2013

Essays on the economics of inequality

BOSTON UNIVERSITY

GRADUATE SCHOOL OF ARTS AND SCIENCES

Dissertation

ESSAYS ON THE ECONOMICS OF INEQUALITY

by

SARAH KROEGER

B.A., College of William and Mary, 2003
M.A., Boston University, 2007

Submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

2013

Approved by

First Reader

Daniele Paserman, Ph.D.
Professor of Economics

Second Reader

Kevin Lang, Ph.D.
Professor of Economics

Third Reader

Claudia Olivetti, Ph.D.
Associate Professor of Economics

Acknowledgments

I would like to thank Daniele Paserman, Claudia Olivetti, Kevin Lang, and Stefania Garetto for their extensive advice and support. I also thank Michael Manove, Randy Ellis, Cem Tintin, Tszkin Julian Chan, Laura Salisbury, Giulia La Mattina, Thomas Lemieux, Kehinde Ajayi, and Paolo Naticchioni for helpful discussions and suggestions. Additionally, I thank David Autor for guidance on the use of O*NET dataset. I thank the participants of the Boston University Empirical Micro lunch, the BU Micro Dissertation Workshop, the 2012 SciencePo Workshop on Inequality and Globalization, and seminar participants at the University of Calgary, the University of South Carolina, and the University of Wisconsin-Milwaukee for their valuable comments and feedback.

This dissertation is dedicated to my parents, Paul and Chaw-nen.

ESSAYS ON THE ECONOMICS OF INEQUALITY

(Order No.)

SARAH KROEGER

Boston University, Graduate School of Arts and Sciences, 2013

Major Professor: Daniele Paserman, Professor of Economics

ABSTRACT

This dissertation looks at three aspects of inequality within labor markets: wage inequality, intergenerational economic mobility, and inequality in higher education between sexes.

The first chapter examines the contribution of offshoring to the relative decline in the wages paid to middle skilled workers. Within a task based model of production, I develop a theoretical framework that demonstrates how increased offshoring is consistent with a decline in domestic employment and a reduction in the wages paid to workers in middle skilled occupations. I test these predictions empirically using a proxy measure of offshoring. I find that industries which engage in offshoring see their domestic employment decline over time and have a wider gap between the wages of their middle and high skilled workers. Current levels of industry offshoring are significantly correlated with an industry's lagged occupational composition. Both material and service offshoring decrease with the share of manual occupations and service offshoring increases with the share of routine occupations.

Chapter two estimates the magnitude of the intergenerational elasticity of income found in the NLSY79, and provides a decomposition of this elasticity into paternal and maternal effects. Roughly one fourth of intergenerational income transmission

can be attributed to maternal earnings, and omitting maternal income biases the estimate of the effect of paternal income by over 20 percent.

The third chapter analyzes the growing inequality in college graduation rates between men and women. Evidence from two cohorts in the National Longitudinal Surveys suggests that although women have performed better in high school than men for several decades, the impact of high school performance on college success has increased dramatically since the 1980s. The increasing weight attributed to academic excellence in high school explains a substantial portion of the female advantage in college graduation over their male peers.

Contents

List of Tables

List of Figures

List of Abbreviations

BEA	....	Bureau of Economic Analysis
BLS	....	Bureau of Labor Statistics
CEPS	....	Center for European Policy Studies
CPS	....	Current Population Study
CPS MORG	....	CPS Merged Outgoing Rotation Groups
IGE	....	Intergenerational Income Mobility
IPUMS	....	Integrated Public Use Microdata Series
NBER	....	National Bureau of Economic Research
NLLS	....	Non-linear Least Squares
NLSY	....	National Longitudinal Study of Youth
NLSY79	....	National Longitudinal Study of Youth 1979
NLSY97	....	National Longitudinal Study of Youth 1997
NLSY79 C/YA	....	Children of the NLSY79
OLS	....	Ordinary Least Squares
O*NET	....	Occupational Information Network
OSM	....	Material Offshoring
OSS	....	Service Offshoring
SBTC	....	Skill Biased Technical Change
NBER	....	National Bureau of Economic Research

Chapter 1

The Contribution of Offshoring to the Convexification of the U.S. Wage Distribution

1.1 Introduction

Although overall wage inequality has been increasing in the U.S. since the 1970s, starting in the mid-1980s, lower-tail inequality stopped growing and declined slightly while upper-tail inequality increased at an accelerating pace. I use the term convexification to describe the accelerating wage growth for high earning workers, and the stagnation and relative decline of the middle class. During this same period, the employment shares of highly paid professionals and low paid service workers rose while the employment shares of mid-level manufacturing workers and office workers fell.[1] These employment and wage changes suggest a decrease in the relative demand for middle skilled labor.

