The Changing Quality of Nonstandard Work Arrangements: Does Skill Matter?

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This article explores the implications of nonstandard employment for types of workers and their change over time. Using data from 1995, 2005, and 2017, we trace the evolving forms of nonstandard employment over the last decade and the associated job-quality patterns for workers with different skills, measured by education levels and occupation tasks. We find that nonstandard employment reduces earnings and weekly work schedule but does not affect the likelihood of feeling insecure about job continuity for workers in general. However, a closer examination reveals considerable variation along these three dimensions: highly educated nonstandard workers have lower earnings and fewer working hours than traditional workers over time and nonstandard routine occupation workers tend to feel greater job insecurity. Variations across gender and race-ethnicity are also discussed.

Keywords: nonstandard work arrangements, job quality, skills

Since the 1970s, demographic and institutional changes such as globalization and market liberalization have led to an internal reorganization of enterprises' business models with direct consequences to employment. Technological advancements and automation also played a role in the changing nature of work by creating new jobs while making others obsolete. The polarization between good and bad jobs, as well as the flexibilization of employment contracts, raised concerns over the impacts of such changes for workers and their families (Weil 2014; Kalleberg, Reskin, and Hudson 2000; Autor 2015a; Abraham et al. 2017).

New forms of work, characterized by higher flexibility and looser ties between workers and employers, started to spread in the United States and elsewhere in the 1990s. Such non-

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standard arrangements, also labeled as marked-mediated arrangements, nontraditional employment relations, or flexible arrangements, are frequently associated with higher insecurity and precarity of work (Kalleberg 2000). Recently, the emergence of work enabled by technological advancements and online platforms has contributed to the debate between flexibility and insecurity that characterizes nonstandard employment. The Great Recession has also intensified insecurity and job-quality concerns in the economy (Howell and Diallo 2008; Holzer et al. 2011; Kalleberg 2009). In this context, it is important to understand the temporal trends and effects of a changing workplace on job quality and worker well-being in order to formulate effective public policy.

To date, the consequences of these employment changes are mixed. On the one hand, the increasing insecurity and precarity of jobs raise concerns regarding the quality of work and impacts on workers' lives and families (Kalleberg 2011; Harris and Krueger 2015). New organizational strategies of firms, such as outsourcing, have been empirically associated with wage penalties to workers, reduction of benefits and unionization, and income inequality (Dube and Kaplan 2010; Goldschmidt and Schmieder 2017). On the other hand, the inherent flexibility of alternative employment and the emergence of new arrangements provide employees with tools to deal with increasing family responsibilities, income volatility, as well as complement their earnings (Farrell and Greig 2016a, 2016b; McKinsey & Company 2015; Golden 2008).

The ability to take advantage of the benefits of nonstandard arrangements and avoid their downsides varies among workers. Existing literature suggests that higher skills increase the odds of benefiting from flexibility given their leveraging power (Golden 2008; Kalleberg 2011, 2003), and that low-skill workers tend to be more vulnerable to precarity and segregation (Kalleberg 2011; Kalleberg, Reskin, and Hudson 2000; Catanzarite 2000). The distinctions among those groups as well as across different types of alternative arrangements, skill levels, and industry sectors are significant (Liu and Kolenda 2012). However, research on the implications of nonstandard work arrangements for workers with different skills is inadequate.

This article addresses the question by distinguishing job-quality patterns between standard and nonstandard employment arrangements for workers with different skills from 1995 to 2017. We are interested in how job quality in traditional and nonstandard employment differs for low-skill, middle-skill, and high-skill workers, as well as how such differences change over time. Although job quality is a multidimensional and broad concept, we focus on three dimensions: earnings, working hours, and expectations regarding job continuity. We measure skill level using two approaches: educational attainment and job task content.

Our results establish the overall negative effects of nonstandard employment on job quality for workers in general, though the exact effects vary by skill. We find stronger effects on high-skill workers, who worked fewer hours and received fewer earnings over time. Low-skill workers in alternative arrangements worked fewer hours, but the gap seems to be gradually closing. For these workers, the wage penalty showed up only when measured as workers in manual nonroutine occupations, but not when measured as low-educated. Meanwhile, evidence is not convincing of differences in wages or work schedules for middle-skill workers in alternative arrangements, despite their feeling increasingly insecure about their job continuity in the future, a fact not shared by the other classes of workers.

The findings for earnings and expectations are robust for all workers and male-only samples, but the difference in the weekly hours worked in nonstandard arrangements disappear or increase if female workers are excluded. Such difference indicates that there might be some self-selection of workers who need to combine paid and unpaid work for family or other reason who opt for such arrangements. We also find evidence of differences in pay and hours worked by race-ethnicity, but a closer look at how such differences interact with nonstandard emloyment is pending. These areas require future investigation.

CONCEPTUALIZING NONSTANDARD EMPLOYMENT ARRANGEMENT

The conceptualization of nonstandard employment distinguishes from traditional nine-to-five work arrangements in which workers are expected to work full time for an indefinite period within the employers' place of business and under their supervision. Such arrangements were labeled with different terms over time, such as alternative arrangements, market-mediated arrangements, nontraditional employment relations, flexible arrangements, and atypical employment, among others (Kalleberg 2000). This essay uses nonstandard and alternative arrangements interchangeably.

In 1995, the Bureau of Labor Statistics (BLS) and the Census Bureau launched the Contingent Work Supplement (CWS) to the Current Population Survey (CPS), a survey designed specifically to provide detailed information on workers with nonstandard employment arrangements. The CWS defines *alternative work arrangements* as those "arranged through an employment intermediary such as a temporary help firm," or involving jobs that the "place, time, and quantity of work are potentially unpredictable" (Polivka 1996, 7).[1] The CWS operationalizes alternative employment in the following categories: independent contractors (including consultants and freelancers), on-call workers and day laborers, temporary help workers (those paid by temporary help agencies regardless of whether their job is temporary), and workers provided by contract firms (BLS 2005).

Workers under alternative employment arrangements include individuals performing varying tasks. Some of these jobs—such as independent contractors in farms and construction, on-call workers as substitute teachers and performance artists—have existed in the United States for decades; the growth of temporary help started in the aftermath of the World War II (Polivka 1996). Contract-out workers gained momentum after the 1970s as a result of the restructuring of the global economy and the adoption of new corporate strategies (Weil 2014). In the past decade, new arrangements enabled by online platforms (also known as gig work) have attracted attention as one of the fastest growing segments of the labor markets (Farrell and Greig 2016a; Abraham et al. 2017).

NONSTANDARD ARRANGEMENTS AND JOB QUALITY

Institutional and demographic changes have had significant impacts on employment from the second half of the twentieth century. The workforce became larger and more diversified through increasing female participation, rising educational attainment, and easier access to global labor markets (Kalleberg 2011; Goldin, Katz, and Kuziemko 2006). At the same time, the search for flexibility and costs reduction originated new business models, in which big enterprises shed employment to networks of smaller firms while setting strict standard controls for their performance and blurring the relationship between workers and employers—a scenario Weil 2014 describes as a "fissuring workplace." Moreover, technological advancements, such as automation and computerization, progressively substituted workers performing routine tasks that characterized many of the middle-skill occupations (Autor 2015a, 2015b).

