When Time Binds: Returns to Working Long Hours and the Gender Wage Gap among the Highly Skilled

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Abstract

This paper explores the relationship between gender differences in hours worked, the returns to working long hours, and the gender pay gap among highly educated workers. Using a cross-section of occupations, Goldin (2014) documents that occupations characterized by high returns to overwork are also those with the largest gender gap in earnings. Using panel data on occupations across cities over time, we show that these associations continue to hold even after accounting for differences across occupations over time, differences across cities over time, and differences in characteristics of occupations that vary by city. To provide causal evidence on the demand for long hours and how it relates to gender wage gaps, we exploit exogenous cross-city variation in low-skilled immigrant flows to proxy for changes in the prices of outsourcing household production. We find that low-skilled immigration leads to a reduction in the gender gap in weekly hours worked, as well as the gender pay gap, particularly in occupations that disproportionately reward longer hours of work. These results highlight the causal role of the returns to overwork in explaining the gender pay gap and suggest that reductions in the cost of supplying longer hours of work may allow women to close the gap in hours of work and to benefit from higher wages.

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1 Introduction

Despite the rapid progress that women have made in reversing the gender gap in education, declines in labor market discrimination and improvements in the continuity of labor market experience, gender differences in earnings have remained remarkably persistent. While women's relative earnings converged rapidly beginning in the late 1970s through the 1980s, the convergence slowed in the 1990s and appears to have stalled since the 2000s (Blau 2012, Blau and Kahn 2006). Moreover, the rate of convergence of the gender pay gap has been quite different across the education distribution. As shown in Figure 1A, in 1980, the gender pay gap for college women was between 10 to 20 percentage points smaller than that of other education groups - strikingly, by 2010, there is little difference in the size of the gender pay gap for individuals with a college degree, relative to those with a high school degree or less. Furthermore, the size of the gender pay gap among those with some college education is about 3 percentage points smaller relative to those with a college degree or more.[1] These patterns are all the more remarkable as college-educated women today are characterized by high labor force attachment and are typically well-represented in many professional spheres.[2]

This paper explores the role of the growing prevalence of overtime work coupled with the increasing returns to providing long hours in explaining the persistence of gender pay gaps, particularly among highly educated workers. Figure 1B depicts the trends in the elasticity of annual earnings to weekly hours worked (a measure of the returns to working long hours) from 1980 to 2010 for males of differing education levels. As shown in the figure, the returns to working long hours have increased consistently for all education groups, with college-educated workers experiencing the largest increase over time. Given that the gender gap in hours worked has remained relatively constant over time for all education groups (Figure 1C), these patterns suggest a potential role for changes in the returns to working long hours to explain the convergence in gender pay gaps across education levels.

The correlation between the gender pay gaps and the returns to working long hours has been documented by Claudia Goldin in her 2014 AEA presidential address. Using a cross-section of occupations, Goldin (2014) finds that occupations characterized by high returns to overwork are also those with the largest gender gap in earnings. Moreover, she argues that a major cause of the remaining gender pay gap lies in the way jobs are organized and the fact that in many occupations, individuals are disproportionately rewarded for providing long hours on the job. Given women's dual roles in the home and in the labor market, gender equality in labor market outcomes is likely to prevail only if jobs can be re-organized in such a way so as to remove the penalties from women's lower hours worked. In a similar vein, Cha and Weeden (2014) document a strong time-series

[1] Arulampalam, Booth and Bryan (2007) document an acceleration in the gender wage gap at the top of the wage distribution in Europe from 1995-2001.

[2] For example, as documented in Goldin (2014), women are as likely as men to go into law and medical fields.

correlation between the gender gap in earnings and the level and returns to overwork (defined as working 50+ hours a week), and note that this relationship is particularly strong when the sample is restricted to managerial and professional occupations.

While the cross-occupation and time-series evidence of the relationship between the returns to working long hours and the gender pay gap are highly suggestive, they do not address the issue that occupations that disproportionately reward individuals who work long hours are likely to differ on other important dimensions that may also be correlated with the gender pay gap. For example, occupations where the incidence of overtime are common, such as financial managers and lawyers, are also characterized as being highly competitive.[3] Recent research suggests that women tend to “opt-out" of competition and males tend to outperform females in competitive settings (Gneezy, Niederle and Rustichini, 2003; Ors, Palomino, and Peyrache, 2012; Flory, Leibbrant an List, 2014). Moreover, the proposed causes of the increase in the returns to overwork such as globalization and changes in the organizational structures within firms might have also affected the returns to other skills and job characteristics that are correlated with working long hours on the job. Simply stated, the observed relationship between the returns to working long hours and the gender wage gap may be confounded by other job characteristics, and without further evidence on causality, it is hard to determine how important gender differences in the propensity to work long hours as well as the rising returns to overwork are to understanding persisting differences in the relative earnings of highly-skilled women.

The main contribution of this paper is to provide causal evidence on the effect of gender differences in the probability of working long hours on the gender wage gap. We test if the higher cost to women of working long hours is an important factor in explaining the persistent pay gap in skilled occupations, particularly in occupations that disproportionately reward individuals who are willing and able to supply longer hours. Following Cortes (2008) and Cortes and Tessada (2011), we use exogenous variation in low-skilled immigrant flows to proxy for changes in the prices of outsourcing household production. The exogeneity of the immigration flows is based on using the historical distribution of low-skilled immigrants to allocate future flows of low-skilled immigrants at the national level. The intuition behind our empirical strategy is the following - cities that receive a large influx of low-skilled immigrants face lower costs of outsourcing household production thus enabling highly-skilled women in these cities to provide longer hours on the job. This reduction in costs of outsourcing household production is likely to have a larger effect on women who work in occupations that demand more temporal flexibility and reward longer hours of work. Therefore, the low-skilled immigration shock provides us with a plausibly exogenous shifter of the cost of working long hours for women across cities and across occupations, thus allowing us to examine whether the gender differences in hours worked is causally related to the gender gap in earnings.

[3] Section 2.1 provides a systematic analysis of the correlation between the returns to working long hours and the degree of competitiveness in the occupation.

Our data comes from the 1980, 1990, and 2000 Census, and the 3-year aggregate 2012 ACS. Our unit of observation is at the MSA[4] by occupation by year level, allowing us to control not only for city, occupation, and year fixed effects, but also for city-specific shocks, occupation-specific shocks and time-invariant occupation-specific characteristics that vary at the city level. We first explore how the correlation between the gender pay gap and the returns to working long hours, estimated using a different source of variation, compares with the cross-occupation and across time correlations documented respectively by Goldin (2014) and Cha and Weeden (2014). We find a robust and statistically significant relationship between the elasticity of earnings to weekly hours and the size of the gender gap: the larger the increase in the returns to working long hours at the occupation*city level, the larger the increase in the gender pay gap. The magnitude of the coefficient is about half that of the estimate obtained when exploiting cross-occupation variation and similar to that obtained by exploiting variation over time. The magnitude of the estimate suggests that if the returns to working long hours for college educated workers had stayed at their 1980 level, the gender pay gap in 2010 would be between one and three percentage points smaller. These numbers are likely to be an overestimate as the returns to other skills are likely to be positively correlated to the returns to working long hours.

Turning to the IV estimates, our variable of interest is the interaction between an occupation-specific measure of the returns to working long hours (measured in 1980 at the national level) and a time-varying city level variable related to the cost of providing long hours, which we instrument using the predicted flow of low skilled immigrants. Our hypothesis is that if the higher cost of working long hours for women is harming their potential earnings, then an exogenous shock that reduces this cost should lead to a reduction in the size of the gender gap in hours worked and the gender pay gap, particularly in those occupations in which the returns to working long hours are higher. Our estimates imply that, for the average city, the decrease in the gender gap in the likelihood of working 50+ hours per week resulting from the low-skilled immigration wave of 1980 to 2010 led to a 2 percentage point decline in the gender wage gap for occupations at the 90th percentile in terms of returns to hours work (lawyers) relative to occupations at the 10th percentile (educators) - the 2010 difference in gender gaps between these two occupations was 11 percentage points.

Besides contributing to the literature on gender gaps, this paper also adds to the literature on the effects of migration on the receiving country. Most of the research on immigration flows have focused on the effects on the labor outcomes of natives via changes in the relative supplies of skilled vs. unskilled workers and the substitutability or complementarity of native-born versus foreign-born workers in the production function. Cortes and Tessada (2011) examined other potential channels, and provided evidence that immigration from low skilled countries by lowering the prices of services

[4] We use the variable *metaread* in the Census and use "MSA" and "city" interchangeably in the text.

that are close to household production, have enabled highly skilled women to work more hours in the market. This paper extends their findings, by showing that low-skilled immigrants not only increase the probability that highly skilled women work long hours, but also leads to a reduction in the gender pay gap in the upper tail of the skill distribution, thereby indirectly contributing to raising the glass ceiling.[5]

The rest of the paper is organized as follows. Section 2 describes the data, the construction of key variables and presents some cross-sectional correlations. Section 3 discusses the empirical strategy and presents results from the panel data and instrumental variable approaches. In Section 4, we discuss the magnitudes and policy implications of our results and how they compare to those in the existing literature. Finally, Section 5 concludes.

2 Data and Descriptive Statistics

The data is drawn from the 1980 to 2000 Censuses and 2012 American Community Survey (ACS) 3-year aggregate (2010-2012).[6] The main sample that we use to estimate the gender wage gap and the returns to working long hours at the occupation level is restricted to native-born individuals age 25-64 with at least a bachelor's degree who report working full-time (35 hours or more) in a given week.[7]

To ensure that we have a consistent set of occupations over the sample time period, we use Dorn's (2009) occupational classification which modifies the *OCC1990* Census classification to create a consistent set of occupations from 1980 to 2010.[8] This consistent occupational coding scheme creates a balanced panel of occupations from 1980 to 2012 and ensures that our results are not affected by changes in the set of occupations over time. Finally, our main empirical analyses focus on skilled occupations, which we define as occupations where the share of college graduates in their workforce exceed that in the population.[9] The full list of the 92 skilled occupations included in our sample is presented in Appendix Table 1.

To estimate the returns to working long hours in each occupation o in Census/ACS year t, we follow the procedure outlined in Goldin (2014). Specifically, we restrict the sample to male workers

[5] Note that, theoretically, the effect could have gone in the opposite direction if males and females are not perfect substitutes in production, and the increase in the labor supply of highly skilled women lowered their wages.

[6] In the text, we refer to the data from the 2012 ACS as corresponding to the 2010 time period.

