

Worker Power and Temporal Rents: How Occupational Closure and Productivity Constraints Shape Schedule Control

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Abstract

While existing literature suggests that workers' schedule control is primarily determined by time-related productivity constraints inherent in their occupations, recent research indicates that low schedule control persists even in jobs with low productivity constraints. This paper argues that workers can capitalize on the potential schedule benefits of low productivity constraints when they possess the power to press employers. In occupations where productivity constraints are high, workers are structurally limited in attaining schedule control regardless of their power. I examine two forms of occupational closure, occupational educational requirements and occupational licensing, as sources of workers' power. The findings from the National Longitudinal Survey of Youth 1997 and the American Time Use Survey show that workers in occupations with lower productivity constraints are able to claim better schedule control when they also work in occupations with higher educational requirements or in occupations that require a license. This research highlights the importance of considering both power and productivity in understanding the factors that shape workers' schedule control.

Keywords: schedule control, occupational closure, power, productivity, job tasks

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1 Introduction

Job quality in the United States has eroded over the past several decades. Although much prior work focuses on diminished pay and fewer fringe benefits, the temporal dimension of job quality is gaining increased attention. A central element is schedule flexibility, whether workers have control over when they engage in work-related tasks (Kelly and Moen 2021; Lambert et al. 2012). A growing body of evidence links greater schedule flexibility to better health, lower work-family conflict, and higher well-being, while its absence intensifies strain and insecurity (Kelly et al. 2011). Despite previous studies offering broad accounts of the causes of growing precarity (Kalleberg 2011; Kelly and Moen 2021), the literature has not extensively examined the factors contributing to variation across workers.

One leading explanation locates this variation in occupational task content itself. Unlike pay or health insurance, which are largely distributive and depend on what workers can negotiate, control over when one works is partly determined by the work itself. Specifically, time-related productivity constraints inherent in certain occupations limit workers' ability to gain schedule flexibility. Goldin (2021) observes that professionals such as lawyers often need to communicate frequently with clients and colleagues and make urgent decisions, resulting in more on-call work hours and less control over their schedules. In contrast, occupations like pharmacy, which involve fewer client-specific relationships and more structured job duties, allow workers greater schedule flexibility (Goldin 2014; Goldin and Katz 2011, 2016). However, workers such as stock clerks and cashiers have little control over when they work despite facing relatively low productivity constraints (Lambert 2008; Schneider and Harknett 2019). This discrepancy implies that although time-related productivity constraints negatively impact workers' potential for schedule flexibility, they do not fully determine whether this potential translates into actual schedule flexibility. Consequently, another source of variation likely exists that influences workers' schedule control.

In this paper, I argue that not only productivity constraints but also worker power are crucial factors in determining workers' schedule flexibility. Building on insights from rent-

based theory, this paper investigates the role of workers' advantageous positions in the labor market in contributing to schedule flexibility ([Kalleberg 2011](#); [Sørensen 2000](#); [Sørensen and Kalleberg 1981](#)). I propose that workers in less advantaged positions may be unable to secure schedule flexibility, even when occupational tasks do not inherently limit it. Employers might still impose inflexible schedules when their workers lack the power to make claims ([Kristal 2017](#); [Kristal et al. 2011](#)). Alternatively, in occupations with high time-related productivity constraints, even powerful workers may struggle to claim schedule flexibility. In summary, I anticipate that workers will attain schedule flexibility only when two conditions converge, relatively low occupational productivity constraints and relatively high worker power that enables employees to press employers for schedule flexibility.

As one source of worker power, I focus on occupational closure, the restriction of entry into an occupation that confers a positional advantage in the labor market ([Weeden 2002](#); [Weeden and Grusky 2005](#)). I examine two institutionally distinct forms of closure that both restrict labor supply and grant incumbents leverage over employment terms, educational credentialing and occupational licensing ([Abbott 1988](#); [Weeden 2002](#)). Although these forms operate through different channels (the educational system versus government licensing), both should follow the same logic of granting workers greater power.

To estimate the combined effects of productivity constraints and worker power on schedule flexibility, this paper draws on detailed occupational task measures from the Occupational Information Network (O*NET). I first examine the relationship between productivity constraints and schedule flexibility across occupations. I then measure two sources of worker power (occupational educational requirements and occupational licensing) and examine how these two sources of worker power make a difference in the association between productivity constraints and schedule flexibility, to determine whether workers in occupations with higher educational requirements or in licensed occupations enjoy greater schedule benefits when productivity constraints are lower.

This paper offers three empirical findings. First, the relationship between productivity

constraints and schedule flexibility is not significant across the entire workforce, indicating that low productivity constraints do not by themselves deliver schedule flexibility. Second, neither higher educational requirements nor licensing produces a significant flexibility advantage on average, and licensed workers in fact show a negative average association, suggesting that closure alone does not purchase schedule flexibility. Third, both forms of closure (occupational educational requirements and occupational licensing) translate into schedule flexibility specifically when productivity constraints are low.

Theoretically, these results first advance our understanding of what determines schedule control. Control over one's time is determined neither by task structure alone nor by worker power alone, but by their intersection. Workers gain control only where the task makes flexible scheduling feasible and they hold the positional power to claim it. Second, the results extend closure and rent theory to the temporal dimension of job quality. Where closure scholarship has shown how restricted entry into an occupation secures higher wages and material fringe benefits, I show that closure also governs workers' control over time, a temporal rent, and that this advantage is gated by productivity constraints in a way that material advantages are not.

2 Time-related Productivity Constraints, Worker Power, and Temporal Rents

2.1 Schedule Flexibility and Time-related Productivity Constraints

The temporal dimension of job quality has drawn increasing attention, as schedule flexibility, control over when one works ([Hill et al. 2008](#)), shapes workers' well-being and their capacity to balance employment with family and the rest of life ([Kelly and Moen 2021](#)). Such control is especially consequential where work is demanding and hours are long ([Goldin 2014, 2021](#)),

yet schedule flexibility is unequally distributed across the labor market.

Existing literature on determinants of schedule flexibility has primarily focused on the impact of time-related productivity constraints stemming from occupational demands. Different occupations impose varying demands on workers, such as meeting frequent and strict deadlines, arranging work around clients' or coworkers' schedules, developing and maintaining cooperative working relationships, and making urgent and critical decisions (Goldin 2014, 2021; Yu and Kuo 2022). For instance, many workplaces expect workers to meet with clients and accumulate knowledge about them, as well as communicate the information to other coworkers through timely interactions. If an employee is unavailable and misses the information exchanged among present clients and coworkers, the employee's productivity at work will decline (Goldin 2014; Goldin and Katz 2011).