Following these changes, recent decades saw a growing polarization between good and bad jobs and a hollowing of the middle occupations. A good job features relatively high earnings, training and promotion opportunities over time, fringe benefits, some worker control over schedule and work content and duration, stability, occupational health, and safety (Kalleberg 2011; Bernhardt et al. 2015; Clark 2005). Conversely, bad jobs are those with lower payments, fewer opportunities and benefits, and more insecurity. Jobs in between are relatively

1. Contingent and nonstandard employment are overlapping yet different concepts in the CWS. *Contingent* is "any job in which an individual does not have an explicit or implicit contract for long-term employment or one in which the minimum hours worked can vary in a nonsystematic manner" (Polivka and Nardone 1989, 11). The key distinction is that contingent workers either do not expect their jobs to last or have a temporary job. As a result, not all workers in alternative arrangements are contingent, and not all contingent workers are in alternative arrangements.

stable and well paid but do not require a high level of skills from workers, such as those in the big corporations and manufactures of the twentieth century. In this context, by the end of the century, education has become the great divide between workers with better and worse jobs, and between high- and low-paid occupations (Fischer and Hout 2016).

Job quality is, therefore, central to the discussion, but measuring it is somewhat challenging given its multidimensional and subjective nature. Often, given data availability, its operationalization captures only some dimensions. Arne Kalleberg, Barbara Reskin, and Ken Hudson, for instance, operationalize the "badness" of a job based on the share of low-wage workers, and workers with no pension and health insurance (2000). In this essay, we focus on three of the dimensions suggested by the literature: earnings, hours worked, and future expectations.

Nonstandard work arrangements have mixed implications for workers. On the one hand, higher flexibility allows workers to deal with personal and family responsibilities, increase work-life satisfaction, as well as their ability to deal with income volatility and complement earnings (Farrell and Greig 2016a; Golden 2008). In particular, the growing willingness of workers to engage in the emerging gig economy supports the notion that they value flexibility (Donovan, Bradley, and Shimabukuro 2016). On the other hand, the flip side of flexibility is insecurity, which tends to be greater for workers with alternative work arrangements who are likely positioned at the periphery of organizations with weaker linkages to the organizational core (Kalleberg, Reskin, and Hudson 2000; Kalleberg 2012, 2003). Job insecurity further intensified after the Great Recession (Holzer 2011).

The implication of nonstandard employment would vary for workers with different skills. The literature suggests that higher skills increase the odds of benefiting from flexibility given its greater leverage power (Golden 2008) and that the correlation between worker skills and job quality over time is increasing (Holzer 2011; Holzer et al. 2011). Having more portable skills elevates workers' likelihood of being employed in diverse organizations and therefore, having relatively more stability in occupations (Kalleberg 2003).

Overall, higher skills are assets that employers value and, consequently, increase the bargaining power of workers (Kalleberg 2011; Catanzarite 2000; Carnoy, Castells, and Benner 1997). Inversely, low-skill workers have less bargaining power and are more easily replaced, thus tend to be more vulnerable to worsening labor market conditions regardless of employment arrangement (Kalleberg 2011). For instance, the outsourcing of typical low-skill occupations such as janitorial, security, and cleaning services have been empirically associated with significant wage and benefit penalties in the United States and Germany (Dube and Kaplan 2010; Goldschmidt and Schmieder 2017).[2] Middle-skill workers make up a large share of the workforce. Given the elimination of many middle-skill jobs by automation, the displacement of workers and mismatch between skills and jobs are both growing (Autor 2015b; Holzer et al. 2011). To our knowledge, research on the effects of nonstandard employment particular to these workers is inadequate.

Workers in alternative arrangements are substantially diverse, and industries with higher contingency rates tend to have a higher share of low-skill workers (Liu and Kolenda 2012). Within the four types of alternative arrangements, the distribution of skills varies. On-call, temporary, and contracted-out workers tend to have higher shares of low-skill workers than standard arrangements, and independent contractors tend to have higher shares of high-skill workers than any of the other nonstandard and standard arrangements (Katz and Krueger 2019; Hippel et al. 2006). Such complexities call for a deeper understanding of the effects of nonstandard employment on job quality for different works. This article contributes to this discussion by testing how the impacts on job quality vary for workers with different skills and how such effects change over time.

2. Outsourcing is a growing trend, but independent from work arrangements as discussed here. The example is only an illustration of the higher vulnerability of low-skill workers in general.

DATA AND METHODOLOGY

Our analysis made use of the 1995, 2005, and 2017 CWS surveys to trace the changing job quality of nonstandard employment over two decades. The Bureau of Labor Statistics and the Bureau of Census introduced the CWS in 1995 to gather detailed information on workers in alternative work arrangements (Census Bureau 1995, 2005, 2017). The survey was carried out in 1995, 1997, 1999, 2001, 2005, and 2017. The recent release of CWS data offers an opportunity to update what is known about nonstandard workers.

Our samples comprise civilian individuals age sixteen and older who worked for either pay or profit in the week previous to the interview: 54,122 observations in 1995, 42,537 in 2005, and 46,144 in 2017. For each year, we used a dummy variable to distinguish between workers in standard versus nonstandard work arrangements. Nonstandard workers include those who are independent contractors, on-call, day laborers, temporary help agency workers, or contracted workers; others are defined as standard workers by a 2005 CWS technical note (BLS 2005). We did not break nonstandard arrangements further in our analysis due to the reduced sample size of some categories.

We operationalized skills through qualifications and occupations, the two most commonly used indirect indicators of skills (Eurostat 2016). We used educational attainment as a signal of worker skills as follows: low-, high-, and middle-skill workers correspond to workers with less than a high school degree, workers with a bachelor's degree or higher, and workers in between, respectively. This approach has the advantage of readily available information, but it is limited when skills are acquired not only through formal education, but also through on-the-job training, and genetic inheritance, such individual characteristics (Becker 1994).

Complementing the first approach, we also categorize workers' skills by the content of the tasks and qualifications required for them to perform their occupations. We follow the skill-biased technological change literature and divided occupations according to cognitive versus manual, and routine versus nonroutine tasks (Acemoglu and Autor 2010; Jaimovich and Siu 2014; Foote and Ryan 2014).[3] Low-, middle-, and high-skill occupations are, respectively, nonroutine manual occupations, routine occupations, and nonroutine cognitive occupations.[4] Nonroutine manual occupations are essentially service occupations, whereas nonroutine cognitive include managers, professionals, and technicians. Routine occupations are the ones in the middle of the skills distribution, including cognitive jobs (such as sales, and office and administrative support) and manual ones (blue-collar jobs) (Jaimovich and Siu 2014).[5]

We capture skills by first running models controlling for educational attainment and occupations for each year. Second, we stratify workers by educational levels and run models controlling for task content of occupations. Third, we stratify by occupations controlling for education. In all models, the variable of interest is the dummy for nonstandard work arrangement, which captures varying job quality for different workers .[6]

Job quality is a multidimensional concept, as discussed earlier, and we focus on three dimen-

3. "The distinction between cognitive and manual jobs is straightforward, characterized by differences in the extent of mental versus physical activity. The distinction between routine and non-routine jobs is based on the work of Autor, Levy, and Murnare (2003). If the tasks involved can be summarized as a set of specific activities accomplished by following well-defined instructions and procedures, the occupation is considered routine. If instead the job requires flexibility, creativity, problem-solving, or human interaction skills, the occupation is non-routine" (Jaimovich and Siu 2014, 8),

4. For a full description of the classification of occupations, see Jaimovich and Siu 2014, A2.

5. Workers in farming, fishing, and forestry were not considered in the analysis. These totaled 1,331 in 1995, 265 in 2005, and 398 in 2017.

