Status and Skill Measure – Men

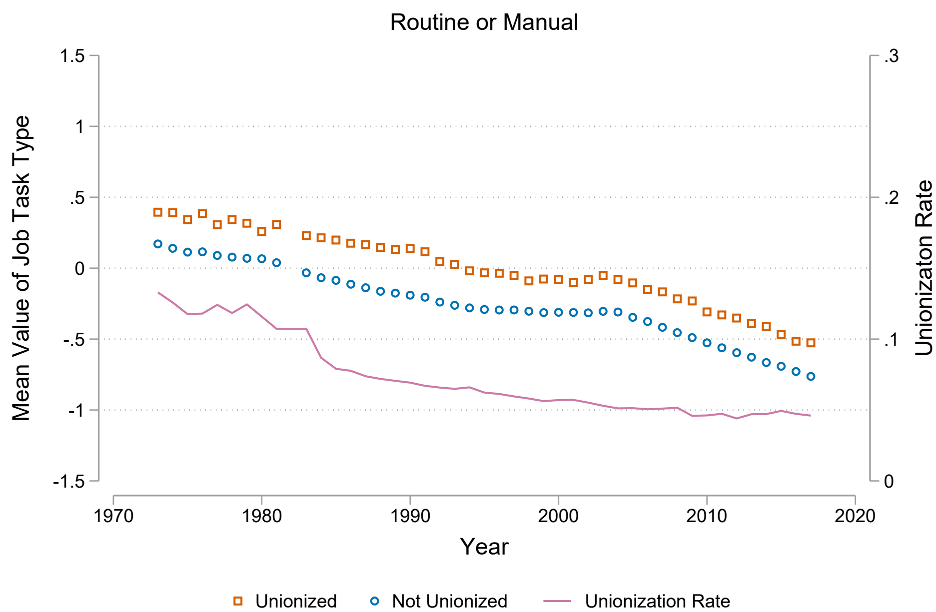




Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

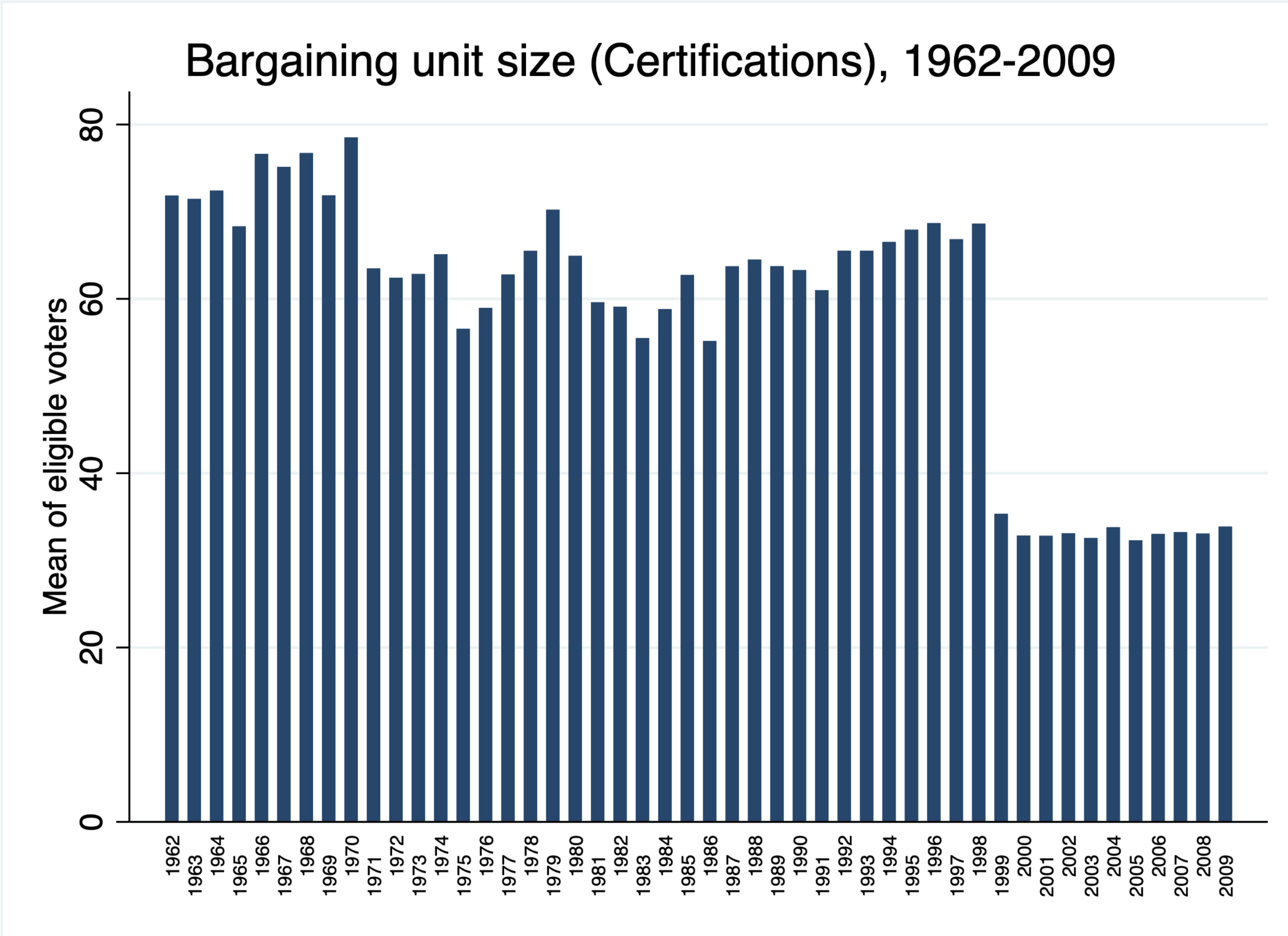
Figure A-2: Trends in Occupational Skill Requirements by Union Status and Skill Measure – Women





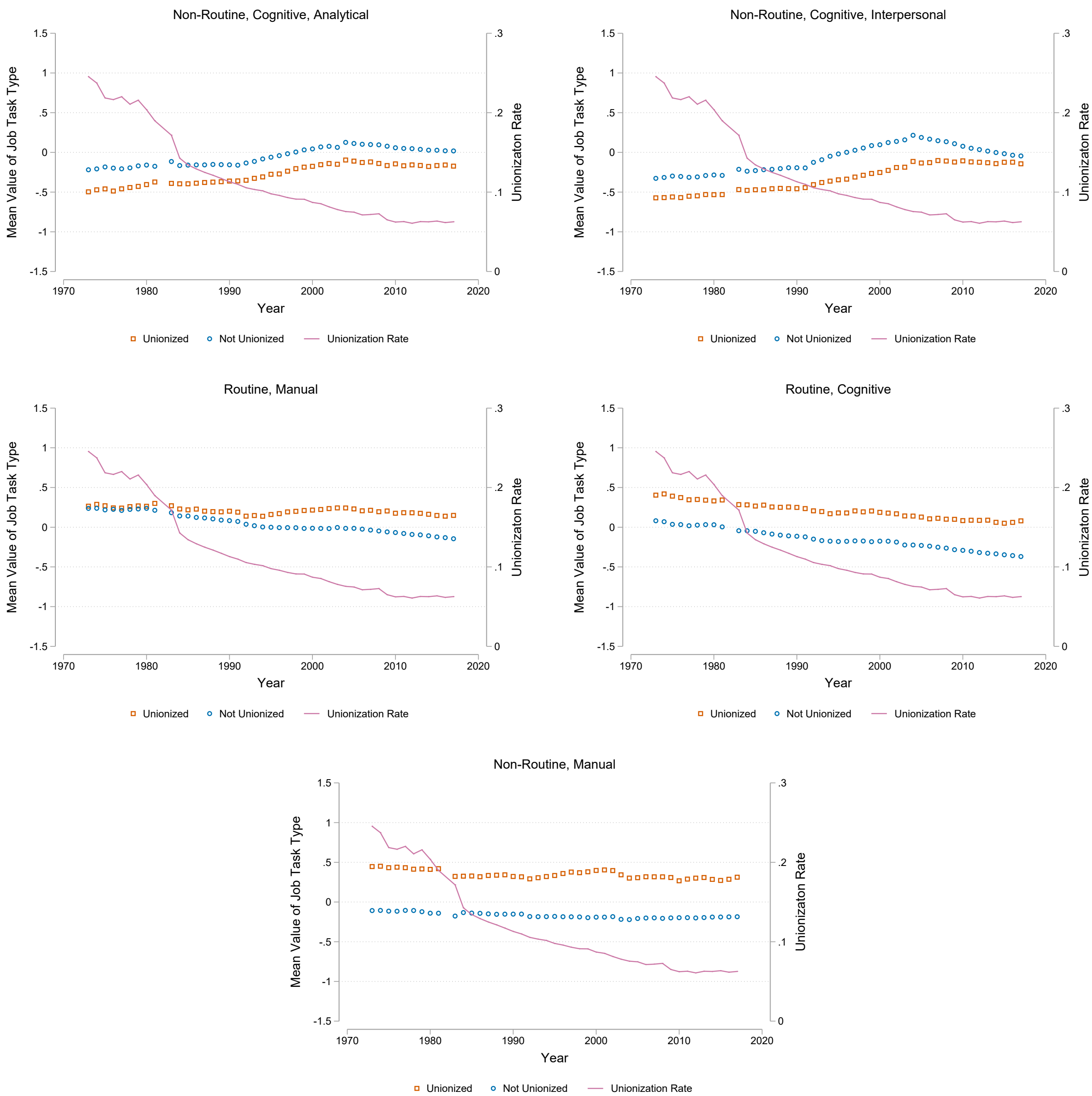
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure A-3: Bargaining Unit Size in Union Representation Elections, 1962-2009



