Can Women "Have It All"? The Trade-Off Between Social Tasks and Workplace Flexibility

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Abstract

Do the jobs that reward women's talents also offer the flexibility that they need? I document that social skill intensity and workplace flexibility are inversely correlated across occupations. Guided by a model of occupational choice, I provide evidence that this correlation generates a trade-off between women's comparative advantage in social tasks and their preference for flexible work hours. As a consequence, women's returns to each job attribute come at the expense of the other, which widens the gender wage gap. Event-studies around first births help confirm that gender gaps in inflexible jobs are driven by women's time constraints rather than other factors. Moreover, flexibility-enhancing technology adoption has been concentrated in jobs that are both social and inflexible, consistent with women's skills being valued but constrained in these settings.

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1 Introduction

Despite the converging roles of men and women in society, gender gaps in wages and career progression persist (Cortés and Pan, 2023). One explanation for this persistence is the prevalence of inflexible (or "greedy") workplaces, where workers are rewarded for supplying long, irregular, or particular hours. Women value customizing their work schedules and, as a result, lag behind men when work is structured in this way (Goldin, 2014). On its own, this fact suggests that flexible workplaces are well-suited to women. Yet a worker's suitability to a job depends not only on when they are expected to work, but also on what kinds of tasks are required – and whether those tasks align with the worker's talents. In this paper, I show that exactly the jobs that play to women's comparative advantage – social task intensive occupations – are also inflexible. Women therefore face a trade-off: in order to be in a job that rewards their skill set, they will have to forgo flexibility, or vice versa. As a result, inflexible work environments exacerbate the gender wage gap more than previously understood.

As prima facie evidence that women face this trade-off, consider a simple but surprising set of facts. Among full-time, college-educated workers in high-income jobs, the gender wage gap is larger in occupations where long, irregular, or particular hours are incentivized (Goldin, 2014). Figure 1a replicates this finding by plotting women's relative earnings against an index that proxies for an occupation's tendency to be structured in this way. In less flexible occupations, the price women pay (in terms of lower wages) to customize their schedules is higher, thus generating a larger gender wage gap. Given that their preferences come at a high cost in these occupations, we would expect women to be discouraged from entering these types of jobs relative to men. However, according to this measure of flexibility, women's relative employment is higher in less flexible occupations (Figure 1b). In tech and science occupations such as computer programmers or engineers, workers can often choose when and how much they work (or even where they work). Yet, the female-male employment ratio is twice as high in occupations such as financial managers, lawyers, or physicians, where workers are disproportionately rewarded for working longer hours or being available continuously for their co-workers, clients, or patients. This puzzle suggests that less flexible occupations have some other attribute which draws women in, despite the larger pay-cut they receive to work flexible hours. As I will demonstrate, this other attribute is an occupation's social task intensity, which acts as a countervailing force on women's wages in less flexible jobs.

In this paper, I begin by drawing on work in psychology and cognitive science to show that women are more skilled in "social perceptiveness," or the ability to accurately infer others' mental states. I then document that jobs requiring these skills also tend to be less flexible. To examine whether and how these facts impact gender dispar-

ities in labor market outcomes, I develop a model of occupational choice that delivers several testable implications. First, the positive impacts of a job's flexibility and social intensity on women's relative wages and employment will be partly offset by the inverse relationship between these two job attributes. Second, highly socially skilled women are underrepresented in inflexible occupations relative to comparably skilled men. Third, a job's inflexibility widens gender gaps even more following a shock to women's time constraints (e.g., parenthood). Fourth, flexibility-enhancing innovations diffuse first in the most socially intensive, inflexible occupations. I find evidence consistent with these implications using the American Community Survey (ACS), National Longitudinal Survey of Youth 1979 (NLSY79), Current Population Survey (CPS), and American Time Use Survey (ATUS).

Gender differences in social skills suggest that occupations intensive in social interactions are particularly well matched to women's talents. Psychologists and cognitive scientists have documented that the average woman reads nonverbal elements of communication, such as body language or tone, more accurately than the average man. Consequently, women tend to excel in "social perceptiveness," or the skill of being aware of others' reactions and understanding why they react the way that they do (Hall, 1978, 1990; Greenberg et al., 2023). These skills are useful in jobs requiring complex social interactions with people, such as psychologists, lawyers, or managers. Consistent with women excelling such tasks, work suggests that the rising importance of social skills and teamwork in the labor market (Atalay et al., 2020; Deming, 2017; Edin et al., 2022) has helped facilitate women's labor market success in recent decades (Cortes et al., 2023; Cortés et al., 2024; Ngai and Petrongolo, 2017).

Yet, as I document, jobs that reward workers' social perceptiveness also tend to be inflexible. While this correlation may arise for different reasons, one explanation is that jobs involving social tasks require workers to build and maintain "relationship-specific capital" with clients or co-workers. As a result, workers are rewarded for being "on call" to meet others' needs and must accept a pay cut to work at their own pace or on their own schedule. To illustrate, compare lawyers to computer programmers. A lawyer must appear in court or meet with clients at specific times; failing to do so may jeopardize the success of a case or result in the loss of a client to a competing firm. In contrast, a computer programmer's primary output is a tangible deliverable, and when it is produced is less directly tied to its quality. Programmers can write or debug the code independently, without needing to interface with clients in real time or synchronize their hours with team members. Therefore, insofar as women value both flexibility and social tasks, they will trade-off between these two attributes when selecting a job.

To build intuition and explore the implications of this trade-off, I develop a simple model of occupational choice. In the model, less flexible jobs are ones for which

a worker's labor supply cannot be easily substituted across time periods. Workers with "particular" preferences for when they work are therefore more productive in jobs with a greater elasticity of substitution. Yet, due to a technology constraint, jobs high in flexibility are low in social task intensity. This bundling disproportionately constrains female workers, whose productivity is more positively impacted by both temporal substitutability and social tasks. The model delivers four testable implications that I use to guide my empirical analysis.

First, the model implies that in highly social (flexible) jobs, women's wages and employment relative to men will be attenuated by a lack of flexibility (social intensity). Consistent with this implication, using ACS data, I find that women's relative employment and wages are positively related to both flexibility and social task intensity, but these relationships are amplified – or sometimes only emerge – when controlling for both attributes simultaneously. For example, while women's relative employment is higher in less flexible occupations (as in Figure 1b), this relationship is completely explained by the social perceptiveness intensity of these jobs. The results are generally robust to limiting the sample to the college educated in high-income occupations, using alternative measures of flexibility, and controlling for other job attributes.

Second, the trade-off also implies that high social skill women will be underrepresented in inflexible jobs, even though those jobs reward such skills. I test this implication in the NLSY79, where I observe individuals' skills and job choices. I find that high social skill men are more likely to be employed in low-flexibility jobs. However, this correlation is significantly weaker among women, in line with the idea that women must weigh the suitability of the job's skill demands against its time demands.

Third, in the model, women's greater demand for flexibility is the mechanism by which inflexible work environments produce wider gender gaps. However, inflexible jobs may have other attributes (e.g. masculine culture, gender discrimination) that deter women or lower their wages. To rule in flexibility as the mechanism, I use childbirth to proxy for a shock to women's relative time constraints. I then implement event-studies and pseudo difference-in-differences around first births in the NLSY79 and CPS. Consistent with the proposed mechanism in the model, I find that the negative impact of first births on female-male employment and wages (the "motherhood penalty")[1] is larger in inflexible occupations vis-à-vis flexible ones.

To derive the fourth model implication, I introduce the possibility of technological advancements in flexibility and ask how the trade-off shapes the diffusion of these advancements across occupations. Past work suggests that new technologies or practices can increase workplace flexibility in certain sectors (e.g., information technology

[1]Following past literature, I use "child penalty" to refer to the effect of children on labor market outcomes and "motherhood penalty" to refer to the disproportionate impact on women (e.g. Kleven et al. (2019)). The terminology is not intended to reflect a normative judgment. These penalties could be driven by a variety of mechanisms, such as norms or preferences for spending time with children.

that enables workers to share clientele (Goldin and Katz, 2016)). The trade-off implies that the value of such advancements will be highest in socially intensive, inflexible occupations, where women are both disproportionately constrained and productive, and, therefore, firms are the most eager to attract and retain additional female talent. To test this implication, I use two proxies for an occupation's adoption of flexibility-enhancing technology: the change in the motherhood penalty estimated in the CPS and the growth in work-from-home (WFH) arrangements based on ATUS data. In both cases, consistent with the model, I find that among inflexible occupations, those with high social skill intensity have seen the highest rates of growth in flexibility.

This paper builds on a literature originating from Goldin (2014) that examines how workplace flexibility (broadly defined) mediates gender differences in labor market outcomes. Results from experimental and quasi-experimental studies are consistent with the notion that women have a higher willingness to pay for various types of workplace flexibility and, consequently, more flexibility (all else constant) can raise women's wages or employment (Mas and Pallais, 2017; Wiswall and Zafar, 2018; Maestas et al., 2023; Wasserman, 2023; Bolotnyy and Emanuel, 2022; Cortés and Pan, 2019; Ciasullo and Uccioli, 2024; Mas and Pallais, 2020). Consistent with these findings, various occupational-level proxies of inflexibility are correlated with larger gender wage gaps (Cubas et al., 2023; Goldin et al., 2024) or employment gaps (Cortés and Pan, 2016; Juhn and Rubinstein, 2022; Erosa et al., 2022; Denning et al., 2022), often especially among parents.

Relative to this literature, my primary contribution is to document a new channel through which inflexible work environments depress women's wages or employment: the loss of women's returns to their comparative advantage in social tasks. In doing so, this paper helps clarify what is at stake if the tension between greedy work environments and women's demands for flexibility is left unresolved. Without accounting for this channel, we would misunderstand how gender disparities are impacted by interventions that either alter workplace flexibility, ease women's time constraints, or reshape gender differences in human capital investments.[2] Beyond distributional impacts, neglecting this mechanism may understate the impacts on aggregate productivity. Reallocating workers to their comparative advantage – rather than constraining women to less time-intensive roles – raises aggregate output (Erosa et al., 2022). The fact that women have a comparative advantage in time-intensive jobs implies even larger gains.

[2]For example, neglecting this channel may lead one to under-predict the extent to which certain types of policies or practices increase women's employment or wages, such as those that: reduce women's relative time constraints (e.g., subsidized childcare as studied in Humphries et al. (2024)), lower the price of flexibility in social task intensive jobs (e.g., work-from-home technologies as studied by Harrington and Kahn (2023)), or reduce gendered specialization in social versus analytical skills (e.g., educational interventions as in Alesina et al. (2024)).

My results also more closely link occupation-level variation in employment and wage gaps to the inflexibility mechanism, thus supporting its role as a key driver of gender disparities. First, I show that occupational task content, which is both correlated with flexibility and a determinant of one's occupational choice, can help explain why women do not always select into flexible jobs (Mas and Pallais, 2020).[3] Second, I leverage event studies around first births to validate that gender gaps in inflexible jobs are not being driven by other job or worker attributes unrelated to flexibility. This demand-side design exploits real-world variation in flexibility without holding all other job attributes constant as in experimental designs (e.g., Mas and Pallais (2017)), which are statistically precise but may not mirror actual labor market conditions.[4]

Finally, my paper sheds light on what may motivate firms to introduce more flexibility to the workplace, therefore potentially providing ways to rationalize the cases where workplace policies or innovations have enhanced flexibility in various sectors (Goldin and Katz, 2011, 2016; Goldin, 2021; Harrington and Kahn, 2023; Wasserman, 2023).

Overall, my results most closely complement work by Juhn and Rubinstein (2022), who explore an analogous trade-off between women's comparative advantage in abstract tasks and disadvantage in supplying long or unusual hours. Motivated by cognitive science and psychology, I focus on social tasks. Moreover, I use event studies around births to verify the flexibility mechanism, show that the trade-off can influence which occupations endogenously become more flexible, and study within-occupation wage gaps to validate that women's employment in social tasks is primarily driven by their abilities (for which firms are willing to pay), rather than their preferences.

I begin by describing the data used throughout the paper in Section 2. Then I document two key stylized facts (Section 3): women are more socially skilled and less flexible jobs tend to be social task intensive. I then present the conceptual framework in Section 4. The subsequent sections test the four predictions of the model (5-8).

[3]More broadly, employment gaps or wage gaps are not always larger in occupations lacking a particular type of flexibility – even when experimental estimates suggest women value it highly. Existing explanations offered by past work include the fact that ability selection into occupations can offset wage gaps (Erosa et al., 2022) or that jobs with certain types of flexibility may systematically lack others (Mas and Pallais, 2020). I replicate a similar puzzle in my setting (Figure 1) and show that accounting for social task intensity can help explain seemingly irreconcilable patterns.

[4]My results are consistent with other quasi-experimental findings that implicitly verify the role of real-world variation in occupational flexibility but are focused on specific subset of professions or dimensions of flexibility. For example, policies that restrict irregular scheduling increase women's labor supply more in occupations characterized by such scheduling (Ciasullo and Uccioli, 2024); among high skilled workers, access to cheaper household services (via immigrant supply shocks) boosts women's success in jobs exhibiting convex returns to hours worked (Cortés and Pan, 2019); event study-based motherhood penalties are lower in the public sector, STEM, and medicine when compared to management, business, and law (Bütikofer et al., 2018; Kleven et al., 2019; Pertold-Gebicka et al., 2016); and the prevalence of part-time work is correlated with these penalties estimated across 22 occupation aggregates (Gulek, 2024).

2 Data

Below I describe the data sources used throughout this paper. Detailed descriptions are provided in the Data Appendix (Appendix A:).

2.1 Occupation-level attributes

I use the U.S. Department of Labor's Occupational Network (O*NET) database to measure key occupation-level attributes, such as flexibility and skill requirements. The O*NET is a survey administered to a sample of workers or occupational experts in each occupation and is commonly used in research on tasks and skills in labor markets (e.g. Acemoglu and Autor (2011)). The survey covers questions about the worker's occupation, such as the typical tasks required for a certain job, how important it is to have certain skills, or features the work environment. To ensure consistency across time and datasets, I aggregate occupations throughout the analyses to 320 3-digit occupation codes (Autor and Dorn, 2013; Deming, 2017; Hanson, 2021).

2.1.1 Flexibility

Workers may wish to customize their schedules by adjusting the total number of hours, the time of day those hours occur, and whether those hours are predictable, regular, or can be changed on short notice to meet personal needs. The ideal measure of an occupation's flexibility would capture the wages a worker would forego to customize their work hours along *any* of these dimensions. A maximally flexible occupation would therefore allow workers to choose when and how long to work without any impact on their hourly wage or their likelihood of employment.

To proxy for this ideal measure, I follow Goldin (2014) and use an index intended to capture features of an occupation's production function that may generate a higher "price" that workers pay – via lower wages – to customize their work hours. The idea, captured by the index, is that firms will find it more costly to offer workers flexibility when tasks are time-sensitive and workers are not easily substitutable for one another. These features of a work environment will vary systematically by occupation. Accordingly, the index is the standardized average of five dimensions (each of which are themselves standardized) from the O*NET: time pressure, contact with others, establishing and maintaining relationships, unstructured work, and the freedom to make decisions. The first dimension captures time sensitivity in task completion. The second two dimensions capture the necessity of being in contact with people at certain times. The final two dimensions capture the level of worker discretion: the more freedom over your task set, the less likely others can seamlessly substitute for you in your absence. Occupations that are ranked highly in this "inflexibility" index include lawyers,

CEO's, and managers.

Heterogeneity in the results by parental status and the event-studies around childbirth help validate that the O*NET index captures meaningful variation in occupational inflexibility. However, other work has also measured flexibility based on observed worker behavior. I incorporate two such measures in my robustness checks. The first is a standardized index of three worker behavior measures that I call the "data-driven index": a measure of coordinated work hours (Cubas et al., 2023), the estimated elasticity of earnings to hours worked (Cortés and Pan, 2019), and the prevalence of long hours (Cortés and Pan, 2016). The second follows Goldin et al. (2024) by combining the O*NET measure with this data-driven approach. This "mixed" measure is a binary variable indicating that an occupation is in the top tercile of both the O*NET index and the long hours measure. Both the data-driven index and mixed measure are highly correlated with the O*NET index (ρ of 0.49 and 0.60, respectively).

I focus on the O*NET index as my primary measure of occupational flexibility for two reasons. First, observed worker behavior may be shaped by constraints or labor demand factors unrelated to flexibility. Second, at the end of the paper, I test whether, among inflexible occupations, the adoption of flexibility-enhancing technologies has been concentrated in those that are especially social skill–intensive. For that analysis, the O*NET index is preferable, as it reflects an occupation's intrinsic tendency toward flexibility based on its underlying production processes.

2.1.2 Skill requirements

To measure an occupation's social skill requirements, I use the O*NET's measure of "social perceptiveness," which captures the degree to which a worker must be "aware of others' reactions and [understand] why they react as they do." I focus on social perceptiveness (rather than a broader measure of social skills as in Deming (2017)) because it most closely reflects the type of social skills in which women seem to excel, which I will discuss in Section 3.1. According to O*NET documentation, a job where workers are required to "notice that customers are angry because they have been waiting too long" requires low levels of social perceptiveness, while a job where workers must "counsel depressive patients during a crisis period" requires a high level. Occupations that rank highly in social perceptiveness include counselors, physicians, social workers, and managers.

I follow Deming (2017) to measure occupations' analytical skill requirements and routine task intensity, which are primarily used as controls throughout the analysis. Analytical intensity is measured via an index of components reflecting the importance of mathematical knowledge and reasoning in an occupation. These skills are most likely to be required in science and technology jobs, but also are relevant for jobs in the business (e.g. financial manager) and health sectors (e.g. physicians). Routine

task intensity is measured via an index capturing the propensity for an occupation's tasks to be subject to repetitive, precise processes, such as typing or working in an assembly line. Occupations scoring highly in the routine intensity measure include plant operators, telephone operators, and bank tellers.

2.2 Other data sources

2.2.1 American Community Survey, 2015-2019

To study the implications of the model on gender gaps in employment and wages across occupations, I rely on the 2019 5-year American Community Survey (ACS) 5% sample where I observe individuals' wages and occupation choices (Ruggles et al., 2024). Employing similar sample restrictions as Goldin (2014), I focus on native-born civilian individuals aged 25-64 who are employed full-time, full-year (at least 40 weeks, at least 35 hours per week), report positive, non-missing annual earnings (wage income plus business and farm income), and are not living in institutional group quarters. To ensure that I can reliably observe the gender wage gap within occupations, I focus on occupation-demographic group cells (the level at which I run my analysis) for which I observe at least 25 men and 25 women.

2.2.2 National Longitudinal Survey of Youth: 1979 Cohort, 1979-2019

I use data from the Weekly Work History files in the National Longitudinal Survey of Youth for the 1979 Cohort (NLSY79) to build a person-year panel of labor market activity (e.g., employment, occupation, and wages) covering years 1979-2019. These data are useful for two separate analyses. First, I study how individuals' social and cognitive skills influences occupation choices differently by gender. Second, I study how childbirth impacts gender gaps in employment and wages for workers in flexible versus less flexible jobs.

Following Deming (2017), I proxy for cognitive skills with the respondent's score on the Armed Forces Qualifying Test (AFQT) residualized by the age at which the respondent took the test. And, to proxy for individuals' social perceptiveness skills, I take the average of three standardized variables: (1) young adulthood self-reported sociability, (2) self-reported retrospective sociability at age 6, and (3) the number of extracurricular activities in which the respondent participated in high school (e.g. yearbook, student government, newspaper). Given that gender equal access to athletic activities in high school was not widespread for this cohort, I diverge from Deming (2017) and do not include a fourth component indicating whether the respondent participated in an high school athletics.[5]

[5] Athletic activities were not widely accessible to girls in the early 1980's, when most of the NLSY79 cohort was in high school. Title IX, intended to prohibit sex-discrimination in educational institutions,

Similar to Guvenen et al. (2020), I focus on individuals in the core sample starting when they are least 22 years old, have signaled strong labor force (e.g. two consecutive years of full-time full-year), and are likely done acquiring their education. I drop observations lacking complete information on labor market activity or individual skills. To ensure some balance in the event studies around births, among individuals who have a child, I only include those who are observed in the period just prior to birth and at least one period after. My final sample is comprised of 3,396 individuals and 103,264 person-year observations.

2.2.3 Current Population Survey, 1979-2019

I use the Current Population Survey (CPS) pooled across years 1979-2019 to build a synthetic panel of individuals before and after the birth of their first child. I use these data for two separate analyses. First, I estimate child penalties in each occupation based on a pseudo difference-in-differences approach (as employed by Kleven (2023)). Second, I repeat this analysis before and after 1995 in order to construct a proxy for the growth of motherhood friendliness within an occupation over time.

I follow Kleven (2023) to build my sample. I focus on individuals aged 20-55 in the CPS basic monthly files and Annual Social and Economic Supplements (ASEC) pooled across years 1979-2019 (Flood et al., 2024a,b). I identify individual's approximate age at first birth based on their own age and the age of the eldest child living with them. I then match these individuals to five pre-birth surrogate observations. To do this, I retrieve outcomes of childless individuals in the same birth cohort who share the same demographic characteristics: gender, age, year, education category, marital status, race, and state. For example, consider a woman observed in year 2000 at age 35 whose eldest child is age 5. To retrieve her surrogate observation in the year prior to birth ($k = -1$), I locate a childless, 30-year old woman in the year 1995 who shares the same demographic characteristics. When there are multiple people with this set of demographic characteristics, I use the average of the outcome for everyone in the cell to form the surrogate observation.

2.2.4 American Time Use Survey, 2003-2019

Finally, I use the American Time Use Survey (ATUS) 2003-2019 to measure the adoption of work from home (WFH) arrangements, an additional way of measuring changes in occupational flexibility over time (Flood et al., 2023). The ATUS is a nationally representative survey conducted annually since 2003. It asks respondents to report the location and duration of each of their activities over a 24 hour period. Following

was first passed in 1972. The U.S. Department of Education Office of Civil Rights later began initiatives specifically promoting equality athletics in 1979. Deming (2017)'s social skill index is highly correlated with my modified version ($\rho = .94$).

Harrington and Kahn (2023), I focus on hours during the 8am - 5pm window and I limit the sample to respondents aged between 22 and 55, who are employed, whose reported time diary covers a non-holiday weekday, and who contribute at least 5 hours of work that day.

3 Two motivating facts

3.1 Women are more socially skilled than men

Among documented gender differences in psychological traits, one of the largest is that women tend to show greater interest in people, while men tend to show greater interest in things (Hyde, 2014; Bertrand, 2020). It is unsurprising, then, that women also tend to be more skilled in empathy, or the "the ability to understand and share in the internal states of others," which in turn facilitates social interactions. For example, studies find that relative to men, women can more accurately decode nonverbal cues, such as body language, tone of voice, and facial expression (Hall, 1978, 1990; Christov-Moore et al., 2014).[6] Developmental psychology and cognitive neuroscience rationalizes these gender differences by positing that men tend to understand the world through explicit, well-defined cause-and-effect systems, while women more willingly infer others' mental states based on subtle cues that enable them to interact more effectively with others (Baron-Cohen, 2002; Greenberg et al., 2018).

As an example of this evidence, Figure 2a depicts gender differences in the "Reading the Mind in the Eyes" test (RMET) scores reported by Greenberg et al. (2023), which capture one's ability to read facial cues. In the test, respondents review a series of pictures of peoples' eyes and are asked to guess how the person is feeling. This measure of social perceptiveness has been psychometrically validated and, more recently, has been shown to predict one's ability to do social tasks such as work in a team (Baron-Cohen et al., 2001; Weidmann and Deming, 2020). These gender differences persist across a number of countries and the age profile (Greenberg et al., 2023).

The remaining panels in Figure 2 show that women often excel in social skills when defined more broadly. Figure 2b reports gender differences in the number of friends one has during adolescence based on data from the AddHealth Longitudinal Study.

[6]There are many facets of empathy and therefore many different ways to measure it. The female advantage is apparent in many, but not all, studies. To explain this lack of consistency, some work suggests these gender differences may be driven by women's greater intrinsic motivation to be emotionally responsive in line with gender stereotypes; that is, men possess social skills in equal quantities but do not care to use them (Ickes et al., 2000). Yet, insofar as this gender difference manifests in the workplace – even if it is driven by differential motivation – then this difference is still meaningful for my purposes. While some evidence suggests that the female advantage disappears when subjects are paid for accuracy (as in workplace-like conditions) (Klein and Hodges, 2001), more recent and larger-scale research finds that the advantage persists even under incentives (Weidmann and Xu, 2024). See Christov-Moore et al. (2014) for more nuance and an overview of the literature.

Following Lleras-Muney et al. (2020), I report the "in-degree," or the number of other peers who list the subject as their friend. Figure 2c depicts averages in self-reported extraversion and sociability from the NLSY79 and NLSY97, described in Section 2. In contrast to the RMET, such self-reported measures may suffer from biases in one's self-perception (Joseph and Newman, 2010). Moreover, both of these measures may partially conflate one's *preferences* for socializing rather than one's skill. Nevertheless, in most cases, women tend to exhibit significantly higher levels of social skills. The NLSY79 measure exhibits the smallest female advantage in social skills, while the NLSY97 measure exhibits the largest. In line with this variation, research on the "Big Five" personality traits finds that gender differences in extraversion vary by which aspect of sociability is being emphasized. For example, men tend to be more assertive, yet women report higher levels of warmth towards others and gregariousness (e.g. Hyde (2014); Costa Jr et al. (2001); Weisberg et al. (2011)).

Throughout this paper, I will take these gender differences as given. Average differences across men and women in personality may arise for a variety of reasons – "nature" (e.g. natural selection pressures), "nurture" (e.g. gender socialization), or some combination of both these factors (Muthukrishna et al., 2021).

3.2 Flexibility & social intensity are inversely correlated across occupations

That women tend to be more socially perceptive suggests that jobs rewarding these skills are well-suited for them. However, using data on job characteristics from the O*NET described in Section 2.1, Figure 3 shows that such jobs also tend to be less flexible. To help interpret the figure, occupations are color-coded by broader one-digit occupational classifications. Occupations in the business, health, and legal sectors are both highly inflexible and social skill intensive. In contrast, science, technology, retail, and administrative work tends to populate the middle of the distribution. Transportation and craft occupations score low on both measures. As presented in Table C.1, this correlation is robust to limiting the sample to high-income occupations (as in Figure 1, which focused on the subsample studied in Goldin (2014)), weighting by only college-educated workers, dropping individual sub-components of the flexibility index, and using the alternative measures of flexibility discussed in Section 2.1.1.