[7] We focus on full-time workers as selection into working part-time, particularly for men, is likely to be very strong. These unobserved factors that drive certain individuals to choose to work part-time are likely to distort our estimates of gender gaps and the return to working long hours.

[8] As Dorn's (2009) crosswalk only provides a consistent classification scheme for occupations until 2009, we extended the crosswalk to include the 2012 ACS occupation classification.

[9] We drop occupations with fewer than 30 males and 30 females in the each Census/ACS year.

and estimate the following regression separately for each Census/ACS year.

$$\begin{aligned}\ln(yearly\_earnings)_{io} &= \alpha + \sum_{o} \beta_o * I(occ_o = 1) * \ln(hours\_week)_{io} \\ &\quad + \eta * \ln(weeks\_year)_{io} + \pi_o + X'_{io}\delta + \varepsilon_{io}, \qquad (1)\end{aligned}$$

where $yearly\_earnings_{io}$ is the annual wage and salary income of individual i in occupation o, $hours\_week$ refers to the usual hours worked per week and $weeks\_year$ is the number of weeks an individual worked in the previous year.[10,11] π_o includes occupation fixed effects and X_i is a vector of demographic characteristics that includes a quartic in age, an indicator for female, race fixed effects and indicators for whether an individual has a masters or doctoral degree.

Our measure of the returns to working long hours is β_o, which indicates the elasticity of yearly earnings to usual hours worked per week. $\beta_o > 1$ implies that yearly earnings increase more than proportionally for a given change in weekly hours worked, suggesting a convex relationship between earnings and working long hours. Conversely, $\beta_o < 1$ implies that a given increase in hours worked is associated with a less than proportional change in yearly earnings. Therefore, occupations with a higher β are characterized by higher returns to working longer hours. We estimate the returns using only full-time male workers to avoid the complex selection issues that are likely to affect the annual wages and hours worked of female workers and workers who choose to work part-time.

It is worth pointing out that there are several important caveats when interpreting β as a measure of the returns to working long hours in an occupation. First, our procedure measures the contemporaneous returns among individuals who work different numbers of hours each week. In some occupations such as law and finance, workers are expected to work long hours at lower wages at the beginning of their career before they can advance to management positions that have significantly higher wages in the future. For these occupations, our measure of the contemporaneous return is likely to underestimate the long-run return of working long hours. For example, a recent paper by Gicheva (2013) shows that among a sample of GMAT takers, working more hours, conditional on having worked at least 47 hours, is associated with a significant increase in annual wage growth and the possibility of promotion.[12]

Second, given our focus on the labor market for skilled workers, top-coding of income is likely to affect a large share of our observations and introduce measurement error. To address this issue, we follow the literature and multiply the income top-code for the 1980 Census by 1.5. In the 1990

[10] Weeks worked in the previous year is only available in intervals in the ACS. For each interval, we assign the mode of the interval as measured in the 2000 Census. For example, for the interval 50-52 weeks, most people report working 52 weeks in the 2000 Census.

[11] We drop observations in cases where based on the information proved on annual salary, hours per week and weeks per year individuals have implied hourly wages (in 1990$) below 3.5 or above 150.

[12] Interestingly, she does not find a similar relationship among employees working fewer than 47 hours.

and 2000 Census, the wages in the top-code are assigned the state median (1990) or mean (2000) of values above the top code. In the 2012 ACS, the top code is assigned the mean of individuals earning above the 99.5th percentile of income within each state. As such, we do not modify the income variable from 1990 to 2010. Nevertheless, while the Census/ACS top coding procedure from 1990 to 2010 ensures that the average income among individuals earning the top-code is accurate at the state level, at the occupation level, we are likely to underestimate the returns for occupations with a large share of workers with incomes at the very top of the distribution. Finally, measurement error in weekly hours worked is also likely to lead to a downward bias in the estimated elasticities. Overall, these limitations inherent in our measure imply that β_c is likely to underestimate the true returns to working long hours.

To estimate the gender gap in each occupation, we estimate the following equation for each Census/ACS year for our main sample:

$$\begin{aligned}\ln(yearly\_earnings)_{io} = \alpha \quad & + \quad \sum_{o} \lambda_o * I(occ_o = 1) * female_{io} + \beta * \ln(hours\_week)_{io} \\ & + \quad \eta * \ln(weeks\_year)_{io} + \pi_o + X_{io}^{\prime}\delta + \varepsilon_{io} \qquad (2)\end{aligned}$$

The controls used in this equation are identical to that in equation (1).The coefficient λ_o is our estimate of the gender earnings gap in occupation o.

2.1 Correlations across Occupations

In Figure 2, we present the correlations between the estimated gender pay gaps and the returns to working long hours by year. There is significant variation in the returns to working long hours and the size of the gender pay gap across occupations. For example, in 2010, the elasticity of annual earnings to weekly hours was lower than 0.3 for occupations such as teachers, scientists, dentists and veterinarians, but was higher than 1.2 for lawyers, financial managers, actuaries, accountants and other financial specialists. The average (unweighted) average return increased substantially from 0.48 in 1980 to 0.73 in 2010. Similarly, the gender gap in earnings also varies considerably across occupations - although the earnings gap is less than five percent for many scientific, engineering and teaching occupations in 2010, they remain very large (higher than 25 percent) for physicians, financial managers and occupations in insurance and financial services.

Consistent with the evidence presented by Goldin (2014), for most years, there is a statistically significant negative correlation between the returns to working long hours and the female-male earnings gap. Occupations that reward long hours of work are also those with higher gender gap gaps. Table 1 presents the regression version of Figure 2. The first four columns estimate the correlation between the returns to working long hours and the gender pay gap for all occupations from 1980 to 2010, while Columns (5) to (8) report the correlations for skilled occupations (those with college share greater than the average college share in the population). As observed from the table, the correlations are typically larger when we weight occupations by their sample size, for skilled occupations and have generally increased over time.

One issue in interpreting these cross-occupation correlations as causal evidence that higher returns to working long hours lead to larger gender earnings gaps is the fact that the observed correlation might be explained by other characteristics of occupations that are correlated with the factors that drive the returns to working long hours. In particular, the occupations in our sample with the highest returns to working long hours, namely lawyers and managers, are typically characterized by being very competitive. Greater competitiveness within the occupation may also drive the returns to working long hours as workers compete to realize larger potential earnings gains. Moreover, there is increasing evidence, both in the laboratory and in the field, that women tend to shy away from competition and perform relatively poorer relative to men in more competitive settings (Gneezy, Niederle, and Rustichini, 2003, Ors, Palomino and Peyrache, 2012, Flory, Leibbrant and List, 2014). This suggests that the observed correlation between the returns to long hours and the gender pay gap might reflect differences in other characteristics of occupations such as the degree of competitiveness within occupations, and not necessarily intrinsic properties such as imperfect substitutability of workers (Goldin, 2014). In other words, it is not clear that by restricting all workers to provide the same number of hours, the gender gap will necessarily shrink much, if competitiveness is embodied in other practices besides the length of the work week.

To examine this possibility more concretely, we use the data from O*NET online to construct a measure of competitiveness in an occupation.[13] We measure competitiveness based on answers to the question: "How competitive is your current job?" where respondents provide answers on a 1-5 scale (1: not competitive at all, 5: extremely competitive). We use the average reported competitiveness in each occupation, standardized to have a mean of zero and a standard deviation of one in the full sample of occupations.[14] In Figure 3, we present the correlation between competitiveness measure from O*Net and gender earnings gap and the returns to working long hours for 2010 among skilled occupations.[15] As observed in Figure 3, we find that more competitive occupations tend to have a larger gender pay gap and are also associated with higher returns to working long hours. Furthermore, we find that the degree of competition in an occupation is strongly correlated to the change in the returns to working long hours from 1980 to 2010. Table 2 presents the regression

[13] O*NET online is a comprehensive database of worker attributes and job characteristics for over 900 occupations.

[14] To merge the O*Net occupations to Census/ACS occupations, we use the crosswalk by Autor and Acemoglu (2011). There are about twice as many O*Net occupations than Census occupations and the crosswalk weights each O*Net characteristic levels with the relative number of individuals in each O*Net occupation to get the characteristic values for each of the Census occupations. In order to use the crosswalk, we use version 14.0 (2009) of the O*Net online database.

[15] Similar results are obtained if we use the other Census years.

version of these correlations for all occupations (Columns (1) and (2)) and for skilled occupations (Columns (3) and (4)). Similar to the patterns shown in Table 1, the correlations between the competitive measure and the gender pay gap and the returns to long hours are generally larger when occupations are weighted by their sample size and among skilled occupations. Finally, in regressions not shown in the table, when both the competitiveness index and the returns to working long hours are included in the gender pay gap regressions, their coefficients are of the expected sign but only the one for the competitiveness index is statisticallly significant.

3 Empirical Strategy and Results

The correlations reported in the previous section suggest that although occupations that reward long hours are associated with larger gender pay gaps, this relationship may be driven, in part, by other characteristics of occupations such as competitiveness. Therefore, we attempt to refine the analysis by including a geographic component to examine how changes in the returns to working long hours across occupations, city and time are correlated with changes in the gender pay gap. Our unit of observation is therefore at the occupation-group*MSA*year level. As we will show in greater detail below, for a given occupation, there is significant variation at the city level in the size of the gender wage gap and the returns to working long hours. We argue that a potentially important source of variation that might explain part of these geographical differences within occupations is the cost of outsourcing household production.

To ensure a reasonable sample size to construct the key variables, in what follows, we aggregate occupations into 11 broad categories.[16] We also restrict the sample to the 59 largest cities.[17] We begin by estimating the gender gap in earnings, the returns to working long hours, and other variables in the following way. For each outcome and each broad occupation group and year, we allow the effect of each of the key independent variables (e.g. female or log of weekly hours worked) to vary separately by MSA. For example, to obtain the gender pay gap for each MSA j in time t for occupation group c, we estimate the following regression separately for each year and occupation group:

$$\begin{aligned}\ln(Yearly\_earnings)_{ij} = \alpha \quad &+ \quad \lambda * female_{ij} + \sum_{j \neq NYC} \lambda_j I(city_j = 1) * female_{ij} \\ &+ \quad \eta * \ln(weeks\_year)_{ij} + \beta * \ln(hours\_week)_{ij} + X'_{ij}\delta + \varepsilon_{ij} \quad (3)\end{aligned}$$

In our regressions, the omitted MSA is New York - therefore, the estimate of the gender pay gap

[16] Appendix Table 1 indicates how each of the 92 skilled occupations in our sample are grouped into the broad occupation category.
[17] Appendix Table 2 provides a list of the MSAs included in the analysis.

for workers in occupation group c in year t in New York is λ and the corresponding estimate for the gender pay gap in each MSA j is given by $\lambda + \lambda_j$. We run equation (3) for each combination of the 11 broad occupation categories and 4 Census/ACS years. We estimate similar models to construct the returns to working long hours, but restrict the sample to males and interact the MSA fixed effects with $\ln(hours\_week)_{ij}$. Appendix Table 3 presents descriptive statistics for the 11 broad occupational groups.

