Women in the City: Agglomeration and the Gender Wage Gap*

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Abstract

This paper contributes to our understanding of gender wage gaps and the urban wage premium. First, the study documents the large variation in gender wage gaps across metropolitan areas in the United States in 2000 and 2010. Gender wage gaps—even for observably equivalent male and female workers—are narrower in larger cities. Skill agglomerations are then considered to explain this pattern. Specifically, if men and women are endowed with heterogeneous skills, and these skills have differential productivities across city sizes, agglomerative forces may differentially reward men and women. This hypothesis is tested using occupational data on male and female workers' cognitive, interactive, and physical skills. Women are comparatively better endowed with interactive and cognitive skills, while men are comparatively better endowed in physical skills. Decomposing the wage gap shows that explanatory factors (education, skills, and location) predict women would out-earn men. Instead, the agglomerative returns to these skills account for the majority of the observed gender wage gap. These estimates suggest that even as women are advantageously endowed with the skills rewarded in agglomerations, they benefit less from agglomerations than men, resulting in the observed gender wage gap.

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1 Introduction

Over the last three decades, women have made dramatic gains in the U.S. labor market, including increased labor force participation, educational attainment, and significant increases in real earnings. In 1970, the median usual weekly earnings of full-time working women was 37.9 percent less than that of men; by 2007, the raw wage gap had shrunk to 21.5 percent (U.S. Dept of Labor 2009). While an extensive literature documenting and understanding gender gaps exists, a significant variation has largely gone unnoticed: gender wage gaps—even for observationally equivalent male and female workers—are narrower in larger cities.

Consider, for example, workers who worked full-time full-year in the following metropolitan areas: Los Angeles, California (2000 population 9.5 million) and Austin, Texas (population 1.2 million).[1] In the 2000 U.S. Census, the hourly wages of full-time full-year working women was 19 percent less than mens' in Los Angeles, compared to 28 percent in Austin, on average. By 2010, women in Los Angeles earned only 13 percent less than men, while women in Austin earned 22 percent less (from the 2010 ACS). Across U.S. metropolitan areas in 2010, the wage gap between observationally equivalent men and women ranged from a high of 52% to as low as 8%.[2]

This paper documents the large variation in gender wage gaps across metropolitan areas in the United States in 2000 and 2010, and considers potential explanations for the observed patterns. As shown in Figure 1, even as the male-female wage gap declined modestly over the 2000s, there are significant differences by city size in this convergence. The narrowing of the gender wage gap over the 2000s is also noteworthy given that multiple studies document the increase in female labor force participation that began around 1979, slowed in the 1990s, and leveled off in the 2000s.[3] These studies raise the possibility that the U.S. labor market has achieved a "natural rate" of female employment in the 2000s. Yet, gender wage gaps persist, particularly among smaller cities.

At the same time, a large theoretical and empirical literature in urban economics has documented and considered explanations for why wages of observationally similar workers—that is, of

[1] Full-time full-year workers are those who report working 35+ hours per week and 48+ weeks in the last year. Also, from hereon, "cities" are used interchangeably with "metro areas."

[2] Gender wage gaps are adjusted for quadratic age; quadratic years of schooling; and indicators for: high school, some college, college, Black, other non-White race, and married. See notes to Figure 1 in Section 3 below.

[3] See for example, Blau and Kahn (2000, 2006), Goldin (2006), and Juhn and Potter (2006), among others.

the same gender, education, and other observable characteristics—differ between cities of different sizes. Glaeser and Mare (2001) document a substantial urban wage premium: workers in dense metropolitan areas have been found to earn 25% more than their non-urban counterparts. Even with individual fixed effects, urban workers are found to earn 4.5 to 11% more than rural workers.

In contrast, both the urban and labor economics literatures are largely silent with respect to the significant cross-city variation in the gender wage *gap*. It is, after all, not readily apparent why women should be observed to have a relatively larger urban wage advantage than male workers. To explain the negative relationship between city size and the gender wage gap, this paper focuses on how economies of agglomeration might differentially affect male and female workers.[4] Specifically, if male and female workers are endowed with heterogeneous skills, and these skills have differential productivities across city sizes, agglomerative forces may reward the skills that women disproportionately possess compared to men.

Consider, for example, the worker skills examined in this paper: cognitive, physical, and interactive or social skills. Suppose—and evidence below suggests this to be the case—that women are comparatively better endowed with social and cognitive skills, while men are comparatively better endowed with physical skills. Surveys of the micro-foundations of agglomeration by Duranton and Puga (2004) and Rosenthal and Strange (2004) identify three ways that agglomeration might increase productivity and wages: learning, matching, and input sharing. All three channels could lead to a greater value of cognitive and social skills in large cities, and perhaps to a lesser extent, physical skills. For instance, male and female workers with high levels of interactive or social skills are likely better able to learn from others, acquire better job matches, and benefit from complementary resources (i.e., share) in a large labor market. If women are better endowed in the skills that are also more productive in larger cities, then the gap in wages between men and women will be smaller in larger cities. In the same way, the negative relationship between gender wage gaps and city size would be observed if physical skills are less productive in thick markets and men are comparatively better endowed in physical skills.

[4]Agglomeration refers to the productivity and efficiency gains and cost savings derived by having workers, firms, and consumers located in proximity to each other.

To test this hypothesis, I use data on occupational skill requirements from the Occupational Information Network (O*NET) merged with worker data from the Census and the American Community Surveys. Indeed, this paper finds that, across U.S. MSAs, doubling the population is associated with a 2% narrower gender wage ratio. In addition, worker-level wage regressions show that while social skills, and to some extent cognitive skills, are relatively more valuable in large cities, such is not the case with physical skills—for *both* men and women.

The findings in this paper thus add to multiple literatures, such as the one that seeks to understand gender wage gaps and the urban wage premium. With respect to the latter, this paper follows the more recent literature that identifies the sorts of skills enhanced by agglomeration (e.g., Bacolod, Blum, and Strange 2009 and others in that vein). Consistent with these studies, the paper finds evidence that agglomeration enhances cognitive and social or interactive skills, but not physical skills. This explains why gender wage gaps are observed to be narrower in larger cities.

Furthermore, the estimates show significant differences in the gender-specific city-size premia paid to skills. Social and cognitive skills in larger cities are relatively more valuable for men than they are for women. To account for the contributing factors of location, skills, and agglomeration on the gender wage gap, I decompose the gap using the Blinder-Oaxaca decomposition method. Decomposing the mean gender wage differential indicates that gender-specific returns to skill agglomeration account for a vast majority of the wage gap. Since women are comparatively better endowed with cognitive and social skills than men, men and women's observable characteristics and skill levels actually predict women to out-earn men. It is the agglomerative effects of male and female worker skills that lead to the observed gender wage gap.

Put another way, these estimates suggest that even as women are advantageously endowed with the skills rewarded in agglomerations, women derive less benefit from skill agglomerations than men, resulting in what we observe as women on average earning less than similar men. That women derive less benefit from agglomerations is consistent with more recent observations on the spatial allocation of female- vs. male-owned businesses. Rosenthal and Strange (2012) consider how female entrepreneurs may benefit less from agglomeration than their male counterparts. If women had less rich professional networks on average than male entrepreneurs, then the networking gap results in lower agglomeration benefits for female entrepreneurs. The effect would be magnified if female business owners' less developed networks limited their access to the credit necessary to gain entry to more expensive, agglomerated locations. Another reason for the spatial mismatch is that household division of labor means a higher effective commuting cost for female entrepreneurs, raising the cost of locating in an agglomerated location for female entrepreneurs relative to male businesspeople. Rosenthal and Strange (2012) develop a theoretical model that leads to a segregated equilibrium and find empirical evidence consistent with this form of spatial mismatch, suggesting that female entrepreneurs derive less benefit from agglomeration economies than male entrepreneurs.

Thus, women may benefit less from agglomerations compared to men due to weaker networks, from male and female differences in household division of labor, or from discrimination. Regardless of the explanation, the findings in this study provide a new and more subtle understanding of gender wage gaps in the context of the urban wage premium.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents the patterns of the gender wage gap across U.S. metropolitan areas and a discussion of possible explanations for the variation. Section 4 presents empirical analysis and a framework relating the gender wage gap with differential agglomerative returns to male and female skills. Finally, Section 5 concludes.

2 Data

Data for this study come from the 2000 5% Census sample Integrated Public Use Microdata Series (IPUMS, Ruggles et al. 2010), the 2010 American Community Survey (ACS), and the Occupational Information Network (O*NET) 13.0 database. Occupation-specific skill measures from the O*NET are merged to workers in the IPUMS and ACS, to characterize the skills of male and female workers across cities.

The sample of men and women from the IPUMS and ACS includes prime-aged workers (aged 25 to 55) who worked full-time full-year: workers who report working 35 or more hours per week and 48 or more weeks in the last year. In addition, workers in the sample had non-missing occupational categories that were merged with skill measures from the O*NET. Skill measures from the O*NET are matched to workers using the Standard Occupational Classification codes (SOC). Finally, boundaries of Metropolitan Statistical Area (MSA), used for calculating the population residing in that MSA, are defined using 2000 Census definitions.[5] Summary statistics of the sample of workers used in the analysis are presented in Table 1 Panel A. Panel B of Table 1 describes this sample aggregated at the MSA-level ($n = 297$).

Meanwhile, occupational data in the O*NET are the result of comprehensive studies of how jobs are performed in establishments across the nation. Job skill measures are composites of data collected from multiple sources: surveys filled by workers performing the job, members of trade and professional associations, and site visits by trained occupational analysts. The period covered in this study coincides well with occupational information from the O*NET 13.0 database, released in June 2008. The O*NET, which began data collection in June 2001, replaced the Dictionary of Occupational Titles (DOT) which was last published in 1991. While previous releases of the O*NET database exist, the earlier versions contained mainly extrapolated data. Occupational analysts were asked to map occupational data from the DOT to the O*NET Content Model, a conceptual framework developed using ideas in organizational analysis. Approximately 100 occupations a year were gradually transitioned from extrapolated data. By version 13.0 of the O*NET database, occupational data collected between 2001 and 2007 from more than 128,000 workers in 95,000 establishments are included (Source: U.S. Department of Labor 2008).

The skill measures used in this study come from the survey question, "How important is ______ (e.g., the skill *Critical Thinking*) to your current job?" Respondents rate the skill on a 1 to 5 scale, with 1 as "not important" and 5 as "extremely important." At the occupation (SOC) level, each O*NET skill is a weighted average of respondents' ratings (on average there are 31 raters per occupation).

Similar to previous studies that utilize information from occupational databases, it is not possible to make simultaneous use of all of the variables capturing job skills. High collinearity makes precise estimation impossible. I use the textual definitions of O*NET variables and the O*NET

[5] A typical MSA is a geographic region of one or more adjacent counties with close economic ties and a relatively dense urban area at its core. MSAs could include a single city (e.g., Chicago) or multiple cities (e.g., Los Angeles-Long Beach).

Content Model to construct interpretable measures of worker skills. These broad skill categories are: Cognitive skills, Social skills and Physical skills. These skill indices are created using principal component (factor) analysis. The indices are constructed from the first factor and are re-scaled to have a mean of 1 and a standard deviation of 0.1.

To capture aspects of Cognitive skills, I use select variables categorized under "Basic Skills" in the O*NET Content Model. These variables relate to a worker's "developed capacities that facilitate learning or more rapid acquisition of knowledge and skills" in order to perform the job. These variables include: *Active Learning, Active Listening, Critical Thinking, Learning Strategies, Mathematics, Monitoring, and Reading Comprehension*, and are further described in Appendix Table 1. These are the sort of skills that urban theory would predict are enhanced by agglomeration. I construct the Cognitive Index from the first factor, which accounts for 100% of variation in all the variables.