As an additional way of visualizing which specific occupations are driving this relationship, Figure D.1 restricts the sample to the largest occupations, shown separately for non-college and college workers in Panels (a) and (b), respectively. Within each panel, the 15 largest occupations are labeled. Among college workers, lawyers and various managerial roles are classified as both highly inflexible and social, while computer scientists, accountants, and lower-level finance positions are comparatively more

flexible and less social. For non-college workers, highly inflexible and social occupations include jobs in sales and management, in contrast to more flexible, less social skill intensive work such as cooking, machine operation, and IT support. Importantly, few occupations populate the northwest or southeast quadrants of the figure. For example, in Panel (b), most occupations requiring a similar level of social perceptiveness as secondary and primary school teachers (northwest quadrant) tend to be less flexible and instead appear in the northeast quadrant – such as management roles in finance and education.

That these two job attributes are bundled is consistent with the idea that jobs involving complex or extended interpersonal interactions reward both social perceptiveness, which improves the quality of interactions, and availability to others, which enables those interactions to occur in the first place. Figure D.2 provides further evidence of this relationship focusing on specific types of time-sensitive demands. Workers in occupations that are high in social perceptiveness also tend to work long hours (suggesting a need for extended or continuous availability), follow synchronized daily schedules (suggesting a need for coordination), and more frequently must respond to work-related matters outside of their work hours (suggesting that their tasks cannot easily be delegated to others or postponed).

In addition to demanding social skills, less flexible occupations are *generally* skill-intensive. The correlation between inflexibility and analytical intensity is 0.434 (0.072 s.e.). That analytical skills are rewarded in less flexible jobs suggests that women's higher willingness to pay for flexibility may also negatively impact women who excel in these skills.

4 Conceptual Framework

Consider a representative worker $g \in \{m, f\}$. In occupation o, a worker's productivity is the product of their talent and effective labor supply:

$$Q_{og} = \theta_{og}(s_o, s_g)^{\mu}\, h_{og}(\sigma_o, t_1, t_2) \tag{1}$$

Talent θ_{og} depends on the worker's social-skill endowment s_g and how strongly the occupation rewards those skills s_o. The productivity returns to talent diminish at rate $\mu \in (0, 1)$. Effective labor supply h_{og} aggregates hours across two periods (t_1, t_2), with intertemporal substitutability σ_o governing the aggregation. The worker chooses an occupation $o = (s_o, \sigma_o)$ and hours (t_1, t_2) to maximize productivity (assumed to be proportional to earnings), subject to a time budget and a technological constraint that

bundles the two job attributes:

$$\max_{s_o,\sigma_o,t_1,t_2} Q_{og} \quad \text{subject to} \quad T = f(\alpha_g, t_1, t_2), \qquad s_o = b(\sigma_o)$$

where T represents the total labor hours and α_g embodies the worker's preferences for how their work time is allocated across the two periods.

Because θ_{og} does not depend on t_1 or t_2 and enters the objective multiplicatively, optimal time allocation (t_1^*, t_2^*) is equivalent to $\underset{t_1,t_2}{argmax}\ h_{og}(\sigma_o, t_1, t_2)$. This problem can therefore be solved in two steps. First, workers determine how they would optimally allocate T across t_1 and t_2 within each occupation. In making this decision, workers weigh their preference for working in a particular time period against the fact that output produced across periods is not perfectly substitutable. Then, having solved this sub-problem for each occupation, workers choose the occupation that yields the highest earnings taking this time allocation choice as given. At this stage, workers trade off between occupation-level attributes s_o and σ_o.

4.1 Time allocation sub-problem

The worker's effective labor supply, conditional on their choice of occupation o, is given by

$$h_{og} = \left(0.5t_1^{\frac{\sigma_o-1}{\sigma_o}} + 0.5t_2^{\frac{\sigma_o-1}{\sigma_o}}\right)^{\frac{\sigma_o}{\sigma_o-1}} \tag{2}$$

where t_1 and t_2 represent labor supplied in two different time periods, such as different parts of the life-cycle, workweek, or workday. Each time period is weighted equally (by 0.5) in total output.

The elasticity of substitution, $\sigma_o \in (1, \infty)$, captures how easily tasks can be substituted across the two time periods and thus reflects the degree of temporal flexibility. High σ_o indicates that workers can supply their labor in one period or the other with little impact on total output. Low σ_o indicates that labor supplied in one period cannot easily "make up for" lack of labor supply in another period. For example, some jobs require workers to respond to emails immediately upon receipt. Or, in some jobs, long hours are concentrated at certain stages of a career (e.g., medical residency) and cannot be redistributed or deferred to later years.

The worker's time constraint is given by

$$T = \alpha_g t_1 + t_2 \tag{3}$$

where the parameter $\alpha_g > 1$ represents the disutility the worker experiences (in terms

of time units) to supply labor in period 1 rather than period 2.[7] The choice to attach the price to period 1 is arbitrary and without loss of generality. Thus, α_g captures a worker's selectivity over when they supply labor. Choosing t_1 and t_2 to maximize 2 subject to 3 yields $t_1^*(\alpha_g, T, \sigma_o)$ and $t_2^*(\alpha_g, T, \sigma_o)$, which are described in Appendix Section B.1. All else constant, as α_g increases, workers find it relatively more expensive to supply labor to period 1 and therefore shift their hours to period 2. As $\alpha_g \to 1$, workers are indifferent over when they supply their labor and split their time evenly between the time periods.

4.2 Occupational choice problem

Having determined time allocation within each possible occupation, the worker chooses the occupation that yields the highest earnings. Substituting $t_1^*(\alpha_g, T, \sigma_o)$ and $t_2^*(\alpha_g, T, \sigma_o)$ into Equation 1, we can write the worker's productivity as:

$$Q_{og}(s_o, \sigma_o; .) \equiv (s_o s_g + \kappa_0)^{\mu} T 0.5^{\frac{\sigma_o}{\sigma_o - 1}} \left[\alpha_g^{1-\sigma_o} + 1\right]^{\frac{1}{\sigma_o - 1}} \tag{4}$$

where I have specified $\theta_{og} = s_o s_g + \kappa_0$ and κ_0 is a constant. Equation 4 clarifies how the workers' two traits complement the two job attributes. First, the productivity losses associated with greater α_g are decreasing in σ_o. A worker's preference for working in one period (embodied by α_g) is more expensive in jobs where time periods are less substitutable for one another (low σ_o). Second, workers with greater s_g will earn more in occupations with greater s_o. These complementarities are summarized in the first two Propositions. Proofs for all propositions can be found in Appendix Section B.2.

Proposition 1. *Worker time-period selectivity, α_g, and an occupation's flexibility, σ_o, are log complements in productivity:* $\frac{\partial^2 ln Q_{og}}{\partial \alpha_g \partial \sigma_o} > 0$

Proposition 2. *Worker social skills, s_g, and an occupation's social task intensity, s_o, are log complements in productivity:* $\frac{\partial^2 ln Q_{og}}{\partial s_g \partial s_o} > 0$

These complementarities, however, cannot be achieved simultaneously due to a technological constraint that restricts the set of feasible occupations. Motivated by my findings in Section 3.2, I assume a technological constraint where social occupations are less flexible:

$$s_o = -\kappa_1 \sigma_o + \epsilon_o \tag{5}$$

where $\kappa_1 > 0$ and ϵ_o is a normally distributed error term with mean zero and standard deviation one to allow for imperfect correlation in these two attributes. I further assume $\kappa_0 > min\{(-\kappa_1 \sigma_o + \epsilon_o) s_g\}$ to ensure that all workers have positive productivity

[7] Viewed through the lens of a worker making a labor-leisure decision within each time period, α_g could encode the difference in a worker's reservation wages. For example, workers may have higher reservation wages for hours worked between 5-10pm relative to the 9am-5pm window.

in all occupations. Workers therefore choose s_o and σ_o to maximize Equation 4 subject to 5.[8]

Rather than solving the model explicitly, I reformulate the occupational choice model as an unconstrained problem where workers choose σ_o to maximize $lnQ_{og}\left(\sigma_o;.\right)$, then apply key theorems on monotone comparative statics to determine how parameters affect optimal flexibility (Ashworth and Bueno de Mesquita, 2006; Topkis, 1978, 1998). Following from Proposition 1, a worker's σ_o^* will be increasing in α_g. However, by Proposition 2 and the inverse correlation between σ_o and s_o (Equation 5), a worker's choice of flexibility is decreasing in s_g:

Proposition 3. *Optimal flexibility, σ_o^*, is increasing in worker's time-period selectivity, α_g:* $\frac{\partial \sigma_o^*}{\partial \alpha_g} > 0$

Proposition 4. *Optimal flexibility, σ_o^*, is decreasing in worker's social skills, s_g:* $\frac{\partial \sigma_o^*}{\partial s_g} < 0$

4.3 Gender differences

Motivated by the literature documenting women's willingness to pay for flexibility (e.g., Mas and Pallais (2017)), I assume that women are more selective than men over when they supply their labor ($\alpha_f > \alpha_m$). This difference could be driven by gender gaps in preferences for work-life balance, societal expectations about domestic responsibilities, or a combination of these factors. And, motivated by the stylized facts presented in Section 3.1, I assume that women are more socially skilled ($s_f > s_m$). These gender differences, combined with the Propositions above, lead to the following two results.

The first result helps us understand how the gender wage gap varies across occupations along the job-attribute frontier. Let $Q_o^* = ln\left(Q_{of}^*/Q_{om}^*\right)$ denote the log female–male earnings ratio in occupation o. Consider how Q_o^* varies with flexibility σ_o along the frontier. By Proposition 1 and $\alpha_f > \alpha_m$, occupational flexibility raises women's relative earnings ($\frac{\partial Q_o}{\partial \sigma_o} > 0$). However, the technological constraint (Equation 5) implies that $\frac{\partial s_o}{\partial \sigma_o} < 0$. And, by Proposition 2 and $s_f > s_m$, social intensity raises women's relative earnings ($\frac{\partial Q_o}{\partial s_o} > 0$). Therefore, while σ_o in isolation disproportionately raises women's relative earnings, along the frontier higher σ_o is paired with lower s_o, which offsets part of that gain. Symmetrically, while higher s_o alone raises women's relative earnings, along the frontier it comes with lower σ_o, again offsetting the gain. Hence, the total effect of either attribute is theoretically ambiguous:

[8] In this setup, choosing an occupation is analogous to a standard consumer choice problem, except the feasible set is a narrow cloud of points clustered around a line and does not include the area underneath it.

Proposition 5. *Occupational flexibility, σ_o, and social intensity, s_o, have ambiguous total effects on equilibrium women's relative earnings in an occupation, Q_o^*: $\frac{\Delta Q_o^*}{\Delta \sigma_o} = \frac{\partial Q_o}{\partial s_o}\frac{\partial s_o}{\partial \sigma_o} + \frac{\partial Q_o}{\partial \sigma_o} \lessgtr 0$ and $\frac{\Delta Q_o^*}{\Delta s_o} = \frac{\partial Q_o}{\partial s_o} + \frac{\partial Q_o}{\partial \sigma_o}\frac{\partial \sigma_o}{\partial s_o} \lessgtr 0$.*

The second result clarifies how the flexibility–social-intensity trade-off affects the representation of high social skill women in inflexible jobs that reward these skills. Consider a man and woman with the same social skill level $s_f = s_m = \tilde{s}$. By Proposition 4, higher social skills push workers toward more socially intensive jobs; along the job-attribute frontier this results in less flexibility, so $\frac{\partial \sigma_o^{*,m}}{\partial \tilde{s}} < 0$ and $\frac{\partial \sigma_o^{*,f}}{\partial \tilde{s}} < 0$. However, by Proposition 2 and $\alpha_f > \alpha_m$, women place a higher marginal value on flexibility and are more reluctant to forgo σ_o in favor of more s_o:

Proposition 6. *Optimal flexibility is decreasing in worker's social skills at a steeper rate for men than for women: $\frac{\partial \sigma_o^{*,m}}{\partial \tilde{s}} < \frac{\partial \sigma_o^{*,f}}{\partial \tilde{s}} < 0$*

4.4 Technology shock

In the model, a technology constraint exogenously links σ_o and s_o. Yet, as I will discuss in Section 8, case studies document instances where technological advancements in equipment (e.g., laptops, video conferencing) or organizational practices (e.g., client or patient sharing) have enhanced flexibility in certain sectors. This section asks which firms would adopt these technologies if the above trade-off holds.

Firms have wage-setting power and face upward sloping (isoelastic) labor supply curves for male and female workers, L_{om} and L_{of}. Let the effective flexibility of the firm representing occupation o be a function of its technology, $\sigma_o(\tau_o)$, which is increasing and concave in τ_o. Initially, firms take their baseline technology $\underline{\tau}_o$ as given. Let $\underline{Q}_{og}$ represent the productivity of g workers in the firm under this baseline technology. After setting gender-specific wages (w_{om} and w_{of}), the firm's equilibrium profit equals the marginal product of labor retained from g workers, scaled by the number of g workers, which reduces to a simple expression increasing in $\underline{Q}_{og}$:

$$\begin{aligned}\pi_o^* &= \sum_g L_{og}(w_{og}^*(\underline{Q}_{og}))\left[p\underline{Q}_{og} - w_{og}^*(\underline{Q}_{og})\right] \\ &= K\sum_g \left(\underline{Q}_{og}\right)^{1+\varepsilon}\end{aligned} \tag{6}$$

where $K > 0$ is a constant and ε is the elasticity of labor supply. See B.3 for a more detailed derivation.

Suppose a new flexibility-enhancing technology becomes available and would allow firms to increase their technology to $\overline{\tau}_o = \underline{\tau}_o + \Delta$ after paying a fixed cost C. The firm will adopt the technology if doing so raises profits:

Proposition 7. *The firm adopts the technology if doing so increases profits ($\Delta\pi_o^* > 0$), or if*

$$K \sum_g \left(\overline{Q}_{og}\right)^{1+\varepsilon} - K \sum_g \left(\underline{Q}_{og}\right)^{1+\varepsilon} > C$$

Recalling that Q_{og} is increasing in both σ_o and s_o (Equation 4), the adoption condition implies larger profit gains where baseline flexibility is low (by the concavity of $\sigma_o(\cdot)$) and social intensity is high. Therefore, firms in highly social and inflexible occupations will be the most likely to pass the adoption threshold: $\frac{\partial^2 \Delta\pi_o^*}{\partial s_o \partial(-\underline{\tau}_o)} > 0$.

This result is reinforced by the fact that women are both disproportionately talented and constrained in such occupations. Because $\alpha_f > \alpha_m$, the productivity boost from greater σ_o in low $\underline{\tau}_o$ occupations is higher for female workers, which is then magnified by the fact that $s_f > s_m$. These facts therefore amplify the magnitude of $\frac{\partial^2 \Delta\pi_o^*}{\partial s_o \partial(-\underline{\tau}_o)}$.

Proposition 8. (i) Sign: *$\Delta\pi_o^*$ has increasing differences in $(s_o, -\underline{\tau}_o)$:*

$$\frac{\partial^2 \Delta\pi_o^*}{\partial s_o \, \partial(-\underline{\tau}_o)} > 0$$

Hence, highly social-intensive, initially inflexible firms are most likely to adopt $\overline{\tau}_o$.
(ii) Amplification: *If $s_f > s_m$ and $\alpha_f > \alpha_m$, then the magnitude of this cross-partial is larger than under $s_f = s_m$ and $\alpha_f = \alpha_m$.*

4.5 Empirical implications

Below I summarize four empirical implications of the model that I test in the data.

1. **The positive impacts of flexibility and social task intensity on women's relative wages (and employment) will be attenuated by the fact that these two job attributes are inversely correlated.**
   This implication follows from Proposition 5. Across occupations, the correlation between an occupation's social perceptiveness and women's relative earnings and employment will become more positive when controlling for the occupation's flexibility. And, conversely, the correlation between an occupation's flexibility and women's relative earnings and employment will become more positive when controlling for occupation's social intensity.[9] Given that individuals choose the occupation which maximizes their wages, this implication extends to women's relative employment (e.g., if women's relative wages are increasing in social task intensity, so too is their propensity to choose that occupation over other ones).

[9] To build further intuition, Appendix B.4 outlines the empirical test through the lens of an omitted variables bias framework.

2. **The correlation between women's social skills and their propensity to choose less flexible jobs (that reward these skills) will be weaker than men's.**
   This implication follows from Proposition 6, which demonstrated that highly social skilled women are more reluctant than their male counterparts to select inflexible jobs.

3. **Flexibility has a larger positive effect on women's relative wages and employment after a shock to women's time constraints (e.g. after parenthood).**
   By Proposition 1, the marginal return to flexibility σ_o rises with workers' selectivity over when they supply labor (α_g). Hence women's earnings are more responsive to flexibility ($\frac{\partial Q_o}{\partial \sigma_o} > 0$; see Proposition 5). In other words, according to the model, women's greater time constraints are the mechanism by which women's relative earnings or employment are increasing in flexibility (all else constant). Therefore, if experiencing a first childbirth increases women's selectivity (increases α_f) while men's preferences are unchanged (consistent with the fact that men's labor market outcomes are unchanged in Kleven et al. (2019)), the model predicts a stronger positive relationship between women's relative wages or employment and job flexibility after parenthood.

4. **Flexibility-enhancing innovations diffuse first in the most socially intensive, inflexible occupations.**
   This implication follows from the fact that socially intensive, inflexible firms will be the most likely to adopt flexibility-enhancing technology as it becomes available (Proposition 8). Since I do not observe firms in my data, I test the analogous prediction at the occupation level.

I test Implication 1 in the ACS data, where I observe gender gaps in employment and wages across occupations. I test Implication 2 in the NLSY data, where I observe individual's skills and their occupation choices. My primary test of Implication 3 are event studies around first births, but I provide additional supportive evidence by assessing heterogeneity by parental status in the analyses for Implications 1 and 2. I test Implication 4 by examining whether an occupation's social intensity and inflexibility predicts its likelihood of adopting flexibility-enhancing technologies, as proxied by two different measures from the CPS and ATUS.

5 How the trade-off influences gender gaps in employment and earnings

In this section, I evaluate whether the positive impact of social tasks and flexibility on women's relative employment and wages is muted by the inverse correlation of

these attributes across jobs (Empirical Implication 1). I use the ACS 2015-2019 data to regress a group's employment or wages within occupations on occupation-level characteristics and a set of fixed effects:

$$\begin{aligned} y_{oegp} =& \beta_0 + \beta_1 Inflexibility_o * Female_g + \beta_2 Social_o * Female_g + X'_{og}\vec{\alpha} \\ &+ \gamma_{oep} + \gamma_{egp} + \varepsilon_{oegp} \end{aligned} \tag{7}$$

where o indexes the occupation, e indexes education (college vs noncollege), p indexes parental status (any kids vs no kids), and g indexes gender (male vs female). The outcome, y_{oegp}, represents either a demographic group's employment share in an occupation ($ln\left(Emp_{oegp}/Emp_{egp}\right)$) or their average log wages ($\overline{ln\left(wage\right)}_{oegp}$). To construct average earnings, I take the average of log earnings residualized with respect to demographic characteristics and hours worked.[10]

The main variables of interest are the interactions between a female dummy ($Female_g$) and occupation-level characteristics measured in the O*NET. β_1 and β_2 represent how employment and wage gaps change with a standard deviation increase in the inflexibility index ($Inflexibility_o$) and social perceptiveness ($Social_o$), respectively, holding the other attribute constant. To test Empirical Implication 1, I examine how each coefficient changes when the other attribute is excluded from the regression. Specifically, I test whether $\tilde{\beta}_1 > \beta_1$ and $\tilde{\beta}_2 < \beta_2$ where $\tilde{\beta}_k$ represents the estimate of β_k when omitting the other attribute k'.

I include demographic group fixed effects γ_{egp} – the interaction of education, gender, and parental status – to account for factors affecting groups' employment or wages that are constant across occupation (e.g. some groups may systematically experience lower pay across all occupations). I also include fixed effects γ_{oep} for combinations of occupation, education, and parental status. These fixed effects ensure estimates are "within" education and parental status, thereby controlling for group differences in skills and preferences for flexibility. These fixed effects absorb occupation fixed effects (γ_o), which account for factors affecting wages and employment that are constant across group within occupation (e.g. some occupations are higher-paying). I additionally control for analytical intensity and routine task intensity interacted with female (vector X_{og}). These controls form the main set of control job characteristics used in Deming (2017); I explore how other tasks and skills influence the main pattern in Section 5.2. Standard errors are robust and clustered on occupation, and observations are weighted by the total employment in the o-e-g-p cell.

[10] I regress log earnings on age dummies, race dummies, year dummies, education year dummies, log weeks worked, and log weekly hours worked. Regressions are weighted by the ACS provided sample weights. I then take the average of the residuals within each occupation and demographic group.

5.1 Results

The results are presented in Table 1. In line with Empirical Implication 1, women's relative employment and earnings are lowered in both flexible and socially intensive jobs by the inverse correlation between these attributes.

Panel A presents the employment results. As in the puzzle depicted in Figure 1, women's relative employment is increasing in $Inflexibility_o$ (Column 1 of Panel A). Why are women likely to enter into inflexible occupations? The facts presented in Section 3 offer a potential answer: less flexible jobs are intensive in social tasks, in which we expect women to have a comparative advantage. Consistent with this notion, Column 2 shows that women's relative employment is increasing in social perceptiveness ($Social_o$). And, Column 3 reveals that $Social_o$ completely explains women's attraction to less flexible jobs. Once controlling for social intensity, the coefficient on $Inflexibility_o$ is negative (but indistinguishable from zero), and the coefficient on $Social_o$ becomes larger in magnitude.

As noted in Section 3.2, less flexible occupations are not only comprised of social tasks. For example, they also often involve analytical tasks (e.g. a financial consultant may perform both social and analytical tasks). To the extent that women dislike or have a comparative disadvantage in these other tasks, we might ask whether inflexibility is the binding constraint in highly social, inflexible jobs. Yet, the same pattern holds when controlling for analytical and routine task intensity in Columns 4-6, suggesting that this trade-off binds even conditional on these other tasks.

Panel B in Table 1 reports the analogous wage results, which capture gender gaps along the intensive margin (e.g., promotion or seniority). Relative to employment gaps across occupations, within-occupation wage gaps are noisier indicators of underlying constraints due to potential Roy selection and composition effects (Hsieh et al., 2019). Nevertheless, a similar pattern emerges: comparing Columns 1 and 2 to Column 3, women's relative wages in less flexible occupations are biased upwards by $Social_o$. And, conversely, women's returns to social tasks increases nearly threefold once controlling for the fact that these occupations tend to lack flexibility. Columns 4-6, which additionally control for analytical and routine task intensity, again depict a similar pattern.

As discussed in Section 3.1, women tend to show greater interest in interacting with people. Especially to the extent that this interest emerges in childhood, it is difficult to imagine that it would not – at least inadvertently – lead women to develop stronger social skills. Nevertheless, it remains possible that, independent of their actual skills, women simply enjoy interactive tasks more than men. To what extent, then, is the observed trade-off driven by women's preferences for social tasks, rather than by a comparative advantage? If women's attraction to social tasks were entirely preference-

based, a trade-off would still exist, but there would be no implications for the allocation of talent.

The wage results help rule in the comparative advantage mechanism. Women's relative attraction to social-intensive occupations, as shown in Panel A of Table 1, is consistent with either mechanism. However, if women excel in social tasks, firms should be willing to pay them more than men to attract them (i.e., social tasks should increase women's relative wages). Conversely, if women prefer social tasks, firms should have to pay men more than women to induce them to perform the same work (i.e., social tasks should decrease women's relative wages). Given these countervailing impacts, the positive relationship between $Social_o$ and women's relative wages supports the interpretation that comparative advantage is the dominant channel. This finding aligns with Cortes et al. (2023), who show that occupations becoming more social over time both experienced wage growth and attracted more women, which is more consistent with a comparative advantage mechanism than a preference-driven one.

5.2 Extensions and robustness

5.2.1 Skilled workers sample

Much of the literature on greedy work and the gender wage gap has focused on highly educated workers, perhaps motivated by the fact that the gender wage gap among such workers has been more persistent and slower to close (Cortés and Pan, 2019). Goldin (2014) specifically focuses on college educated workers in high-income occupations, as in Figure 1. In these jobs, there are well-documented vignettes and case studies of firms rewarding long or irregular hours (e.g., lawyers). Because I aim to explain sorting patterns across occupations, I broaden my focus to the full set of occupations and workers.

However, there is merit to the claim that the lack of workplace flexibility plays a larger role in explaining the gender wage gap among the highly educated. Table C.2 reports the results when limiting the sample to the college-educated. Table C.3 limits the sample further to the top-income occupations populating Figure 1. Moreover, to provide continuity with Figure 1, regressions at the occupation level in this sample are reported in Table C.4. In both samples, the same pattern holds; the key difference is that the negative relationship between an occupation's inflexibility and the gender wage gap is larger in magnitude and more statistically significant.

5.2.2 Heterogeneity by parental status

To explore heterogeneity in the ACS results based on parental status, I modify Equation 7 to incorporate additional interaction terms with a dummy variable indicating

parental status ($Parent_p$):

$$\begin{aligned} y_{oegp} =& \beta_0 + \beta_1 Inflexibility_o * Female_g + \beta_2 Social_o * Female_g \\ &+ \beta_3 Inflexibility_o * Female_g * Parent_p + \beta_4 Social_o * Female_g * Parent_p \\ &+ X'_{og}\vec{\alpha} + X'_{ogp}\vec{\mu} + \gamma_{oep} + \gamma_{egp} + \varepsilon_{oegp} \end{aligned} \tag{8}$$

where estimates of the coefficients on the interaction terms, β_3 and β_4, reflect how gender gaps in employment and wages change by parental status. For example, β_3 can be interpreted as representing the expected change in the gender gap for each standard deviation increase in the inflexibility index among parents relative to non-parents. The fixed effects γ_{oep} absorb the interaction between parental status and occupation characteristics. I also interact parental status with the control tasks (X_{ogp}).

Table C.5 reports the results. The relationship between the inflexibility index and women's relative employment is more negative among parents (Columns 1-2). A similar pattern emerges for wage gaps, yet this is only true when controlling for simultaneous interactions with other task intensities (Column 4). And, women's relative wages are more positively related to social tasks among parents, which could indicate that women's relative social skill advantage is larger among parents. Such a pattern could occur if the women who remain in high-social occupations after becoming parents are positively selected. Section 7 more comprehensively examines the role of parenthood by testing Empirical Implication 3 using event studies around first births. That analysis circumvents some selection concerns by leveraging longitudinal data to retrieve within-person estimates of how gender gaps in inflexible jobs change around births.