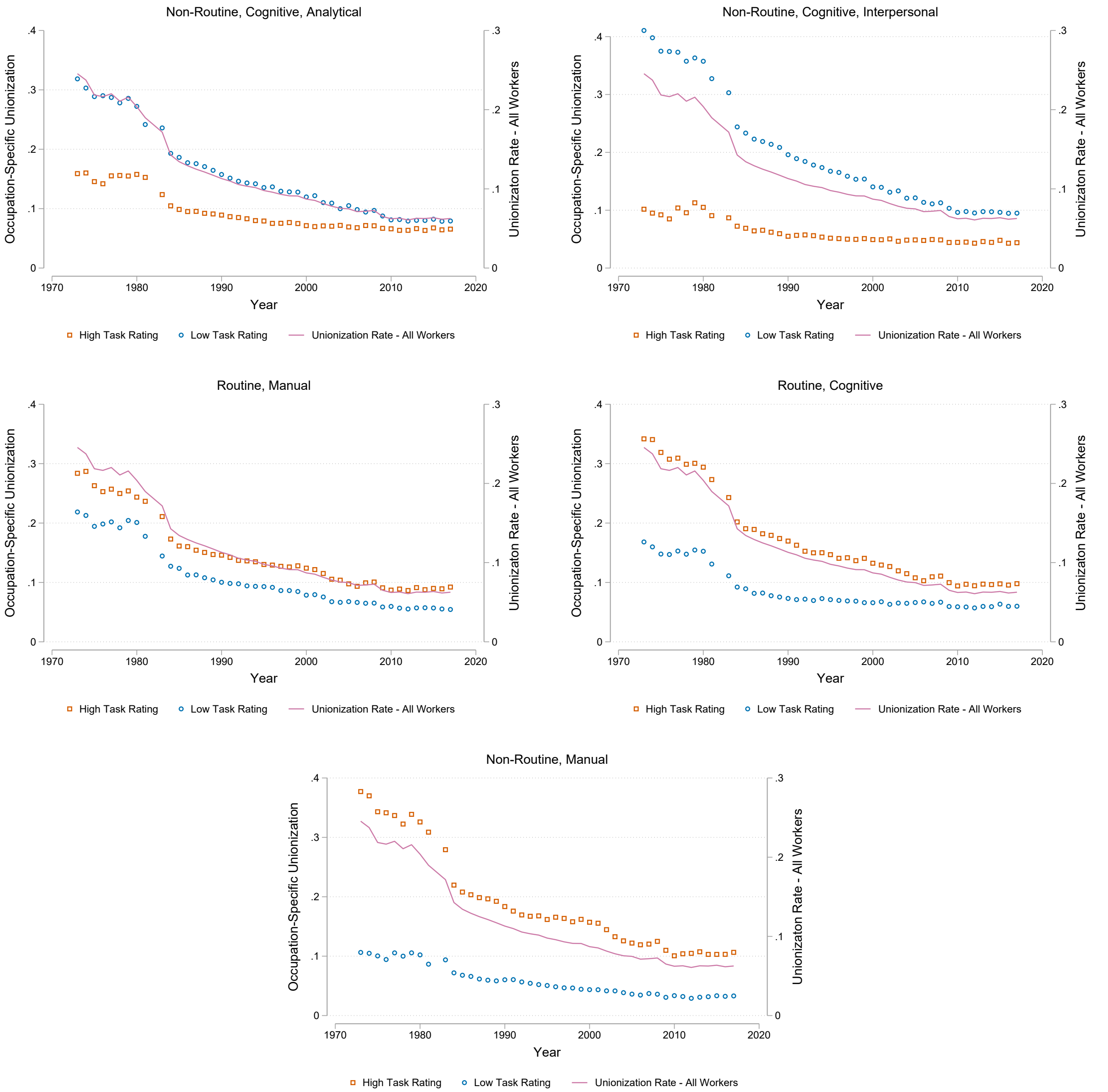
Source: Authors' tabulations from National Labor Relations Board Data.

Figure A-4: Trends in Occupational Skill Requirements by Union Status, Disaggregated Skill Measures



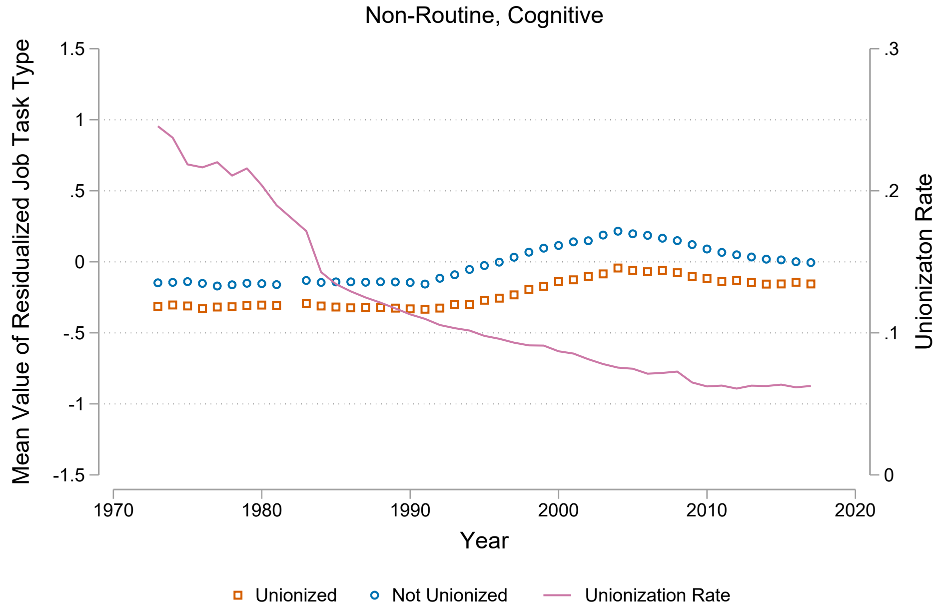
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

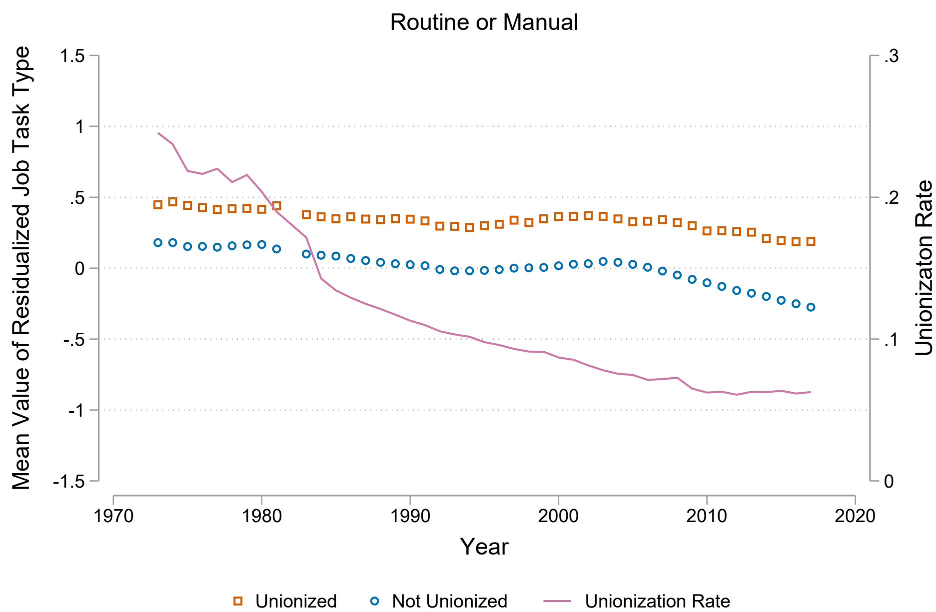
Figure A-5: Trends in Occupational Skill Requirements Among Unionized Occupations by Top and Bottom Quartile of Skill Level, Disaggregated Skill Measures