A high value on the Cognitive skills index indicates skills such as *Critical Thinking, Mathematics,* etc., are very important in carrying out the job. Indeed, the top five cognitive-intensive occupations (for both men and women) are: College and High School Subject Instructors ($Cognitive = 1.23$), Physicians ($Cognitive = 1.2$), Managers in Education ($Cognitive = 1.19$), Aerospace Engineers ($Cognitive = 1.18$), and Medical Scientists ($Cognitive = 1.18$). In contrast, the least cognitively demanding occupations are: Crossing Guards ($Cognitive = 0.69$), Graders and Sorters of Agricultural Products ($Cognitive = 0.71$), Mail Handlers ($Cognitive = 0.73$), Maids and Lodging Cleaners ($Cognitive = 0.73$), and Vehicle Washers ($Cognitive = 0.75$). Clearly, the first set of occupations demands more cognition than the latter.

In a similar fashion, the Social skills index is constructed from variables that relate to the "developed capacities used to work with people to achieve goals." Variables included in constructing Social skills refer to the importance of: *Coordination, Instructing, Negotiation, Persuasion, Service Orientation, and Social Perceptiveness* in job performance. Again, these variables are described further in Appendix Table 1. The first factor in the principal components analysis accounts for 100% of the variation in these variables.

Some of these variables—e.g., *Coordination*—are clearly forms of interactions that one would expect to be more productive in a thick urban market. On the other hand, it is less clear that the skill *Social Perceptiveness* is more productive in a large city. However, the occupations along the Social skills distribution clearly reflect that higher values correspond to occupations involving more interaction. The most Social skill-intensive occupations (again for both men and women) are: Sales Engineers ($Social = 1.27$), Clergy ($Social = 1.25$), Managers in Education ($Social = 1.24$), Education Counselors ($Social = 1.22$), Chief Executives and Public Administrators ($Social = 1.22$). In contrast, the least socially interactive are: Furniture Finishers ($Social = 0.74$), Drillers of Earth ($Social = 0.75$), Metal Platers ($Social = 0.77$), and Graders and Sorters of Agricultural Products ($Social = 0.77$).

Finally, I construct a Physical skills index from variables that reflect the importance of "abilities that influence strength, endurance, flexibility, balance, and coordination" in job performance. These variables include: *Dynamic Strength, Explosive Strength, Static Strength, Trunk Strength, Stamina, Dynamic Flexibility, Extent Flexibility, Gross Body Coordination, and Gross Body Equilibrium.* The first factor in the principal components analysis accounts for 96% of variation of these variables.

As with the previous indices, a high value on the Physical skills index indicates a job that requires greater physical demands. The top occupations are: Dancers ($Physical = 1.33$), Firefighting ($Physical = 1.24$), Mechanics ($Physical = 1.22$), Construction Helpers ($Physical = 1.19$), and Roofers ($Physical = 1.19$). The bottom occupations in this Physical skills index are: Mathematicians ($Physical = 0.85$), College subject instructors ($Physical = 0.85$), and Purchasing Managers, Economists, Chief Executives and Public Administrators (the last four are all tied at $Physical = 0.87$).

The virtue of summarizing job skills in these indices, as opposed to occupational categories, is that it allows a characterization of the allocation of job skills men and women bring to their city's workforce. One concern with using occupational requirements from the O*NET, however, is that skills are defined nationally. Characterizing the geographic distribution of worker skills is thus driven by the local economy's occupational structure. There would be significant measurement error for this study if the ratings of an occupational skill are somehow correlated with *both* gender and city size.[6] This error is not very likely, however, given that the studies by the O*NET Data Collection Program show a lack of gender bias in occupational ratings and profiles (Rounds et al. 1999).

3 Urbanization and the Gender Wage Gap: Description and Literature Review

Before moving on to a regression analysis, I will first describe the geography of these gender gaps. Several potential sources of explanation are explored in the context of a literature review.

3.1 Urbanization and the Gender Wage Gap

Panel B of Table 1 presents summary statistics aggregated for the 297 U.S. MSA in the analysis sample. On average, men earned 1.35 times more per hour than women in MSAs in 2000, with a standard deviation of 0.07. In 2010, the MSA-average gender wage ratio (w_m/w_f) is 1.27 (std deviation 0.07). What is striking about these numbers is the range of variation across cities in the gender gap. In both years, men earned from 1.1 to 1.6 times as much as women across cities.

To calculate the adjusted wage gap, first wage residuals were formed from individual-level regression of natural log wages on quadratic age, quadratic years of education, and indicators for: high school, some college, college, Black, other non-White race, and married. This log-wage residual (referred to from hereon out as the adjusted wage) is then averaged over each MSA separately for men and women. The adjusted wage gap between men and women ranges across cities from just under 10% to as much as 43% in 2000, and from 8% to as much as 52% in 2010. This is a huge range of gender gaps across MSAs, even adjusting for workers' individual characteristics.

Figure 1 illustrates the gender wage gap for four classes of cities: small cities (population between 100,000 and 500,000), medium-sized cities (population between 500,000 and 1,000,000), large cities (population between 1,000,000 and 4,000,000) and very large cities (population more

[6] For instance, if larger cities had women whose individual skill levels were greater than the national average for the same job, while men in the same larger cities at the same job had actual skills lower than the national average, then the results in this paper would be driven by measurement error.

than 4,000,000). Similar to the "adjusted wage gap" in Panel B of Table 1, first individual wage residuals were formed then averaged over each city-size category separately for men and women. The difference in adjusted log wage between men and women in each city-size category is plotted in Figure 1.

Figure 1 shows that, while the gender gap remains positive, women's earnings approach closer to similar men as city size increases. In addition, even as the adjusted gender wage gap narrowed between 2000 and 2010, the gap is still least in the largest city-size category.

Figure 1 reports the gender gap averaged for cities in a given size category. However, even within city-size categories, the negative relationship between city size and gender gaps persists. Figure 2 presents evidence of this negative gradient among large and very large cities (population more than 1,000,000). Figure 2 shows that in both 2000 and 2010, the adjusted gender wage gap declines with city size even among the largest cities.

Table 2 reports the actual values of the gender wage gap for select cities, as raw ratios and adjusted for observed characteristics as in Figure 1. These values are reported for large and very large cities (ordered by population), and the raw gender wage ratio is also reported for various sub-samples. Again we see the general pattern: the larger the city, the lower the gender wage gap tends to be. There are exceptions to this general trend, of course, in part because of how MSAs are defined. For instance, examine two very large cities: Chicago (with MSA population 8.2 million) and San Francisco (population 1.7 million). Chicago's FTFY women earned approximately 23% (20%) less than men in 2000 (2010) in adjusted terms, while women in San Francisco-Oakland earned only 16% (15%) less than men in 2000 (2010). However, San Francisco-Oakland seems small, compared to Chicago, when the rest of the Bay Area is ignored.

Moving away from the average further confirms the negative relationship between city size and the gender wage gap even among the largest cities. Figure 3 plots the percentage of women in that city whose hourly wages are at or above the 75th percentile and at or below the 25th percentile of the national wage distribution. For the largest cities, between 20% and 30% of their women are in the top 25% of the national wage distribution, while about 20% to 30% of women are in the bottom 25%. In contrast, in the smallest of large cities, less than 15% of women are in the top 25%

nationally while 30% to 40% are in the bottom 25% nationally. The larger the city, the more there are top-earning women; simultaneously, there are fewer bottom-earning women the larger the city size.

Taken together, there is a clear pattern of a narrower gender wage gap the larger the city. The first two columns of Table 3 show economically and statistically significant estimates from MSA-level linear regressions of the adjusted gender wage gap on city size. Doubling a city's population (100% increase) is associated with a 1.7% narrower gender wage ratio (w_m/w_f) in both 2000 and 2010 (statistically significant at the 1% level).

3.2 Possible Explanations: Brief Literature Review and MSA-Level Regressions

As discussed in the Introduction, a large literature in urban economics documents real wage differentials among observationally equivalent urban and rural workers. This literature also offers a multitude of competing explanations for the source of the urban productivity advantage. Perhaps the oldest explanation for this is that workers are more productive in urban areas due to agglomeration economies. For example, see Marshall (1890). An alternative hypothesis is that cities are observed to pay more because they attract the most able workers. Thus, the urban wage premium simply reflects a return to unobserved skill. Others posit that the observed urban wage premium is due to externalities in learning and human capital production (e.g., Moretti 2004) or efficiencies in job search and matching (e.g., Helsey and Strange 1990)

The pattern uncovered above is not about workers' *absolute* urban wage advantage, however, but an urban wage advantage observed for women *relative* to men. Why might the gap in wages between observably similar men and women differ systematically with city size?

3.2.1 Differences in Female Labor Supply

One explanation may be regional differences in female labor supply. While national trends on female labor supply appear stable and reached an apparent plateau in the 2000s as noted in the Introduction, a forthcoming paper by Black, Kolesnikova and Taylor (2014) titled "Why Do So Few Women Work in New York (And So Many in Minneapolis)?" highlights the large degree of variation in married women's labor supply across the 50 largest U.S. cities. The authors point to the substantial difference in commuting costs across cities in accounting for regional differences in married women's labor supply. In their analysis, they also find that MSA-level variation in married women's labor supply is uncorrelated with variation in local wage rates.

To explore this issue, Columns (3) and (4) of Table 3 relate male and female labor supply (average male and female weekly hours worked) with the adjusted male-female wage gap at the MSA level. Consistent with the findings by Black et al. (2014) relating female labor supply with local wage levels, Table 3 shows no significant systematic relationship. The adjusted log hourly gender gap *is* higher (men earn relatively more than women) in cities where men work less; the coefficients on male hours are negative in Cols (3) and (4). At the same time, cities where women work more also have higher gender gaps. While the direction of these relationships suggests the income effect may be stronger than the substitution effect, none of these estimates are statistically significantly different from zero. This is not surprising since a broad literature in labor supply shows that large permanent wage changes induce at most modest changes in labor supply. While it may still be the case that within-household variation in labor supply is significantly related to local wages, at the regional level variations in the gender wage gap appear to be uncorrelated with regional differences in male and female labor supply.

On the other hand, the selectivity of women who enter the labor force may systematically vary by city size due to commuting costs. Mulligan and Rubinstein (2008) highlight married women's increased positive selection into the labor market in accounting for the convergence of the U.S. gender wage gap over time. Thus, it may be that we observe a narrower gender wage gap in large cities with higher commuting costs because these wages belong to positively selected women.

To explore this issue, I restrict the females in the sample to include only unmarried women before aggregating to the MSA level.[7] The assumption is that unmarried women are less likely to be burdened by commuting costs associated with household division of labor, and thus less likely to be positively self-selected into the labor market by city size.

[7]That is, I first drop all married women from the worker sample. Then, as before, I calculate the adjusted wage gap by forming wage residuals from individual-level log-wage regressions. This log-wage residual is averaged for each MSA separately for men and women.

The results from this sample restriction are tabulated in Appendix Table 2. The negative relationship between gender wage gaps and city size remain statistically robust even after eliminating the subset of workers most likely to be positively self-selected into the labor market. The first two columns of Appendix Table 2 show that doubling a city's population (100% increase) is associated with a 1.8% narrower gender wage ratio (w_m/w_f) in 2000 and 2.3% in 2010 (statistically significant at the 1% level). Relating the gender wage ratio with male and female labor supply among this restricted sample (Cols (3) and (4)) show the same relationships discussed earlier. The exception is that cities where unmarried women work more now have *statistically* higher gender wage gaps at a diminishing rate with city size in 2000. This may simply be a statistical artifact, however, as there is no such statistically significant relationship in 2010.

Appendix Table 2 basically tells us is that it is not the subset of married women driving the observed negative gradient between city size and the gender wage gap. Since married women are the ones most likely to self-select into the labor market by city size due to household division of labor, positive self-selection does not seem to account for the observed patterns.

3.2.2 More College-Educated Women than Men in Cities

Another potential explanation could be that more highly-educated women than men are attracted to urban areas. They may value urban amenities such as museums and the opera more than highly-educated men. Since larger cities also have higher returns to education (Moretti 2004), the observed pattern in gender wage gaps could be the result of a greater share of highly-educated women than men in larger cities.

