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Estimating Firm-, Occupation-, and Job-Level Gender Pay Gaps with U.S. Linked Employer-Employee Population Data, 2005 to 2015

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Abstract

Merging 2005 to 2015 Internal Revenue Service, Social Security, and Census records, the authors calculate national average gender pay gaps for various population definitions and then decompose trends in the contribution of firm, occupation, and job segregation to these pay gaps, as well as the size of the average residual "within-job" pay gap. In general, observed segregation tends to explain about half of age, education, and hours of work adjusted gender pay gaps, but the other half remains within occupations in the same firm. Although between-firm pay gaps rose and within-job pay gaps declined through 2009, the authors find little decline in firm- or job-level gender pay gaps after 2009. The results indicate that to reduce gender pay gaps, public policy and employers should target gender disparities in hiring and job assignment as well as potential disparities in pay setting.

Keywords

gender gap, within-job inequality, segregation, discrimination, linked employer-employee data

Although the U.S. gender pay gap declined rapidly from 1970 to the early 1990s, movement toward pay equality between men and women has since largely stalled (England, Levine, and Mishel 2020). At the current slow rate of pay convergence, policy advocates have estimated that it will take somewhere between 60 and more than 100 years for the United States to reach equal pay for men and women otherwise equivalent in terms of human capital and hours of work (Leisenring 2020; World Economic Forum 2019). Our estimates suggest that if the rate of change remains at the 2009 to 2015 trend level, convergence will never occur.

Current research using individual survey data estimates gender pay gaps net of hours worked, education and experience, occupation, and sometimes industry, treating the gender residual as an indicator of unobserved differences in employer and employee behavior, including employer bias (e.g., Blau and Kahn 2017; Foster et al. 2020). This research identifies gender differences in lifetime labor force participation, current hours worked, and occupational segregation as the most important observed sources of earnings disparities between men and women but also reveals large residual disparities.

The importance of workplace segregation as well as within workplace and within-job pay disparities are not observable with conventional survey data. Increasingly, social scientists have been able to access government generated administrative data from tax or social insurance programs and observe firm and workplace level earnings dynamics. For example, recent research using Internal Revenue Service (IRS) linked employee-employer data suggest that most of the rapid rise in U.S. earnings inequalities is a between firm phenomenon (Song et al. 2019). Although there is recent research exploring gender pay gaps within and between workplaces in other countries (Barth and Dale-Olsen 2009; Bassier 2019; Card, Cardoso, and Kline 2016), we lack recent estimates for the United States. There are 1980-era estimates using linked

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employer-employee data for particular subpopulations (Avent-Holt and Tomaskovic-Devey 2012; Groshen 1991; Petersen and Morgan 1995) and one for 1990 for which shared workplace is imputed rather than observed (Bayard et al. 2003). More recent analyses have focused on career mobility within and between workplaces, but have not produced workplace segregation or within-job pay gap estimates (e.g., Barth, Kerr, and Olivetti 2021).

Scholars and regulators have been particularly interested in identifying gender disparities within jobs in the same firm as this closely matches the definition of pay discrimination in the 1963 U.S. Equal Pay Act, which prohibited gender pay disparities within jobs in the same workplace not associated with seniority, merit or other reasonable productivity distinctions. Title VII of the 1964 U.S. Civil Rights Act identified segregation as equally prohibited, but the role of segregation produced by employer discrimination has been difficult to observe in the absence of firm- and job-level data, and even then because segregation is often jointly produced by the labor market decisions of both workers and employers.

During the Obama administration, there was a proposal by the U.S. Equal Employment Opportunity Commission to collect firm-level pay data. This initiative was opposed by segments of the business and legal communities, which argued, in part, that the data collection was not necessary because firms were already monitoring and addressing within-job gender pay disparities. This may not be an unreasonable claim, as the available, if quite old (circa 1980), estimates of within-job pay disparities from high-quality linked employer-employee data suggested an average within-job gender pay gap of only 3 percent or less (Groshen 1991; Petersen and Morgan 1995). If that pay gap has in the meantime narrowed further, then within-job gender pay gaps may be trivially small and increased federal data collection and regulatory efforts misplaced.

In this article we provide estimates of the average within-job gender earnings and hourly wage gaps for various definitions of the U.S. employed population and calculate the relative impact of segregation across firms, occupations, and detailed occupations within firms (our proxy for jobs) on these gaps. This exercise also produces estimates of the average pay gap between women and men working in the same "job" (i.e., three-digit occupation within the same firm). Our estimates suggest that half of the adjusted gender pay gap results from segregation at the job level and the remainder from within-job pay disparities. From a policy point of view these estimates support the need for both regulatory attention to segregation in hiring and job assignment, as well as within-job gender bias in pay practices.

We build on the work of the Comparative Organizational Inequalities Network, an interdisciplinary group of social scientists in multiple countries developing theory and methods for the analysis of linked employer-employee administrative data. The Comparative Organizational Inequalities Network has recently published a paper decomposing the gender earnings gap in 15 countries (Penner et al. 2023). The current article developed out of the U.S. estimates from that project and deepens those results with new information on multiple additional populations of formal economy workers and trends over time, while providing a much more extensive and dynamic interpretation.[1] These U.S. estimates are based on employer-employee administrative data from the IRS combined with individual-level gender and age information from Social Security Administration records and occupation, education, and hours worked responses to the U.S. Census Bureau's American Community Survey (ACS). The key limitation of these data is that the ACS is a 1 percent population sample, and when matched to IRS workplaces produces a sample biased toward larger workplaces.

We make three primary scientific contributions. The first is to produce estimates of the aggregate impact of firm, occupation, and "job" segregation on national gender pay disparities. The second is to document that the average degree of within-job pay disparity in the United States is surprisingly high. We observe these processes from 2005 to 2015 and so cannot comment on more recent trends, but our estimates suggest that in the absence of regulatory intervention and changes in employer behavior, the intensity of gender pay disparities will not inevitably diminish. Third, we interrogate the quality of available U.S. linked employer-employee data for examining gender and other employment disparities and engage a recent National Academies of Sciences, Engineering, and Medicine (2022) report advocating improved workplace pay data collection.

We follow Petersen and Morgan (1995) and Smith-Doerr et al. (2019) in conceptualizing pay disparities as a result of gender differences in firm, occupation, and job segregation and within-job processes. The within-job pay gap can be interpreted in this framework as an upper-bound estimate of the average level of gender discrimination as defined under the 1963 Equal Pay Act. This is not, however, a strictly legal notion of discrimination, for which employer bias must be demonstrated, but rather a social science conceptualization of aggregate bias processes, only some of which might be illegal. Segregation components of the gender pay gap also may result from employer bias in hiring, job assignment, promotion, and firing, although the legal basis for establishing discrimination is ambiguous because there is ample room for self-selection into firms, occupations, and jobs.

[1]Specifically, Table 1 is entirely novel; Figure 1 contains results for four population definitions, only one of which appears in an online supplement in prior work (Penner et al. 2023, Table S21); and the hourly earnings trends in Table 3 and Figure 3 are novel (prior work reported only the results for a single year). Table 2 presents results previously reported in an online supplement (Penner et al. 2023, Table S20 and Figure S18). Figures A1 to A3 and Tables A1 to A3 are all new.

We first observe national gender pay gaps after adjusting for human capital and hours worked, which we bracket as premarket distinctions, and then use an ordinary least squares estimation strategy in which sequential models add fixed effects for firm, detailed occupation, and their cross-classification, which we treat as a proxy for jobs. This produces estimates of the relative contribution of the three forms of segregation, plus within-job pay disparities, to the total national average gender pay gap. Our data are quite robust for estimating firm and occupation segregation, but job and within-job estimates are more fragile because of the low ACS sampling rate.

We find that women are more likely than men to be employed in low earning firms, occupations, and especially jobs. Occupational and firm gender segregation are roughly equivalent in their contribution to pay disparities, suggesting that focusing on occupation alone, which is common in the scientific literature, misses the important role of employers in producing gender disparities. Empirically, it is jobs—the intersection of detailed occupation and firm in our analyses—that are the most powerful segregation context, consistent with previous estimates (e.g., Petersen and Morgan 1995; Smith-Doerr et al. 2019). Consistent with recent research on rising between-firm earnings inequalities affecting workers generally (Song et al. 2019), the firm segregation component of the gender gap is strengthening over time. Finally, we find that about half of the gender pay gap for both yearly and hourly earnings is found within jobs and that this proportion is relatively stable over our observation period. Because of ACS sampling, these firm and job estimates primarily describe pay gaps in larger firms, a consideration we return to in the discussion.

Data and Methods

Linking Employer-Employee Data

In these analyses we use earnings and employer information for each individual's employment spell(s) from IRS form W-2 covering tax years 2005 to 2015. As submitted to the IRS, the W-2 form contains both employee's Social Security number (SSN) and an employer identification number (EIN). The EIN in most cases identifies a firm or a firm in a state (see discussion in Song et al. 2019). In the file available at the Census Bureau for research, personally identifying information such as SSNs and names are removed, with the Census Bureau assigning a unique, anonymous protected identification key (PIK) that enables linkages of records across data sources. Using PIKs, we match W-2 reports to the Social Security Administration's 2016 Numerical Identification File, retrieving our measures of age and gender. Again using PIKs, we link individuals to their responses to the ACS, a 1 percent random sample of U.S. households. Importantly, some 99 percent of individuals in IRS records receive PIKs, while the ACS had a 94 percent PIK assignment rate, allowing a very high match rate between W-2 and ACS data.