6. For the correspondence of our two measures of skills, see table A1. In all years, around 73 percent of highly educated workers were performing high-skill jobs (nonroutine cognitive occupations), however the correspondence is worse for middle- and low-skill workers. To the former, 60 percent of middle-educated workers were

Table 1. Workers by Employment Arrangement

	1995		2005		2017	
Employment Arrangement	Frequency	Percent	Frequency	Percent	Frequency	Percent
Standard	48,757	90.1	37,884	89.1	41,307	89.5
Nonstandard	5,365	9.9	4,653	10.9	4,837	10.5
Independent contractors, consultants, and freelancers	3,348	62.4	2,948	63.4	3,082	63.7
On-call workers and day laborers	867	16.2	826	17.8	761	15.7
Paid by temporary help agencies	522	9.7	366	7.9	413	8.5
Contracted out	628	11.7	512	11.0	582	12.0
Total	54,122	100	42,537	100	46,144	100

Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).
Note: Data weighted using CWS supplement weights.

sions: hourly earnings, weekly hours worked, and expected job continuity. We used the logarithm of the hourly earnings from the main job to test the hypothesis that nonstandard employment has a depressing effect on earnings. We calculated hourly earnings by dividing weekly earnings[7] by the total hours worked weekly at the main job. We trimmed the extreme values of hourly earnings below $1 and above $100 following the literature (Lemieux 2010; Spletzer and Handwerker 2014; Schmitt 2003).

The second dependent variable is total weekly hours worked in all jobs, a variable created by adding total hours worked on the main job and all other jobs combined. We used it to test the hypothesis that nonstandard workers have different work schedules from comparable traditional workers. Because both earnings and hours worked are interval variables, we used ordinary least squares to test the first and the second hypotheses.

To test whether nonstandard employment caused higher insecurity, the last dependent variable was a dummy for expected job continuity, coded one for workers who said that they could continue to work at their current job as long as they wished, provided that the economy did not change and their job performance was adequate, and zero otherwise. To test this hypothesis, we used logistic regressions. All models include standard demographic control variables for race-ethnicity, sex, age, marital status, and nativity.

Finally, to test the robustness of our results, we ran all models for male workers only. The rationale for the test is to capture potential unobservable factors that may result in self-selection of workers in nonstandard work arrangements, such as the willingness to combine paid and unpaid work in their schedules.

DESCRIPTIVE STATISTICS

Nonstandard workers remained roughly 10 percent of the workforce during the entire period (table 1). Around 63 percent of the nonstandard workers remained as independent contractors, independent consultants, and freelancers. On-call workers and day laborers, and temporary help agency employees' shares decreased slightly from 16.2 percent to 15.7 percent and from 9.7 percent to 8.5 percent respectively from 1995 to 2017. Contracted workers experienced a slight growth from 11.7 percent to 12.0 percent.

performing routine occupations in 1995 and 2005, dropping to 54 percent in 2017. To the latter, the correspondence fluctuated from 41 percent in 1995 to 32 percent in 2005 and 35 percent in 2017.

7. Due to the rotation groups methodology, CWS included information only on earnings of workers who were on rotation groups four and eight in February of each year. For the remaining workers, we used the earnings information from the earnings files, where available.

Table 2. Share of Workers by Skill Level and Employment Arrangement

	1995		2005		2017	
	Standard	Non-standard	Standard	Non-standard	Standard	Non-standard
Skills as educational attainment						
Low education	11.8	11.1	10.8	11.2	8.1	9.6
Middle education	62.0	58.7	59.0	56.8	54.1	52.7
High education	26.2	30.3	30.2	32.0	37.8	37.7
Skills as occupational tasks content						
Nonroutine manual	17.9	17.5	15.6	16.6	17.2	19.5
Routine	49.5	48.0	49.2	45.9	41.9	40.0
Nonroutine cognitive	32.6	34.6	35.3	37.5	40.9	40.6

Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).
Note: Data weighted using CWS supplement weights. N in 1995, 2005, and 2015 are, respectively, 54,122, 41,829, and 46,144.

CWS 2017 data portray a pattern that contradicts previous findings that the share of nonstandard workers reached 15 percent in 2015 driven mostly by the growth on contract-out workers (Katz and Krueger 2019). These estimates used the Rand-Princeton Contingent Worker Survey (RPCWS) data, a survey inspired on CWS and intended to fill its ten-year void. A possible explanation for the differences in estimates between CWS 2017 and RPCWS 2015 are the surveys' designs, which may have led to comparisons that are possible in concept but not in practice (see Abraham et al. 2017).[8]

Breaking down both the standard and nonstandard workers by their educational attainment levels, we see that all three levels are well represented in the nonstandard workforce (table 2), consistent with previous studies (Liu and Kolenda 2012; Hippel et al. 2006). More than half of all workers are in the middle-educated category—those with a high school diploma but without a college degree. Although their share is decreasing, they remain the largest section of the U.S. workforce and make up 53 percent of standard workers and 54 percent of nonstandard workers in 2017. Highly educated workers—the fastest growing share of the workforce—were equally represented in standard and nonstandard work arrangements in 2017 (roughly 38 percent). Meanwhile, low-educated workers in traditional arrangements experienced an overall decline during these twenty years from 12 percent to around 8 percent, but the drop in nonstandard arrangements accounted for 1.5 percentage points only.

By measuring skills through occupational task content, we observe a decline in the routine occupations in both standard and nonstandard work arrangements from nearly 50 percent in 1995 to 40 percent in 2017, illustrating the hollowing of the middle-skill occupations' thesis (Kalleberg 2011; Autor 2015b; Acemoglu and Autor 2010; Foote and Ryan 2014). Although nonroutine manual occupations re-

8. Abraham and her colleagues discuss some items that may have turned the Rand data incomparable to CWS, such as: internet-based survey rather than interviews; in RPCWS respondents answer questions about themselves whereas in CWS they answer to all members of the household; the sample of respondents of RPCWS was assembled from a variety of sources with unknown nonresponse rates, which may lead to a lesser representativeness of the U.S. population, and so on (2017). The authors also point to the stability in the share of nonstandard arrangements found in the General Social Survey 2002, 2006, 2010, and 2014 as grounds for caution in comparing the Rand survey and CWS.

Table 3. Demographic Characteristics of Workers by Employment Arrangement

	1995		2005		2017	
	Standard	Non-standard	Standard	Non-standard	Standard	Non-standard
Mean age	38.2	41.1	40.3	43.5	41.7	46.2
Female (share)	47.7	37.9	47.8	38.5	47.9	38.1
Married (share)	60.3	64.6	58.4	62.9	54.5	58.8
Foreign born (share)	10.0	10.0	15.2	15.6	17.3	20.1
Race-ethnicity (share)						
White	77.6	82.3	70.2	75.5	63.5	65.0
Black	10.9	8.1	10.6	7.9	11.6	10.5
Hispanic	8.5	6.9	13.0	12.4	16.6	16.9
Other	3.0	2.7	6.2	5.3	8.3	7.7

Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).
Note: Data weighted using CWS supplement weights. N in 1995, 2005, and 2015 are, respectively, 54,122, 41,829, and 46,144.

mained relatively stable in standard arrangements over the period, in the nonstandard group it increased by 2 percentage points up to 19 percent in 2017. Nonroutine cognitive occupations grew steadily from around 33 percent in 1995 to roughly 40 percent in 2017.

Educational attainment is a common measure of skills' supply (it corresponds to each individual worker characteristic); occupations provide a measure of demand for skills (tasks are essentially a job characteristic). The increase of educational levels accompanied by the decrease in middle-skill occupations (routine) and stability of low-skill occupations (nonroutine manual) supports the hypothesis of a skill mismatch between workers and jobs (Eurostat 2016; Holzer 2011).

Demographic Characteristics

Table 3 provides a demographic overview of workers, displaying the variables we used as controls in the empirical analysis. Female workers made up nearly half of the standard workforce but remained less represented among nonstandard workers over the period (roughly 38 percent). In the three observation years, workers were on average older in nonstandard than in standard arrangements, and such differences became even larger in 2017.