As a result, time-related occupational demands that necessitate workers to be on call, offer face time, and attend meetings during specific hours often lead to reduced schedule flexibility (Goldin 2014). Workers who cannot meet these demands may face detrimental productivity consequences (Goldin 2014; Goldin and Katz 2011). Consequently, flexible schedules often impose significant costs on employers, and workers who enjoy schedule flexibility experience corresponding wage penalties. These wage penalties compel workers to accept lower schedule flexibility (Goldin 2014; Goldin and Katz 2016; Yu and Kuo 2017, 2022). However, if the time-related productivity constraint or the cost of providing schedule flexibility diminishes for employers, the wage penalty associated with schedule flexibility would decrease, allowing more workers to enjoy schedule flexibility (Goldin 2014; Goldin and Katz 2011).

Previous research has employed variations in productivity constraints to explain wage disparities across occupations (Yu and Kuo 2017, 2022) and gender wage gaps, assuming that women seek greater schedule flexibility and consequently experience larger wage penalties (Goldin 2014, 2021). However, this body of work has not examined differences in schedule flexibility across occupations. This omission is important because it is hypothesized that occupational-level productivity constraints affect wage differential through workers' expe-

rience of schedule flexibility. While studies have identified a positive association between productivity constraints and gender wage gaps (Goldin 2014, 2021; Goldin and Katz 2016; Yu and Kuo 2022), the relationship between productivity constraints and schedule flexibility remains underexplored. Therefore, demonstrating a negative association between productivity constraints and schedule flexibility is essential for validating the theoretical framework that links wage gaps to time-related productivity constraints and penalizes wages for workers with flexible work schedules (Goldin and Katz 2011, 2016).

Moreover, while the existing literature emphasizes the role of technical factors inherent in occupations that shape a negative association between productivity constraints and schedule flexibility, there could be other sources of variation in schedule flexibility. Goldin and Katz (2016) suggests that changes in technology such as uniform training, standardization of products, and extensive use of information technology in the pharmacy sector have significantly reduced the cost of schedule flexibility for pharmacists by enhancing their ability to hand off clients. As a result, pharmacists can enjoy greater schedule flexibility since the occupational demands to arrange work around clients' schedules and make urgent decisions that cannot be conveyed to other coworkers are reduced. Indeed, the wage penalty for not working on-call and irregular hours has substantially diminished (Goldin 2014, 2021; Goldin and Katz 2016).

On the other hand, another line of literature shows that workers in service occupations often have less flexible schedules, even though their occupational requirements do not inherently prevent flexibility (Schneider and Harknett 2019, 2021). For instance, while cashiers and stock clerks interact with customers and handle merchandise throughout their work, these tasks typically do not involve client-specific relationships and are not tied to individual workers (Kesavan et al. 2014; Kesavan et al. 2022; Lambert et al. 2019). In other words, customers generally do not prefer which worker assists them, and workers do not need to arrange schedules around customers' needs. Additionally, these jobs usually have more structured job duties and do not require workers to make frequent and urgent decisions,

allowing coworkers to cover for each other more easily (Kesavan et al. 2014). That is, having more schedule flexibility does not necessarily harm an employee’s productivity in terms of completing their tasks.

Despite facing relatively low time-related productivity constraints, stock clerks and cashiers continue to have limited control over their work schedules. Consequently, it remains an open question whether a negative association exists between productivity constraints and schedule flexibility among the entire workforce across various occupations.

Hypothesis 1. *Workers in occupations with lower productivity constraints are more likely to have schedule flexibility than those in occupations with higher productivity constraints.*

2.2 Worker Power and Temporal Rents

The case of stock clerks and cashiers, who have little schedule flexibility despite facing low productivity constraints, highlights that occupational productivity constraints alone do not fully determine whether workers can realize potential schedule flexibility. Employer discretion also plays a significant role. Employers may prioritize capturing the gains of scheduling practices for their own profits rather than granting workers greater control over their schedules, especially when workers lack the bargaining power to demand better schedules for themselves (Goyal and Netessine 2011; Kesavan et al. 2014; Lambert 2008). Employers often structure schedules to reduce labor costs and keep headcount low, varying how many hours employees work and how those hours are distributed to keep labor supply tightly linked to fluctuating demand, and workers who cannot push back have little say over when they work (Lambert 2008).

However, focusing solely on employer discretion is not sufficient to explain how schedule flexibility is distributed between employers and employees. It is also important to consider the bargaining power of workers to claim a larger share of compensation (Benton and Kim 2022; Bidwell 2013). Workers’ ability to pressure employers is crucial in securing better

schedules, as employers may not voluntarily offer more flexible schedules ([Kesavan et al. 2022](#); [Lambert et al. 2019](#)). In other words, if workers cannot pressure employers to provide better schedules, the potential benefits may not be transferred to workers but instead captured by employers to generate more profits.

Previous studies have highlighted the role of structurally advantageous positions in the market and employment relations in providing additional rewards to workers. These rewards, also referred to as “rents,” represent returns above what would be expected in a baseline condition, typically a perfectly competitive market ([Avent-Holt 2022](#)). Occupations with high entry barriers, such as those requiring specialized education or training, often generate rents. One well-known example of rents in the labor market is the wage premiums associated with occupational closure, the restriction of access to certain occupations through means such as licensing or credentialing requirements ([Weeden and Grusky 2014](#)). Workers in such positions may also be able to extract greater fringe benefits, such as better pension plans and health insurance ([Kristal et al. 2011](#); [Kristal 2017](#); [Kristal et al. 2020](#)). I extend this logic to the temporal dimension of job quality. Schedule flexibility is itself a temporal rent that workers in advantaged positions can extract. The rent takes the form of an entitlement, the worker’s authority to vary the start and end times of the workday. What closure derived leverage should purchase is the right to vary one’s schedule, not necessarily the exercise of it on any given day.

Productivity concerns are essential to consider when examining the association between workers’ positional power and temporal rents. In some occupations, workers face low time-related productivity constraints, which allow them to leverage their position to secure greater schedule flexibility. However, this requires workers to be able to negotiate with their employers to realize these potential gains. In contrast, workers in occupations with high time-related productivity constraints may be structurally limited in their schedule flexibility, regardless of their positional power. Therefore, to understand the mechanisms through which certain workers improve their work schedules, it is important to take into account both the level

of productivity constraints and the bargaining power of workers in different occupations. I propose two key indicators of workers' power to secure schedule flexibility, occupational educational requirements and occupational licensing.

Both indicators are forms of occupational closure, the restriction of entry into an occupation that confers positional advantage (Weeden 2002; Weeden and Grusky 2005). Educational credentialing and occupational licensing operate through different channels (the educational system and the state), but both restrict the supply of qualified workers and grant incumbents leverage over the terms of employment.

Educational requirements can serve as closure mechanisms, making some people eligible for jobs and excluding others, while not implying that they always reflect the skills a particular job requires (Tåhlin 2023). Workers in occupations with high educational requirements occupy positions with a limited labor supply, enabling them to leverage their advantageous positions in the labor market to negotiate with employers for better pay and greater schedule flexibility. In contrast, workers in occupations with lower educational requirements may have limited bargaining power and less schedule flexibility, given the larger pool of available labor for those jobs (Kristal et al. 2011; Kristal 2017; Kristal et al. 2020).