Figure 4 illustrates the variation across occupation groups, cities and time in the gender pay gap and the returns to working long hours. Figures A and B show the variation for a particular occupation group - business and financial operations - across the 59 cities, and Figures C and D show the variation in a particular city, New York, across the 11 occupation groups. Appendix Table 4 reports the mean and interquartile range (75th percentile-25th percentile) of the gender pay gap and returns to overwork for the full sample (Panel A), within cities (Panel B) and within occupation groups (Panel C) for each year. Both Figure 4 and Appendix Table 4 provide strong evidence of significant variation in the gender pay gap and the returns to working long hours, even within cities and occupations.

3.1 Panel data evidence

We begin by examining the correlation between the returns to working long hours and the gender pay gap within occupation-group*MSA*year. As described in the previous section, the advantage of this set-up is that we are able to include a flexible set of fixed effects that net out the effects of differences across occupations, cities and time. Moreover, we can exploit variation within occupations, cities and time, to examine the relationship between changes in the returns and gender pay gaps, while accounting for unobservable shocks that vary by occupation-group*year, city*year and city*occupation-group. The inclusion of these fixed effects enable us to glean a more causal interpretation of the relationship between the returns to overwork and the gender pay gap by removing occupational characteristics that are intrinsic to each occupation that do not vary across city (but may vary across time) as well as characteristics of each city that do not vary across occupations (but may vary across time). The regression specification is as follows:

$$Gender\_gap_{cjt} = \alpha + \beta * Returns\_overwork_{cjt} + \kappa * X_{cjt} + \pi_c + \theta_j + \mu_t + \varphi_{cj} + \tau_{ct} + \gamma_{jt} + \varepsilon_{cjt} \quad (4)$$

where c refers to an occupation group, j refers to an MSA and t refers to each Census/ACS year. π_c, θ_j and μ_t denote the set of occupation, MSA and year fixed effects, respectively. φ_{cj} is a set of occupation-group*MSA fixed effects that capture time-invariant characteristics of occupation-specific gender gaps that vary at the city level (for example, the types of clients and cases that a law firm based in New York City has may be different from that in Chicago). τ_{ct} is a set of occupation-group*year fixed effects that capture occupation-specific changes that vary over time (for example, technological changes or occupation-specific legislation changes). γ_{jt} is a set of MSA*year fixed effects that capture city-specific changes that vary over time (for example, state-level legislations that might change over time). Finally, in some specifications, we control for variables that vary at the occupation-group*MSA*year level (X_{cjt}) and that might affect the gender gap. These variables include the log of the wage of males working exactly 40 hours a week, the share of males working at least 50 hours per week, and the gender gap in the probability of working more than 50 hours.

As observed, our identification for the effect of changes in the returns to overwork on the gender wage gap (β) comes from changes over time in a given occupations within a given city. Table 3 presents the estimates from equation (4). We find that occupation-group*city cells that experienced the largest increases in the returns to overwork (for men) also experienced an increase in the gender pay gap. The magnitude of the coefficients suggests that an increase in the returns to working long hours of 0.4 (the magnitude of the increase in the returns for workers in skilled occupations from 1980 to 2010) is associated with a widening of the gender wage gap by between 0.8 to 2 percentage points.

One concern with these estimates is the potential endogeneity of our key independent variable - therefore, at best, these estimates can only be interpreted as correlations. To shed some light on the causal mechanism, in the next section, we will introduce an instrument that exploits an exogenous change in the cost of providing long hours across cities.

3.2 IV estimates using immigrant shocks to exogenously vary cost of providing long hours

In this section, we examine the extent to which the higher cost for women to work long hours, particularly in occupations where overwork has high returns, is an important factor in explaining the persistent gender wage gap in skilled occupations. To identify this effect, we exploit cross-city variation in the cost of providing long hours for skilled women. More specifically, we build on earlier work by Cortes (2008) that demonstrates that the influx of low-skilled immigration leads to lower prices of services that are close substitutes for household production.[18] Moreover, Cortes and Tessada (2011) show that the reduction in the price of outsourcing household production and the increased availability of flexible childcare has led to a decrease in time spent on household work and an increase in the supply of market work among highly skilled women. Following both papers,

[18] Using confidential data from the CPS, Cortes (2008) shows how the inflow of low-skilled immigrants to the US has lowered significantly the prices of services in which they concentrate, in particular, of housekeeping, babysitting, and gardening. Due to price data limitations, her analysis is restricted to the US 25 largest city. To be able to extend our analysis to more cities, we follow Cortes and Tessada (2011) and use a reduced form. Note that the functional form of the key explanatory variable (Log of number of low-skilled immigrants) is derived from Cortes (2008)'s model.

we utilize plausibly exogenous variation in low-skilled immigrant flows across cities to instrument for changes in the prices of outsourcing household production. This provides us with an arguably exogenous shifter of the cost to women of providing long hours in the labor market.

Before turning to the main regression specification, we extend the analysis in Cortes and Tessada (2011) to show that the immigration instrument does have an effect on the probability that a skilled women works long hours and on reducing the gender gap in hours worked. We follow a similar empirical specification as that in Cortes and Tessada (2011) with a few extensions and differences:

1. We extend the sample period to include the 2012 ACS 3-year aggregate (2010-2012) and restrict the sample to the 59 MSAs for which we can construct occupation specific outcomes. We also restrict the sample to individuals who work full-time.

2. In some specifications, we use the gender gap (female-male) in usual hours worked per week as the key dependent variable. Arguably, as compared to using changes in the levels of hours worked, it is less likely that the initial distribution of immigrants is correlated with unobserved determinants of changes in gender gaps.

We estimate the following reduced form regressions:

$$Weekly\_hrs_{ijt} = \alpha + \beta * \ln(Predicted\_LS\_Immigrants)_{jt} + \theta_j + \mu_t + \varepsilon_{jt} \tag{5}$$

$$Gender\_gap\_weekly\_hrs_{jt} = \alpha + \beta * \ln(Predicted\_LS\_Immigrants)_{jt} + \theta_j + \mu_t + \varepsilon_{jt} \tag{6}$$

where the subscripts i refers to the individual, j the city and t the Census/ACS year. θ_j and μ_t denote city and year fixed effects, respectively. $\ln(Predicted\_LS\_Immigrants)_{jt}$ is the natural logarithm of the predicted number of low-skilled immigrants constructed using exogenous variation. As in Cortes and Tessada (2011), we also estimate both equations using an indicator variable for working at least 50 hours a week as the dependent variable.

To identify a plausibly exogenous component in the cross-city distribution of low-skilled immigrants, we use the 1970 distribution of immigrants from a given country to allocate future flows of low-skilled immigrants at the national level. The instrument exploits the tendency of immigrants to settle in a city with an existing enclave of immigrants from the same country (Munshi, 2003, Cortes, 2008, Cortes and Tessada, 2011). For example, if a third of Mexican immigrants in 1970 were living in Los Angeles, the instrument allocates one third of all Mexicans in the 1990s to Los Angeles. Formally, the instrument for the number of low-skilled immigrants in city j and decade t can be written as:

$$Predicted\_LS\_Immigrants_{jt} = \sum_{p} \frac{Immigrants_{pj,1970}}{Immigrants_{p,1970}} * LS\_Immigrants_{pt} \tag{7}$$

where p are all countries of origin included in the 1970 Census, $\frac{Immigrants_{pj,1970}}{Immigrants_{p,1970}}$ is the share of immigrants in 1970 originating from country p living in city j, and $LS\_Immigrants_{pt}$ stands for the aggregate number of low-skilled immigrants from country p to the United States in year t. To account for the fact that the main dependent variable varies only at the city*year level, standard errors are clustered at the city level to allow for the possibility of serial correlation within cities across years.

Table 4 presents the OLS estimates of equations (5) and (6). The coefficient on the instrument is of the expected sign and is statistically significant at the 5 percent level. The magnitude of the estimate implies that an increase in the predicted low-skilled immigration flow from 1980 to 2010 led to an increase in the usual hours worked per week of full-time college educated women by a quarter of an hour and increased the probability that she works 50 or more hours per week by 1.3 percentage points (relative to a baseline of about 20 percent).[19] Columns (3) to (6) show that the same immigration flow reduced the gender gaps in these labor supply outcomes by approximately the same magnitude at the city level. The latter finding supports the idea that low-skilled immigration flows impacted the labor supply decisions of highly-skilled women, but had little effect on the labor supply of highly-educated men.

Having shown that exogenous low-skilled immigrant flows across cities increase the working hours of full-time college educated women, the probability that they work overtime and reduces the gender gap in these labor supply outcomes, we turn to examine, if indeed, reducing the cost of providing long hours for skilled females (through the reduction in price of outsourcing household production) has an impact on the gender gap in earnings. Our basic hypothesis is that, by reducing the cost of supplying longer hours of market work, an exogenous increase in low-skilled immigration to city j is likely to benefit highly skilled women in occupations that have a (pre-existing) high demand for long hours of work. To test this hypothesis, we use a triple difference strategy: the first difference is between two occupations with different returns to long hours in a given city and year; the second, is the change over time in that difference; and the third is how this change over time varies by city depending on its low-skilled immigration concentration.

To implement the triple difference approach, we require an occupation-specific measure of the returns to working long hours. Moreover, given that changes over time in this variable are likely to capture other unobserved demand side shocks that might impact gender pay gaps, we construct

[19] This result is very similar to the one reported by Cortes and Tessada (2011) who found that the low-skilled immigration flows from 1980 to 2000 increased the probability of working 50 hours or more by 1.8 percentage points, for women working in occupations in which men work very long hours.

the returns to long hours at the occupation-level using data from 1980. This variable is meant to capture an intrinsic component of the occupation that creates an incentive to disproportionately reward individuals working long hours (Goldin, 2014), hence, we do not allow it to vary at the city level.[20] To estimate the occupation-group specific returns to working long hours, we estimate equation (1) using the sample of male full-time college educated workers from the 1980 Census and the 11 broad occupation classifications.