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

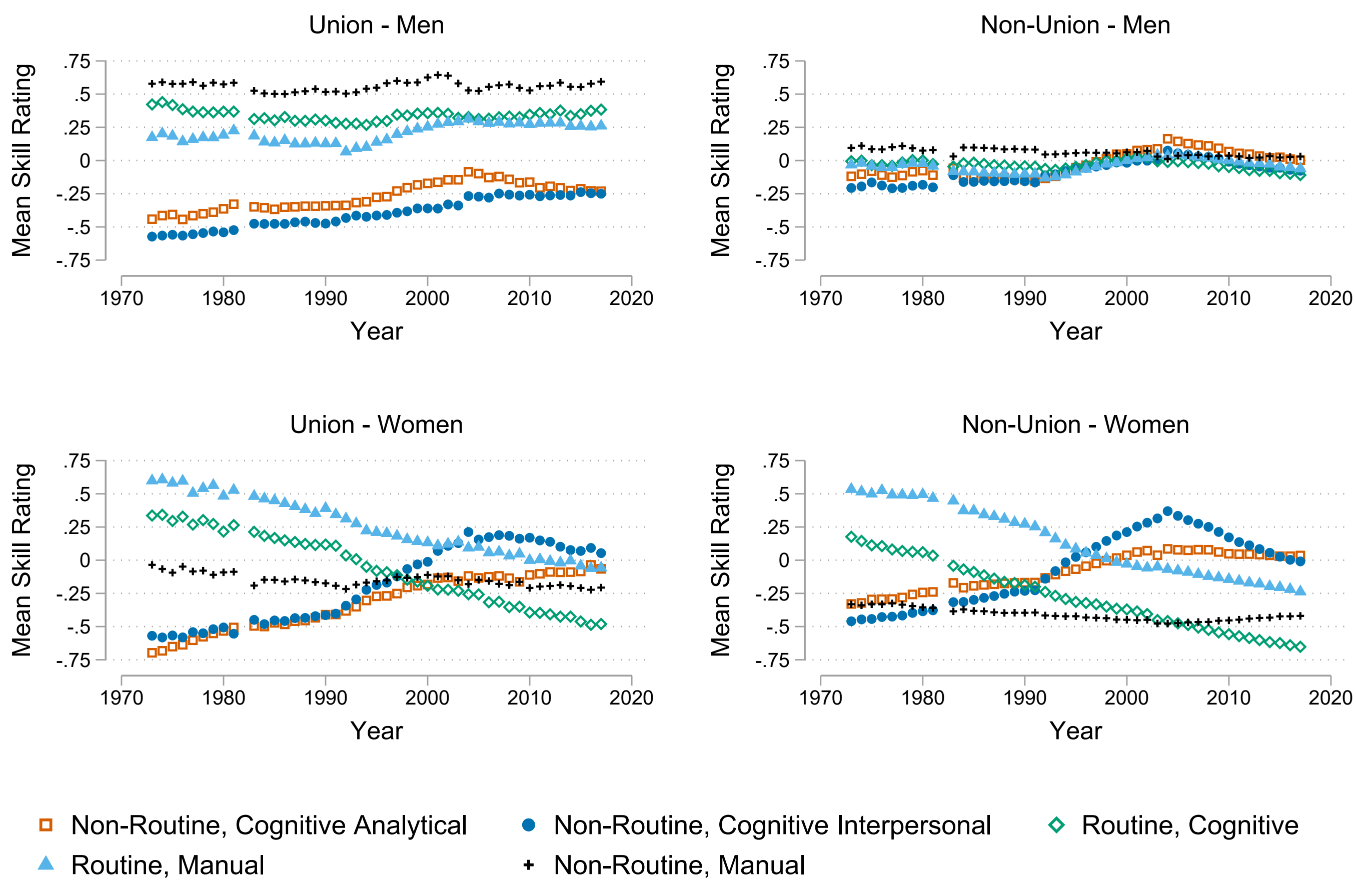
Figure A-6: Trends in Residualized Occupational Skill Requirements by Union Status and Skill Measure





Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET. Skill measures are residualized with respect to age, race/ethnicity, educational attainment, and gender.

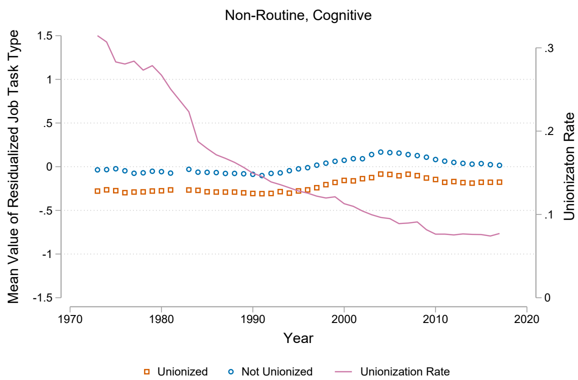
Figure A-7: Trends in Occupational Skill Requirements by Union Status and Gender, Disaggregated Skill Measures

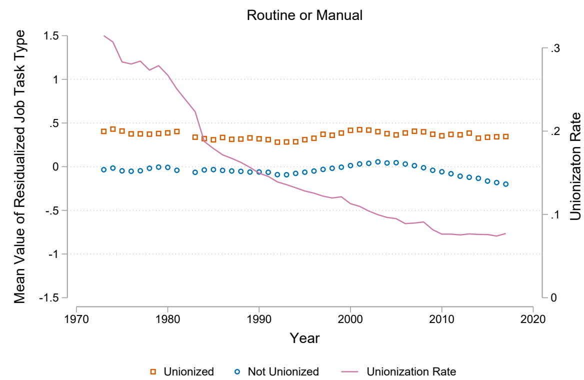


Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

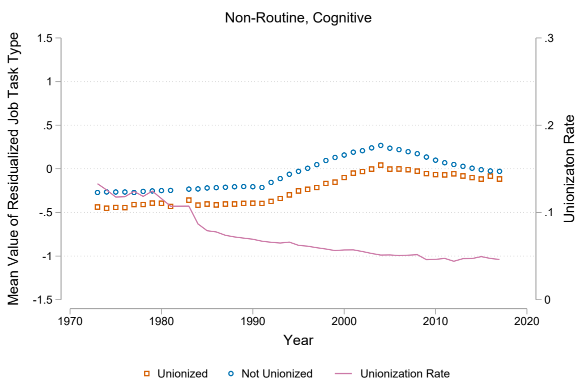
Figure A-8: Trends in Residualized Occupational Skill Requirements by Union Status, Skill Measure, and Gender