This paper expands on prior research on workers' positional power by considering its interaction with time-related productivity constraints. In this account, positional power is not an unconditional advantage but a capacity whose value depends on the task structure workers confront. Drawing on rent-based theory, I predict that workers in occupations with low productivity constraints are more likely to enjoy schedule flexibility when those occupations also have high educational requirements. In other words, workers in occupations with higher educational requirements are better positioned to capitalize on the potential schedule flexibility that emerges where productivity constraints are low.

Hypothesis 2. *Workers in occupations with higher rather than lower educational requirements are more likely to have schedule flexibility when productivity constraints are lower.*

Occupational licensing restricts entry more strictly still. The state reserves the legal

right to practice for those who meet its requirements, so that unauthorized practice carries civil or criminal penalties (Redbird 2017; Weeden 2002). Licensing is occupational closure in its most durable, official form (Redbird 2017), and it measurably reduces the supply of labor to licensed occupations (Blair and Chung 2019). A large literature documents that licensing shapes the terms of employment, most prominently a wage premium, although its magnitude is debated (Kleiner and Krueger 2013; Gittleman et al. 2018; Redbird 2017), and that its effects extend beyond wages to non-wage benefits such as employer-sponsored health insurance (Gittleman et al. 2018). Licensing may also function as a signal of competence and reliability that earns workers employer trust (Blair and Chung 2022). Whether licensing confers greater schedule flexibility, however, has not been examined. If schedule flexibility is a temporal rent, licensed workers, like highly credentialed ones, should be positioned to claim it. As with educational credentialing, I expect this advantage to be concentrated where productivity constraints are low.

Hypothesis 3. *Workers in licensed occupations are more likely to have schedule flexibility than workers in unlicensed occupations when productivity constraints are lower.*

3 Data and Methods

3.1 Data

National Longitudinal Survey of Youth 1997. The primary source is the NLSY97, a nationally representative panel that follows Americans born between 1980 and 1984 across 21 survey waves from 1997 to 2023. I restrict the panel to civilian wage and salary workers aged 18 or older with a reported main job and complete information on the study variables. The final panel includes 70,354 person years from 8,310 workers, and all descriptive statistics and models are estimated on this same sample.¹

¹Among 111,250 person years as adult civilian wage and salary workers holding a main job, I excluded 40,896 (36.8 percent). The exclusions comprise 23,229 (20.9 percent) in which the job had lasted less than 13 weeks, the tenure threshold below which the survey does not field the schedule flexibility item, 789 (0.7

American Time Use Survey. The second source is the ATUS Leave Module, fielded in 2017 and 2018. The ATUS is a nationally representative, cross-sectional survey of the U.S. civilian non-institutionalized population, and the Leave Module collects information on employer scheduling policies. I restrict the sample to wage and salary workers aged 18 to 64 with complete information on the study variables. The final sample includes 8,107 workers, and all descriptive statistics and models are estimated on this same sample.²

The two surveys cover each other’s blind spots. The NLSY97 follows a single cohort observed between ages 18 and 43, so its results could in principle reflect the experience of workers early in their careers. The ATUS covers workers of all ages and cohorts and shows that the patterns are not specific to one generation or life stage. Conversely, the ATUS’s cross-sectional estimates cannot rule out sorting of workers into occupations on unobserved schedule preferences. The NLSY97 person fixed effects models address that concern directly. In addition, the ATUS identifies each respondent’s state of residence, which supports a licensing measure that varies at the occupation-by-state level, while the NLSY97 supports only an occupation level measure.

Occupational Information Network. Occupation level measures come from O*NET, a comprehensive database of job characteristics based on surveys of job incumbents, occupational experts, and occupational analysts. I merge the measures to each survey by Census occupation codes, using the release matched to each survey’s period and classification, the 21.1 release from 2017 for the ATUS on 2010 Census codes and the 2009 release for the NLSY97 on 2002 Census codes, with identical item selection and index construction in the two releases.³ The final analytic samples cover 420 occupations in the NLSY97 and 283

percent) without an occupation that links to the O*NET measures, 7,119 (6.4 percent) in occupations without licensing information, 9,704 (8.7 percent) missing control variables, and 55 (0.05 percent) in occupations with three or fewer person years. None of the three largest exclusions appears to drive the results.

²The Leave Module universe is wage and salary workers, so self-employed workers are excluded by design. Module respondents aged 18 to 64 number 9,319. Of these, I excluded 1,212 (13.0 percent), leaving the 8,107 worker analytic sample. The exclusions comprise 150 (1.6 percent) in occupations not matched to O*NET by the crosswalk, 491 (5.3 percent) in occupations without licensing coverage, 346 (3.7 percent) missing information on work hours, and 225 (2.4 percent) in occupations with three or fewer respondents.

³For the NLSY97, I aggregate the 2009 release to the SOC 2000 level and convert to 2002 Census codes, taking labor force weighted averages where multiple SOC occupations map to a single Census occupation.

occupations in the ATUS.

3.2 Variables

Dependent variable: schedule flexibility. In the NLSY97, schedule flexibility is measured by a binary indicator of whether the employer makes a flexible work schedule available to the respondent, drawn from the employer benefits battery asked at every wave.⁴ Respondents also report the occupation of their main job in each wave, which links them to the occupation level measures described below. In the ATUS, flexibility is measured by a binary indicator of whether the respondent’s employer has a flexible work policy that allows workers to change their start and end times. The two items capture the same entitlement from different angles, a benefit available to the worker in the NLSY97 and a formal employer policy in the ATUS.⁵

Independent variable: time-related productivity constraints. I measure time-related productivity constraints with six items from O*NET, following [Goldin \(2014\)](#). The items capture the degree to which a job’s tasks are relational and require real-time coordination such that a coworker cannot easily step in for an absent worker, the condition under which granting schedule flexibility imposes costs on employers. The items are the degree of contact with others in performing the job, the frequency of face-to-face discussions, the importance of establishing and maintaining interpersonal relationships, the level of freedom to make decisions without supervision, the frequency of making decisions that affect others and the organization, and the degree of structure in job tasks. Each item is rescaled to a 0 to 10 range using min-max normalization, following [Deming \(2017\)](#), so that items measured on different

The 2009 release is the earliest comparable to later releases, following a 2008 change in O*NET’s work context measurement, and sits within the panel window. For the ATUS, I aggregate O*NET-SOC extensions to the six digit SOC 2010 level and convert SOC 2010 to 2010 Census occupation codes with the same aggregation rule, using the crosswalk documentation provided by IPUMS ([Integrated Public Use Microdata Series 2018](#)).