In the matching process we first unduplicate EIN-PIK-year, taking the most recently dated form available. For individuals who work at multiple firms in a year, we focus on their highest earning W-2 report, selecting one at random in the very rare case of individuals with multiple equally well-compensated W-2s. We link individuals' highest paid W-2 report to the concurrent ACS year; for example, W-2s from tax year 2015 are linked to respondents to the 2015 ACS. We were able to link 19.6 million total workers, yielding about 1.6 million to 2.0 million individuals per year, averaging very close to 1 percent per year of the W-2 earner population. In all linked data analyses, we use ACS sample weights. The median firm size among (weighted) matched respondents was 1,030, which was nearly identical to the median number of workers per EIN in the analytic administrative data set. The median number of workers per EIN and year linked to the ACS was 10.

There is some evidence that sample construction through this matching process may influence estimates relative to the universe of reported W-2 earnings. For example, fitting the same basic model to both the W-2-only and the W-2-to-ACS matched samples adjusting only for age, age squared, and indicators for full-time and marginal earnings yields gender gap estimates 4 to 6 percentage points higher in the ACS matched sample (in which women earn 22 percent to 27 percent less than similar men depending on year) than in the full W-2 sample (18 percent to 23 percent less). This most likely reflects that the matching process is more likely to be successful for workers in larger firms and that the earnings increment associated with larger firm size is larger for men than for women (Hollister 2004).

There are other limitations to these data. First, the employer information is at the firm level, rather than the workplace (i.e., establishment) level. We lacked access to geographic information from form W-2 and so were unable to further stratify firms by region or state. Thus, workplace variation in the gender earnings gap is not observed separately for multiple work sites in multiestablishment firms. We know from prior research that this is likely to be a small source of error (Tomaskovic-Devey et al. 2020). Second, for the ACS variables we have the normal measurement error associated with self-reported occupation and hours worked but also additional ambiguity in computing hourly earnings for multiple job holders (Kim and Tamborini 2014; Perales 2014; Speer 2016).

Measures

Yearly Earnings. Our earnings concept is all federal taxable earnings in a calendar year. We take box 1 from form W-2, which reports total annual taxable Social Security earnings for each individual at a particular EIN, including salary, wages, and bonuses, but excluding deferred compensation.

We adjust to real earnings in 2015 prices using the Consumer Price Index for All Urban Consumers. Using administrative data on earnings has multiple advantages over conventional survey data. The first, and by far most important, is that we can create employer-employee data. This makes it possible to observe gender pay gaps at the firm and job levels, the level at which hiring and pay decisions occur and equal opportunity legal rights are defined. Second, the earnings data are of very high quality and do not suffer from the large levels of misreporting and missing data in self-reported earnings (Kim and Tamborini 2012). There is very little measurement error in the earnings measure.

Hourly Earnings. We calculate hourly earnings as yearly earnings divided by ACS-reported weeks and hours worked. In the ACS normal hours worked and weeks worked pertain to the previous 12 months. We multiply hours worked by weeks worked (using interval midpoints for weeks worked) to obtain an estimate of the total annual number of hours worked. We divide total W-2 earnings by annual hours worked to arrive at our estimate of hourly earnings in a typical week, excluding a small fraction of individuals with hourly earnings less than $1 or more than $100. This measure is error prone to the extent that the individual worked multiple jobs in the past year. Workers who hold multiple jobs average 12 total hours a week more than single job holders, who average 39.7 hours (Hirsch, Husain, and Winters 2016). Thus, average hourly earnings will be depressed by about 30 percent (12 divided by 39.7) using the ACS hours worked measure for multiple job holders. As only 5 percent of workers hold multiple jobs and they are 2 percent more likely to be women than men, this source of bias will reduce the gender earnings gap on average by a trivial .003 percent. In addition, we match last year's hours to this year's earnings, which will introduce error at the individual level but is unlikely to bias aggregate estimates one way or the other.

Marginal Jobs. Some observed job spells have very low earnings and are most likely to be held by young workers (Spletzer and Handwerker 2014). The W-2 reports are annual summaries, but include jobs of very short duration. Such jobs represent up to 30 percent of hires in any quarter, but there are no average gender differences in marginal job employment (Hyatt and Spletzer 2017). In addition, it seems likely that some of these marginal jobs are associated with the fraudulent use of SSNs by employers or workers (Abowd, McKinney, and Zhao 2018). In every model we include a control for marginal jobs, defined as those earning less than the equivalent of the federal minimum wage $\times$ 10 hours $\times$ 52 weeks. In the U.S. W-2 population, 14 percent of jobs are marginal by this definition.

Full-Time. We define individuals as working full-time if their total nominal W-2 earnings surpassed the equivalent of working the federal minimum wage in that year $\times$ 40 hours $\times$ 50 weeks (see Song et al. 2019 for a similar strategy using similar data). Analyses using ACS self-reported hours worked yield gender earnings gaps that are comparable with our estimates on the basis of these W-2 full-time earnings threshold. Individuals whose W-2 earnings did not reach the full-time earnings threshold worked on average 35 weeks over the previous 12 months and on average 985 total hours during this period. This contrasts with the average 49 weeks and 1,985 total hours of individuals whose W-2 earnings exceeded this threshold. We foreground our full-time imputation because it can be applied to both the full W-2 and ACS matched samples and does not suffer from the sampling issues associated with the ACS matched data.

Occupation. Self-reported occupations from the ACS are coded by trained Census Bureau coders into one of 520 three-digit categories from the Standard Occupation Classification system. Because occupation is reported by employees and then coded by Census Bureau workers, there is some measurement error relative to employer job titles as well as potential slippage when the most recent job is not the highest paid job in the past year.

Job. Our job concept is the intersection of detailed occupation and firm. For some firms, particularly larger ones, because of the potential for even finer detail in job distinctions at the workplace level, this measure may not match the actual job concept used by employers. For this reason, our estimates of within-job gender pay gaps may be higher than those based on job titles, at least for larger multisite firms. On the other hand, our measurement of jobs on the basis of detailed occupation is likely to be quite close to the concept of performing the same or very similar work. More concerning is that we observe job pay gaps only when a man and a woman work in the same detailed occupation in the firm. Thus, our observations at the job level are biased toward larger firms.

Age and Age Squared. We use Social Security Administration measures of age and its square to adjust for career stage in both the W-2-only and ACS samples.

Education. For the matched ACS sample, we have self-reports of employees' education levels, which we measure as a series of indicator variables for five levels of education: less than high school, high school graduate or equivalent, some college or associate's degree, bachelor's degree, and graduate or professional degree.

Unobserved Covariates. We lack direct estimates of employee total labor force experience, firm tenure, and performance. The latter two are unlikely to bias national estimates. A meta-analysis of all published work shows no mean gender differences in performance evaluations (Joshi, Son, and Roh 2015). Similarly, during our observation period there are no mean gender differences in employee tenure with their current employer (Bureau of Labor Statistics 2020). There are, however, average gender differences in total labor force experience and these may be consequential for estimates (Foster et al. 2020).

Statistical Estimation

The unit of analysis is an employee-employer match, sometimes called a job spell, which we refer to as an individual or worker. We focus on two logged measures as dependent variables: yearly earnings and hourly earnings. As is conventional, regression coefficients on the gender indicator are interpreted as the proportional relative difference between average male and female earnings. More formally these estimates refer to the difference in relative geometric means for unlogged earnings (see discussion in Petersen 2017).

We focus on the relative impact of firm, occupation, and job segregation on these gender gap estimates, replicating our analysis for all job spells, for the highest paid job for workers with multiple jobs, and for full-time workers only. We further distinguish between all workers and those in the prime earning years, which we define as ages 30 to 55. For the W-2 population analyses we focus on the impact of firm segregation. For the ACS matched samples, we additionally explore occupation and job segregation.

Our core analyses focus on four sets of ordinary least squares regression models. The first model adjusts only for individual-level covariates and provides our baseline estimate of the overall gender pay gap. In subsequent models we compare only women and men who work in the same firm (model 2), only women and men who work in the same occupation (model 3), and only women and men who work in the same job (i.e., occupation-firm unit; model 4). We estimate these models separately by year, allowing us to examine trends in pay gap components. Comparing the results of these four models enables us to see the degree to which gender differences in pay in any given year are accounted for by sorting across occupations, firms, and occupation-firm units.

The equations estimated for these four models follow the same general form, using four different specifications:

$$\ln\ earnings_{it} = \theta_{B,t} x_{it} + \eta_{ft} + \varepsilon_{it}, \tag{1}$$

$$\ln earnings_{it} = \theta_{E,t} x_{it} + \eta_{eft} + \varepsilon_{it}, \tag{2}$$

$$\ln earnings_{it} = \theta_{O,t} x_{it} + \eta_{oft} + \varepsilon_{it}, \tag{3}$$

and

$$\ln earnings_{it} = \theta_{OE,t} x_{it} + \eta_{oeft} + \varepsilon_{it}, \tag{4}$$

where the subscripts represent i for individual, f for full- versus part-time status, o for occupations, e for EIN (firm), and t for years. The dependent variable is the natural logarithm of yearly (or hourly) earnings (ln earnings$_{it}$) for individual (or job spell) i in year t, and the independent variables are collected in the vector x_{it}, which includes a constant, the gender, age, and age squared of individual i, a series of indicator variables for the education of individual i, and an indicator variable for marginal jobs, defined in terms of very low earnings. Education is available only for ACS matched sample estimations.