Regarding racial-ethnic composition, the share of white workers has declined over the period, dropping by 14 percentage points in standard and 17 percentage points in nonstandard arrangements from 2005 to 2017. The share of African American workers in the nonstandard workforce grew by 2.5 percentage points over the period but remained at around 11 percent in standard arrangements. Further, the growing participation of Hispanic and other racial-ethnical groups reflect an increasingly diverse workforce. In 2017, Hispanic workers accounted for roughly 17 percent of standard and nonstandard workers, a growth of 195 and 245 percent from 1995 respectively. Other racial-ethnic groups also registered greater shares in the workforce, increasing from 3 percent in 1995 to 8.3 percent in 2017 for standard workers and from 2.7 percent to 7.7 percent among nonstandard workers during the same period.

Finally, although the foreign-born shares were similar between two types of workers in 1995 (around 10 percent) and 2005 (around 15 percent), their share in nonstandard employment exceeded that in standard employment in 2017. Like the racial-ethnical composition, foreign-born individuals have experienced considerable growth in the period.

Indicators of Job Quality

Table 4 provides the comparison of job-quality indicators for workers with different skills in standard and nonstandard work arrangements. Hourly earnings of workers in nonstandard arrangements were higher for low- and middle-educated workers, and those in routine occupations. Although we do not explore each alternative arrangements in detail in this article, we should expect to see considerable variation in earnings across alternative arrangements as some tend to pay better than others (Kalleberg 2003). Low- and middle-educated workers worked more hours in alternative arrangements over the years, whereas the opposite is true for high-skill workers in both measures.

The share of workers who feel uncertain about their job continuity fluctuated over time among nonstandard workers but remained relatively stable among traditional workers. Among highly educated workers in 1995 and 2005, as well as workers in routine occupations in 2005 and 2017, a significantly lower share of workers in nonstandard arrangements expect jobs to continue. Although the literature suggests increasing insecurity and anxiety in the labor markets in general in the aftermath of the Great Recession (Holzer et al. 2011), our data suggest that this phenomenon is particularly related to nonstandard workers in routine occupations, which may be a consequence of automation-related job losses.

REGRESSION RESULTS

We start this section by presenting the effects of nonstandard employment on job quality, assuming those are the same across skill levels. For workers with similar skills (both measured as educational attainment and occupation task content) and demographic characteristics, nonstandard work had a growing depressing effect on earnings over time of roughly 3 percent in 1995 to 7 percent in 2017 (see table 5).[9] Likewise, the differences in work schedules increased over the period. Workers in nonstandard arrangements worked 0.7 fewer hours than traditional workers in 1995 and 1.2 fewer hours in 2017. Nonstandard employment also decreased confidence in job continuity. The log-odds of expecting job continuity were smaller for comparable nonstandard than standard workers in 1995 and 2005, growing from –0.3 to –0.4, but in 2017 was no longer significant.

As expected, higher skills increased expected earnings. Low- and middle-educated workers' predicted earnings were less than comparable highly educated workers over the entire period.[10] Similarly, workers performing nonroutine manual occupations (representing low skills) and routine occupations (middle skills) earned less than comparable workers performing nonroutine cognitive occupations (high skills). High-skill workers, measured by both education and occupation task content, had longer work schedules in all years.

Demographic variables have the expected signs regarding earnings and hours worked. Both earnings and hours worked increased with age, but at a decreasing rate. Females earned approximately 26 percent less and worked six fewer hours than comparable males in 1995; these differences decreased to 20 percent and 4.4 hours in 2017, respectively. Black and Hispanic workers earned less than comparable white workers, but the data revealed diverging trends, the gap increasing from roughly 10 to 12 percent less for blacks and decreasing from 7 to 5 percent less for Hispanics from 1995 to 2017. Meanwhile, workers of other races and ethnicities had higher expected earnings than whites in 2017. Blacks and Hispanics have higher expected weekly working hours, but the differences have decreased from 2005 to 2017. Further analysis of the interactions between such differences and nonstandard employment is needed to understand the underlying dynamics. However, like skills, demographic characteristics of individuals did not seem to affect expectations, except in the case of foreign-born

9. Due to limited space, we do not show the coefficients for demographics control variables in most tables. Full results are available on request.

10. We use the terms *comparable* and *similar* to denote that all other variables in the model are held constant. In this case, a comparable worker has similar demographic characteristics, same type of work arrangement (standard or nonstandard), and similar occupation.

Table 4. Job Quality by Skill Level and Employment Arrangement

	1995		2005		2017	
	Standard	Nonstandard	Standard	Nonstandard	Standard	Nonstandard
Panel A. Skills as educational attainment						
Low-educated						
Mean hourly earnings	8.1*	8.9	10.9*	12.0	14.4*	17.6
Mean weekly hours (all jobs)	34.6	34.5	35.4*	36.0	34.4*	36.7
Expect job to continue (%)	96.5	93.7	94.6	91.8	96.2	94.2
Middle-educated						
Mean hourly earnings	11.3*	12.6	15.9*	18.0	19.8*	21.0
Mean weekly hours (all jobs)	39.4*	40.0	39.4*	39.8	38.9*	39.4
Expect job to continue (%)	96.8	96.6	96.1	95.3	96.3	95.9
Highly educated						
Mean hourly earnings	18.4*	19.3	26.0	26.0	32.4*	31.4
Mean weekly hours (all jobs)	43.3*	42.1	42.3*	40.6	41.7*	38.2
Expect job to continue (%)	96.6*	94.2	95.9*	93.0	96.4	96.3
Panel B. Skills as occupational tasks content						
Nonroutine manual occupation						
Mean hourly earnings	7.9	8.0	12.1	12.1	15.8	16.1
Mean weekly hours (all jobs)	35.1	34.0	35.9	34.5	35.3	35.4
Expect job to continue (%)	96.9	96.4	95.9	95.7	96.1	97.8
Routine occupation						
Mean hourly earnings	11.6*	13.6	15.9*	18.5	20.2*	22.0
Mean weekly hours (all jobs)	39.7*	41.0	39.6*	40.7	39.4	39.7
Expect job to continue (%)	96.8	95.4	95.8*	93.5	96.4*	93.7
Nonroutine cognitive occupation						
Mean hourly earnings	17.3*	18.3	24.6	25.0	31.7	31.3
Mean weekly hours (all jobs)	42.7*	41.8	42.0*	40.6	41.6*	39.3
Expect job to continue (%)	96.6	95.3	95.9	94.0	96.4	96.8

Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).
Note: Data weighted using CWS supplement weights.
*Standard and nonstandard workers' means statistics are significantly different at least at the 0.05 level in two-tailed t-tests of means (nonweighted).