(a) Men





(b) Women



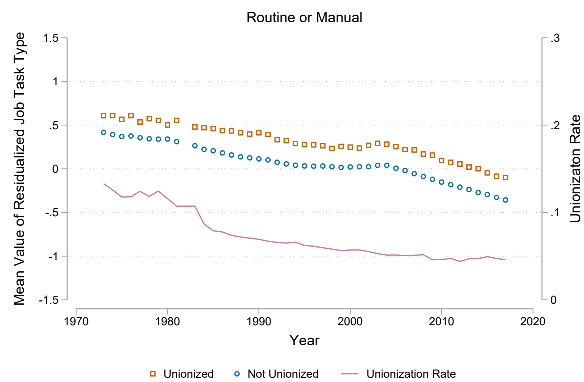
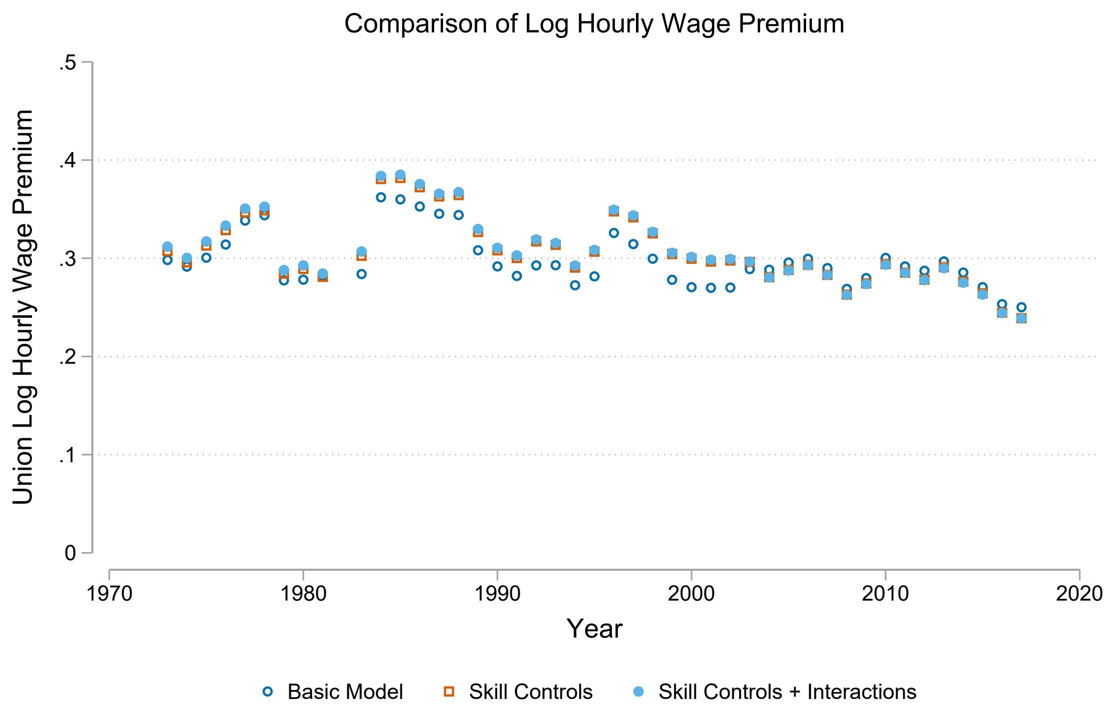


Figure A-9: Trends in the Union Wage Premium, Disaggregated Skill Measures

(a) Men



(b) Women

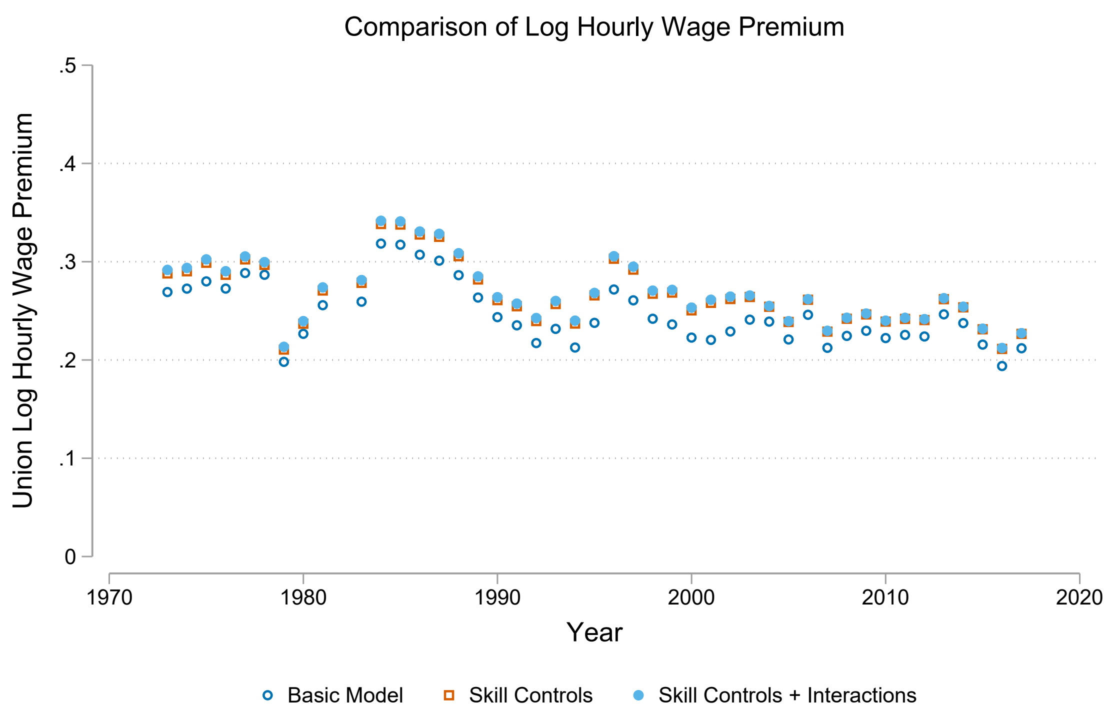
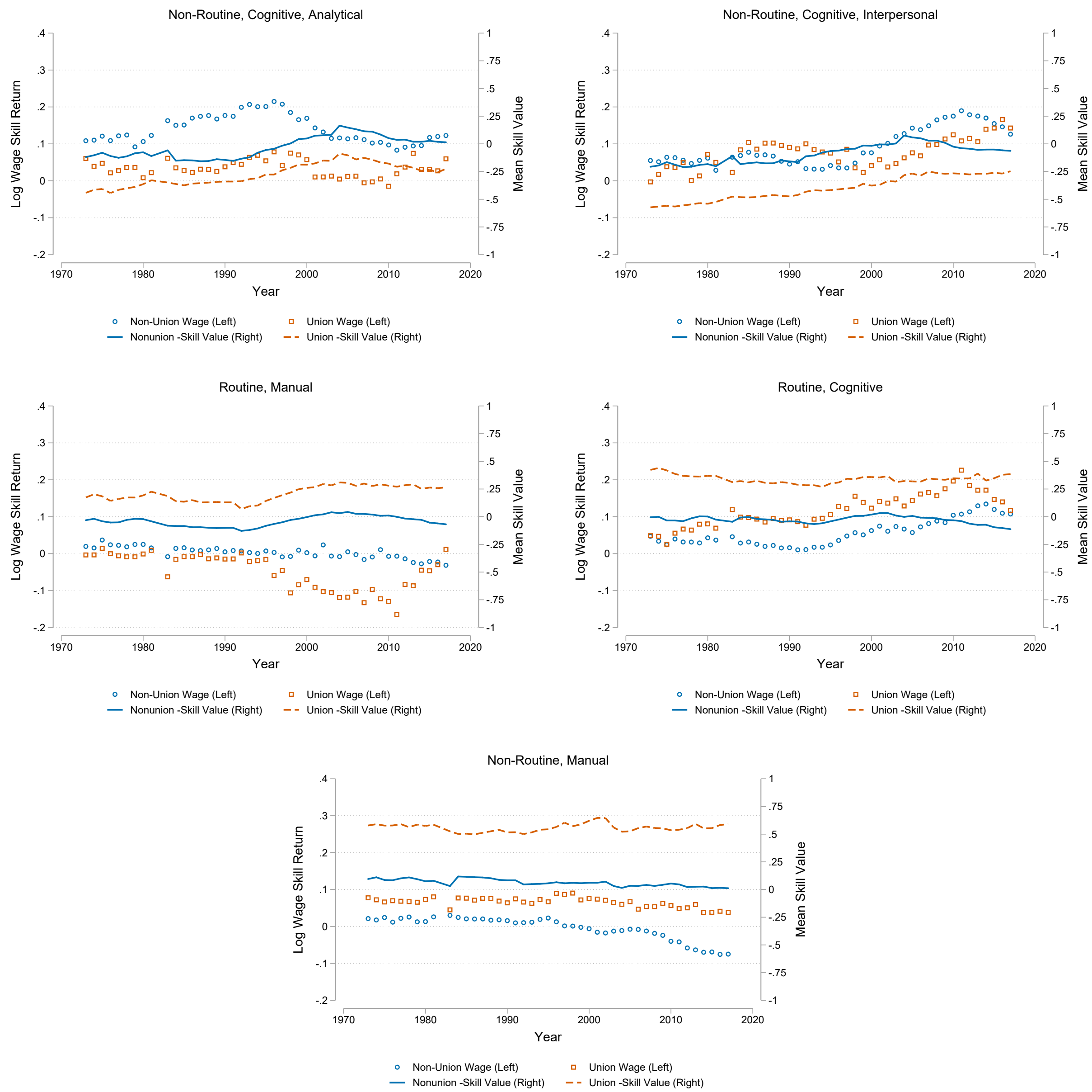
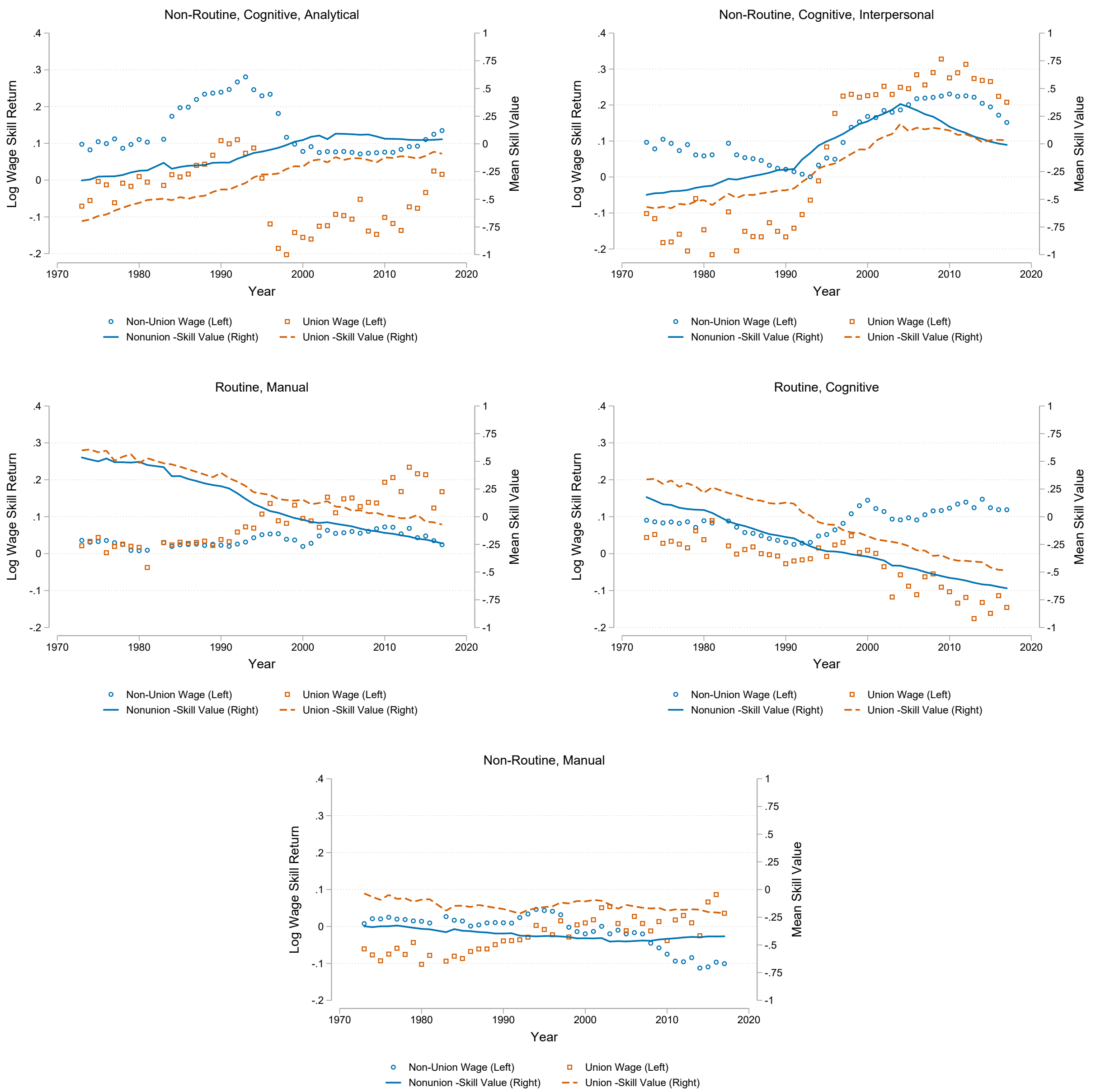