⁴The NLSY97 benefits battery changed response format in 2017, from a showcard on which respondents selected applicable benefits to separate yes or no questions for each benefit, and reported flexibility rises with the format change. Year fixed effects absorb the level shift, and Appendix Table [A2](#) shows that the interactions do not differ across the two formats.

⁵The results partially replicate in the General Social Survey (GSS), a nationally representative survey of U.S. adults whose Quality of Worklife module measures flexibility with a different instrument, a composite of items on the difficulty of taking time off and the ability to change work times. I present the GSS analyses as robustness checks in Appendix Table [A3](#).

scales have equal intervals and a meaningful zero point before averaging.⁶ The composite is the mean across the six items, with higher scores indicating more relational, less coverable work. The six items span two related components of this construct, the intensity of relational coordination, captured by the contact, discussion, and relationship items, and the worker’s discretion over tasks and priorities, captured by the decision and structure items. I retain the full composite as the focal measure to remain consistent with prior work, with item-level results in Appendix Table A4.

Moderating variable: occupational closure as worker power. I use two variables to evaluate occupational closure as a source of worker power, the required level of education by occupation and occupational licensing. Each is separately interacted with the productivity constraint measure.⁷

Educational requirements. The first closure measure is the occupation level required education from O*NET, scored on a continuous 1 to 12 scale in which approximately 2 corresponds to a high school diploma, 6 to a bachelor’s degree, and 11 to a doctoral degree. This is an occupation level measure of how much formal education an occupation systematically demands, distinct from individual workers’ own educational attainment, which enters all models separately as a control. As a robustness check, I replace the O*NET measure with the occupation mean years of schooling among employed workers from the American Community Survey, which captures the schooling that occupation members actually hold rather than the level analysts judge the occupation to require, and the results remain the same (Appendix Table A1). The two measures correlate at 0.92 across occupations.

Occupational licensing. The second closure measure is occupational licensing, drawn from Haupt (2023), who hand-collected licensing requirements from state licensing board records for all fifty states as of approximately 2018. Licensing operates at the state level,

⁶The rescaling subtracts the minimum value from each observation, divides the result by the range of the data, the difference between the maximum and minimum values, and multiplies by 10.

⁷At the occupation level, educational requirements and licensing correlate at 0.34 in the ATUS and 0.38 in the NLSY97, so the two forms of closure are tested on substantially distinct occupational terrain rather than relabeling the same occupations.

so the same occupation can be licensed in some states and not others. In the NLSY97, which does not identify respondents' states in the public release, I measure licensing at the occupation level as the fraction of states licensing the occupation, ranging from 0 for occupations licensed nowhere to 1 for occupations licensed in every state.⁸ This occupation level measure captures how widely a license is required rather than whether a particular worker faces the requirement, and blurring that distinction should, if anything, attenuate licensing effects in the NLSY97. In the ATUS, which identifies each respondent's state, licensing is a binary indicator of whether the occupation is licensed in the respondent's state, so the measure reflects the requirement each worker actually faces. Because the licensing records are a single snapshot, I treat licensing as a stable occupational trait across the panel, as I do all occupation level measures.⁹

Control variables. All models control for survey year and a set of individual and workplace characteristics. In the NLSY97, the individual controls are age and its square, sex, race and ethnicity (non-Hispanic white, non-Hispanic Black, Hispanic, other),¹⁰ immigrant status, marital status (married with spouse present, previously married or spouse absent, never married), the number of own children in the household,¹¹ and the respondent's own educational attainment in five categories (less than high school, high school diploma, some college, bachelor's degree, post-bachelor's degree), which separates the occupation level credential requirement from workers' own schooling. The workplace controls are part time

⁸I zero out twenty SOC codes that Haupt (2023) identifies as business permits rather than occupational licenses, and crosswalk his SOC 2010 codes to the Census occupation codes used in each survey. Where several SOC occupations map to a single Census occupation and disagree on licensing within a state, I code the Census occupation as licensed if most of its component codes are licensed.

⁹States rarely repeal licensing requirements, so the major licensed occupations were licensed long before 1997. The likely error concerns occupations that first became licensed between 1997 and 2018. Because the records date from 2018, such an occupation is coded as licensed across the whole panel, including the early waves before its license existed, and misclassifying those years works against finding licensing effects. Restricting the estimation to the 2017 to 2023 waves, when the records are current, yields similar estimates (Appendix Table A2).

¹⁰The NLSY97 public release provides a single combined race and ethnicity variable, so its four groups are Black, Hispanic, mixed race, and non-Black non-Hispanic.

¹¹Children are topcoded at four. In the ATUS, the count refers to own children under 18 in the household. The NLSY97 count refers to biological children in the household through 2017 and to children under 18 from 2019 onward. The redefinition arrives when the cohort is 35 to 43 years old, so children aged past 18 are still uncommon at that point.

status, holding multiple jobs, public sector employment, census region, metropolitan residence, and industry fixed effects, which ensure that closure effects are identified within rather than across industries.¹² The ATUS models include the same controls, with state fixed effects in place of census region and metropolitan area size in place of the metropolitan residence indicators.

Both datasets additionally include four occupation level task measures from O*NET, grouped following the task-content literature that separates routine, nonroutine analytic, and cognitive job content (Autor et al. 2003; Deming 2017). Time pressure averages the frequency of time pressure and the level of competition, two workplace-demand items from Goldin (2014). Routine intensity averages the degree of automation, machine paced work, the importance of repeating the same tasks, and the importance of being exact. Nonroutine analytic content averages mathematical reasoning, number facility, mathematics skill and knowledge, programming, and computer knowledge. Higher order cognitive demands average active learning, active listening, complex problem solving, critical thinking, learning strategies, monitoring, and time management. These traits matter because closed occupations also tend to be analytic, nonroutine, and cognitively demanding, and such occupations may receive schedule flexibility because their work is portable and autonomous rather than because their workers hold closure based leverage. Controlling for them keeps the closure estimates from absorbing that alternative channel.¹³ ATUS models are weighted with the Leave Module weight, and NLSY97 models are unweighted, as appropriate for the fixed effects design.

¹²The industry classification distinguishes agriculture, forestry, and fishing, mining and utilities, construction, manufacturing, wholesale and retail trade, transportation, information, finance, insurance, and real estate, professional services, management and administrative services, education and health services, leisure and hospitality, personal and organizational services, and public administration.

¹³These task measures are themselves O*NET occupational attributes, and the time pressure control in particular is built from items in the same family as the productivity constraint measure, so adjusting for them risks absorbing variation that belongs to the constraint construct rather than to a distinct confounder, which would attenuate the interaction. I therefore also report the specification without them: the interactions are as strong or stronger in both datasets (Appendix Table A1), so the main estimates are conservative with respect to this choice.