Table 5. Job Quality of Workers in Standard and Nonstandard Work Arrangements

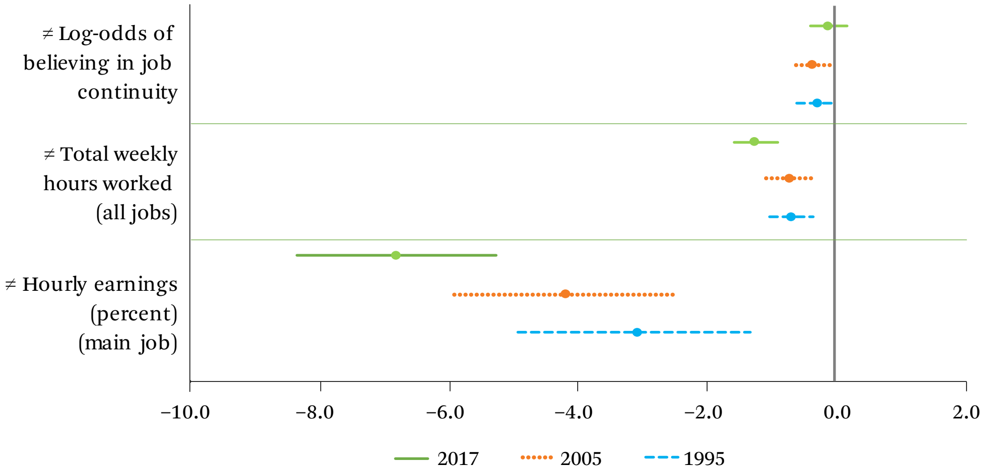
	Log Weekly Hourly Earnings (Main Job)			Weekly Hours Worked (All Jobs)			Expected Continuity		
	1995	2005	2017	1995	2005	2017	1995	2005	2017
Nonstandard arrangement	−0.03***	−0.04***	−0.07***	−0.69***	−0.71***	−1.25***	−0.27*	−0.37***	−0.11
	(0.01)	(0.01)	(0.01)	(0.17)	(0.18)	(0.17)	(0.15)	(0.14)	(0.15)
Low education	−0.42***	−0.50***	−0.46***	−4.01***	−3.95***	−4.31***	0.05	−0.12	0.04
	(0.02)	(0.01)	(0.01)	(0.20)	(0.22)	(0.22)	(0.12)	(0.12)	(0.14)
Middle education	−0.27***	−0.29***	−0.29***	−1.47***	−1.32***	−1.05***	0.17**	0.05	−0.00
	(0.01)	(0.01)	(0.01)	(0.13)	(0.14)	(0.12)	(0.08)	(0.08)	(0.07)
Nonroutine manual occupation	−0.44***	−0.41***	−0.41***	−4.16***	−3.40***	−3.75***	0.21**	0.12	−0.02
	(0.01)	(0.01)	(0.01)	(0.17)	(0.18)	(0.16)	(0.10)	(0.11)	(0.10)
Routine occupation	−0.19***	−0.22***	−0.26***	−1.30***	−1.06***	−1.26***	0.11	0.01	−0.00
	(0.01)	(0.01)	(0.01)	(0.13)	(0.14)	(0.13)	(0.07)	(0.08)	(0.08)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,957	35,855	38,330	50,679	38,994	43,597	45,338	35,822	39,404

Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).

Note: Data weighted using CWS supplement weights. Table reports results of OLS regressions on the hourly earnings and weekly hours worked, and results of Logit regressions on expected job continuity. Standard errors (for OLS models) and robust standard errors (for logit) in parentheses.

*$p < .1$; **$p < .05$; ***$p < .01$

Figure 1. Effects of Nonstandard Work Arrangements on Job Quality of Workers



Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).

Note: Coefficients and confidence intervals on nonstandard employment (dummy) obtained from OLS regressions on hourly earnings and weekly hours worked, and logit regressions on expected job continuity. Models control for education, occupation, and demographics.

workers, who were less likely to expect their job to continue, holding the remaining variables constant.[11]

In summary, we find overall evidence that workers in nonstandard employment arrangements have shorter working schedules and feel more insecure about their job continuity, than workers with similar skills and demographic characteristics in traditional arrangements (figure 1). Differences in earnings are increasing, though a further investigation would require more information on nonpecuniary benefits. Next, we drop the assumption that the effect of nonstandard employment is the same across skill levels by stratifying our models.

Nonstandard Employment Effects by Educational Attainment Levels

Nonstandard employment arrangements did not significantly affect earnings of comparable low- and middle-educated workers in 1995 and 2005 but had a positive effect for the former and a negative effect for the latter in 2017 (table 6). For highly educated workers, nonstandard employment represented an increasing wage penalty over the years, growing from roughly −6 to −12 percent from 1995 to 2017. Highly educated workers in nonstandard arrangements also worked significantly fewer hours than their counterparts in traditional arrangements, and the difference expanded from 1.4 to 3.2 hours less over time. The effect was not significant for low- and middle-educated workers in most years, except for low-educated workers in 1995. Finally, there is not enough evidence of differences regarding job continuity expectations between standard and nonstandard workers in the stratified models, except for highly educated workers in 2005.

Within all educational levels, tasks content performed in each occupational group significantly differentiated workers' earnings and weekly schedules (see table A3). Workers in nonroutine manual occupations earned less and worked fewer hours than those in nonroutine cognitive occupations over time, and the difference steadily decreased at all educational levels. Distinctly, the earnings gap between routine occupations (the "middle" jobs) and the reference group slightly increased for workers

11. For full models' results, see table A2.

Table 6. Effects of Nonstandard Work Arrangements on Job Quality of Workers by Education

	Low-Educated			Middle-Educated			Highly Educated		
	1995	2005	2017	1995	2005	2017	1995	2005	2017
Log hourly earnings (main job)	−0.01	0.01	0.06**	−0.02	−0.00	−0.05***	−0.06***	−0.13***	−0.12***
Observations	1,982	3,323	2,759	11,544	21,334	20,839	5,431	11,198	14,732
Weekly hours worked (all jobs)	−1.38**	−1.07*	−0.65	−0.23	−0.12	−0.10	−1.37***	−1.80***	−3.19***
Observations	5.457	3,770	3,233	31,187	23,260	23,647	14,035	11,964	16,717
Expected job continuity	−0.66	−0.42	−0.50	−0.09	−0.22	−0.10	−0.41	−0.59**	−0.03
Observations	5,015	3,550	2,863	28,169	21,521	21,572	12,154	10,751	14,969
Occupational and demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).

Note: Data weighted using CWS supplement weights. Table reports coefficients for the nonstandard employment dummy in each regression. Coefficients from OLS regressions on the hourly earnings and weekly hours worked, and logit regressions on expected job continuity. Standard errors (for OLS models) and robust standard errors (for logit) in parentheses.

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

in all models. We find no evidence that occupations differentiated workers regarding future expectations.

Therefore, stratifying workers by education levels showed that nonstandard employment is consistently associated with all three indicators of job quality for highly educated workers. One possible explanation for such significant effects is that this is the group who prefers and can afford to have more flexibility and fewer hours worked to combine job and household responsibilities (Goldin, Katz, and Kuziemko 2006). If that is the case, the effects we found should not be interpreted as indicators of precarity.

Nonstandard Employment Effects by the Content of Tasks Performed in Occupations

The stratification of workers by occupational tasks content paints a slightly different picture. Figure 2 illustrates the summary findings of the stratification by education and occupations. In line with the previous stratification, nonstandard employment significantly reduced the earnings of high-skill workers (now taken as those in nonroutine cognitive occupations) by 4 percent in 1995, and 13 percent in 2017 (table 7). Unlike low-educated workers, nonstandard employment represented a wage penalty of roughly 4 percent for those in nonroutine manual occupations over the entire period. Regarding weekly schedule, the conclusions are similar and indicate that low- and high-skill workers tend to work fewer hours in nonstandard arrangements than comparable traditional workers.

An important distinction from the previous stratification concerns future expectations for middle-skill workers: those performing routine jobs are increasingly less secure about their job continuity—which may be a consequence of the reduction of middle-skill jobs (Jaimovich and Siu 2014; Foote and Ryan 2014). Within all occupations, education is significantly and positively related to earnings. Over time, the work schedule increased with education for similar workers in all occupational categories, but education does not significantly differentiate workers performing similar tasks (see table A4).

Robustness Check

Due to the higher flexibility of nonstandard arrangements, it is possible that our findings are partially influenced by self-selection of workers who might need to combine paid and unpaid work and who are less worried about work schedule, wage differentials, or job continuity. Evidence indicates, for instance, that highly educated female workers experience a discontinuity in their careers following motherhood and move to jobs with reduced earnings and work schedules (Bertrand, Goldin, and Katz 2010).