Formally, the regression specification for the reduced form is as follows:

$$\begin{aligned} Gender\_gap\_pay_{cjt} = \alpha \quad &+ \quad \Phi * Return\_overwork_{c,1980} * \ln(Predicted\_LS\_Immigrants)_{jt} \\ &+ \quad \kappa * X_{cjt} + \pi_c + \theta_j + \mu_t + \varphi_{cj} + \tau_{ct} + \gamma_{jt} + \varepsilon_{cjt}. \end{aligned} \tag{8}$$

Our key variable of interest is the interaction $Return\_overwork_{c,1980} * \ln(Predicted\_LS\_Immigrants)_{jt}$. The first component in the interaction is the occupation-specific measure of the returns to overwork for occupation-group c in 1980. The second variable in the interaction, $\ln(Predicted\_LS\_Immigrants)_{jt}$ captures the exogenous shifter of the cost of providing long hours across cities j over time t, as discussed above. If our hypothesis is true, we expect the coefficient on the interaction term (Φ) to be positive - that is, an increase in predicted low-skilled immigrant flows should decrease the cost to providing long hours, thereby reducing the gender gap in occupations where the returns to overwork are the highest.[21]

Next, we can also use $\ln(Predicted\_LS\_Immigrants)_{jt}$ as an instrument for the gender gap in the likelihood of working overtime and estimate the following 2SLS specification:

$$\begin{aligned} Gender\_gap\_pay_{cjt} = \alpha \quad &+ \quad \phi * Return\_overwork_{c,1980} * Gender\_gap\_long\_week_{jt} \\ &+ \quad \kappa * X_{cjt} + \pi_c + \theta_j + \mu_t + \varphi_{cj} + \tau_{ct} + \gamma_{jt} + \varepsilon_{cjt} \end{aligned} \tag{9}$$

Similar to the interpretation for the reduced form model, $\phi > 0$ would imply that a decrease in the gender gap in working long hours (i.e. $Gender\_gap\_long\_week_{ij}$ becomes less negative) leads to a reduction in the gender pay gap, particularly for occupations with a high return to working long hours. For both regression specifications, we cluster standard errors at the occupation-group level, and also present standard errors clustered at the city level. It is worth highlighting that one important advantage of the triple difference approach is that concerns about the exogeneity and interpretation of the instrument is likely to be mitigated since we are able to include a full set of

[20] Goldin (2014) provides some examples of occupation characteristics that might be correlated with a high return to working long hours. Fundamentally, she points out that nonlinearities in the relationship between work hours and earnings is likely to arise whenever an employee does not have perfect substitutability. Imperfect substitutability of workers is more likely arise in occupations that are more client-oriented, are more structured, have greater degree of time pressure and require more flexibility of decision making.

[21] Note that the gender gap in pay is defined as female - male, and thus it is negative.

city*year fixed effects in the regression. Therefore, in this setting, the identification assumption is only violated if unobserved determinants of the location choice of immigrants in 1970 are correlated with shocks to gender gaps in particular occupations.

Table 5 presents the results. Columns (1) to (4) present the coefficient estimates for the reduced form specification as detailed in equation (8). The coefficients are all positive and statistically significant at conventional levels. The results are also similar whether we use the unweighted sample or choose to weight the estimates using the number of observations in each cell. The magnitude of the estimate implies that for the average city, comparing two occupations, one in the 10th percentile of distribution of the returns to overwork in 1980 (educators) and another in the 90th percentile (lawyers), the increase in low-skilled immigration from 1980-2010 led to a 0.95 percentage point decline in the gender wage gap for lawyers relative to educators.[22] This is about 8.6% of the standard deviation of the gender pay gap across cities and occupations and about 20% of the standard deviation of the mean gender pay gap across cities.

Alternatively, comparing two cities, Los Angeles and Philadelphia, our estimate suggests that if Philadelphia received the same number of low-skilled immigrants between 1980 and 2010, the change in the gender wage gap between lawyers and educators would have been 1.2 percentage points smaller. The actual change in the gender wage gap between the two cities across the two occupations was approximately 14 percentage points, suggesting that low-skilled immigration explains about 10 percent of the change in the gender wage gap between lawyers and educators across the two cities.

Columns (5) to (8) present the 2SLS estimates using $\beta_{c,1980}*\ln(Predicted\_LS\_ImmigrantFlow)_{jt}$ to instrument for the returns $\beta_{c,1980}$ interacted with the gender gap in working 50+ hours across cities over time.[23] Similarly, Columns (9) to (12) present the 2SLS estimates instrumenting for the gender gap in weekly hours worked. In each of these specifications, the coefficients are positive and significant at conventional levels. For the average city, comparing lawyers and educators, the decrease in the gender gap in the likelihood of working 50+ hours per week from 1980 to 2010 led to a 2 percentage point decline in the gender wage gap for lawyers relative to educators.[24] We obtain similar results when we consider the gender gap in weekly hours worked. Comparing Philadelphia and Los Angeles, the magnitude of these estimates imply that changes over time in the gender gap in overwork between the two cities can explain approximately 12 percent of the change in the gender pay gap between lawyers and educators across the two cities.

[22] This was obtained by multiplying the coefficient estimate from Column (4) with the change in $\ln(Predicted\_LS\_ImmigrantFlow)$ from 1980 to 2010 and the difference in the returns to overwork between lawyers and educators (from Appendix Table 3): 0.044*0.98*0.22=0.0095.

[23] For the 2SLS models, Table 5 includes the cluster-robust first-stage F-stat for the excluded instruments reported by the stata command ivreg2.

[24] The decline in gender gap in the probability of working 50+ hours per week from 1980 to 2010 among college-plus workers is approximately 2.9 percentage points.

4 Discussion

Our results provide causal evidence that the gender gap in working long hours contributes to perpetuating the gender wage gap among highly skilled, full-time workers. The gender gap in overwork is particularly detrimental to the labor market success of women in occupations that disproportionately reward individuals who work long hours. While there has been a slowdown in share of skilled males working 50+ hours in 2010, this is likely to be due to the recession. If the labor market recovers and the pattern in overtime work reverts back to the 1980-2000 trend (Kuhn and Lozano, 2008), our results suggest that it is likely that the gender gap in hours worked will continue to widen in the near future.[25] A larger gender gap in overtime work, combined with increasing returns to long hours imply that these forces are likely to play an increasingly large role in slowing the convergence in gender wage gaps in the future.

Using our estimates, we can get a sense of the extent to which the gender gap in overwork might impact the gender wage gap moving forward. Our panel regression estimates of the correlation between the returns to working long hours and the gender pay gap suggests that an increase in the returns to working long hours of 0.4 - about the increase observed for skilled workers in skilled occupations from 1980 to 2010 - is correlated with a widening of the gender wage gap by between 0.8 to 2 percentage points. Given that the gender wage gap in 2010 for the sample of skilled occupations included in our analysis was close to 16 percent, in the absence of the increase in the returns to working long hours, the gender wage gap may have been between 5 to 12 percent smaller.[26] On the other hand, our causal estimates suggest that if the gender gap in hours worked was eliminated, this would reduce the gender pay gap by about two-thirds. These sizable effects suggest that the increase in returns to overwork, coupled with the persistent gap in the propensity to work overtime across genders, is an important factor that limits the convergence in gender pay gaps across occupations.

5 Conclusion

Women have made enormous gains in reversing the education gap and increasing their representation in skilled occupations. Despite these gains, the gender gap at the top of the skill distribution, has stalled for the past three decades. This paper highlights the importance of a particular occu-

[25] Appendix Table 3 shows that there is a very strong correlation between the gender gap in overwork and the share of males working more than 50 hours a week.

[26] Our estimate is very much in line with that of Cha and Weeden (2014) who found that size of the effect of the change in the price hourly wage returns to working more than 50 hours on the gender gap was 30 percent of the 1979 to 2007 change in the gender wage gap for professionals, 20 percent for managers and 9 percent for other (including non-skilled workers). Our estimates vary between 8 and 20 percent of the observed change in the gender gap between 1980 and 2010.

pational characteristic - the returns to working long hours - and examines the causal mechanism through which it contributes to the perpetuating gender pay gaps among highly skilled workers. Identifying the sources of the high levels and increasing rewards to working long hours is fundamental to addressing these biases in the most efficient way.

What are the ways to address this mechanism? Goldin (2014) suggests several examples of occupations and sectors that have moved toward greater hours flexibility such as physicians, pharmacists and veterinarians. The causes of these changes are varied, ranging from re-organizing work to take advantage of economies of scale, lower labor costs or because of employee pressure. Some countries such as Korea and Japan have moved toward legislations that restrict the maximum number of hours of work per week with the explicit aim to reduce working hours and to promote work-life balance. The effectiveness and desirability of such a policy will depend on the source of the returns to working long hours. If the returns to overtime are the result of market imperfections such as incomplete information as suggested by Landers, Rebitzer and Taylor (1996), a policy to reduce hours of work through government intervention may be welfare enhancing. On the other hand, if the higher returns to hours worked is an optimal response to technological change and globalization (Cha and Weeden, 2014), or an intrinsic characteristic of how work in an occupation is organized (Goldin, 2014), such policies could have detrimental effects on firm productivity. If the key driver of the returns to overwork are the latter, then policies to promote the redesign and the reorganization of work to enhance temporal flexibility are likely to be more effective.

Finally, in this paper, we have focused exclusively on one outcome, namely, the gender gap in earnings. Nevertheless, the effects of the increasing returns to overwork are likely to extend to decisions of occupational choice and whether to drop out of the labor force. We hope to address these important questions in future research.

