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What Explains Racial/Ethnic Inequality in Job Quality in the Service Sector?

Adam Storer,[a] Daniel Schneider,[b] and Kristen Harknett[c]

Abstract

Precarious work in the United States is defined by economic and temporal dimensions. A large literature documents the extent of low wages and limited fringe benefits, but research has only recently examined the prevalence and consequences of unstable and unpredictable work schedules. Yet practices such as on-call shifts, last minute cancellations, and insufficient work hours are common in the retail and food-service sectors. Little research has examined racial/ethnic inequality in this temporal dimension of job quality, yet precarious scheduling practices may be a significant, if mostly hidden, site for racial/ethnic inequality, because scheduling practices differ significantly between firms and because front-line managers have substantial discretion in scheduling. We draw on innovative matched employer-employee data from The Shift Project to estimate racial/ethnic gaps in these temporal dimensions of job quality and to examine the contribution of firm-level sorting and intra-organizational dynamics to these gaps. We find significant racial/ethnic gaps in exposure to precarious scheduling that disadvantage non-white workers. We provide novel evidence that both firm segregation and racial discordance between workers and managers play significant roles in explaining racial/ethnic gaps in job quality. Notably, we find that racial/ethnic gaps are larger for women than for men.

Keywords

inequality, precarious work, race/ethnicity, racial/ethnic discrimination, organizations

Over the past 50 years, work in the United States has become more polarized and more precarious (Kalleberg 2009). This precarity is multi-dimensional. Scholars and policymakers often focus on economic dimensions of job quality, including low and stagnant wages and retrenchment in fringe benefits, but recent research calls attention to the importance of the "temporal" dimension of job quality (Kalleberg 2011, 2018). Although scholars have long been concerned with nonstandard work schedules (Presser 1999) and limited workplace flexibility (Galinsky, Sakai, and Wigton 2011), research and policy has more recently recognized the importance of unstable and unpredictable work schedules. In this emerging research on temporal job quality, the service sector stands out as a setting where large proportions of workers have highly variable

[a]UC-Berkeley
[b]Harvard University
[c]UC-San Francisco

Corresponding Author:
Adam Storer, Department of Sociology, UC Berkeley, 410 Barrows Hall, Berkeley, CA 94720
Email: adamstorer@berkeley.edu

schedules with as little as a few days of advance notice (Lambert, Fugiel, and Henly 2014). These workers are subject to last-minute shift cancellations and on-call shifts (Schneider and Harknett 2019a). Such scheduling practices occur against a backdrop of involuntary part-time work and limited employee schedule flexibility (Lambert 2008). Moreover, exposure to these scheduling practices appears to have significant negative effects on worker and family well-being (Carrillo et al. 2017; Henly and Lambert 2014; Schneider and Harknett 2019a).

A large literature documents the size and sources of racial and ethnic gaps in hiring, wages, and access to fringe benefits, but we know very little about how exposure to these unstable and unpredictable scheduling practices may be patterned by race/ethnicity or about the underlying sources of such inequalities, in large part because exposure to precarious scheduling practices is rarely measured in existing data sources. Yet, precarious scheduling practices may be a significant, if mostly hidden, site for racial/ethnic inequality. One potential source of racial/ethnic inequality in work scheduling is differential sorting of workers by race/ethnicity, not just by occupation but by firm. Prior research shows substantial heterogeneity across firms in work scheduling practices, with "high road firms" offering more stability and predictability (Bach, Kalloch, and Ton 2018). Research on hiring suggests non-white workers might be sorted into lower job-quality firms through a process of allocative discrimination (Blau 1977; Blau and Kahn 2017) or due to less access to informal referral networks (Smith 2005). Thus, between-firm segregation may be one source of racial/ethnic inequalities in scheduling. A second potential source of racial/ethnic inequality in scheduling is intra-organizational (Avent-Holt and Tomaskovic-Devey 2010). Within firms, exposure to such scheduling practices is highly contingent on managerial practices and supervisors' discretion (Lambert 2008; Wood 2018). In the context of widespread conscious and unconscious bias (Greenwald, Banaji, and Nosek 2015) and against a reality of an overwhelmingly white managerial corps (Stainback and Tomaskovic-Devey 2009), non-white workers could be assigned worse schedules. However, prior research lacks the kind of employer-employee data needed to examine these potential sources of racial/ethnic gaps in precarious scheduling or in other dimensions of job quality.

We address the pronounced lack of data on precarious scheduling and of data that links employees and employers by drawing on the novel Shift Project data. The Shift Project uses an innovative approach to gather employer-employee linked data using social media platforms as both sampling frame and survey recruitment channel. Our analysis draws on data on more than 32,000 hourly workers employed at 123 of the largest retail and food-service firms in the United States. These data contain detailed measures of work scheduling exposures, demographics, human capital, and other labor market characteristics (Schneider and Harknett 2019a). These data are quite unusual in that they comprise a matched employer-employee sample that allows us to examine firm-level sorting and intra-organizational dynamics.

We find that white workers are significantly advantaged in terms of temporal job quality: they are less likely to have canceled shifts, work on-call, work consecutive closing then opening shifts ("clopens"), be involuntary part-time workers, or have trouble getting time off. The unique matched employer-employee data allow us to examine the explanatory power of firm-level sorting by race/ethnicity, which accounts for 16 percent of the gap for Black workers. These data also include information on supervisors' race/ethnicity, with which we show that racial/ethnic discordance between workers and managers explains 11 percent of the racial/ethnic gap in job quality overall, and 25 percent of the gap for Black workers. We also find that racial/ethnic gaps in job quality are larger for women than for men, and racial discordance with managers and occupational segregation between white women and women of color explain a portion of the gap. Our results provide novel empirical evidence that firm-level sorting and intra-organizational dynamics help explain labor market inequalities, and they underscore the importance of intersectional analyses of these inequalities and their explanations.

TEMPORAL PRECARITY

In addition to low pay, few fringe benefits, little autonomy, and high rates of turnover, jobs in the U.S. service sector are characterized by significant temporal instability. This instability is multi-dimensional and includes short advance notice of work schedules, variability in the timing of work shifts and in the number of hours worked each week, and involuntary part-time work (Halpin 2015; Lambert 2008; Lambert et al. 2014; Rubery et al. 2005). Work schedules are typically determined by employers with little input from workers about when they are available or would prefer to work, and schedules are often set without regard for workers' need to rest, to care for children or other family members, to pursue schooling or hold second jobs, or to anticipate and plan for non-work time (Golden 2015).

This temporal instability is the result of a set of human resource management strategies, used by employers to closely align staffing with consumer demand and thus minimize labor costs (Lambert 2008). These scheduling practices, sometimes called "just-in-time" scheduling, are part of a broader "risk shift" in which employers have offloaded more of the risk, uncertainty, and costs of doing business onto workers (Hacker 2008). These "just-in-time" scheduling practices have some advantages from the employer perspective in terms of lower labor costs, but from workers' perspective these practices create routine instability and chronic uncertainty.

This routine uncertainty manifests in a number of ways. Many workers experience canceled shifts, often with less than a day's notice. Workers are not typically paid for these canceled shifts, so each cancellation represents an unexpected earnings shock. Workers are also often expected to keep their schedules open and available for "on-call" work shifts, with no guarantee these shifts will translate into actual hours worked and actual earnings. Another form of temporal precarity is the common practice of scheduling back-to-back closing then opening ("clopening") shifts with little time for workers to rest in between (Kantor 2014).

One key driver of this temporal precarity is the prevalence of involuntary part-time work. Workers often receive fewer hours than they desire and fewer hours than they need to make ends meet. As a result, and out of economic necessity, workers will remain open and available to pick up new shifts, even on short notice and at inconvenient times.

This "flexibility" in work scheduling should not be confused with desirable flexibility for workers. Instead, this flexibility is beneficial for employers, and it usually represents undesirable instability from the perspective of workers. Few workers have much input into their work schedules, and workers often lack the flexibility to get time off from work when needed. Schedules are primarily dictated by employer needs.

Unstable and unpredictable work schedules are a potential source of stress and economic insecurity. When workers are paid hourly, fluctuations in work hours mechanically lead to fluctuations in earnings, and work schedule instability has been shown to lead to material hardship (Schneider and Harknett 2019b). Prior research also documents the work-life conflict caused by these scheduling practices (Henly and Lambert 2014), as well as the negative consequences for worker health and well-being (Schneider and Harknett 2019a). Temporal precarity is a prevalent and consequential dimension of job quality.

RACIAL/ETHNIC INEQUALITY IN TEMPORAL PRECARITY

Unstable schedules are common, yet they may be unevenly allocated within and between firms. In particular, we expect schedule quality to vary by race/ethnicity. This expectation is based on evidence of racial/ethnic bias in the workplace in hiring, pay, and benefits. In the hiring process, experimental audit studies show that Black and Hispanic applicants are significantly less likely to receive interview call-backs than are their otherwise identically qualified white peers (Pager 2003; Pager and Shepherd 2008; Quillian et al. 2017). With respect to wages, Mandel and Semyonov (2016) show that since 2000, wage gaps between racial/ethnic groups have widened significantly. Finally, racial/ethnic inequality also appears in the allocation of fringe benefits, with white workers the most likely to have an employer-provided pension plan or health insurance, Hispanic workers the least likely, and Black workers in between (Kristal, Cohen, and Navot 2018). Given these widespread accounts of racial/ethnic gaps in hiring, pay, and benefits, we turn our focus to studying the extent of this gap in scheduling.

Although unstable and unpredictable work scheduling practices appear to be common and consequential for employee well-being, very little research examines racial/ethnic inequality in exposure to this aspect of job quality. Swanberg, Watson, and Eastman (2014) use data from the 2008 National Study of the Changing Workforce to examine inequality between workers in terms of scheduling. Comparing across multiple measures of scheduling, including schedule control, being asked to work overtime, experiencing hour reductions, and being involuntarily part-time, Swanberg and colleagues (2014) do not find evidence of racial/ethnic inequality in work schedules among low-wage workers. However, they also find little evidence of any patterning of scheduling exposures by any explanatory variable, and the failure to detect significant effects may be driven by the relatively small sample size of just 645 respondents.

In contrast, Ruetschlin and Asanta-Muhammad (2015) use Current Population Survey (CPS) data from 2012 to 2015 and find that Black and Hispanic workers in retail are substantially more likely to be involuntary part-time than their white, non-Hispanic counterparts. Lambert and colleagues (2014) use a broader set of scheduling measures from the National Longitudinal Survey of Youth 97 (NLSY97) for workers across the full range of occupations. Black and Hispanic workers receive less advance notice of their work schedules than white workers and have less schedule control, but they do not experience more work-hour volatility. Finnigan and Hunter (2018) show that during the Great Recession, Hispanic workers saw the greatest increase in work-hour volatility, but whereas for Hispanics this increase was concentrated among workers in primarily minority occupations (defined as a continuous variable for percent white in approximately 12,000 state-occupation-industry cells), for Black workers the growth in volatility was greatest in predominately white occupations.

These studies have produced useful information about the extent of unstable scheduling in the United States, but they are limited in a number of ways. First, this prior research is constrained by the available data and thus has not assessed racial/ethnic inequality in such practices as on-call shifts, clopening, and schedule cancellation, which have proven important for worker well-being (Schneider and Harknett 2019a). Second, these studies do not decompose racial/ethnic gaps in scheduling to show the extent to which factors such as human capital, demographics, or occupation contribute to these inequalities, as they do for a portion of the racial/ethnic inequalities in wages (Mandel and Semyonov 2016; Snipp and Cheung 2016) and fringe benefits (Hersch and White-Means 1993; Kristal et al. 2018; Semyonov, Lewin-Epstein, and Bridges 2011). Finally, as is the case broadly in research on racial/ethnic inequality in job quality, little attention has been paid to the role of between- and within-firm factors in producing stratified outcomes. We will outline two processes by which firms may structure racial/ethnic differences in scheduling. We argue that these processes are especially likely to give rise to racial/ethnic inequality in terms of work schedule quality.