To address concerns regarding the comparability of full- versus part-time workers, we consider full- versus part-time status as a defining characteristic of a job and include this axis in constructing fixed effects for all models. Thus, model 1 includes the term η_{ft}, a fixed effect (i.e., indicator variable) for full- versus part-time work, so that it adjusts for age, age squared, education, marginal earnings, and full- versus part-time work. Model 2 includes the covariates in model 1, as well as fixed effects η_{eft} representing the unique units formed by combining the establishment and full- versus part-time indicators. Model 2 thus provides estimates of the gender gap obtained from comparing women and men who work in the same firm; for each firm it estimates the gender gap separately for full-time workers and part-time workers and then takes a weighted average of these two gender gaps across all firms. Models 3 and 4 are analogous to model 2 but contain the fixed effects η_{oft} and η_{oeft} referring, respectively, to the unique units formed by combining full- versus part-time status with either occupation (η_{oft}) or job (occupation-firm) units (η_{oeft}). This interaction of firm and occupation with full-time earnings indicator increases the observed units from 520 to 1,040 for occupation, 2,800,000 to 3,435,000 for firms, and 8,690,000 to 9,235,000 for firms by occupations.

Importantly, the analytic sample for each fixed-effects model is restricted to gender-integrated units. This is a necessary aspect of the estimation strategy, as we compare only men and women at risk for having different within unit earnings. The subscripts to the θ parameters indicate that these are different coefficients, pertaining to different levels: baseline (B), EIN or firm (E), occupation (O), and occupation-firm (OE). When decomposing gender pay gap components we take this shift in sample into account by subtracting lower nested unit gender pay gaps (e.g., job) from higher unit (e.g., firm) pay gaps (see Petersen and Morgan 1995; Smith-Doerr et al. 2019).

To compare the pay of women and men in the same occupation and firm, it is important to have good coverage of employees within firms. The W-2 sample, which includes nearly all individuals in the workforce, provides such coverage. The matched ACS to W-2 sample observes only 10 workers in the median firm. Thus, we must be concerned about sparseness created by ACS sampling. For example, for W-2 population estimates, restricting the sample to gender-integrated firms reduces the sample by only 4 percent, but in the ACS matched sample, sample size is reduced between 30 percent and 40 percent. At the job level the sample is further reduced by some 35 percentage points. Some of this represents actual segregation between firms and jobs, but most reflects sampling constraints introduced by the ACS match.

Table 1. Coefficients on Female Indicator Variable in Earnings Models Net of Controls for Age, Age Squared, and Marginal Earnings Indicator in 2015: Varying Samples and Earnings Measures.

	Full W-2 Population		W-2-ACS Matched Sample			
	Log Yearly Earnings		Log Yearly Earnings		Log Hourly Earnings	
Full-Time Indicator	No	Yes	No	Yes	No	Yes
All workers, all jobs	−.184	−.113				
SE	(.000)	(.000)				
n	235,300,000	235,300,000				
All workers, main job	−.263	−.164	−.319	−.218	−.173	−.106
SE	(.000)	(.000)	(.001)	(.079)	(.001)	(.094)
n	160,200,000	160,200,000	1,975,000	1,975,000	1,975,000	1,975,000
Age 30–55 years, all jobs	−.235	−.151				
SE	(.000)	(.000)				
n	116,500,000	116,500,000				
Age 30–55 years, main job	−.322	−.212	−.359	−.251	−.196	−.118
SE	(.000)	(.000)	(.002)	(.058)	(.002)	(.094)
n	82,750,000	82,750,000	1,091,000	1,091,000	1,091,000	1,091,000

Source: Authors' calculations from Internal Revenue Service W-2 tax records linked to Social Security records and Census Bureau American Community Survey data.
Note: Supercolumns indicate sample data and dependent variable. Columns differentiate model specifications (with or without indicator variable for full-time earnings equivalent included in regression). Rows differentiate sample restrictions.

Given the central limit theorem, sampling errors should be randomly distributed, and so we proceed with these sparse estimations of national gender gaps and component decompositions. Still, we run some risk of overestimating firm segregation components of the gender gap in the ACS hourly earnings analyses. The firm component of the gender gap averages 5 percent larger in the ACS than the W-2 estimations. The within-firm decomposition of job versus firm components will tend to be dominated by larger firms with multiple person observations at the job level. We return to issues of sampling coverage in the discussion.

Results

We begin in Table 1 by documenting the gross gender pay gap for logged yearly and hourly earnings for various population definitions in 2015, our most recent estimate year. The first column shows estimates for the total population of employment relationships in the United States reported to the IRS. All jobs and all workers are our most inclusive population, numbering 235.3 million, while restricting to the highest paid "main" job reduces the sample to 160.2 million. The bottom two rows restrict the samples to prime-age workers.

Using the conventional approximation of the percentage gap as $100 \times (e^{b}-1)$, the coefficients in the first columns show that across all job spells we find a 16.8 percent ($b=-0.184$) gross yearly gender earnings gap, after adjusting for age, age squared, and an indicator for jobs with such low earnings that they are marginal to the labor force or represent very short employment spells. Adjusting further with an indicator for estimated full-time employment, this gap shrinks to 10.7 percent ($b=-0.113$). When we focus on only the highest paid "main" job, the gender yearly earnings gap is considerably higher, at 23.1 percent ($b=-0.263$) for all employees and 15.1 percent ($b=-0.164$) with the full-time adjustment. Confirming prior research (Goldin et al. 2017), gaps are larger for prime-age workers aged 30 to 55 years than among all workers. For prime-age workers in their highest paid job the gender pay gap is 27.5 percent ($b=-0.322$) for yearly earnings and 19.1 percent ($b=-0.212$) with the full-time adjustment. The middle two columns of the table show results for the same models estimated on the smaller W-2 to ACS matched sample of workers. These coefficients illustrate that the smaller sample yields gap estimates 2 to 4 percentage points larger than those found from the full population, reflecting the bias toward larger firms in the matched sample. The final two columns of the table change the outcome from annual to hourly earnings, again using the W-2-ACS sample. The 17.8 percent ($b=-0.196$) estimate for the full-time prime-age hourly earnings gap is quite close to a previous estimate of 17.4 percent for a similarly defined sample (Blau and Kahn 2017).[2]

Figure 1 reports trends in earnings differentials over time for the W-2-only sample for each of these populations and adds estimates of the gender pay gap net of a firm fixed effect.

[2]We calculate this 17.4 percent as Blau and Kahn's (2017:798–99) reported 2010 unadjusted Panel Study of Income Dynamics gender hourly wage gap of 20.7 percent reduced by the 15.9 percent attributed to gender differences in experience in their decomposition ($20.7-[0.159 \times 20.7]=17.4$), experience being the closest adjustment to our age adjustment.

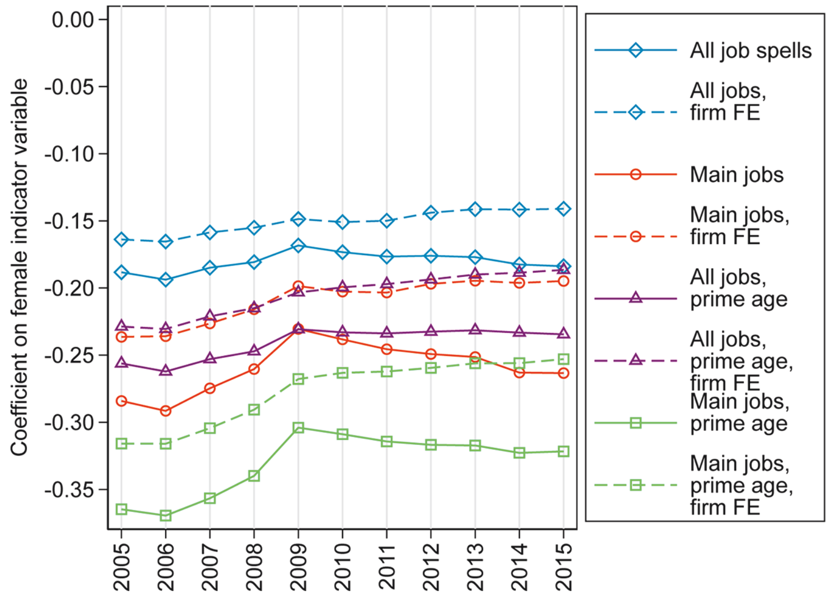

Figure 1. Estimated gender log yearly earnings gaps, varying W-2-only samples.
Note: Solid lines are net of age, age squared, and marginal job indicator. Dashed lines are residual pay gaps after firm fixed effects are added to the former. Ninety-five percent confidence intervals are smaller than line widths (see Table A1 for standard errors).

The general pattern is that the gender pay gap for all populations was declining until 2009, most dramatically for samples restricted to the primary job. After 2009 the gender gap rises for most populations, but is relatively flat among prime-age workers when second jobs are included, suggesting that women added more second jobs than men during and after the Great Recession. For each population, introducing firm fixed effects reduces the gender earnings gap, indicating that between-firm segregation is an important source of gender earnings inequalities. This firm segregation effect is most dramatic for the main job. Furthermore, although overall gender gaps tend to worsen from 2009 to 2015, the within-firm gender gaps all decrease, confirming the increasing importance of between-firm segregation to the overall gap over time.

Figure 1 shows trends corresponding to Table 1's first column. Figure A1 shows time series corresponding to Table 1's second column, including a control for part-time versus full-time earnings. The results also show a worsening overall gap with a decreasing within-firm gap between 2009 and 2015, indicating the increasing importance of between-firm segregation even after accounting for full-time earnings level.[3] All regression results for the W-2-only samples are reported in Table A1.

We now move to our more fully specified segregation analyses, focused on four sets of ordinary least squares regression models fit to the W-2-ACS matched sample. The first model provides our baseline estimate of the overall gender pay gap net of age, age squared, education, full- versus part-time job, and marginal job status. Thus, our segregation analysis begins after adjustment for individual characteristics and two proxies for hours worked. In subsequent models, we compare only women and men who work in the same firm (model 2), only women and men who work in the same occupation (model 3), and only women and men who work in the same job (i.e., occupation-firm unit; model 4). Comparing the results of these four models enables us to see the degree to which average gender differences in pay in any given year are explained by sorting across firms, occupations, and occupation-firm units. We estimate these models separately by year.