3.3 Analytic Strategy

The analyses test the three hypotheses with the same models in both datasets. For each closure measure, a series of linear probability models predicts schedule flexibility first with the productivity constraint measure and the controls described above, next adds the closure measure, and finally adds their interaction. If Hypothesis 1, which examines whether there is a negative association between productivity constraints and schedule flexibility, is supported, the constraint coefficient in the first model should be negative, indicating that workers in occupations with lower productivity constraints are more likely to have schedule flexibility than those in occupations with higher productivity constraints. If Hypothesis 2, which examines whether the schedule flexibility advantage of educational requirements is concentrated where productivity constraints are low, is supported, the interaction between educational requirements and productivity constraints should be negative, indicating that workers in occupations with higher educational requirements are more likely to have schedule flexibility than those in occupations with lower educational requirements when productivity constraints are lower. If Hypothesis 3, which examines the same conditional pattern for occupational licensing, is supported, the interaction between licensing and productivity constraints should be negative, indicating that workers in licensed occupations are more likely to have schedule flexibility than workers in unlicensed occupations when productivity constraints are lower. Standard errors are clustered by occupation in all models, including the person fixed effects models, because the closure and constraint measures vary at the occupation level.

In the NLSY97, I estimate each model twice, first as a pooled specification and second with person fixed effects. The person fixed effects models absorb all time invariant worker characteristics.¹⁴ Because the closure and constraint measures are attributes of occupations, they change for a worker only when the worker changes occupations. The person fixed effects estimates therefore rest on the 7,329 workers who change occupations over the panel,

¹⁴Linear age is omitted from the person fixed effects models because, once the person fixed effect absorbs year of birth, it is exactly collinear with the year fixed effects. The quadratic age term is retained because its curvature is not absorbed.

comparing each worker’s schedule flexibility across the occupations that worker holds.¹⁵

In the ATUS, the models are estimated on the cross section and weighted with the Leave Module weight. The main tables report the person fixed effects estimates alongside the ATUS estimates, and the pooled NLSY97 estimates appear in Appendix Table A5.

I interpret the estimates as conditional associations consistent with the leverage mechanism rather than as causal effects.

4 Results

4.1 Descriptive Statistics

Table 1 presents descriptive statistics for the two analytic samples. In the NLSY97 panel, 41.2 percent of person years carry an employer that makes a flexible schedule available. In the ATUS Leave Module, 56.2 percent of workers report an employer policy that allows them to change their start and end times. The flexibility rates differ across the two datasets, reflecting the different survey items, a benefit available to the worker versus a formal employer policy, and the different periods and populations, with the panel observing a single cohort from age 18 onward. Average time-related productivity constraints are 6.8 in the NLSY97 and 7.1 in the ATUS on the 0 to 10 composite scale, which ranks occupations relative to one another, running from food preparation workers near 4 through cashiers and stock clerks around 6 in the middle range to teachers, nurses, and physicians between roughly 8 and 9 near the top.

¹⁵Flexibility itself also changes within workers, as 6,621 of the 8,310 are observed both with and without it, so the estimates draw on widespread rather than rare within person variation.

Table 1: Descriptive Statistics

Variable	Mean	SD	Min	Max
<i>Panel A. NLSY97, 70,354 person years, 1997–2023</i>				
Schedule flexibility	0.412	0.492	0.000	1.000
Educational requirements (1–12)	3.346	1.794	1.240	11.338
Licensed state fraction (0–1)	0.206	0.361	0.000	1.000
Time-related productivity constraints	6.753	1.094	0.338	9.714
Age	27.2	6.6	18	43
<i>Panel B. ATUS Leave Module, 8,107 workers, 2017–18</i>				
Schedule flexibility	0.562	0.496	0.000	1.000
Educational requirements (1–12)	4.440	2.160	1.354	11.278
Licensed occupation in state (0/1)	0.297	0.457	0.000	1.000
Time-related productivity constraints	7.129	1.062	3.198	9.175
Age	40.0	12.7	18	64

Panel A reports unweighted statistics for civilian wage and salary workers. Panel B reports statistics weighted with the Leave Module weight for wage and salary workers.

On the required education scale, 2 corresponds to a high school diploma and 6 to a bachelor’s degree, so the NLSY97 mean of 3.3 and the ATUS mean of 4.4 fall in the range of postsecondary training short of a four year degree. Most workers hold jobs in occupations that demand more than a high school diploma, 76.6 percent of NLSY97 person years and 93.5 percent of ATUS workers, and 12.5 and 29.5 percent respectively work in occupations requiring at least a bachelor’s degree. The gap between the samples reflects the panel’s younger cohort, visible in the age rows of Table 1. For licensing, the average NLSY97 occupation is licensed in about a fifth of states, and 29.7 percent of ATUS workers hold occupations that are licensed in their state.

Table 2 grounds the occupational closure and productivity constraint measures in occupations, listing two large occupations from each cell. The educational requirements panel displays the conditional pattern directly. Occupations that combine bachelor’s level requirements with low productivity constraints average a flexibility rate of 0.75, against 0.51 for occupations with low productivity constraints but without high educational requirements, a gap of 24 percentage points. At high productivity constraints the gap nearly disappears, 0.59 against 0.56. This narrowing is the pattern the models estimate.

Table 2: Featured Occupations by Occupational Closure and Productivity Constraints

Low constraints			High constraints	
	Occupation	Flex.	Occupation	Flex.
<i>Panel A. Educational requirements</i>				
High closure	Computer systems analysts	0.84	Elementary/middle school teachers	0.13
	Accountants and auditors	0.71	Physicians and surgeons	0.44
	<i>Cell mean 0.75 (8.2% of workers)</i>		<i>Cell mean 0.59 (21.4% of workers)</i>	
Low closure	Cashiers	0.65	Retail salespersons	0.60
	Truck drivers	0.42	Carpenters	0.28
	<i>Cell mean 0.51 (45.3% of workers)</i>		<i>Cell mean 0.56 (25.1% of workers)</i>	
<i>Panel B. Occupational licensing</i>				
Licensed	Civil engineers	0.88	Registered nurses	0.41
	Electricians	0.36	Preschool and kindergarten teachers	0.22
	<i>Cell mean 0.55 (10.7% of workers)</i>		<i>Cell mean 0.41 (16.6% of workers)</i>	
Unlicensed	Secretaries	0.65	General and operations managers	0.66
	Waiters and waitresses	0.72	Customer service representatives	0.65
	<i>Cell mean 0.55 (42.3% of workers)</i>		<i>Cell mean 0.67 (30.5% of workers)</i>	

ATUS Leave Module 2017–18, weighted. Constraints are split at the sample median, education closure is an O*NET required education of bachelor’s degree or higher, and licensing means licensed in a majority of the worker’s occupation and state cells.