BETWEEN-FIRM SORTING AND SCHEDULE INEQUALITY

One reason why workers of color earn less and have less access to fringe benefits is that they are disproportionately concentrated in occupations where all incumbents earn less and have less access to fringe benefits (Grodsky and Pager 2001; Huffman and Cohen 2004; Kristal et al. 2018). However, building on the insights of Baron and Bielby (1980), we note that occupations do not directly set wages, benefit levels, or work schedules, firms do. Yet, between-firm segregation could only contribute to broader racial/ethnic inequalities in job quality if there were significant differences in job quality between firms, and if firms were segregated by race/ethnicity along the lines of job quality. For the purposes of this article, we use firm, employer, company, and organization interchangeably.

Simple economic models predict that within the same sector, firms will be relatively similar in terms of wages and other aspects of job quality. Although the firm-level data needed to empirically test that proposition is scarce, scattered research over the past several decades finds significant within-sector, between-firm heterogeneity in wages (Groshen 1991; Lane, Salmon, and Spletzer 2007). Furthermore, research in industrial relations points to a set of firms in the retail and food-service industries that take a "high road" approach to job quality (Osterman 2018). These firms pay higher wages, have more generous benefits, and provide more stable and predictable work schedules than do their competitors within the same sector (Ton 2014). Costco is perhaps the exemplar of this approach (Ben-Ishai, Hammad, and Warden 2014; Swanberg et al. 2014), but it is not alone (Ton 2012).

The existence of between-firm variation in scheduling practices could contribute to broader racial/ethnic disparities in job quality if there is differential sorting of workers across firms by race/ethnicity. Here, there is substantial evidence of between-firm segregation by race/ethnicity (Lang, Manove, and Dickens 2005; Tomaskovic-Devey, Thomas, and Johnson 2005). Indeed, Ferguson and Koning (2018) show that, although occupational differences between race within an organization are becoming less likely, establishments themselves are becoming more racially segregated. Less is known about the extent to which this segregation is patterned by job quality, but several potential mechanisms suggest such patterning is likely.

First, if workers prefer firms that offer higher-quality jobs (e.g., in terms of wages, benefits, or schedules) and employers have widespread racially discriminatory preferences, then higher-quality firms would be better able to act on these discriminatory preferences, leading to between-firm segregation in job quality by race/ethnicity (Blau 1977; Blau and Kahn 2017). This sort of social closure process, in which white incumbents restrict access by non-white entrants to valued positions (Tomaskovic-Devey 1993), is well supported by results from experimental audit studies. Black and Hispanic applicants are significantly less likely to receive interview call-backs than their otherwise identically qualified white peers (Pager and Shepherd 2008; Quillian et al. 2017). These gaps are found in entry-level blue-collar jobs for both Black (Pager 2003) and Hispanic (Pager, Bonikowski, and Western 2009) applicants, in sales and administrative positions (Bertrand and Mullainathan 2004), and in professional occupations (Gaddis 2015; Nunley et al. 2015). In general, audit studies find that both African American and Hispanic applicants are disadvantaged compared to white applicants, but the penalty for African Americans is larger (Quillian et al. 2017).

Second, social networks play an important role in the job-finding process (Cingano and Rosolia 2012; McDonald, Lin, and Ao 2009). Personal referrals of prospective hires made by current employees increase the likelihood that an applicant will be hired at a firm (Brown, Setren, and Topa 2016; Burks et al.

2015). In the context of racial/ethnic homophily in friendship networks (McPherson, Smith-Lovin, and Cook 2001; Wimmer and Lewis 2010), between-firm segregation stemming from employment discrimination and queuing may be amplified by the lower likelihood that Black or Hispanic applicants can obtain a referral from a current employee at a higher job-quality firm (Newman 2000; Smith 2016; Stainback 2008).

Furthermore, even when employed at firms with good job quality, Black incumbent workers may be reluctant to refer someone they know for a position (Smith 2005), which Pedulla and Pager (2019) show accounts for as much as a fifth of the Black-white job offer gap. This reluctance stems, in part, from the concern that, should the referred applicant fail to perform well on the job, such negative performance could reflect poorly on the referrer (Smith 2010). However, turnover rates in the retail and food-service sectors are extremely high (Carré, Tilly, and Holgate 2008; Lambert 2008). Would such reputational concerns apply given workers' relatively low attachment to their current employers? Here, we might expect the reputational costs of referral would further entrench firm-level segregation by job quality because turnover is lower at firms with more stable schedule practices (Choper, Schneider, and Harknett 2019; Lambert and Henly 2012); incumbent workers at such firms may be more attached to their jobs and so less inclined to refer.

These two mechanisms are interrelated and likely reinforcing. Allocative discrimination results in fewer non-white incumbents who are structurally positioned to make referrals of non-white alters into good jobs, and the paucity of non-white workers in such firms may, in turn, reproduce processes of allocative discrimination that lead to few non-white incumbents (Tomaskovic-Devey 1993). However, research on inequality and firm-level sorting is quite limited because little matched employer-employee data exist for the United States. One tranche of literature examines the contribution of between-firm differences in pay to overall earnings inequality and finds an important role for the firm in explaining the rise of top-end earnings inequality (e.g., Abowd, McKinney, and Zhao 2018; Card et al. 2018). Another, more limited, line of literature uses matched data to examine the role of firms in producing gender inequality in wages in the United States (e.g., Barth, Kerr, and Olivetti 2017; Bayard et al. 2003; Groshen 1991; Petersen and Morgan 1995; Webber 2016) and Portugal (Card, Cardoso, and Kline 2016) and in producing motherhood wage gaps in Canada (Fuller 2018) and Norway (Petersen, Penner, and Høgsnes 2014). These studies find that women and mothers are sorted into lower-paying firms, which accounts for a fraction of the gaps. However, prior work has not examined the role of similar allocative processes in racial/ethnic gaps or in other dimensions of job quality.

In summary, prior research suggests firm segregation by race/ethnicity in the context of between-firm heterogeneity in job quality could contribute to racial/ethnic gaps in exposure to unstable and unpredictable work schedules. However, prior research in the United States that investigates the role of firm-segregation in generating categorical inequality focuses on gender inequality in wages, likely in large part because of the scarcity of employer-employee linked data containing information on race/ethnicity and on other aspects of job quality, such as exposure to unstable and unpredictable work scheduling.

WITHIN-FIRM DYNAMICS AND SCHEDULING INEQUALITY

Racial/ethnic inequality in work scheduling may also be shaped by within-firm dynamics. Wages and benefit levels may be formalized and set as a function of job tenure or grade, but front-line managers are granted substantial discretion when it comes to scheduling (Lambert 2008). For the purposes of this article, we use the terms manager and supervisor interchangeably. For instance, studying a single firm, Lambert and Henly (2012) find retail front-line managers' scheduling practices are constrained by and highly responsive to company labor budgets and staffing constraints, but managers retain latitude to grant more stability and hours to certain workers. Wood (2018:1070, 2020), studying a large retailer in the United States, identifies a pattern of "flexible discipline," in which "managers had the capacity to give workers they liked more hours, the shifts which they desired, and greater schedule stability," which workers experienced as favoritism.

This managerial discretion in scheduling could result in racial/ethnic inequalities in scheduling if it occurs in the context of bias. One expectation is that non-white workers will be discriminated against once hired, just as they are at the time of hire. DiTomaso and colleagues (2007) uses the term "normative in-group" to describe those who, as a group, become associated with success and competence and are thus given benefits as a group. In a survey of scientists and engineers, DiTomaso and colleagues (2007) find, for instance, that U.S.-born white men receive more favorable performance evaluations from their managers. This argument is in line with qualitative research that documents the discrimination non-white employees report in the workplace. Deitch and colleagues (2003), for instance, argue that Black employees confront regular discrimination at the workplace, in a more subtle and pervasive form they call "everyday discrimination." Cortina (2008) argues that racial disparities may persist through what she calls "selective incivility" in the workplace, where veiled manifestations of racism may enter into an organization. This persistence of racial bias in the workplace does not seem to be the effect merely of relational dynamics in a workplace, but a reflection of the racial hierarchy in the United States. According to these theories of a normative in-group, even among individuals within a firm, a national racial hierarchy that puts white people above all other groups may bleed into an organization and put non-white people at risk of worse treatment.

However, a large body of research on the distribution of job rewards given to workers with supervisors of a different race, what we call "racial discordance," suggests it is actually the composition of the worker–manager dyad that shapes differential treatment, rather than simply the worker's own race. Giuliano, Levine, and Leonard (2009) find significant racial bias in hiring at a large retail firm, in which Black and Hispanic workers are more likely to be hired by managers of the same race. They also find that manager–worker pairs of the same race tend to have better outcomes in terms of quits, dismissals, and promotions (Giuliano, Levine, and Leonard 2011). Maume, Rubin, and Brody (2014) find that managers' technical competence at work increases job satisfaction, organizational commitment, and mental health among subordinates, but only for same-race dyads. Another strand of research finds that racial concordance—between job-seekers and the employees who referred them for the job—lowers job turnover (Kmec 2007).

Benefits to having a manager of the same race have been studied outside of the private sector as well. Grissom and Keiser (2011) demonstrate that teachers are more satisfied and less likely to quit when the principals of their schools are of the same race. Hensvik (2014) uses matched data to study employers in Sweden, finding that female managers are associated not only with more female hires, but also with a reduction in the gender wage gap. Tomaskovic-Devey, Hällsten, and Avent-Holt (2015) find that in Sweden, workplace inequality between natives and immigrants decreases once immigrants become represented in management. Drawing on Tilly (1998), Tomaskovic-Devey and Avent-Holt show how relationships within a firm generate inequality, and they build an explanatory model of how intra-firm inequality may progress (Avent-Holt and Tomaskovic-Devey 2010, 2014; Tomaskovic-Devey et al. 2015).

This literature identifies a discordance effect that could theoretically function to disadvantage both non-white and white workers whose managers are of another race/ethnicity. However, this dynamic operates within a context of often very unequal organizational demography. White workers are over-represented among managerial ranks, with the consequence that non-white workers are much more likely to have a discordant manager than are white workers (Stainback and Tomaskovic-Devey 2009). Thus, symmetrical discordance effects are still likely to contribute to racial/ethnic inequality given the unequal demography of managers and workers.

In summary, we would observe a contribution of racial discordance to racial/ethnic inequality in work scheduling if discordant worker–manager pairs were associated with more precarious schedules, given that workers of color are far more likely to have racially-discordant managers than are white workers. In addition, if racial/ethnic gaps persist after controlling for racial discordance and all other measured explanatory pathways, we would take this as evidence consistent with a process of normative in-group bias, operating at the intra-firm level, that acts to disadvantage non-white workers. Melamed and colleagues (2019) argue, for instance, that third-order status beliefs that white people are higher in the racial hierarchy than black people may produce unconscious bias, even if individuals hold opposing beliefs themselves. However, and importantly, normative in-group bias may also operate via other more traditional explanations. For instance, this bias may lead to racial/ethnic disparities in education or job tenure, so the residual racial/ethnic gap after accounting for explanatory variables should be interpreted as only a partial accounting of the extent of normative in-group bias.

GENDER DIFFERENCES IN THE RACIAL/ETHNIC GAP

A large literature documents significant gender disparities in job quality alongside racial/ethnic gaps (Blau and Khan 2017; Petersen and Morgan 1995). How might these two axes of disadvantage, race/ethnicity and gender, intersect to shape labor market inequality? Scholars such as Collins (2015), hooks (1984), and Glenn (1992) argue that race and gender are not simply separate dimensions of disadvantage but are intersectional, that is, "race, class, gender, sexuality, ethnicity, nation, ability, and age operate not as unitary, mutually exclusive entities, but as reciprocally constructing phenomena that in turn shape complex social inequalities" (Collins 2015:1). However, there is ambiguity and disagreement about the empirical predictions of an intersectional approach (Grollman 2014; Mandel and Semyonov 2016; McCall 2005).

One possibility is that racial/ethnic and gender disadvantages will be additive, such that white men would have the most advantageous position in the labor market and women of color the most disadvantaged. The literature on wages and the literature on fringe benefits provides evidence that women of color earn the lowest wages and have the least access to benefits, compared to men of color, white men, and white women (e.g., Jones and Schmitt 2016; Mandel and Semyonov 2016).