The literature on power couples offers a potential mechanism for this. Costa and Kahn (2000) show that between 1970 and 1990 it is mainly the "power couples"—couples in which both husband and wife have college degrees—who are increasingly likely to be located in larger cities. In 1970, only 39% of power couples were in cities of at least 2,000,000; this figure jumped to 50% by 1990. The increase in urbanization among "part-power couples"—where only one spouse has a college degree—and "low-power couples"—where neither has a college degree—was significantly slower (4% to 6% points less) over the same period.

Costa and Kahn (2000) consider that because larger cities have thicker markets, cities offer a potentially inefficient bargaining solution to power couples' co-location problem—the desire to satisfy both spouses' careers, preferences for urban amenities, and/or family proximity. However, to account for the observed negative relationship between gender wage gaps and city size, the female half of the power couple would have to be more productive or better matched than the male half of the power couple.

Columns (5) and (6) of Table 3 explore the hypothesis that a narrower gender gap in large cities is because more highly-educated women than men are drawn to large cities. First, note that we still see the negative association between population size and the adjusted gender gap (though it is not statistically significant). Also, the gender wage gap is *larger* in MSAs with a greater proportion of women with college, though the gap associated with % of women with college+ declines with population size. However, the estimates do not show a significant association of the gender gap with the proportion of men and women with college, either linearly or interacted with population size.

3.2.3 Gender Differences in Unobserved Skill, Matching, Search, and Discrimination

Similar to Fuch's hypothesis, the explanation may simply be a differential return to unobserved skill. There are many reasons to suspect that men and women are sorting differentially across cities so that the local composition of measured and unmeasured skills vary. Working with French data, Combes, Duranton, Gobillon and Roux (2010) find skills-based sorting matters very much. The wage elasticity with respect to urban density is cut by about half when worker fixed-effects are controlled for. While these estimates identify skills-based sorting off of migrants, one can interpret this as evidence that sorting on unobserved skills is important.

Thus, it may be that women in large cities are observed to be paid more than women in small cities because large cities attract the most able women at rates greater than they attract the most able men. If so, then the pattern of a narrower gender wage gap the larger the city is likely due to a return to unobserved skill. This makes it crucial to have good data on productivity-related skills of male and female workers.

In a forthcoming paper, Beaudry and Lewis (2014) explore the hypothesis that the decline in the gender wage gap between 1980 and 2000 across U.S. metro areas reflects changes in the relative price of latent (unobserved) skills. They find evidence that the decline in the gender gap during this period was in part driven by regional variation in adoption of personal computers. By 2000, however, personal computers were fairly diffuse across the U.S. The findings below show the importance of the returns to human capital—in particular, changes in relative skill prices—in explaining regional variation in the gender gap in the 2000s.

It may also be the case that the negative relationship between gender gap and city size is because of labor market matching. Because larger cities have thicker labor markets, large cities may offer better opportunities for matching workers' skills to jobs (see Helsley and Strange 1990 for a formal argument). However, for matching to result in a narrower gender wage gap in larger cities, job search and matching would have to be relatively more efficient for women than for men in large cities, or equivalently, less efficient in small cities. This might be the case if, for example, hiring discrimination against women in rural areas is more likely than in urban areas. Also, if women possess a more diverse (and/or more productive) set of skills than men, women would be more efficiently matched in a thicker market.

Empirically testing whether or not women in large cities are more efficiently matched is not the goal of this paper, however. The evidence presented below that agglomeration accounts for a significant portion of the regional variation in gender wage gaps is also consistent with more efficient matching and/or fewer discriminatory barriers in thicker markets. While matching and other issues in labor supply are certainly important, this study focuses on possible differences across cities in labor demand resulting in differences in skill prices.

3.3 Urbanization and the Skill Distribution by Gender

Figure 4 provides empirical support for the hypothesis that women are advantageously endowed in the skills that agglomerative forces may enhance. The panels in Figure 4 show the empirical distribution of Cognitive skills (Panel A), Social skills (Panel B), and Physical skills (Panel C) for men vs. women in the 2010 sample.[8] One can see that while there is overlap in their distributions, women tend to be concentrated in jobs requiring more cognitive and social skills than men (see Panels A and B). In contrast, more men are concentrated in jobs requiring physical skills.

The disproportional allocation of men in physically-intensive jobs compared to women in cognitive and socially-intensive jobs are equilibrium outcomes. One way to interpret this is that women are in these jobs because of a comparative advantage in cognitive and social skills. In the same way, the disproportional allocation of men in physically demanding jobs arises from men's comparative advantage in physical skills.

Figure 5 explores the relationship between gender gaps in average skill ratios with gender gaps in wages among large MSAs, those with a population of 1 million or more. The size of each symbol is proportional to MSA population. Figure 5 Panel A(B) plots gender wage gaps on the y-axis and the gap between men and women in average cognitive/physical(social/physical) skills on the $x-$axis. The range of values on the x-axis are negative because women's ratios of cognitive/physical and social/physical are both greater than men's ratios on average.

First, as previous figures indicate, the gender wage gap is lower in larger cities; the symbols get larger moving down the y-axes. Second, the scatterplot shows negative relationships between the wage gap and the gender gap in skills ratios. That is, in MSAs where women are relatively better endowed in cognitive and social skills compared to men, the lower the adjusted gender wage gap. Turning to the size of the symbols, Figure 5 does *not* clearly show the relationship between city size with gender gaps in wages and skills. That is, at the same time that larger cities tend to have lower gender wage gaps, the clustering of data points around the average skill ratios indicate gender gaps in skills are similar across city size.

To explore the possibility of skill uniformity across city sizes, Table 4 presents figures on the distribution of men and women's skills within a city size category. The table exhibits a striking pattern. First, within gender, there is a positive but very weak relationship between city size and skills: positive for cognitive and social, and negative for physical. However, the difference in average skills between small and large cities is very small (first column for each gender). In fact, there is

[8] To conserve space, I illustrate the densities for the 2010 sample only. The densities for the 2000 sample look very similar to these, as the numbers in Table 4 show.

very little difference in skill values across city size at each point of the respective gender's skill distributions.

While there are few differences within gender, Table 4 does show significant differences across gender in the allocation of skills. As illustrated in Figure 4, compared to men, women have higher average values of social skills, and to a lesser extent, also higher average values of cognitive skills. Men have higher physical skills than women, on average. Again, what is surprising in Table 4 is that within gender, the difference in skill distributions is uniform across city size categories.

The higher average cognitive skill values among women is primarily due to fewer of them at the lower tail than there are more highly-skilled women. As shown in Figure 4 Panel A, at the upper tail men and women overlap in cognitive skills while women are better skilled than men at the lower end. Looking at the 25th percentile in Table 4, the least cognitively skilled women in large cities are still better ($Cognitive = 0.97$) than the least cognitively skilled men ($Cognitive = 0.91$). At the 75th percentile in Table 4, the most cognitively skilled men and women in large cities have equal values ($Cognitive = 1.06$). Strikingly, the same difference holds for the least and most skilled men and women in small cities.

With respect to social skills, the higher average value for women is due to more of the highly-skilled at the upper tail and to some extent, fewer low-skilled women at the bottom. Figure 4 Panel B illustrates the rightward shift of social skill distribution for women compared to men. At the 25th and 75th percentiles in Table 4, women have higher levels of social skills than men (women's $Cognitive = 1.10(0.93)$ at the 75th (25th) vs. men's $Cognitive = 1.08(0.92 - 0.93)$ at the 75th (25th)). Across city size categories, the values of these skills at each point of the distribution are nearly the same.

Finally, the distribution of physical skills for men is shifted to the right of women's physical skills distribution. This results in a greater average value of physical skills for men. On average, men have $Physical = 1.0$ while women have $Physical = 0.96$. At each point of the physical skill distribution, men also have higher values of physical skills than women (see Table 4). As with cognitive and social skills, the difference in physical skills across men and women are bigger than across city size categories.

The finding of skill uniformity across city size within gender is similar to that for all workers in Bacolod, Blum, and Strange (2009), which found significantly larger variation in education and in industrial and occupation localization than in job skills across city size categories. This previous study concluded that both industries and occupations are much more unevenly distributed across city size categories than are worker skills. Using the NLSY79, for instance, they show that in a very large city, the top-end lawyers are on average more intelligent (score higher on the AFQT) than top-end lawyers in small cities. The average skill of lawyers is not that much greater in a large city, however, because the low-end lawyers in large cities are also less intelligent than low-skilled lawyers in a small city. In other words, the average skill is not greater in large cities because big cities are also home to some very low-skill workers, giving rise to skill uniformity. The pattern is also consistent with a more refined division of labor in larger cities.

4 Urbanization and the Gender Wage Gap: Econometric Analysis

4.1 Empirical Framework

Given the extent of variation in gender wage gaps across cities documented above, the next natural step is to account for them. The descriptive patterns in the distributions of skills by gender suggest that gender differences in skills may to some extent account for the regional variation in the gap.

To begin, consider the individual worker's wage equation:

$$ln(w_{ij}) = \alpha_i + \gamma f_i + \alpha_j + \gamma_j f_i + \varepsilon_{ij}, \tag{1}$$

where w_{ij} represent worker i's wage earnings in city of size j and $f_i = 1$ if i is female. In the standard framework for analyzing gender wage gaps, α_i represents wage determinants such as education, experience, and other measures of human capital. Meanwhile, γ is thought to capture forms of gender wage discrimination arising from a gender gap in returns to observed human capital and in unmeasured human capital.

The goal of this paper is to explore the relationship between agglomeration economies and the gender wage gap. Multiple empirical studies in urban economics focus on the effect of α_j on wages, such as the role of urban amenities vs. agglomeration effects on wages. In equation (1), both α_j and γ_j are location-specific factors that also determine wages. The parameter of primary interest here, however, is γ_j, which captures location-specific effects that may be separate by gender.

We can then think of α_i and α_j as wage determinants common to both men and women, such as individual and regional factors affecting the supply and demand for human capital. While γ captures gender-specific returns to this human capital, γ_j can be interpreted as gender-specific agglomerative returns to human capital.

To account for the portion of the gender wage gap that is attributable to differences in men and women's skill distributions as opposed to differences in the returns to those skills, I implement the Blinder-Oaxaca decomposition method. That is, first recast wage equation (1) and estimate separately by gender $g = \{male, female\}$,

$$ln(w_i^g) = \alpha_1^g x_i + \alpha_2^g ln(skill_i) + \alpha_3^g * ln(citysize) + \gamma^g * ln(citysize) * ln(skill) + \varepsilon_i^g \tag{2}$$

where x_i is a vector of individual characteristics such as age, education, marital status, race, and region of residence. $skill_i$ represents the cognitive, social, and physical skill measures from the O*NET. To enable a unit-free (elasticity) interpretation, skill measures enter in $ln(.)$ form.[9]

In the canonical decomposition method, if we let the vector $\beta = \{\alpha_1, \alpha_2, \alpha_3, \gamma\}$ and X represent the regressors including $x, citysize, skill$, the mean gender wage gap can be expressed as:

$$ln(w^m) - ln(w^f) = [X^m - X^f]\beta^f + X^f[\beta^m - \beta^f] + [X^m - X^f][\beta^m - \beta^f]. \tag{3}$$

The gender gap in wages can be thought of as deriving from a gender gap in endowments X (first component), a gap in the returns to or effects of those endowments β's (second component), and the interaction of differences in endowments and coefficients.

Note that in this formulation of the gap, the part attributed to difference in endowments is weighted by the coefficients from the female regression. In addition, the differences in coefficients are weighted by the female sample mean X^f. The second component is the contribution to the wage gap

[9] Skill indices are also rescaled in these regressions by 10. Recall that the indices are centered around 1 and $ln(1) = 0$.

of the gender gap in coefficients, evaluated at the sample mean endowment among women. There are, of course, alternative methods of statistically decomposing the gender gap, including alternative weighting procedures of each component or using estimates from a regression model pooling men and women together. Below I also present results from alternative statistical approaches for partitioning the gender wage gap.

Finally, note that each of the decomposition components can be further decomposed into proportions for which specific explanatory variables (or subsets of the X's) and coefficients account statistically for the gap.