Figure A-10: Trends in the Return to Job Skills by Union Status - Men, Disaggregated Skill Measures



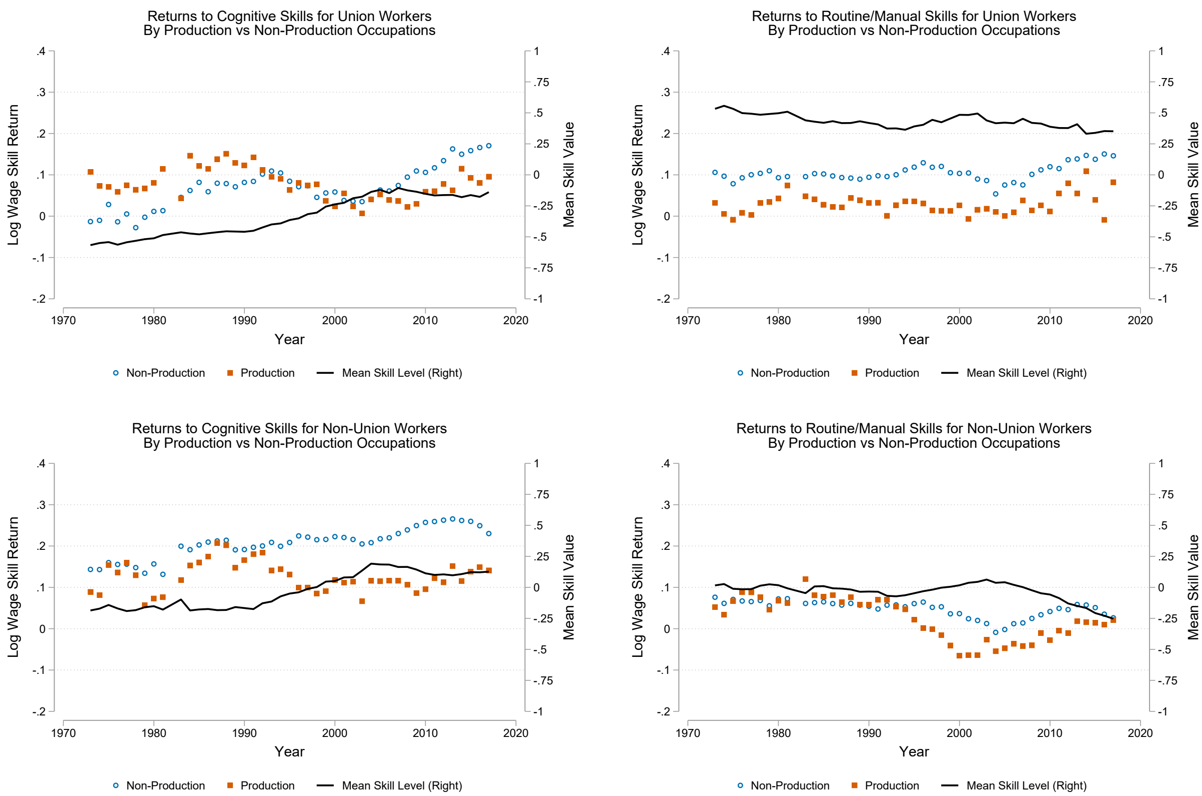
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure A-11: Trends in the Return to Job Skills by Union Status - Women, Disaggregated Skill Measures