Table 2 produces the basic results of the fixed-effects analyses limited to the main job of workers 30 to 55 years old. Both firm and occupational segregation are important sources of the gender pay gap. In 2005 the residual pay gap in all years is marginally smaller for occupation (−0.234 or 20.9 percent) than for firm (−0.255 or 22.5 percent), suggesting that occupational segregation is a slightly more important source of gender pay disparities than firm segregation. This pattern is the same across all years, although the residual gender pay gap within firms drops further and continuously across the time period. Within occupation gender pay gaps decline from 2005 to about 2013, with a slight rise thereafter. Within-job (firm-by-occupation) pay gaps are considerably smaller and tend to be about half the magnitude of the baseline pay gap.

Figure 2 displays the same information as Table 2 but instead highlights the reduction in the baseline pay gap

[3]These series suggest less of a role for between-firm segregation in explaining earnings gap once full-time earnings is accounted for. This would be expected if firm segregation proceeds on the basis of earnings levels or hours worked: high-paid women work with high-paid women, while low-paid women work with low-paid women.

Table 2. Trends in U.S. Gender Yearly Earnings Gaps for Workers Aged 30 to 55 Years, Primary Job, Controlling for Age, Age Squared, Education, Full-Time Earnings Threshold, and Marginal Job Indicators: Without (Baseline) and with Fixed Effects for Firm, Occupation, and Firm by Occupation.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Baseline model											
Coefficient	−.332	−.334	−.321	−.302	−.275	−.279	−.282	−.285	−.286	−.290	−.296
SE	(.061)	(.059)	(.064)	(.069)	(.073)	(.073)	(.073)	(.072)	(.073)	(.073)	(.071)
n	998,300	1,036,000	997,300	1,002,000	947,100	931,200	995,000	1,125,000	1,061,000	1,100,000	1,091,000
R^2	.593	.588	.602	.623	.641	.641	.636	.629	.623	.618	.610
Firm fixed effects											
Coefficient	−.255	−.254	−.245	−.235	−.219	−.215	−.209	−.209	−.211	−.21	−.214
SE	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
n	590,800	618,000	591,600	594,200	559,100	550,700	593,400	685,100	645,700	673,100	667,800
R^2	.670	.668	.681	.698	.713	.718	.725	.717	.714	.713	.708
Occupation fixed effects											
Coefficient	−.234	−.236	−.226	−.213	−.197	−.198	−.195	−.196	−.195	−.199	−.202
SE	(.010)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
n	997,600	1,036,000	997,000	1,002,000	946,700	930,800	993,300	1,124,000	1,060,000	1,099,000	1,090,000
R^2	.675	.672	.683	.699	.714	.712	.708	.703	.695	.688	.683
Firm-by-occupation fixed effects											
Coefficient	−0.165	−0.163	−0.159	−0.155	−0.142	−0.14	−0.134	−0.135	−0.136	−0.135	−0.141
SE	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
n	238,900	252,400	242,200	241,900	231,100	227,900	238,900	283,500	258,900	269,600	269,200
R^2	0.749	0.747	0.759	0.771	0.790	0.795	0.801	0.796	0.794	0.790	0.785

Source: Authors' calculations from Internal Revenue Service W-2 tax records linked to Social Security Records and Census Bureau American Community Survey data.
Note: Regressions use American Community Survey survey weights and robust standard errors.

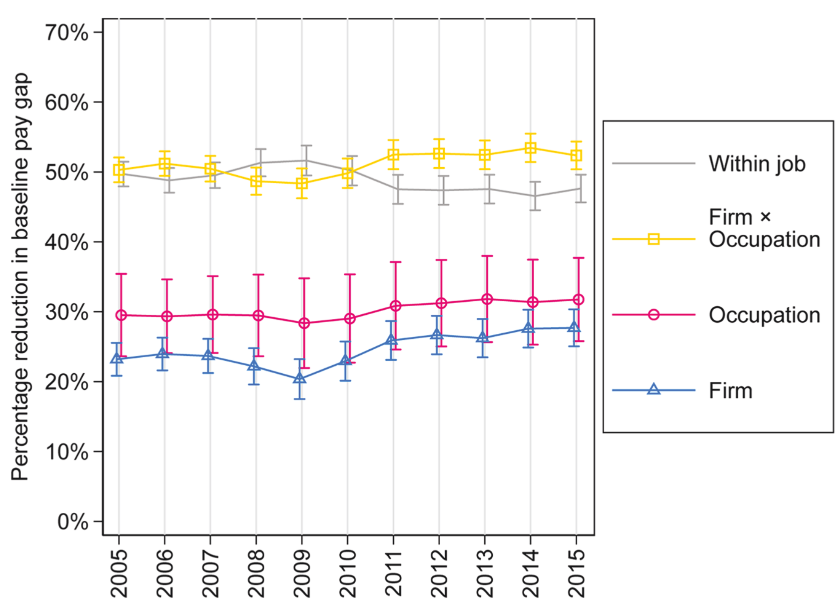

Figure 2. Percentage of the baseline gender yearly earnings gap associated with between-firm, between-occupation, and between-job (firm-by-occupation) pay differences, with remainder within jobs for prime-age workers, 2005 to 2015.
Source: Authors' calculations from Table 2.
Note: All models control for age, age squared, and education levels, as well as marginal and full-time earnings threshold indicators. Ninety-five percent confidence intervals are indicated.

Table 3. Trends in U.S. Gender Hourly Earnings Gaps for Workers Aged 30 to 55 Years, Primary Job, Controlling for Age, Age Squared, Education, Full-Time Earnings Threshold, and Marginal Job Indicators: Without (Baseline) and with Fixed Effects for Firm, Occupation, and Firm by Occupation.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Baseline model											
Coefficient	−.161	−.166	−.158	−.156	−.146	−.164	−.154	−.155	−.151	−.153	−.159
SE	(.102)	(.098)	(.106)	(.109)	(.112)	(.100)	(.104)	(.101)	(.103)	(.104)	(.104)
n	998,300	1,036,000	997,300	1,002,000	947,100	931,200	995,000	1,125,000	1,061,000	1,100,000	1,091,000
R^2	.352	.356	.370	.404	.415	.398	.392	.392	.385	.385	.390
Firm fixed effects											
Coefficient	−.144	−.144	−.140	−.141	−.135	−.139	−.121	−.122	−.118	−.117	−.122
SE	(.003)	(.004)	(.004)	(.004)	(.004)	(.004)	(.003)	(.003)	(.003)	(.003)	(.004)
n	590,800	618,000	591,600	594,200	559,100	550,700	593,400	685,100	645,700	673,100	667,800
R^2	.515	.519	.529	.561	.568	.557	.567	.558	.552	.554	.558
Occupation fixed effects											
Coefficient	−.117	−.120	−.114	−.115	−.107	−.118	−.100	−.102	−.100	−.102	−.106
SE	(.010)	(.009)	(.010)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
n	997,600	1,036,000	997,000	1,002,000	946,700	930,800	993,300	1,124,000	1,060,000	1,099,000	1,090,000
R^2	.433	.438	.451	.484	.493	.472	.468	.468	.457	.456	.462
Firm-by-occupation fixed effects											
Coefficient	−.086	−.087	−.085	−.089	−.083	−.088	−.076	−.078	−.077	−.077	−.085
SE	(.003)	(.003)	(.004)	(.004)	(.004)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
n	238,900	252,400	242,200	241,900	231,100	227,900	238,900	283,500	258,900	269,600	269,200
R^2	.613	.618	.628	.662	.674	.662	.675	.667	.661	.661	.667

Source: Authors' calculations from Internal Revenue Service W-2 tax records linked to Social Security Records and Census Bureau American Community Survey data.
Note: Regressions use American Community Survey survey weights and robust standard errors.

associated with including the successive fixed effects as a percentage of the baseline gender pay gap. This serves as our indicator of the extent to which between-context (job, firm, occupation) segregation contributes to the baseline gap. In Figure 2 we see that within-job pay differences and between job segregation are roughly equivalent in importance through 2010, but thereafter job segregation becomes a marginally larger component of the total gender earnings gap. Occupational segregation alone explains about 30 percent of the gender earnings gap, rising slowly over time. Firm segregation explains less, dropping to a low of 20 percent during the Great Recession, but rises dramatically thereafter, with firm contributions to pay gaps almost converging with occupation by 2014.

Table 3 shows the hourly earnings results for workers 30 to 55 years of age in their main jobs. Again, we find that gender segregation between high- and low-earnings firms and occupations produces substantial portions of the gender pay gap. Both the firm and occupation segregation effects grow over time, although the firm component grows at a faster pace. Within-job (occupations within firms) earnings gaps range between 7.3 percent and 8.5 percent, showing no dramatic changes over time. Figure 3 reports the reduction in the baseline gap following inclusion of job, firm, and occupation fixed effects as a percentage of the baseline gender pay gap. About half of the gender earnings gap is produced by the intersection of firm and occupation (i.e., job segregation). The remaining half is between men and women in the same firm working in the same detailed occupational titles. Job segregation is an increasing source of the gender earnings gap during the Great Recession. As with annual earnings, the between-firm component of the overall gap rises significantly between 2009 and 2015 for hourly earnings.

The Appendix includes analyses fit to the wider sample of workers aged 16 and older. Tables A2 and A3 can be compared with Tables 2 and 3, respectively, and show that the estimated gaps are smaller for the larger population. Figures A2 and A3, corresponding to Figures 2 and 3, display the same general trends in the proportion of the gap explained by firm, occupational, and job segregation over time.