5.2.3 Alternative measures of flexibility

As discussed in Section 2.1.1, the index I construct follows Goldin (2014) and is based on features of the work environment which may lead firms to reward workers for working long, irregular, or particular hours. Alternative measures may have the upside of ensuring some real-world manifestation of flexibility but potentially conflate general equilibrium features of labor markets. I report the results when using these alternative approaches in Tables C.6 and C.7. The same patterns emerge. The main difference is that the initial "puzzle" from Figure 1 is no longer as apparent – women are not, on net, drawn to less flexible jobs. Still, Empirical Implication 1 is supported: women are more deterred by inflexibility and more drawn to social intensity, after holding the other job attribute constant.

5.2.4 Alternative measure of social intensity

Motivated by the discussion in Section 3.1, I focus on social perceptiveness in order to more precisely capture the skills in which women excel. This is one of four components employed by the social skill composite used in Deming (2017), which additionally includes coordination ("adjusting actions in relation to others' actions"), persuasion ("persuading others to approach things differently"), and negotiation ("bringing others together and trying to reconcile differences"). Social perceptiveness is highly correlated with the Deming (2017) composite measure ($\rho = 0.93$). And, the social composite is even more highly correlated with the inflexibility index (ρ of 0.79 vs 0.74).

Table C.8 reports the results when using this social composite. Consistent with the notion that this less precisely captures women's comparative advantage, this version of social tasks is less predictive of women's relative employment and wages. Interestingly, despite being highly positively correlated with both the inflexibility index and social perceptiveness, controlling for this measure of social skills no longer leads the coefficient on $Inflexibility_o$ to flip to a negative sign. One explanation is that there is not enough variation to separately identify these factors. To explore this possibility, I test whether the pattern emerges when using the alternative flexibility measures, which are less correlated with social perceptiveness (Table C.9 and C.10). Consistent with this explanation, we see the main pattern emerge.

5.2.5 Non-routine manual tasks and physical strength

My controls for analytical skill demands and routine task intensity follow Deming (2017). Comparing this control set to the taxonomy of task intensities put forward in Acemoglu and Autor (2011), these controls may fail to capture *non-routine* manual tasks. Non-routine manual tasks require "situational adaptability, visual and language recognition, and in-person interactions" and characterize jobs like pilots, crane and tower operators, and mechanics. Especially insofar as these tasks require physical strength, these are likely to be jobs in which men have a comparative advantage. And, these tasks are less likely to be important in social-intensive jobs, which begs the question: is women's comparative advantage in social jobs driven by their comparative disadvantage in non-routine manual tasks (or physical strength more broadly)? If so, this would not negate the existence of a trade-off, but it would shift our understanding of its underlying source.

The non-routine manual task index and an index capturing physical strength requirements are both inversely correlated with social perceptiveness ($\rho = -0.62$ and $\rho = -0.30$, respectively).[11] Tables C.11 and Table C.12 report the results when control-

[11]The non-routine manual task index follows Acemoglu and Autor (2011) and takes the average of the following dimensions from the O*NET: the importance of operating vehicles, mechanized devices,

ling for non-routine manual tasks and physical strength demands, respectively. The relationship between social perceptiveness and women's relative wages or employment weakens in some cases but is qualitatively similar to Table 1, suggesting that while this explanation has some merit, it does not fully account for the observed patterns.

6 Skill-based employment gaps in inflexible occupations

In this section, I test the second implication of the model: that women's social skills are less predictive of their entry into less flexible jobs.

The model assumes, for simplicity, that occupations differ along a single skill dimension. In practice, however, jobs tend to reward multiple skills. For example, less flexible occupations also place a premium on analytical skills (as discussed in Section 3.2). To account for this multidimensionality, I test a slightly broader implication: that women's social or cognitive skills are less predictive of their propensity to sort into less flexible jobs. The goal is not to isolate the effect of one skill type over another, but rather to assess whether, conditional on skill, women are systematically less likely to enter less flexible roles.

I use the NLSY79, where I observe individuals' skills and their job choices, to run the following regression:

$$y_{it} = \alpha + \beta Female_i + \boldsymbol{\gamma}' \vec{Skill}_i + \boldsymbol{\delta}' \vec{Skill}_i * Female_i + \boldsymbol{\zeta}' \vec{X}_{it} + \varepsilon_{it} \tag{9}$$

where i indexes individuals and t indexes the year. $\vec{Skill}_i$ is a vector of individual i's social skills and cognitive skills as defined in Section 2.2.2. $\vec{X}_{it}$ is a vector of age fixed effects, year fixed effects, noncognitive skills, a dummy indicating the noncognitive skills were missing (and filled in with zeros), and a dummy for college completion.[12]

I construct two outcomes. The first is a dummy indicating employment in a low flexibility occupation (meaning, above median in $Inflexibility_o$). The second is a dummy indicating employment in a high flexibility occupation. Both dummies are equal to zero when the person is not employed. Given that inflexible jobs are intensive in social and cognitive skills, we expect $\vec{Skill}_i$ to predict employment in less flexible jobs but not in flexible ones: $\boldsymbol{\gamma} > 0$ for jobs with low flexibility and $\boldsymbol{\gamma} < 0$ for jobs with high flexibility. However, Empirical Implication 2 suggests that this correlation should be less pronounced for women. Put differently, relative to highly skilled men, highly skilled

or equipment; spending time using hands to handle, control or feel objects, tools or controls; manual dexterity; spatial orientation. To more directly capture physical strength requirements, I construct a physical strength index based on the standardized average of four O*NET measures: the level of static strength, explosive strength, dynamic strength, and trunk strength that the job requires.

[12]Three individuals have missing noncognitive skills. My measure of noncognitive skills follows Deming (2017) and represents the normalized average of the Rotter Locus of Control and the Rosenberg Self-Esteem Scale.

women will be under-represented in inflexible jobs: $\boldsymbol{\delta} < 0$ for jobs with low flexibility and $\boldsymbol{\delta} > 0$ for jobs with high flexibility.

6.1 Results

Regression results from estimating Equation 9 are presented in Table 2. Columns 1-2 and Columns 3-4 report the results for employment in jobs with low and high flexibility, respectively. Columns 1 and 3 evaluate the gender gap in skill-based sorting for social skills, and Columns 2 and 4 evaluate social and cognitive skills jointly.

Echoing the pattern in Figure 1, women are more likely to be employed in low-flexibility jobs. And, consistent with the correlation between the occupation-level measures of inflexibility and social perceptiveness presented in Figure 3, highly socially skilled men are more (less) likely to enter into jobs with low (high) flexibility. However, in line with Empirical Implication 2 of the model, this pattern is partially reversed among women. For example, Column 1 of Table 2 suggests that a one standard deviation increase in social skills is associated with a 0.047 increase in probability that men are employed in a less flexible job. But, for women, this increase in probability is only 0.012. The opposite pattern emerges in Column 3, where highly socially skilled men are less likely to be employed in high-flexibility jobs, but this relationship is muted for women.

Columns 2 and 4 of Table 2 reveal an analogous pattern for cognitive skills. At the bottom of the table, I report the joint significance on the female dummy interacted with social and cognitive skills ($\delta_{social} + \delta_{cognitive} = 0$). While the coefficient on cognitive skills and the female dummy is not statistically distinguishable from zero, social and cognitive skills are jointly less predictive of women's entry into inflexible jobs relative to men (p-value of 0.006).

I examine heterogeneity by parental status in Table C.13, where I include additional interactions with a dummy indicating the individual has had a child. In these regressions, I additionally include female by age fixed effects to account for the fact that women have their first child at different ages than men do. Interestingly, there is no heterogeneity by social skills. In other words, the smaller correlation between women's social skills and their employment in inflexible jobs is the same among parents and non-parents. However, the under-representation of highly cognitively skilled women in low-flexibility jobs is driven by women with children.[13]

In line with Empirical Implication 2, these results suggest that women's skills are less predictive of their employment in low-flexibility jobs. And, consistent with the notion that women's time constraints are driving these results, there is some evidence

[13] Juhn and Rubinstein (2022) find that highly cognitively skilled women are under-represented in abstract task intensive jobs, and that this under-representation is primarily driven by women with children. My findings here could partially reflect the tension they explore.

that this gender gap is driven by mothers.

7 Mechanism: women's time constraints

Through the lens of the model, women's greater time constraints are the mechanism by which women's relative earnings or employment are increasing in flexibility (all else constant). In this section, I test whether gender gaps in inflexible occupations widen following a shock to women's relative time constraints (Empirical Implication 3), providing a more direct test of this proposed mechanism.

The negative relationship between women's relative labor market outcomes and occupational inflexibility is consistent with the notion that their time constraints bind more in less flexible jobs. However, inflexible jobs may possess characteristics unrelated to demands on workers' time that also deter women or limit their success. For example, such occupations may foster a "masculine" firm culture that impedes women's advancement or be associated with higher levels of discrimination. In this analysis, I leverage the fact that the birth of a (first) child will disproportionately shock women's time constraints. A greater widening of gender gaps in inflexible jobs after childbirth would align with the notion that these gaps are at least partially driven by women's relative time constraints.

To build intuition for this analysis, consider the "ideal experiment." In this experiment, workers would be randomized into occupations, and a randomly subset of workers in each occupation would be required to work flexible hours (for example, fewer or more predictable hours). I would then compare treated and control workers' wages (intensive margin) and probability of employment (extensive margin) within each occupation. Because the only difference between the two groups is their labor supply, any drop in outcomes among treated workers would reveal the penalty for needing flexibility in that occupation, i.e. the "price" of flexibility. Although occupations may differ in other ways, this experiment isolates the effect of inflexibility as long as these other features (e.g. discrimination) do not also penalize those who work flexible hours.

In my analyses, I use two complementary approaches designed to mimic this ideal experiment. First, I leverage the longitudinal panel of the National Longitudinal Survey of Youth 1979 (NLSY79) and an event study design to estimate the impact of first births on women's (and men's) employment and wages (the so-called "child penalty") in flexible versus inflexible jobs. Second, I use repeated cross-sections from the Current Population Survey (CPS) to build a synthetic panel, which affords me statistical power to estimate the child penalty separately by occupation.

7.1 Event-studies around first births

Following the growing child penalty literature, I exploit variation in the timing of first births to estimate the impact of children on labor market outcomes (e.g. Kleven et al. (2019)). To avoid comparisons between treated and already-treated individuals, I adapt the original child penalty event study framework by incorporating a "stacked" design, as used by Cengiz et al. (2019) and Deshpande and Li (2019).[14] To execute this approach, for each treatment cohort (meaning, age at which the individual has their first child), I create a dataset that contains their observations and all pre-birth observations of a set of control individuals. Because I am interesting in outcomes that may take time to materialize, my main specification uses individuals who never have kids as a control group, but I also show the results are robust to using individuals who have children at least 3 or 5 years later than the treatment cohort. Each dataset, comprised of a treatment cohort and its corresponding control group, can be viewed as a separate experiment with its own treatment effect. I then stack these datasets and estimate the event study on the combined sample, including fixed effects to index each experiment. Specifically, I run the following regression separately for men ($g = m$) and women ($g = f$):

$$y^g_{itc} = \beta^g_0 + \underbrace{\sum_{\forall\, k \neq -1} \beta^g_k \mathbf{1}\{t \in k\}}_{\text{event time dummies}} + \gamma^g_{ac} + \gamma^g_{rc} + \gamma^g_{ic} + \varepsilon^g_{itc} \tag{10}$$

where i indexes individual, t indexes event time (years since the individual's first-birth), and c indexes the observations associated with each treatment cohort. $\mathbf{1}\{t \in k\}$ are a dummy variables indicating event time.[15] $\mathbf{1}\{t \in k\} = 0\ \forall\, k$ for individuals in the control group, thus indicating they are "never treated" over the window of time relevant to the treatment cohort. The period just prior to first-birth, -1, is omitted from the regression. I additionally include age (a) fixed effects, year (r) fixed effects, and individual (i) fixed effects, each interacted with fixed effects for experiment c. These fixed effects are represented by γ^g_{ac}, γ^g_{rc}, and γ^g_{ic}, respectively. Standard errors are robust and clustered on individual.[16] To aid interpretation, estimates of β^g_k are converted to percentage changes by dividing the estimates and the confidence interval by the

[14] See Dube et al. (2024) for an overview of the issues that arise in two-way fixed effects designs with staggered adoption. While event study specifications can accommodate dynamic treatment effects (e.g., the emergence of a larger treatment effect over time), the leads and lags may be contaminated by effects in other periods insofar as treatment effects are heterogeneous (e.g., larger treatment effects for women who give birth at an earlier versus later age).

[15] k varies from -27 to 39 but my plots focus on $k \in \{-6, 9\}$ for visibility.

[16] Given my stacked event study approach, individuals may appear multiple times. Clustering standard errors on the individual accounts for this redundancy.

average of the outcome for the pre-birth observations of the treated g individuals. The β_k^g coefficients represent the average within-person percentage change in y_{itc} at event time k (relative to $t = -1$), net of the corresponding change for control individuals of the same age observed in the same year.

I first examine how births impact women's relative propensity to sort into less flexible jobs. My main outcome of interest is a dummy indicating employment in a low flexibility occupation, defined as above-median in the Inflexibility Index, $Inflexibility_o$. Estimates of β_k^g therefore capture the effect of first births on the probability of being employed in a less flexible job, as opposed to either a flexible job or nonemployment. I compare these results to the impact on a dummy variable indicating employment in a flexible occupation (below-median in $Inflexibility_o$).[17] According to Empirical Implication 3 of the model, childbirth will have a more negative effect on the probability of employment in low-flexibility jobs than in high-flexibility ones.

I then examine whether births disproportionately lower women's wages in less flexible occupations. To do this, I run the same specification as Equation 10 and additionally include interaction terms with a variable equal to the average inflexibility index of the individuals' occupation prior to birth ($\overline{Inflexibility_i}$):

$$y_{itc}^g = \beta_0^g + \sum_{\forall\, k \neq -1} \beta_k^g \mathbf{1}\{t \in k\} + \sum_{\forall\, k \neq -1} \alpha_k^g \mathbf{1}\{t \in k\} * \overline{Inflexibility_i} \tag{11}$$
$$+ \gamma_a^g * \overline{Inflexibility_i} + \gamma_r^g * \overline{Inflexibility_i} + \gamma_{ac}^g + \gamma_{rc}^g + \gamma_{ic}^g + \varepsilon_{itc}^g$$

For the never-treated individuals, $\overline{Inflexibility_i}$ is the average inflexibility of their occupations across all observations. To avoid conditioning on an outcome, I let wages equal zero if the person is not employed. I again divide by the average pre-birth outcome among the treated group to give the coefficients a percentage change interpretation. The coefficients of interest, α_k^g, represent how the percentage impact on wages varies for a one standard deviation increase in the inflexibility of the individual's pre-birth occupations (on average). Empirical Implication 3 of the model implies that $\alpha_k^g < 0$ for $k > 0$.

7.1.1 Results

Figure 4 reports the employment results. In Panel A, the outcome is a dummy variable indicating employment in a job with low flexibility. After childbirth, women

[17] Adding these two outcomes together yields a dummy variable equal to 1 if the person is employed. A simpler approach would be to use a variable equal to the inflexibility index of the person's job in period t. However, doing so conditions on employment (which is itself an outcome affected by childbirth), given that the index is defined only for occupations. I instead binarize the outcome in this way so that I accommodate nonemployment spells. The analysis in the next section leveraging the CPS data does not require me to binarize the flexibility index.

become approximately 20% less likely to be in these jobs. Their male counterparts experience no change in the likelihood of being employed in such jobs. In contrast, Panel B depicts a similarly sized (though noisier) treatment effect on women's relative employment in flexible jobs initially, but this effect begins to fades five years after the birth.[18]

The fact that women become relatively less represented in low-flexibility occupations after childbirth could reflect either that men outpace women in entering these jobs, or that women disproportionately drop out of them. The former may be more relevant for roles like CEOs or managers, where workers often start their careers in lower-ranked occupations within the firm, and childbirth differentially slows women's progression into higher-level roles. The latter may better describe the impact of childbirth on employment in occupations like lawyers or physicians, where individuals typically enter directly into their occupation after earning the requisite degree and the key margin is retention rather than promotion.

Shifting focus to the intensive margin, Figure 5 reports the wage results. The figure plots the estimates of α_k^f and α_k^m from Equation 11, which represent the coefficients on the interaction between the event dummies and the flexibility of one's occupation prior to birth. Beginning in the second year after childbirth, women who held less flexible jobs prior to giving birth experience a significantly larger decline in wages. For example, a one standard deviation increase in the average Inflexibility of a woman's pre-birth occupation is associated with a 5% larger wage drop two years after childbirth. This effect grows over time, reaching over 10% in years five and beyond.

The opposite is true for men in inflexible jobs: after childbirth, men's wages are (if anything) higher in these occupations. This disproportionately positive effect may reflect an amplification of the "fatherhood premium," wherein entering into parenthood may cause men to spend more time in the labor market (see Goldin et al. (2024) for a more thorough discussion). If new fathers increase their labor supply, the associated wage gains may be especially pronounced in inflexible jobs, where longer hours or greater availability are more heavily rewarded.

How would forward-looking behavior – where career investments are made with these impacts in mind – affect the interpretation of these results? While women tend to under-predict the time demands of motherhood (Kuziemko et al., 2018), there is evidence that anticipated marriage and fertility impacts human capital decisions (e.g., college major) to some extent (Wiswall and Zafar, 2021). If such forward-looking behavior leads women to make choices that minimize the post-childbirth dip in wages or employment in inflexible careers (e.g. female physicians choose a more flexible spe-

[18] As discussed above, these estimates are in terms of percentage change. Much of the initial large decrease observed in Panel B is due to this transformation because women are less likely to be in these jobs relative occupations with low flexibility. In the absence of this transformation, the drop observed in Panel A is larger than that observed in Panel B in all years.

cialty, such as pediatrics or radiology), such behavior would bias the disproportionate impact of childbirth on gender gaps in inflexible jobs (vis-á-vis flexible ones) towards zero. More generally, understanding how forward-looking behavior (or lack thereof) influences how the trade-off between women's skills (which do not vary over the life-cycle) and flexibility preferences (which do) is an interesting area of research, albeit one that is outside the scope of this paper.

Overall, these results support the idea that women's time constraints bind more in jobs with low versus high flexibility. Below I present two robustness checks before presenting the pseudo difference-in-differences analysis.

7.1.2 Robustness: alternative control group

As described above, I use the never-treated (childless) individuals as the control group for each treatment cohort. When choosing control individuals, there is a trade-off between assessing long-run effects and comparing groups of people who are likely to be similar along unobservables (due to their current or eventual parental status). If I limit the control group for each treatment cohort to individuals who eventually have children x years later, then I can only assess outcomes up to the point at which the control has children (i.e., x years after the treatment cohort gives birth), at which point they become treated. The advantage of this approach is that for small values of x (e.g., 3 or 5), it is easier to argue that the treatment and control groups are comparable on unobservables. However, treatment effects in my setting may take several years to materialize, which this approach would miss, since outcomes for the control group are only observed up to x years after childbirth. Reassuringly, the lack of pre-trends suggest the never-treated individuals provide suitable control group. Nevertheless, Figure D.3 and D.4 report the results when setting $x = 3$ and $x = 5$. Results are similar when using the longer time horizon ($x = 5$) but are less apparent when comparing to those who give birth three years later.

7.1.3 Robustness: spouse's income

I interpret the wage results as providing evidence that women's demand for flexibility is more costly in inflexible occupations (those with high $Inflexibility_o$). This interpretation assumes that all women in the sample experience a similar shift in their demand for flexibility after childbirth, but that the price they pay (in the form of reduced wages) is higher within inflexible jobs. An alternative explanation is that women in high $Inflexibility_o$ jobs prior to birth happen to demand more flexibility after childbirth than those in low $Inflexibility_o$ jobs. One plausible explanation along these lines is that women in inflexible occupations may have higher-earning husbands and therefore have higher reservation wages. To explore this possibility, I construct a proxy for

spousal income prior to childbirth,[19] and I rerun the wage results while controlling for this proxy interacted with the event dummies, age dummies, and year dummies. Results are in Figure D.5. Consistent with this interpretation having some merit, I find that spousal income explains part – but not all – of the heterogeneity in wage impacts across occupations with differing levels of pre-birth inflexibility. It is worth noting that women in inflexible careers may endogeneously choose to marry higher-earning husbands precisely because their own careers are difficult to maintain alongside childrearing. In this case, the presence of such a mechanism would not undermine the notion that time constraints bind more in inflexible careers.

7.2 Pseudo difference-in-difference around births

In this section, I use cross-sectional data from the CPS to estimate child penalties on employment in each occupation using a pseudo difference-in-differences approach around childbirth. I then test whether these occupation-level estimates are correlated with the Inflexibility Index.

This analysis serves two purposes. First, it corroborates the NLSY results on employment presented above. In those results, I compared employment outcomes in high- versus low-flexibility occupations, defined using the median value of $Inflexibility_o$. The large sample size of the CPS allows me to estimate child penalties for each occupation, yielding a continuous version of the prior result that does not rely on defining a threshold for what constitutes an inflexible occupation. Second, it introduces and validates my empirical strategy in Section 8 (which tests Empirical Implication 4), where I use this approach to measure changes in an occupations' motherhood-friendliness over time.

As described in Section 2.2.3, this analysis relies a synthetic panel of individuals pre- and post-first birth built on CPS data pooled between 1972-2019. To build this panel, following Kleven (2023), I proxy for an individual's age at first birth based on the eldest child in their household. I then retrieve their pre-birth observations by matching them to childless individuals with the same demographic characteristics (gender, age, year, education category, marital status, race, and state).

Using these data, I run the following regression separately by gender g and occupation o:

$$y_{it}^{o,g} = \alpha^{o,g} + \beta^{o,g} Post_{it} + \gamma_{ard}^{o,g} + \varepsilon_{iard}^{o,g} \tag{12}$$

where i indexes synthetic individuals, t indexes event time, a indexes age, r indexes year, and d indexes the demographic group defined by all other matching characteris-

[19] Spousal income is only observed in survey years and is therefore missing for many observations. To circumvent this, I take the average spousal income conditional on being observed. For individuals who not married, spouse income is set to zero.

tics. $Post_{it}$ is a dummy indicating the individual has given birth ($k \geq 0$). $\gamma_{ard}^{o,g}$ are fixed effects at the level of the cell defined by all matching characteristics.

The outcome is a dummy variable indicating employment in occupation o. It equals zero when the person is not employed or employed in different occupation. To aid interpretation, I divide the estimates by the average in the outcome among the childless sample. $\hat{\beta}^{o,g}$ can thus be interpreted as the percentage change in the likelihood that g sort into occupation o after they experience their first birth. I then take these estimates and calculate $\hat{\beta}^{o,f} - \hat{\beta}^{o,m} = \hat{\beta}^{o}$ for each occupation, then correlate $\hat{\beta}^{o}$ with $Inflexibility_o$.

My goal with this analysis is to validate that gender gaps in employment widen more in inflexible jobs vis-á-vis flexible ones after childbirth. Accordingly, in my analysis below, I standardize the outcome $\hat{\beta}^{o}$ to emphasize the focus on the relative magnitude across occupations. The exact magnitude of any individual estimate may lack interpretability for two reasons. First, estimates are based on a synthetic panel of parents and demographically similar childless individuals and, therefore, may partially reflect unobserved differences in these groups' characteristics. Using a similar approach and dataset, Kleven (2023) show that pseudo event studies yield estimates comparable to those from longitudinal data. They argue this approach may perform well because the matching characteristics do a reasonable job of predicting when childless individuals have children. Even so, some differences between the surrogate and actual parents may remain. My focus on the relative gender difference in employment across occupations circumvents these concerns to the extent that unobserved differences between parents and non-parents are similar across genders or occupations. Second, some plotted points will exceed 100% because the original estimates for men and women (which range between –0.04 and 0.02) are divided by the (gender-specific) occupation employment rate in the childless sample to yield percentage change interpretations. This normalization helps account for the fact that some occupations are very large and others very small, but sometimes leads plotted points to exceed 100%.

7.2.1 Intuition: pseudo event study estimates for a few illustrative occupations

To build intuition, I first present the results from an event study version of Regression Equation 12 for a few illustrative occupations:

$$y_{it}^{o,g} = \alpha^{o,g} + \sum_{\forall\, k \neq -1} \beta_k^{og} \mathbf{1}\{t = k\} + \gamma_{ard}^{o,g} + \varepsilon_{iard}^{o,g} \tag{13}$$

where, again, I divide the estimates $\hat{\beta}_k^{o,g}$ by the average in the outcome among the childless sample and take the gender difference $\hat{\beta}_k^{o,f} - \hat{\beta}_k^{o,m} = \hat{\beta}_k^{o}$. $\hat{\beta}_k^{o}$ therefore represent the change in women's relative employment k years after the (approximate) first birth

relative to the year prior, $k = -1$.

Figure 6a reports the estimates $\hat{\beta}_k^o$ for two of the largest college-intensive occupations and two of the largest non-college-intensive occupations as shown in Figure D.1. The corresponding female and male estimates ($\hat{\beta}_k^{o,f}$ and $\hat{\beta}_k^{o,m}$) are reported in Appendix Figure D.6.[20] In each of these occupations, the gender gap in probability of employment evolves in parallel leading up to the first birth. Following childbirth, women's likelihood of being employed as lawyers vis-á-vis men's declines sharply and continues to fall in the years that follow. Among computer scientists, a similar dip appears initially, but it is less steep and stabilizes over time; if anything, mothers in this occupation catch up to their male counterparts. A similar contrast emerges in two less–college-intensive occupations from the sales sector. Women's relative employment in retail sales – where customer interactions tend to be brief, routine, and transactional – remains fairly stable around first births. In contrast, sales representative roles, which often demand personalized client engagement and greater worker availability, show a noticeably steeper motherhood penalty.

The results presented below extend to all occupations and are based on the difference-in-difference design in Equation 12, thereby pooling pre- and post-event years.

7.2.2 Results

Extending the analysis across the full distribution of occupations using the pseudo difference-in-differences approach (Equation 12), Figure 6b presents the relationship between $\hat{\beta}^o$ and the Inflexibility Index. To focus on the relative variation across occupations, I standardize $\hat{\beta}^o$ to have a mean of zero and standard deviation of one. Consistent with the notion that less flexible jobs are more difficult to balance with time constraints, the change in women's relative employment after childbirth is decreasing in $Inflexibility_o$, signifying that women fall further behind men in these occupations following the transition to parenthood.

I build on this empirical strategy in next section, where I use this approach to measure the change in motherhood friendliness over time within each occupation.