The licensing panel shows the conditional pattern more weakly. Among licensed occupations, average flexibility is higher where productivity constraints are low than where they are high, 0.55 against 0.41. Among unlicensed occupations the gradient runs the other way, 0.55 where constraints are low and 0.67 where they are high. This contrast in gradients is what the models estimate. At high productivity constraints licensed workers report less flexibility than unlicensed workers, 0.41 against 0.67, a pattern I attribute in the Discussion to institutionally fixed scheduling that the constraint measure does not capture.

4.2 Time-Related Productivity Constraints and Schedule Flexibility

Hypothesis 1 predicts that workers in occupations with lower productivity constraints enjoy greater schedule flexibility. Model 1 of Tables 3 and 4, which is the same model in both tables because both occupational closure measures are tested on one analytic sample per dataset,

does not support this prediction in either dataset. The productivity constraint coefficient is small and not statistically significant in the ATUS cross section and in the person fixed effects models. This null is consistent with the conditional account, in which workers in low constraint occupations vary widely in whether they convert feasibility into actual flexibility.

Table 3: Educational Requirements, Productivity Constraints, and Schedule Flexibility

	NLSY97 person fixed effects			ATUS		
	M1	M2	M3	M1	M2	M3
Productivity constraints	0.006 (0.005)	0.006 (0.005)	0.021* (0.009)	-0.003 (0.019)	0.001 (0.019)	0.050 (0.033)
Educational requirements		0.001 (0.004)	0.038* (0.016)		0.019 (0.014)	0.130* (0.057)
Educational requirements $\times$ constraints			-0.005* (0.002)			-0.014* (0.007)
N (person years / workers)	70,354	70,354	70,354	8,107	8,107	8,107
R^2	0.330	0.330	0.330	0.132	0.133	0.135

Linear probability models with the full control set described in the text. NLSY97 models include person fixed effects; ATUS models are weighted with the Leave Module weight. Standard errors clustered by occupation in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.3 Educational Requirements and Schedule Flexibility

Model 2 of Table 3 shows the average association between educational requirements and schedule flexibility. The coefficient is positive but not significant in the ATUS (0.019) and essentially zero within person (0.001). On average, occupations that demand more schooling do not deliver more schedule flexibility once constraints and controls are held, a pattern the conditional account anticipates.

Hypothesis 2 predicts that the educational advantage is concentrated where constraints are low. Model 3 of Table 3 supports this prediction in both datasets. The interaction between educational requirements and productivity constraints is negative and significant in the ATUS (-0.014) and in the person fixed effects models (-0.005), where it is identified by workers who change occupations. Figure 1 shows the pattern. At low constraint levels,

workers in occupations with high educational requirements are substantially more likely to have schedule flexibility, and the advantage narrows as constraints rise.

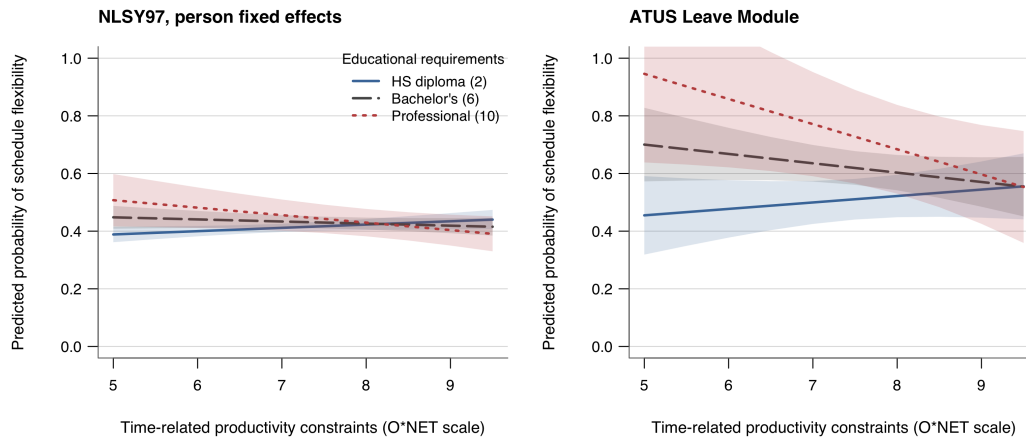


Figure 1: Predicted Schedule Flexibility by Educational Requirements and Time-related Productivity Constraints

4.4 Occupational Licensing and Schedule Flexibility

Model 2 of Table 4 shows the average association for licensing. The licensing coefficient is negative in the ATUS (-0.123) and small and not statistically significant within person (-0.028). The negative average association is consistent with the concentration of licensed occupations in high constraint work, though the cross section cannot separate that composition from a penalty of licensing itself. The within person estimate, which nets out stable worker characteristics, is close to zero.

Table 4: Occupational Licensing, Productivity Constraints, and Schedule Flexibility

	NLSY97 person fixed effects			ATUS		
	M1	M2	M3	M1	M2	M3
Productivity constraints	0.006 (0.005)	0.008 (0.005)	0.011 (0.006)	-0.003 (0.019)	-0.000 (0.019)	0.011 (0.020)
Licensing		-0.028 (0.016)	0.194 (0.103)		-0.123*** (0.029)	0.320* (0.160)
Licensing $\times$ constraints			-0.031* (0.015)			-0.060** (0.022)
N (person years / workers)	70,354	70,354	70,354	8,107	8,107	8,107
R^2	0.330	0.330	0.330	0.132	0.141	0.144

Linear probability models; specifications as in Table 3. The two licensing measures differ across panels, so magnitudes are not comparable. Standard errors clustered by occupation in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Hypothesis 3 predicts that a licensing advantage emerges where constraints are low. Model 3 of Table 4, which compares licensed and unlicensed occupations at the same constraint level, supports this prediction in both datasets. The interaction is negative and significant in the ATUS (-0.060) and within person (-0.031), and the licensing main effect evaluated at low constraints is positive. Figure 2 shows the crossover pattern. Licensed workers are more likely than unlicensed workers to have schedule flexibility where constraints are low, and the relationship reverses where constraints are high (see Appendix Table A6).