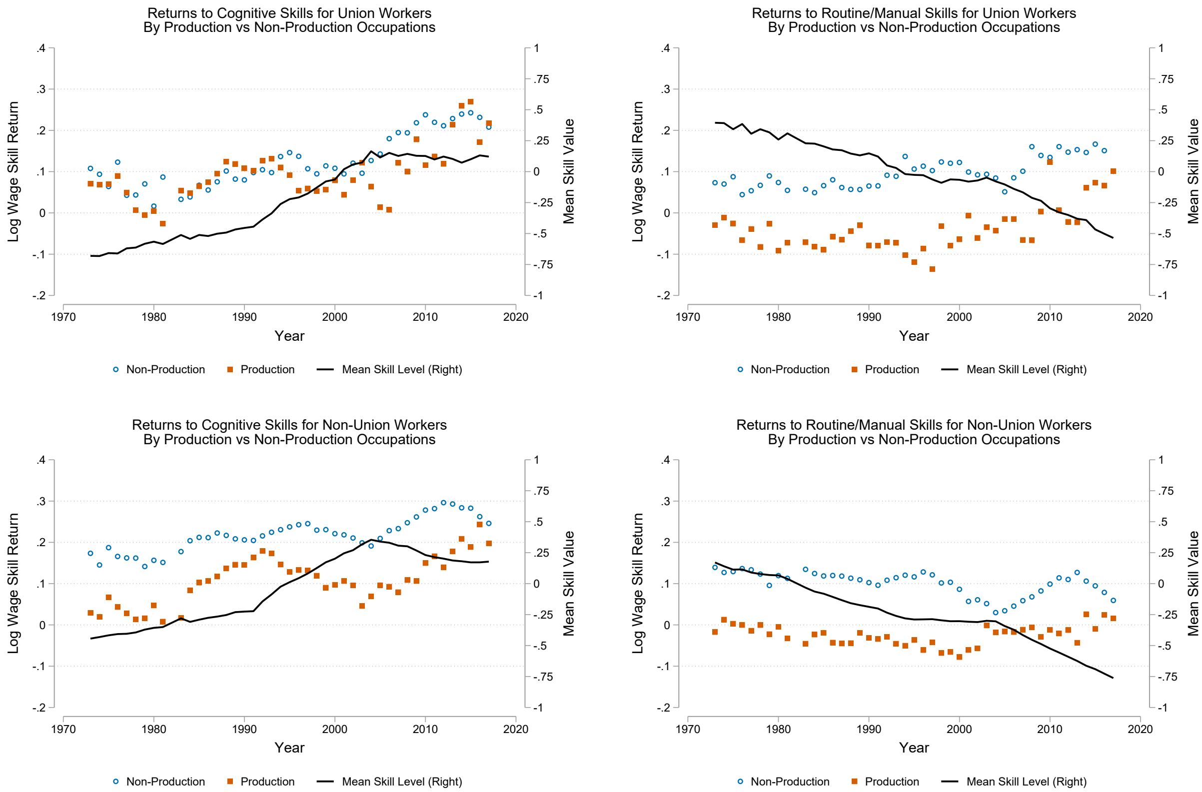
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure A-12: Trends in the Return to Job Skills by Union Status, Production versus Non-production Workers - Men



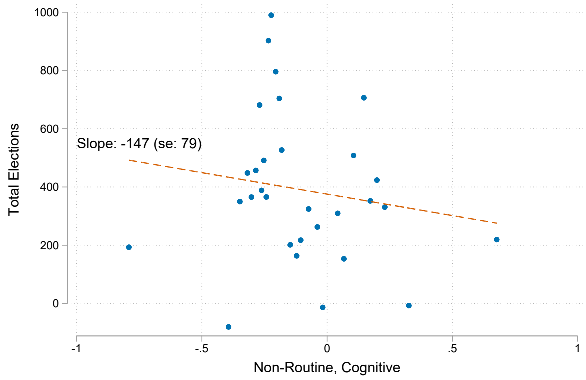
Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

Figure A-13: Trends in the Return to Job Skills by Union Status, Production versus Non-production Workers - Women

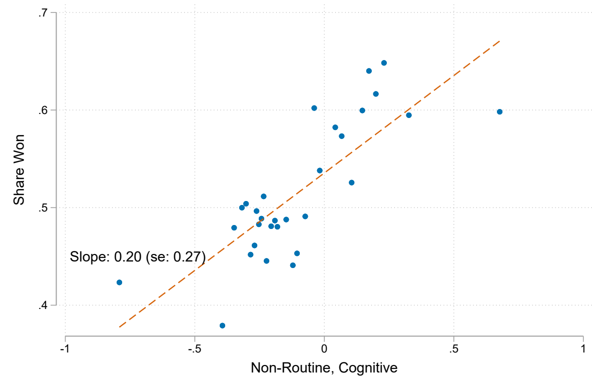


Source: Authors' calculations as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET.

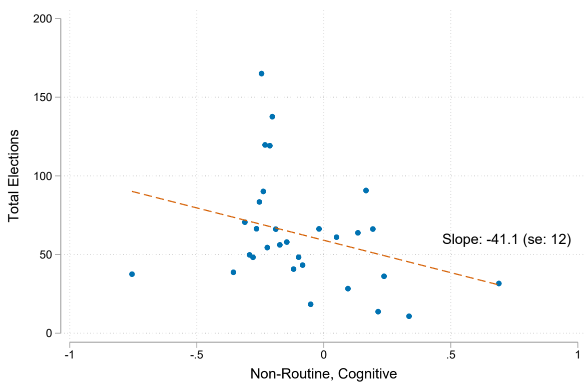
Figure A-14: Relationship between union elections, election success, and cognitive skills



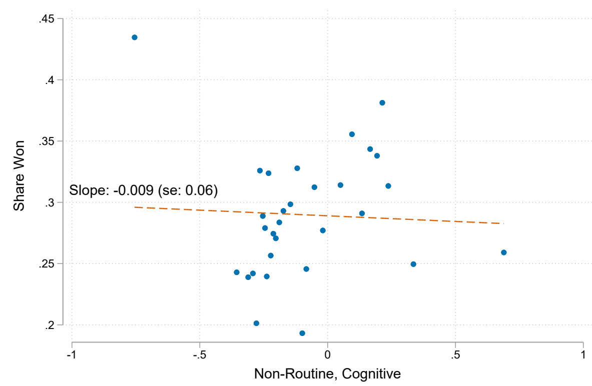
(a) Total certification elections



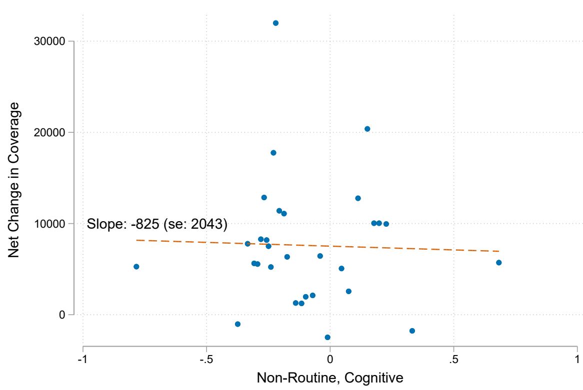
(b) Share won of certification elections



(c) Total decertification elections



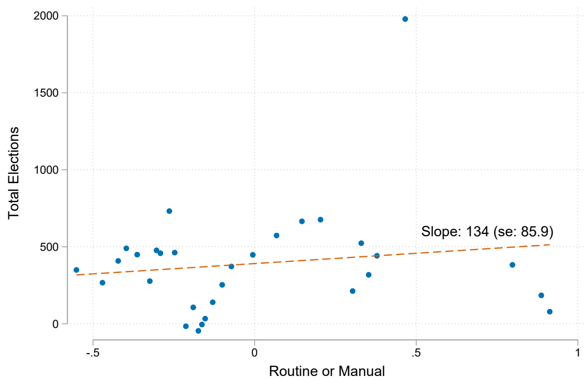
(d) Share won decertification elections



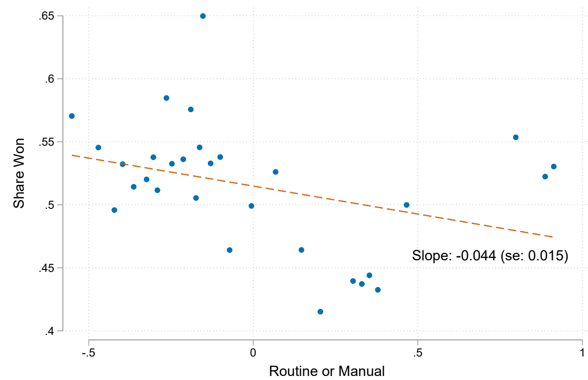
(e) Net change in coverage

Source: Authors' calculations as described in the text.