8 Adoption of flexibility-enhancing technology across occupations

The analysis so far has focused on how the trade-off shapes workers' decisions, taking as given the relationship between an occupation's inflexibility and social task

[20] Level differences pre- and post-birth for men at times exhibits unintuitive behavior (e.g. small post-birth dip in men's employment in computer science (Panel C)). As alluded to in the discussion above, these patterns could be attributable to unobserved differences between parents and non-parents unaccounted for by the matching strategy.

intensity. In this section, I provide evidence that the trade-off also has the potential to shape firms' decisions. Specifically, I provide evidence that flexibility-enhancing innovations diffuse first in the most socially intensive, inflexible occupations (Empirical Implication 4), consistent with the notion that the trade-off amplifies the gains to doing so among firms in these sectors.

A range of technologies, practices, and policies can reduce the wage penalty workers experience to customize their schedule, thereby enhancing flexibility. The most effective approach likely depends on the specific job and context. My model offers a unifying principle for identifying effective strategies: those that make time periods in a worker's production process more substitutable.[21] For example, law firms may offer part-time contracts to associates who aspire to make partner but cannot meet billable hour requirements during their prime childbearing years. Or, when possible, firms can schedule essential team meetings for times that are not likely to conflict with family responsibilities (e.g. hold meetings prior to school dismissal at 3 p.m.). Case studies highlight additional solutions. For example, information technology can enable workers to efficiently store and share clients' information, which can then allow workers to operate as a "team of substitutes" and reduce the need for any particular worker to be present at certain times. Evidence suggests that this technology has facilitated more predictable schedules for OB-GYNs and increased part-time opportunities for pharmaceutical workers (Goldin and Katz, 2016; Goldin, 2021). Work can also be reorganized to separate on-call tasks from predictable tasks, as seen in the case of veterinarians, who eventually created distinct roles for managing day-to-day care and emergency care (Goldin and Katz, 2011). Occupation-level associations may also consider imposing norms or rules, such as the cap on hours worked in medical residency (Wasserman, 2023).

The breadth of approaches to making work more flexible poses a significant measurement challenge. I develop two proxies for changes to an occupation's flexibility that attempt to capture this breadth. The first is a "data driven" measure of changes in flexibility within occupations over time based on child penalties estimated separately for each occupation. This measure has the upside of capturing potentially a wide-range of ways that firms may adjust, but in doing so, it may also capture other factors (e.g., shifting ability composition of women) while also lacking interpretability. Therefore, to complement this measure, I also study the growth in the prevalence of *specific* practice that applies fairly widely across occupations – work-from-home arrangements.

Before discussing the measures, it is worth noting that firms' decisions to enhance flexibility need not stem from deliberate efforts by firms to attract female talent. Technology shocks unrelated to such efforts may persist in occupations that benefit from

[21] This principle nests the more specific proposal made by Goldin (2014), who argued that firms can make work more flexible by allowing workers to substitute for one another.

female talent due to market-driven selective pressures rather than firms' intentional pursuit of strategies that retain women. In fact, this "spontaneous order" model may better explain the pharmacy case study in Goldin and Katz (2016), where seemingly unrelated macro trends contributed to the restructuring of pharmaceutical work.[22] However, as institutions become more aware of the unique challenges women face in the workplace, firms may increasingly pursue such restructuring efforts with the explicit goal of attracting female talent.

Measure 1: motherhood-friendliness, 1979-2019 The first measure relies on the pseudo DiD strategy presented in Section 7.2. Specifically, I re-run equation 12 for two separate periods, 1979-1995 and 1996-2019. I then store estimates $\hat{\beta}^{j,o,g}$ for each period j, occupation o, and gender g. As in Section 7.2, I transform these estimates to percentage changes by dividing the estimates by the share of childless g individuals in that occupation in the relevant period. $\hat{\beta}^{j,o,g}$ therefore represents the percentage change in the propensity for g to sort into occupation o after childbirth in period j. I then calculate

$$\Delta Mother\hat{F}riendly_o = [\hat{\beta}_{o,f}^{\text{1996-2019}} - \hat{\beta}_{o,m}^{\text{1996-2019}}] - [\hat{\beta}_{o,f}^{\text{1972-1995}} - \hat{\beta}_{o,m}^{\text{1972-1995}}]$$

which represents the change over time (in percentage points) in women's relative tendency to be employed in an occupation after the birth of their first child. A positive $\Delta Mother\hat{F}riendly_o$ indicates a reduction in the employment penalty experienced by mothers in that occupation.

The main advantage of this measure is that it uses occupational sorting behavior to identify which occupations have become more "motherhood-friendly." This revealed preference approach avoids the need to pinpoint specific innovations or technologies, whose relevance for occupational flexibility may vary across sectors.

Measure 2: supply of work-from-home arrangements, 2003-2019 My second measure captures the rise of a specific innovation in temporal flexibility: work-from-home (WFH) arrangements. While often considered a way to enable location flexibility, WFH also likely enables greater temporal flexibility by eliminating the need to budget time for commutes and allowing workers to break up their work day to accommodate family obligations.[23] Harrington and Kahn (2023) provide evidence that WFH in the 2000's reduced the motherhood penalty by a substantial margin, which they argue may reflect

[22] Goldin and Katz (2016) credit three trends with making the pharmaceutical industry more egalitarian: the expansion of pharmacy chains, the adoption of information technology for storing client data, and the standardization of pharmaceutical products.

[23] For example, in the absence of WFH, workers may be required to stay late at the office to ensure a deadline is met. Doing so may not be possible for those responsible for making dinner or reading the bedtime story. With the possibility of WFH, however, workers can make up hours in the evening after addressing the family's needs.

the combined benefits of both forms of flexibility.

I use ATUS's time diary information to calculate the share of work hours in which a worker reports doing their work from home ($ShareWFH_i$). In an attempt to isolate changes in the supply of WFH technologies (rather than shifts in demand, e.g. due to the influx of women into an occupation), I residualize $ShareWFH_i$ with demographic characteristics to form $\tilde{ShareWFH_i}$.[24] I then take the average of $\tilde{ShareWFH_i}$ in each occupation to get $Avg\tilde{ShareWFH_o}$. I repeat this process for two different periods, 2003-2010 and 2011-2019, then I take the difference:

$$\Delta Avg\tilde{ShareWFH_o} = Avg\tilde{ShareWFH_o^{2011\text{-}19}} - Avg\tilde{ShareWFH_o^{2003\text{-}10}}$$

The measure therefore proxies for the change in the prevalence of WFH technologies in occupation o. Relative to the first measure, this measure has the advantage of capturing a clearly defined and widely studied form of flexibility. Due to the small sample size in the ATUS, only 313 occupations are represented.

8.1 Estimating equation

I then use these measures as outcomes and run the following regression to test Empirical Implication 4:

$$\Delta y_o = \beta_0 + \beta_1 Inflexibility_o + \beta_2 Social_o + \beta_3 Inflexibility_o * Social_o + X_o'\alpha + \varepsilon_o \quad (14)$$

where y_o is either $\hat{MotherFriendly_o}$ or $\widetilde{ShareWFH_o}$. $Inflexibility_o$ and $Social_o$ are the O*NET characteristics used in previous sections of the paper. X_o is a vector of base period controls and their interactions with $Social_o$ and $Inflexibility_o$. These controls include the share of those employed in the occupation who are college educated and the share of those employed who are female, both calculated in the CPS for the relevant set of base years. Because I am interested in the coefficient on the interaction term (β_3), I interact these base period controls with $Inflexibility_o$ and $Social_o$. These base period controls are based on the CPS data and calculated in the period one years relevant to the outcome in question (e.g. either 1972-1995 or 2003-2010). Standard errors are robust and the regressions are weighted by total employment in the base period.

[24] I residualize with respect to female, number of kids, female by number of kids, age (5 year bins) dummies, age dummies by female, married dummy, race dummies, education dummies (below high school, high school, some college, college, advanced degree), foreign born dummy, year dummies, and class of worker dummies. Regressions are weighted with ATUS sampling weights.

8.2 Results

Table 3 reports the results using the motherhood friendliness measure in Panel A and the WFH measure in Panel B. Both panels display remarkably similar patterns. On its own, an occupation's social skill intensity does not predict growth in flexibility under either measure (Column 1). In contrast, an occupation's predisposition to inflexibility does predict growth in motherhood friendliness and work from home arrangements (Column 2). Importantly, Column 3 reveals that this growth is concentrated in the most social skill intensive occupations, consistent with the idea that the marginal returns to these technologies are highest in jobs where female talent is both most valued and most constrained.

As a placebo test, I examine whether a similar pattern holds for analytical tasks, in which women are not necessarily expected to have a comparative advantage. To do so, I additionally include $Analytical_o$ and its analogous interaction terms in Column 4 of Table 3. In both Panels A and B, the interaction term between $Inflexibility_o$ and $Analytical_o$ is close to zero and statistically insignificant. This finding is consistent with the notion that these changes are driven by efforts to attract and retain female talent, which is comparatively more productive in social tasks.

Neither outcome perfectly captures firms' investments in flexibility. How does this influence how we interpret these results? For example, $\Delta Mother\hat{F}riendly_o$ may partially reflect the propensity for some occupations to be increasingly comprised of high ability women whose reservation wages are lower. Or, although worker characteristics have been residualized from $\widetilde{ShareWFH_o}$, shifts in worker composition along unobservables could lead some occupations to experience greater demand for WFH. Such labor supply shifts are certainly plausible. However, it is worth nothing that for these alternative explanations to account for the observed patterns, the compositional changes would need to be systematically larger in occupations that are high in both $Inflexibility_o$ and $Social_o$.

9 Conclusion

In this paper, I have presented evidence that the lack of workplace flexibility constrains women's ability to leverage their comparative advantage in the labor market. While women tend to excel in social tasks, jobs involving people-oriented tasks also tend to require long, irregular, or specific hours. This correlation in job attributes may arise, for example, because clients, team members, or supervisees have time-sensitive needs that can only be met by a particular worker with whom they have built relationship-specific capital. As a result, in order to be in careers which reward their skills, women often face a trade-off between their desire for flexible hours and

earning returns to their unique set of skills.

To understand what empirical patterns would be consistent with this trade-off, I presented a simple conceptual framework. Jobs vary in whether they reward social skills and whether the tasks involved are time-sensitive. The latter is represented by an occupation's elasticity of intertemporal substitution for production in two separate periods. Women, who are more "selective" over the time periods in which they supply their labor, must trade-off between flexibility and being in a job which rewards their social skills.

I show evidence consistent with the model's four predictions. First, I showed that women's relative employment and wages in both highly social and highly flexible jobs are lowered by the inverse correlation between these two job attributes. Second, I showed that while one's social (and cognitive) skills positively predict entry into less flexible jobs, this correlation is weaker for women. Third, I used childbirth as a shock to women's relative demand for flexibility to confirm that time constraints, rather than other unobserved job characteristics, limit women's success in less flexible occupations. Fourth, among inflexible occupations, the most social occupations are the most likely to adopt flexibility-enhancing technologies, in line with the notion that doing so facilitates greater access to talented (female) workers.

This trade-off amplifies the potential impacts of a range of policies and interventions on the gender wage gap. On the labor supply side, public policies such as funding for childcare or pre-kindergarten could enable women to excel in time-intensive careers (e.g. Humphries et al. (2024)). Childhood interventions could promote analytical skills among girls or social skills among boys, thus enabling women and men's skills to better match with jobs that match their desired flexibility.[25] On the labor demand side, professional associations may consider regulating work hours, similar to the cap on hours worked among medical residents implemented by the American Medical Association (Wasserman, 2023). Or, more broadly, institutions and firms may consider investing in technologies that reduce the cost of flexibility, such as information technologies that enable workers to seamlessly hand-off clients (Goldin and Katz, 2016).

The fact that there are potential talent losses stemming from the lack of workplace flexibility implies that firms may benefit from enhancing flexibility. Consistent with this notion, my final analysis suggests that firms, driven by the need to attract talented female workers, have introduced more flexible work structures in highly social-intensive occupations. A promising area for future research is to explore whether this process is slowed by frictions (e.g., adjustment costs or organizational inertia) and

[25]Making teachers aware of their biases can reduce the extent to which their stereotyping negatively impact students' performance (Alesina et al., 2024), which evidence suggests partially drives the gender gap in math performance in school (Carlana, 2019). Social interactions during elementary school can impact childrens' acquisition of cognitive empathy (Alan and Turkum, 2024).

whether policies can be developed to address these barriers.

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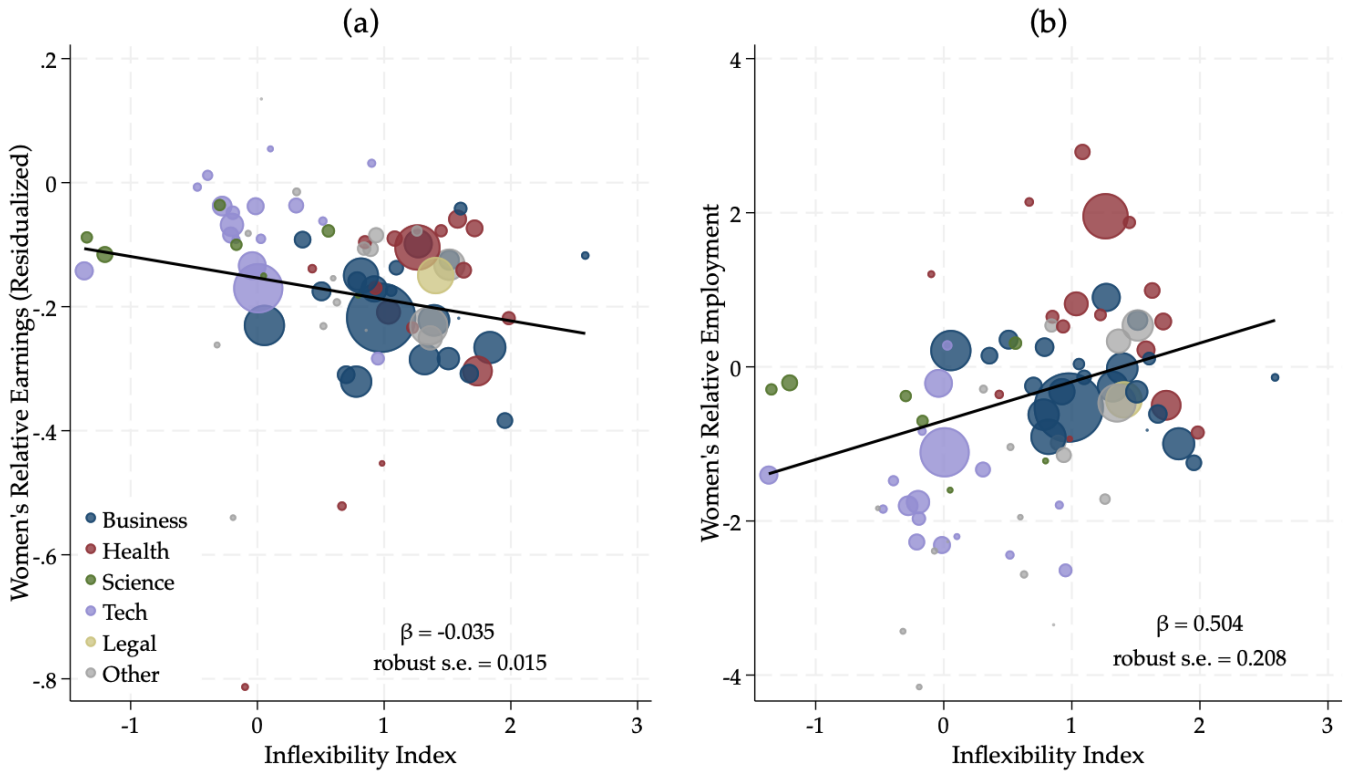
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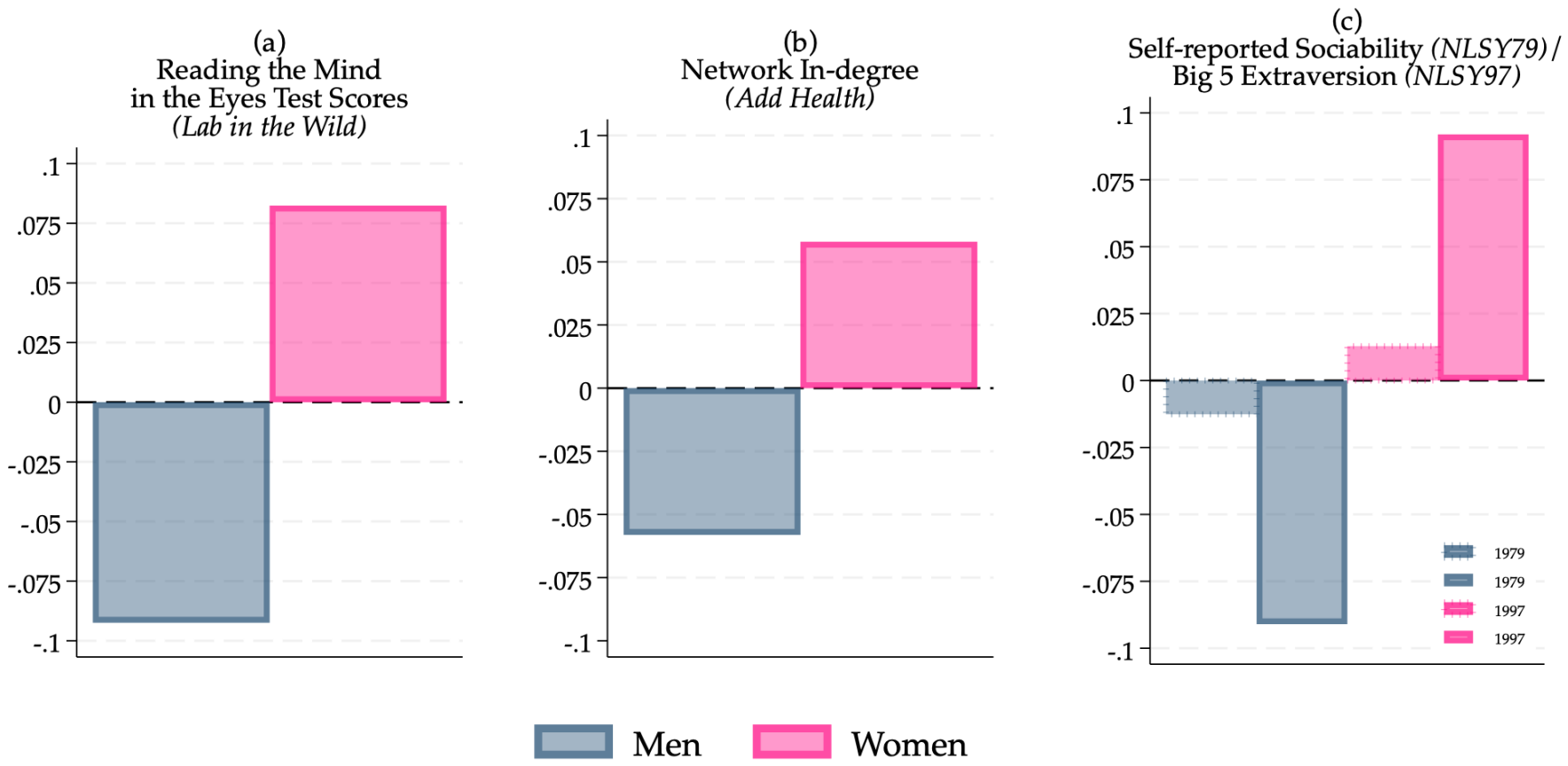
10 Main Figures and Tables

FIGURE 1: RELATIONSHIP BETWEEN AN OCCUPATION'S FLEXIBILITY AND GENDER GAPS IN WAGES AND EMPLOYMENT



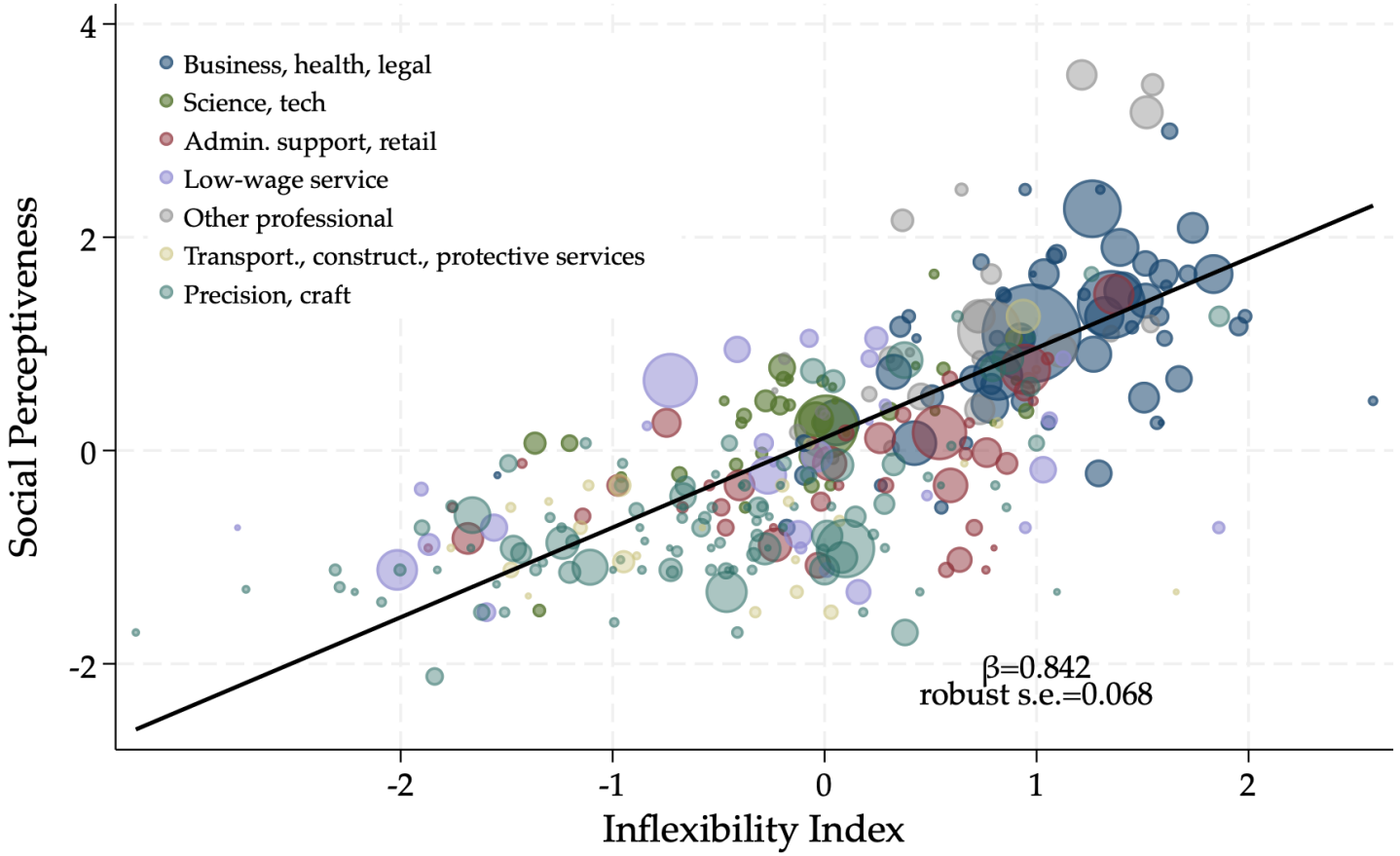
Notes: data are from the ACS (2015–2019) and O*NET (2013). Each observation represents a 3-digit occupation. The sample is restricted to occupations in the top quartile of average male income. The worker sample includes native-born, college-educated, full-time, full-year workers ages 25–64. The left panel replicates Figure 5 from Goldin (2014) and plots the relationship between the female-to-male ratio of log earnings within occupations (residualized with respect to hours worked and demographic characteristics) and an index proxying for occupational inflexibility (described in Section 2.1.1). The right panel plots the female-to-male log ratio of employment shares against the same index. Observations are weighted by total employment.

FIGURE 2: GENDER DIFFERENCES IN SOCIAL SKILLS



Notes: bar graphs depict average sociability by gender using various measures of social skills. The leftmost figure is based on standardized test scores in the Reading the Mind in the Eyes test from a Lab in the Wild dataset, as used in Greenberg et al. (2023) (reported in Table 1 and Figure 3 of their paper). The middle figure is based on the number of other students who nominated you as their friend in middle school or high school (standardized), as used in Lleras-Muney et al. (2020). The rightmost figure is based on NLSY79 and NLSY97 data, similar to the measures used by Deming (2017) (see Section 2 for details).

FIGURE 3: SOCIAL SKILL INTENSITY AND INFLEXIBILITY ACROSS OCCUPATIONS



Notes: This figure depicts the relationship between an occupation's social perceptiveness intensity and the index proxying for its inflexibility. Both occupation attributes are measured in the O*NET 2013 and described in greater detail in Section 2.1. Observations are 320 3-digit occupations and are weighted by total employment.