To test such a hypothesis, we ran all models for male workers only, given that women are still those who carry most of the housework (Blau and Kahn 2000). Conclusions remained unchanged regarding hourly earnings and work expectations. Important differences, however, were found in work schedule, and we report those in table 8.

First, the full model (which assumed the same effect for all workers) predicted that nonstandard workers had reduced weekly work schedules, but the opposite is true when considering males only. Second, we previously found that low and highly educated workers worked fewer hours in nonstandard arrangements, whereas evidence of differences for middle-educated workers was insufficient. In the males-only models, we do not find significant differences for low- and high-skill workers (there is variation across years for the latter), but middle-educated workers have longer schedules. Finally, stratifying by occupation task content, we find similar inconclusive evidence of different working schedules for low- and high-skill workers (nonroutine manual and cognitive occupations), but middle-skill workers (routine occupations) have longer schedules in nonstandard arrangements.

Therefore, some self-selection of workers in nonstandard arrangements to combine paid and unpaid work across skill levels seems plausible. By restricting the sample to males, the reduced work schedule effect disappears for low- and high-skill workers, whereas for middle-skill workers, nonstandard employment represents an increase in the number of hours worked.

Table 7. Effects of Nonstandard Work Arrangements on Job Quality of Workers by Occupational Tasks

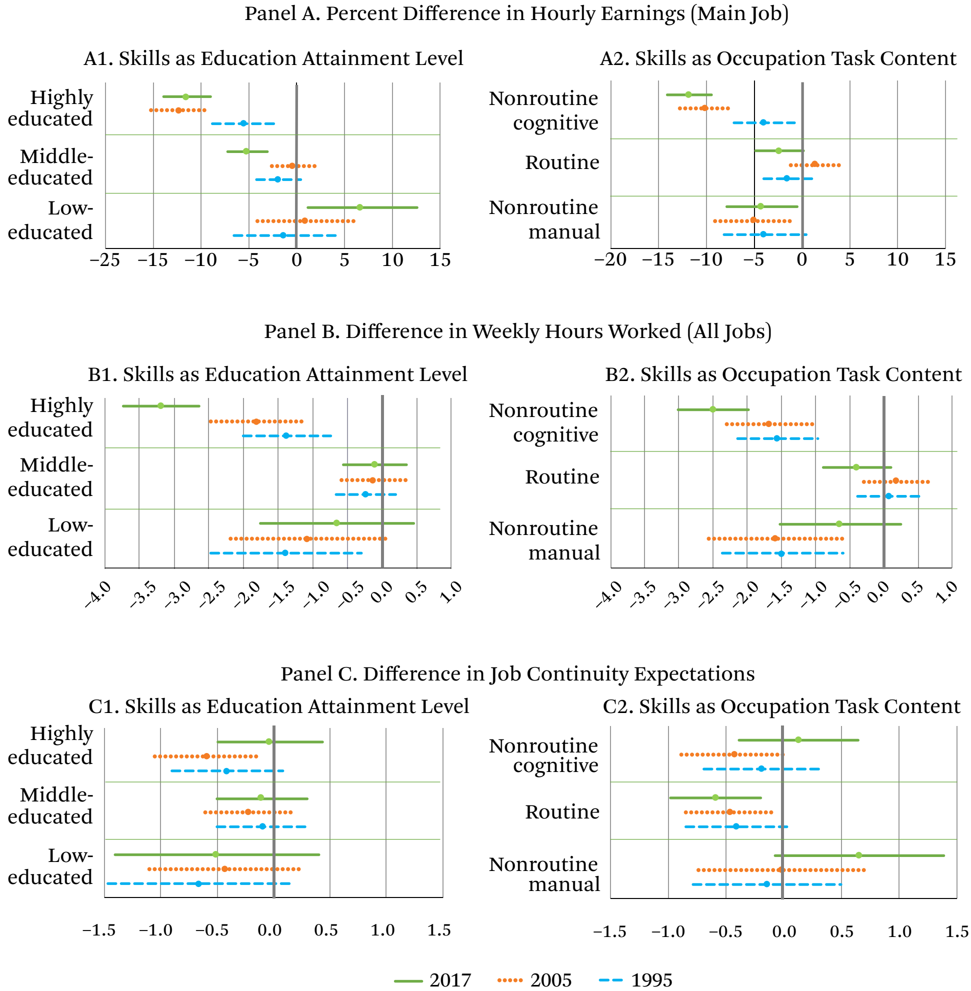
	Nonroutine Manual Occupation			Routine Occupation			Nonroutine Cognitive Occupation		
	1995	2005	2017	1995	2005	2017	1995	2005	2017
Log hourly earnings (main job)	−0.04*	−0.05**	−0.04**	−0.01	0.01	−0.02*	−0.04**	−0.11***	−0.13***
Observations	3,283	5,345	6,220	9,097	17,202	16,088	6,577	13,308	16,022
Weekly hours worked (all jobs)	−1.48***	−1.58***	−0.64	0.08	0.19	−0.39	−1.56***	−1.67***	−2.50***
Observations	8,687	5,980	7,226	24,784	18,807	18,061	17,208	14,207	18,310
Expected job continuity	−0.15	−0.02	0.65*	−0.41*	−0.46**	−0.59***	−0.19	−0.43*	0.13
Observations	8,043	5,580	6,478	22,249	17,562	16,623	15,046	12,680	16,303
Educational and demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).

Note: Data weighted using CWS supplement weights. Table reports coefficients for the nonstandard employment dummy in each regression. Coefficients from OLS regressions on the hourly earnings and weekly hours worked, and logit regressions on expected job continuity. Standard errors (for OLS models) and robust standard errors (for logit) in parentheses.

*$p < .1$; **$p < .05$; ***$p < .01$

Figure 2. Effects of Nonstandard Work Arrangements on Job Quality by Skill



Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).

Note: Panels A and B obtained from OLS regressions. Panel C obtained from logit regressions. For A1, B1, and C1, models control for occupation task content and demographics. For A2, B2, and C2, models control for education attainment and demographics.

DISCUSSION AND CONCLUSION

In a context of changing nature of employment driven by technological and institutional transformations, identifying and monitoring their effects on workers is a necessary task to inform public policy. Nonstandard arrangements raise concerns over employment quality and workers' well-being, given that these jobs are often associated with higher insecurity and fewer benefits and protections to workers (Kalleberg 2011) despite offering more flexibility and new tools to deal with volatility (Golden 2008; Farrell and Greig 2016a; Abraham et al. 2017).

Nonstandard employment arrangements should have different implications for different types of workers. This article contributes to this literature by providing evidence on the differentiating effects of nonstandard work on job quality of workers with different skills in 1995, 2005, and 2017. Our analysis focused on three indicators of job quality: earnings, hours worked, and expected job continuity. We op-

Table 8. Gender Differences in Effects of Nonstandard Employment on Weekly Hours Worked

	1995	2005	2017
Full model			
All workers	−0.69***	−0.71***	−1.25***
Males only	0.97***	0.70***	−0.09
Stratified by educational attainment			
All low-educated	−1.38**	−1.07*	−0.65
Low-educated males	−0.09	−0.07	−0.74
All middle-educated	−0.23	−0.12	−0.10
Middle-educated males	1.27***	0.97***	0.76***
All highly educated	−1.37***	−1.80***	−3.19***
Highly educated males	0.87**	0.48	−1.38***
Stratified by occupation task content			
All workers in nonroutine manual occupation	−1.48***	−1.58***	−0.64
Males in nonroutine manual occupation	−0.84	−0.30	−0.31
All workers in routine occupation	0.08	0.19	−0.39
Males in routine occupation	1.63***	1.17***	0.14
All workers in nonroutine cognitive occupation	−1.56***	−1.67***	−2.50***
Males in nonroutine cognitive occupation	0.46	0.14	−0.47

Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).