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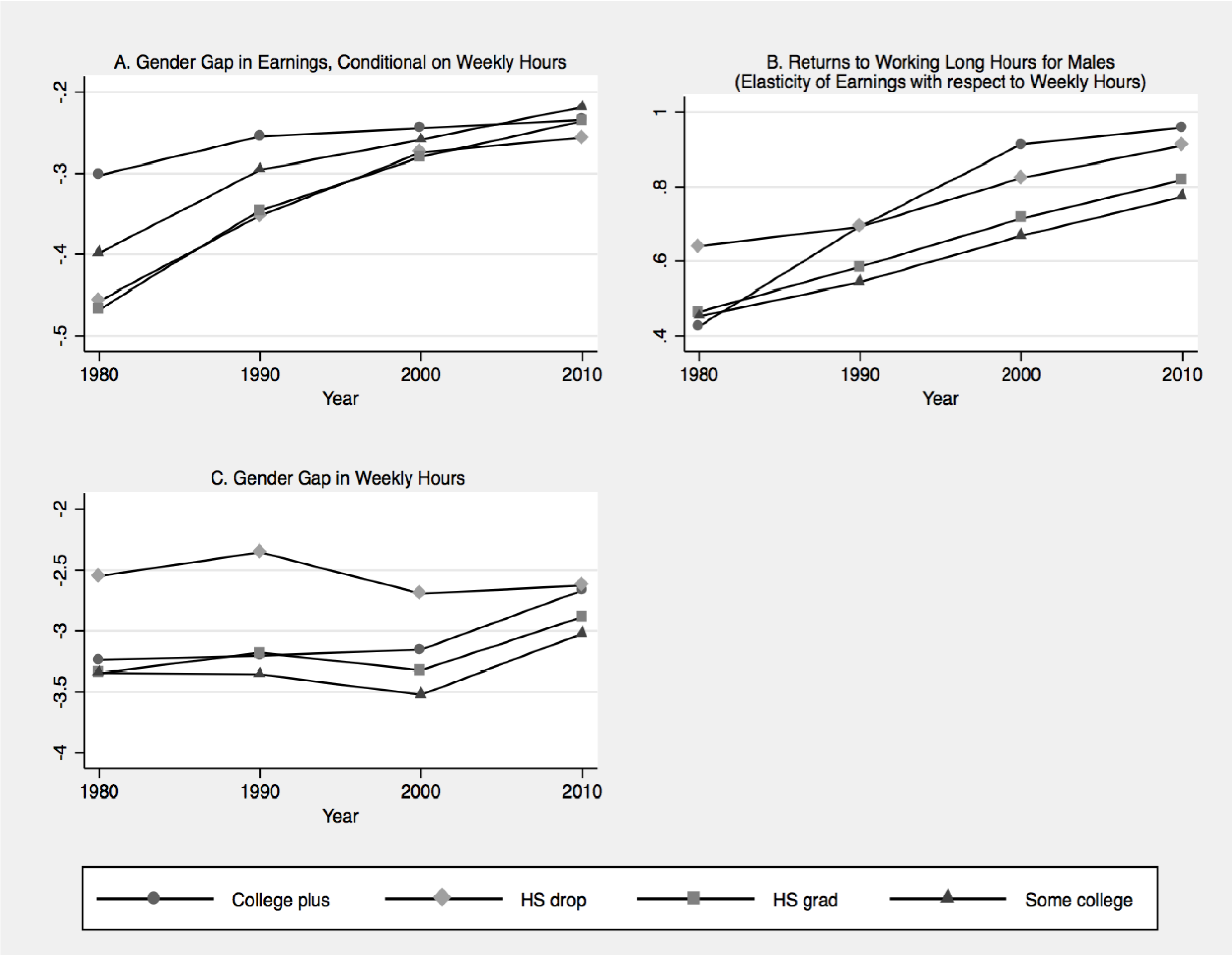
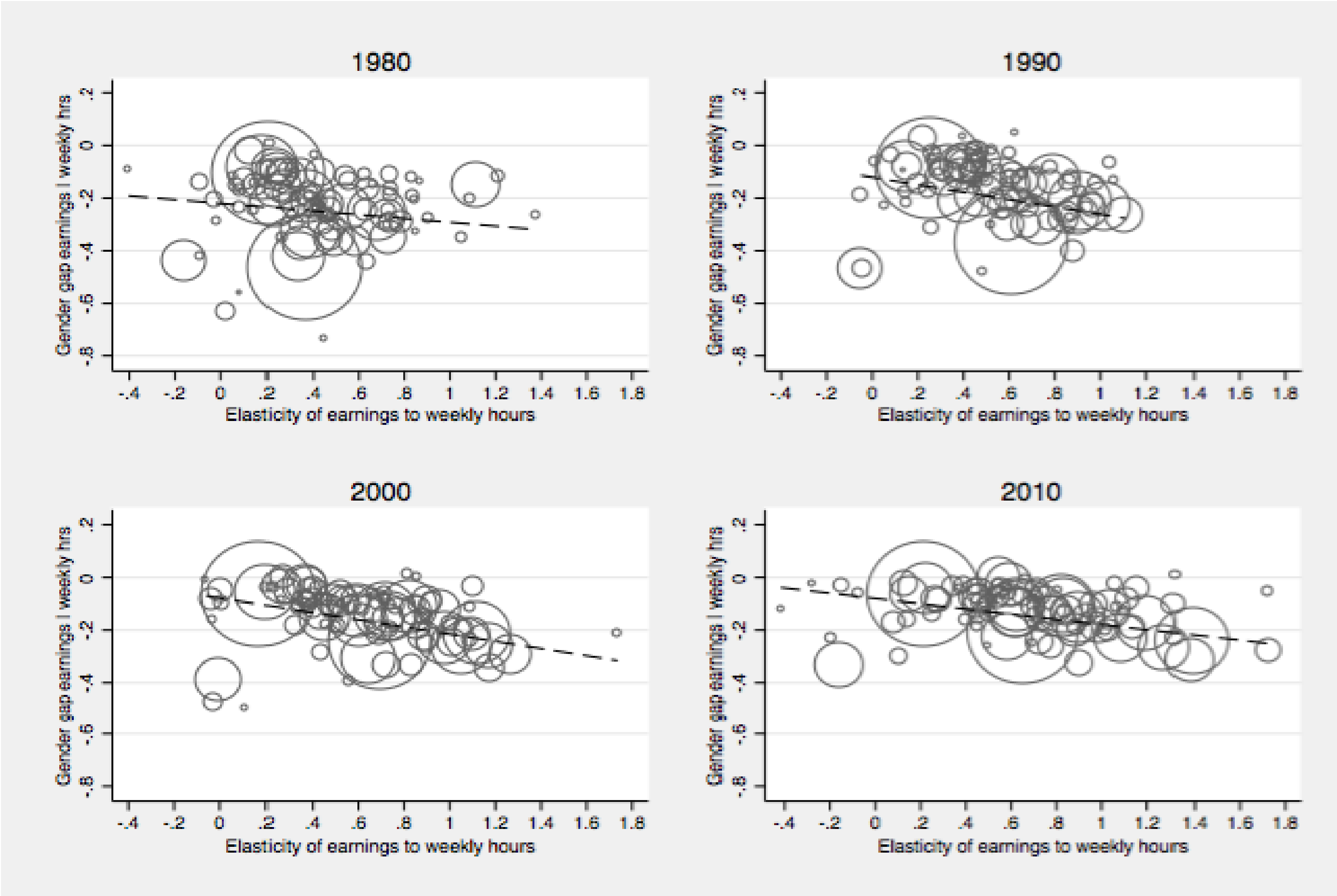
Figure 1. Labor Supply Outcomes for Full-time Workers



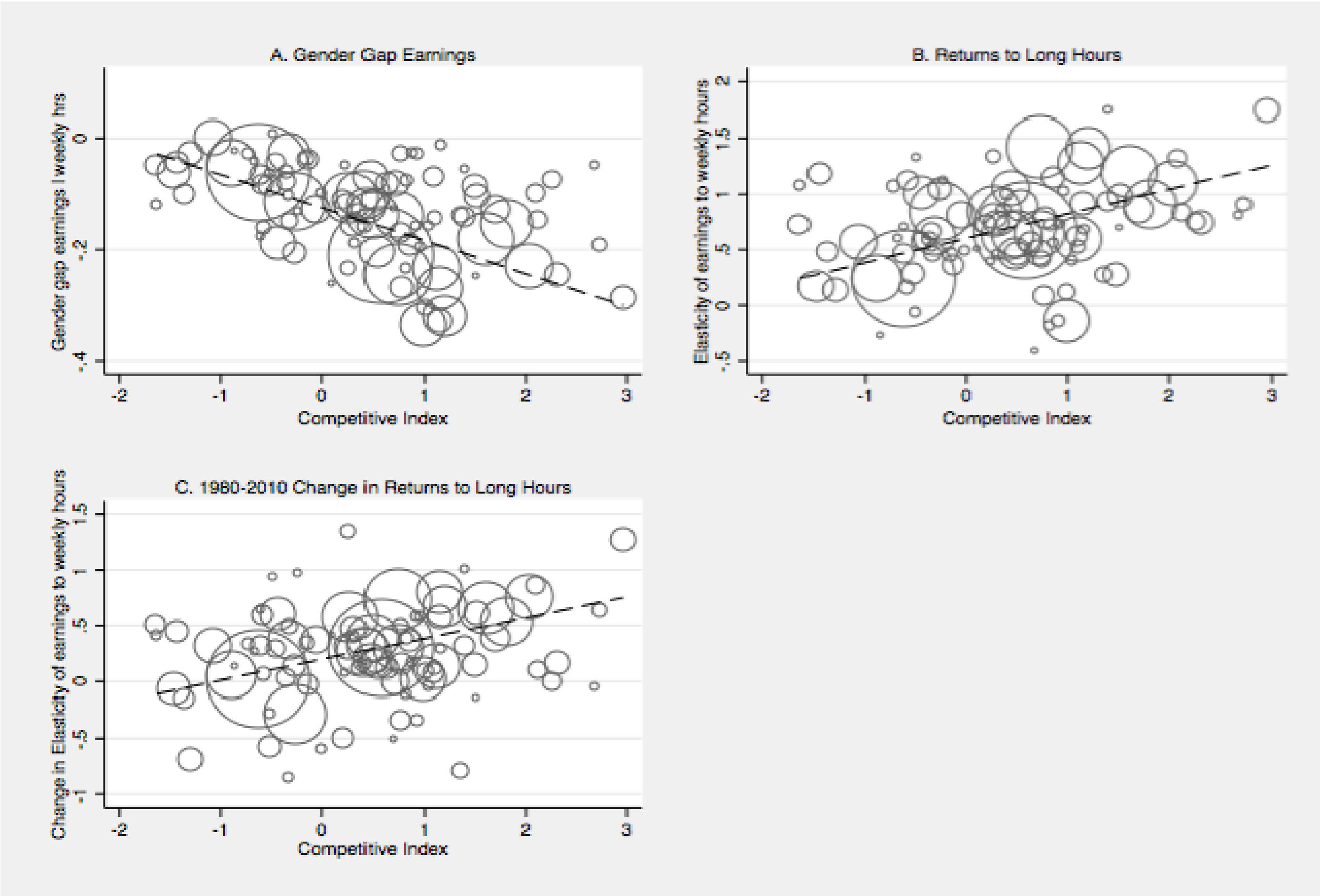
Note. The data is from the 1980, 1990, 2000 Census and 3-year aggregate 2012 ACS (2010-2012). The sample is restricted to native-born age 25-64 with at least a bachelor's degree who report working full-time (35 hours or more) in a given week.