4.2 Returns to Skill Agglomeration

Table 5 presents estimates of various skill returns. Columns (1) and (2) of both Panels indicate positive wage elasticities with respect to cognitive skills, zero with respect to social skills, and negative elasticities with physical skills for both men and women. That is, a 1% increase in cognitive skills is associated with 0.76% higher wages for both men and women in 2000 (0.98% increase for men and 0.73% increase for women in 2010). At the same time, a 1% increase in physical skills is associated with 0.77% lower men's wages and 0.65% lower women's wages in 2000 (0.9% lower for men and 0.94% lower for women in 2010).

Moving to Columns (3) and (4), we see the expected relationship between city size and workers' wages. We can also see that the coefficients on skills and city size (the α^g's) are not significantly different across gender.

As discussed in the Introduction, Duranton and Puga (2004) identify three ways that agglomeration might increase wages: learning, matching, and input sharing. Male and female workers with high levels of cognitive and social skills are likely better able to learn from others, acquire better job matches, and benefit from complementary resources (i.e., share) in a large labor market.

Indeed, Columns (5) and (6) in both Panels of Table 5 show that while social skills are relatively more valuable in large cities, such is not the case with physical skills. In fact, physical skills are significantly relatively *less* valuable in large cities. Even with industry fixed effects in Columns

(7) and (8) and utilizing variation across jobs within the same industry, the relationships between $ln(skill) * ln(citysize)$ and $ln(wages)$ persist in the same direction.

Taken as a whole, Table 5 provides estimates consistent with the hypothesis that agglomeration could lead to a greater value of social and cognitive skills in large cities, and less so for physical skills. More notable about these estimates are the significant differences in coefficients across gender in Columns (5) vs. (6), particularly agglomerative returns to skills (the γ_j's).[10] Recall that in this framework, γ_j's capture location-specific effects that may be separate by gender. To more precisely account for the statistical contribution of γ_j to the gender wage gap, I turn to implementing the Blinder-Oaxaca decomposition method using estimates from Columns (5) and (6).

4.3 Decomposition of the Gender Wage Gap

Table 6 shows that across regression models, the gap in coefficients accounts for a majority, if not all, of the gender wage gap. Panel A of Table 6 decomposes the gender wage gap according to equation (3). Differences in endowments actually *reverse* the gender wage gap, especially when we account for occupational worker skills. In the 2000 model without skills and without city size ("Baseline" column), differences in endowments account for very little of the gender wage gap. Focusing on the final columns within each year in Panel A, we see that differences in endowments would lead to women out-earning men by 3% in 2000 and by 7.2% in 2010.

Meanwhile, the differences in coefficients account for more than 100% of the gender wage gap in both years. All else equal, differences in coefficients predict men would out-earn women by 25.1% instead of just 23.6% in 2000, and by 23.7% instead of just 18.4% in 2010 (final columns within each year in Panel A of Table 6).

As mentioned earlier, there are alternative methods for decomposing the gender wage gap. For example, equation (3) can be expressed as

$$ln(w^m) - ln(w^f) = [X^m - X^f]\beta^f + X^m[\beta^m - \beta^f] \tag{4}$$

[10] F-tests indicate these coefficients are significantly different across gender, and are available from the author on request.

or

$$ln(w^m) - ln(w^f) = [X^m - X^f]\beta^m + X^f[\beta^m - \beta^f]. \tag{5}$$

In each of these equations, the first component is generally referred to as the "explained" component of the gender wage gap while the second component is called the "unexplained" component. The first components reflect the proportion of the gender gap attributable to differences in the explanatory factors (X's), if men's endowments and skills were paid the returns of those of women's in equation (4) or women's endowments and skills were paid the returns of those of men's in equation (5). Meanwhile, the second component reflects the proportion of the gap attributable to differences in coefficients evaluated at the sample mean of men's endowments (equation (4)) or women's endowments (equation (5)).

A third alternative decomposition method is to use estimates from a pooled regression of men and women (β^p):

$$ln(w^m) - ln(w^f) = [X^m - X^f]\beta^p + X^m[\beta^m - \beta^p] + X^f[\beta^p - \beta^f]. \tag{6}$$

Panel B of Table 6 reports results from these alternative decomposition methods. The columns titled "MEN (D=0)" correspond to partitioning the gender wage gap as formulated in equation (5). The columns titled "WOMEN (D=1)" correspond to equation (4), and the "Pooled Regression" columns correspond to equation (6).

Clearly, Table 6 shows that regardless of the decomposition method used, it is the gap in coefficients that accounts for a vast majority of the gender wage gap. The gender gap in endowments favors women, whether differences in endowments are weighted by β^m, β^f, or β^p. Explanatory factors predict women would out-earn men, and it is the coefficients or effects of these explanatory factors that lead to the observed gender wage gap.

This result is consistent with the literature accounting for the increase in relative female/male wages over time. Women's gains in experience and education over the 1980s and 1990s are considered major factors in explaining the convergence of the gender gap, while changes in the returns to education have worked to widen the wage gap (Altonji and Blank 1999).

To separately account for the contributions of male/female gaps in each factor to the total gender wage gap, Table 7 reports the Blinder-Oaxaca decomposition for individual X's and β's. For example, examining the "Endowments" columns, it is actually the gaps in *age*, *cognitive* skill, and $physical * popn$ that favor women in both years.[11] That is, all else equal, the gender wage gap would be reversed and women out-earn men allowing only for differences in *age*, *cognitive*, and $physical * popn$ in 2000. In 2010, the gender gap would be reversed and women out-earn men by as much as 7.2% from male and female differences in *age*, *cognitive*, $physical * popn$, education, $cognitive * popn$, and $social * popn$.

So, what explains the overall gender wage gap? Focusing on the middle column in each year of Table 7, we see that the gaps in coefficients for $ln(MSApopn)$, *cognitive*, *social*, and *physical* are all negative. That is, the statistical contributions to the gender wage gap of the coefficients or premia to city size and skills is to *favor* women. The effect of city size and occupational skills is to reverse the gender gap. However, these effects are offset by the relatively larger and positive gaps in the constant and in coefficients for skills interacted with city size (the γ_j's in equation (1)). This indicates that the agglomerative returns to skills (and intercept) account for a vast majority, if not all, of the gender wage gap.

Taken together, the simplest interpretation of these results is that even though women are advantageously endowed with the skills rewarded in agglomerations, women derive less benefit from agglomerations than men. Recall that the coefficient estimates of γ_j in Table 5 show that agglomerative returns to cognitive and social skills ($cognitive * popn$ and $social * popn$) are higher for men than for women, while the coefficient on $physical * popn$ is lower for men than women. Decomposing the gender wage gap shows that these differences in the agglomerative returns to skills account in a major way for the observed gender gap.

Furthermore, the estimates in Table 5 can be used to calculate the marginal effects of city size on wages ($\alpha_3 + \gamma * ln(skill)$) evaluated at gender-specific mean skill levels. In 2000, this marginal effect is 1.238 (standard error of 0.582) for men and $-1.81(0.82)$ for women. In 2010, the marginal effect of city size evaluated at gender-specific mean skills is 0.489(0.664) for men and $-1.452(0.731)$

[11] Note that *age* essentially measures potential years of work experience= $age - 6 - schooling$, since the census data do not report actual years of experience and the regressions control for both *age* and *schooling*.

for women. Within each year, the estimated city size effects are statistically significantly different across gender. Men statistically benefit more from agglomerations than women.

There is not much in the literature to account for why women benefit less from agglomerations than men. On the other hand, there is a relatively substantial literature on the spatial mismatch hypothesis, and the extent to which spatial mismatch accounts for the gaps in employment and wages of blacks vs. whites. Spatial mismatch posits that the movement of people and jobs during the postwar period from central cities to suburbs created a lack of employment opportunities for inner city residents, particularly blacks who face constraints on housing choices due to discrimination and/or a lack of social networks or financial resources to allow the move.[12]

More recently, Rosenthal and Strange (2012) develop a model to analyze the spatial mismatch in the locations of male and female entrepreneurs, and thus consider how female entrepreneurs may benefit less from agglomerations than their male counterparts. In particular, if women had less developed professional networks on average than male entrepreneurs, the networking gap results in lower agglomeration benefits for female entrepreneurs. This effect would be further amplified if female business owners' limited network restricted their access to the credit necessary to gain entry to more expensive, agglomerated locations.

Rosenthal and Strange (2012) then empirically establish the extent of segregation of male and female entrepreneurial locations. Using Dun and Bradstreet and Census data, they show female-owned businesses tend to be located farther away from valuable concentrations of economic activity, with a degree of segregation similar to black-white residential segregation. In exploring the underlying mechanisms that generate this pattern of segregation, they consider the impact of agglomerations on sales per worker. They find compelling empirical evidence that the effects of various measures of agglomeration is lower on female-owned businesses' sales compared to other establishments. Some of the analysis also suggests that differential access to business networks contributes to the gender segregation of entrepreneurial locations. Thus, women may benefit less from agglomerations compared to men due to weaker networks, which may also arise from discrimination.

[12] This hypothesis was first advanced by Kain (1968). Also, see surveys by Holtzer (1991) and Jencks and Mayer (1990).

5 Summary

This paper systematically documents the largely unstudied yet significant variation in gender wage gaps across U.S. metropolitan areas in 2000 and 2010. Even after accounting for individual characteristics such as age, education, and race, the gap in wages between full-time full-year working men and women across MSAs is between 9% and 43% in 2000 and 8% and 52% in 2010. A striking systematic pattern emerges when relating city size with the gender wage gap: gender wage gaps are narrower in larger cities.

To explain this spatial variation in gender gaps, I explore the relationship between agglomerations and the gender wage gap. In particular, if the skills men and women possess have differential productivities across city sizes, agglomerative forces may reward the particular skills that women disproportionately possess compared to men.

Indeed, occupational skills measures show that women are disproportionately in jobs requiring more cognitive and social skills, while men are in comparatively more physical-intensive jobs. However, for all three skill measures, there is striking skill uniformity for both men and women distributed across city-size. This pattern is consistent with results from a Blinder-Oaxaca wage decomposition of the gender wage gap: most of the gap is explained by the differential productivities of these skills across city sizes, not the differential allocation of skills by gender. All else equal, the location and skills distributions of men and women predict women would out-earn men. It is the agglomerative returns to these skills that statistically account for the majority of the gender wage gap.

Furthermore, men's agglomerative returns to cognitive and social skills are significantly larger than women's. The total marginal effect of city size for men is also larger than that for women. The simplest interpretation of these results is that women are benefitting less from agglomeration even as they are advantageously endowed with the skills rewarded in agglomeration.

That agglomeration accounts for a significant portion of the variation in gender wage gaps is also consistent with mechanisms underlying the micro-foundations of agglomeration economies. The findings in this study suggest that men's skills are more efficiently matched in thicker labor markets compared to the efficiency of matching female workers' skills to firms. Then again it may also be that thicker markets confer greater networking advantages to men than to women. Labor market discrimination may also explain some of the observed patterns. An interesting follow-up would be to distinguish between various underlying mechanisms giving rise to observed gender differences in agglomerative skill returns. Regardless of the explanation, the findings in this study provide a new and more subtle understanding of gender wage gaps in the context of the urban wage premium.