TABLE 1: RELATIONSHIP BETWEEN OCCUPATION CHARACTERISTICS AND GENDER GAPS IN EMPLOYMENT AND WAGES

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Log share employed, ln($\frac{Emp_{oegp}}{Emp_{egp}}$)					
$Female_g \times Inflexibility_o$	0.199*		-0.102	0.300***		-0.084
	(0.106)		(0.165)	(0.104)		(0.154)
$Female_g \times Social_o$		0.321***	0.393**		0.481***	0.538***
		(0.105)	(0.163)		(0.105)	(0.155)
$Female_g \times Analytical_o$				-0.263**	-0.347***	-0.335***
				(0.106)	(0.116)	(0.116)
$Female_g \times Routine_o$				0.246**	0.338***	0.343***
				(0.112)	(0.117)	(0.117)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.792	0.801	0.801	0.802	0.818	0.818
Panel B	Avg. log earnings (resid.), $\overline{ln(earnings_{oegp})}$					
$Female_g \times Inflexibility_o$	-0.002		-0.019**	0.001		-0.016*
	(0.007)		(0.009)	(0.007)		(0.009)
$Female_g \times Social_o$		0.008	0.022**		0.013*	0.024***
		(0.007)	(0.009)		(0.007)	(0.008)
$Female_g \times Analytical_o$				-0.008	-0.014	-0.012
				(0.008)	(0.009)	(0.009)
$Female_g \times Routine_o$				-0.003	-0.000	0.001
				(0.008)	(0.008)	(0.008)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.967	0.968	0.968	0.968	0.968	0.968
γ_{egp}	X	X	X	X	X	X
γ_o	X	X	X	X	X	X
γ_{oep}	X	X	X	X	X	X

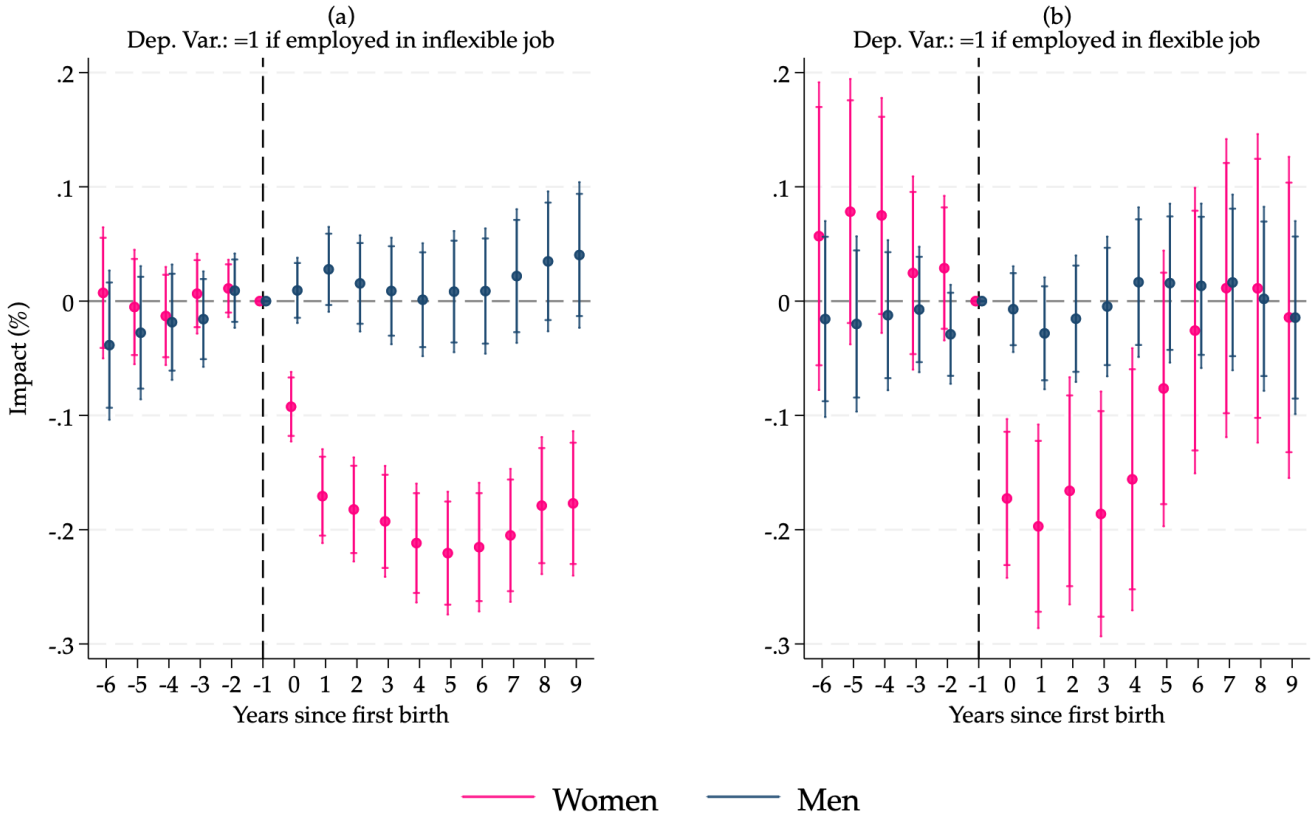
Notes: data are from ACS 2015-2019 and O*NET 2013. This table reports results from regressions of log employment shares and wages on occupation attributes interacted with a dummy for female, Female_g. Observations are a cells at the occupation $o \times$ education (college versus noncollege) $e \times$ gender $g \times$ parental-status p (at least one child versus no children) level. Observations are weighted by number employed in the cell. The outcome in the top panel is the log employment share of a demographic group in that occupation. The outcome in the bottom panel is the average of log earnings (residualized with respect to hours worked and demographic characteristics). The first three columns regress the outcome on an occupation's Inflexibility Index ($Inflexibility_o$) and an occupation's social perceptiveness skill intensity ($Social_o$). The next three columns additionally include controls for occupation's analytical skill intensity and routine task intensity. All columns include fixed effects for demographic group FE (γ_{egp}) and all two-way and three-way interactions of occupation, parental status, and education FE (γ_{oep}). Standard errors are robust and clustered on occupation.

TABLE 2: CORRELATION BETWEEN AN INDIVIDUAL'S SKILLS AND THEIR EMPLOYMENT IN A JOB WITH HIGH/LOW FLEXIBILITY

	(1)	(2)	(3)	(4)
	=1 if employed in a job with low flexibility		=1 if employed in a job with high flexibility	
$Female_i$	0.026**	0.020*	-0.103***	-0.099***
	(0.012)	(0.012)	(0.011)	(0.011)
$SocialSkills_i$	0.047***	0.030***	-0.044***	-0.032***
	(0.009)	(0.009)	(0.008)	(0.008)
$CognitiveSkills_i$		0.103***		-0.072***
		(0.008)		(0.008)
$Female_i \times SocialSkills_i$	-0.035***	-0.023**	0.024**	0.016
	(0.012)	(0.012)	(0.010)	(0.011)
$Female_i \times CognitiveSkills_i$		-0.016		0.010
		(0.012)		(0.012)
Person-Year Obs.	103264	103264	103264	103264
Person Obs.	3396	3396	3396	3396
R-sq.	0.094	0.121	0.104	0.118
F-test: $\delta_{soc} + \delta_{cog} = 0$		0.006		0.052

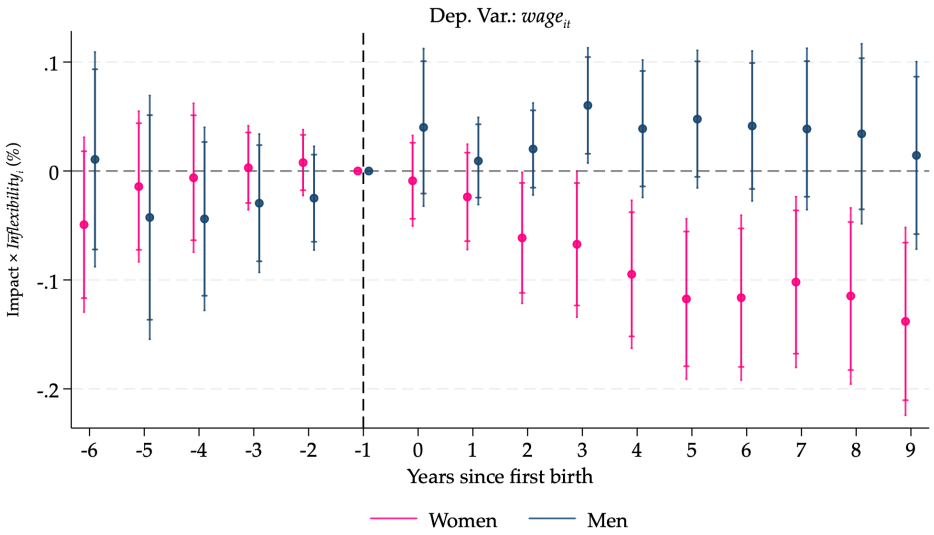
Notes: data are from the NLSY79. The outcome in columns 1-2 is a dummy indicating the person is employed in an occupation with low flexibility (i.e., above median in $Inflexibility_o$). The outcome in columns 3-4 is a dummy indicating the person is employed in an occupation with high flexibility (i.e., below median in $Inflexibility_o$). Each column presents results from separate regressions of the outcomes on a female dummy, an individual's social skills, and the interactions of these two terms. All regressions include age fixed effects, year fixed effects, noncognitive skills, a dummy indicating noncognitive skills were missing (and imputed with zero's), and a dummy for college completion. Columns 2 and 4 additionally include an individual's cognitive skills and its interaction with a female dummy. The bottom of the table reports the p-value from an F-test of the joint significance of the coefficients on $Female_i \times SocialSkills_i$ and $Female_i \times CognitiveSkills_i$. Standard errors are robust and clustered on individual.

FIGURE 4: CHANGE IN PROBABILITY OF EMPLOYMENT IN JOBS WITH LOW/HIGH FLEXIBILITY AFTER CHILDBIRTH



Notes: data are from the NLSY79. This figure presents event studies of first child birth separately by gender. In Panel A, the outcome is whether the person is employed in a job with low flexibility (above median in $Inflexibility_o$). In Panel B, the outcome is whether the person is employed in a job with high flexibility (below median in $Inflexibility_o$). The plotted points represent coefficients on dummies indicating the number of years (k) since an individual's first child birth. These coefficients are estimated from $k \in \{-27, 39\}$, but my plots focus on $k \in \{-6, 9\}$ for visibility. Estimates have been divided by pre-birth averages in the outcomes and therefore can be interpreted as percentage changes. 90% and 95% confidence intervals displayed. Standard errors robust and clustered on individual. As discussed in the text, the control group are individuals who never give birth over the sample period.

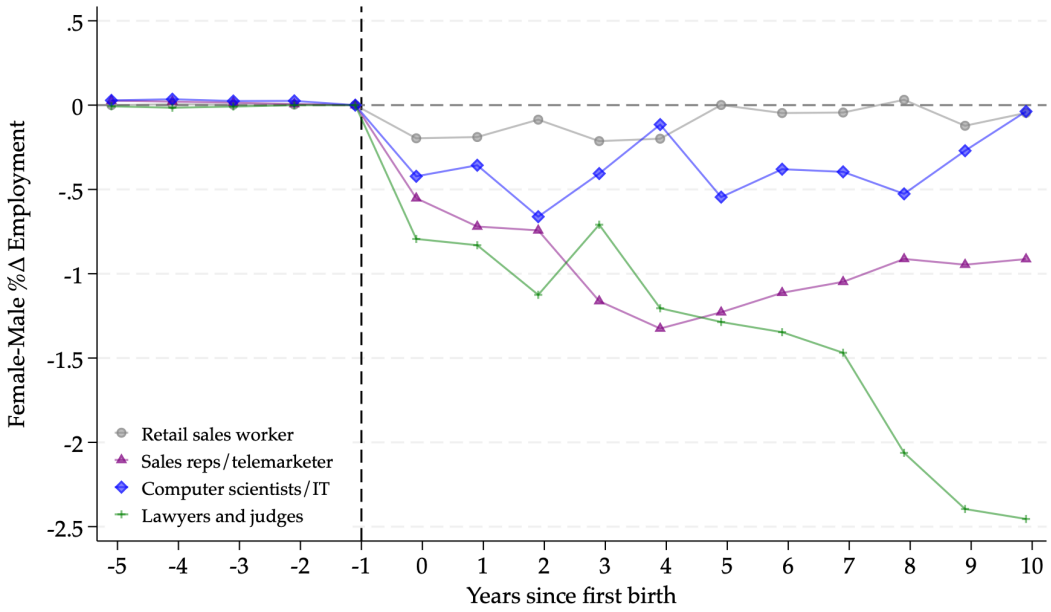
FIGURE 5: HETEROGENEITY IN WAGE CHANGES AFTER CHILDBIRTH BY FLEXIBILITY OF PRE-BIRTH OCCUPATION



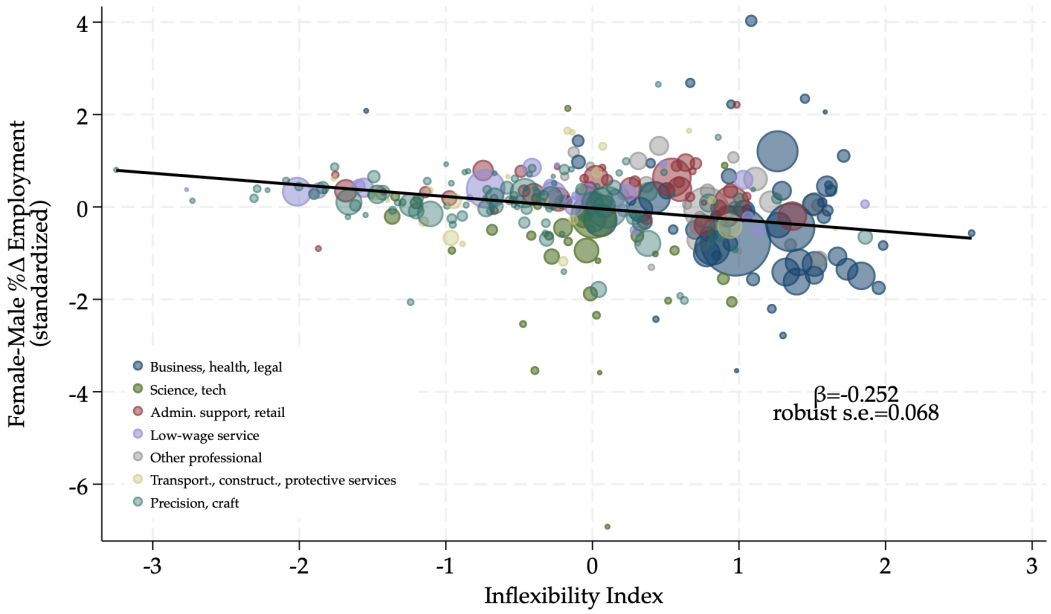
Notes: data are from the NLSY79. This figure presents heterogeneity in how wages respond to child birth by the flexibility of the individual's occupation prior to birth. The outcome is an individual's wage (coded as zero if they are not working). The plotted points represent coefficients on event time dummies interacted with a variable representing the lack of flexibility in the individual's occupation prior to the birth. Specifically, the variable is the average of the Inflexibility Index ($Inflexibility_o$) over all pre-birth observations for the individual. These coefficients are estimated from $k \in \{-27, 39\}$ but my plots focus on $k \in \{-6, 9\}$ for visibility. Estimates are divided by pre-birth averages in the outcome and therefore represent percentage changes. The estimates in pink represent the results for women, while the estimates in blue represent the results for men. 90% and 95% confidence intervals displayed. Standard errors robust and clustered on individual. As discussed in the text, the control group are individuals who never give birth over the sample period.

FIGURE 6: CHANGE IN FEMALE-MALE PROBABILITY OF EMPLOYMENT ACROSS OCCUPATIONS AFTER CHILDBIRTH

(A) PSEUDO EVENT STUDIES FOR FOUR ILLUSTRATIVE OCCUPATIONS



(B) CORRELATION BETWEEN PSEUDO DIFFERENCE-IN-DIFFERENCES ESTIMATES AND INFLEXIBILITY



Notes: Both panels use synthetic panel data constructed from the CPS pooled from 1972–2019. See Section 7.2 for details on sample construction and estimation. Panel (A): This panel reports results from pseudo event studies of first births, estimated separately by gender for four illustrative occupations (as indicated in the legend). The outcome is a dummy for employment in the occupation. The plotted points represent the difference between female and male estimates. Appendix Figure D.6 plots the female and male estimates separately. Panel (B): This panel plots the estimated change in women's relative employment in an occupation after childbirth against that occupation's Inflexibility Index ($Inflexibility_o$). Estimates are based on pseudo difference-in-differences around first births, computed separately by gender and occupation. The outcome is again a dummy for employment in the occupation, and the y-axis represents the female-minus-male estimate, standardized to have mean zero and standard deviation one. Occupations are weighted by total employment.

TABLE 3: ADOPTION OF FLEXIBILITY-ENHANCING TECHNOLOGY ACROSS OCCUPATIONS

	(1)	(2)	(3)	(4)
Panel A	Dep. Var.: Δ $\widehat{MotherFriendly}$ (CPS)			
$Social_o$	0.019		0.020	0.028
	(0.052)		(0.096)	(0.106)
$Inflexibility_o$		0.090***	0.249**	0.258**
		(0.034)	(0.101)	(0.121)
$Inflexibility_o \times Social_o$			0.128**	0.124*
			(0.055)	(0.065)
$Analytical_o$				0.002
				(0.115)
$Inflexibility_o \times Analytical_o$				0.005
				(0.056)
$Social_o \times Analytical_o$				0.026
				(0.074)
Obs.	320	320	320	320
R-squared	0.002	0.016	0.065	0.071
Panel B	Dep. Var.: Δ Avg. $\widetilde{ShareWFH}$ (ATUS)			
$Social_o$	0.006		0.001	0.001
	(0.005)		(0.008)	(0.009)
$Inflexibility_o$		0.008**	0.013	0.006
		(0.004)	(0.010)	(0.011)
$Inflexibility_o \times Social_o$			0.013***	0.011*
			(0.005)	(0.006)
$Analytical_o$				0.012
				(0.011)
$Inflexibility_o \times Analytical_o$				-0.004
				(0.007)
$Social_o \times Analytical_o$				0.010
				(0.006)
Obs.	313	313	313	313
R-squared	0.022	0.033	0.063	0.071
Base Pd. Controls	x	x	x	x
Base Pd. Controls $\times$ All o attributes			x	x

Notes: The outcome in Panel A is the change between periods 1972-1995 and 1996-2019 in the female-male employment penalty in each occupation. As discussed in the text, these are estimated for each occupation via pseudo difference in differences in the CPS data. The outcome in Panel B is the change in the average share of hours workers work-from-home in each occupation between periods 2003-2010 and 2011-2019. As discussed in the text, the share of a hours a worker works from home has been residualized by demographic characteristics. Both panels report the results from regressing these outcomes on various occupation-level characteristics from the O*NET. In all columns, I have included controls for the fraction of workers with a college education in the occupation and the fraction of workers who are female, both calculated in the CPS for the relevant base period. I additionally interact these controls with inflexibility and social skill intensity in Column 3, and also analytical skill intensity in Column 4. Standard errors are robust and observations are weighted by the number employed in the occupation in the relevant base period.

Appendix

Appendix A: Data Appendix

This data appendix describes the occupation codes, data sources, and various indices or measures I use in the paper in more detail.

A.1 Occupation codes

Across the various datasets and time periods I analyze in this paper, I rely on a consistent and balanced set of 3-digit occupation codes first created by Autor and Dorn (2013), then subsequently modified by Deming (2017) and, later, Hanson (2021) to accommodate more recent changes to the occupational classification system. For clarity, I will refer to these codes as "*occ1990ddgh*". These codes represent 325 unique (non-military) occupations, but the number of occupations represented in each analysis is sometimes smaller because certain occupations are not represented in the dataset or the occupation is too small.

A.2 Main data sources

Each of these data sources are summarized in the main text (Section 2). Below, I give additional details such as how I aggregate the occupation codes.

A.2.1 Occupational Network (O*NET)

I use the 2013 O*NET data to measure various attributes of occupations. More recent versions of the O*NET are available, but I use this version in order to most closely mimic Goldin (2014).

The raw O*NET data are at the 8-digit 2010 SOC level. Before constructing the indices and measures used in the analysis (e.g. the Inflexibility Index), I aggregate the O*NET variables up to *occ1990ddgh*. To do so, I:

1. Collapse the raw O*NET data (at the 8-digit 2010 SOC level) to the 6-digit 2010 SOC level by taking a simple average.

2. In preparation for the next step in which I apply a crosswalk from the Census Bureau, I reassign some of the 6-digit 2010 SOC codes to the 2010 SOC codes that appear in the Census Bureau crosswalk, which are mostly at the 6-digit level but sometimes are slightly more aggregate or differ. For example, the O*NET splits each type of Postsecondary teacher (e.g. music, business, religion, sociology) into its own 6-digit code. The Census Bureau crosswalk groups all Postsecondary teachers together.

3. Using a bridge developed by the Census Bureau,[26] I collapse the 2010 SOC codes to the 2010 ACS occupation codes by taking a simple average.

[26]The file can be found here: https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html

4. In preparation for the next step in which I apply a crosswalk from Deming (2017), I manually aggregate some 2010 ACS occupation codes to the codes available in the public-use 2010 ACS 1% sample.[27]

5. Using the crosswalk provided by the replication files for Deming (2017), I collapse the 2010 ACS (public-use) codes to the more aggregate Deming occupation codes by taking the weighted average. The weights are the number employed in the 2010 ACS occupation according to the 2010 ACS 1% sample.

6. Finally, using a crosswalk developed by Hanson (2021), I aggregate these codes to *occ1990ddgh* by taking the weighted average. The weights are the number employed in the Deming occupation code based on the 2010 ACS 1% sample.

Three *occ1990ddgh* codes do not appear in the O*NET data: auctioneers and sales support occupations not elsewhere classified, other telecom operators, and supervisors of guards. Consequently, I have 322 occupations for which I can measure various attributes.

A.2.2 American Community Survey (2015-2019) 5% Sample

I rely on the 2019 5-year American Community Survey (ACS) 5% sample where I observe individuals' wages and occupation choices. My sample restrictions primarily follow Goldin (2014). I restrict the sample to native-born, civilian individuals aged 25-64 who are employed full-time, full-year (at least 40 weeks, at least 35 hours per week) and report positive, non-missing annual earnings (wage income plus business and farm income). I omit occupation-demographic group cells for which I do not observe at least 25 men and 25 women so that I can reliably observe the gender wage gap within occupations. Note that weeks worked is only provided in binned values for years 2015-2018. Therefore, I impute the average number of weeks worked within each bin using the individuals in the 2019 sample.

A.2.3 National Longitudinal Survey of Youth - 1979 Cohort

I use the Weekly Work History files in the National Longitudinal Survey of Youth for the 1979 Cohort to build a person-year panel of labor market activity (e.g., employment, occupation, and wages) covering years 1979-2019. The NLSY79 Weekly Work History files compile information reported by respondents about their job held at the time of the survey as well as retrospective information on any jobs since the last interview. This allows me to form a relatively complete annual panel.

Most of my sample restrictions follow Guvenen et al. (2020) and are intended to focus on individuals who signal some initial attachment to the labor market and observations for which all I observe sufficient information. Table 4 summarizes how each restriction affects the number of observations. The raw data are at the person-job (or nonemployment) spell level. In each year, I focus on the job to which the respondent contributed the most hours. I begin by dropping observations in which the individual is not yet 22 or who are likely still in school (based on their age relative to their current

[27] I use this webpage (which concords more detailed codes from earlier ACS samples to less detailed codes from more recent samples) as a guide to map the codes into the 2010 ACS 1% sample codes: https://usa.ipums.org/usa/volii/occ_acs.shtml. Four codes are not found on this page, in which case I assign to it the 2010 ACS 1% sample code that has the closest title.

years of education). I then drop observations prior to the person reporting 2 consecutive years of full-time full-year (1400 annual hours) work. Next, I drop individuals with two or more years of military experience as well as any observations constituting military spells. I also drop brief labor market spells which occur prior to finishing one's education. Specifically, I drop observations where the person had 7 or less years of experience before pausing to acquire another degree. In order to clean the observations pertaining to one's job, I temporarily drop spells where the individual is not working (but I append these back to the panel later). I then clean duplicated information about a job within a year, given that I am aggregating the panel to the person-year level.[28] Next, I drop observations with missing occupation or wage information. I also drop observations with wages either below the 0.5th or above the 99.5th percentile of wage distribution in a given interview year. I drop individuals without information on social skills, cognitive skills, or their age at first birth. At this point, I merge back in the non-working spells and drop years for which there is no information on labor market status in any week. Finally, among individuals who have a child, I drop individuals who are not observed in the period just prior to birth and at least one period after treatment. While sample size precludes me from forcing a perfectly balanced sample, this helps me ensure a reasonable amount of balance in the sample. The final sample is 3,396 individuals and 103,264 observations.

TABLE 4: SUMMARY OF SAMPLE RESTRICTIONS

	Person-Year Obs.	**Individuals**	**% Obs. Remaining**
Full Sample	360221	6111	100.00
Reason observations dropped			
Below age 22 or in school	311403	6111	86.45
Prior to working FTFY for 2 years	281811	5755	78.23
Military individuals/spells	280674	5732	77.92
Prior to finishing education	280213	5732	77.79
Temporarily dropping non-working spells	232247	5732	64.47
Clean duplicates	154243	5732	42.82
Missing labor market info	146357	5716	40.63
Missing demographic info	180329	5229	50.06
Missing labor market status	154585	5229	42.91
Not observed pre/post birth	103264	3396	28.67

A.2.4 Current Population Survey, 1972-2019

I follow Kleven (2023) to build "synthetic" individuals in pooled CPS data in order to estimate difference-in-differences in Sections 7.2 and 8.

I focus on individuals aged 20-55 in the CPS ASEC and basic monthly files pooled for years 1972-2019. I drop active duty military and those without an identifiable race or occupation (conditional on being employed). I identify individual's approximate age at first birth based on their own age and the age of the eldest child living with them. I then match these individuals to 5 pre-birth surrogate observations. To do this, I retrieve outcomes of childless individuals in the same birth cohort who share the

[28] This occurs because people report their labor market information for each job between the current and last interview. In this process, I favor observations with more information, e.g. sometimes the person reports the wage a job in one survey round but not the other.

same demographic characteristics. For example, consider a woman observed in year 2000 at age 35 whose eldest child is age 5. To retrieve her surrogate observation in the year prior to birth ($k = -1$), I locate a childless, 30-year old woman in the year 1995 who shares the same demographic characteristics. The same process is performed for surrogate observations $k \in [-5, -4]$.

The demographic characteristics that I match on include: gender (male/female), age, year, education category (below high school, high school, some college, BA or more), marital status (married with spouse present, separated or spouse absent, divorced, widowed, never married), race (white non-hispanic, black non-hispanic, hispanic, other), and state. When there are multiple people with this set of demographic characteristics, I use the average of the outcome for everyone in the cell to form the surrogate observation. Among the treated individuals, I focus on those whose approximate first birth occurred between ages 25-45 and observations up to 10 years after the event. My final sample is comprised of synthetic individuals, each with 6 observations (1 post birth and 5 pre-birth).

A.3 Occupation-level attributes

Below I describe how I construct each of the occupation-level attributes used in the paper. Each measure is standardized to have mean 0 and standard deviation 1 unless stated otherwise. When a measure is formed out of multiple individual components, I first standardize the components individually, take the average, then re-standardize the resulting measure.

Inflexibility Index (O*NET): My flexibility measure follows Goldin (2014) and represents the average of five components from the O*NET. Below I list the survey questions and response scales for each component. For each component, the larger the value, the less flexible. Each of these dimensions come from the Work Context module, except the Establishing and Maintaining Interpersonal Relationships, which comes from Work Activities.

1. *Time pressure*: How often does this job require the worker to meet strict deadlines? Never/Once a year or more but not every month/Once a month or more but not every week/Once a week or more but not every day/Every day.

2. *Contact with others*: How much does this job require the worker to be in contact with others (face-to-face, by telephone, or otherwise) in order to perform it? No contact with others/Occasional contact with others/Contact with others about half the time/Contact with others most of the time/Constant contact with others.

3. *Establishing and Maintaining Interpersonal Relationships*: How important is establishing and maintaining interpersonal relationships to the performance of this job? (Establishing and maintaining interpersonal relationships is defined as "developing constructive and cooperative working relationships with others, and maintaining them over time.") Not important/Somewhat important/Important/Very important/Extremely important.