However, the intersectional relationship between race and gender and job quality may be more nuanced than a simple additive relationship. For instance, the magnitude of racial/ethnic gaps may differ between men and women. There is some evidence for this more nuanced relationship in intersectional analyses of wages. Contrasting racial/ethnic gaps in wages by gender, it appears the gaps are larger for men than for women (see Cancio, Evans, and Maume 1996; Greenman and Xie 2008; Mandel and Semyonov 2016; Snipp and Cheung 2016), and the same holds true of racial/ethnic gaps in fringe benefits such as health insurance and pension coverage (Kristal et al. 2018).

Finally, we might expect gender differences in the extent to which racial/ethnic gaps in job quality can be "explained" by the factors discussed above, such as human capital differences or occupational segregation. Here, scholarship suggests men of color may experience the highest levels of direct discrimination in the labor market (Grodsky and Pager 2001). The literature on wages shows some evidence that differences in demographics, human capital, and occupation explain more of the gap for women than for men (Mandel and Semyonov 2016), in line with the expectation that men of color may experience the most direct discrimination. However, when looking at fringe benefits, these explanatory factors account for a similar share of Black and Hispanic disadvantage in coverage for women as for men (Semyonov et al. 2011).

HYPOTHESES

We expect non-white workers will experience higher levels of exposure to precarious scheduling than their white counterparts. Prior theory and empirical research is ambiguous with respect to whether these racial/ethnic gaps will be larger or smaller for women compared to men, as well as with respect to the relative disadvantage of Black and Hispanic workers compared to white workers.

We hypothesize that in the context of between-firm variation in job quality and widespread racial discrimination in hiring, firm-level sorting will explain a portion of racial/ethnic gaps in scheduling, above and beyond "standard" controls for demographic and economic characteristics, occupation, and union affiliation. Given that Black workers appear to face a greater degree of discrimination in hiring, we expect between-firm sorting may explain a larger portion of the gap for these workers. We also expect that within firms, workers will be more likely to be exposed to precarious schedules when they have a manager of a different race/ethnicity than their own and that, in the context of occupational segregation in which white people are far more likely to hold managerial roles, this discordance will further contribute to racial/ethnic inequalities in scheduling. Finally, we expect that, collectively, these factors will explain a larger portion of racial/ethnic gaps among women than among men, because men of color may be subject to the most direct discrimination.

DATA AND METHODS

Data

We draw on innovative survey data from The Shift Project, an ongoing survey of retail and food-service workers employed at large firms in the United States run by the University of California-Berkeley and the University of California-San Francisco. We use survey data from Shift collected between March 2017 and April 2019. The survey sample represents hourly workers employed at one of 123 of the largest retail or food-service firms in the country, including Walmart, Target, Costco, Home Depot, McDonald's, Starbucks, Kroger, and Whole Foods. The survey data contain detailed respondent reports of job quality, including work scheduling practices, demographic information, and human capital measures. The survey sample includes front-line food-service and retail workers as well as low-level managers, who are also paid by the hour and whose job characteristics and schedule quality are similar, on average, to front-line workers.

The dataset nests these survey respondents within the 123 targeted firms and so constitutes matched employer-employee data. Such data are very rare in the United States (Kmec 2003). Datasets commonly used to describe employees' job conditions, such as the NLSY, Panel Study of Income Dynamics, or CPS, do not allow a link to identifiable employers. Studies such as the Longitudinal Employer Household Dynamics or the Bureau of Labor Statistics' Occupational Employment Statistics are limited because they contain little information on demographics, human capital, or compensating differentials that are potentially important explanations for the racial/ethnic job quality gap. They also contain no data on the dimensions of temporal precarity we focus on here.

The innovation that permits the construction of this matched data is to use the targeting capabilities of Facebook to assemble a sampling frame of workers at specific retail/food-service companies. Facebook allows advertisers to target messages to users based on characteristics provided by users and on characteristics derived from user activity data—including employer. The Shift data are constructed by using this infrastructure to sample and recruit respondents employed at the 123 targeted firms. Acting as an "advertiser," the survey team purchased advertisements that placed survey recruitment messages in the newsfeeds of Facebook and Instagram users who work at the targeted companies. Potential respondents saw an advertisement that used a message "Working at [EMPLOYER]? Take survey and tell us about your job," where [EMPLOYER] was the name of the firm targeted in the advertising interface, and a licensed image resembled their type of workplace.

The advertisement was labeled as falling under the auspices of the sponsoring university and contained an offer for the chance to enter a drawing for an Apple iPad. The advertisement provided a link to a Qualtrics survey, and potential respondents who clicked on the link were taken to the web survey where they were asked to consent and then answer the survey questions. For instance, to survey Walmart workers, this approach involved purchasing an advertisement and specifying the "audience" of Walmart workers. Facebook and Instagram users meeting this profile then saw advertisements in their Facebook and Instagram feeds with the message "Working at Walmart? Take survey and tell us about your job" and an image of a worker in a blue uniform in a big-box retail setting. For users who clicked through to the survey, the first question confirmed their current employer. In essence, Facebook serves as both the stratified sampling frame and the recruitment channel.

This approach to data collection departs from traditional probability sampling, and it raises some methodological concerns (Groves 2011; Smith 2013). One potential concern arises from the sampling frame of Facebook users. However, approximately 89 percent of working Americans age 18 to 50 are active on Facebook/Instagram (Perrin 2015), on par with telephone frames (Christian et al. 2010). Furthermore, Facebook/Instagram activity is widespread across socioeconomic groups. Analyzing data from a 2018 Pew Survey of internet use, we find that 81 percent of all workers age 18 to 65 are active on Facebook or Instagram, and that share is only marginally lower among workers with a high school degree or less (76 percent); there is essentially no gradient in activity by household income.

Another potential concern is non-random non-response to the recruitment advertisement. Overall, we estimate that 6.7 percent of users who saw a survey recruitment advertisement clicked through to the survey, and 17.5 percent of those users contributed some data, for an overall participation rate of 1.1 percent. Shift's response rate is low, but this approach to data collection follows emerging research that demonstrates non-probability samples drawn from online platforms, in combination with statistical adjustment, yield similar distributions of outcomes and estimates of relationships as probability-based samples. This prior work has drawn data from Xbox users (Wang et al. 2015), MTurk (Mullinix et al. 2015), and Pollfish (Goel, Obeng, and Rothschild 2015). In comparison to these platforms, Facebook is the most widely used by the public.

Some direct validation of the Shift data comes from a set of benchmarking tests, reported by Schneider and Harknett (2019c), which show The Shift Project data are comparable to samples of retail and food-service workers in the gold-standard NLSY97 and CPS surveys in terms of wage levels and job tenure; moreover, the regression-adjusted wage returns to tenure are similar in all three sources.

Using the Shift data, we conduct multiple imputation to account for individuals with missing data due to either skipped questions or attrition. Our analysis sample is composed of 32,056 respondents nested within 123 firms. Our mean sample size per firm is 261.

Dependent Variables

We include five key measures of job quality that we use as our dependent variables. These questions are designed to measure workers' exposure to unstable and unpredictable work schedules, access to working hours, and schedule flexibility.

Canceled shifts. This variable is constructed with the question, "In the last month, was one of your scheduled shifts canceled with less than 24 hours' notice?" A 1 indicates the respondent answered yes, 0 indicates a no.

On-call. This variable is constructed with the question, "In the past month or so, have you ever been asked to be 'on-call' for work at [EMPLOYER NAME]? By 'on-call,' we mean you have to be available to work, and you find out if you are needed to work just a few hours before your shift." A 1 indicates the respondent answered yes, 0 indicates a no.

Involuntary part-time. This variable is constructed using two questions. First, we ask "Do you agree or disagree?: I would like to work more hours." Respondents are given four choices from "strongly agree" to "strongly disagree." If respondents select either "agree" or "strongly agree," we check responses to the question, "How many hours per week do you usually work . . . " Respondents are given options at five-hour intervals from zero to 50. *Involuntary part-time* is a dummy variable where 1 indicates the worker would like to work more hours, and the respondent reports usually working fewer than 30 hours per week.

Get time off. This variable is constructed with the question, "Do you agree or disagree?: It is easy to get time off from work when I need it." Respondents are given four choices from "strongly agree" to "strongly disagree." For consistency with the directionality of the other dependent variables, we code this variable to indicate difficulty getting time off. A 1 indicates respondents answered that they strongly disagree or disagree that it is easy to get time off, 0 indicates the respondent agreed or strongly agreed.

Clopening. This variable is constructed with the question, "In the last month, have you ever worked a closing shift and the very next opening shift (clopening)?" We create a dummy indicator of 1 if the respondent answered yes, and a 0 if the respondent answered no.

Precarious schedule scale. Finally, we create an additive scale of precarious scheduling conditions that measures these five variables. This variable ranges from 0 to 5. A value of 0 indicates a worker did not experience any of the precarious scheduling conditions among shift cancellation, on-call work, involuntary part-time work, difficulty getting time off, and working a clopening shift. A value of 5 on the scale indicates a worker experienced all five of these precarious scheduling conditions. We use this scale for greater parsimony in presenting results separately for men, women, Black workers, Hispanic workers, and other racial/ethnic groups.

Independent Variables

We derive our measures of race/ethnicity by asking respondents to check all race or ethnicities that apply to themselves from among white, Hispanic or Latino/Latina, Black or African American, Asian or Pacific Islander, American Indian or Alaskan Native, or other. From the question about respondent's own race/ethnicity, we create the measure *non-white*. Non-white is a simple dummy variable indicating 1 if the respondent did not check white, or if white was checked in combination with any other response, and 0 if the respondent checked white and only white. The non-white category consists of approximately 51 percent Hispanic or Latino/Latina, 16 percent Black or African American, and around 33 percent who indicated a racial/ethnic category of "Other" or marked that they were Asian, Pacific Islander, Alaskan Native, or multiracial, non-Hispanic.

We also construct a variable for gender based on respondents' self-reports. This variable is coded 1 if respondents said their gender is male, and 0 if respondents said their gender is female. We primarily use this variable to stratify our analyses of the racial/ethnic job quality gap.

Sources of Racial/Ethnic Gaps in Job Quality

Employer. We hypothesize that sorting between firms may account for a portion of gaps in schedule quality by race/ethnicity. To account for this sorting in our models, we introduce a set of employer fixed-effects that isolate within-firm variation from between-firm variation. When the indicator "employer" is followed by "yes," we include a fixed effect for the respondent's employer. Respondent's employer is usually first identified by surveying individuals who marked that they were employees of the specific organization on Facebook. In the first question of the survey, individuals are asked to confirm that they do in fact work for this employer. If they do not, they are asked to write in their employer and are re-categorized. Respondents who work at an employer not included among the 123 target firms are excluded. By including the employer fixed-effect, we account for the explanatory role of firm-level sorting in racial/ethnic inequality in job quality.

Discordant race/ethnicity. In addition to reporting on their own race/ethnicity, respondents are asked to report the race/ethnicity of their supervisor with the same response options. To measure racial/ethnic discordance, we collapse the respondent and supervisor racial/ethnic categories into four categories: white, Black, Hispanic, and multiracial or other race. We then create a dummy variable indicating 1 if the four-category respondent race/ethnicity variable is the same as the supervisor's four-category race/ethnicity variable, and 0 otherwise. Therefore, white workers with a non-white manager are coded 1 to indicate racial/ethnic discordance, as are Black workers with a non-Black manager, and so on. White workers with a white manager, Black workers with a Black manager, and Hispanic workers with Hispanic managers are all coded 0 to indicate racial/ethnic concordance between worker and manager. There is some ambiguity in the measure of discordance for workers and supervisors categorized as multiracial or other. As a robustness check, we omit workers from our sample who identify as multiracial/other or who report having a supervisor who is multiracial/other; this exclusion does not change the pattern of results. These separate results are included in Appendix Table A2.