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FIGURE 1

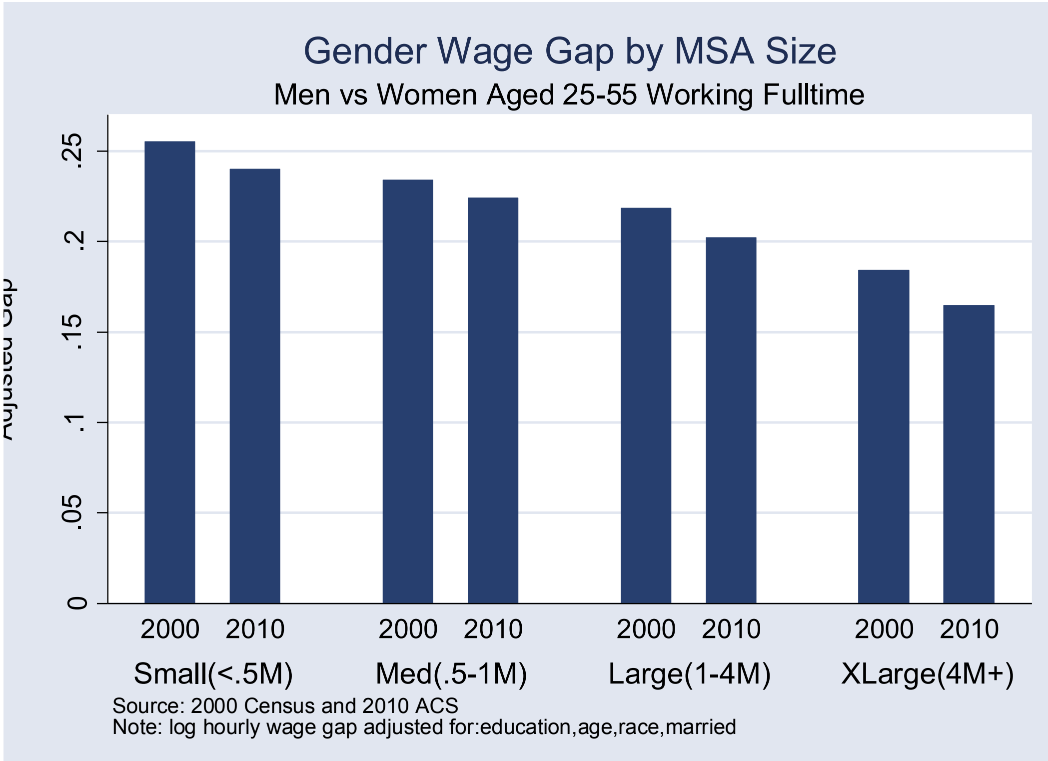


FIGURE 2

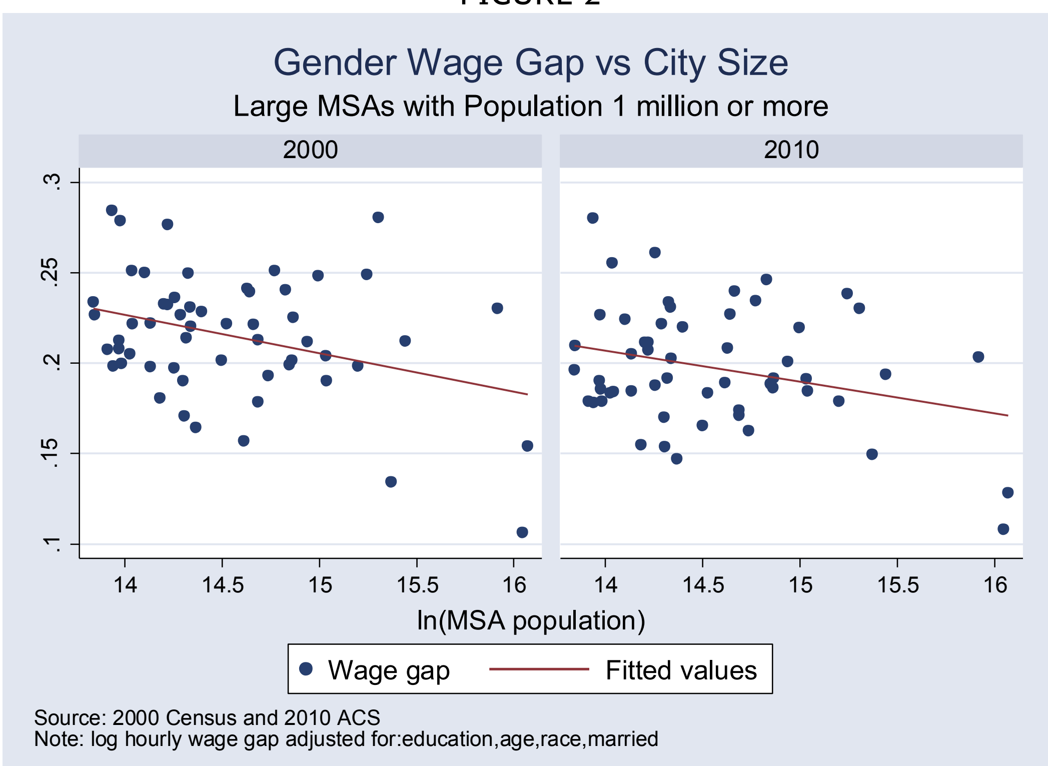


FIGURE 3

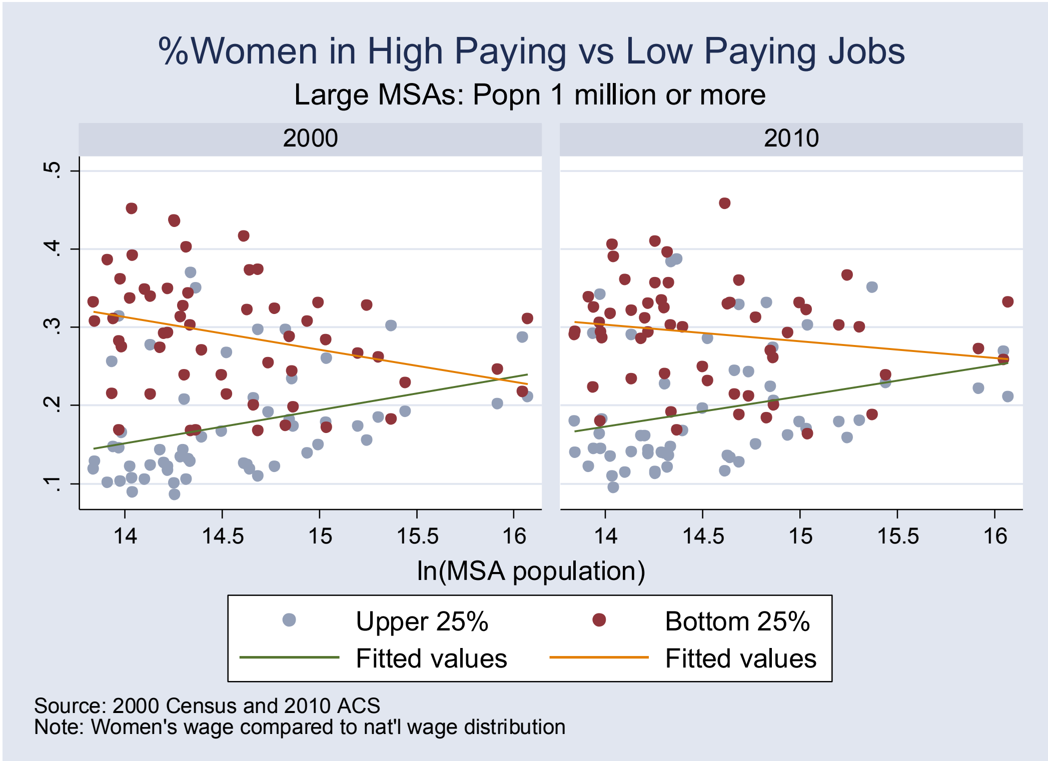
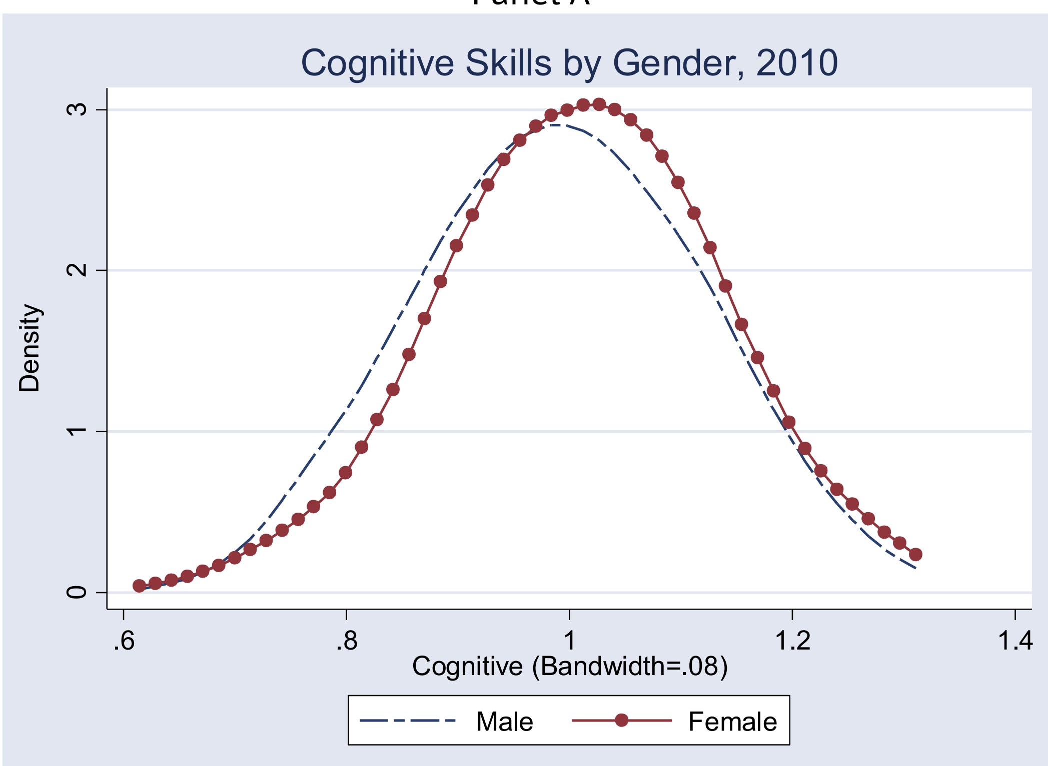
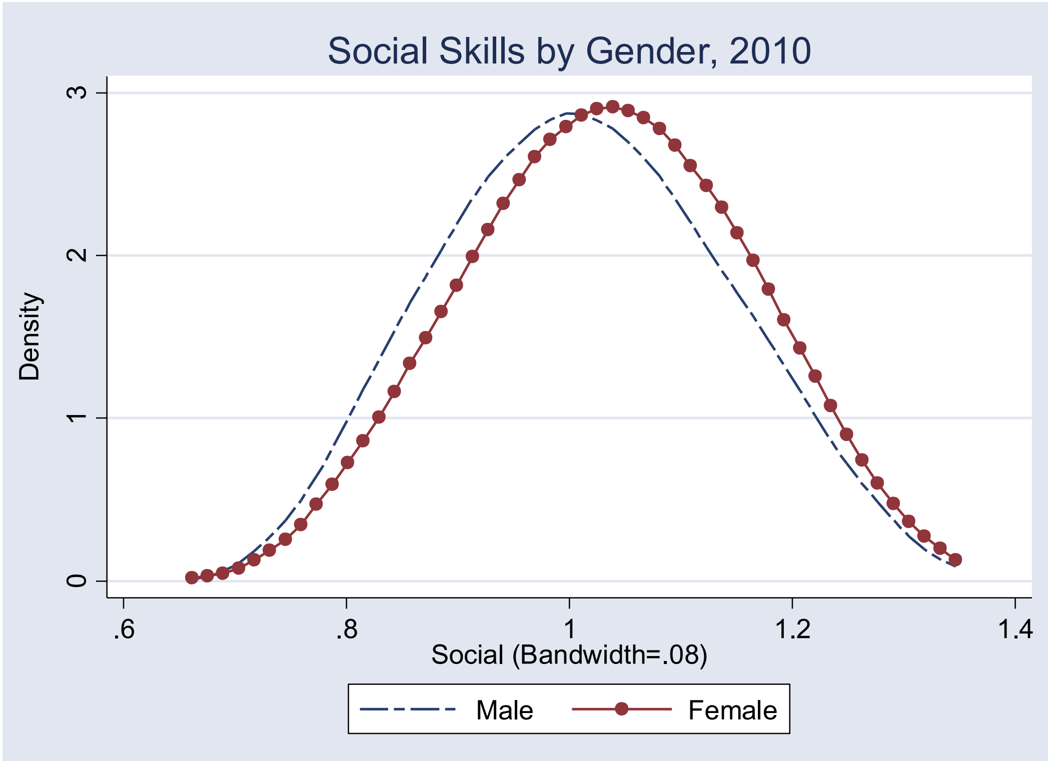