Figure 2. Cross-occupation Correlation between Gender Pay Gap and Returns to Working Long Hours



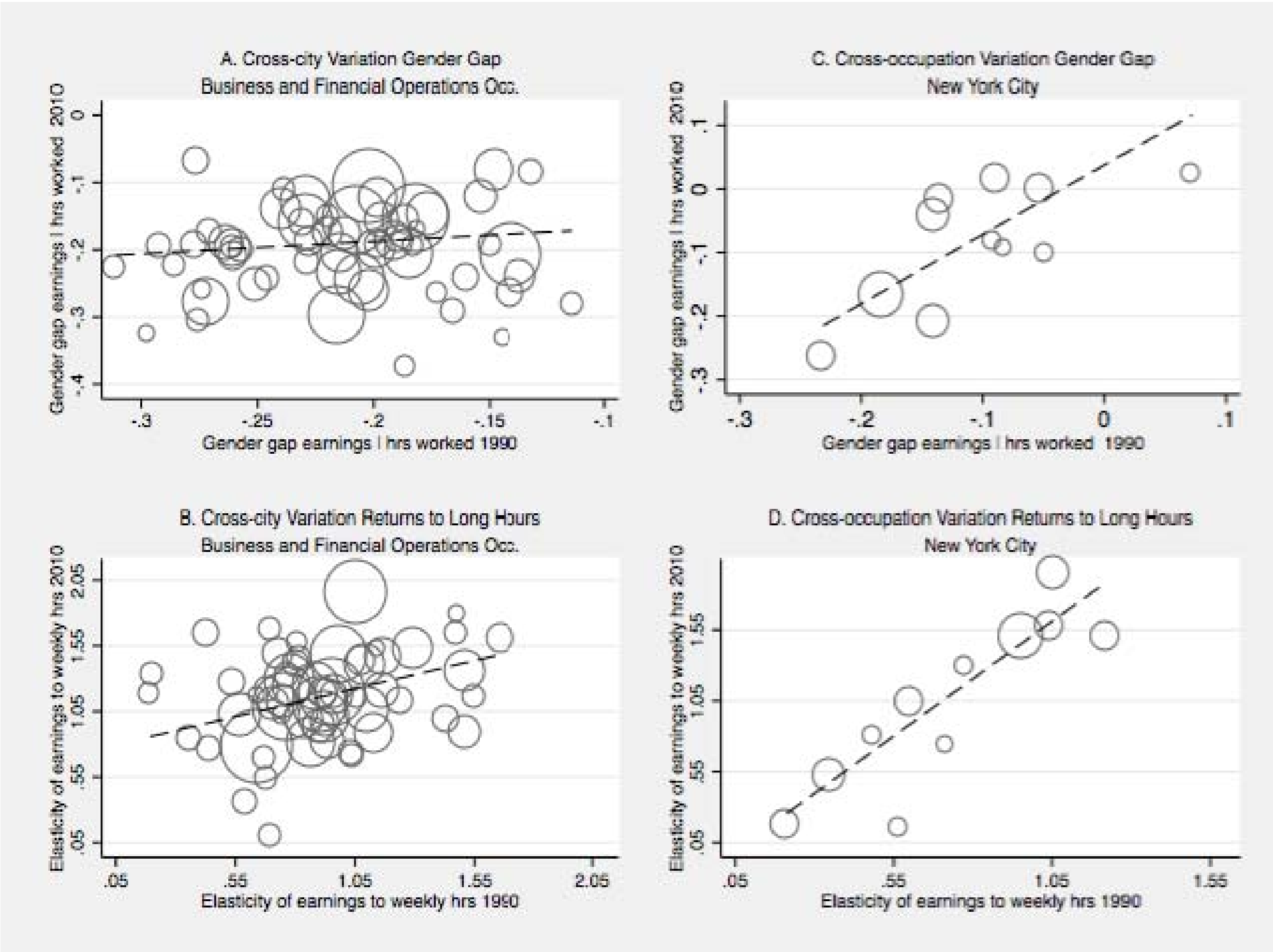
Note. The data is from the 1980, 1990, 2000 Census and 3-year aggregate 2012 ACS (2010-2012). The sample is restricted to native-born age 25-64 with at least a bachelor's degree who report working full-time (35 hours or more) in a given week. The figures include all skilled occupations and each occupation is weighted by sample size.

Figure 3. Cross-occupation Correlations between Competitiveness, Gender Pay Gap and Returns to Working Long Hours in 2010



Note. The data is from the 1980, 1990, 2000 Census and 3-year aggregate 2012 ACS (2010-2012). The sample is restricted to native-born age 25-64 with at least a bachelor's degree who report working full-time (35 hours or more) in a given week. The figures include all skilled occupations and each occupation is weighted by sample size. The competitive index is computed using ONET and standardized to have a mean of 0 and standard deviation of 1 in the full sample of occupations.

*Figure 4: Variation at the Occupation*City*Year Level*



Note. The data is from the 1980, 1990, 2000 Census and 3-year aggregate 2012 ACS (2010-2012).

Table 1. Cross-occupation Correlation between Returns to Working Long Hours and the Gender Pay Gap by Year

		Outcome: Gender Pay Gap (Female - Male)							
		All Occupations				Skilled Occupations			
	Weights	1980	1990	2000	2010	1980	1990	2000	2010
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Returns to working long hours	None	0.041*	-0.030	-0.046**	-0.004	0.020	-0.074	-0.065	-0.045*
		[0.021]	[0.030]	[0.021]	[0.023]	[0.019]	[0.051]	[0.039]	[0.026]
Returns to working long hours	Sample	-0.041	-0.095*	-0.110***	-0.078**	-0.046	-0.141	-0.137***	-0.099**
		[0.061]	[0.052]	[0.034]	[0.031]	[0.082]	[0.085]	[0.047]	[0.042]
Observations		236	239	240	241	92	92	92	92

Note. The data is from the 1980, 1990, 2000 Census and 2012 3-year aggregate ACS (2010-2012). The unit of observation is an occupation. The sample is restricted to native-born age 25-64 with at least a bachelor's degree who report working full-time (35 hours or more) in a given week. The gender pay gap is the coefficient on female*occupation dummy in a regression of log annual earnings on the full set of female*occupation dummies controlling for the hours worked per week, weeks worked per year, occupation fixed effects and a vector of demographic characteristics that include a quartic in age, a female dummy, race fixed efects and an indicator for whether an individual has a masters or doctoral degree (see equation (1) for more details). The returns to working long hours is estimated on the sample of male workers and is the coefficient on the interaction between log hours worked per week and the occupation dummy in the regression of log yearly earnings on the full set of interactions between occupations*ln(hours worked per week) conditional on the weeks worked per year, occupation fixed effects and the same set of demographic characteristics listed above (see equation (2) for more details). Both the gender pay gap and returns to working long hours were estimated separately for each Census/ACS year. Skilled occcupations are defined as those where the share of college graduates in the occupation exceeds that in the population. Robust standard errors are reported in brackets. ***significant at 1%, **5%, *10% level.

Table 2. Correlations of Competitive Index with Gender Gap and Returns to Long Hours in 2010

	(1)	(2)	(3)	(4)
	A. Outcome: Gender Pay Gap (Female - Male)			
Competitive Index	-0.006	-0.043***	-0.035***	-0.059***
	[0.009]	[0.005]	[0.008]	[0.007]
	231	231	92	92
	B. Outcome: Returns to Long Hours			
Competitive Index	-0.053	0.116***	0.106**	0.219***
	[0.035]	[0.029]	[0.041]	[0.038]
	231	231	92	92
	C. Outcome: 1980-2010 Change in the Returns to Working Long Hours			
Competitive Index	0.011	0.146***	0.114*	0.194***
	[0.049]	[0.029]	[0.062]	[0.038]
Sample	All	All	Skilled	Skilled
Weighted	No	Yes	No	Yes
No. Observations	231	231	92	92

Note. The data is from the 1980, 1990, 2000 Census and 2012 3-year aggregate ACS (2010-2012). The unit of observation is an occupation. The sample is restricted to native-born age 25-64 with at least a bachelor's degree who report working full-time (35 hours or more) in a given week. Please see Table 1 and the text for details on the outcome variables. The competitive index is constructed using data from ONET and is standardized with a mean of 0 and standard deviation of 1 in the full sample of occupation (see text for details). Skilled occcupations are defined as those where the share of college graduates in the occupation exceeds that in the population. Robust standard errors are reported in brackets. ***significant at 1%, **5%, *10% level.

Table 3. Panel Correlation between Returns to Long Hours and the Gender Gap

	Outcome: Gender Gap in Earnings | weekly hours			
	(1)	(2)	(3)	(4)
Elasticity of earnings to weekly hours$_{cjt}$	-0.022***	-0.057***	-0.019**	-0.052***
	[0.005]	[0.007]	[0.007]	[0.008]
	(0.009)	(0.007)	(0.009)	(0.007)
Controls				
Year FE	X	X	X	X
City FE	X	X	X	X
Occ FE	X	X	X	X
Year*City FE	X	X	X	X
Year*Occ FE	X	X	X	X
City*Occ FE	X	X	X	X
Other Controls		X		X
Weights	None	None	Cell size	Cell size
Observations	2,087	2,083	2,087	2,083
R-squared	0.888	0.913	0.836	0.870

Note. The data is from the 1980, 1990, 2000 Census and 2012 3-year aggregate ACS (2010-2012). The unit of observation is an occupation-group*city*year. The sample includes 59 MSAs, 11 occupation groups and 4 time periods. The sample is restricted to native-born age 25-64 with at least a bachelor's degree who report working full-time (35 hours or more) in a given week. See text for details on the construction of the gender gap in earnings and the elasticity of earnings to weekly hours. The "Other Controls" include the log wage of males working exactly 40 hours a week, the share of males working at least 50 hours per week, and the gender gap in the probability of working more than 50 hours. Robust standard errors clustered at the broad occupation level are reported in brackets and at the MSA level in parentheses.***significant at 1%, **5%, *10% level.