Discussion and Conclusion

Examining linked employer-employee data that locate workers within firms as well as within occupations suggests that firm and occupational segregation are both important sources of U.S. average gender pay gaps, and that firm segregation is increasingly important over time. The significance of between-firm segregation is consistent with research showing that earnings inequality growth in the United States more

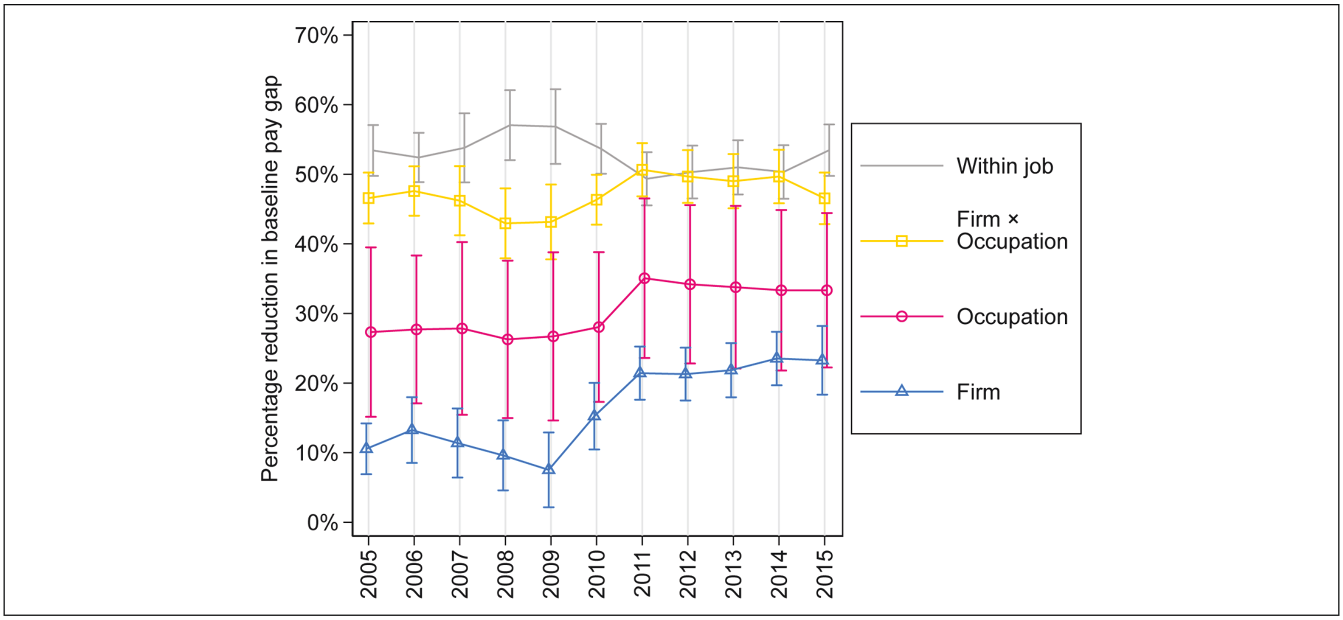

Figure 3. Percentage of the baseline gender hourly earnings gap associated with between-firm, between-occupation, and between-job (firm-by-occupation) pay differences, with remainder within job for prime-age workers, 2005 to 2015.
Source: Authors' calculations from Table 3.
Note: All models control for age, age squared, and education, as well as marginal and full-time earnings threshold indicators.

generally is primarily a between firm phenomena (Song et al. 2019). The within-job gender pay gap is about half of the baseline gender pay gap for both yearly and hourly earnings, with the other half associated with job-level segregation.

These estimates are broadly consistent with recent high-quality research on the gender pay gap (e.g., Barth et al. 2021; Blau and Kahn 2017; Foster et al. 2020). One area of concern relative to that literature is that we do not have individual level measures of cumulative labor force experience in our models. In the United States, we know that the rise of very long hours work has increased the gender pay gap (Cha and Weeden 2014). The difference between the size of the within job earnings gap for yearly and hourly earnings confirms that gender differences in hours worked is a major driver of U.S. gender pay disparities even within the same job.

There is considerable evidence in these analyses that within-job gender pay gaps are quite high in the contemporary United States. The hourly earnings estimate of within-job pay gaps hovers around 8 percent, while the yearly earnings gap averages around 14 percent. Given the sampling limitations associated with the ACS match, this conclusion holds most clearly for larger firms, at which we are more likely to observe gender-integrated jobs. As we do know that larger firms tend to pay higher earnings but that women receive less of a pay premium in larger firms (Hollister 2004), it seems likely that our matched W-2-to-ACS sample produces larger average within-firm pay gaps than in the population of all jobs. Larger firms are also more likely to have gender-integrated jobs (Tomaskovic-Devey, Kalleberg, and Marsden 1996), thus our matched sample is also likely to overestimate within-job pay gap components relative to within-firm occupational segregation. The sizes of these overestimations are a matter of speculation, but we suspect that they are not so large as to challenge our comparisons with earlier estimates. Relative to actual employer job titles, these are nearly certainly overestimates of within-job pay gaps, but again we do not know whether the magnitude is small or large.

Compared with past U.S. within-job gender gap estimates, our estimate is considerably smaller than the 16.2 percent 1990 lower-bound estimate (Bayard et al. 2003) and considerably larger than the 1980-era estimates of 0 percent to 3 percent (Groshen 1991; Petersen and Morgan 1995). All three studies use very large sample linked employer-employee data but diverge on other dimensions. Like the 1990 estimate, our measure of earnings is relatively inclusive: overtime, shift differentials, and bonuses are all included. The earlier papers used measures of contractual hourly or weekly pay and lack these various forms of supplemental wages. Thus, our higher within-job estimate may reflect that men have more access to within-job wage supplements of various types. We also know that high-performance work, merit pay, and bonus pay practices have all become more prevalent since 1980 (Cappelli 1999) and that these practices have been associated with rising gender earnings inequalities (Castilla 2012; Davies, McNabb, and Whitfield

2015; Drolet 2002; Elvira and Graham 2002). We suspect that the larger within-job gender pay gap in our estimates relative to 1980 estimates may reflect our potentially less precise job measure, the more inclusive earnings measure, and the rising use of various forms of supplemental pay. It is also plausible that as the human capital differences between men and women shrank and occupational segregation declined that within-job gender distinctions became more salient and within job bias processes grew. Reskin (1988) and Tilly (1998) both made the prediction that when inequality-installing mechanisms decline in legitimacy or effectiveness, others may emerge to reinstall inequalities.

Clearly, with better data we could improve estimates of the relative size of segregation and within job components. Administrative data holds the most promise in this regard. Estimates would be enhanced considerably if the occupation self-reports in IRS annual tax filings were merged with W-2 records so that we need not rely on relatively sparse within workplace sample data for job analyses. Even better would be if W-2 filings by employers included occupation codes as is common in many other countries (Penner et al. 2023). Most ambitiously, we concur with a recent conclusion from the National Academies of Sciences, Engineering, and Medicine (2022) recommending that future pay data collection by the Equal Employment Opportunity Commission collect individual-level pay data; sex, race, and ethnicity information; job titles; and precise measures of hours and weeks worked as well as firm-specific tenure. Such data would go a long way toward improving both scientific estimations and regulatory analyses of firm-level processes.

Establishing an average gender (or between race or ethnic group) national pay gap is only a beginning. Occupations vary a great deal in the sizes of their gender pay gaps, with some displaying very large gaps and others near gender equality (Foster et al. 2020). We suspect that this is true at the firm and job levels as well. Studies using administrative data from Portugal, Germany, France, and Norway show large gender pay gap variation among workplaces (Abowd, Kramarz, and Roux 2006; Barth and Dale-Olsen 2009; Card et al. 2016; Tomaskovic-Devey and Avent-Holt 2019). Linked employer-employee data for seven U.S. federal government science agencies show agency variation in the levels of gender pay disparity, the mechanisms that produce them, and trends over time (Smith-Doerr et al. 2019). Examining workplace heterogeneity in the extent of pay disparities and the mechanisms producing them is an obvious next step if we are to better understand the generation of gendered (or race/ethnic) earnings inequalities.

Linked employer-employee data have many applications beyond studying gender inequalities. For example, they can be used to decompose earnings inequalities into individual and workplace components (Song et al. 2019), explore workplace variation in immigrant-native inequalities (Tomaskovic-Devey, Hällsten, and Avent-Holt 2015), demonstrate the role of networks in career mobility (Collet and Hedström 2013), and show firm variation in scheduling practices (Storer, Schneider, and Harknett 2020), to name just a few applications. Linked employer-employee data may provide the means to finally fulfill Baron and Bielby's (1980) call to "bring the firm back in."

From the point of view of regulatory targeting of firms for segregation or within-job disparities it is this firm-level variation, rather than the national mean gender pay gap, that is of primary concern. It seems quite likely given our estimates that in most firms, job segregation is the more important source of gender pay gaps but also that both job segregation and within-job pay gaps will vary greatly from firm to firm. Since the Equal Pay Act and the Civil Rights Act prohibit both employment segregation and job-level pay discrimination, it seems that it is long past time for both social scientists and equal opportunity regulators to develop and take advantage of workplace level data.

England et al. (2020) documented the stalled progress toward gender equality in the United States and identified three necessary policy interventions to move toward a more gender equal society: increased access to publicly supported child care and men's participation in household work on the supply side and reduced discrimination by employers on the demand side. We show for the first time that within-job gender earnings gaps are stably high. It is also well documented in prior research that both occupational and within-firm gender segregation have also been stably high in recent decades (Stainback and Tomaskovic-Devey 2012; Zhu and Grusky 2022). Although our results are silent on the supply side, they confirm the need for changes in employer hiring and pay practices if the United States is to move toward a more gender equalitarian society.