4. *Unstructured Work*: How much freedom do you have to determine the tasks, priorities, or goals of your current job? No freedom/Very little freedom/Limited

freedom/Some freedom/A lot of freedom.[29]

5. *Freedom to Make Decisions*: How much decision making freedom, without supervision, does the job offer? No freedom/Very little freedom/Limited freedom/Some freedom/A lot of freedom.

The first dimension captures some time sensitivity in task completion. The second two dimensions capture the necessity of working alongside people (who may need to be served at certain times), with the latter specifically capturing the continuity of relationships. The final two dimensions capture the level of worker discretion; the more freedom over one's task set, the less likely others can easily substitute for you in your absence. These components are intended to triangulate on time-intensity (first component) and how easily workers can substitute for one another (last four components), which jointly make it more valuable for workers to work particular, long, or continuous hours. Time intensity and worker substitutability could be considered two complementary features in inflexibility. Each feature is necessary but not sufficient. Consider one extreme: if workers are not substitutable for another, but there is no time-sensitivity in task completion, then workers can do their tasks whenever they want. Consider another extreme: if there is time-sensitivity, but workers are perfectly substitutable for one another, then it does not matter *who* the firm calls on to complete a task.

Social perceptiveness intensity (O*NET): My measure of social perceptiveness is based on the *Social Perceptiveness* component from the Skills module in the O*NET. The question asks "What level of social perceptiveness is needed to perform your current job?" and defines social perceptiveness as "being aware of others' reactions and understanding why they react as they do." The response scale ranges from 1-7.

[29]Two details may be worth clarifying. First, the O*NET documentation is slightly unclear about whether a higher numeric scale rating indicates less or more structure. On the one hand, the "Content Model Reference" lookup file describes the variable as "To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals?". This wording makes it sound like a higher value indicates *more structure*. On the other hand, "Survey Booklet Location" lookup file references O*NET Work Context questionnaire question #52. It is unclear which archived questionnaire maps to O*NET 2013, but across the questionnaires from 2008, 2012, and 2015, a higher value on the scale indeed indicates *less structure*. I default to this interpretation of the data. Intuitively, the Unstructured Component and the Freedom to Make Decisions component (described below) are positively correlated, suggesting that I have interpreted the documentation correctly. Moreover, I was able to locate the question "To what extent is this job structured for the worker..." in the 1998 O*NET documentation, which describes the response scale where a higher value indicates less structure, despite the misleading wording of the question text. Finally, I also cross-checked that my standardized value for this dimension for Lawyers and Judges (1.04) is similar to the value printed in Table 2 of Goldin (2014), which is 1.22. (They will not line up exactly because I am standardizing within a set of occupations that may be aggregated slightly differently.) Second, my interpretation that less structure indicates less flexibility is in line with the description of flexibility in Goldin (2014) (see, for example, the first full paragraph on page 1108) and with the data displayed in Table 2 (as I just described). However, the notes in Table 2 reference the "To what extent is this job structured for the worker..." wording of the question and say that "If the job is highly structured to the worker, there would be a lower chance that the worker would have close substitutes." I interpret this as a clerical error based on the discrepancies in the O*NET documentation, and I continue with the assumption that less structure (or, equivalently, more freedom) indicates less flexibility.

Routine task intensity (O*NET): My measure for routine task intensity follows Deming (2017) and is the average of two components from the Work Context module. The first component is the *Degree of Automation*, which asks "How automated is the job? Not at all automated/Slightly automated/Moderately automated/Highly automated/Completely automated." The second component is the *Importance of Repeating Same Tasks*, which asks "How important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job? Not important at all/Fairly important/Important/Very important/Extremely important."

Analytical (or cognitive) skill intensity (O*NET): My measure for analytical intensity follows Deming (2017) and is the average of three components. The first is *Mathematical Reasoning* from the Abilities module, which captures the level of "the ability to choose the right mathematical methods or formulas to solve a problem" needed in a job. The second is *Mathematics* from the Knowledge module and captures the level of "knowledge of arithmetic, algebra, geometry, calculus, statistics, and their applications" required in the job. The third is *Mathematics* from the Skills module and captures the level of "using mathematics to solve problems" required in the job. Each has a response scale varying from 1-7.

Social Composite (O*NET): This composite measure is from Deming (2017) and is the average of four components from the Skills module, each of which indicate the level of a specific skill that is needed in a job: *Social Perceptiveness* (described above), *Coordination* (adjusting actions in relation to others' actions), *Persuasion* (persuading others to change their minds or behavior), and *Negotiation* (bringing others together and trying to reconcile differences). Each has a response scale varying from 1-7.

Non-routine manual physical task intensity (O*NET): This composite measure is from Acemoglu and Autor (2011) and is the average of four components, each of which indicate the importance of certain tasks or skills in a job: *Operating Vehicles, Mechanized Devices, or Equipment* (running, maneuvering, navigating, or driving vehicles or mechanized equipment, such as forklifts, passenger vehicles, aircraft, or water craft) from the Work Activities module; *Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls* from the Work Context module; *Manual Dexterity* (the ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects from the Abilities module; and *Spatial Orientation* (the ability to know your location in relation to the environment or to know where other objects are in relation to you) from the Abilities module. Each has a response scale varying from 1-5.

Physical strength index (O*NET): This composite measure is the average of four components from the Abilities module, each of which indicate the level of a specific skill that is needed in a job: *Static Strength* (the ability to exert maximum muscle force to lift, push, pull, or carry objects), *Explosive Strength* (the ability to use short bursts of muscle force to propel oneself as in jumping or sprinting, or to throw an object), *Dynamic Strength* (the ability to exert muscle force repeatedly or continuously over time. This involves muscular endurance and resistance to muscle fatigue), and *Trunk Strength* (the ability to use your abdominal and lower back muscles to support part of

the body repeatedly or continuously over time without 'giving out' or fatiguing). Each has a response scale varying from 1-7.

Mixed measure of inflexibility, =1 if top $Inflexibility_o$ and Overwork (O*NET and ACS): This measure follows (Goldin et al., 2024) and is a binary variable equal to one if the occupation is in the top tercile of both the O*NET index ($Inflexibility_o$) and a measure of overwork, which is measured as the share of men in an occupation who work over 50 hours per week. Consistent with the other ACS data I use throughout the paper, I base my measure on of overwork on the 2015-2019 5% sample (described above). (Goldin et al., 2024)'s measure uses a 45 hour cut-off, but I follow (Cortés and Pan, 2016) and use a 50 hour cut-off.

Data-driven measure of inflexibility, $AltInflexIndex_o$ (various sources): This measure is the average of three standardized components, each from a separate paper in the literature:

- The first is the **overwork** measure referenced in the paragraph above.
- The second is a measure of **coordinated work hours** from Cubas et al. (2023). It represents the ratio of hours worked in the 8am to 5pm interval based on time diary data from the American Time Use Survey (ATUS), pooled between 2003-2019. To construct this, following Cubas et al. (2023), I limit the sample to 18-65 year old full time workers who worked full-time (minimum of 35 hours) in their main job. Both week days and weekends are included. Then, for each occupation I construct $ratio8to5_o = \frac{B_o}{A_o+B_o+C_o}$ where A, B, and C are the total minutes worked by individuals in the occupation (weighted by their sample weight) for time intervals 12-8am, 8am-5pm, and 5pm-12am, respectively. This ratio is higher if individuals' work hours are more concentrated in the 8am-5pm window. Cubas et al. (2023) show that the gender wage gap, especially among parents, is increasing in this measure.
- The third is a measure of the **convexity of earnings with respect to hours** worked similar to that used by Cortés and Pan (2019). I use the ACS 2015-2019 sample (described below) to regress log annual income on log annual hours, occupation fixed effects, and log annual hours interacted with occupation fixed effects. I also control for a female dummy, parental status dummy, age dummies, race dummies, year dummies, and dummies for years of education. The regression is weighted by the ACS sampling weights. I store the coefficient on the interaction between log annual hours and the occupation fixed effects. For interpretability, I then add these coefficients to the coefficient on log annual hours. The final measure thus varies at the occupation level and represents the elasticity of earnings with respect to hours worked. In contrast to Cortés and Pan (2019), I use annual hours worked (rather than weekly), I include the full sample of occupations rather than limit to skilled occupations, I include both men and women, and I do not limit to college educated individuals (although I do control for education).

Occupation-level attributes used in Figure D.2 (various sources): Figure D.2 plots an occupation's social perceptiveness against three different types of time demands:

- Panel (a): the **overwork** measure referenced in the paragraph above.
- Panel (b): the **coordinated work hours** measure referenced in the paragraph above.
- Panel (c): a measure of being **on-call for others** from the 2014 General Social Survey. The survey question asks "Some workers must respond to coworkers, supervisors, managers, customers, or clients about work-related matters when they are not working. These contacts may be by phone, text, instant message, email, etc. How often are you contacted about work-related matters when you are not working?" with the responses: never, less than once a month, once or twice a month, once a week, several times a week, once a day, or two or more times a day. Respondents can also refuse to answer or say they do not know/cannot choose, in which case they are dropped. In each occupation, I calculate the share of people who report being contacted "at least several times a week" or more. GSS sampling weights are applied.

Appendix B: Conceptual Framework

B.1 Labor supply sub-problem solutions

The labor supply sub-problem is given by

$$\underset{t_1,t_2}{max}\ \theta_g^{\mu}\left(0.5t_1^{\rho}+0.5t_2^{\rho}\right)^{\frac{1}{\rho}}+\lambda\left(T-\alpha_g t_1-t_2\right)$$

where I have dropped the occupation (o) subscripts and let $\rho \equiv \frac{\sigma-1}{\sigma}$ for brevity. The First Order Conditions are:

$$\theta_g^{\mu}\left(0.5t_1^{\rho}+0.5t_2^{\rho}\right)^{\frac{1}{\rho}-1}0.5t_1^{\rho-1}-\alpha_g\lambda=0$$

$$\theta_g^{\mu}\left(0.5t_1^{\rho}+0.5t_2^{\rho}\right)^{\frac{1}{\rho}-1}0.5t_2^{\rho-1}-\lambda=0$$

$$T-\alpha_g t_1-t_2=0$$

The solutions are therefore:

$$t_1^*\left(\alpha_g,T,\sigma\right)=\left(\frac{0.5}{\alpha_g}\right)^{\sigma}\frac{T}{\alpha_g^{1-\sigma}0.5^{\sigma}+0.5^{\sigma}}$$

$$t_2^*\left(\alpha_g,T,\sigma\right)=0.5^{\sigma}\frac{T}{\alpha_g^{1-\sigma}0.5^{\sigma}+0.5^{\sigma}}$$

B.2 Proofs of propositions

Proving propositions 1 and 2 requires taking derivatives of the expression for a worker's log earnings in an occupation:

$$\begin{aligned} lnQ_{og}\left(s_o,\sigma_o;.\right)=&\ \mu ln\left(s_o s_g+\kappa_0\right)+ln\left(T\right)\\ &+\sigma_o\left(\sigma_o-1\right)^{-1}ln\left(0.5\right)+\left(\sigma_o-1\right)^{-1}ln\left(\alpha_g^{1-\sigma_o}+1\right)\end{aligned} \tag{15}$$

Proof of Proposition 1 Recalling that $\alpha_g > 1$ and $\sigma_o > 1$,

$$\frac{\partial lnQ_{og}}{\partial \alpha_g} = \frac{-\alpha_g^{-\sigma_o}}{\alpha_g^{1-\sigma_o}+1} < 0$$

and

$$\begin{aligned}\frac{\partial^2 lnQ_{og}}{\partial \alpha_g \partial \sigma_o} &= \frac{\left(\alpha_g^{1-\sigma_o}+1\right)\left(ln\left(\alpha_g\right)\alpha_g^{-\sigma_o}\right) - \left(\alpha_g^{-\sigma_o}\right)\left(ln\left(\alpha_g\right)\alpha_g^{1-\sigma_o}\right)}{\left(\alpha_g^{1-\sigma_o}+1\right)^2} \\ &= \frac{\left(ln\left(\alpha_g\right)\alpha_g^{-\sigma_o}\right)}{\left(\alpha_g^{1-\sigma_o}+1\right)^2} > 0\end{aligned}$$

■

Proof of Proposition 2

$$\frac{\partial lnQ_{og}}{\partial s_g} = \frac{\mu s_o}{s_o s_g + \kappa_0} > 0$$

$$\frac{\partial^2 lnQ_{og}}{\partial s_g \partial s_o} = \frac{\mu\left(s_o s_g + \kappa_0\right) - \mu s_o s_g}{\left(s_o s_g + \kappa_0\right)^2} = \frac{\mu\kappa_0}{\left(s_o s_g + \kappa_0\right)^2} > 0$$

■

Propositions 3 and 4 are easily shown if we formulate the worker's occupational choice problem as an unconstrained problem where they choose σ_o to maximize the logged objective function

$$\begin{aligned}lnQ_{og}\left(\sigma_o;.\right) = \mu ln\left(-\kappa_1\sigma_o s_g + \epsilon_o s_g + \kappa_0\right) + ln\left(T\right) \\ + \sigma_o\left(\sigma_o - 1\right)^{-1} ln\left(0.5\right) + \left(\sigma_o - 1\right)^{-1} ln\left(\alpha_g^{1-\sigma_o}+1\right)\end{aligned} \tag{16}$$

Proof of Proposition 3 Expression 16 has increasing differences in α_g and σ_o:

$$\frac{\partial^2}{\partial \alpha_g \sigma_o}\left[\mu ln\left(-\kappa_1\sigma_o s_g + \epsilon_o s_g + \kappa_0\right) + ln\left(T\right) + \sigma_o\left(\sigma_o - 1\right)^{-1} ln\left(0.5\right) + \left(\sigma_o - 1\right)^{-1} ln\left(\alpha_g^{1-\sigma_o}+1\right)\right]$$

$$\begin{aligned}&= \frac{\partial}{\partial \sigma_o}\left[\left(\sigma_o - 1\right)^{-1}\frac{\left(1-\sigma_o\right)\alpha_g^{-\sigma_o}}{\alpha_g^{1-\sigma_o}+1}\right] \\ &= \frac{\partial}{\partial \sigma_o}\left[\frac{-\alpha_g^{-\sigma_o}}{\alpha_g^{1-\sigma_o}+1}\right] \\ &= \frac{ln\left(\alpha_g\right)\alpha_g^{-\sigma_o}\left(\alpha_g^{1-\sigma_o}+1\right) - ln\left(\alpha_g\right)\alpha_g^{-\sigma_o}\alpha_g^{1-\sigma_o}}{\left(\alpha_g^{1-\sigma_o}+1\right)^2} \\ &= \frac{ln\left(\alpha_g\right)\alpha_g^{-\sigma_o}}{\left(\alpha_g^{1-\sigma_o}+1\right)^2} > 0\end{aligned}$$

Therefore, the function $Q_{og}\left(\sigma_o;.\right)$ is log-supermodular in α_g and σ_o. By the key theorems on monotone comparative statics (Ashworth and Bueno de Mesquita, 2006; Top-

kis, 1978, 1998),

$$\frac{\partial \sigma_o^*}{\partial \alpha_g} > 0$$

■

Proof of Proposition 4 Expression 16 has increasing differences in $-s_g$ and σ_o:

$$\frac{\partial^2}{\partial\left(-s_g\right)\sigma_o}\left[\mu ln\left(-\kappa_1\sigma_o s_g+\epsilon_o s_g+\kappa_0\right)+ln\left(T\right)+\sigma_o\left(\sigma_o-1\right)^{-1}ln\left(0.5\right)+\left(\sigma_o-1\right)^{-1}ln\left(\alpha_g^{1-\sigma_o}+1\right)\right]$$

$$\begin{aligned}
&= \frac{\partial}{\partial\sigma_o}\left[\frac{\mu\left(\kappa_1\sigma_o-\epsilon_o\right)}{-\kappa_1\sigma_o s_g+\epsilon_o s_g+\kappa_0}\right] \\
&= \frac{\mu\kappa_1\left(-s_g\left(\kappa_1\sigma_o-\epsilon_o\right)+\kappa_0\right)-\mu\left(\kappa_1\sigma_o-\epsilon_o\right)\left(-\kappa_1 s_g\right)}{\left(-\kappa_1\sigma_o s_g+\epsilon_o s_g+\kappa_0\right)^2} \\
&= \frac{\mu\kappa_1\left(-s_g\left(\kappa_1\sigma_o-\epsilon_o\right)+\kappa_0\right)-\mu\kappa_1\left(-s_g\left(\kappa_1\sigma_o-\epsilon_o\right)\right)}{\left(-\kappa_1\sigma_o s_g+\epsilon_o s_g+\kappa_0\right)^2} \\
&= \frac{\mu\kappa_1\kappa_0}{\left(-\kappa_1\sigma_o s_g+\epsilon_o s_g+\kappa_0\right)^2} > 0
\end{aligned}$$

Therefore, the function $Q_{og}\left(\sigma_o;.\right)$ is log-supermodular in $-s_g$ and σ_o. By the key theorems on monotone comparative statics (Ashworth and Bueno de Mesquita, 2006; Topkis, 1978, 1998),

$$\frac{\partial \sigma_o^*}{\partial\left(-s_g\right)} > 0 \rightarrow \frac{\partial \sigma_o^*}{\partial s_g} < 0$$

■

Proof of Proposition 5 We can write the log wage gap in equilibrium between a representative female and male worker in the same occupation, $ln\left(Q_{of}^*/Q_{om}^*\right)$,as

$$\begin{aligned}
Q_o^* = ln\left(Q_{of}^*/Q_{om}^*\right) =& \mu ln\left[s_f s_o+\kappa_0\right]+\frac{1}{\sigma_o-1}ln\left[\alpha_f^{1-\sigma_o}+1\right] \\
&-\mu ln\left[\left(s_m s_o+\kappa_0\right)\right]-\frac{1}{\sigma_o-1}ln\left[\alpha_m^{1-\sigma_o}+1\right]
\end{aligned}$$

where $s_o = -\kappa_1\sigma_o + \varepsilon_o$. Consider the total effect of choosing a more flexible or a more social occupation:

$$\begin{aligned}
\frac{\Delta Q_o^*}{\Delta\sigma_o} &= \frac{\partial Q_o}{\partial s_o}\frac{\partial s_o}{\partial\sigma_o}+\frac{\partial Q_o}{\partial\sigma_o} \\
\frac{\Delta Q_o^*}{\Delta s_o} &= \frac{\partial Q_o}{\partial s_o}+\frac{\partial Q_o}{\partial\sigma_o}\frac{\partial\sigma_o}{\partial s_o}
\end{aligned}$$

By Proposition 1 and the assumption $\alpha_f > \alpha_m$, it follows that σ_o has a positive impact on women's relative earnings ($\frac{\partial Q_o}{\partial\sigma_o} > 0$). Likewise, by Proposition 2 and the assumption $s_f > s_m$, it follows that s_o has a positive impact on women's relative earnings ($\frac{\partial Q_o}{\partial s_o} > 0$). However, the technological constraint (Equation 5) implies that $\frac{\partial s_o}{\partial\sigma_o} = -\kappa_1 < 0$ and $\frac{\partial\sigma_o}{\partial s_o} = -\frac{1}{\kappa_1} < 0$. Therefore:

$$\frac{\Delta Q_o^*}{\Delta \sigma_o} = \underbrace{\frac{\partial Q_o}{\partial s_o}}_{+}\underbrace{\frac{\partial s_o}{\partial \sigma_o}}_{-} + \underbrace{\frac{\partial Q_o}{\partial \sigma_o}}_{+} \Longrightarrow \frac{\partial Q_o}{\partial \sigma_o} > \frac{\Delta Q_o^*}{\Delta \sigma_o}$$

$$\frac{\Delta Q_o^*}{\Delta s_o} = \underbrace{\frac{\partial Q_o}{\partial s_o}}_{+} + \underbrace{\frac{\partial Q_o}{\partial \sigma_o}\frac{\partial \sigma_o}{\partial s_o}}_{+\quad -} \Longrightarrow \frac{\partial Q_o}{\partial s_o} > \frac{\Delta Q_o^*}{\Delta s_o}$$

That is, while moving to an occupation with higher σ_o results in disproportionately higher wages for women, this transition is bundled with a *lower* s_o, which acts as a countervailing force on their wages. Or, equivalently, an occupation with higher s_o results in higher female-male wages, but this increase is offset by lower σ_o.■

Proof of Proposition 6 I show that because women value σ_o more, they *less willingly forgo* σ_o in favor of more s_o. Workers choose σ_o and s_o to maximize log earnings (Expression 15) subject to the constraint given by Equation 5.

$$\underset{\sigma_o, s_o}{max} \quad ln\left((s_o s_g + \kappa_0)^{\mu} T 0.5^{\frac{\sigma_o}{\sigma_o - 1}} \left[\alpha_g^{1-\sigma_o} + 1\right]^{\frac{1}{\sigma_o - 1}}\right) - \lambda\left(s_o + \kappa_1 \sigma_o - \epsilon_o\right)$$

The First Order Conditions are

$$\frac{\partial \mathcal{L}}{\partial \sigma_o} = \underbrace{\frac{\partial ln Q_{og}}{\partial \sigma_o}}_{MU^g_{\sigma_o}} - \lambda \kappa_1 = 0$$

$$\frac{\partial \mathcal{L}}{\partial s_o} = \underbrace{\frac{\partial ln Q_{og}}{\partial s_o}}_{MU^g_{s_o}} - \lambda = 0$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = s_o + \kappa_1 \sigma_o - \epsilon_o = 0$$

These conditions imply that in equilibrium, the marginal rate of substitution must equal κ_1:

$$\underbrace{\frac{MU^g_{\sigma_o}}{MU^g_{s_o}}}_{MRS^g} = \kappa_1$$

Because $\alpha_f > \alpha_m$, Proposition 1 implies that $MU^f_{\sigma_o} > MU^m_{\sigma_o}$. Likewise, because $s_f > s_m$, Proposition 2 implies that $MU^f_{s_o} > MU^m_{s_o}$. Notice that $MU^g_{s_o}$ only depends on gender through s_g. Therefore, at $s_f = s_m = \tilde{s}$, $MU^f_{s_o} = MU^m_{s_o}$ and thus $MRS^f > MRS^m$. In other words, holding worker social skills constant, women more willingly trade s_o for σ_o and, conversely, less willingly give up σ_o in favor of more s_o. Therefore, as $\tilde{s}$ increases, both men and women will choose less σ_o^*, but women will make this trade off at a slower rate:

$$\frac{\partial \sigma_o^{*,m}}{\partial \tilde{s}} < \frac{\partial \sigma_o^{*,f}}{\partial \tilde{s}} < 0$$

■

Proof of Proposition 8 Let the profit gain from adopting $\overline{\tau}_o$ be

$$\Delta\pi_o^* = K\sum_g \Big(s_o s_g + \kappa_0\Big)^{\mu(1+\varepsilon)}\Big[\Psi_g\big(\sigma_o(\overline{\tau}_o)\big)^{1+\varepsilon} - \Psi_g\big(\sigma_o(\underline{\tau}_o)\big)^{1+\varepsilon}\Big]$$

where $\Psi_g = T0.5^{\frac{\sigma_o(\tau_o)}{\sigma_o(\tau_o)-1}}\left[\alpha_g^{1-\sigma_o(\tau_o)}+1\right]^{\frac{1}{\sigma_o(\tau_o)-1}}$.

(i) Differentiating $\Delta\pi_o^*$ with respect to s_o gives

$$\frac{\partial\Delta\pi^*}{\partial s_o} = K\sum_g \underbrace{\mu(1+\varepsilon)s_g\Big(s_o s_g+\kappa_0\Big)^{\mu(1+\varepsilon)-1}}_{A_g(s_o)>0}\Delta{\Psi_g}^{1+\varepsilon}$$

Differentiating with respect to $\underline{\tau}_o$ gives

$$\frac{\partial^2\Delta\pi^*}{\partial s_o\partial\left(-\underline{\tau}_o\right)} = \sum_g A_g(s_o)\underbrace{\frac{\partial\Delta{\Psi_g}^{1+\varepsilon}}{\partial\left(-\underline{\tau}_o\right)}}_{B_g(\underline{\tau}_o)>0}$$

where $B_g(\underline{\tau}_o)>0$ follows by the concavity of σ_o in $\underline{\tau}_o$. Therefore, $\frac{\partial^2\Delta\pi^*}{\partial s_o\partial(-\underline{\tau}_o)}>0$.

(ii) $A_g(s_o)$ is increasing in s_g. Moreover, $B_g(\underline{\tau}_o)$ is increasing in α_g. Therefore, $\frac{\partial^2\Delta\pi^*}{\partial s_o\partial(-\underline{\tau}_o)}$ is larger when $s_f>s_m$ and $\alpha_f>\alpha_m$ relative to a case where either $s_f=s_m$ or $\alpha_f=\alpha_m$. I assume away the cases where $s_f<s_m$ or $\alpha_f<\alpha_m$ for simplicity. ■

B.3 Firms' profit maximization

Let labor supply curves for male and female workers be given by $L_{og}=\kappa w_{og}^{\varepsilon}$, where κ is a labor supply shifter and ε is the elasticity. Firms choose wages to maximize profits, taking labor supply curves as given:

$$\begin{aligned}\underset{w_{of},w_{om}}{max}\ \pi_o &= \sum_g pQ_{og}L_{og} - w_{og}L_{og}\\ &= \sum_g pQ_{og}\kappa w_{og}^{\varepsilon} - \kappa w_{og}^{\varepsilon+1}\end{aligned}$$

The First Order Conditions are

$$\frac{\partial\pi_o}{\partial w_{og}} = pQ_{og}\kappa\varepsilon w_{og}^{\varepsilon-1} - \kappa\left(\varepsilon+1\right)w_{og}^{\varepsilon} = 0$$

which implies

$$w_{og}^* = pQ_{og}\frac{\varepsilon}{\varepsilon+1}$$

for $g = \{m, f\}$. Equilibrium profit is

$$\begin{aligned}\pi_o^* &= \sum_g pQ_{og}\kappa \left(pQ_{og}\frac{\varepsilon}{\varepsilon+1}\right)^{\varepsilon} - \kappa\left(pQ_{og}\frac{\varepsilon}{\varepsilon+1}\right)^{\varepsilon+1} \\ &= K\sum_g (Q_{og})^{1+\varepsilon}\end{aligned}$$

where $K = p^{1+\varepsilon}\kappa\left(\frac{\varepsilon}{\varepsilon+1}\right)^{\varepsilon}\left(\frac{1}{\varepsilon+1}\right)$.