Demographics. Demographic differences may also contribute to racial/ethnic gaps in scheduling between non-white and white workers. For instance, if parents are disadvantaged (or advantaged) in their schedules by employers and the distribution of parenthood varies by race/ethnicity, then this, and other similarly arrayed demographic characteristics, could contribute to schedule inequality. Parents may be advantaged if managers are more accommodating of their requests for time off, or disadvantaged if managers give priority to scheduling non-parents because they perceive they will be more open and available for work. To account for such factors, we include a series of demographic characteristics as controls for our models. We adjust for *age*, which is a continuous variable coded as respondent's age. *Age squared* is the squared value of age. *Relationship status* categorizes whether an individual is unmarried and living with a partner, married and living with a partner, or not living with a spouse or a partner. *Kids* is a series of dummy variables, coded 1 if respondents indicate they have any children of varying ages (i.e., zero to 4, 5 to 9, 10 to 14, or over 15 years old); and 0 if respondents indicate they have no children. The *mother* variable indicates whether the respondent is a mother.

Human capital. Differences in human capital are typically associated with the wage gap between white and non-white workers (Mandel and Semyonov 2016; Snipp and Cheung 2016), and these differences may also be associated with schedules. Workers with more human capital, in terms of tenure on the job, level of education, and English language ability, may be preferred by managers in both formal systems of scheduling and informal decision-making. This would give preferred workers more hours, better shifts, and more notice. To the extent that human capital is unequally distributed by race/ethnicity, due to unequal opportunities and discrimination earlier in the life course, these factors could explain inequalities in scheduling by race/ethnicity. To account for this possibility, we include a set of controls for human capital. The *tenure* variable measures how long respondents have worked at their current job: less than one year, one to two years, two to three years, three to four years, five to six years, or over six years. *Education* indicates the highest level of education the respondent has completed. Respondents can indicate they have no degree, a high school diploma/GED, some college, an associate's degree, a bachelor's degree, or a master's degree/advanced degree. *Enrolled* is a dummy variable coded 1 if the respondent is currently enrolled in school, and 0 if the respondent is not. *English as a second language* is a dummy variable coded 1 if a worker speaks a language other than English at home, and 0 if not.

Labor market characteristics. Labor market characteristics, such as the unemployment rate (Silver 2003), whether the job itself is unionized (Finnigan and Hale 2018), and the market unionization rate (Western and Rosenfeld 2011), may affect a worker's ability to demand better schedules and to leave jobs with worse schedules. Workers may be unequally exposed to such labor market conditions by race/ethnicity. To account for these factors, we control for multiple characteristics of the labor market. *Union membership* is reported by workers on the Shift Survey; it is coded 1 if a worker is in a union, and 0 otherwise. *State-industry unionization* rates are derived from the CPS question asking if an individual was in or covered by a union from 2014 to 2017. Each unique response to this question is then averaged over state and industry measured in the CPS and merged at the state-industry level. The analysis includes 11 industries. We also include *previous-year unemployment rates* compiled from the Bureau of Labor Statistics for the county respondents lived in.

Occupation. Occupational segregation plays an important role in accounting for wage gaps (Grodsky and Pager 2001; Huffman and Cohen 2004), but it is less important for explaining racial/ethnic gaps in health and pension coverage (Semyonov et al. 2011). If white workers sort into occupations (whether through supply-side or discriminatory demand-side processes) that have better schedules, this could explain a part of any racial/ethnic gap in scheduling. Our research design, focusing on a subset of industries, limits the variation in occupation by examining only service sector workers. Our sample does not include corporate workers. However, within our sample, workers vary based on occupation, and we capture this variation here. Using workers' open-ended responses for their job title, we coded workers into one of 10 occupations based on occupations in the Bureau of Labor Statistics and the Current Population Survey. In the regression models, when "occupation" is followed by "yes," occupation fixed-effects are included to account for this form of segregation. Appendix Table A1 shows the full list of occupations.

Analytic Approach

We estimate a series of linear probability models to describe the racial/ethnic gap in job quality. We first take each measure of job quality (Y) for each individual (i) and regress it on the dichotomous indicator for race/ethnicity, $Nonwhite_i$.

$$Y_i = \beta_0 + \beta_1 Nonwhite_i \quad (1)$$

We will find evidence of a racial/ethnic gap in these novel dimensions of job quality if the coefficient on $Nonwhite_i$ is positive and significant.

Next, we account for a vector of demographic characteristics, D, human capital, HC, labor market characteristics, LM, and occupation, Occ; firm-level sorting by introducing a firm fixed-effect, γ_f; and a measure of racial/ethnic discordance between workers and their supervisors, $Discord$:

$$Y_i = \beta_0 + \beta_1 Nonwhite_i + \beta_2 D + \beta_3 HC + \beta_4 LM + \beta_5 Occ + \gamma_f + \beta_6 Discord \quad (2)$$

We will find evidence that the racial/ethnic gap in job quality is at least in part attributable to differences in our hypothesized explanatory mechanisms if the β_1 are attenuated between Models 1 and 2. In these models, we cluster standard errors by employer. In addition, we present the results of an F-test of the joint firm fixed-effects for each regression that includes these effects.

To understand the contribution of each of the hypothesized explanatory mechanisms to explaining the racial/ethnic gap in job quality, we next conduct an Oaxaca-Blinder decomposition of the racial/ethnic gap. These decompositions are done using pooled two-fold linear decompositions as described by Jann (2008), and non-continuous variables in the model are normalized to control for biased results as a function of the choice of reference category, as suggested by Yun (2005). In these decompositions, the sample is stratified into white and non-white subsamples and job quality is estimated as a function of explanatory variables in nested models. The decompositions compare three regression models, for white respondents, non-white respondents, and with a pooled non-white variable. The pooled model is identical to the model described in the previous equation. The decomposition separates out explained and unexplained components of the variation. Each explanatory variable can be broken down into these two components.

Equation 3 shows the decomposition for the portion of the gap derived from racial/ethnic discordance, $\beta_6 Discord$. To derive these statistics, three separate regression models are calculated and compared. First, a pooled model is calculated, including the full sample of white and non-white respondents, equivalent to the regression described in Equation 2. Coefficients from this model are identified by the subscript p. Next, models are run for the subsamples of white and non-white respondents separately, creating separate coefficients for white and non-white respondents. These coefficients are indicated by the subscripts w and nw. The gap between white and non-white respondents is then calculated using the following decomposition equation:

$$\Delta\bar{Y} = (\bar{X}_w - \bar{X}_{nw})'\hat{\beta}_p + \bar{X}_w{}'(\hat{\beta}_w - \hat{\beta}_p) + \bar{X}_{nw}{}'(\hat{\beta}_{nw} - \hat{\beta}_p) \quad (3)$$

The explained portion of the decomposition refers to the difference in levels of explanatory variables between white and non-white respondents, using the coefficients produced by the pooled model. This is the first term in Equation 3. The unexplained portion refers to the differences in the size of the coefficients between white and non-white respondents. This is demonstrated in the second and third terms of Equation 3. The unexplained component also contains differences in the regression constant. The decomposition essentially simulates how much the racial/ethnic gap would narrow after accounting for differences between white and non-white groups in each set of explanatory variables, and it allows for a parsing of the racial/ethnic gap in job quality into "explained" and "unexplained" components. Importantly, any of these explained or unexplained components may be suppressive factors, reducing the racial/ethnic gap rather than increasing it.

We combine demographic characteristics, human capital, and labor market characteristics into the category of “traditional explanations,” and we include a separate category for occupational explanation by including a set of occupational fixed-effects. We then parse out the role played by “between-firm” processes, captured by employer fixed-effects, and “within-firm” processes, captured by racial discordance between workers and managers.

We run this decomposition for the full sample for each scheduling outcome. We then decompose the job quality gap using the precarious scheduling scale, stratifying by gender and disaggregating the non-white group into separate Black, Hispanic, and other race/ethnicity groups. For each decomposition, we use linear probability models. We draw on guidance from Angrist and Pischke (2009), who suggest linear models often perform as well as other more complicated, less easily interpretable models. Another reason we use linear probability models, rather than count models, is that the combined schedule quality scale is not strictly a count variable, but instead combines a mixture of activities, such as whether a worker was on-call in the past week, had difficulty getting time off, and reported a desire to work full-time. This scale provides insight into the overall quality of an individual’s schedule, and each of the component questions are indicators that capture, in a more limited sense, how workers are treated. Given the overall frequency of poor schedule characteristics in this sector, we do not see zero inflation in the scale, a characteristic that may necessitate the use of a count model. The use of linear probability models also creates a second advantage, in that the regression decomposition techniques we deploy here have been developed and are most frequently used with linear models. For the binary schedule characteristics, we also present logit and probit decompositions in Appendix Table A4.

RESULTS

Descriptive Statistics

Table 1 presents descriptive statistics of our main variables for white and non-white workers for the unimputed data. Of primary interest, we find that non-white workers report worse job quality. Indeed, non-white workers, on average, report a higher likelihood of each of our poor job-quality characteristics. They are more likely to have canceled shifts, to work on-call, to be involuntary part-time workers, to have trouble getting time off, and to work clopening shifts.

Turning to potential explanatory variables, the most pronounced differences are in demographics. Gender composition is similar between white and non-white workers, but white workers are more likely to have older children and to be cohabitating, and non-white workers are somewhat younger than their white counterparts. There are notably few differences in human capital by race/ethnicity. Educational attainment is almost identical in the two groups, as is job tenure. We do not see large differences in unionization or unemployment rates.

Important to our analysis, non-white workers are over three times more likely than their white co-workers to have managers of a different race/ethnicity than their own. Therefore, if a disadvantage in job quality stems from having a manager from a different racial/ethnic group, non-white workers are likely to be significantly more disadvantaged by this discordance than are their white counterparts.

These tabulations suggest a job quality gap, but they do not decompose the sources of this gap. We next present results from our regressions accounting for several likely sources of the job quality gap. We first show how the explanatory variables collectively account for a sizeable portion of the racial/ethnic gap in job quality. We then decompose the sources of the racial/ethnic gap to show the contribution of each of the hypothesized explanations.

Racial/Ethnic Gaps in Schedule Precarity

For each job quality characteristic, we present unadjusted regression models and models that control for an array of explanatory variables

Table 1. Descriptive Statistics of White and Non-White Front-Line Food-Service and Retail Workers

	White Mean	Non-White Mean
Demographics		
Female	.73	.70
Cohabitating	.50	.40
Any Children		
0 to 4 Years Old	.10	.13
5 to 9 Years Old	.09	.10
10 to 14 Years Old	.10	.10
15+ Years Old	.29	.19
Age Brackets		
18 to 19	.13	.15
20 to 29	.35	.47
30 to 39	.16	.17
40 to 49	.14	.10
50 to 59	.16	.09
60 to 69	.07	.02
70+	.00	.00
Human Capital		
Education		
No Degree	.04	.05
High School/GED	.33	.31
Some College	.39	.42
Associate's Degree	.12	.11
Bachelor's Degree	.10	.10
Advanced Degree	.01	.01
Enrolled	.25	.34
English as a Second Language	.05	.39
Job Tenure		
Less Than 1 Year	.19	.19
1 Year	.14	.16
2 Years	.16	.18
3 Years	.11	.12
4 Years	.07	.07
5 Years	.06	.06
6+ Years	.27	.23
Labor Market Characteristics		
Union	.06	.07
Previous-Year County Unemployment Rate	4.44	4.60
State-Industry Unionization Rate	4.91	4.88
Manager Race		
Discordant Manager Race	.22	.70
Job Quality		
Canceled Shift	.14	.18
On-Call	.23	.28
Involuntary Part-Time	.21	.26
Get Time Off	.25	.28
Clopening	.47	.50
N	22,815	6,398

(see Table 2). The first model of each set (models "a") includes no controls and simply shows the raw racial/ethnic gap in the measure. The second set of models (models "b") includes controls for demographics, human capital, labor market characteristics, and occupation; employer fixed-effects to account for firm-level sorting; and racial discordance between workers and their managers.