Table 4. Predicted Low-skilled Immigration flows and High Skilled Female Labor Supply

	A. Micro Data, Female Sample		B. City Level Data			
	Indicator for Working 50+ hrs	Usual Weekly Hours	Gender Gap (Female-Male) for Working 50+ hrs		Gender Gap (Female-Male) in Weekly Hours Worked	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Predicted LS Immigration)	0.010**	0.191**	0.015***	0.013**	0.289***	0.208**
	[0.004]	[0.078]	[0.005]	[0.005]	[0.097]	[0.099]
Weights	Person	Person	Unweighted	Cell size	Unweighted	Cell size
Controls						
Demographic controls	X	X				
City FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Observations	579,638	578,656	236	236	236	236
R-squared	0.043	0.049	0.757	0.804	0.755	0.793

Note. The data is from the 1980, 1990, 2000 Census and 2012 3-year aggregate ACS (2010-2012). The sample is restricted to native-born age 25-64 with at least a bachelor's degree who report working full-time (35 hours or more) in a given week. See text for details on the construction of the Ln(Predicted LS Immigration) flows and for the gender gaps. The unit of analysis for Panel B is at the city*year level. There are 59 MSAs and 4 time periods. "Demographic controls" include dummies for a masters degree, more than a masters degree, a quartic in age, race dummies and an indicator for being single. Robust standard errors clustered at the MSA level are reported in parentheses. ***significant at 1%, **5%, *10% level.

Table 5. Causal Effect of Working Long Hours on the Gender Gap

	Outcome: Gender Gap in Earnings | Weekly Hours											
	OLS				2SLS				2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\text{Beta}_{c,\,1980}$ x Ln(Predicted LS Immigrant $\text{Flow})_{jt}$	0.029***	0.047*	0.032**	0.044***								
	[0.008]	[0.022]	[0.011]	[0.009]								
	(0.027)	(0.028)	(0.028)	(0.034)								
$\text{Beta}_{c,\,1980}$ x Gender Gap Work 50+ hrs_{jt}					2.321***	3.876***	2.407***	3.213***				
					[0.536]	[1.424]	[0.692]	[0.540]				
					(1.838)	(2.251)	(1.815)	(2.187)				
$\text{Beta}_{c,\,1980}$ x Gender Gap Weekly Hours_{jt}									0.153***	0.255***	0.134***	0.178***
									[0.034]	[0.091]	[0.039]	[0.030]
									(0.132)	(0.175)	(0.110)	(0.135)
Controls												
Year, City, Occ FE	X	X	X	X	X	X	X	X	X	X	X	X
Year*City FE	X	X	X	X	X	X	X	X	X	X	X	X
Year*Occ FE	X	X	X	X	X	X	X	X	X	X	X	X
City*Occ FE	X	X	X	X	X	X	X	X	X	X	X	X
Other Controls		X		X		X		X		X		X
F-stat for Instrument					80.28	79.5	92.79	93.51	54.28	54.15	89.25	90.57
Weights	None	None	Cell size	Cell size	None	None	Cell size	Cell size	None	None	Cell size	Cell size
Observations	2,087	2,083	2,087	2,083	2,087	2,083	2,087	2,083	2,087	2,083	2,087	2,083
R-squared	0.887	0.913	0.835	0.870	0.886	0.908	0.831	0.862	0.885	0.906	0.831	0.862

Note. The data is from the 1980, 1990, 2000 Census and 2012 3-year aggregate ACS (2010-2012). The sample is restricted to native-born age 25-64 with at least a bachelor's degree who report working full-time (35 hours or more) in a given week. The unit of observation is an occupation-group*MSA*year. There are 59 MSAs, 11 occupation groups and 4 time periods. "Beta" is a measure of the return to overwork in each broad occupation group in 1980 obtained from the estimation of equation (1). See text for details on the construction of the Ln(Predicted LS Immigration) flows and for the gender gaps. The "Other Controls" include the log wage of males working exactly 40 hours a week, the share of males working at least 50 hours per week, and the gender gap in the probability of working more than 50 hours. Robust standard errors clustered at the broad occupation level are reported in brackets and at the MSA level in parentheses.***significant at 1%, **5%, *10% level.

Appendix Table 1. List of Skilled Occupations

occ1990dd code	Occupation	Occupation Category
4	Chief executives, public administrators and legislators	Managerial Occupations
7	financial managers	Managerial Occupations
8	Funeral directors	Managerial Occupations
13	Human resources and labor relations managers	Managerial Occupations
14	managers and admin, nec	Managerial Occupations
15	Managers and specialists in marketing, advert, PR	Managerial Occupations
18	Managers in education and related fields	Managerial Occupations
19	Managers of medicine and health occupations	Managerial Occupations
22	Managers of properties and real state	Managerial Occupations
23	Accountants and auditors	Business and Financial Operations Occupations
24	Business and promotion agents	Business and Financial Operations Occupations
25	Inspectors and compliance officers, outside	Business and Financial Operations Occupations
26	Insurance adjusters, examiners, and investigators	Business and Financial Operations Occupations
27	Insurance underwritters	Business and Financial Operations Occupations
33	Management analysis	Business and Financial Operations Occupations
34	Management support occupations	Business and Financial Operations Occupations
36	Other financial specialists	Business and Financial Operations Occupations
37	Personnel, HR, training	Business and Financial Operations Occupations
43	Aerospace engineers	Architects and Engineers
44	Architects	Architects and Engineers
45	Chemical engineers	Architects and Engineers
47	Civil engineers	Architects and Engineers
48	Electrical Engineers	Architects and Engineers
53	Engineers and other proefessionals n.e.c	Architects and Engineers
55	Industrial engineers	Architects and Engineers
56	Mechanical engineers	Architects and Engineers
57	Metallurgical and materials engineers	Architects and Engineers
59	Petroleum, mining and geological engineers	Architects and Engineers
64	Actuaries	Computer and Mathematical Occupations
65	Computer software developers	Computer and Mathematical Occupations
66	Computer systems analysists and computer scientists	Computer and Mathematical Occupations
68	mathematicians and statisticians	Computer and Mathematical Occupations
69	Agricultural and food scientists	Life, Physical, and Social Science Occupations
73	Atmospeheric and space scientists	Life, Physical, and Social Science Occupations
74	Biological scientists	Life, Physical, and Social Science Occupations
75	Chemists	Life, Physical, and Social Science Occupations
76	Economists, market and survey researchers	Life, Physical, and Social Science Occupations
77	Foresters and conservations scientists	Life, Physical, and Social Science Occupations
78	Geologists	Life, Physical, and Social Science Occupations
79	Medical scientists	Life, Physical, and Social Science Occupations
83	Physical scientists, n.e.c.	Life, Physical, and Social Science Occupations
84	Dentists	Health Diagnosing and Treating Practitioners
85	Dieticians and nutritionists	Health Diagnosing and Treating Practitioners
86	Occupational Therapists	Health Diagnosing and Treating Practitioners
87	Optometrists	Health Diagnosing and Treating Practitioners

Appendix Table 1. List of Skilled Occupations (Continued)

occ1990dd code	Occupation	Occupation Category
88	Other health and therapy occupations	Health Diagnosing and Treating Practitioners
89	Pharmacists	Health Diagnosing and Treating Practitioners
95	Physical therapists	Health Diagnosing and Treating Practitioners
96	Physicians	Health Diagnosing and Treating Practitioners
97	Physicians assistants	Health Diagnosing and Treating Practitioners
99	Podiatrists	Health Diagnosing and Treating Practitioners
103	Registered Nurse	Health Diagnosing and Treating Practitioners
104	Speech therapists	Health Diagnosing and Treating Practitioners
105	Therapists, n.e.c	Health Diagnosing and Treating Practitioners
106	Veterinarians	Health Diagnosing and Treating Practitioners
154	Archivists and curators	Education, Training, and Library Occupations
155	Kindergarten and earlier school teachers	Education, Training, and Library Occupations
156	Librarians	Education, Training, and Library Occupations
157	Primary school teachers	Education, Training, and Library Occupations
158	Secondary school teachers	Education, Training, and Library Occupations
163	Special education teachers	Education, Training, and Library Occupations
164	Subject instructors, college	Education, Training, and Library Occupations
165	Vocational and educational counselors	Education, Training, and Library Occupations
166	Physicists and astronomists	Life, Physical, and Social Science Occupations
167	Psychologists	Life, Physical, and Social Science Occupations
169	Social scientists and sociologists, n.e.c.	Life, Physical, and Social Science Occupations
173	Urban and regional planners	Life, Physical, and Social Science Occupations
174	Cleargy and religious workers	Community and Social Service Occupations
176	Eligibility clerks for government prog., social welfare	Community and Social Service Occupations
177	Social workers	Community and Social Service Occupations
178	Lawyers and judges	Lawyers
183	Actors, directors, and producers	Arts, Design, Entertainment, Sports, and Media
184	Announcers	Arts, Design, Entertainment, Sports, and Media
185	Art/entertainment performers and related occs	Arts, Design, Entertainment, Sports, and Media
186	Athletes, sports instructors, and officials	Arts, Design, Entertainment, Sports, and Media
187	Broadcast equipment operators	Arts, Design, Entertainment, Sports, and Media
188	Designers	Arts, Design, Entertainment, Sports, and Media
189	Editors and reporters	Arts, Design, Entertainment, Sports, and Media
194	Musicians and composers	Arts, Design, Entertainment, Sports, and Media
195	Painters, sculptors, craft-artists, and print-makers	Arts, Design, Entertainment, Sports, and Media
198	Photographers	Arts, Design, Entertainment, Sports, and Media
199	Techinical writers	Arts, Design, Entertainment, Sports, and Media
228	Writers and authors	Arts, Design, Entertainment, Sports, and Media
229	Operations and systems reserachers and analyssts	Computer and Mathematical Occupations
253	Advertising and related sales jobs	Sales and Related Occupations
254	Financial services sales occupations	Sales and Related Occupations
255	Insurance sales occupations	Sales and Related Occupations
256	Real estate sales occupations	Sales and Related Occupations
258	Sales engineers	Sales and Related Occupations
274	Salespersons, n.e.c	Sales and Related Occupations
375	Purchasing managers, agents and buyers, n.e.c	Business and Financial Operations Occupations
377	Welfare service workers	Community and Social Service Occupations