FIGURE 4
Panel A



Panel B



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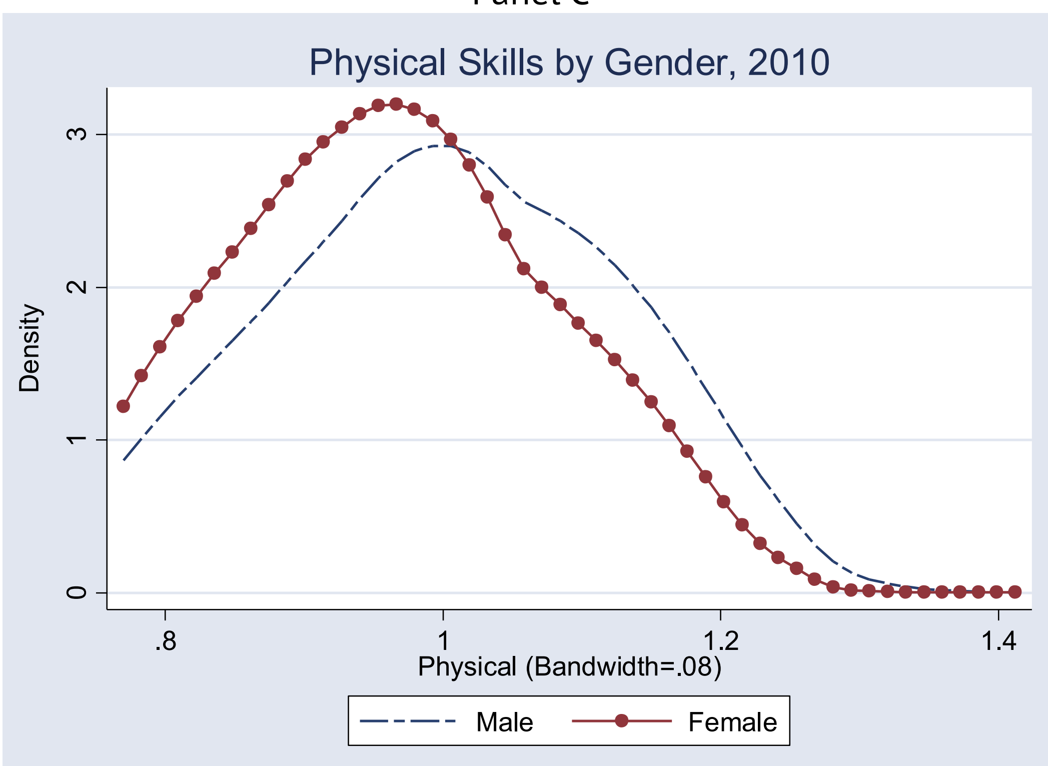
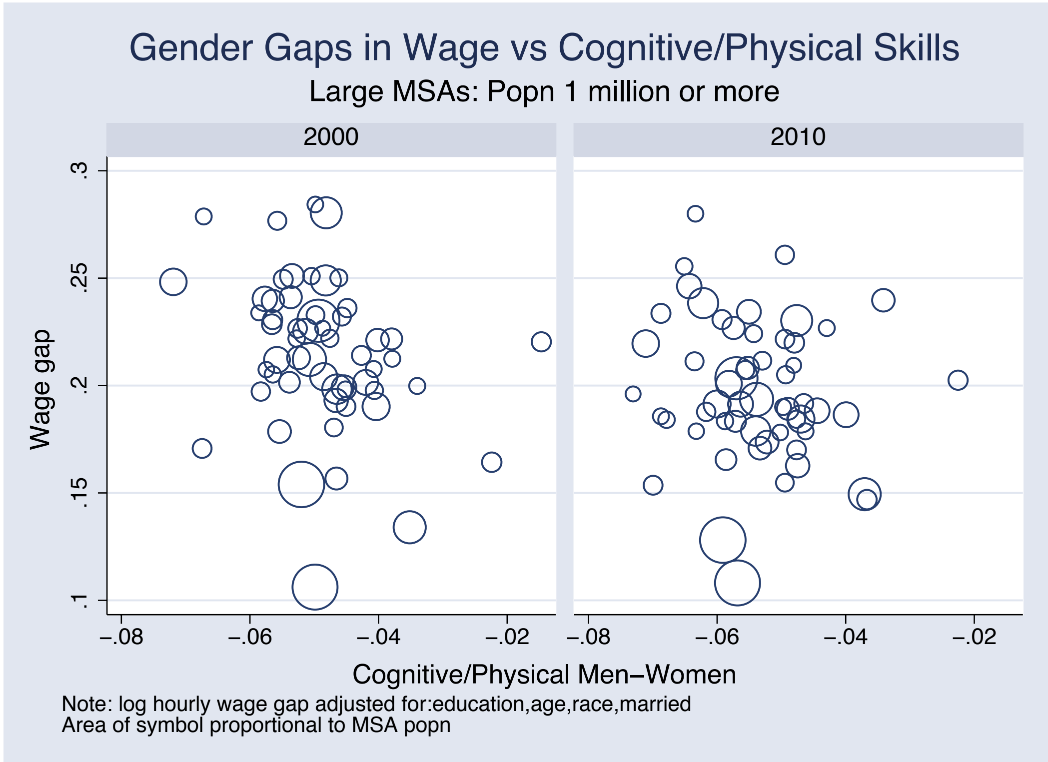


FIGURE 5

Panel A



Panel B

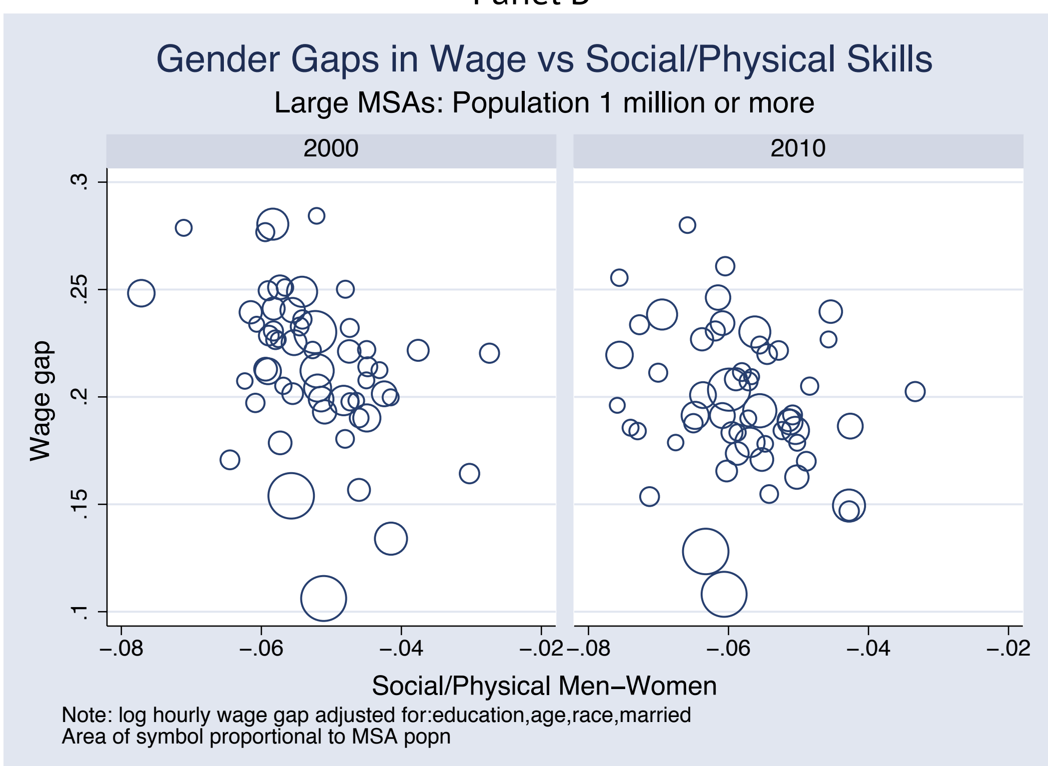


Table 1. Summary Statistics

Panel A. Census Sample of Workers

	2000				2010			
	Men		Women		Men		Women	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
ln (hourly wage)	2.857	0.656	2.621	0.571	3.062	0.709	2.878	0.64
Yrs of schooling	13.691	3.076	13.75	2.746	13.669	3.194	14.093	2.891
Age	39.493	8.33	39.72	8.484	40.049	8.77	40.136	8.965
Black	0.095	0.293	0.146	0.353	0.107	0.309	0.161	0.368
Other non-white race	0.124	0.329	0.118	0.322	0.153	0.36	0.143	0.35
Married	0.684	0.465	0.567	0.495	0.634	0.482	0.537	0.499
High School	0.269	0.444	0.262	0.44	0.261	0.439	0.219	0.414
Some College	0.31	0.462	0.355	0.479	0.289	0.453	0.329	0.47
College+	0.343	0.475	0.33	0.47	0.356	0.479	0.396	0.489
South	0.332	0.471	0.347	0.476	0.348	0.476	0.365	0.481
Midwest	0.224	0.417	0.221	0.415	0.201	0.401	0.2	0.4
West	0.236	0.425	0.223	0.416	0.252	0.434	0.235	0.424
Northeast	0.207	0.405	0.208	0.406	0.199	0.399	0.2	0.4
MSA Population	2.58E+06	2.63E+06	2.61E+06	2.67E+06	2.65E+06	2.70E+06	2.65E+06	2.70E+06
Cognitive skills	0.993	0.099	1.003	0.093	0.992	0.103	1.01	0.101
Social skills	1.01	0.101	1.023	0.098	1.013	0.103	1.034	0.101
Physical skills	0.998	0.098	0.959	0.088	1.001	0.099	0.964	0.087

Panel B. MSA-level statistics

	2000				2010			
	Mean	Std Dev	Max	Min	Mean	Std Dev	Max	Min
No of Male Obs in MSA	4480.96	6937.87	51171	484	3094.791	4890.006	37383	316
No of Female Obs in MSA	3202.532	5043.568	36569	283	2499.047	3964.68	29019	275
Hourly wage_f/wage_m	1.347	0.074	1.645	1.088	1.27	0.067	1.651	1.064
Adjusted gender wage gap	0.219	0.05	0.431	0.096	0.204	0.048	0.518	0.078
Yrs of schooling (Men)	13.653	0.531	15.301	11.46	13.659	0.572	15.089	11.074
Yrs schooling (Women)	13.719	0.419	14.968	12.14	14.077	0.465	15.346	11.966
Gender gap in schooling	-0.066	0.211	0.636	-0.862	-0.418	0.211	0.477	-1.467
% college (Men)	0.339	0.078	0.625	0.122	0.352	0.084	0.625	0.113
% college (Women)	0.326	0.076	0.554	0.12	0.393	0.08	0.621	0.161

Table 2. Gender Wage Gaps in Large MSA's (Population 1 million+)