At the same time, improvements in communication and transportation technology contributed to offshoring in both manufacturing and service. The ability to hire cheap foreign workers should decrease the relative demand for the domestic workers of similar abilities. Recent work by Goos and Manning (2007), and Autor and Dorn (2012), offers a "routinization hypothesis:" mid-level jobs are highly routine, and therefore have the highest degree of substitutability with foreign labor. While some

[1] See Autor and Acemoglu (2011).

circumstantial evidence links routine tasks to wage convexification, the wage inequality literature lacks a direct empirical analysis of the impact of offshoring on relative wages. Moreover, the existing research focuses on manufacturing even though the majority of jobs in the American economy are comprised of services.

In this paper I measure the extent to which offshoring by U.S. industries has increased the wage gap between the median wage and the 90th percentile wage but narrowed the gap between the 10th percentile and the median, thereby contributing to the observed convexification. First, I present a simple task-based model of labor supply and wages to illustrate the predicted effects of offshoring on upper and lower tail wage inequality. I represent offshoring by a drop in the global price for routine task inputs, and show how this differs from a skill-biased technological change. Secondly, I construct a measure of offshoring for both material and service inputs, and apply this measure to 128 industries in both the manufacturing and service sectors for the years 1990, 2000, and 2011. This approach for offshoring measurement was initially introduced by Feenstra and Hanson (1996) for material offshoring, and to my knowledge only Amiti and Wei (2009) have employed this measure for service offshoring. Rather than focusing solely on either the manufacturing or service sector in isolation, I include the full economy to provide a comprehensive view of the impact of offshoring. The analysis also covers a relatively long time frame, using wage and industry data that span a 21 year period. Thirdly, I employ a fixed effects regression model to estimate the effect of offshoring on wages and employment and test the implications of the model. I estimate separately the effects on the lower half of the wage distribution (the 50/10 spread) from the effects on the upper half of the distribution (the 90/50 spread).

The results of the empirical analysis show that offshoring has a positive effect on wages throughout the wage distribution. The magnitude of this impact is greatest at the top of the distribution; hence there is a statistically significant positive impact of offshoring on upper tail wage inequality. An increase in service offshoring of one standard deviation explains about 6% of the observed increase in the upper tail wage spread, and one standard deviation increase in material offshoring can explain nearly 13% of the observed change. Controlling for industry productivity does not alter the estimated effect of offshoring on wage levels and spreads. It is plausible that selection in layoffs is driving this effect: if industries are offshoring jobs previously done by workers from the bottom half of the wage distribution, the measured wages in those industries will be higher than they were prior to the introduction of offshoring. I apply a bounding exercise to provide an upper bound estimate of the effects of selection on wages, and show that all of the wage effects could be due to selection. Finally, in order to investigate the impact of routinization, I control for the task composition of each industry. The estimated offshoring effect does change when lagged industry occupational shares are included in the regression. This suggests that the current industry-specific patterns of offshoring are influenced by the past occupational distributions. The analysis on occupational composition shows that the lagged task content of each industry is a statistically significant predictor of both material and service offshoring. In particular, the share of routine occupations has a positive causal effect on service offshoring. However, this same measure has a significantly negative causal effect on material offshoring. These results offer empirical support for the routinization hypothesis when it is applied to service offshoring, but not with respect to material offshoring.

In Section 2 I provide an overview of U.S. wage convexification, and highlight how my paper contributes to the literature. Section 3 describes offshoring and discusses the associated measurement challenges. Section 4 explains the theoretical model that serves as a framework for the empirical analysis. Section 5 discusses the empirical methods. Section 6 examines the results in the context of three mechanisms that potentially connect offshoring with the wage distribution, and section 7 concludes.

1.2 Wage Convexification Overview

In addition to the increase in overall wage inequality, the change in relative wages has not been homogenous over the entirety of the distribution. This heterogeneity is especially pronounced with regards to the last two decades. Figure 1·1 displays the evolution over time of three points in the male wage distribution: the 10th percentile, 50th percentile, and 90th percentile. We can see that the gap between low-skilled workers (represented by the 10th percentile position) and median wage earners increased from the mid 1970s until the mid-1980s, but for later periods this 50/10 gap is either constant or decreasing. In contrast, the gap between the 90th percentile wage earner and the median wage earner continued to increase throughout the entire time span of the graph. In particular, the 90/50 gap shows a large expansion from the late 1990s to 2010, indicating a sharp rise in the high-skill premium. The same data for female wages (Figure 1·2) shows a wage distribution that is slightly less polarized, but still reflects a greater spread increase in upper half of the distribution than the lower half.