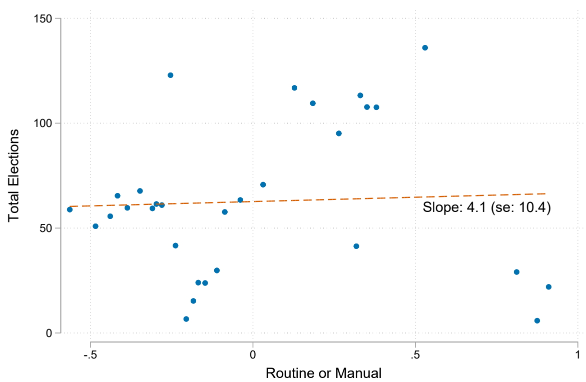
Figure A-15: Relationship between union elections, election success, and routine/manual skills



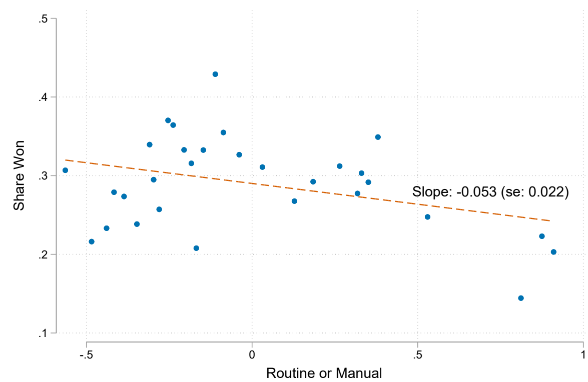
(a) Total certification elections



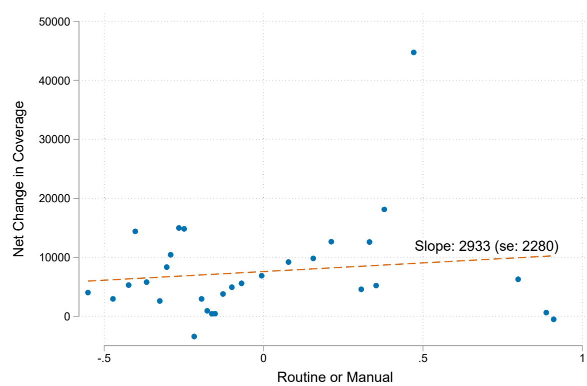
(b) Share won of certification elections



(c) Total decertification elections



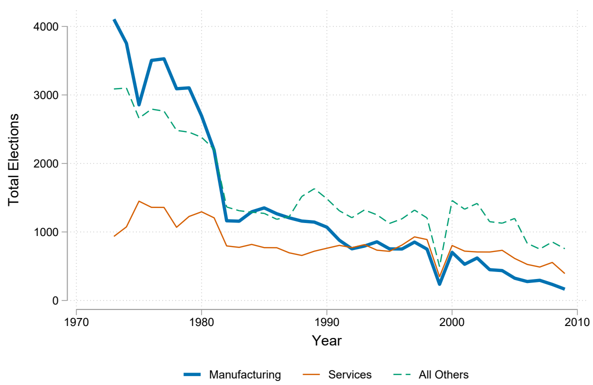
(d) Share won decertification elections



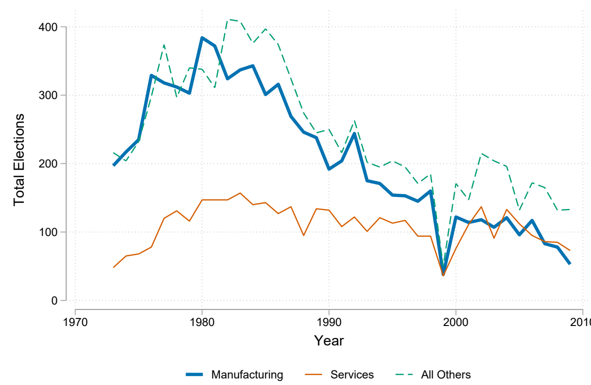
(e) Net change in coverage

Source: Authors' calculations as described in the text.

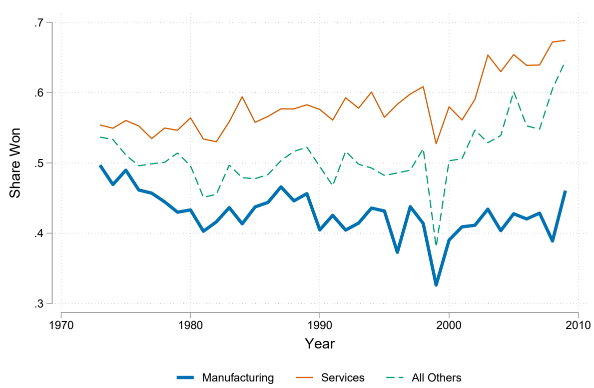
Figure A-16: Union elections and election success over time by industry



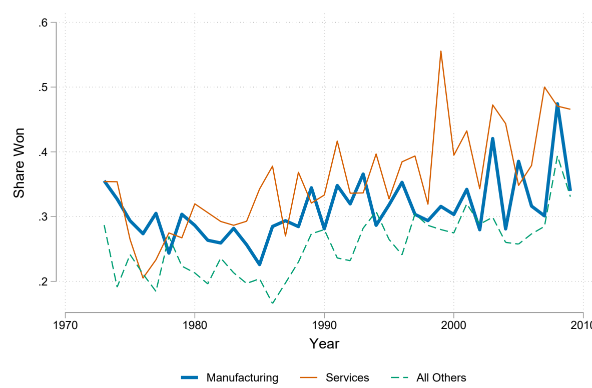
(a) Total certification elections



(b) Total decertification elections



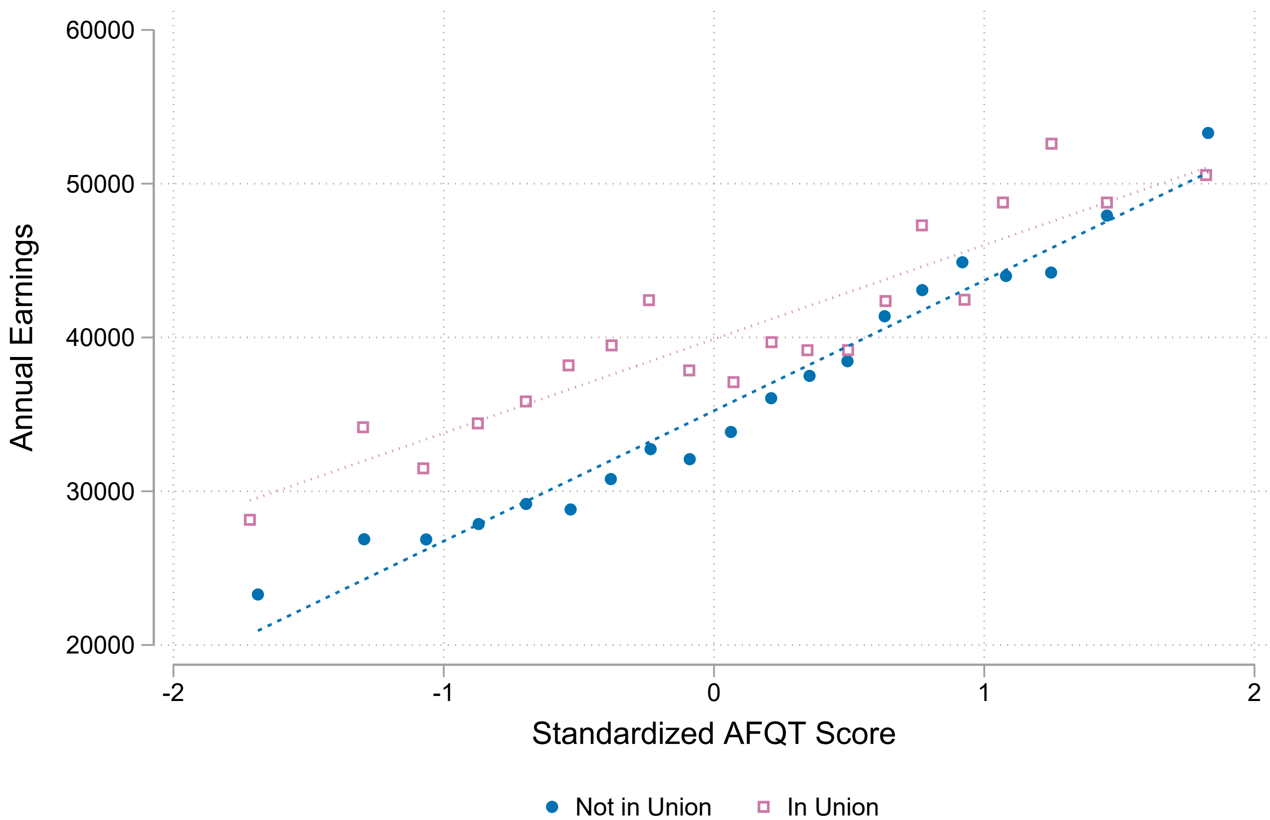
(c) Share won certification elections



(d) Share won decertification elections

Source: Authors' calculations as described in the text.