		ADJUSTED ln(wage_m/wage_f)		UNADJUSTED Hourly wage_f/wage_m					
		2000	**2010**	**2000**			**2010**		
MSA	**Population in 2000**	**Sample:** ALL FTFY workers		ALL	College+ Unmarried	College+ Unmarried White, Age 25-40	ALL	College+ Unmarried	College+, Unmarried White, Age 25-40
Los Angeles-Long Beach, CA	9.5E+06	0.154	0.128	0.814	0.843	0.838	0.868	0.872	0.834
New York-Northeastern NJ	9.3E+06	0.106	0.108	0.834	0.851	0.825	0.849	0.827	0.775
Chicago-Gary-Lake, IL	8.2E+06	0.230	0.203	0.724	0.886	0.889	0.777	0.847	0.840
Philadelphia, PA/NJ	5.1E+06	0.212	0.194	0.735	0.880	0.867	0.769	0.905	0.917
Washington, DC/MD/VA	4.7E+06	0.134	0.149	0.801	0.901	0.903	0.817	0.893	0.862
Detroit, MI	4.4E+06	0.281	0.230	0.699	0.841	0.851	0.765	0.856	0.874
Houston-Brazoria, TX	4.2E+06	0.249	0.238	0.708	0.824	0.863	0.750	0.806	0.864
Atlanta, GA	4.0E+06	0.198	0.179	0.735	0.867	0.862	0.792	0.863	0.841
Boston, MA	3.4E+06	0.190	0.184	0.754	0.879	0.866	0.781	0.905	0.908
Dallas-Fort Worth, TX	3.4E+06	0.204	0.191	0.736	0.823	0.857	0.783	0.856	0.925
Riverside-San Bernardino,CA	3.3E+06	0.248	0.220	0.783	0.882	0.847	0.827	0.884	0.902
Phoenix, AZ	3.1E+06	0.212	0.201	0.748	0.816	0.830	0.801	0.818	0.873
Minneapolis-St. Paul, MN	2.9E+06	0.225	0.191	0.728	0.822	0.839	0.779	0.862	0.879
Orange County, CA	2.8E+06	0.201	0.186	0.731	0.781	0.765	0.788	0.850	0.821
San Diego, CA	2.8E+06	0.199	0.188	0.765	0.818	0.820	0.808	0.870	0.868
Nassau Co, NY	2.8E+06	0.240	0.246	0.712	0.899	0.941	0.761	0.929	0.889
St. Louis, MO-IL	2.6E+06	0.251	0.234	0.710	0.870	0.869	0.749	0.857	0.900
Baltimore, MD	2.5E+06	0.193	0.163	0.758	0.857	0.869	0.799	0.916	0.921
Oakland, CA	2.4E+06	0.213	0.174	0.741	0.875	0.880	0.819	0.937	0.965
Tampa-St. Petersburg-Clearwater FL	2.4E+06	0.179	0.171	0.766	0.818	0.832	0.809	0.849	0.846
Seattle-Everett, WA	2.3E+06	0.221	0.240	0.734	0.817	0.793	0.764	0.823	0.815
Pittsburgh-Beaver Valley, PA	2.3E+06	0.239	0.227	0.722	0.894	0.930	0.759	0.893	0.906
Cleveland, OH	2.3E+06	0.241	0.208	0.716	0.869	0.857	0.760	0.942	0.949
Miami-Hialeah, FL	2.2E+06	0.157	0.189	0.772	0.771	0.813	0.789	0.801	0.785
Newark, NJ	2.0E+06	0.222	0.183	0.704	0.848	0.857	0.769	0.957	0.929
Denver-Boulder-Longmont, CO	2.0E+06	0.201	0.166	0.756	0.880	0.835	0.814	0.885	0.907
Portland-Vancouver, OR	1.8E+06	0.229	0.220	0.739	0.805	0.819	0.771	0.845	0.825
San Francisco-Oakland-Vallejo, CA	1.7E+06	0.164	0.147	0.789	0.867	0.863	0.818	0.826	0.812
San Jose, CA	1.7E+06	0.220	0.203	0.723	0.804	0.838	0.794	0.868	0.806
Kansas City, MO-KS	1.7E+06	0.231	0.231	0.738	0.881	0.861	0.767	0.880	0.897
Fort Worth-Arlington, TX	1.7E+06	0.249	0.234	0.720	0.856	0.849	0.771	0.838	0.782
Orlando, FL	1.7E+06	0.214	0.192	0.718	0.798	0.851	0.773	0.855	0.872
Sacramento, CA	1.6E+06	0.171	0.154	0.788	0.889	0.910	0.855	0.927	0.949
FtLauderdale-Hollywood-Pompano FL	1.6E+06	0.190	0.170	0.750	0.850	0.871	0.776	0.830	0.806
Indianapolis, IN	1.6E+06	0.227	0.222	0.735	0.910	0.898	0.762	0.920	0.928
Norfolk-VA Beach-Newport News VA	1.6E+06	0.236	0.261	0.745	0.777	0.773	0.763	0.896	0.878

Table 2 (con't)

		ADJUSTED ln(wage_m/wage_f)		UNADJUSTED Hourly wage_f/wage_m					
		2000	2010	2000			2010		
MSA	**Population in 2000**	Sample: ALL FTFY workers		ALL	College+ Unmarried	College+, Unmarried White, Age 25-40	ALL	College+, Unmarried	College+, Unmarried White, Age 25-40
San Antonio, TX	1.6E+06	0.197	0.188	0.769	0.853	0.810	0.821	0.876	0.817
Charlotte-Gastonia-Rock Hill, SC	1.5E+06	0.232	0.207	0.720	0.818	0.845	0.772	0.852	0.861
Milwaukee, WI	1.5E+06	0.277	0.211	0.704	0.867	0.843	0.778	0.878	0.843
Cincinnati OH/KY/IN	1.5E+06	0.233	0.212	0.701	0.862	0.866	0.762	0.920	0.957
Columbus, OH	1.4E+06	0.180	0.155	0.754	0.878	0.866	0.805	0.891	0.878
Las Vegas, NV	1.4E+06	0.198	0.184	0.775	0.826	0.856	0.832	0.938	0.985
Bergen-Passaic, NJ	1.4E+06	0.222	0.205	0.715	0.869	0.864	0.773	0.923	0.911
Salt Lake City-Ogden, UT	1.3E+06	0.250	0.224	0.711	0.838	0.903	0.749	0.859	0.842
Greensboro-WinstonSalem-HighPt, NC	1.3E+06	0.222	0.184	0.741	0.881	0.923	0.814	0.798	0.897
New Orleans, LA	1.2E+06	0.251	0.255	0.724	0.869	0.895	0.772	0.881	0.949
Nashville, TN	1.2E+06	0.205	0.183	0.742	0.886	0.942	0.800	0.861	0.944
Raleigh-Durham, NC	1.2E+06	0.200	0.179	0.756	0.857	0.881	0.798	0.880	1.020
Buffalo-Niagara Falls, NY	1.2E+06	0.279	0.186	0.716	0.849	0.812	0.849	0.886	0.884
Middlesex-Somerset-Hunterdon, NJ	1.2E+06	0.208	0.227	0.745	0.954	0.941	0.755	0.845	0.990
Austin, TX	1.2E+06	0.212	0.190	0.725	0.786	0.780	0.776	0.872	0.921
WestPalmBeach-BocaRaton-DelrayBeach FL	1.1E+06	0.198	0.178	0.719	0.769	0.777	0.758	0.801	0.855
Monmouth-Ocean, NJ	1.1E+06	0.284	0.280	0.677	0.799	0.872	0.739	0.825	0.775
Jacksonville, FL	1.1E+06	0.207	0.179	0.723	0.853	0.884	0.783	0.853	0.888
Rochester, NY	1.0E+06	0.227	0.209	0.751	0.866	0.821	0.785	0.868	0.884
Providence-FallRiver-Pawtucket MA/RI	1.0E+06	0.234	0.196	0.770	0.894	0.859	0.849	0.965	0.931

Table 3. MSA-Level Regressions

	DEPVAR: Adjusted ln(wage_m)-ln(wage_f)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2000	2010	2000	2010	2000	2010	2000	2010
ln(MSA population)	-0.0169	-0.0172	-0.0347	0.0176	-0.0177	-0.0149	-0.0029	-0.0134
	[0.0029]***	[0.0030]***	[0.2612]	[0.2621]	[0.0117]	[0.0150]	[0.0458]	[0.0449]
Men Avg Wkly Hours			-0.0645	-0.0158				
			[0.0590]	[0.0508]				
Women Avg Wkly Hours			0.0573	0.0253				
			[0.0756]	[0.0789]				
ln-pop*men hours			0.0062	0.0035				
			[0.0047]	[0.0041]				
ln-pop*women hours			-0.0062	-0.0044				
			[0.0059]	[0.0063]				
% Men College+					-2.1707	-1.9908		
					[1.2928]*	[1.3878]		
% Women College+					1.8504	1.5584		
					[1.3306]	[1.4621]		
ln-pop*men college+					0.1737	0.1545		
					[0.1028]*	[0.1114]		
ln-pop*women college+					-0.1631	-0.1323		
					[0.1054]	[0.1167]		
% Men Married							-0.6645	1.4646
							[1.4564]	[1.5110]
% Women Married							1.5742	-1.1453
							[1.3463]	[1.3100]
ln-pop*men married							0.087	-0.0793
							[0.1145]	[0.1200]
ln-pop*women married							-0.1132	0.093
							[0.1081]	[0.1062]
Constant	0.4619	0.4513	0.936	0.0015	0.5231	0.4721	-0.1101	0.0861
	[0.0368]***	[0.0390]***	[3.3149]	[3.2783]	[0.1475]***	[0.1898]**	[0.5954]	[0.5755]
Observations	297	297	297	297	297	297	297	297
R-squared	0.11	0.1	0.15	0.26	0.18	0.15	0.26	0.22

NOTE: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. Unit of observation is MSA. Regressions weighted by no of observations in MSA.

Table 4. Summary Statistics of Skills by City Size and Gender

	Men					Women				
MSA Size	Mean	Std Dev	p25	p50	p75	Mean	Std Dev	p25	p50	p75
2000										
Cognitive Skills										
Small(<.5M)	0.987	0.1	0.909	0.992	1.051	0.996	0.094	0.949	0.999	1.049
Med(.5-1M)	0.988	0.099	0.909	0.992	1.052	0.999	0.093	0.96	1.004	1.049
Large(1-4M)	0.997	0.098	0.917	0.999	1.06	1.005	0.091	0.967	1.012	1.051
XLarge(4M+)	0.996	0.101	0.912	0.999	1.066	1.005	0.094	0.966	1.012	1.059
Social Skills										
Small(<.5M)	1.003	0.102	0.92	0.99	1.082	1.018	0.099	0.934	1.016	1.089
Med(.5-1M)	1.005	0.102	0.924	0.994	1.082	1.019	0.098	0.934	1.019	1.097
Large(1-4M)	1.014	0.1	0.936	1.001	1.083	1.025	0.097	0.938	1.019	1.097
XLarge(4M+)	1.013	0.101	0.936	1	1.085	1.026	0.099	0.934	1.022	1.104
Physical Skills										
Small(<.5M)	1.01	0.096	0.91	1.033	1.09	0.968	0.09	0.879	0.946	1.051
Med(.5-1M)	1.006	0.096	0.894	1.025	1.089	0.964	0.089	0.879	0.921	1.05
Large(1-4M)	0.993	0.099	0.88	1.005	1.087	0.955	0.087	0.877	0.916	1.033
XLarge(4M+)	0.992	0.098	0.879	1.004	1.082	0.955	0.087	0.877	0.916	1.033
2010										
Cognitive Skills										
Small(<.5M)	0.986	0.104	0.904	0.992	1.058	1.007	0.101	0.954	1.01	1.06
Med(.5-1M)	0.987	0.103	0.904	0.992	1.059	1.007	0.1	0.96	1.01	1.06
Large(1-4M)	0.996	0.102	0.91	0.999	1.067	1.012	0.1	0.966	1.015	1.064
XLarge(4M+)	0.992	0.105	0.909	0.997	1.067	1.01	0.102	0.966	1.015	1.064
Social Skills										
Small(<.5M)	1.006	0.104	0.919	0.992	1.082	1.031	0.102	0.934	1.026	1.108
Med(.5-1M)	1.008	0.104	0.924	0.994	1.083	1.032	0.101	0.938	1.026	1.108
Large(1-4M)	1.017	0.102	0.936	1.012	1.103	1.036	0.1	0.951	1.041	1.114
XLarge(4M+)	1.014	0.103	0.934	1.008	1.097	1.036	0.102	0.944	1.041	1.114
Physical Skills										
Small(<.5M)	1.012	0.096	0.91	1.034	1.092	0.971	0.088	0.879	0.964	1.051
Med(.5-1M)	1.009	0.097	0.901	1.033	1.092	0.968	0.088	0.879	0.946	1.05
Large(1-4M)	0.996	0.1	0.884	1.011	1.088	0.961	0.087	0.877	0.927	1.034
XLarge(4M+)	0.997	0.1	0.884	1.011	1.088	0.962	0.087	0.878	0.927	1.043