What is driving this wage convexification? In very broad terms, the research on wage inequality points to changes in institutional factors, and skill biased technical change (SBTC). Institutional factors such as unionization and declining real minimum wage are credited in driving lower tail inequality (see Lee (1999), Card and Dinardo (2002), Lemieux (2006)). However, by 1990, the real minimum wage had fallen sufficiently that minimum wage laws were no longer binding above the 10th percentile wage level.[2] A growing body of work in the early 2000s focused on SBTC

[2] See Autor, Manning and Smith (2010).

as the source of upper tail inequality (including Katz and Autor (1999), Katz and Acemoglu (2002)). This branch of research argues that an increased use of computers among college educated workers meant that the productivity of these workers outpaced non-college educated labor. The relative demand for skilled labor grew quickly enough to outpace the concurrent rise in relative supplies and the college wage premium ballooned.

But, increasing returns to education is only part of the story of the upper tail wage spread, since residual (within group) inequality tracks a similar pattern to the divergence we see in Figure 1.1 (see Card and Dinardo (2002), Bogliacino (2008 wp)). Autor, Levy and Murnane (2003) and Autor and Acemoglu (2011) point out that the canonical model used in the SBTC thesis is insufficient for explaining the type of convexification observed in the U.S. distribution. The key shortcoming in the canonical SBTC model is that it does not distinguish between skills (college versus high school education) and tasks (occupational characteristics that are not perfectly mapped to educational background).

As an alternative framework, Autor et al. (2011, 2012) lay out the "routinization" hypothesis as follows: workers in the middle of the wage distribution are primarily in occupations with a high level of routine tasks (for example: record keeping, routine customer service jobs, repetitive assembly, or sorting goods in a warehouse). These occupations are characterized by the fact that they can be fully described in a computer algorithm or in a list of instructions to a foreign worker. As a result, they are highly prone to substitution by technology or offshore labor.[3] Along a similar vein, Autor Katz and Kearney (2006, 2008) propose a model of computerization to explain the divergence in lower tail and upper tail inequality: computerization complements complex cognitive tasks, replaces routine tasks, and has little impact on nonroutine

[3] Blinder (2007) estimates that over 20 million domestic jobs are potentially offshorable due to their task characteristics.

manual tasks.

The critical contribution of the task based framework is that it distinguishes between the demand for middle and low level tasks rather than lumping them together under the label of "low skilled labor". In contrast to the mid-level occupations, many low skill manual occupations are actually non-routine. That is, since the nature of such tasks demands human interaction these workers are not as easily replaced by computers or remote labor. These occupations are primarily of the low skilled service variety: for example, jobs in maintenance, janitorial work, sanitation , childcare, and hair and nail salons. On the other end of the complexity spectrum, highly analytic occupations require complicated decision making beyond the scope of what can be contained in a computer algorithm. These jobs are concentrated at the top of the wage distribution. The task based model offers a plausible explanation for why workers near the median are in decline relative to both the top and the bottom earners.

Figure 1.3 depicts the 1990-2000 and 2000-2010 changes in employment share by occupational complexity.[4] The data show a striking distinction between these two periods. During the 1990s, occupation employment share expansion was roughly monotonic in complexity. The least complex occupations declined while the most complex occupations gained employment share, and the relative employment in occupations near the middle of the ranking changed the least. However, in the latter period the occupations in the middle of the distribution actually lost employment shares, while both the least and most complex occupations increased their shares. Since the complexity rankings are highly correlated to wage rankings, similar patterns are observed when we use the occupation's mean 1990 wage percentile on the horizontal axis.

Figure 1.4 ranks occupations by their offshorability, and shows the relative change

[4] Occupation complexity measures the degree to which the occupation is classified as "Nonroutine Cognitive Analytic." The raw data is from the O*NET dataset, and the measure is constructed following Autor Katz and Kearney (2006).

in employment by percentile. The offshorability measure follows the methodology used by Autor and Acemoglu in the Handbook of Labor Economics (2011). It aggregates (normalized) O*NET measures regarding two task characteristics: each occupation's intensity of routine tasks, and the intensity of face to face interactions.[5] According to the routinization hypothesis, routine task intensity causes an occupation to be more easily offshored while the amount of face to face interactions limits offshorability. Consequently, the offshorability measure is defined as (routine intensity) $+(-1)*$(face to face intensity) and normalized in the typical fashion. Unlike the convex effect of the complexity measure, the change in relative employment is strongly and monotonically negative in offshorability for both decades. Occupations that require face to face contact from workers appear to be protected from employment loss, whereas occupations that engage heavily in routine tasks are highly susceptible to declining employment.