Figure A-17: AQFT and earnings by union status controlling for cognitive skills of occupation and year FE



Source: Authors' tabulations using data from NLSY79.

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
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, Manual	Eye, hand, foot coordination	Gross body equilibrium; Spatial orientation
Non-Routine, Cognitive	An additive combination of Non-Routine, Cognitive/Analytical and Non-Routine, Cognitive/Interpersonal	
Routine or Manual	An additive combination of Routine, Cognitive; Routine, Manual; and Non-Routine, Manual	

Table A-2: Decomposition of Changes in Skill Content of Unionized Occupations, 1973-1990

	Panel A: Men	
	Skill Type	:
Change Category	Non-Routine Cognitive	Routine or Manual
Total Change	0.107	-0.117
Change due to Worker Share	0.040	-0.018
	[37.16%]	[15.55%]
Change due to Intra-Occ. Skills	0.003	-0.078
	[3.15%]	[66.97%]
Change due to Occupation Entry/Exit	0.064	-0.020
	[59.69%]	[17.48%]
	Panel B: Women	
	Skill Type	:
Change Category	Non-Routine Cognitive	Routine or Manual
Total Change	0.229	-0.255
Change due to Worker Share	0.126	0.011
	[55.14%]	[-4.46%]
Change due to Intra-Occ. Skills	0.005	-0.149
	[2.02%]	[58.55%]
Change due to Occupation Entry/Exit	0.098	-0.117
	[42.84%]	[45.91%]

Authors' estimation of equation (5) in the text. 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	
	Skill Type	:
	Non-Routine	Routine
Change Category	Cognitive	or Manual
Total Change	0.315	-0.065
Change due to Worker Share	0.165	-0.191
	[52.37%]	[295.40%]
Change due to Intra-Occ. Skills	0.068	0.242
	[21.58%]	[-375.28%]
Change due to Occupation Entry/Exit	0.082	-0.116
	[26.04%]	[179.88%]

	Panel B: Women	
	Skill Type	:
	Non-Routine	Routine
Change Category	Cognitive	or Manual
Total Change	0.600	-0.666
Change due to Worker Share	0.367	-0.191
	[61.17%]	[28.74%]
Change due to Intra-Occ. Skills	0.159	-0.425
	[26.44%]	[63.80%]
Change due to Occupation Entry/Exit	0.074	-0.050
	[12.39%]	[7.46%]

Authors' estimation of equation (5) in the text. 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	
	Skill Type	:
	Non-Routine	Routine
Change Category	Cognitive	or Manual
Total Change	0.297	-0.257
Change due to Worker Share	-0.019	-0.078
	[-6.22%]	[30.30%]
Change due to Intra-Occ. Skills	0.077	-0.013
	[25.95%]	[5.19%]
Change due to Occupation Entry/Exit	0.238	-0.166
	[80.27%]	[64.50%]

	Panel B: Women	
	Skill Type	:
	Non-Routine	Routine
Change Category	Cognitive	or Manual
Total Change	0.618	-0.934
Change due to Worker Share	0.185	0.026
	[29.91%]	[-2.74%]
Change due to Intra-Occ. Skills	0.186	-0.803
	[30.07%]	[85.96%]
Change due to Occupation Entry/Exit	0.247	-0.157
	[40.02%]	[16.78%]

Authors' estimation of equation (5) in the text. The sum of the three change categories equals the total change by definition. The contribution of each category to the overall change is shown, with the percent effect in brackets below. All skill measures are in standard deviation units.

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

	Panel A: Men			
	Skill Type			:
Change Category	Non-Routine Cognitive Analytical	Non-Routine Cognitive Interpersonal	Routine Manual	Routine Cognitive	Non-Routine Manual
Total Change	0.211	0.323	0.087	-0.039	0.016
Change due to Worker Share	0.139	0.085	-0.144	-0.179	-0.149
	[65.95%]	[26.22%]	[-166.32%]	[462.69%]	[-952.49%]
Change due to Intra-Occ. Skills	-0.042	0.055	0.343	0.292	0.227
	[-20.01%]	[17.16%]	[395.67%]	[-753.27%]	[1455.44%]
Change due to Occupation Entry/Exit	0.114	0.183	-0.112	-0.151	-0.063
	[54.07%]	[56.62%]	[-129.35%]	[390.58%]	[-402.95%]
		Panel B: Women			
		Skill Type			:
Change Category	Non-Routine Cognitive Analytical	Non-Routine Cognitive Interpersonal	Routine Manual	Routine Cognitive	Non-Routine Manual
Total Change	0.632	0.622	-0.657	-0.817	-0.171
Change due to Worker Share	0.274	0.509	-0.149	-0.249	-0.095
	[43.37%]	[81.75%]	[22.64%]	[30.53%]	[55.64%]
Change due to Intra-Occ. Skills	0.158	-0.118	-0.254	-0.287	0.011
	[24.94%]	[-18.89%]	[38.63%]	[35.17%]	[-6.23%]
Change due to Occupation Entry/Exit	0.200	0.231	-0.254	-0.280	-0.087
	[31.69%]	[37.14%]	[38.73%]	[34.30%]	[50.59%]

Authors' estimation of equation (5) in the text. The sum of the three change categories equals the total change by definition. The contribution of each category to the overall change is shown, with the percent effect in brackets below. All skill measures are in standard deviation units.

Table A-6: Union Wage Premium Estimates by Decade, Disaggregated Skill Measures

	Panel A: Men					
	Basic Model	Skill Controls	Skill Interactions	Basic Model	Skill Controls	Skill Interactions
Year	(i)	(ii)	(iii)	(iv)	(v)	(vi)
1975	0.224***	0.281***	0.281***	0.301***	0.313***	0.317***
	(0.026)	(0.028)	(0.023)	(0.019)	(0.021)	(0.018)
1985	0.301***	0.354***	0.354***	0.360***	0.382***	0.385***
	(0.026)	(0.022)	(0.020)	(0.017)	(0.015)	(0.014)
1995	0.228***	0.281***	0.281***	0.282***	0.307***	0.308***
	(0.028)	(0.019)	(0.016)	(0.018)	(0.015)	(0.011)
2005	0.243***	0.236***	0.236***	0.296***	0.288***	0.288***
	(0.028)	(0.023)	(0.019)	(0.019)	(0.019)	(0.015)
2015	0.219***	0.215***	0.215***	0.271***	0.264***	0.263***
	(0.035)	(0.026)	(0.0228)	(0.023)	(0.022)	(0.021)
Occupation FE	No	No	No	Yes	Yes	Yes
	Panel B: Women					
	Basic Model	Skill Controls	Skill Interactions	Basic Model	Skill Controls	Skill Interactions
Year	(i)	(ii)	(iii)	(iv)	(v)	(vi)
1975	0.253***	0.266***	0.266***	0.28***	0.299***	0.302***
	(0.030)	(0.032)	(0.024)	(0.026)	(0.027)	(0.029)
1985	0.292***	0.311***	0.311***	0.317***	0.338***	0.341***
	(0.027)	(0.031)	(0.023)	(0.022)	(0.023)	(0.014)
1995	0.219***	0.245***	0.245***	0.238***	0.266***	0.268***
	(0.025)	(0.023)	(0.020)	(0.0150)	(0.016)	(0.016)
2005	0.218***	0.220***	0.220***	0.221***	0.239***	0.240***
	(0.040)	(0.031)	(0.027)	(0.018)	(0.018)	(0.020)
2015	0.219***	0.217***	0.217***	0.216***	0.231***	0.232***
	(0.049)	(0.026)	(0.021)	(0.021)	(0.020)	(0.019)
Occupation FE	No	No	No	Yes	Yes	Yes

Notes: Authors' estimation of equation (1) as described in the text using 1973-2017 CPS data combined with occupational skill requirements in DOT and O*NET. Only results for selected years are shown: full estimates are presented in Figure 5. 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.