As suggested by the descriptive statistics and as we hypothesized, we find significant racial/ethnic gaps in job quality for each of our measures. Non-white workers are more likely, by between 3 and 5 percentage points, to have had a shift canceled, to have worked on-call shifts, to be involuntarily part-time, to have trouble getting time off from work, and to work clopening shifts. All of these differences are statistically significant. In percentage terms, non-white workers are about 7 to 30 percent more likely to have a precarious work schedule across the five outcome measures.

This racial/ethnic gap may in part be attributable to differences by race/ethnicity in demographics, human capital, labor market characteristics, and occupation; racial/ethnic segregation at the firm level; or differences in racial/ethnic discordance with managers. In the second set of models (models "b"), we introduce a wide array of controls that may explain racial/ethnic gaps in job quality. We include all explanatory variables at once to see how much of the racial/ethnic gap is explicable by these observed variables, and how much of the racial/ethnic gap persists.

For most measures of job quality, the explanatory variables account for a large portion of the racial/ethnic gap. For clopening shifts, the racial/ethnic gap is entirely explained, and for the ability to get time off, on-call work, and involuntary part-time work, the full set of explanatory variables account for nearly all of the gap and leave the differences by race/ethnicity insignificant. The explanatory variables account for a smaller, but not insubstantial, portion of the racial/ethnic gap in canceled shifts (60 percent). However, there is still a significant gap between white and non-white workers (.016, or 1.6 percentage points). These model results do not allow us to determine which of the explanatory variables play the most important roles in reducing or closing the racial/ethnic gaps.

Predictors of Schedule Precarity

Along with estimates of the unadjusted and adjusted racial/ethnic gap, Table 2 also shows the relationships between explanatory variables and job quality. If the racial/ethnic gap in precarious schedules is explained by our hypothesized factors, then these factors should be significantly related to work schedule quality.

We hypothesized that between-firm segregation may partially explain racial/ethnic disparities in work schedules, and we thus expect employer fixed-effects will be significant predictors of schedule precarity. The F-tests of the joint significance of all employer fixed-effects, presented at the bottom of Table 2, are highly statistically significant, suggesting there is meaningful between-employer variation in work schedule quality.[1]

We also hypothesized that worker–manager racial/ethnic discordance may be explanatory, and therefore we expect this discordance to be predictive of schedule precarity. Here, we find that for two of our five scheduling outcomes, having a manager of a different race/ethnicity is indeed associated with worse job quality. In particular, worker–manager discordance is associated with canceled shifts and inability to get time off. These relationships are noteworthy, because worker–manager racial/ethnic discordance is ordinarily an unobserved, omitted variable, yet this discordance does seem to be predictive of job quality. Discordance is associated with a 1.2 percentage-point increase in canceled shifts, and a 1.7 percentage-point increase in difficulty getting time off.

These models also include the full set of other factors that might account for racial/ethnic gaps in work schedule precarity. In terms of demographics, women are 4.4 percentage points more likely to be involuntary

Table 2. Negative Schedule Characteristics Regressed on Non-White Workers' Racial Identity

	Canceled Shift		On-Call		Involuntary Part-Time		Hard to Get Time Off		Clopening	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Non-White	.044***	.016*	.048***	.010	.045***	.011	.030***	.005	.034***	–.000
	(.00)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Discordant Manager		.012*		.010		–.001		.017**		.011
		(.01)		(.01)		(.00)		(.01)		(.01)
Traditional Explanations										
Demographics										
Female		.001		.000		.044***		.010		–.021*
		(.01)		(.01)		(.01)		(.01)		(.01)
Cohabitating		–.006		–.008		–.035***		–.001		–.008
		(.00)		(.01)		(.00)		(.01)		(.01)
Mother		–.004		–.013		–.017		–.025*		–.009
		(.01)		(.01)		(.01)		(.01)		(.01)
Any Children Age										
0 to 4		.004		.011		.026**		.048***		–.030*
		(.01)		(.01)		(.01)		(.01)		(.01)
5 to 9		.002		.005		.019*		.010		–.012
		(.01)		(.01)		(.01)		(.01)		(.01)
10 to 14		.012		.011		.020*		.005		.008
		(.01)		(.01)		(.01)		(.01)		(.01)
15+		–.001		.016		.005		.000		.012
		(.01)		(.01)		(.01)		(.01)		(.01)
Age		–.006***		–.007***		–.003*		–.004*		–.011***
		(.00)		(.00)		(.00)		(.00)		(.00)
Age Squared		.000***		.000**		.000		.000		.000***
		(.00)		(.00)		(.00)		(.00)		(.00)
Human Capital										
English as a Second Language		.018**		.073***		.017**		.032***		.013
		(.01)		(.01)		(.01)		(.01)		(.01)
Education										
High School/GED		–.010		–.017		–.066***		–.028*		.022
		(.01)		(.01)		(.01)		(.01)		(.01)
Some College		–.006		–.046***		–.079***		–.028*		.041**
		(.01)		(.01)		(.01)		(.01)		(.01)
Associate's Degree		–.007		–.045**		–.084***		–.029*		.069***
		(.01)		(.01)		(.01)		(.01)		(.02)
Bachelor's Degree		–.014		–.067***		–.090***		–.006		.045**
		(.01)		(.01)		(.01)		(.01)		(.02)
Advanced Degree		.011		–.040		–.047*		–.016		.064*
		(.02)		(.02)		(.02)		(.02)		(.03)
Enrolled		.004		–.011		.126***		–.020**		–.015
		(.01)		(.01)		(.01)		(.01)		(.01)
Job Tenure										
1 to 2 Years		.010		.019		–.059***		.023**		.080***
		(.01)		(.01)		(.01)		(.01)		(.01)
2 to 3 Years		.000		.006		–.103***		.038***		.102***
		(.01)		(.01)		(.01)		(.01)		(.01)
3 to 4 Years		.002		–.008		–.123***		.024*		.107***
		(.01)		(.01)		(.01)		(.01)		(.02)
4 to 5 Years		–.001		–.001		–.140***		.034**		.110***
		(.01)		(.01)		(.01)		(.01)		(.01)
5 to 6 Years		.012		–.008		–.124***		.027		.079***
		(.01)		(.01)		(.01)		(.01)		(.02)

(continued)

Table 2. *(continued)*

	Canceled Shift		On-Call		Involuntary Part-Time		Hard to Get Time Off		Clopening	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
6+ Years		–.004		–.008		–.163***		.021*		.064***
		(.01)		(.01)		(.01)		(.01)		(.01)
Labor Market Conditions										
Union Member		–.003		.040*		–.013		.038**		–.014
		(.01)		(.02)		(.01)		(.01)		(.03)
Previous-Year Unemployment Rate		.004*		.003		.010***		.000		.003
		(.00)		(.00)		(.00)		(.00)		(.00)
State-Industry Unionization Rate		–.000		–.001		.001		.001		–.001
		(.00)		(.00)		(.00)		(.00)		(.00)
Constant	.138***	.205***	.229***	.513***	.219***	.020	.249***	.489***	.465***	.712***
	(.00)	(.03)	(.00)	(.03)	(.00)	(.04)	(.00)	(.04)	(.00)	(.04)
Employer	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Occupation	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Employer F-Test		909		193		12743		2724		567
N	32,056	32,056	32,056	32,056	32,056	32,056	32,056	32,056	32,056	32,056

Note: Standard errors are in parentheses, clustered by employer. F-Test for the joint effect of each employer fixed-effect. All *P*-values associated with the F-tests are less than .000.
*$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

part-time workers, although they are 2.1 percentage points less likely to work clopening shifts. In comparison to cohabitating workers, single respondents are more likely to be working involuntarily part-time. Across outcomes, we observe a significant age gradient, with older workers (net of tenure and education) less likely to have canceled shifts, on-call shifts, involuntary part-time, trouble getting time off, or clopening shifts.

In terms of human capital, we see that education is at times protective, reducing exposure to on-call and involuntary part-time work. Longer tenure also reduces the risk of involuntary part-time work, but it is weakly related to other dimensions of job quality and is in fact predictive of working clopenings. Our measures of labor market characteristics are also associated with job quality. When the previous-year county unemployment rate is 1 percent higher, canceled shifts are .4 percentage points more likely and involuntary part-time work is 1 percentage point more likely. We find what appears to be a surprising association between union membership and worse job quality, but separate analyses reveal this is driven by collinearity with the state unionization rate. When the state-level unionization measure is omitted from the models, union membership is associated with significantly better job quality, in particular, on the dimensions of canceled shifts and clopenings (not shown). Although not shown in Table 2, we also find that occupational fixed-effects are collectively a statistically significant predictor of work schedule precarity, suggesting there is meaningful variation in work schedule quality for separate occupations (F-test value = 12.21, *P*-value = .0000).

Decomposing the Racial/Ethnic Gap in Precarious Schedules

Next, we conduct a decomposition of the racial/ethnic gap in scheduling conditions using an Oaxaca-Blinder decomposition. This allows us to determine the portion of the racial/ethnic gap that is accounted for by

Table 3. Oaxaca-Blinder Decomposition of the White/Non-White Gap in Five Indicators of Schedule Quality for Service Sector Workers

	(1)	(2)	(3)	(4)	(5)
	Canceled Shift	On-Call	Involuntary Part-Time	Hard To Get Time Off	Clopening
White	.138	.229	.219	.249	.465
	(.00)	(.00)	(.00)	(.00)	(.00)
Non-White	.183	.278	.264	.287	.498
	(.00)	(.01)	(.01)	(.01)	(.01)
Difference	–.044***	–.048***	–.045***	–.039***	–.034***
	(.01)	(.01)	(.01)	(.01)	(.01)
Explained (Percent of Difference)					
Traditional Explanations	36.55***	81.27***	65.98***	62.12***	83.78***
	(5.69)	(6.25)	(6.82)	(7.96)	(10.01)
Employer Fixed-Effects	12.77**	–12.38**	–4.88	4.96	9.22
	(3.89)	(4.48)	(4.16)	(4.54)	(6.92)
Occupation	2.29**	.42	14.78***	–2.57*	–7.70
	(.83)	(1.00)	(3.08)	(1.20)	(4.69)
Racial Discordance	13.23*	10.30	–.63	21.47**	15.35
	(5.14)	(5.44)	(5.38)	(7.21)	(8.83)
Total (Percent of Difference)					
Explained	64.85***	79.61***	75.25***	85.98***	100.65***
	(8.51)	(9.38)	(10.19)	(11.47)	(15.35)
Unexplained	35.15*	20.39	24.75	14.02	–.65
	(13.79)	(14.32)	(14.26)	(18.95)	(22.86)
N	32,056	32,056	32,056	32,056	32,056

Note: Regressions conducted using linear probability models. Standard errors are in parentheses. All factor variables are normalized.
**p* < .05; ***p* < .01; ****p* < .001 (two-tailed tests).

different types of explanatory variables. These results are presented in Table 3 and Figure 1.

The top panel of Table 3 presents the predicted probabilities of the five schedule outcomes for white workers and for non-white workers and shows the difference between the two groups. This difference is equivalent to the unadjusted racial/ethnic gap presented in models "a" of Table 2. That is, the lines for white and non-white workers indicate the proportion of workers experiencing each outcome. As before, we see significant racial/ethnic gaps in each measure of job quality.

The middle panel of Table 3 decomposes the portion of the racial/ethnic gap explained, and Figure 1 summarizes the relative power of each explanation for each outcome. The "traditional explanations" are shown first and include demographics, human capital, and labor market characteristics. The traditional explanations account for a significant portion of the racial/ethnic gap for each of the five measures of job quality, explaining between 37 and 84 percent of the racial/ethnic gap in scheduling. In contrast, occupational segregation within these industries generally accounts for very little of the gap, between –8 percent (a suppressing effect) and 3 percent, with the exception being involuntary part-time work, where occupational segregation accounts for 15 percent of the gap.