Table 5. Skill Premia and Returns to Agglomeration

Panel A. 2000 Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	skills only		+ MSA size		Full Model		With Industry FE's	
	Men	Women	Men	Women	Men	Women	Men	Women
Cognitive	0.764	0.756	0.772	0.773	0.29	1.5	0.147	1.196
	[0.041]***	[0.054]***	[0.039]***	[0.051]***	[0.457]	[0.594]**	[0.417]	[0.565]**
Social	-0.028	-0.027	-0.044	-0.05	-1.698	-1.545	-1.248	-1.097
	[0.042]	[0.048]	[0.039]	[0.043]	[0.435]***	[0.487]***	[0.393]***	[0.468]**
Physical	-0.775	-0.654	-0.743	-0.597	0.13	2.336	0.075	2.46
	[0.029]***	[0.047]***	[0.026]***	[0.044]***	[0.316]	[0.565]***	[0.277]	[0.557]***
ln(MSA pop'n)			0.044	0.056	-0.046	0.198	-0.038	0.197
			[0.002]***	[0.002]***	[0.044]	[0.061]***	[0.039]	[0.060]***
Cognitive*ln(MSA popn)					0.034	-0.051	0.038	-0.037
					[0.034]	[0.044]	[0.031]	[0.042]
Social*ln(MSA popn)					0.117	0.105	0.099	0.085
					[0.032]***	[0.036]***	[0.029]***	[0.035]**
Physical*ln(MSA popn)					-0.061	-0.207	-0.056	-0.198
					[0.023]***	[0.042]***	[0.020]***	[0.042]***
Constant	0.996	0.877	0.33	-0.01	1.608	-2.023	1.218	-2.408
	[0.055]***	[0.074]***	[0.064]***	[0.090]	[0.591]***	[0.812]**	[0.528]**	[0.798]***
Observations	1330845	951152	1330845	951152	1330845	951152	1330845	951152
Adjusted R-squared	0.27	0.25	0.27	0.26	0.27	0.26	0.29	0.28
F test of addt'l regressors	800.33	591.26	730.09	628.06	602.41	521.33		

Panel B. 2010 Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	skills only		+ MSA size		Full Model		With Industry FE's	
	Men	Women	Men	Women	Men	Women	Men	Women
Cognitive	0.981	0.726	0.994	0.758	-0.037	0.424	-0.34	0.302
	[0.044]***	[0.055]***	[0.044]***	[0.054]***	[0.535]	[0.637]	[0.473]	[0.601]
Social	-0.023	0.078	-0.039	0.051	-1.047	-0.746	-0.675	-0.483
	[0.045]	[0.053]	[0.043]	[0.050]	[0.506]**	[0.597]	[0.441]	[0.567]
Physical	-0.903	-0.945	-0.881	-0.901	0.71	2.004	0.579	2.243
	[0.034]***	[0.049]***	[0.032]***	[0.047]***	[0.386]*	[0.560]***	[0.325]*	[0.542]***
ln(MSA pop'n)			0.035	0.05	0.004	0.166	0.001	0.169
			[0.003]***	[0.003]***	[0.050]	[0.054]***	[0.042]	[0.052]***
Cognitive*ln(MSA popn)					0.072	0.024	0.08	0.026
					[0.039]*	[0.047]	[0.035]**	[0.044]
Social*ln(MSA popn)					0.072	0.056	0.059	0.046
					[0.037]*	[0.044]	[0.033]*	[0.042]
Physical*ln(MSA popn)					-0.112	-0.205	-0.104	-0.2
					[0.029]***	[0.042]***	[0.024]***	[0.040]***
Constant	0.951	1.303	0.428	0.521	0.871	-1.122	0.83	-1.563
	[0.063]***	[0.069]***	[0.073]***	[0.095]***	[0.678]	[0.725]	[0.570]	[0.703]**
Observations	919153	742217	919153	742217	919153	742217	919153	742217
Adjusted R-squared	0.32	0.29	0.32	0.29	0.32	0.3	0.34	0.31
F test of addt'l regressors	1158.37	661.44	917.38	545.19	731.83	433.87		

NOTES:
Robust standard errors in brackets, clustered by MSA and occupation code. * significant at 10%; ** significant at 5%; *** significant at 1%
All regressions weighted by IPUMS weights "perwt." Other regressors include: quadratic age, quadratic years of schooling, and indicators for: high school, some college, college, black, other race, married, midwest, south, west, and a constant.

Table 6. Oaxaca-Blinder Decomposition of Gender Wage Gap

Panel A. Across regression models

	2000				2010			
MODEL	Baseline	+skills ($\alpha_i+\gamma f_i$)	+skills, MSA size ($\alpha_i+\gamma f_i+\alpha_j$)	+skills,size, interactions $\alpha_i+\gamma f_i+\alpha_j+\gamma_j f_i$	Baseline	+skills ($\alpha_i+\gamma f_i$)	+skills, MSA size ($\alpha_i+\gamma f_i+\alpha_j$)	+skills,size, interactions $\alpha_i+\gamma f_i+\alpha_j+\gamma_j f_i$
Male ln(w)	2.857				3.062			
Female ln(w)	2.621				2.878			
Gender wage gap	0.236				0.184			
Decomposition								
Endowments [$(X_m-X_f)B_f$]	-0.002	-0.034	-0.031	-0.030	-0.035	-0.076	-0.073	-0.072
Coefficients [$X_f(B_m -B_f)$]	0.215	0.253	0.252	0.251	0.200	0.240	0.238	0.237
Interaction [$(X_m-X_f)'(B_m -B_f)$]	0.023	0.017	0.015	0.015	0.019	0.021	0.019	0.019

Panel B. Across various reference groups (using full regression model)

	2000			2010		
Decomposition based on X's of:	MEN (D=0)	WOMEN (D=1)	Pooled Regression	MEN (D=0)	WOMEN (D=1)	Pooled Regression
Explained [Endow + D*Interaction]	-0.030	-0.015	-0.002	-0.072	-0.053	-0.046
Unexplained [Coeffs+(1-D)Interact]	0.266	0.251	0.238	0.257	0.237	0.230
% Explained [Endow + D*Interact]	-12.9	-6.5	-0.9	-39.3	-28.8	-24.8
% Unexplained [Coeffs+(1-D)Inter]	112.9	106.5	100.9	139.3	128.8	124.8

Table 7. Oaxaca-Blinder Decomposition for Variables

	2000			2010		
Decomposition for Variables	Endowments $[(X_m-X_f)B_f]$	Coefficients $[X_f(B_m-B_f)]$	Interaction $[(X_m-X_f)'(B_m-B_f)]$	Endowments $[(X_m-X_f)B_f]$	Coefficients $[X_f(B_m-B_f)]$	Interaction $[(X_m-X_f)'(B_m-B_f)]$
Yrs of Educ	0.000	0.103	0.000	0.005	0.216	-0.007
Educ-squared	0.000	-0.079	0.000	-0.022	-0.17	0.008
Age	-0.012	0.194	-0.001	-0.005	0.584	-0.001
Age-squared	0.012	-0.019	0	0.006	-0.241	0.001
Black	0.003	-0.014	0.005	0.003	-0.015	0.005
Other	-0.001	-0.008	0	-0.001	-0.008	-0.001
Married	0.003	0.079	0.016	0.005	0.057	0.01
High School	0.001	0	0	0.005	-0.002	0
Some College	-0.011	-0.023	0.003	-0.009	-0.015	0.002
College	0.005	-0.03	-0.001	-0.014	-0.028	0.003
South	0	0.003	0.001	0.002	0.002	0
Midwest	0	0.009	0	0	0.003	0
West	0.001	0.001	-0.001	0	-0.001	0
ln(MSA popn)	-0.002	-3.471	0.003	0	-2.312	0
Cognitive	-0.014	-1.213	0.011	-0.008	-0.466	0.008
Social	0.019	-0.157	0.002	0.016	-0.312	0.007
Physical	0.092	-2.115	-0.086	0.075	-1.247	-0.048
Cognitive*ln(MSA popn)	0.007	1.209	-0.012	-0.006	0.7	-0.012
Social*ln(MSA popn)	-0.02	0.17	-0.002	-0.017	0.227	-0.005
Physical*ln(MSA popn)	-0.113	1.982	0.079	-0.108	1.273	0.049
Constant	0	3.631	0	0	1.993	0
Total	-0.03	0.251	0.015	-0.072	0.237	0.019

Appendix Table 1. Description of O*NET Variables

Variable Name	Description
Cognitive Skills	
Active Learning	Understanding the implications of new information for both current and future problem-solving and decision-making
Active Listening	Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate
Critical Thinking	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems
Learning Strategies	Selecting and using training/instructional methods and procedures appropriate for the situation when learning or teaching new things
Mathematics	Using mathematics to solve problems
Monitoring	Monitoring/assessing performance of yourself, other individuals or organizations to make improvements or take corrective action
Reading Comprehension	Understanding written sentences and paragraphs in work related documents
Social Skills	
Coordination	Adjusting actions in relation to others' actions
Instructing	Teaching others how to do something
Negotiation	Bringing others together and trying to reconcile differences
Persuasion	Persuading others to change their minds or behavior
Service Orientation	Actively looking for ways to help people
Social Perceptiveness	Being aware of others' reactions and understanding why they react as they do
Physical Skills	
Dynamic Strength	Ability to exert muscle force repeatedly or continuously over time
Explosive Strength	Ability to use short bursts of muscle force to propel oneself as in jumping or sprinting, or to throw an object
Static Strength	Ability to exert maximum muscle force to lift, push, pull or carry objects
Trunk Strength	Ability to use abdominal and lower back muscles to support part of the body repeatedly or continuously over time without fatiguing
Stamina	Ability to exert physically over long periods of time without getting winded or out of breath
Dynamic Flexibility	Ability to quickly and repeatedly bend, stretch, twist, or reach with body, arms, and/or legs
Extent Flexibility	Ability to bend, stretch, twist, or reach with your body, arms, and/or legs
Gross Body Coordination	Ability to coordinate the movement of arms, legs, and torso together when the whole body is in motion
Gross Body Equilibrium	Ability to keep or regain body balance or stay upright when in an unstable position

Appendix Table 2. MSA-Level Regressions, All Men and Unmarried Women Only

	DEPVAR: Adjusted ln(wage_m)-ln(wage_f)					
	(1)	(2)	(3)	(4)	(5)	(6)
	2000	2010	2000	2010	2000	2010
ln(MSA population)	-0.0184	-0.0226	0.3184	0.3873	-0.0016	-0.0286
	[0.0031]***	[0.0037]***	[0.2725]	[0.3120]	[0.0127]	[0.0151]*
Men Avg Wkly Hours			-0.0688	0.0179		
			[0.0623]	[0.0625]		
Unmarried Women Wkly Hours			0.1699	0.1206		
			[0.0722]**	[0.0888]		
ln-pop*men hours			0.006	0.0005		
			[0.0050]	[0.0050]		
ln-pop*unmarried women hours			-0.0143	-0.0101		
			[0.0057]**	[0.0072]		
% Men College+					-1.3261	-2.34
					[1.1707]	[1.2136]*
% Women College+					1.8492	1.8236
					[1.0851]*	[1.1611]
ln-pop*men college+					0.1087	0.1883
					[0.0929]	[0.0973]*
ln-pop*women college+					-0.1599	-0.157
					[0.0862]*	[0.0930]*
Constant	0.5051	0.554	-3.6319	-5.4149	0.3254	0.6666
	[0.0394]***	[0.0471]***	[3.4383]	[3.8588]	[0.1596]**	[0.1897]***
Observations	297	297	297	297	297	297
R-squared	0.11	0.11	0.14	0.22	0.16	0.15

NOTE: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. Unit of observation is MSA. Regressions weighted by no of observations in MSA. Sample of women includes only unmarried females.