Appendix

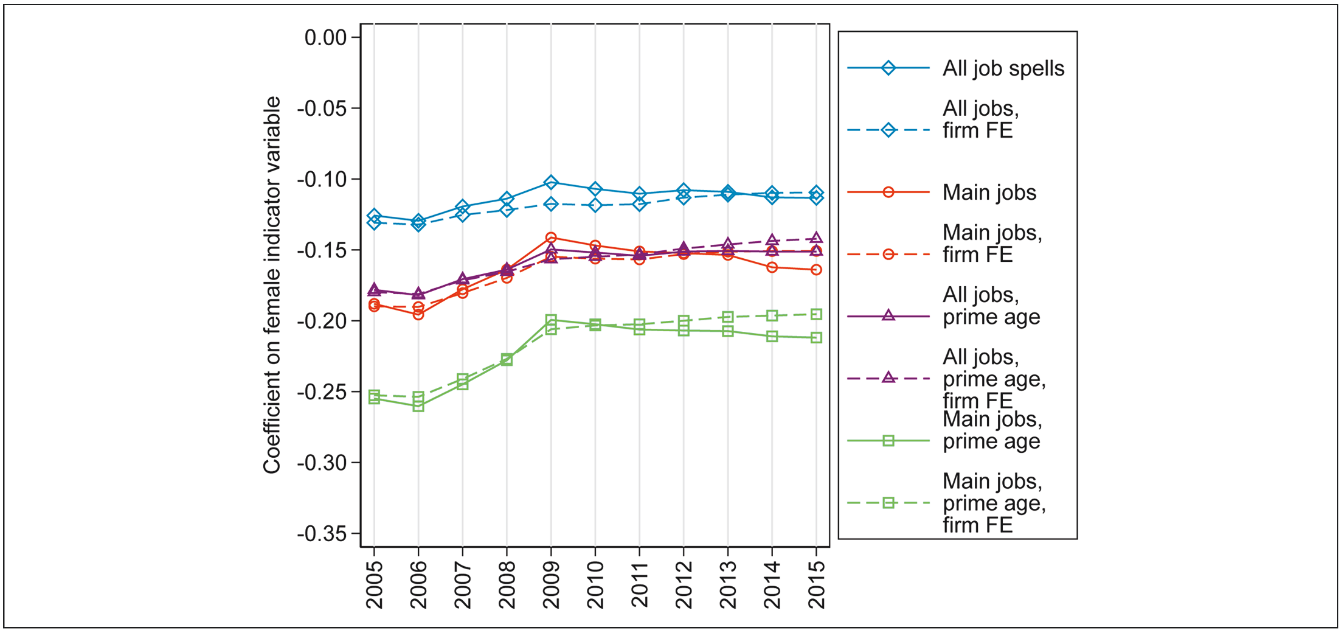

Figure A1. Estimated gender log yearly earnings gaps, various W-2-only samples, including full-time earnings-level indicator variable.
Note: Solid lines are net of age, age squared, and full-time and marginal jobs indicators. Dashed lines are residual pay gaps after firm fixed effects are added to the former. Ninety-five percent confidence intervals are smaller than line widths (see Table A1 for standard errors).

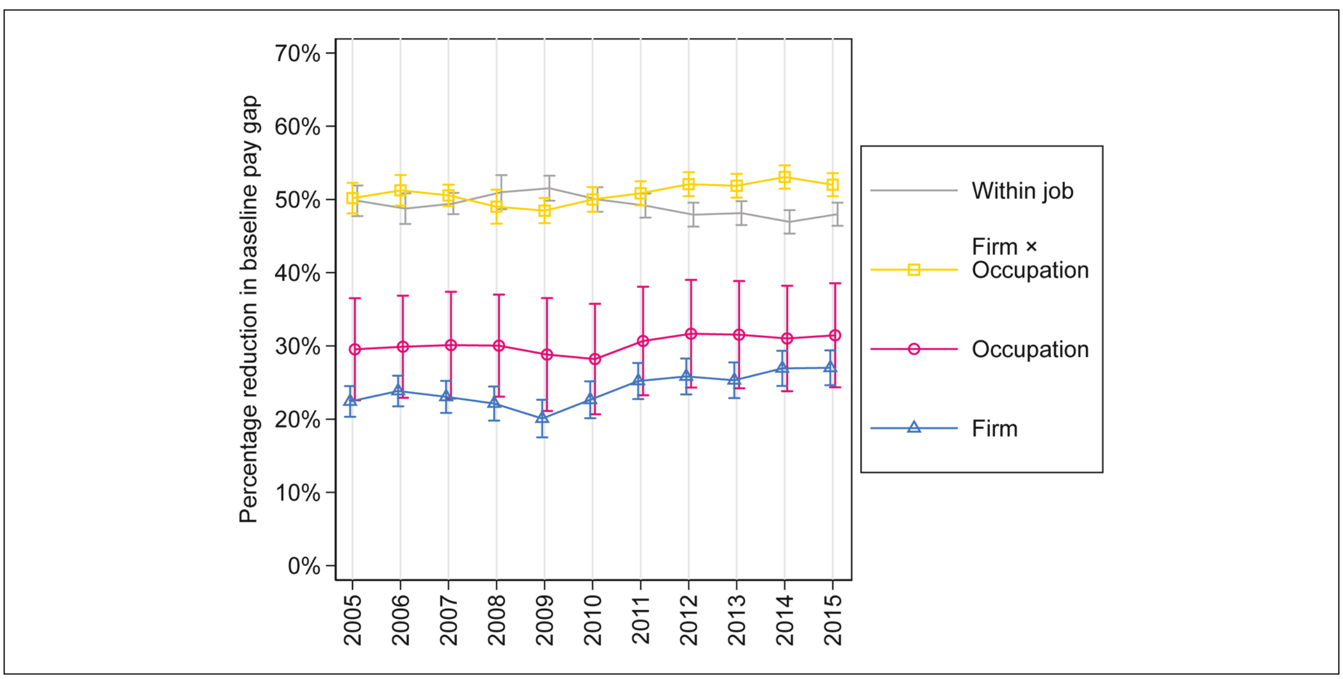

Figure A2. Percentage of the baseline gender yearly earnings gap associated with between-firm, between-occupation, and between-job (firm-by-occupation) pay differences, with remainder within job for workers aged 16 and older, 2005 to 2015.
Source: Authors' calculations from Table A2.
Note: All models control for age, age squared, and education, as well as marginal and full-time earnings threshold indicators.

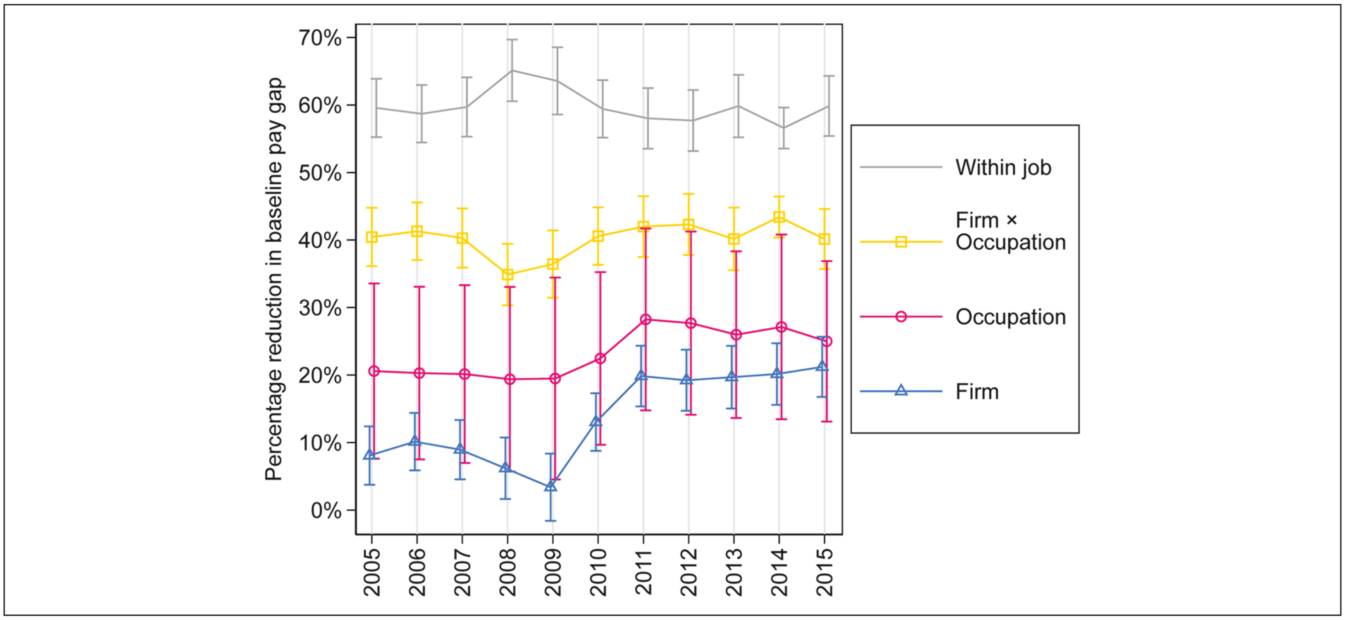

Figure A3. Percentage of the baseline gender hourly earnings gap associated with between-firm, between-occupation, and between-job (firm-by-occupation) pay differences, with remainder within job for workers aged 16 and older, 2005 to 2015.
Source: Authors' calculations from Table A3.
Note: All models control for age, age squared, and education, as well as marginal and full-time earnings threshold indicators.

Table A1. All Gender Gap Estimates, Multiple Models, Multiple Sample Definitions, Applied to Internal Revenue Service W-2, Social Security Linked Only Data.