We next turn to a set of potential explanations that have received less attention in previous research because they often go unmeasured: firm-level racial sorting and within-firm racial discordance between workers and

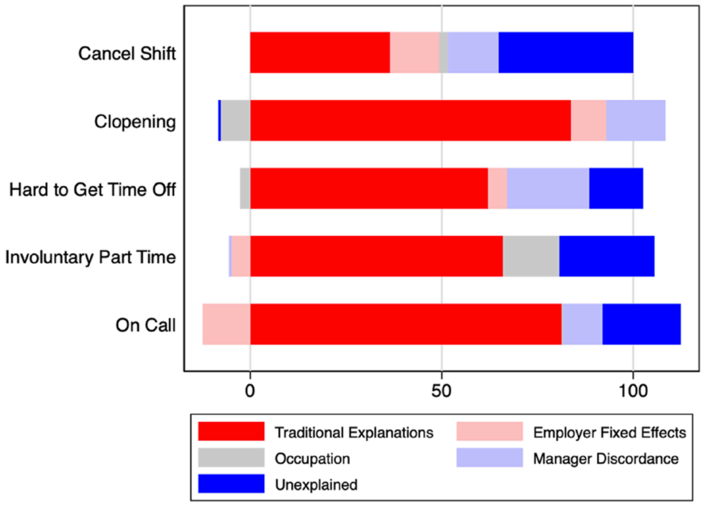

Figure 1. Oaxaca-Blinder Decomposition of the White/Non-White Gap in Schedule Quality for Food-Service and Retail Workers; Five Separated Categories

managers. Racial inequality in sorting into firms with better or worse job quality plays some role in explaining gaps in job quality, most notably for canceled shifts. We find that firm-level sorting by race/ethnicity significantly contributes to the racial/ethnic gap in canceled shifts (13 percent, .6 percentage points). This result implies that if white and non-white workers had equivalent distributions across firms, there would be a smaller racial/ethnic gap in canceled shifts. Although not statistically significant, firm-level sorting explains an estimated 9 percent of the racial inequality in clopening shifts.

Firm-level sorting by race/ethnicity across firms does not contribute to the racial/ethnic gap in involuntary part-time work or the ability to get time off. Surprisingly, for on-call shifts, sorting by race/ethnicity across firms acts as a suppressor with respect to the racial/ethnic gap. The decomposition results suggest that if white and non-white workers had the same distribution across firms, the racial/ethnic gap in on-call shifts would be even larger.

Racial/ethnic discordance contributes to racial/ethnic gaps in job quality in the context of unequal organizational demography. Recall that only 22 percent of white workers had non-white managers, whereas the share of non-white workers with managers of a different race/ethnicity was over three times as large (70 percent). After we adjust for discordance, and in light of these differences in exposure, we see that the racial/ethnic gaps in canceled shifts and difficulty getting time off are significantly narrowed. Workers are disadvantaged by having a racially discordant manager, and the greater exposure to this disadvantage for non-white workers manifests as more canceled shifts and more difficulty getting time off. Discordance between workers' and managers' race/ethnicity explains 13 percent of the racial/ethnic gap in canceled shifts and 21 percent of the gap in difficulty getting time off. In raw percentage points, racial/ethnic discordance accounts for .6 percentage points of the 4.4 percentage-point difference in canceled shifts, and .8 percentage points of the 3.9 percentage-point difference in difficulty getting time off. For two other characteristics, on-call work and clopening shifts, racial discordance appears to explain a portion of the gap—10 percent of the gap for on-call work and 15 percent of the gap in clopenings—but falls short of statistical significance.

Our a priori hypotheses did not specify which indicators of work schedule quality were most likely to be explained by firm-level sorting or worker–manager racial discordance.

Table 4. Oaxaca-Blinder Decomposition of the White/Non-White Gap in Schedule Quality for Service Sector Workers by Demographic Group; Scale of Precarious Scheduling (0 = least to 5 = most precarious)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Female	Male	Black	Hispanic	Other
White	1.300	1.316	1.257	1.300	1.300	1.300
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Non-White	1.510	1.550	1.414	1.455	1.562	1.459
	(.01)	(.02)	(.03)	(.03)	(.02)	(.02)
Difference	–.210***	–.235***	–.158***	–.155***	–.262***	–.159***
	(.02)	(.02)	(.03)	(.03)	(.02)	(.03)
Explained (Percent of Difference)						
Traditional Explanations	65.42***	61.63***	77.57***	33.76***	75.22***	67.52***
	(3.95)	(4.14)	(10.23)	(5.64)	(5.30)	(5.40)
Employer Fixed-Effects	1.21	1.91	1.82	15.66*	1.11	–4.66
	(2.58)	(2.82)	(6.70)	(6.90)	(2.80)	(4.71)
Occupation	2.01**	4.11***	–4.02	2.01	2.50**	0.30
	(.73)	(.85)	(2.18)	(2.09)	(.78)	(1.41)
Racial Discordance	11.47***	11.39**	9.89	24.76***	9.03***	27.26***
	(3.22)	(3.58)	(7.19)	(5.51)	(2.27)	(5.65)
Total (Percent of Difference)						
Explained	80.11***	79.03***	85.25***	76.18***	87.87***	90.41***
	(5.73)	(6.19)	(14.16)	(10.61)	(6.39)	(9.28)
Unexplained	19.89*	20.97*	14.75	23.82	12.13	9.59
	(8.45)	(9.10)	(20.74)	(21.93)	(9.18)	(16.28)
N	32,056	23,352	8,731	26,097	28,527	27,313

Note: Regressions conducted using linear probability models. Standard errors are in parentheses. All factor variables are normalized.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$ (two-tailed tests).

Note that both of these explanatory variables play a role in explaining racial gaps in canceled shifts. Moreover, canceled shifts are a highly undesirable occurrence from workers' perspective. Hourly workers whose shifts are canceled typically receive little notice; they sometimes report for work and then are sent home without pay. These shift cancelations represent an income shock and, not surprisingly, a large share of workers express unhappiness with canceled shifts (according to survey reports in The Shift Project survey data [author tabulations]).

The lower panel of Table 3 shows the cumulative portion of the racial/ethnic gap accounted for by all hypothesized explanations. As shown in models "b" of Table 2, explanatory mechanisms account for most or all of the racial/ethnic gap in being on-call (80 percent), getting time off (86 percent), working clopening shifts (100 percent), and involuntary part-time work (75 percent). These factors explain somewhat less of the racial/ethnic gap in canceled shifts (65 percent). The unexplained portion of the racial/ethnic gap in canceled shifts is potentially due to normative in-group bias at the intra-firm level. This is because, even after controlling for all explanations, workers see differential returns to the variables included in the model. This would be consistent with other evidence pointing toward a pervasive bias against people of color in U.S. society.

We have shown that gaps in job quality exist between white and non-white workers. In Table 4, we unpack these racial/ethnic gaps in job quality in two ways: by examining racial/ethnic gaps separately for men and women and by disaggregating the non-white group into separate Black, Hispanic, or other race/ethnicity groups. Table 4 combines the five dimensions of work schedule quality into a scale of precarious scheduling conditions, ranging from 0 to 5, with higher values indicating more types of temporal precarity.

The first column of Table 4 shows that white workers averaged 1.3 types of precarious scheduling conditions, and non-white workers averaged 1.51 types, a .21 point difference on the five-point scale. The next two columns compare racial/ethnic gaps in precarious scheduling experiences between female and male worker subgroups.

First, looking at the predicted scores in the first two lines of the female and male columns, we see that white men have the lowest exposure to precarious scheduling (1.26), followed closely by white women (1.32) and then non-white men (1.41). Women of color have the highest degree of exposure to precarious scheduling, with an average of 1.55 exposures.

Interestingly, the racial/ethnic gap in precarious scheduling is larger among women than among men. For female workers, the racial/ethnic gap in the precarious scheduling scale is .235 points (an 18 percent difference), and for men the gap is .158 points (a 12 percent difference). Using the Clogg test, the difference in racial/ethnic gaps between men and women is statistically significant (t = 2.25). Women of color appear to face the most inequality in job quality, consistent with a process of dual disadvantage stemming from the compounding of gender and race discrimination.

Table 4 decomposes the contribution of various explanations of the racial/ethnic gaps in precarious scheduling conditions. Traditional explanations, including demographics, human capital, and labor market characteristics, explain a larger portion of the racial/ethnic gap for men (78 percent) than for women (62 percent). However, occupation explains a positive share of the gap for women (4 percent) and suppresses the gap for men (4 percent), although for men the coefficient is not statistically significant. Between-firm sorting explains about 2 percent of the racial/ethnic gap for women and men (not statistically significant). Racial discordance between managers and workers explains a significant portion of the gap among women (11 percent) and a similar share among men (10 percent, not statistically significant). Overall, a slightly greater share of the racial/ethnic gap in job quality is explained for men (85 percent) than for women (79 percent). We had hypothesized that the unexplained portion of racial inequality in job quality would be larger for men of color, because they face the most direct discrimination, but we did not find that to be the case. Figure 2 depicts these decompositions visually.

The final three columns of Table 4 disaggregate the non-white racial/ethnic group into separate Black, non-Hispanic; Hispanic; and other race/ethnicity, non-Hispanic categories. These results are summarized in Figure 3. For these subgroups, each of the non-white racial/ethnic groups are compared with white, non-Hispanic workers to estimate the racial/ethnic gaps in job quality. Compared with white workers, each of the non-white groups experience significantly more precarious scheduling conditions. Black workers average .16 points higher on the precarious scheduling scale compared with white workers, Hispanic workers are .26 points higher, and other racial/ethnic groups are .16 points higher. The Clogg test shows the racial/ethnic gap is significantly higher for Hispanic workers than for Black workers (t = 2.64) and the "other race" category (t = 3.15).

Traditional explanations explain a sizable portion of the racial/ethnic gap for Hispanic (75 percent) and other race group workers (68 percent), but much less of the gap for Black workers (34 percent). For Black workers, between-firm segregation explains another significant portion of the racial scheduling gap (16 percent), substantially more than the share explained by occupational segregation (2 percent). This suggests Black workers experience more precarious scheduling conditions than their white counterparts in part

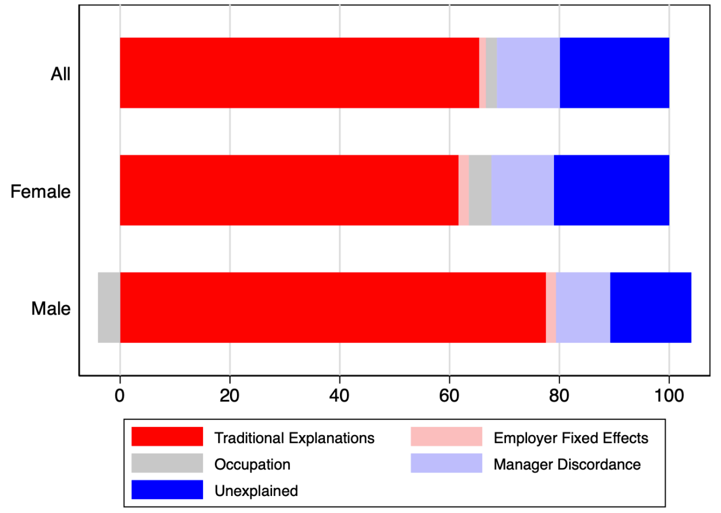

Figure 2. Gender Breakout of Oaxaca-Blinder Decomposition of the White/Non-White Gap in Combined Schedule Quality Score for Food-Service and Retail Workers

because of a selection process that leads Black workers to be concentrated in firms with more precarious scheduling practices. In contrast, for Hispanic workers and for workers in the other race category, firm sorting plays little or no role in explaining racial/ethnic gaps in job quality.

We also find differences across groups in the contribution of worker–manager racial discordance to racial/ethnic gaps in scheduling. For Black workers and workers in the other race group, managerial discordance is a sizeable and significant source of scheduling disadvantage (25 and 27 percent of the gap, respectively). Hispanic workers are also disadvantaged by discordance, but it explains somewhat less of the scheduling gap with white workers (9 percent).

Overall, most (80 percent) of the racial/ethnic gap in job quality is explained by a combination of traditional explanations (demographics, human capital, labor market characteristics), occupational segregation, firm-level sorting, and racial/ethnic discordance between workers and managers. Among demographic groups, this explained share is largest for other race workers (90 percent) and smallest for Black workers (76 percent).