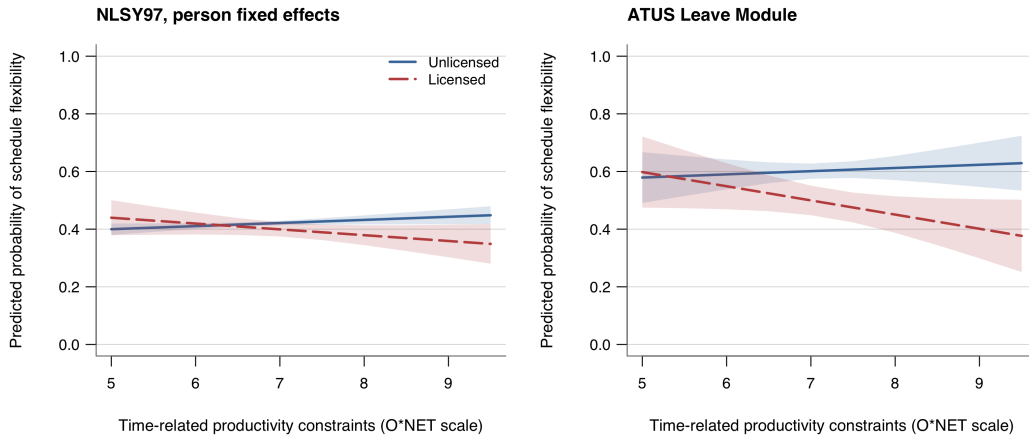


Figure 2: Predicted Schedule Flexibility by Occupational Licensing and Time-related Productivity Constraints

4.5 Possible Mechanisms

The results establish that neither low productivity constraints nor occupational closure alone delivers schedule flexibility. Their intersection does, with both forms of closure translating into flexibility where productivity constraints are low. This pattern supports the paper’s argument that productivity constraints set the room that tasks leave for flexibility while worker power determines whether workers claim that room. I provide more direct evidence on the mechanism theorized to underlie this pattern. Occupational closure gives workers bargaining power, and that power should yield compensation in both material and temporal forms. Only the temporal form is gated by productivity constraints, which raise the cost of granting schedule flexibility but not the cost of paying for benefits or wages. The prediction is that material benefits show no interaction with productivity constraints while schedule flexibility does, and that where high productivity constraints make the temporal payoff unavailable the rent appears in pay instead. I test these predictions with employer provided health insurance, dental coverage, and retirement plans, drawn from the same NLSY97 benefits battery as the flexibility item, and with the log hourly wage. All models use the person fixed effects specification of the main analysis.

Table 5 collects the estimated interaction between occupational closure and productivity constraints for each outcome. For the three material benefits, this interaction is close to zero. Occupational closure raises wages within person for both forms, 0.029 log points per step of educational requirements and 0.065 for licensing, so the leverage is real wherever workers hold it. For wages the interaction is positive (education +0.012, licensing +0.061), the mirror image of the interaction for schedule flexibility. One reading is that where productivity constraints are low, part of the rent from occupational closure is taken as schedule control, while where they are high the rent appears in pay instead. A simpler reading is also possible, that credentials earn a larger wage premium where productivity constraints are high because the skills they certify are more valuable in such work, not because a schedule rent is converted into pay. I therefore treat the wage evidence as consistent with the rent interpretation rather

than decisive (full models in Appendix Table A7).

Table 5: The Interaction between Occupational Closure and Productivity Constraints across Outcomes

Outcome	Occupational closure $\times$ productivity constraints	
	Educational requirements	Licensing
Schedule flexibility	-0.005* (0.002)	-0.031* (0.015)
Health insurance	0.002 (0.003)	-0.005 (0.020)
Dental coverage	0.000 (0.003)	0.001 (0.019)
Retirement plan	0.001 (0.003)	0.021 (0.016)
Log hourly wage	0.012*** (0.003)	0.061*** (0.015)

NLSY97 person fixed effects estimates, one model per cell, with the full control set. The benefit outcomes are observed 1997 to 2013 ($N = 53,137$). Flexibility is estimated on the common sample ($N = 70,354$) and wages on 66,186 person years. Standard errors clustered by occupation in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5 Discussion and Conclusion

The temporal aspect of job quality has become a growing concern in the US labor market, and previous literature has mainly focused on how productivity constraints inherent in occupations hinder workers from accessing schedule benefits. In this paper, I argue that worker power is equally central to understanding how workers gain control over their work schedules.

To investigate this, I draw on two complementary data sources merged with occupational measures of productivity constraints from the Occupational Information Network (O*NET). The National Longitudinal Survey of Youth 1997 has a panel structure that allows stronger identification within a single cohort. The American Time Use Survey Leave Module is nationally representative, so the results generalize to workers of all ages. Across both datasets, I analyze how two sources of worker power, an occupation’s educational requirements and its licensing, shape the association between productivity constraints and schedule flexibility.

The results reveal that productivity constraints alone do not predict schedule flexibility across the full workforce, and neither form of closure delivers greater flexibility on average. Instead, closure converts into schedule flexibility where productivity constraints are low. Workers in occupations with higher educational requirements are more likely to gain schedule flexibility when constraints are low, and licensed workers show the same conditional advantage.

These findings extend theories of occupational closure and labor market rents to the temporal dimension of job quality. Where occupational closure scholarship has shown how restricted entry secures higher wages and material benefits, I show that closure also governs workers' control over their time, a temporal rent, and that this temporal advantage is gated by productivity constraints in a way that material advantages are not.

Both forms of closure follow the same conditional logic, translating into schedule flexibility only where productivity constraints are low, but they differ in their baseline level of flexibility. This difference need not mean that licensing confers weaker power. Licensed occupations concentrate in settings where schedules are set by institutions outside the firm, such as teaching, so worker power has less room to operate.

Three limitations scope these findings. The first concerns the constraint measure. The O*NET composite captures relational intensity and coordination demands, but not institutional temporal rigidity, whether tasks must occur at fixed, institutionally determined times. The contrast within the high constraint closed occupations between school teachers, whose flexibility rate is 13 percent, and postsecondary teachers and lawyers, whose rates exceed 75 percent, suggests that what matters is not only coordination but where scheduling authority resides. When timing is fixed by institutions outside the firm, positional power has nothing to move.

The second limitation concerns identification. The person fixed effects models rule out sorting on stable worker traits, but not changes that coincide with an occupation move. A switch can bring a new employer or a promotion alongside the change in closure and

constraints, and workers whose schedule preferences shift over time, for example around parenthood, may time their moves accordingly. The estimates therefore remain conditional associations rather than causal effects.

The third limitation is that worker bargaining power, the mechanism I posit between occupational closure and schedule control, is not directly measured. The wage results show that occupational closure commands a wage premium within person, which is consistent with real bargaining power, but the pathway from closure to bargaining power to schedule control remains indirect. Each of these limitations marks a direction for future research.

Schedule flexibility, then, is not merely a technical feature of a job, fixed by its task structure and productivity constraints. It is part of the compensation over which workers and employers bargain, a form of worker control over time, and workers secure it when they hold power that the task structure lets them use. Understanding which institutions confer that power is a first step toward extending schedule control to the workers who currently lack it.