Appendix Table 2. List of MSAs

Albany-Schenectady-Troy, NY	Miami-Hialeah, FL
Albuquerque, NM	Milwaukee, WI
Atlanta, GA	Minneapolis-St. Paul, MN
Austin, TX	Nashville, TN
Baltimore, MD	New Orleans, LA
Birmingham, AL	New York-Northeastern NJ
Boston, MA	Nassau Co, NY
Buffalo-Niagara Falls, NY	Newark, NJ
Charlotte-Gastonia-Rock Hill, SC	Oklahoma City, OK
Chicago-Gary-Lake, IL	Orlando, FL
Cincinnati OH/KY/IN	Philadelphia, PA/NJ
Cleveland, OH	Phoenix, AZ
Columbus, OH	Pittsburgh-Beaver Valley, PA
Dallas-Fort Worth, TX	Portland-Vancouver, OR
Dayton-Springfield, OH	Richmond-Petersburg, VA
Denver-Boulder-Longmont, CO	Rochester, NY
Detroit, MI	Sacramento, CA
Fort Lauderdale-Hollywood-Pompano Beach	St. Louis, MO-IL
Greensboro-Winston Salem-High Point, NC	Salt Lake City-Ogden, UT
Hartford-Bristol-Middleton-New Britain,	San Antonio, TX
Honolulu, HI	San Diego, CA
Houston-Brazoria, TX	San Francisco-Oakland-Vallejo, CA
Indianapolis, IN	San Jose, CA
Kansas City, MO-KS	Seattle-Everett, WA
Knoxville, TN	Syracuse, NY
Los Angeles-Long Beach, CA	Tampa-St. Petersburg-Clearwater, FL
Louisville, KY/IN	Tucson, AZ
Madison, WI	Tulsa, OK
Memphis, TN/AR/MS	Washington, DC/MD/VA
	West Palm Beach-Boca Raton-Delray Beach

Appendix Table 3. Broad Occupation Characteristics for Fulltime Workers

	Gender Gap in Earnings				Returns to Overwork			
Broad Occupational Category	1980	1990	2000	2010	1980	1990	2000	2010
Architects and Engineers	-0.20	-0.11	-0.11	-0.10	0.33	0.42	0.49	0.46
Arts, Design, Entertainment, Sports, and Media	-0.22	-0.15	-0.10	-0.10	0.53	0.64	0.78	0.78
Business and Financial Operations	-0.27	-0.23	-0.22	-0.24	0.66	0.91	1.16	1.26
Community and Social Service	0.07	0.08	0.07	0.06	-0.22	-0.01	0.00	0.01
Computer and Mathematical Occupations	-0.12	-0.09	-0.13	-0.13	0.37	0.44	0.70	0.74
Education, Training, and Library	-0.13	-0.10	-0.08	-0.06	0.31	0.31	0.36	0.38
Health Diagnosing and Treating Practitioners	-0.47	-0.42	-0.43	-0.32	0.37	0.51	0.69	0.64
Lawyers	-0.23	-0.23	-0.23	-0.18	0.53	1.02	0.98	1.20
Life, Physical, and Social Science Occupations	-0.23	-0.17	-0.15	-0.13	0.41	0.52	0.53	0.58
Managerial Occupations	-0.42	-0.33	-0.29	-0.25	0.38	0.65	0.88	0.82
Sales and Related Occupations	-0.36	-0.23	-0.22	-0.21	0.39	0.64	0.91	1.05
	Gender Gap in Weekly Hrs				Weekly Hours - Males			
Broad Occupational Category	1980	1990	2000	2010	1980	1990	2000	2010
Architects and Engineers	-0.87	-1.11	-1.48	-1.50	43.19	44.82	45.95	45.52
Arts, Design, Entertainment, Sports, and Media	-1.76	-1.96	-1.95	-1.78	45.42	46.52	47.52	46.95
Business and Financial Operations	-1.56	-2.21	-2.53	-2.26	44.06	45.85	47.29	46.57
Community and Social Service	-6.62	-5.32	-5.13	-3.88	48.78	48.33	48.48	46.93
Computer and Mathematical Occupations	-0.72	-1.36	-1.49	-1.02	42.56	43.93	45.35	44.63
Education, Training, and Library	-2.12	-1.83	-1.48	-1.18	44.44	45.00	45.88	45.48
Health Diagnosing and Treating Practitioners	-7.50	-6.34	-5.37	-4.43	50.60	49.72	49.37	48.02
Lawyers	-2.51	-1.97	-2.28	-2.26	45.89	46.40	47.49	47.21
Life, Physical, and Social Science Occupations	-1.12	-1.32	-1.27	-1.11	43.19	44.64	45.00	44.84
Managerial Occupations	-2.77	-3.05	-3.01	-2.58	46.67	48.20	49.88	48.92
Sales and Related Occupations	-2.19	-2.15	-2.37	-2.17	46.27	47.48	48.85	48.16
	Gender Gap Working 50+ Hours				Share of Males Working 50+ Hours			
Broad Occupational Category	1980	1990	2000	2010	1980	1990	2000	2010
Architects and Engineers	-0.04	-0.06	-0.07	-0.08	0.16	0.26	0.33	0.31
Arts, Design, Entertainment, Sports, and Media	-0.10	-0.11	-0.11	-0.09	0.29	0.36	0.41	0.39
Business and Financial Operations	-0.08	-0.13	-0.15	-0.13	0.22	0.34	0.42	0.38
Community and Social Service	-0.33	-0.28	-0.27	-0.23	0.45	0.46	0.46	0.41
Computer and Mathematical Occupations	-0.03	-0.07	-0.08	-0.06	0.14	0.21	0.30	0.26
Education, Training, and Library	-0.12	-0.11	-0.09	-0.06	0.25	0.29	0.35	0.32
Health Diagnosing and Treating Practitioners	-0.33	-0.27	-0.22	-0.18	0.48	0.44	0.43	0.39
Lawyers	-0.16	-0.12	-0.12	-0.12	0.36	0.41	0.46	0.44
Life, Physical, and Social Science Occupations	-0.06	-0.07	-0.07	-0.06	0.18	0.26	0.29	0.28
Managerial Occupations	-0.16	-0.18	-0.17	-0.14	0.37	0.47	0.57	0.51
Sales and Related Occupations	-0.13	-0.13	-0.15	-0.13	0.36	0.44	0.52	0.48

Source: 1980, 1990, and 2000 Census and 3-year aggregate 2012 ACS (2010-2012). See text for details on how the variables were constructed.

Appendix Table 4.1: Variation in the Gender Pay Gap across Occupations and Time

	1980		1990		2000		2010-2012	
	Mean	p75 - p25	Mean	p75 - p25	Mean	p75 - p25	Mean	p75 - p25
	A. Full Sample							
Gender Pay Gap	-0.254	0.217	-0.191	0.178	-0.175	0.156	-0.151	0.157
	B. By Cities							
25th Percentile City	-0.325	0.138	-0.234	0.106	-0.215	0.113	-0.199	0.110
Median City	-0.260	0.258	-0.196	0.079	-0.177	0.181	-0.149	0.120
75th Percentile City	-0.234	0.236	-0.174	0.191	-0.153	0.179	-0.135	0.181
	C. By Occupation Group							
Architects and Engineers	-0.153	0.104	-0.113	0.061	-0.130	0.088	-0.105	0.093
Arts, Design, Entertainment, Sports, and Media	-0.231	0.118	-0.153	0.133	-0.110	0.118	-0.109	0.102
Business and Financial Operations Occupations	-0.261	0.061	-0.213	0.075	-0.200	0.063	-0.203	0.087
Community and Social Service Occupations	-0.079	0.109	-0.054	0.118	-0.061	0.096	-0.053	0.114
Computer and Mathematical Occupations	-0.121	0.052	-0.091	0.076	-0.130	0.056	-0.126	0.098
Education, Training, and Library Occupations	-0.141	0.049	-0.105	0.047	-0.086	0.044	-0.067	0.051
Health Diagnosing and Treating Practitioners	-0.368	0.124	-0.366	0.121	-0.361	0.140	-0.267	0.092
Lawyers	-0.182	0.124	-0.195	0.132	-0.182	0.133	-0.142	0.154
Life, Physical, and Social Science Occupations	-0.217	0.097	-0.166	0.095	-0.161	0.100	-0.143	0.121
Managerial Occupations	-0.396	0.081	-0.320	0.077	-0.278	0.066	-0.227	0.052
Sales and Related Occupations	-0.370	0.116	-0.232	0.083	-0.198	0.142	-0.179	0.136

Appendix Table 4.2: Variation in the Returns to Overwork across Occupations and Time

	1980		1990		2000		2010-2012	
	Mean	p75 - p25	Mean	p75 - p25	Mean	p75 - p25	Mean	p75 - p25
	A. Full Sample							
Returns to overwork	0.402	0.403	0.593	0.494	0.693	0.560	0.715	0.648
	B. By Cities							
25th Percentile City	0.285	0.410	0.402	0.688	0.529	0.555	0.521	0.554
Median City	0.388	0.767	0.603	0.762	0.701	0.736	0.691	0.693
75th Percentile City	0.453	0.344	0.704	1.160	0.771	0.406	0.808	0.710
	C. By Occupation Group							
Architects and Engineers	0.312	0.142	0.494	0.346	0.559	0.253	0.579	0.308
Arts, Design, Entertainment, Sports, and Media	0.594	0.499	0.751	0.747	0.718	0.478	0.903	0.659
Business and Financial Operations Occupations	0.727	0.416	0.912	0.394	1.039	0.382	1.153	0.446
Community and Social Service Occupations	0.106	0.540	0.182	0.590	0.242	0.386	0.267	0.644
Computer and Mathematical Occupations	0.392	0.225	0.531	0.284	0.656	0.340	0.717	0.353
Education, Training, and Library Occupations	0.351	0.198	0.374	0.253	0.436	0.311	0.442	0.225
Health Diagnosing and Treating Practitioners	0.150	0.234	0.389	0.378	0.557	0.417	0.383	0.517
Lawyers	0.572	0.346	1.052	0.432	1.062	0.608	1.089	0.624
Life, Physical, and Social Science Occupations	0.440	0.503	0.586	0.588	0.595	0.540	0.639	0.750
Managerial Occupations	0.461	0.186	0.695	0.205	0.879	0.288	0.813	0.381
Sales and Related Occupations	0.475	0.320	0.622	0.360	0.860	0.272	0.881	0.347

Note. The data is from the 1980, 1990, and 2000 Census and 3-year aggregate 2012 ACS (2010-2012). Each cell is the mean gender pay gap or returns to overwork for the full sample (Panel A), by city (Panel B) or by occupation group (Panel C) for each year. The "25th percentile" city is defined based on the average outcome across the occupation groups for each city in each year. The "median" and "75th percentile" cities are defined similarly. See text for details on how the variables were constructed.