B.4 Empirical Implication 1 and Omitted Variable Bias

To build intuition, I sketch the empirical test of Empirical Implication 1 and show its connection to the omitted-variable-bias formula. Let y_o represent either women's relative average wages ($ln\left(\bar{wage}_o^f\right) - ln\left(\bar{wage}_o^m\right)$) or women's relative propensity to sort into an occupation ($ln\left(\frac{employed_o^f}{employed^f}\right) - ln\left(\frac{employed_o^m}{employed^m}\right)$), which I measure in the ACS. Let s_o and σ_o represent social task intensity and flexibility as measured in the O*NET. Consider the regression models:

$$y_o = \beta_0 + \beta_1\sigma_o + \beta_2 s_o + \varepsilon_o \tag{17}$$
$$y_o = \rho_0 + \rho_1\sigma_o + u_o \tag{18}$$
$$y_o = \gamma_0 + \gamma_1 s_o + \upsilon_o \tag{19}$$

Empirical Implication 1 implies that

$$\begin{aligned}\beta_1 &> 0 \\ \beta_2 &> 0 \\ \beta_1 &> \rho_1 \\ \beta_2 &> \gamma_1\end{aligned}$$

To see why the final two inequalities hold, notice that $\rho_1 = \beta_1 - \kappa_1\beta_2 \implies \beta_1 > \rho_1$ and $\gamma_1 = \beta_2 - \frac{1}{\kappa_1}\beta_1 \implies \beta_2 > \gamma_1$ where κ_1 represents the relationship between flexibility and social task intensity from the regression model $s_o = -\kappa_1\sigma_o + \epsilon_o$. In other words, the positive relationship between flexibility and social task intensity and women's relative wages and employment is biased towards $-\infty$ in models 18 and 19.■

Appendix C: Additional Tables

TABLE C.1: ROBUSTNESS OF CORRELATION BETWEEN SOCIAL PERCEPTIVENESS AND INFLEXIBLITY ACROSS OCCUPATIONS

	Coefficient	Robust S.E.
Benchmark:		
O*NET Index: $Inflexibility_o$	0.842***	(0.068)
Sensitivity to components, sample, weighting:		
$Inflexibility_o$ weighted by college; top income occs	0.755***	(0.090)
$Inflexibility_o$ weighted by college	0.868***	(0.081)
$Inflexibility_o$ omitting Time Pressure	0.923***	(0.068)
$Inflexibility_o$ omitting Contact with Others	0.789***	(0.070)
$Inflexibility_o$ omitting Maintaining Relationships	0.719***	(0.075)
$Inflexibility_o$ omitting Contact *and* Relations	0.625***	(0.081)
$Inflexibility_o$ omitting Unstructure Work	0.823***	(0.066)
$Inflexibility_o$ omitting Freedom Over Decisions	0.842***	(0.068)
Alternative measures:		
Data-driven: $AltInflexIndex_o$	0.225**	(0.110)
Mixed: =1 if Top $Inflexibility_o$ and Overwork	1.117***	(0.143)

Notes: This table reports results from regressions of an occupation's social perceptiveness demands on a measure of its inflexibility. Every row represents a different regression and reports the coefficient on inflexibility. The first row provides the main measure of inflexibility used throughout the paper, the next set of rows weight occupations different and omit specific components of the index, and the final two rows use the alternative measures of inflexibility discussed in Section 2.

TABLE C.2: RELATIONSHIP BETWEEN OCCUPATION CHARACTERISTICS AND GENDER GAPS IN EMPLOYMENT AND WAGES - LIMIT SAMPLE TO COLLEGE EDUCATED

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Log share employed, $\ln(\frac{Emp_{oegp}}{Emp_{egp}})$					
$Female_g \times Inflexibility_o$	0.192		-0.131	0.195		-0.140
	(0.127)		(0.155)	(0.120)		(0.142)
$Female_g \times Social_o$		0.314***	0.393**		0.346***	0.434***
		(0.119)	(0.152)		(0.115)	(0.143)
$Female_g \times Analytical_o$				-0.289***	-0.310***	-0.311***
				(0.096)	(0.098)	(0.096)
$Female_g \times Routine_o$				-0.009	0.079	0.089
				(0.140)	(0.147)	(0.146)
Obs.	1210	1210	1210	1210	1210	1210
Adj. R-sq.	0.855	0.863	0.864	0.863	0.873	0.873
Panel B	Avg. log earnings (resid.), $\overline{ln(earnings_{oegp})}$					
$Female_g \times Inflexibility_o$	-0.014		-0.053***	-0.021**		-0.047***
	(0.011)		(0.013)	(0.010)		(0.012)
$Female_g \times Social_o$		0.015	0.047***		0.004	0.033***
		(0.010)	(0.010)		(0.010)	(0.009)
$Female_g \times Analytical_o$				-0.012	-0.014	-0.014*
				(0.008)	(0.008)	(0.007)
$Female_g \times Routine_o$				-0.034***	-0.030***	-0.027***
				(0.009)	(0.010)	(0.010)
Obs.	1210	1210	1210	1210	1210	1210
Adj. R-sq.	0.963	0.964	0.966	0.968	0.967	0.970
γ_{egp}	X	X	X	X	X	X
γ_o	X	X	X	X	X	X
γ_{oep}	X	X	X	X	X	X

Notes: data are from ACS 2015-2019 and O*NET 2013. This table reports results from regressions of log employment shares and wages on occupation attributes interacted with a dummy for female, Female_g. Observations are a cells at the occupation $o \times$ gender $g \times$ parental-status p (at least one child versus no children) level. Sample is limited to college educated individuals. Observations are weighted by number employed in the cell. The outcome in the top panel is the log employment share of a demographic group in that occupation. The outcome in the bottom panel is the average of log earnings (residualized with respect to hours worked and demographic characteristics). The first three columns regress the outcome on an occupation's Inflexibility Index ($Inflexibility_o$) and an occupation's social perceptiveness skill intensity ($Social_o$). The next three columns additionally include controls for occupation's analytical skill intensity and routine task intensity. All columns include fixed effects for demographic group FE (γ_{egp}) and all two-way and three-way interactions of occupation, parental status, and education FE (γ_{oep}). Standard errors are robust and clustered on occupation.

TABLE C.3: RELATIONSHIP BETWEEN OCCUPATION CHARACTERISTICS AND GENDER GAPS IN EMPLOYMENT AND WAGES - LIMIT SAMPLE TO COLLEGE EDUCATED, HIGH INCOME SAMPLE

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Log share employed, ln($\frac{Emp_{oegp}}{Emp_{egp}}$)					
$Female_g \times Inflexibility_o$	0.329*		-0.146	0.339*		-0.215
	(0.183)		(0.300)	(0.186)		(0.304)
$Female_g \times Social_o$		0.511**	0.629		0.616**	0.767*
		(0.249)	(0.389)		(0.250)	(0.386)
$Female_g \times Analytical_o$				-0.095	-0.068	-0.129
				(0.183)	(0.179)	(0.194)
$Female_g \times Routine_o$				0.152	0.256*	0.260*
				(0.136)	(0.146)	(0.143)
Obs.	316	316	316	316	316	316
Adj. R-sq.	0.850	0.866	0.866	0.852	0.874	0.874
Panel B	Avg. log earnings (resid.), $\overline{ln(earnings_{oegp})}$					
$Female_g \times Inflexibility_o$	-0.024		-0.067***	-0.050***		-0.080***
	(0.014)		(0.019)	(0.014)		(0.020)
$Female_g \times Social_o$		0.002	0.056**		-0.014	0.042**
		(0.017)	(0.022)		(0.019)	(0.019)
$Female_g \times Analytical_o$				-0.023	-0.002	-0.025
				(0.015)	(0.016)	(0.015)
$Female_g \times Routine_o$				-0.036***	-0.032***	-0.030***
				(0.011)	(0.012)	(0.010)
Obs.	316	316	316	316	316	316
Adj. R-sq.	0.933	0.930	0.938	0.943	0.936	0.946
γ_{egp}	X	X	X	X	X	X
γ_o	X	X	X	X	X	X
γ_{oep}	X	X	X	X	X	X

Notes: data are from ACS 2015-2019 and O*NET 2013. This table reports results from regressions of log employment shares and wages on occupation attributes interacted with a dummy for female, Female_g. Observations are a cells at the occupation $o \times$ gender $g \times$ parental-status p (at least one child versus no children) level. Sample is limited to college educated individuals and occupations in the top quartile of average male income (as in Figure 1). Observations are weighted by number employed in the cell. The outcome in the top panel is the log employment share of a demographic group in that occupation. The outcome in the bottom panel is the average of log earnings (residualized with respect to hours worked and demographic characteristics). The first three columns regress the outcome on an occupation's Inflexibility Index ($Inflexibility_o$) and an occupation's social perceptiveness skill intensity ($Social_o$). The next three columns additionally include controls for occupation's analytical skill intensity and routine task intensity. All columns include fixed effects for demographic group FE (γ_{egp}) and all two-way and three-way interactions of occupation, parental status, and education FE (γ_{oep}). Standard errors are robust and clustered on occupation.

TABLE C.4: RELATIONSHIP BETWEEN OCCUPATION CHARACTERISTICS AND GENDER GAPS IN EMPLOYMENT AND WAGES - HIGH INCOME, COLLEGE EDUCATED SAMPLE

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Women's Relative Employment					
$Inflexibility_o$	0.504**		-0.175	0.418**		-0.340
	(0.208)		(0.339)	(0.203)		(0.333)
$Social_o$		0.763**	0.899*		0.827***	1.052**
		(0.295)	(0.460)		(0.306)	(0.442)
Obs.	80	80	80	80	80	80
R-squared	0.13	0.28	0.29	0.15	0.34	0.36
Other Task Controls				X	X	X
Panel B	Women's Relative Earnings (Residualized)					
$Inflexibility_o$	-0.035**		-0.085***	-0.056***		-0.093***
	(0.015)		(0.020)	(0.015)		(0.021)
$Social_o$		0.001	0.066***		-0.010	0.052**
		(0.021)	(0.021)		(0.024)	(0.021)
Obs.	80	80	80	80	80	80
R-squared	0.09	0.00	0.22	0.24	0.10	0.32
Other Task Controls				X	X	X

Notes: data are from ACS 2015-2019 and O*NET 2013. As in Figure 1, each observation is a 3-digit occupation in at least the 75th percentile in male earnings, and the sample of workers is limited to the college educated. The outcome in Panel A is the female-to-male ratio of log earnings (residualized with respect to hours worked and demographic characteristics) and the outcome in Panel B is the female-to-male log ratio of employment shares. Columns 1-3 regress these outcomes on social intensity and the inflexibility index, and columns 4-6 repeat these regressions while additionally controlling for routine task intensity and analytical skill demands. Standard errors are robust and observations are weighted by employment.

TABLE C.5: RELATIONSHIP BETWEEN OCCUPATION CHARACTERISTICS AND GENDER GAPS IN EMPLOYMENT AND WAGES - HETEROGENEITY BY PARENTAL STATUS

	(1)	(2)	(3)	(4)
	Sorting, $\ln(\frac{Emp_{oegp}}{Emp_{egp}})$		Earnings, $\overline{ln(earnings_{oegp})}$	
$Female_g \times Inflexibility_o$	-0.055	-0.044	-0.017*	-0.011
	(0.150)	(0.144)	(0.008)	(0.008)
$Female_g \times Social_o$	0.538***	0.514***	0.024***	0.016**
	(0.155)	(0.145)	(0.008)	(0.008)
$Female_g \times Analytical_o$	-0.335***	-0.316***	-0.012	-0.011
	(0.116)	(0.110)	(0.009)	(0.008)
$Female_g \times Routine_o$	0.343***	0.346***	0.001	0.006
	(0.117)	(0.105)	(0.008)	(0.007)
$Female_g \times Parent_p \times Inflexibility_o$	-0.068**	-0.095**	0.001	-0.013**
	(0.028)	(0.042)	(0.005)	(0.007)
$Female_g \times Parent_p \times Social_o$		0.055		0.018***
		(0.041)		(0.006)
$Female_g \times Parent_p \times Analytical_o$		-0.042		-0.000
		(0.031)		(0.006)
$Female_g \times Parent_p \times Routine_o$		-0.008		-0.013**
		(0.047)		(0.006)
Obs.	2440	2440	2440	2440
Adj. R-sq.	0.818	0.817	0.968	0.969
γ_{egp}	X	X	X	X
γ_{oep}	X	X	X	X

Notes: data are from ACS 2015-2019 and O*NET 2013. This table reports results from regressions of log employment shares and wages on occupation attributes interacted with a dummy for female (Female_g) and female times parental status ($\text{Female}_g \times \text{Parent}_p$). Observations are a cells at the occupation $o \times$ education (college versus noncollege) $e \times$ gender $g \times$ parental-status p (at least one child versus no children) level. Observations are weighted by number employed in the cell. The outcome in columns 1-2 is log employment share of a demographic group in that occupation. The outcome in columns 3-4 is the average of log earnings (residualized with respect to hours worked and demographic characteristics). All columns include fixed effects for demographic group FE (γ_{egp}) and all two-way and three-way interactions of occupation, parental status, and education FE (γ_{oep}). Standard errors are robust and clustered on occupation.

TABLE C.6: RELATIONSHIP BETWEEN OCCUPATION CHARACTERISTICS AND GENDER GAPS IN EMPLOYMENT AND WAGES - USING ALTERNATIVE FLEXIBLITY INDEX ($Inflexibility_o$ AND OVERWORK)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Log share employed, ln($\frac{Emp_{oegp}}{Emp_{egp}}$)					
$Female_g \times$ top $Inflexibility_o$ and Overwork	-0.252		-0.712***	-0.119		-0.524**
	(0.210)		(0.226)	(0.238)		(0.231)
$Female_g \times Social_o$		0.321***	0.508***		0.481***	0.584***
		(0.105)	(0.093)		(0.105)	(0.104)
$Female_g \times Analytical_o$				-0.099	-0.347***	-0.271**
				(0.113)	(0.116)	(0.112)
$Female_g \times Routine_o$				0.192*	0.338***	0.268**
				(0.108)	(0.117)	(0.111)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.789	0.801	0.815	0.793	0.818	0.825
Panel B	Avg. log earnings (resid.), $\overline{ln(earnings_{oegp})}$					
$Female_g \times$ top $Inflexibility_o$ and Overwork	-0.033**		-0.053***	-0.038***		-0.054***
	(0.014)		(0.015)	(0.014)		(0.014)
$Female_g \times Social_o$		0.008	0.022***		0.013*	0.023***
		(0.007)	(0.006)		(0.007)	(0.005)
$Female_g \times Analytical_o$				0.001	-0.014	-0.006
				(0.007)	(0.009)	(0.007)
$Female_g \times Routine_o$				-0.010	-0.000	-0.007
				(0.009)	(0.008)	(0.008)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.969	0.968	0.970	0.969	0.968	0.970
γ_{egp}	X	X	X	X	X	X
γ_o	X	X	X	X	X	X
γ_{oep}	X	X	X	X	X	X

Notes: data are from ACS 2015-2019 and O*NET 2013. This table reports results from regressions of log employment shares and wages on occupation attributes interacted with a dummy for female, $Female_g$. Observations are a cells at the occupation $o \times$ education (college versus noncollege) $e \times$ gender $g \times$ parental-status p (at least one child versus no children) level. Observations are weighted by number employed in the cell. The outcome in the top panel is the log employment share of a demographic group in that occupation. The outcome in the bottom panel is the average of log earnings (residualized with respect to hours worked and demographic characteristics). The first three columns regress the outcome on an occupation's social perceptiveness skill intensity ($Social_o$) and a dummy indicating that the occupation is in the top tercile of the $Inflexibility_o$ and Overwork measures. See 2.1.1 for full details. The next three columns additionally include controls for occupation's analytical skill intensity and routine task intensity. All columns include fixed effects for demographic group FE (γ_{egp}) and all two-way and three-way interactions of occupation, parental status, and education FE (γ_{oep}). Standard errors are robust and clustered on occupation.

TABLE C.7: RELATIONSHIP BETWEEN OCCUPATION CHARACTERISTICS AND GENDER GAPS IN EMPLOYMENT AND WAGES - USING ALTERNATIVE FLEXIBLITY INDEX (OVERWORK, COORDINATED HOURS, AND EARNINGS CONVEXITY)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Log share employed, $\ln(\frac{Emp_{oegp}}{Emp_{egp}})$					
$Female_g \times AltInflexIndex_o$	-0.135		-0.222**	-0.151		-0.205**
	(0.089)		(0.087)	(0.111)		(0.092)
$Female_g \times Social_o$		0.321***	0.402***		0.481***	0.513***
		(0.105)	(0.100)		(0.105)	(0.098)
$Female_g \times Analytical_o$				-0.015	-0.347***	-0.211*
				(0.134)	(0.116)	(0.121)
$Female_g \times Routine_o$				0.216**	0.338***	0.349***
				(0.105)	(0.117)	(0.111)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.791	0.801	0.811	0.796	0.818	0.824
Panel B	Avg. log earnings (resid.), $\overline{ln(earnings_{oegp})}$					
$Female_g \times AltInflexIndex_o$	-0.027***		-0.031***	-0.033***		-0.035***
	(0.005)		(0.005)	(0.006)		(0.006)
$Female_g \times Social_o$		0.008	0.020***		0.013*	0.018***
		(0.007)	(0.005)		(0.007)	(0.005)
$Female_g \times Analytical_o$				0.016*	-0.014	0.009
				(0.008)	(0.009)	(0.009)
$Female_g \times Routine_o$				-0.003	-0.000	0.002
				(0.006)	(0.008)	(0.006)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.972	0.968	0.973	0.972	0.968	0.973
γ_{egp}	X	X	X	X	X	X
γ_o	X	X	X	X	X	X
γ_{oep}	X	X	X	X	X	X

Notes: data are from ACS 2015-2019 and O*NET 2013. This table reports results from regressions of log employment shares and wages on occupation attributes interacted with a dummy for female, Female_g. Observations are a cells at the occupation $o \times$ education (college versus noncollege) $e \times$ gender $g \times$ parental-status p (at least one child versus no children) level. Observations are weighted by number employed in the cell. The outcome in the top panel is the log employment share of a demographic group in that occupation. The outcome in the bottom panel is the average of log earnings (residualized with respect to hours worked and demographic characteristics). The first three columns regress the outcome on an occupation's social perceptiveness skill intensity ($Social_o$) and an alternative index proxying for inflexibility, which is the average of three standardized components: long hours, coordinated hours, and elasticity of earnings to hours. See 2.1.1 for full details. The next three columns additionally include controls for occupation's analytical skill intensity and routine task intensity. All columns include fixed effects for demographic group FE (γ_{egp}) and all two-way and three-way interactions of occupation, parental status, and education FE (γ_{oep}). Standard errors are robust and clustered on occupation.

TABLE C.8: RELATIONSHIP BETWEEN OCCUPATION CHARACTERISTICS AND GENDER GAPS IN EMPLOYMENT AND WAGES - USING BROADER SOCIAL SKILL COMPOSITE

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Log share employed, $\ln(\frac{Emp_{oegp}}{Emp_{egp}})$					
$Female_g \times Inflexibility_o$	0.199*		0.351*	0.300***		0.288
	(0.106)		(0.186)	(0.104)		(0.184)
$Female_g \times SocialComposite_o$		0.084	-0.178		0.241**	0.016
		(0.105)	(0.183)		(0.120)	(0.205)
$Female_g \times Analytical_o$				-0.263**	-0.285**	-0.268**
				(0.106)	(0.122)	(0.122)
$Female_g \times Routine_o$				0.246**	0.277**	0.249**
				(0.112)	(0.122)	(0.123)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.792	0.788	0.793	0.802	0.798	0.801
Panel B	Avg. log earnings (resid.), $\overline{ln(earnings_{oegp})}$					
$Female_g \times Inflexibility_o$	-0.002		-0.001	0.001		-0.000
	(0.007)		(0.010)	(0.007)		(0.010)
$Female_g \times SocialComposite_o$		-0.003	-0.002		0.001	0.001
		(0.007)	(0.010)		(0.008)	(0.012)
$Female_g \times Analytical_o$				-0.008	-0.009	-0.009
				(0.008)	(0.010)	(0.010)
$Female_g \times Routine_o$				-0.003	-0.003	-0.003
				(0.008)	(0.008)	(0.008)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.967	0.967	0.967	0.968	0.968	0.968
γ_{egp}	X	X	X	X	X	X
γ_o	X	X	X	X	X	X
γ_{oep}	X	X	X	X	X	X

Notes: data are from ACS 2015-2019 and O*NET 2013. This table reports results from regressions of log employment shares and wages on occupation attributes interacted with a dummy for female, $Female_g$. Observations are a cells at the occupation $o \times$ education (college versus noncollege) $e \times$ gender $g \times$ parental-status p (at least one child versus no children) level. Observations are weighted by number employed in the cell. The outcome in the top panel is the log employment share of a demographic group in that occupation. The outcome in the bottom panel is the average of log earnings (residualized with respect to hours worked and demographic characteristics). The first three columns regress the outcome on an occupation's Inflexibility Index ($Inflexibility_o$) and an occupation's social skill intensity index as defined by Deming (2017) ($SocialComposite_o$). The next three columns additionally include controls for occupation's analytical skill intensity and routine task intensity. All columns include fixed effects for demographic group FE (γ_{egp}) and all two-way and three-way interactions of occupation, parental status, and education FE (γ_{oep}). Standard errors are robust and clustered on occupation.

TABLE C.9: RELATIONSHIP BETWEEN OCCUPATION CHARACTERISTICS AND GENDER GAPS IN EMPLOYMENT AND WAGES - USING BROADER SOCIAL SKILL COMPOSITE AND ALTERNATIVE FLEXIBLITY INDEX (OVERWORK, COORDINATED HOURS, AND EARNINGS CONVEXITY)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Log share employed, ln($\frac{Emp_{oegp}}{Emp_{egp}}$)					
$Female_g \times AltInflexIndex_o$	-0.135		-0.230**	-0.151		-0.247**
	(0.089)		(0.110)	(0.111)		(0.115)
$Female_g \times SocialComposite_o$		0.084	0.231*		0.241**	0.353***
		(0.105)	(0.128)		(0.120)	(0.129)
$Female_g \times Analytical_o$				-0.015	-0.285**	-0.177
				(0.134)	(0.122)	(0.129)
$Female_g \times Routine_o$				0.216**	0.277**	0.310***
				(0.105)	(0.122)	(0.117)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.791	0.788	0.796	0.796	0.798	0.806
Panel B	Avg. log earnings (resid.), $\overline{ln(earnings_{oegp})}$					
$Female_g \times AltInflexIndex_o$	-0.027***		-0.035***	-0.033***		-0.038***
	(0.005)		(0.005)	(0.006)		(0.006)
$Female_g \times SocialComposite_o$		-0.003	0.020***		0.001	0.018***
		(0.007)	(0.006)		(0.008)	(0.007)
$Female_g \times Analytical_o$				0.016*	-0.009	0.008
				(0.008)	(0.010)	(0.009)
$Female_g \times Routine_o$				-0.003	-0.003	0.002
				(0.006)	(0.008)	(0.006)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.972	0.967	0.973	0.972	0.968	0.973
γ_{egp}	X	X	X	X	X	X
γ_o	X	X	X	X	X	X
γ_{oep}	X	X	X	X	X	X

Notes: data are from ACS 2015-2019 and O*NET 2013. This table reports results from regressions of log employment shares and wages on occupation attributes interacted with a dummy for female, Female_g. Observations are a cells at the occupation $o \times$ education (college versus noncollege) $e \times$ gender $g \times$ parental-status p (at least one child versus no children) level. Observations are weighted by number employed in the cell. The outcome in the top panel is the log employment share of a demographic group in that occupation. The outcome in the bottom panel is the average of log earnings (residualized with respect to hours worked and demographic characteristics). The first three columns regress the outcome on an occupation's social skill intensity index as defined by Deming (2017) ($SocialComposite_o$) and the alternative flexibility index, which is the average of three standardized components: long hours, coordinated hours, and elasticity of earnings to hours. See 2.1.1 for full details. The next three columns additionally include controls for occupation's analytical intensity and routine task intensity. All columns include fixed effects for demographic group FE (γ_{egp}) and all two-way and three-way interactions of occupation, parental status, and education FE (γ_{oep}). Standard errors are robust and clustered on occupation.

TABLE C.10: RELATIONSHIP BETWEEN OCCUPATION CHARACTERISTICS AND GENDER GAPS IN EMPLOYMENT AND WAGES - USING BROADER SOCIAL SKILL COMPOSITE AND ALTERNATIVE FLEXIBLITY INDEX (OVERWORK, COORDINATED HOURS, AND EARNINGS CONVEXITY)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Log share employed, ln($\frac{Emp_{oegp}}{Emp_{egp}}$)					
$Female_g \times$ top $Inflexibility_o$ and Overwork	-0.252		-0.545*	-0.119		-0.432
	(0.210)		(0.303)	(0.238)		(0.301)
$Female_g \times SocialComposite_o$		0.084	0.254*		0.241**	0.360**
		(0.105)	(0.132)		(0.120)	(0.145)
$Female_g \times Analytical_o$				-0.099	-0.285**	-0.262**
				(0.113)	(0.122)	(0.119)
$Female_g \times Routine_o$				0.192*	0.277**	0.230*
				(0.108)	(0.122)	(0.118)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.789	0.788	0.795	0.793	0.798	0.802
Panel B	Avg. log earnings (resid.), $\overline{ln(earnings_{oegp})}$					
$Female_g \times$ top $Inflexibility_o$ and Overwork	-0.033**		-0.047**	-0.038***		-0.051***
	(0.014)		(0.021)	(0.014)		(0.019)
$Female_g \times SocialComposite_o$		-0.003	0.012		0.001	0.015
		(0.007)	(0.009)		(0.008)	(0.009)
$Female_g \times Analytical_o$				0.001	-0.009	-0.006
				(0.007)	(0.010)	(0.008)
$Female_g \times Routine_o$				-0.010	-0.003	-0.009
				(0.009)	(0.008)	(0.009)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.969	0.967	0.969	0.969	0.968	0.969
γ_{egp}	X	X	X	X	X	X
γ_o	X	X	X	X	X	X
γ_{oep}	X	X	X	X	X	X

Notes: data are from ACS 2015-2019 and O*NET 2013. This table reports results from regressions of log employment shares and wages on occupation attributes interacted with a dummy for female, Female_g. Observations are a cells at the occupation $o \times$ education (college versus noncollege) $e \times$ gender $g \times$ parental-status p (at least one child versus no children) level. Observations are weighted by number employed in the cell. The outcome in the top panel is the log employment share of a demographic group in that occupation. The outcome in the bottom panel is the average of log earnings (residualized with respect to hours worked and demographic characteristics). The first three columns regress the outcome on an occupation's social skill intensity index as defined by Deming (2017) ($SocialComposite_o$) and a dummy indicating that the occupation is in the top tercile of the $Inflexibility_o$ and Overwork measures. See Appendix A: for full details. The next three columns additionally include controls for occupation's analytical intensity and routine task intensity. All columns include fixed effects for demographic group FE (γ_{egp}) and all two-way and three-way interactions of occupation, parental status, and education FE (γ_{oep}). Standard errors are robust and clustered on occupation.