DISCUSSION

Racial/ethnic gaps in job quality are well established and persistent. White workers have a significant advantage in the hiring process and earn more and have more access to fringe benefits once on the job. However, in the contemporary service sector, job quality is defined by more than compensation. Scholars increasingly recognize the role of precarious scheduling practices in shaping job quality (Kalleberg 2011, 2018). In particular, retail and food-service workers are exposed to “just-in-time” scheduling practices that are characterized by instability, unpredictability, insufficient work hours, and inflexible schedules (Lambert 2008; Lambert et al. 2014). Exposure to these practices has negative effects on worker health and well-being (Schneider and Harknett 2019a). However, little research has examined racial/ethnic gaps in these important indicators of job quality. Furthermore, individual differences in demographics and human capital, along with occupational sorting, explain a portion of racial/ethnic gaps in compensation, but research has been unable to go further and investigate the between- and within-firm

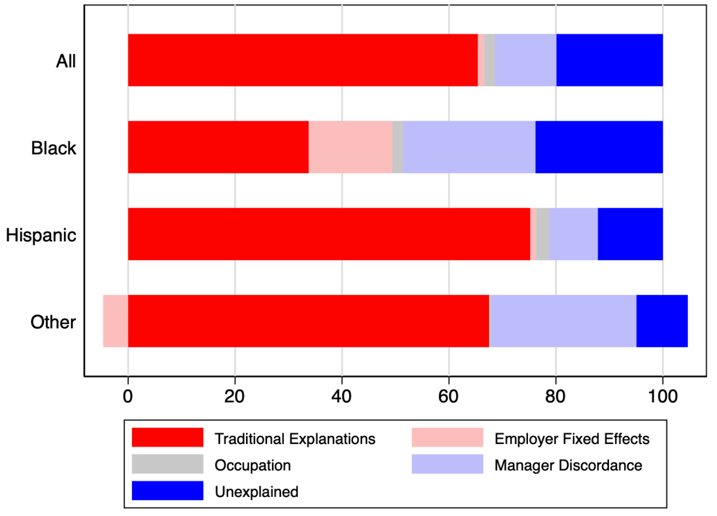

Figure 3. Racial/Ethnic Breakout of Oaxaca-Blinder Decomposition of the White/Non-White Gap in Combined Schedule Quality Score for Food-Service and Retail Workers

dynamics that may produce racial inequality (Tilly 1998), dynamics that may be especially salient in the domain of scheduling.

We draw on unique matched employer-employee data from The Shift Project that contain detailed measures of this temporal dimension of job quality for a sample of more than 30,000 hourly retail and food-service workers. We find significant gaps in each of five indicators of job quality. Non-white workers are more likely to have canceled shifts, to work on-call, to have insufficient hours, to have trouble getting time off, and to work clopening shifts. We show that 37 to 84 percent of these gaps are accounted for by differences in demographics, human capital, and labor market characteristics. We find that relatively little of the remaining gaps are explained by occupational segregation within the service sector, with the exception of involuntary part-time work. We next account for between-firm sorting on race/ethnicity, that is, the clustering of non-white workers in firms with lower job quality. We find that this dynamic accounts for roughly 12 percent of the gap in job quality for canceled shifts, 9 percent in clopening, but much less for involuntary part-time work and ability to get time off. Finally, we look within the firm. We show that racial/ethnic discordance between workers and their direct supervisors reduces job quality. In the context of unequal organizational demography, in which non-white workers are far more likely to have a supervisor of a different race/ethnicity than are white workers, this dynamic contributes meaningfully to overall racial/ethnic gaps in job quality, explaining an additional 13 to 21 percent of the gap for canceled shifts, ability to get time off, and clopening shifts.

Our approach documents significant racial/ethnic inequality in an understudied but highly salient dimension of job quality. We decompose these significant racial/ethnic gaps into several sources. The significant residual is perhaps the clearest manifestation of racial/ethnic discrimination, but we emphasize that many of the other pathways to racial/ethnic inequality are also mechanisms of discrimination—in human capital disparities and in the allocative discrimination of between-firm sorting.

Although we did not offer an ex-ante hypothesis regarding which dimensions of precarious scheduling might be most affected by between-firm segregation versus within-firm managerial discordance, there is some post-hoc evidence that racial/ethnic gaps in shift cancellation, ability to get time off, and perhaps clopening shifts, are most driven by managerial discordance, whereas gaps in on-call shifts and involuntary part-time work are not so structured. This seems consistent with the idea that managerial discretion might play a larger role in these scheduling practices than for involuntary part-time work or on-call shifts. Yet, we do find that racial/ethnic gaps in shift cancellation, most notably, and clopening shifts, to a lesser extent, are also driven by between-firm segregation, suggesting these are not simply discretionary practices at the managerial level but also are shaped by firm-level policies. In contrast, on-call shifts are the one exceptional case in which a potential explanatory variable was found to operate as a suppressor. Our results imply that racial/ethnic inequalities in on-call shifts would be even greater were it not for observed patterns of firm sorting by race/ethnicity.

We also provide new insight into the intersectional nature of racial/ethnic and gender inequality. We find that women of color are most disadvantaged in terms of exposure to temporal precarity, followed by men of color, white women, and then, with the best job quality, white men. We also find that racial/ethnic gaps are larger among women than among men. Contrary to our predictions, a slightly larger fraction of the racial gaps for men than for women are explicable in terms of the identifiable pathways, a result at odds with the expectation that men of color experience the most direct discrimination on the job. Notably, in the domain of scheduling, we find the hypothesized larger racial/ethnic differences among women, which have not been documented in the empirical literature on wages.

In our main results, we aggregate race/ethnicity and compare white, non-Hispanic workers with all others. To maintain cell sample size, our aggregation averages disadvantage. However, by doing so we may obscure some patterns of racial/ethnic difference in job quality and the variation in the role of potential explanations for these gaps across racial/ethnic group. When we disaggregate, we document similar gaps for each racial/ethnic group, but we find that for Black workers, between-firm sorting is a much more significant source of disadvantage than it is for Hispanic workers or workers of other races/ethnicities. This suggests Black workers may experience more allocative discrimination at the point of hire. Similarly, we find that managerial discordance is a much more significant source of disadvantage for Black workers and workers of other races/ethnicities than for Hispanic workers.

We acknowledge that our analysis is subject to some important limitations. First, The Shift Project data are based on a non-probability sample in which workers are sampled using Facebook's targeting platform and then recruited using paid advertisements. This approach generates uniquely rich data on scheduling practices for a matched sample of workers nested within firms, which is not otherwise available for the United States, but the risk of bias in the sample is real. If there is differential selection into the sample by race/ethnicity, that could bias estimates of job quality gaps. If there is differential selection into the survey based on demographics, human capital, or occupation, that could bias the decomposition of the gaps. However, we note that prior validation work with The Shift Project finds the data closely align with gold-standard sources such as the NSLY97 and CPS on univariate statistics and associations (Schneider and Harknett 2019b). Furthermore, The Shift Project data are cross-sectional rather than longitudinal and thus do not permit us to estimate the individual fixed-effects models used in recent research that use within-person variation in employer to gauge the effects of firm-level processes (e.g., Card et al. 2016).

Second, The Shift Project study is limited to the retail and food-service sectors. Although these sectors are large, approaching almost 20 percent of the total U.S. labor force, this focus mechanically will reduce the contribution of occupational segregation to the racial/ethnic job quality gap. Therefore, our finding that occupational sorting plays a minimal role in explaining racial/ethnic gaps in job quality is not surprising. In more heterogeneous samples, occupational sorting plays a larger role (Grodsky and Pager 2001; Huffman and Cohen 2004). However, it is striking that even within the retail and food-service sector, sorting between firms plays a sizable role in accounting for racial/ethnic gaps. Third, The Shift Project survey was conducted in English and may thus underrepresent workers with limited English proficiency. Nevertheless, a sizable portion of the sample (41 percent of non-white workers) reported speaking a language other than English at home, and we were able to include that characteristic in our analysis.

A final limitation is some ambiguity in sizing the share of racial/ethnic disparities in job quality that stem from processes of discrimination and normative in-group bias. Methodological approaches such as experimental audit studies allow for causal estimation of a discrimination effect, but a non-experimental approach such as ours does not allow a precise sizing of the role of discrimination. The explanatory variables in our model, such as education and job tenure, are endogenous with respect to race/ethnicity, and we cannot determine the extent to which discrimination or bias earlier in the life course led to observed levels of human capital. The persistence of racial/ethnic disparities in job quality after accounting for explanatory variables provides some evidence of direct discrimination. We may overstate the extent of discrimination if this residual disparity is caused by non-discriminatory omitted variables, but we are also likely to understate the extent of discrimination because of endogeneity of explanatory variables with respect to race/ethnicity and the real possibility that bias earlier in the life course shaped explanatory variables. Furthermore, it is not possible to interpret how different regression coefficients for white and non-white workers contribute to discrimination, because decompositions are sensitive to omitted variables that may alter these coefficients. However, we do find that a statistically significant 20 percent of the overall gap is unexplained, which is consistent with residual inequality operating within firms.

It would be valuable for future work to extend these analyses by going beyond the inclusion of firm fixed-effects to include specific firm-level characteristics such as firm ownership structure, individual-level worker surplus, racial/ethnic composition of firm executives, and human resource management policies. These data, constructed from external sources, could allow for a more fine-grained decomposition of the firm effects we document here.

We bring new innovative data to bear on an old question. In doing so, we expose the degree of racial/ethnic inequality in an emergent and important domain of job quality—precarious scheduling. We show that, as for wages and benefits, a significant portion of the gap can be explained by individual differences. But, we also present novel results on how the between-firm sorting of non-white workers into lower job-quality firms also contributes to the gap and how, within firms, managerial racial discordance in the context of an unequal organizational demography also structures racial/ethnic inequality.

METHODOLOGICAL APPENDIX

Table A1 shows occupational categories for white and non-white workers for the full sample of imputed respondents. These results indicate that white and non-white workers have roughly the same occupations overall.

Table A1. Occupational Distribution for White and Non-White Workers

	White Mean	Non-White Mean
Manager	.25	.23
Cashier/Clerk	.23	.23
Salesperson	.18	.20
Food Preparation	.16	.18
Server	.04	.04
Customer Service	.03	.03
Butcher/Meat Cutter	.02	.01
Delivery	.02	.01
Cook	.01	.01
Baker	.01	.01
Other	.05	.04
N	28,412	8,368

In addition to the decompositions breaking down the non-white category into its components, we also test for sensitivity to the "other" category in our regression analysis. The results of this are depicted in Table A2. These results show that the patterns we see in the analysis are largely the same when excluding the "other" category.