Note: Data weighted using CWS supplement weights. Table reports coefficients for the nonstandard employment dummy obtained from OLS regressions on weekly hours worked.

*$p < .1$; **$p < .05$; ***$p < .01$

erationalized skills both using educational attainment levels and occupational task content. Our general finding is that workers in nonstandard employment receive increasingly lower earnings and work fewer hours than comparable workers in traditional arrangements. No evidence indicates differences in expectations of job continuity. However, the effects are heterogeneous for subgroups of workers.

Earnings-wise, nonstandard employment is increasingly reducing the earnings of high-skill workers whereas, for middle-skill workers, the wage penalty was significant only in 2017. For low-skill workers, on the other hand, the skills' operationalization pointed to different conclusions: in alternative arrangements, nonroutine manual workers received 5 percent lower earnings over the entire period and low-educated workers earned 7 percent more in 2017. The positive difference seem to be a growing trend.

Regarding weekly hours worked, high-skill workers in alternative arrangements are increasingly working fewer hours than comparable traditional workers. Low-skill workers are also working fewer hours, but the overtime trend seems to close the gap. For middle-skill workers, no evidence suggests different schedules by employment arrangement. The reduced working schedules are at least partly explained by self-selection of workers who may need to combine paid and unpaid work—by restricting the samples to male workers, the differences in working hours disappear for low- and high-skill workers, and middle-skill workers work longer hours in alternative arrangements.

Finally, we did not find evidence of nonstandard employment being associated with lower expectations of job continuity, except for workers in routine occupations, who are increasingly feeling insecure about the future. This is in line with the literature stressing the reduction of middle jobs in the U.S. economy due to automation and institutional changes (Weil

2014; Acemoglu and Autor 2010). Insecurity for routine occupations may also have increased in the aftermath of the Great Recession because job losses were concentrated in the middle segment (Foote and Ryan 2014).

High-skill workers are the fastest growing share of the workforce and, in theory, are in the best position to benefit from the flexibility and protect themselves against insecurity (Golden 2008; Kalleberg 2011; Holzer 2011). We find that in nonstandard arrangements they receive increasingly fewer earnings and work fewer hours. Such differences may be explained by self-selection of workers who prefer or can afford to be in such a position. If that is the case, they should not be interpreted as indicators of job precarity.

Low-skill workers, on the contrary, are more vulnerable to worsening working conditions. These workers have worse jobs regarding earnings and working hours, and, in the educational operationalization, least expectations regarding continuity of their jobs. Therefore, although we confirm the literature that associates lower skills with worse jobs (Kalleberg 2011; Holzer et al. 2011; Catanzarite 2000; Fischer and Hout 2016), we do not find that nonstandard employment has a worsening effect. Rather, it seems that low-skill workers are in equally bad jobs regardless of work arrangement, at least according to the dimensions we assessed.

Although our analysis provides nuanced evidence on the association between skills and nonstandard employment quality, more research is needed to further unpack the underlying dynamics. In particular, differences between types of nonstandard employment need clarification, the mechanisms that lead workers to nonstandard arrangements (self-selection versus lack of alternatives), as well as the inclusion of other dimensions of job quality such as health insurance, pensions, and paid vacation. A closer examination of how nonstandard employment would affect workers with different race-ethnicity and immigrant status can also reveal important variations. Evidence is convincing that the slow adjustments of legislation in the face of new arrangements have opened the room for misclassification of workers and reduction of their rights (Harris and Krueger 2015; Weil 2014). A better understanding of these workers will help inform future policy design.

Table A1. Correspondence of Skill Measurement: Education Levels and Occupation's Task Content

	Education Attainment Level								
	1995			2005			2017		
Occupation Task Content	Low	Middle	High	Low	Middle	High	Low	Middle	High
Nonroutine manual	41.3	19.4	4.0	32.3	18.1	5.0	35.5	22.2	6.7
Routine	53.3	59.8	23.3	62.3	59.8	22.8	56.8	54.2	20.6
Nonroutine cognitive	5.5	20.8	72.8	5.4	22.1	72.2	7.7	23.6	72.8
Total	100	100	100	100	100	100	100	100	100

Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).
Note: Data weighted using CWS supplement weights. N in 1995, 2005 and 2015 are, respectively, 54,122, 41,829, and 46,144.

Table A2. Job Quality of Workers in Standard and Nonstandard Work Arrangements

	Log Weekly Hourly Earnings (Main Job)			Weekly Hours Worked (All Jobs)			Expected Continuity		
	1995	2005	2017	1995	2005	2017	1995	2005	2017
Nonstandard arrangement	−0.03***	−0.04***	−0.07***	−0.69***	−0.71***	−1.25***	−0.27*	−0.37***	−0.11
	(0.01)	(0.01)	(0.01)	(0.17)	(0.18)	(0.17)	(0.15)	(0.14)	(0.15)
Low Education	−0.42***	−0.50***	−0.46***	−4.01***	−3.95***	−4.31***	0.05	−0.12	0.04
	(0.02)	(0.01)	(0.01)	(0.20)	(0.22)	(0.22)	(0.12)	(0.12)	(0.14)
Middle Education	−0.27***	−0.29***	−0.29***	−1.47***	−1.32***	−1.05***	0.17**	0.05	−0.00
	(0.01)	(0.01)	(0.01)	(0.13)	(0.14)	(0.12)	(0.08)	(0.08)	(0.07)
Nonroutine manual occupation	−0.44***	−0.41***	−0.41***	−4.16***	−3.40***	−3.75***	0.21**	0.12	−0.02
	(0.01)	(0.01)	(0.01)	(0.17)	(0.18)	(0.16)	(0.10)	(0.11)	(0.10)
Routine occupation	−0.19***	−0.22***	−0.26***	−1.30***	−1.06***	−1.26***	0.11	0.01	−0.00
	(0.01)	(0.01)	(0.01)	(0.13)	(0.14)	(0.13)	(0.07)	(0.08)	(0.08)
Female	−0.26***	−0.23***	−0.20***	−6.10***	−5.00***	−4.44***	−0.09	−0.02	0.04
	(0.01)	(0.01)	(0.01)	(0.10)	(0.11)	(0.10)	(0.06)	(0.06)	(0.06)
Black	−0.10***	−0.12***	−0.12***	−0.22	0.81***	0.49***	−0.18*	−0.26**	−0.16
	(0.01)	(0.01)	(0.01)	(0.16)	(0.18)	(0.16)	(0.10)	(0.11)	(0.10)
Latino	−0.07***	−0.06***	−0.05***	0.26	1.34***	0.32**	−0.04	−0.14	−0.11
	(0.02)	(0.01)	(0.01)	(0.20)	(0.19)	(0.16)	(0.13)	(0.10)	(0.11)
Other race-ethnicity	−0.02	−0.00	0.03***	−0.60*	0.66***	−0.63***	0.14	0.17	0.11
	(0.02)	(0.01)	(0.01)	(0.31)	(0.25)	(0.20)	(0.16)	(0.15)	(0.13)
Foreign born	−0.06***	−0.04***	−0.04***	0.69***	0.15	−0.03	−0.34***	−0.56***	−0.22**
	(0.02)	(0.01)	(0.01)	(0.19)	(0.18)	(0.16)	(0.11)	(0.10)	(0.10)
Married	0.05***	0.04***	0.07***	−0.37***	−0.03	−0.18	−0.01	−0.02	0.11
	(0.01)	(0.01)	(0.01)	(0.11)	(0.12)	(0.11)	(0.07)	(0.07)	(0.07)
Age	0.05***	0.05***	0.04***	1.49***	1.32***	1.20***	−0.00	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
Age^2	−0.00***	−0.00***	−0.00***	−0.02***	−0.01***	−0.01***			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
Constant	1.71***	2.12***	2.54***	16.60***	17.47***	19.42***	3.38***	3.33***	3.42***
	(0.04)	(0.03)	(0.02)	(0.47)	(0.51)	(0.46)	(0.13)	(0.13)	(0.12)
Observations	18,957	35,855	38,330	50,679	38,994	43,597	45,338	35,822	39,404

Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).