TABLE C.11: RELATIONSHIP BETWEEN OCCUPATION CHARACTERISTICS AND GENDER GAPS IN EMPLOYMENT AND WAGES - CONTROLLING FOR NON-ROUTINE MANUAL TASKS

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Log share employed, ln($\frac{Emp_{oegp}}{Emp_{egp}}$)					
$Female_g \times Inflexibility_o$	0.199*		-0.102	0.021		-0.149
	(0.106)		(0.165)	(0.122)		(0.141)
$Female_g \times Social_o$		0.321***	0.393**		0.175	0.271
		(0.105)	(0.163)		(0.141)	(0.172)
$Female_g \times Analytical_o$				-0.542***	-0.574***	-0.555***
				(0.125)	(0.126)	(0.126)
$Female_g \times Routine_o$				0.193**	0.238**	0.246**
				(0.098)	(0.105)	(0.104)
$Female_g \times NonroutineManual_o$				-0.970***	-0.878***	-0.889***
				(0.139)	(0.157)	(0.156)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.792	0.801	0.801	0.855	0.858	0.859
Panel B	Avg. log earnings (resid.), $\overline{ln(earnings_{oegp})}$					
$Female_g \times Inflexibility_o$	-0.002		-0.019**	-0.001		-0.016*
	(0.007)		(0.009)	(0.008)		(0.009)
$Female_g \times Social_o$		0.008	0.022**		0.014	0.024***
		(0.007)	(0.009)		(0.009)	(0.009)
$Female_g \times Analytical_o$				-0.010	-0.013	-0.011
				(0.009)	(0.009)	(0.009)
$Female_g \times Routine_o$				-0.004	0.000	0.001
				(0.008)	(0.008)	(0.008)
$Female_g \times NonroutineManual_o$				-0.006	0.003	0.001
				(0.010)	(0.010)	(0.011)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.967	0.968	0.968	0.968	0.968	0.968
γ_{egp}	X	X	X	X	X	X
γ_o	X	X	X	X	X	X
γ_{oep}	X	X	X	X	X	X

Notes: data are from ACS 2015-2019 and O*NET 2013. This table reports results from regressions of log employment shares and wages on occupation attributes interacted with a dummy for female, Female_g. Observations are a cells at the occupation $o \times$ education (college versus noncollege) $e \times$ gender $g \times$ parental-status p (at least one child versus no children) level. Observations are weighted by number employed in the cell. The outcome in the top panel is the log employment share of a demographic group in that occupation. The outcome in the bottom panel is the average of log earnings (residualized with respect to hours worked and demographic characteristics). The first three columns regress the outcome on an occupation's Inflexibility Index ($Inflexibility_o$) and an occupation's social perceptiveness skill intensity ($Social_o$). The next three columns additionally include controls for occupation's analytical skill intensity, routine task intensity, and non-routine manual task intensity. All columns include fixed effects for demographic group FE (γ_{egp}) and all two-way and three-way interactions of occupation, parental status, and education FE (γ_{oep}). Standard errors are robust and clustered on occupation.

TABLE C.12: RELATIONSHIP BETWEEN OCCUPATION CHARACTERISTICS AND GENDER GAPS IN EMPLOYMENT AND WAGES - CONTROLLING FOR PHYSICAL STRENGTH INTENSITY

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Log share employed, $\ln(\frac{Emp_{oegp}}{Emp_{egp}})$					
$Female_g \times Inflexibility_o$	0.199*		-0.102	0.252**		-0.191
	(0.106)		(0.165)	(0.124)		(0.157)
$Female_g \times Social_o$		0.321***	0.393**		0.475***	0.602***
		(0.105)	(0.163)		(0.119)	(0.156)
$Female_g \times Analytical_o$				-0.405***	-0.531***	-0.524***
				(0.142)	(0.138)	(0.139)
$Female_g \times Routine_o$				0.190*	0.278**	0.284**
				(0.114)	(0.121)	(0.119)
$Female_g \times PhysicalStrength_o$				-0.285	-0.326*	-0.363**
				(0.216)	(0.180)	(0.179)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.792	0.801	0.801	0.808	0.826	0.828
Panel B	Avg. log earnings (resid.), $\overline{ln(earnings_{oegp})}$					
$Female_g \times Inflexibility_o$	-0.002		-0.019**	0.003		-0.013
	(0.007)		(0.009)	(0.007)		(0.009)
$Female_g \times Social_o$		0.008	0.022**		0.013*	0.022***
		(0.007)	(0.009)		(0.007)	(0.008)
$Female_g \times Analytical_o$				-0.001	-0.006	-0.006
				(0.009)	(0.009)	(0.009)
$Female_g \times Routine_o$				-0.001	0.002	0.003
				(0.008)	(0.008)	(0.008)
$Female_g \times PhysicalStrength_o$				0.014**	0.014**	0.011*
				(0.007)	(0.006)	(0.006)
Obs.	2440	2440	2440	2440	2440	2440
Adj. R-sq.	0.967	0.968	0.968	0.968	0.969	0.969
γ_{egp}	X	X	X	X	X	X
γ_o	X	X	X	X	X	X
γ_{oep}	X	X	X	X	X	X

Notes: data are from ACS 2015-2019 and O*NET 2013. This table reports results from regressions of log employment shares and wages on occupation attributes interacted with a dummy for female, $Female_g$. Observations are a cells at the occupation $o \times$ education (college versus noncollege) $e \times$ gender $g \times$ parental-status p (at least one child versus no children) level. Observations are weighted by number employed in the cell. The outcome in the top panel is the log employment share of a demographic group in that occupation. The outcome in the bottom panel is the average of log earnings (residualized with respect to hours worked and demographic characteristics). The first three columns regress the outcome on an occupation's Inflexibility Index ($Inflexibility_o$) and an occupation's social perceptiveness skill intensity ($Social_o$). The next three columns additionally include controls for occupation's analytical skill intensity, routine task intensity, and physical strength intensity. All columns include fixed effects for demographic group FE (γ_{egp}) and all two-way and three-way interactions of occupation, parental status, and education FE (γ_{oep}). Standard errors are robust and clustered on occupation.

TABLE C.13: HETEROGENEITY BY PARENTAL STATUS IN CORRELATION BETWEEN AN INDIVIDUAL'S SKILLS AND THEIR EMPLOYMENT IN A JOB WITH HIGH/LOW FLEXIBILITY

	(1)	(2)	(3)	(4)
	=1 if employed in a job with low flexibility		=1 if employed in a job with high flexibility	
$Female_i$	0.135***	0.125***	-0.142***	-0.136***
	(0.020)	(0.020)	(0.020)	(0.020)
$SocialSkills_i$	0.042***	0.030***	-0.039***	-0.032***
	(0.011)	(0.011)	(0.010)	(0.010)
$CognitiveSkills_i$		0.087***		-0.055***
		(0.010)		(0.009)
$HasChild_{it}$	0.061***	0.051***	-0.011	-0.005
	(0.016)	(0.016)	(0.015)	(0.015)
$HasChild_{it} \times SocialSkills_i$	0.006	-0.002	-0.008	-0.000
	(0.014)	(0.015)	(0.014)	(0.014)
$HasChild_{it} \times CognitiveSkills_i$		0.031**		-0.031**
		(0.013)		(0.013)
$Female_i \times HasChild_{it}$	-0.102***	-0.102***	-0.023	-0.021
	(0.024)	(0.023)	(0.022)	(0.022)
$Female_i \times SocialSkills_i$	-0.024*	-0.023	0.017	0.016
	(0.014)	(0.014)	(0.013)	(0.014)
$Female_i \times CognitiveSkills_i$		0.019		-0.015
		(0.016)		(0.016)
$Female_i \times HasChild_{it} \times SocialSkills_i$	-0.016	0.002	0.013	-0.001
	(0.020)	(0.020)	(0.018)	(0.018)
$Female_i \times HasChild_{it} \times CognitiveSkills_i$		-0.064***		0.050**
		(0.022)		(0.021)
Person-Year Obs.	103264	103264	103264	103264
Person Obs.	3396	3396	3396	3396
R-sq.	0.099	0.126	0.106	0.121
$Female_i \times Age_{it}$ controls	x	x	x	x
F-test: $\delta_{soc} + \delta_{cog} = 0$		0.821		0.936
F-test: $\delta_{soc,child} + \delta_{cog,child} = 0$		0.013		0.040

Notes: data are from the NLSY79. The outcome in columns 1-2 is a dummy indicating the person is employed in an occupation with low flexibility (i.e., above median in $Inflexibility_o$). The outcome in columns 3-4 is a dummy indicating the person is employed in an occupation with high flexibility (i.e., below median in $Inflexibility_o$). Each column presents results from separate regressions of the outcomes on a female dummy, an individual's social skills, a dummy indicating parental status, and all interactions between these terms. All regressions include age fixed effects, year fixed effects, noncognitive skills, a dummy indicating noncognitive skills were missing (and imputed with zero's), a dummy for college completion, and age by female fixed effects. Columns 2 and 4 additionally include an individual's cognitive skills and all interactions with indicators for female and parental status. The bottom of the table reports the p-value from two F-tests. The first tests the joint significance of the coefficients on $Female_i \times SocialSkills_i$ and $Female_i \times CognitiveSkills_i$. The second tests the joint significance of the coefficients on $Female_i \times HasChild_{it} \times SocialSkills_i$ and $Female_i \times HasChild_{it} \times CognitiveSkills_i$. Standard errors are robust and clustered on individual.

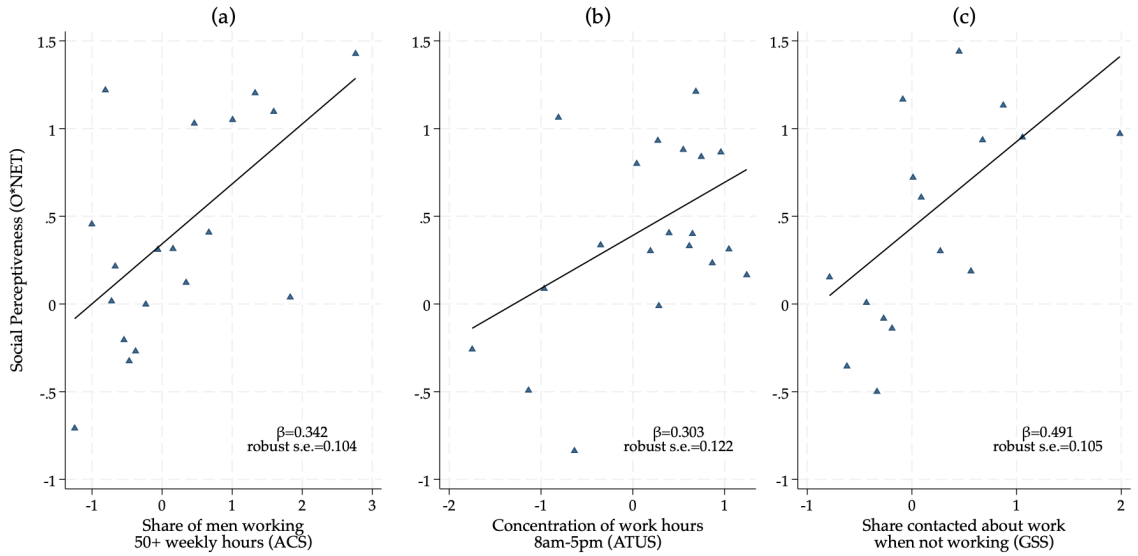
Appendix D: Additional Figures

FIGURE D.1: CORRELATION BETWEEN SOCIAL PERCEPTIVENESS AND INFLEXIBILITY AMONG LARGEST OCCUPATIONS, SPLIT BY EDUCATION



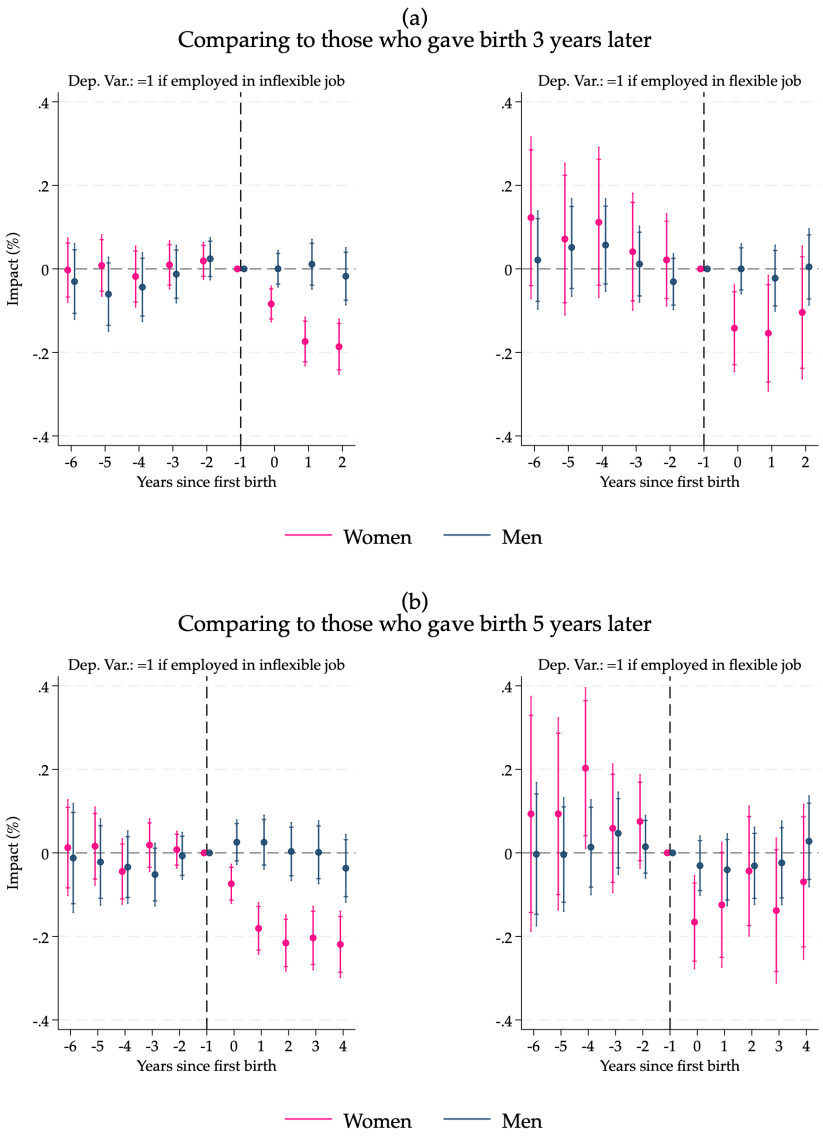
Notes: both panels depicts the relationship between an occupation's social perceptiveness and inflexibility. The left (right) panel is restricted to occupations in the top employment quartile for noncollege (college) workers. Occupations are weighted by noncollege (college) employment. In each panel, the largest 15 occupations are labeled. Dashed gray lines represent the median in each measure within the corresponding sample of occupations.

FIGURE D.2: CORRELATION BETWEEN SOCIAL PERCEPTIVENESS AND SPECIFIC TYPES OF TIME DEMANDS



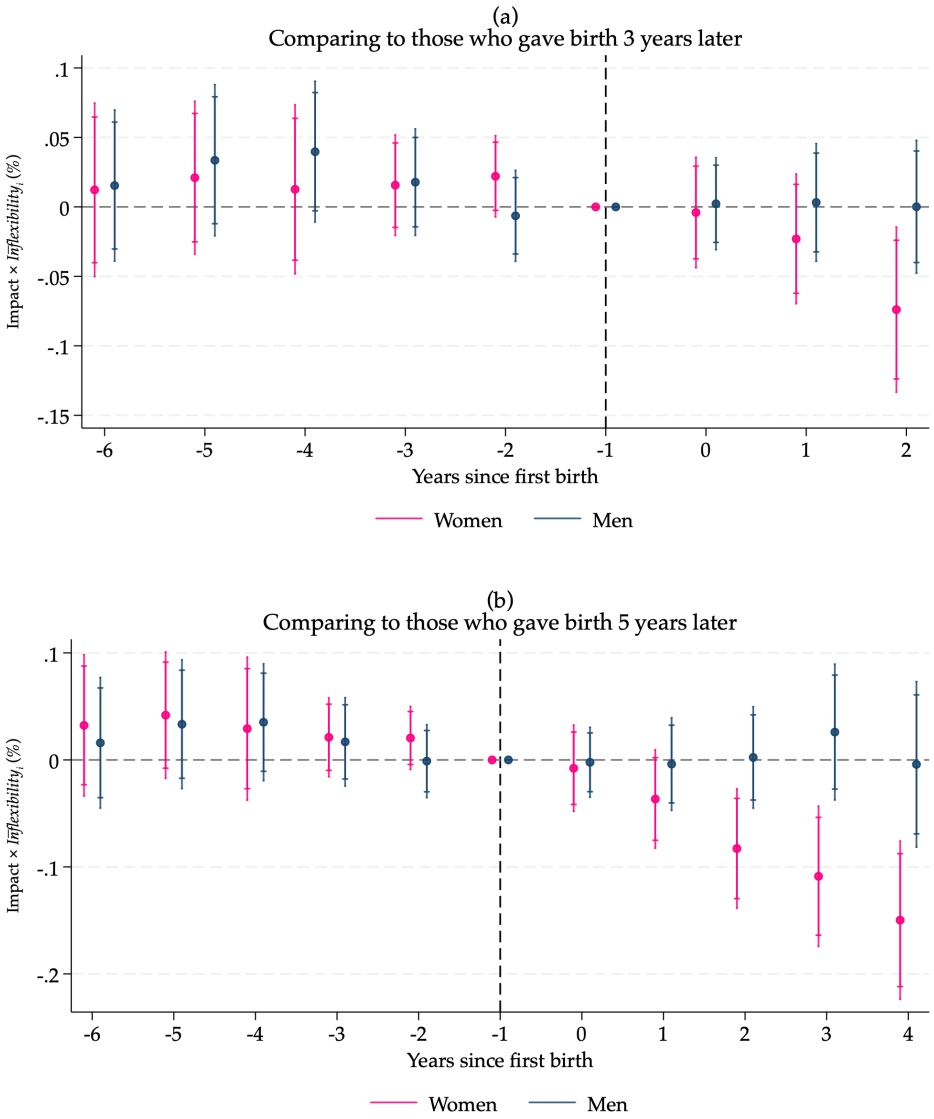
Notes: these binscatters plot an occupation's social perceptiveness against specific types of inflexibility. The first is the share of men in an occupation working over 50 hours per week (measured in the ACS). The second is the concentration of work hours within the 8am-5pm window for a given occupation (measured in the ATUS). The third measure reflects the share of individuals in an occupation who report having to respond to work-related matters outside of their work hours at least several times per week (measured in the General Social Survey). See Appendix Section **??** for details.

FIGURE D.3: CHANGE IN THE PROPENSITY TO BE IN JOBS WITH LOW/HIGH FLEXIBILITY AFTER CHILDBIRTH



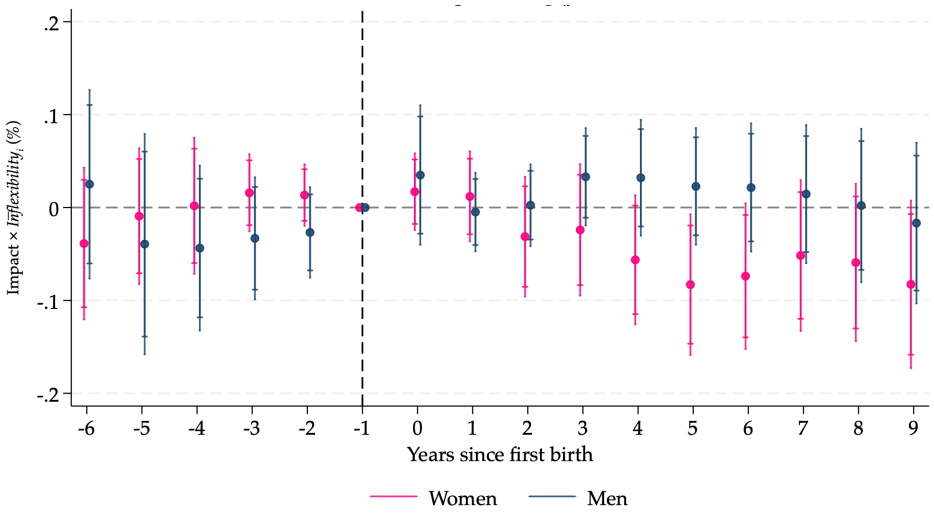
Notes: this figure presents event studies of first child birth separately by gender. In the figures on the left, the outcome is whether the person is employed in a job with low (below median) flexibility (i.e. a high "price" of flexibility according to the index, $Inflexibility_o$). In the figures on the right, the outcome is whether the person is employed in a job with high (above median) flexibility. In both cases, the outcome equals 0 if the person is not employed. The plotted points represent coefficients on dummies indicating the number of years since an individual's first child birth. The estimates in pink represent the results for women, while the estimates in blue represent the results for men. 90% and 95% confidence intervals displayed. Standard errors are robust and clustered on individual. Data are from the NLSY79. As discussed in the text, the "control group" are those who gave birth 3 years later in Panel A and those who gave birth 5 years later in Panel B.

FIGURE D.4: HETEROGENEITY IN WAGE CHANGES AFTER CHILDBIRTH BY FLEXIBILITY OF PRE-BIRTH OCCUPATION



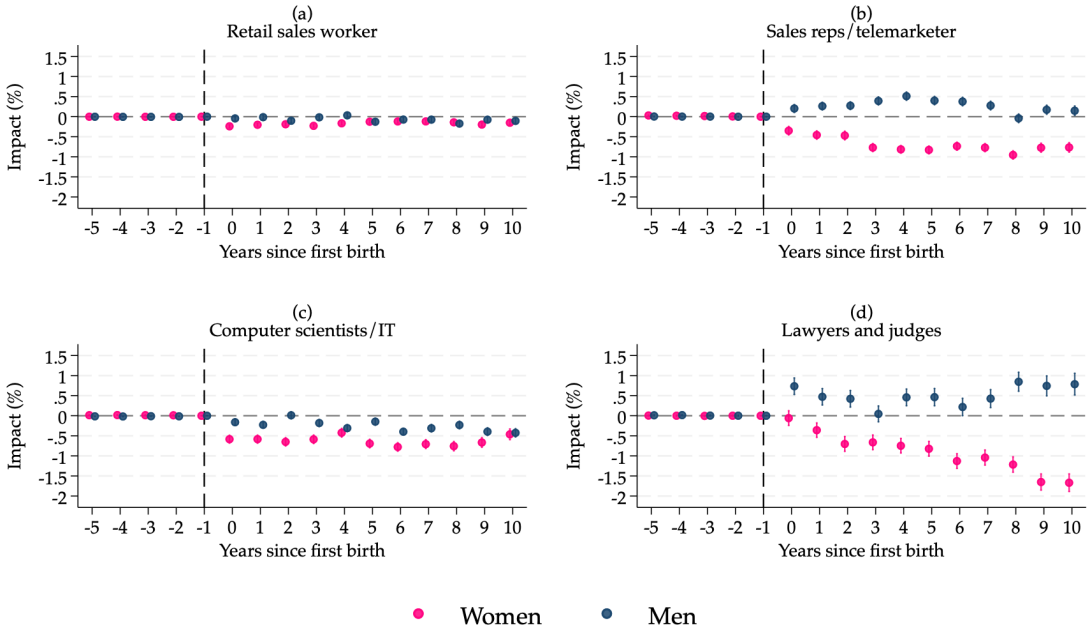
Notes: this figure presents heterogeneity in how wages respond to child birth by the flexibility of the individual's occupation prior to birth. The outcome is an individual's wage (coded as zero if not working). The plotted points represent coefficients on event time dummies interacted with a variable representing the lack of flexibility in the individual's occupation. Specifically, the variable is the average of the index proxying for the "price of flexibility" ($Inflexibility_o$) over all pre-birth observations for the individual. Estimates are divided by pre-birth averages in the outcome and therefore represent percentage changes. The estimates in pink represent the results for women, while the estimates in blue represent the results for men. 90% and 95% confidence intervals displayed. Standard errors are robust and clustered on individual. Data are from the NLSY79. As discussed in the text, the "control group" are those who gave birth 3 years later in Panel A and those who gave birth 5 years later in Panel B.

FIGURE D.5: HETEROGENEITY IN WAGE CHANGES AFTER CHILDBIRTH BY FLEXIBILITY OF PRE-BIRTH OCCUPATION, CONTROLLING FOR PRE-BIRTH SPOUSAL INCOME



Notes: this figure presents heterogeneity in how wages respond to child birth by the flexibility of the individual's occupation prior to birth. The outcome is an individual's wage (coded as zero if not working). The plotted points represent coefficients on event time dummies interacted with a variable representing the lack of flexibility in the individual's occupation. Specifically, the variable is the average of the index proxying for the "price of flexibility" ($Inflexibility_o$) over all pre-birth observations for the individual. Estimates are divided by pre-birth averages in the outcome and therefore represent percentage changes. The estimates in pink represent the results for women, while the estimates in blue represent the results for men. 90% and 95% confidence intervals displayed. Standard errors are robust and clustered on individual. Data are from the NLSY79. As discussed in the text, the "control group" are individuals who never give birth over the sample period. In contrast to the main results, this controls for a proxy for spousal income interacted with event dummies, age dummies, and year dummies. Due to this variable being missing, there are 33 fewer men and 37 fewer women represented in this sample relative to the main results.

FIGURE D.6: CHANGE IN FEMALE-MALE PROBABILITY OF EMPLOYMENT ACROSS OCCUPATIONS AFTER CHILDBIRTH (PSEUDO EVENT STUDIES)



Notes: this figure presents the pseudo event studies of first child birth separately gender as described in Section 7.2. In Panel A, the outcome is a dummy indicating that the (synthetic) person is employed as a retail sales worker. The outcome is zero if the person is not employed or is employed in another occupation. Panel B, C, and D present the analogous results for sales representative or telemarketer, computer scientists/IT, and lawyers/judges. The plotted points represent coefficients on dummies indicating the number of years since an individual's first child birth. The estimates in pink represent the results for women, while the estimates in blue represent the results for men. 95% confidence intervals displayed. Data are from a matched sample in the CPS covering years 1972-2019.