Year	Female Indicator Coefficient	*SE*	*t*	*n*	Model
2005	−.1883	.000141	−1,338	224,500,000	pop_all
2005	−.2841	.000150	−1,899	149,900,000	pop_all_main
2005	−.2562	.000190	−1,348	118,800,000	pop_prime
2005	−.3648	.000193	−1,894	83,810,000	pop_prime_main
2005	−.1258	.000112	−1,127	224,500,000	fulltime_all
2005	−.1881	.000114	−1,650	149,900,000	fulltime_all_main
2005	−.1782	.000145	−1,233	118,800,000	fulltime_prime
2005	−.2549	.000148	−1,727	83,810,000	fulltime_prime_main
2005	−.1638	.000146	−1,121	217,300,000	firm_all
2005	−.2364	.000151	−1,568	144,900,000	firm_all_main
2005	−.2287	.000196	−1,165	112,400,000	firm_prime
2005	−.3159	.000190	−1,666	79,250,000	firm_prime_main
2005	−.1309	.000120	−1,095	212,100,000	firm_ft_all
2005	−.1899	.000116	−1,632	141,600,000	firm_ft_all_main
2005	−.1798	.000156	−1,150	108,600,000	firm_ft_prime
2005	−.2526	.000151	−1,670	77,020,000	firm_ft_prime_main
2006	−.1938	.000140	−1,386	229,500,000	pop_all
2006	−.2915	.000149	−1,963	152,400,000	pop_all_main
2006	−.2622	.000191	−1,376	119,800,000	pop_prime
2006	−.3695	.000193	−1,912	84,120,000	pop_prime_main
2006	−.1295	.000111	−1,173	229,500,000	fulltime_all
2006	−.1957	.000113	−1,733	152,400,000	fulltime_all_main
2006	−.1820	.000144	−1,260	119,800,000	fulltime_prime
2006	−.2603	.000149	−1,752	84,120,000	fulltime_prime_main
2006	−.1654	.000145	−1,143	222,300,000	firm_all

(continued)

Table A1. (continued)

Year	Female Indicator Coefficient	*SE*	*t*	*n*	Model
2006	−.2359	.000149	−1,583	147,400,000	firm_all_main
2006	−.2305	.000196	−1,174	113,400,000	firm_prime
2006	−.3160	.000189	−1,668	79,550,000	firm_prime_main
2006	−.1322	.000118	−1,118	217,100,000	firm_ft_all
2006	−.1903	.000116	−1,645	144,000,000	firm_ft_all_main
2006	−.1812	.000156	−1,160	109,600,000	firm_ft_prime
2006	−.2537	.000152	−1,671	77,360,000	firm_ft_prime_main
2007	−.1849	.000140	−1,320	231,700,000	pop_all
2007	−.2747	.000148	−1,859	155,200,000	pop_all_main
2007	−.2530	.000190	−1,329	120,400,000	pop_prime
2007	−.3566	.000192	−1,859	84,860,000	pop_prime_main
2007	−.1194	.000113	−1,059	231,700,000	fulltime_all
2007	−.1778	.000113	−1,568	155,200,000	fulltime_all_main
2007	−.1707	.000147	−1,160	120,400,000	fulltime_prime
2007	−.2449	.000148	−1,657	84,860,000	fulltime_prime_main
2007	−.1586	.000145	−1,094	224,600,000	firm_all
2007	−.2264	.000148	−1,528	150,100,000	firm_all_main
2007	−.2211	.000197	−1,125	113,900,000	firm_prime
2007	−.3044	.000188	−1,617	80,260,000	firm_prime_main
2007	−.1254	.000121	−1,041	219,300,000	firm_ft_all
2007	−.1805	.000116	−1,562	146,700,000	firm_ft_all_main
2007	−.1715	.000159	−1,078	110,200,000	firm_ft_prime
2007	−.2411	.000152	−1,592	77,990,000	firm_ft_prime_main
2008	−.1807	.000142	−1,273	224,300,000	pop_all
2008	−.2604	.000147	−1,771	155,100,000	pop_all_main
2008	−.2472	.000191	−1,296	116,800,000	pop_prime
2008	−.3399	.000191	−1,783	84,350,000	pop_prime_main
2008	−.1139	.000116	−985.6	224,300,000	fulltime_all
2008	−.1639	.000113	−1,445	155,100,000	fulltime_all_main
2008	−.1639	.000149	−1,100	116,800,000	fulltime_prime
2008	−.2279	.000147	−1,556	84,350,000	fulltime_prime_main
2008	−.1551	.000145	−1,072	217,400,000	firm_all
2008	−.2158	.000146	−1,475	150,000,000	firm_all_main
2008	−.2150	.000195	−1,101	110,600,000	firm_prime
2008	−.2906	.000186	−1,562	79,780,000	firm_prime_main
2008	−.1219	.000121	−1,010	212,400,000	firm_ft_all
2008	−.1698	.000115	−1,483	146,600,000	firm_ft_all_main
2008	−.1655	.000159	−1,043	106,900,000	firm_ft_prime
2008	−.2269	.000149	−1,519	77,470,000	firm_ft_prime_main
2009	−.1683	.000145	−1,159	204,900,000	pop_all
2009	−.2305	.000148	−1,555	150,500,000	pop_all_main
2009	−.2307	.000193	−1,196	108,300,000	pop_prime
2009	−.3040	.000192	−1,586	82,070,000	pop_prime_main
2009	−.1023	.000118	−864.1	204,900,000	fulltime_all
2009	−.1413	.000115	−1,233	150,500,000	fulltime_all_main
2009	−.1497	.000151	−990.7	108,300,000	fulltime_prime
2009	−.1994	.000146	−1,365	82,070,000	fulltime_prime_main
2009	−.1486	.000148	−1,006	198,300,000	firm_all
2009	−.1986	.000147	−1,352	145,500,000	firm_all_main
2009	−.2033	.000197	−1,032	102,300,000	firm_prime
2009	−.2678	.000188	−1,428	77,540,000	firm_prime_main
2009	−.1176	.000123	−952.6	193,600,000	firm_ft_all

(continued)

Table A1. (continued)

Year	Female Indicator Coefficient	*SE*	*t*	*n*	Model
2009	−.1548	.000116	−1,335	142,100,000	firm_ft_all_main
2009	−.1566	.000161	−973.9	98,960,000	firm_ft_prime
2009	−.2060	.000150	−1,375	75,190,000	firm_ft_prime_main
2010	−.1733	.000148	−1,175	202,200,000	pop_all
2010	−.2383	.000150	−1,590	148,800,000	pop_all_main
2010	−.2330	.000197	−1,180	106,500,000	pop_prime
2010	−.3089	.000196	−1,578	80,860,000	pop_prime_main
2010	−.1070	.000121	−887.8	202,200,000	fulltime_all
2010	−.1469	.000117	−1,259	148,800,000	fulltime_all_main
2010	−.1519	.000155	−978	106,500,000	fulltime_prime
2010	−.2025	.000150	−1,351	80,860,000	fulltime_prime_main
2010	−.1509	.000149	−1,014	195,400,000	firm_all
2010	−.2027	.000148	−1,370	143,700,000	firm_all_main
2010	−.1995	.000199	−1,001	100,500,000	firm_prime
2010	−.2632	.000190	−1,387	76,250,000	firm_prime_main
2010	−.1185	.000124	−954.5	190,700,000	firm_ft_all
2010	−.1562	.000117	−1,336	140,200,000	firm_ft_all_main
2010	−.1549	.000162	−954.7	97,080,000	firm_ft_prime
2010	−.2033	.000152	−1,339	73,940,000	firm_ft_prime_main
2011	−.1766	.000146	−1,213	205,900,000	pop_all
2011	−.2456	.000149	−1,646	150,000,000	pop_all_main
2011	−.2338	.000196	−1,192	107,500,000	pop_prime
2011	−.3143	.000196	−1,604	80,880,000	pop_prime_main
2011	−.1104	.000118	−933.4	205,900,000	fulltime_all
2011	−.1511	.000116	−1,301	150,000,000	fulltime_all_main
2011	−.1542	.000153	−1,007	107,500,000	fulltime_prime
2011	−.2062	.000150	−1,375	80,880,000	fulltime_prime_main
2011	−.1499	.000148	−1,012	199,100,000	firm_all
2011	−.2034	.000147	−1,382	144,900,000	firm_all_main
2011	−.1971	.000199	−988.9	101,400,000	firm_prime
2011	−.2622	.000189	−1,385	76,270,000	firm_prime_main
2011	−.1178	.000124	−951.6	194,200,000	firm_ft_all
2011	−.1568	.000117	−1,341	141,400,000	firm_ft_all_main
2011	−.1532	.000162	−943.4	97,990,000	firm_ft_prime
2011	−.2025	.000152	−1,331	74,010,000	firm_ft_prime_main
2012	−.1760	.000144	−1,221	214,600,000	pop_all
2012	−.2492	.000149	−1,674	153,200,000	pop_all_main
2012	−.2325	.000196	−1,184	110,300,000	pop_prime
2012	−.3168	.000196	−1,614	81,500,000	pop_prime_main
2012	−.1079	.000117	−920.1	214,600,000	fulltime_all
2012	−.1523	.000115	−1,321	153,200,000	fulltime_all_main
2012	−.1512	.000154	−981.8	110,300,000	fulltime_prime
2012	−.2069	.000151	−1,373	81,500,000	fulltime_prime_main
2012	−.1439	.000146	−987.8	207,900,000	firm_all
2012	−.1969	.000146	−1,347	148,200,000	firm_all_main
2012	−.1936	.000198	−977.6	104,200,000	firm_prime
2012	−.2595	.000189	−1,376	76,990,000	firm_prime_main
2012	−.1132	.000122	−928.1	203,200,000	firm_ft_all
2012	−.1530	.000116	−1,323	144,900,000	firm_ft_all_main
2012	−.1491	.000162	−920.6	100,800,000	firm_ft_prime
2012	−.2000	.000152	−1,315	74,780,000	firm_ft_prime_main
2013	−.1770	.000142	−1,248	220,100,000	pop_all
2013	−.2514	.000147	−1,705	155,300,000	pop_all_main