Table A2. Negative Schedule Characteristics Regressed on Non-White Workers' Racial Identity, Excluding "Other Race" Category

	Canceled Shift		On-Call		Involuntary Part-Time		Hard to Get Time Off		Clopening	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Non-White	.050***	.015*	.055***	.007	.050***	.010	.040***	.003	.041***	.003
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Discordant Manager		.015**		.009		.001		.017**		.011
		(.01)		(.01)		(.00)		(.01)		(.01)
Traditional Explanations										
Demographics										
Female		.001		–.002		.043***		.012		–.018*
		(.00)		(.01)		(.01)		(.01)		(.01)
Cohabitating		–.008		–.010		–.034***		–.002		–.010
		(.00)		(.01)		(.01)		(.01)		(.01)
Mother		–.006		–.015		–.018		–.031*		–.010
		(.01)		(.01)		(.01)		(.01)		(.01)
Any Children Age										
0 to 4		.004		.008		.027**		.052***		–.033*
		(.01)		(.01)		(.01)		(.01)		(.01)
5 to 9		–.003		.005		.020*		.013		–.011
		(.01)		(.01)		(.01)		(.01)		(.01)
10 to 14		.011		.010		.023**		.003		.005
		(.01)		(.01)		(.01)		(.01)		(.01)
15+		.001		.017		.004		.001		.013
		(.01)		(.01)		(.01)		(.01)		(.01)
Age		–.005***		–.007***		–.004*		–.004*		–.010***
		(.00)		(.00)		(.00)		(.00)		(.00)
Age Squared		.000**		.000**		.000*		.000		.000**
		(.00)		(.00)		(.00)		(.00)		(.00)
Human Capital										
English as a Second Language		.020**		.071***		.018*		.036***		.017
		(.01)		(.01)		(.01)		(.01)		(.01)
Education										
High School/GED		–.013		–.018		–.070***		–.023		.023
		(.01)		(.01)		(.01)		(.01)		(.01)
Some College		–.009		–.045***		–.085***		–.025*		.043**
		(.01)		(.01)		(.01)		(.01)		(.01)
Associate's Degree		–.011		–.045**		–.089***		–.024		.069***
		(.02)		(.01)		(.01)		(.01)		(.02)
Bachelor's Degree		–.017		–.066***		–.097***		.001		.052***
		(.01)		(.01)		(.01)		(.01)		(.02)
Advanced Degree		.002		–.053*		–.060*		–.008		.077**
		(.02)		(.02)		(.02)		(.03)		(.03)
Enrolled		.003		–.013		.129***		–.016*		–.016
		(.01)		(.01)		(.01)		(.01)		(.01)

(continued)

Table A2. *(continued)*

	Canceled Shift		On-Call		Involuntary Part-Time		Hard to Get Time Off		Clopening	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Job Tenure										
1 to 2 Years		.012		.021		–.060***		.024**		.080***
		(.01)		(.01)		(.01)		(.01)		(.01)
2 to 3 Years		–.001		.004		–.103***		.038***		.099***
		(.01)		(.01)		(.01)		(.01)		(.01)
3 to 4 Years		.005		–.010		–.121***		.025**		.109***
		(.01)		(.01)		(.01)		(.01)		(.01)
4 to 5 Years		–.002		.002		–.140***		.032*		.110***
		(.01)		(.01)		(.01)		(.01)		(.02)
5 to 6 Years		.011		–.009		–.126***		.028*		.082***
		(.01)		(.01)		(.01)		(.01)		(.02)
6+ Years		–.003		–.010		–.163***		.021*		.067***
		(.01)		(.01)		(.01)		(.01)		(.01)
Labor Market Conditions										
Union Member		–.006		.040*		–.017		.039*		–.009
		(.01)		(.02)		(.01)		(.02)		(.03)
Previous-Year Unemployment Rate		.004*		.002		.011***		–.001		.003
		(.00)		(.00)		(.00)		(.00)		(.00)
State-Industry Unionization Rate		–.000		–.001		.001		.000		–.001
		(.00)		(.00)		(.00)		(.00)		(.00)
Constant	.138***	.223***	.229***	.494***	.219***	.022	.249***	.465***	.465***	.758***
	(.00)	(.04)	(.00)	(.04)	(.00)	(.04)	(.00)	(.04)	(.00)	(.04)
Employer	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Occupation	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Employer F		723		218		10,208		2,073		569
N	29,686	29,686	29,686	29,686	29,686	29,686	29,686	29,686	29,686	29,686

Note: Standard errors are in parentheses, clustered by employer. F-Test for the joint effect of each employer fixed effect.
*$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

We also produce the same table but excluding employers for whom our survey sample received more than 1,000 responses. This was the case for four of the 123 employers we included. The results from this sensitivity analysis are included in Table A3.

Finally, we show the decompositions of the separated schedule characteristics using probit and logit in addition to linear models. These results indicate that the explanations are relatively stable with respect to functional form. However, for probit and logistic regressions, racial discordance is also significant for on-call work. However, the proportion explained changes by less than half a percentage point.

Table A3. Negative Schedule Characteristics Regressed on Non-White Workers' Racial Identity, Excluding the Four Largest Employers by Sample Size

	Canceled Shift		On-Call		Involuntary Part-Time		Hard to Get Time Off		Clopening	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Non-White	.043***	.013*	.052***	.009	.046***	.012	.041***	.007	.033***	–.003
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Discordant Manager		.010		.011		–.005		.018**		.013
		(.01)		(.01)		(.00)		(.01)		(.01)
Traditional Explanations										
Demographics										
Female		–.001		–.002		.044***		.009		–.018*
		(.01)		(.01)		(.01)		(.01)		(.01)
Cohabitating		–.007		–.008		–.032***		.000		–.013*
		(.00)		(.01)		(.00)		(.01)		(.01)
Mother		.001		–.015		–.018		–.030*		–.007
		(.01)		(.01)		(.01)		(.01)		(.01)
Any Children Age										
0 to 4		.002		.007		.028**		.043***		–.030*
		(.01)		(.01)		(.01)		(.01)		(.01)
5 to 9		–.001		.005		.017		.014		–.011
		(.01)		(.01)		(.01)		(.01)		(.01)
10 to 14		.015*		.013		.022**		.001		.007
		(.01)		(.01)		(.01)		(.01)		(.01)
15+		–.004		.019		.005		.006		.008
		(.01)		(.01)		(.01)		(.01)		(.01)
Age		–.007***		–.007***		–.005**		–.004*		–.012***
		(.00)		(.00)		(.00)		(.00)		(.00)
Age Squared		.000***		.000*		.000**		.000		.000***
		(.00)		(.00)		(.00)		(.00)		(.00)
Human Capital										
English as a Second Language		.013		.073***		.018*		.036***		.018
		(.01)		(.01)		(.01)		(.01)		(.01)
Education										
High School/GED		–.012		–.016		–.071***		–.029*		.027*
		(.01)		(.01)		(.01)		(.01)		(.01)
Some College		–.005		–.043**		–.083***		–.030*		.044**
		(.01)		(.01)		(.01)		(.01)		(.01)
Associate's Degree		–.004		–.044**		–.082***		–.027*		.070***
		(.02)		(.02)		(.01)		(.01)		(.02)
Bachelor's Degree		–.016		–.065***		–.093***		–.005		.049**
		(.01)		(.02)		(.01)		(.01)		(.02)
Advanced Degree		.010		–.041		–.053*		–.029		.067*
		(.02)		(.02)		(.02)		(.03)		(.03)
Enrolled		.004		–.012		.129***		–.020*		–.019
		(.01)		(.01)		(.01)		(.01)		(.01)
Job Tenure										
1 to 2 Years		.005		.018		–.063***		.019*		.080***
		(.01)		(.01)		(.01)		(.01)		(.01)
2 to 3 Years		–.006		.007		–.109***		.030**		.104***
		(.01)		(.01)		(.01)		(.01)		(.01)
3 to 4 Years		–.002		–.007		–.125***		.023*		.115***
		(.01)		(.01)		(.01)		(.01)		(.02)
4 to 5 Years		–.002		–.001		–.145***		.038**		.117***
		(.01)		(.01)		(.01)		(.01)		(.01)

(continued)

Table A3. *(continued)*

	Canceled Shift		On-Call		Involuntary Part-Time		Hard to Get Time Off		Clopening	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
5 to 6 Years		.005		–.011		–.128***		.031*		.091***
		(.01)		(.01)		(.01)		(.01)		(.02)
6+ Years		–.010		–.008		–.170***		.023*		.074***
		(.01)		(.01)		(.01)		(.01)		(.01)
Labor Market Conditions										
Union Member		.003		.033		–.016		.038**		–.018
		(.01)		(.02)		(.01)		(.01)		(.03)
Previous-Year Unemployment Rate		.005**		.005		.011***		.003		.004*
		(.00)		(.00)		(.00)		(.00)		(.00)
State-Industry Unionization Rate		–.000		–.001		.000		.000		–.001
		(.00)		(.00)		(.00)		(.00)		(.00)
Constant	.135***	.226***	.224***	.504***	.205***	.065	.246***	.478***	.456***	.710***
	(.00)	(.03)	(.00)	(.04)	(.00)	(.04)	(.00)	(.04)	(.00)	(.04)
Employer	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Occupation	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Employer F		865		196		12,102		2,950		544
N	28,317	28,317	28,317	28,317	28,317	28,317	28,317	28,317	32,872	28,317

* $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed tests).

Table A4. Oaxaca-Blinder Decomposition of the White/Non-White Gap in Five Indicators of Schedule Quality for Service Sector Workers; Test of Functional Form

	(1) Canceled Shift	(2) On-Call	(3) Involuntary Part-Time	(4) Hard To Get Time Off	(5) Clopening
Linear Probability Model – Explained (Percent of Difference)					
Traditional Explanations	36.55***	81.27***	65.98***	62.12***	83.78***
	(5.69)	(6.25)	(6.82)	(7.96)	(10.01)
Employer Fixed-Effects	12.77**	–12.38**	–4.88	4.96	9.22
	(3.89)	(4.48)	(4.16)	(4.54)	(6.92)
Occupation	2.29**	.42	14.78***	–2.57*	–7.70
	(.83)	(1.00)	(3.08)	(1.20)	(4.69)
Racial Discordance	13.23*	10.30	–.63	21.47**	15.35
	(5.14)	(5.44)	(5.38)	(7.21)	(8.83)
Linear Probability Model – Total (Percent of Difference)					
Explained	64.85***	79.61***	75.25***	85.98***	100.65***
	(8.51)	(9.38)	(10.19)	(11.47)	(15.35)
Unexplained	35.15*	20.39	24.75	14.02	–.65
	(13.79)	(14.32)	(14.26)	(18.95)	(22.86)
Logit – Explained (Percent of Difference)					
Traditional Explanations	34.20***	76.53***	55.92***	64.82***	87.78***
	(5.32)	(6.47)	(6.59)	(8.15)	(10.25)
Employer Fixed-Effects	13.76***	–8.50*	–.69	1.92	6.90
	(3.63)	(4.22)	(4.24)	(4.83)	(7.47)
Occupation	1.76*	.48	17.41***	–2.47*	–8.07
	(.81)	(.98)	(3.96)	(1.20)	(4.81)
Racial Discordance	12.57**	10.62*	.47	21.65**	16.20
	(4.71)	(5.16)	(5.29)	(7.29)	(9.26)
Logit – Total (Percent of Difference)					
Explained	62.30***	79.12***	73.11***	85.93***	102.81***
	(8.28)	(9.61)	(10.35)	(11.89)	(15.80)
Unexplained	37.70**	20.88	26.89	14.07	–2.81
	(13.46)	(14.55)	(14.08)	(19.41)	(23.34)
Probit – Explained (Percent of Difference)					
Traditional Explanations	34.92***	77.25***	57.74***	64.86***	86.97***
	(5.27)	(6.35)	(6.58)	(8.04)	(10.10)
Employer Fixed-Effects	13.04***	–9.13*	–1.07	2.24	7.59
	(3.52)	(4.15)	(4.27)	(4.71)	(7.25)
Occupation	1.72*	0.34	17.06***	–2.49*	–8.08
	(.79)	(.97)	(3.84)	(1.20)	(4.73)
Racial Discordance	13.39**	10.39*	.54	21.07**	16.43
	(4.70)	(5.17)	(5.39)	(7.24)	(9.08)
Probit – Total (Percent of Difference)					
Explained	63.08***	78.85***	74.27***	85.68***	102.90***
	(8.11)	(9.44)	(10.27)	(11.71)	(15.56)
Unexplained	36.92**	21.15	25.73	14.32	–2.90
	(13.26)	(14.40)	(14.10)	(19.21)	(23.03)
N	32,056	32,056	32,056	32,056	32,056

*$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

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ORCID iDs

Adam Storer https://orcid.org/0000-0002-8181-7025

Daniel Schneider https://orcid.org/0000-0001-6786-0302

Note

1. To confirm that racial composition of firms is related to job quality, we also separately examined the association between percent white, non-Hispanic and exposure to each work scheduling indicator for white workers at the firm. Percent white varies across firms, ranging from 34 to 98 percent, and is associated with four of the five individual indicators of schedule quality as well as the scale. For instance, at the firm with the lowest share of white workers, average schedule quality is 1.6 on our scale versus 1.2 at the firm with the largest share of white workers.

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Adam Storer is a graduate student in Sociology at the University of California-Berkeley.

Daniel Schneider is Professor of Public Policy and Professor of Sociology at Harvard University. His research focuses on social demography, inequality, and precarious work.

Kristen Harknett is Associate Professor of Sociology at the University of California-San Francisco.