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Appendix

Table A1: Sensitivity of the Interaction between Occupational Closure and Productivity Constraints

Specification	NLSY97 person FE		ATUS	
	Education	Licensing	Education	Licensing
Main specification	−0.005* (0.002)	−0.031* (0.015)	−0.014* (0.007)	−0.060** (0.022)
Without O*NET task controls	−0.005** (0.002)	−0.030* (0.014)	−0.023*** (0.005)	−0.075*** (0.022)
Maximal per-arm sample	−0.004* (0.002)	—	−0.014* (0.007)	−0.061** (0.022)
ACS education measure	—	—	−0.013* (0.006)	—
Missing controls recovered	−0.006** (0.002)	−0.039** (0.014)	—	—

The maximal sample row uses the largest sample each arm allows before the common sample restriction, omitted for NLSY97 licensing where it nearly coincides with the common sample. The missing controls row recovers NLSY97 observations dropped for missing controls, omitted for the ATUS. Standard errors clustered by occupation in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A2: Interaction Estimates by NLSY97 Survey Era

	Educational requirements		Licensing	
	1997–2015	2017–2023	1997–2015	2017–2023
Closure $\times$ constraints	−0.0017 (0.0026)	−0.0056 (0.0041)	−0.0267 (0.0162)	−0.0244 (0.0225)
N (person years)	56,786	13,568	56,786	13,568

Person fixed effects interaction estimates by survey era. Era subsamples contain far fewer within person occupation changes, so the estimates are less precise. Standard errors clustered by occupation in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3: Occupational Closure, Productivity Constraints, and Schedule Flexibility in the General Social Survey

	Educational requirements			Licensing (fraction of states)		
	M1	M2	M3	M1	M2	M3
Productivity constraints	0.134*	0.139*	0.359***	0.134*	0.147*	0.167**
	(0.055)	(0.056)	(0.102)	(0.055)	(0.058)	(0.060)
Closure		0.068	0.599**		-0.428**	0.316
		(0.040)	(0.204)		(0.137)	(0.762)
Closure $\times$ constraints			-0.065*			-0.100
			(0.025)			(0.107)
N	4,817	4,817	4,817	4,817	4,817	4,817
R^2	0.154	0.156	0.158	0.154	0.161	0.161

GSS Quality of Worklife module, pooled waves, weighted with the survey weight. The dependent variable is the flexibility composite (2 to 8 scale), so coefficient magnitudes are not comparable to the binary outcome tables. Standard errors clustered by occupation in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A4: The Interaction between Occupational Closure and Productivity Constraints under Each Constraint Measure Variant

Constraint measure	ATUS		NLSY97 person FE	
	Education	Licensing	Education	Licensing
Composite (six items)	−0.0135*	−0.0618**	−0.0050*	−0.0304*
	(0.0066)	(0.0221)	(0.0020)	(0.0145)
Contact with others	−0.0266***	−0.0782**	−0.0107***	−0.0061
	(0.0073)	(0.0301)	(0.0024)	(0.0130)
Face-to-face discussions	−0.0144*	−0.0098	−0.0018	−0.0309*
	(0.0066)	(0.0231)	(0.0019)	(0.0145)
Interpersonal relationships	0.0010	−0.0145	−0.0032*	−0.0209**
	(0.0051)	(0.0160)	(0.0014)	(0.0072)
Frequency of decision making	−0.0081*	−0.0373*	−0.0037*	−0.0103
	(0.0040)	(0.0152)	(0.0015)	(0.0119)
Freedom to make decisions	0.0024	−0.0361*	−0.0004	−0.0139
	(0.0050)	(0.0140)	(0.0012)	(0.0101)
Structured vs. unstructured work	0.0012	−0.0478**	0.0014	−0.0146
	(0.0065)	(0.0152)	(0.0019)	(0.0095)
Time pressure	0.0035	0.0060	0.0020	0.0222*
	(0.0041)	(0.0162)	(0.0016)	(0.0090)
Level of competition	0.0085	0.0175	0.0040**	0.0070
	(0.0055)	(0.0181)	(0.0014)	(0.0094)
Eight item composite	−0.0061	−0.0463	−0.0017	−0.0196
	(0.0072)	(0.0262)	(0.0019)	(0.0152)

Each row replaces the constraint composite with the listed measure. All models drop the time pressure control, so the composite row differs slightly from Tables 3 and 4. The eight item composite adds time pressure and level of competition to the six focal items. Standard errors clustered by occupation in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A5: Pooled NLSY97 Estimates

	Educational requirements			Licensing (fraction of states)		
	M1	M2	M3	M1	M2	M3
Productivity constraints	0.014	0.014	0.041**	0.014	0.017*	0.024**
	(0.007)	(0.007)	(0.013)	(0.007)	(0.008)	(0.008)
Closure		0.004	0.072**		−0.046	0.410*
		(0.007)	(0.026)		(0.030)	(0.192)
Closure $\times$ constraints			−0.008**			−0.063*
			(0.003)			(0.027)
N (person years)	70,354	70,354	70,354	70,354	70,354	70,354
R^2	0.094	0.094	0.095	0.094	0.095	0.097

Pooled specifications mirroring the ATUS design, without person fixed effects, with the full control set. Standard errors clustered by occupation in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A6: Occupational Closure Effects Within Productivity Constraint Quartiles

Constraint quartile	Educational requirements			Licensing		
	NLSY pooled	NLSY FE	ATUS	NLSY pooled	NLSY FE	ATUS
Q1 (lowest)	0.0144 (0.0188)	0.0060 (0.0116)	0.0449* (0.0216)	-0.1334*** (0.0290)	-0.1265*** (0.0331)	-0.0645 (0.0469)
Q2	0.0295* (0.0118)	0.0167* (0.0071)	0.0083 (0.0188)	0.0611 (0.0348)	0.0353 (0.0214)	-0.0524 (0.0298)
Q3	0.0216* (0.0091)	0.0130* (0.0055)	0.0423* (0.0180)	-0.0403 (0.0371)	-0.0105 (0.0204)	-0.3385*** (0.0759)
Q4 (highest)	-0.0051 (0.0087)	-0.0066 (0.0048)	0.0094 (0.0118)	-0.1460** (0.0499)	-0.0905** (0.0291)	-0.0975* (0.0416)

Marginal effect of the closure measure within quartiles of the constraint distribution. Licensing barely varies in the lowest NLSY97 quartile (three majority licensed occupations), so the Q1 licensing estimates rest on very few occupations. Standard errors clustered by occupation in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A7: Occupational Closure, Productivity Constraints, and Log Hourly Wages, NLSY97

	Pooled		Person fixed effects	
	M2	M3	M2	M3
<i>Panel A. Educational requirements (N = 66,186)</i>				
Closure	0.0409*** (0.0091)	-0.0535 (0.0470)	0.0291*** (0.0051)	-0.0637* (0.0256)
Closure $\times$ constraints		0.0118* (0.0058)		0.0117*** (0.0032)
<i>Panel B. Licensing (N = 66,186)</i>				
Closure	0.0929*** (0.0246)	-0.3658 (0.1924)	0.0646*** (0.0177)	-0.3767*** (0.1022)
Closure $\times$ constraints		0.0637* (0.0274)		0.0613*** (0.0146)

The dependent variable is the log hourly wage, trimmed to one to five hundred dollars per hour, on the common analytic sample. Specifications mirror the flexibility models. Standard errors clustered by occupation in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.