(continued)

Table A1. (continued)

Year	Female Indicator Coefficient	*SE*	*t*	*n*	Model
2013	−.2315	.000195	−1,190	111,400,000	pop_prime
2013	−.3173	.000196	−1,623	81,640,000	pop_prime_main
2013	−.1091	.000115	−950.2	220,100,000	fulltime_all
2013	−.1536	.000114	−1,353	155,300,000	fulltime_all_main
2013	−.1508	.000151	−996.2	111,400,000	fulltime_prime
2013	−.2073	.000150	−1,387	81,640,000	fulltime_prime_main
2013	−.1413	.000144	−978.5	213,400,000	firm_all
2013	−.1946	.000145	−1,342	150,300,000	firm_all_main
2013	−.1900	.000198	−961.3	105,300,000	firm_prime
2013	−.2561	.000188	−1,362	77,130,000	firm_prime_main
2013	−.1111	.000121	−918.4	208,500,000	firm_ft_all
2013	−.1513	.000115	−1,320	147,000,000	firm_ft_all_main
2013	−.1462	.000162	−904.5	101,900,000	firm_ft_prime
2013	−.1973	.000152	−1,301	74,950,000	firm_ft_prime_main
2014	−.1825	.000140	−1,302	227,900,000	pop_all
2014	−.2630	.000146	−1,799	157,700,000	pop_all_main
2014	−.2332	.000194	−1,201	114,100,000	pop_prime
2014	−.3228	.000196	−1,648	82,170,000	pop_prime_main
2014	−.1130	.000113	−997.3	227,900,000	fulltime_all
2014	−.1623	.000112	−1,448	157,700,000	fulltime_all_main
2014	−.1512	.000151	−1,001	114,100,000	fulltime_prime
2014	−.2110	.000150	−1,406	82,170,000	fulltime_prime_main
2014	−.1416	.000142	−994.7	221,200,000	firm_all
2014	−.1962	.000143	−1,370	152,700,000	firm_all_main
2014	−.1886	.000197	−959.4	107,900,000	firm_prime
2014	−.2560	.000187	−1,368	77,670,000	firm_prime_main
2014	−.1098	.000119	−921	216,300,000	firm_ft_all
2014	−.1509	.000113	−1,331	149,400,000	firm_ft_all_main
2014	−.1437	.000160	−896.4	104,500,000	firm_ft_prime
2014	−.1964	.000151	−1,301	75,520,000	firm_ft_prime_main
2015	−.1838	.000138	−1,330	235,300,000	pop_all
2015	−.2634	.000145	−1,820	160,200,000	pop_all_main
2015	−.2345	.000193	−1,216	116,500,000	pop_prime
2015	−.3217	.000195	−1,649	82,750,000	pop_prime_main
2015	−.1134	.000111	−1,018	235,300,000	fulltime_all
2015	−.1640	.000111	−1,481	160,200,000	fulltime_all_main
2015	−.1512	.000150	−1,012	116,500,000	fulltime_prime
2015	−.2119	.000150	−1,418	82,750,000	fulltime_prime_main
2015	−.1410	.000140	−1,004	228,400,000	firm_all
2015	−.1948	.000142	−1,376	155,200,000	firm_all_main
2015	−.1865	.000195	−954.9	110,300,000	firm_prime
2015	−.2530	.000186	−1,362	78,260,000	firm_prime_main
2015	−.1095	.000118	−931.3	223,500,000	firm_ft_all
2015	−.1508	.000112	−1,348	151,900,000	firm_ft_all_main
2015	−.1422	.000159	−893.1	106,900,000	firm_ft_prime
2015	−.1954	.000150	−1,300	76,140,000	firm_ft_prime_main

Note: All models condition on age, age squared, and marginal part-time work indicator. The dependent variable is log total annual earnings of given W-2 job spell. "All" refers to all workers and "prime" to prime-age workers. "Main" refers to the highest paying job; otherwise all jobs are included. "Fulltime" indicates the inclusion of an indicator variable in the regression for job earnings above the full-time earnings threshold (see text); otherwise it is omitted. "Firm" indicates that firm fixed effects are included without reference to the full-time earnings indicator, while "firm_ft" indicates firm by full-time indicator fixed effects are included; otherwise no firm fixed effects are included. Gender-integrated firms only in firm fixed-effects models; entirely gender homogenous firms are dropped. At least 94.3 percent of workers are in gender-integrated firms each year under any model specification.

Table A2. Trends in U.S. Gender Yearly Earnings Gaps for Workers Aged 16 and Older, Primary Job, Controlling for Age, Age Squared, Education, Full-Time Earnings Threshold, and Marginal Job Indicators: Without (Baseline) and with Fixed Effects for Firm, Occupation, and Firm by Occupation.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Baseline model											
Coefficient	−.281	−.281	−.269	−.253	−.229	−.234	−.238	−.240	−.241	−.245	−.248
SE	(.088)	(.089)	(.094)	(.098)	(.098)	(.098)	(.098)	(.099)	(.099)	(.097)	(.096)
n	1,612,000	1,696,000	1,655,000	1,682,000	1,597,000	1,584,000	1,721,000	1,965,000	1,871,000	1,971,000	1,975,000
R^2	.700	.701	.711	.725	.737	.734	.723	.717	.714	.711	.704
Firm fixed effects											
Coefficient	−.218	−.214	−.207	−.197	−.183	−.181	−.178	−.178	−.180	−.179	−.181
SE	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
n	988,100	1,051,000	1,023,000	1,044,000	991,200	985,400	1,084,000	1,262,000	1,199,000	1,271,000	1,275,000
R^2	.778	.78	.788	.799	.809	.81	.805	.799	.797	.795	.791
Occupation fixed effects											
Coefficient	−.198	−.197	−.188	−.177	−.163	−.168	−.165	−.164	−.165	−.169	−.170
SE	(.010)	(.010)	(.010)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
n	1,612,000	1,696,000	1,655,000	1,682,000	1,597,000	1,584,000	1,720,000	1,964,000	1,871,000	1,970,000	1,974,000
R^2	.760	.762	.768	.779	.788	.785	.777	.772	.768	.764	.759
Firm-by-occupation fixed effects											
Coefficient	−.140	−.137	−.133	−.129	−.118	−.117	−.117	−.115	−.116	−.115	−.119
SE	(.003)	(.003)	(.002)	(.003)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
n	423,300	453,800	443,600	449,900	435,500	434,200	464,600	551,100	510,500	538,200	544,800
R^2	.842	.843	.848	.855	.865	.866	.865	.861	.86	.857	.854

Source: Authors' calculations from Internal Revenue Service W-2 tax records linked to Social Security Records and Census Bureau American Community Survey data.
Note: Regressions use American Community Survey survey weights and robust standard errors.

Table A3. Trends in U.S. Gender Hourly Earnings Gaps for Workers Aged 16 and Older, Primary Job, Controlling for Age, Age Squared, Education, Full-Time Earnings Threshold, and Marginal Job Indicators: Without (Baseline) and with Fixed Effects for Firm, Occupation, and Firm by Occupation.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Baseline model											
Coefficient	−.136	−.138	−.134	−.129	−.118	−.138	−.131	−.130	−.127	−.129	−.132
SE	(.110)	(.108)	(.111)	(.119)	(.120)	(.110)	(.112)	(.112)	(.111)	(.111)	(.111)
n	1,612,000	1,696,000	1,655,000	1,682,000	1,597,000	1,584,000	1,721,000	1,965,000	1,871,000	1,971,000	1,975,000
R^2	.338	.342	.356	.388	.400	.379	.368	.363	.361	.362	.363
Firm fixed effects											
Coefficient	−.125	−.124	−.122	−.121	−.114	−.120	−.105	−.105	−.102	−.103	−.104
SE	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
n	988,100	1,051,000	1,023,000	1,044,000	991,200	985,400	1,084,000	1,262,000	1,199,000	1,271,000	1,275,000
R^2	.514	.517	.526	.557	.565	.547	.549	.537	.535	.536	.538
Occupation fixed effects											
Coefficient	−.108	−.110	−.107	−.104	−.095	−.107	−.094	−.094	−.094	−.094	−.099
SE	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)	(.008)	(.009)	(.008)
n	1,612,000	1,696,000	1,655,000	1,682,000	1,597,000	1,584,000	1,720,000	1,964,000	1,871,000	1,970,000	1,974,000
R^2	.415	.421	.432	.462	.473	.449	.440	.434	.428	.429	.432
Firm-by-occupation fixed effects											
Coefficient	−.081	−.081	−.080	−.084	−.075	−.082	−.076	−.075	−.076	−.073	−.079
SE	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.002)	(.003)
n	423,300	453,800	443,600	449,900	435,500	434,200	464,600	551,100	510,500	538,200	544,800
R^2	.608	.614	.621	.653	.664	.645	.652	.643	.641	.641	.644

Source: Authors' calculations from Internal Revenue Service W-2 tax records linked to Social Security Records and Census Bureau American Community Survey data.
Note: Regressions use American Community Survey survey weights and robust standard errors.

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Data Availability

All data available to evaluate this article are included in the article and its appendix. The source data used to create the estimates presented in this article are highly confidential and can be accessed only by Census Bureau employees with permission from the IRS. Generic replication code is included in the online supplement.

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Supplemental Material

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