Note: Data weighted using CWS supplement weights. Table reports the results of OLS regressions on the hourly earnings and weekly hours worked, and results of Logit regressions on expected job continuity. Standard errors (for OLS models) and robust standard errors (for logit) in parentheses.

$^*p < .1$; $^{**}p < .05$; $^{***}p < .01$

Table A3. Effects of Nonstandard Work Arrangements on Job Quality of Workers Stratified by Educational Levels

	Low-Educated			Middle-Educated			Highly Educated		
	1995	2005	2017	1995	2005	2017	1995	2005	2017
Panel A. OLS regression on log hourly earnings (main job)									
Nonstandard arrangement	−0.01	0.01	0.06**	−0.02	−0.00	−0.05***	−0.06***	−0.13***	−0.12***
	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Nonroutine manual occupation	−0.37***	−0.36***	−0.35***	−0.42***	−0.38***	−0.36***	−0.56***	−0.44***	−0.50***
	(0.05)	(0.04)	(0.04)	(0.02)	(0.01)	(0.01)	(0.04)	(0.03)	(0.02)
Routine occupation	−0.16***	−0.15***	−0.18***	−0.16***	−0.20***	−0.22***	−0.23***	−0.26***	−0.31***
	(0.05)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Observations	1,982	3,323	2,759	11,544	21,334	20,839	5,431	11,198	14,732
Panel B. OLS regression on weekly hours worked (all jobs)									
Nonstandard arrangement	−1.38**	−1.07*	−0.65	−0.23	−0.12	−0.10	−1.37***	−1.80***	−3.19***
	(0.55)	(0.57)	(0.56)	(0.22)	(0.23)	(0.23)	(0.32)	(0.34)	(0.28)
Nonroutine manual occupation	−4.79***	−5.92***	−4.33***	−4.02***	−3.29***	−3.58***	−4.05***	−3.23***	−3.66***
	(0.69)	(0.81)	(0.73)	(0.19)	(0.22)	(0.20)	(0.50)	(0.48)	(0.33)
Routine occupation	−1.70**	−2.65***	−1.52**	−1.29***	−1.14***	−1.28***	−1.80***	−1.05***	−1.39***
	(0.67)	(0.78)	(0.70)	(0.15)	(0.17)	(0.17)	(0.23)	(0.25)	(0.20)
Observations	5,457	3,770	3,233	31,187	23,260	23,647	14,035	11,964	16,717
Panel C. Logit regression on expected job continuity									
Nonstandard arrangement	−0.66	−0.42	−0.50	−0.09	−0.22	−0.10	−0.41	−0.59**	−0.03
	(0.41)	(0.34)	(0.46)	(0.21)	(0.20)	(0.20)	(0.25)	(0.24)	(0.24)
Nonroutine manual occupation	−0.06	−0.45	0.52	0.18	0.09	−0.14	0.14	0.26	−0.08
	(0.44)	(0.53)	(0.49)	(0.13)	(0.14)	(0.13)	(0.30)	(0.28)	(0.21)
Routine occupation	−0.22	−0.56	0.01	0.07	−0.03	−0.09	0.25*	0.08	0.16
	(0.42)	(0.51)	(0.45)	(0.10)	(0.11)	(0.11)	(0.14)	(0.14)	(0.13)
Observations	5,015	3,550	2,863	28,169	21,521	21,572	12,154	10,751	14,969

Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).
Note: Data weighted using CWS supplement weights. All models control for demographic characteristics. Table reports coefficients for the nonstandard employment dummy in each regression. Coefficients from OLS regressions on the hourly earnings and weekly hours worked, and Logit regressions on expected job continuity. Standard errors (for OLS models) and robust standard errors (for logit) in parentheses.
$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Table A4. Effects of Nonstandard Work Arrangements on Job Quality of Workers Stratified by the Content of Tasks Performed in Occupation

	Nonroutine Manual Occupation			Routine Occupation			Nonroutine Cognitive Occupation		
	1995	2005	2017	1995	2005	2017	1995	2005	2017
Panel A. OLS regression on log hourly earnings (main job)									
Nonstandard arrangement	−0.04*	−0.05**	−0.04**	−0.01	0.01	−0.02*	−0.04**	−0.11***	−0.13***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Low education	−0.33***	−0.50***	−0.40***	−0.39***	−0.46***	−0.41***	−0.50***	−0.55***	−0.53***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.04)	(0.04)
Middle education	−0.19***	−0.27***	−0.22***	−0.22***	−0.25***	−0.25***	−0.30***	−0.31***	−0.34***
	(0.04)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	3,283	5,345	6,220	9,097	17,202	16,088	6,577	13,308	16,022
Panel B. OLS regression on weekly hours worked (all jobs)									
Nonstandard arrangement	−1.48***	−1.58***	−0.64	0.08	0.19	−0.39	−1.56***	−1.67***	−2.50***
	(0.45)	(0.50)	(0.45)	(0.24)	(0.25)	(0.25)	(0.30)	(0.32)	(0.27)
Low education	−4.96***	−5.10***	−5.29***	−3.31***	−3.78***	−3.72***	−3.20***	−2.44***	−4.04***
	(0.59)	(0.61)	(0.53)	(0.27)	(0.29)	(0.29)	(0.66)	(0.76)	(0.65)
Middle education	−1.60***	−1.53***	−1.14***	−1.24***	−1.42***	−0.96***	−1.68***	−1.28***	−1.10***
	(0.54)	(0.53)	(0.41)	(0.20)	(0.21)	(0.19)	(0.18)	(0.20)	(0.17)
Observations	8,687	5,980	7,226	24,784	18,807	18,061	17,208	14,207	18,310
Panel C. Logit regression on expected job continuity									
Nonstandard arrangement	−0.15	−0.02	0.65*	−0.41*	−0.46**	−0.59***	−0.19	−0.43*	0.13
	(0.33)	(0.37)	(0.37)	(0.22)	(0.20)	(0.20)	(0.26)	(0.23)	(0.26)
Low education	0.18	−0.27	0.46	−0.04	−0.14	−0.31*	0.19	0.43	−0.03
	(0.33)	(0.33)	(0.30)	(0.18)	(0.17)	(0.19)	(0.40)	(0.50)	(0.43)
Middle education	0.34	−0.06	0.06	0.08	0.01	−0.18	0.17	0.07	0.09
	(0.31)	(0.29)	(0.23)	(0.13)	(0.14)	(0.13)	(0.10)	(0.11)	(0.11)
Observations	8,043	5,580	6,478	22,249	17,562	16,623	15,046	12,680	16,303

Source: Authors' compilation based on CWS 1995, 2005, and 2017 (U.S. Census Bureau 1995, 2005, 2017).

Note: Data weighted using CWS supplement weights. All models control for demographic characteristics. Table reports coefficients for the nonstandard employment dummy in each regression. Coefficients from OLS regressions on the hourly earnings and weekly hours worked, and Logit regressions on expected job continuity. Standard errors (for OLS models) and robust standard errors (for logit) in parentheses.

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

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