In these figures we see that the data offer strong circumstantial evidence that the decline in mid-level employment and wages is linked to task characteristics. Whether an occupation is concentrated in routine or abstract tasks is clearly important in explaining changes in relative demand. However, the existing literature lacks direct empirical tests of this link, particularly with respect to offshoring (with the exception of a new working paper by Oldenski).[6] It is also important to point out that either type of middle task substitution, computerization or offshoring, is consistent with the routinization hypothesis.[7] Either mechanism, or a combination of the two, would

[5]The measure for routine task intensity comes from the extent to which workers carry out physical assemply or equipment inspections, calibrations, and repairs based on established checklists or guidelines. "Face to face interaction" refers specifically to transactions that require physical proximity of the worker, for example: caring for patients in a hospital, or serving food to a restaurant patron.

[6]Recent work by Oldenski (October 2012) supports the claim that offshoring can be explained by routinization in the years 2002 to 2008.

[7]Feenstra and Hanson (1999) remains one of the primary studies that aims to directly compare the two.

result in a decrease in the relative demand for workers in the mid-level occupations, and produce a decline in the relative wage of median workers. Given this theoretical ambiguity, the relative importance of offshoring to expanding wage inequality is an empirical question that needs to be addressed.

The objective of this paper is to address this gap in the empirical literature. Specifically, this paper asks the following questions:

1. How much of the observed increase in upper tail inequality can be explained by offshoring?

2. Are these effects due to selection?

3. How well does the task based model apply to the contribution of offshoring: does offshoring act as a substitute for routine tasks, and/or does offshoring increase the relative returns to nonroutine cognitive tasks?

1.3 Offshoring

Public opinion polls show that a majority of Americans believe that increased globalization, in the forms of immigration, trade, and offshoring, is harmful to the wages and employment prospects of native workers.[8] Whereas in the past it was primarily manufacturing workers who held the view that offshoring was depressing American jobs and diminishing American wages, workers in the service sector are increasingly adopting this aversion to offshoring. In a 2004 Gallup poll, two-thirds of investors reported that they believed offshoring was harmful to the US economy's overall strength.[9] There is some recent research supporting the point of view that American workers are harmed by trade and offshoring. Autor, Dorn and Hanson (2012) show that exposure to

[8] http://www.people-press.org/2011/02/24/public-favors-tougher-border-controls-and-path-to-citizenship/; http://www.gallup.com/poll/115240/Americans-Negative-Positive-Foreign-Trade.aspx

[9] http://www.gallup.com/poll/11506/Investors-Support-Outsourcing.aspx

Chinese imports has negative effects on local labor market employment and wages. However, most academic studies on offshoring highlight the labor market benefits. Ottaviano, Peri and Wright (2010) conclude that offshoring has no negative effects on Employment. Using a different measurement technique, Wright (2011) finds that offshoring (in the US manufacturing sector 1997-2007) did displace domestic production workers, but because offshoring industries have greater output, overall employment in these industries increases. Like Wright, Olney (2011) considers offshoring in the framework of traded tasks (from Grossman and Rossi-Hansberg (2008)). Comparing the wage effects of immigration and offshoring, he finds stronger (positive) effects for wages from offshoring, which he cites as evidence of a productivity effect. Amiti and Wei (2009) also stress the productivity effect: they credit service offshoring with 10 percent of the increase in labor productivity between 1992 and 2000.

Although these studies provide valuable insights to the aggregate effects of offshoring, these effects may not be felt equally throughout the wage distribution. It is essential to also investigate whether offshoring changes the shape of the wage distribution. Crinó (2010), shows that medium and low-skilled occupations see a negative employment response to service offshoring. Although Crino looks exclusively at service industries, my analysis of both services and manufacturing confirms his results. Feenstra and Hanson (1996, 1999) conduct the most rigorous studies on the effects of offshoring for the wage distribution in the US [10], and show that offshoring is an important channel through which trade affects the demand for labor of different skill types. They find that that the increase in imported intermediates explains 11% to 51% of high-skilled labor's increased share of the total wage bill (the estimate varies based on the definition of offshoring that is used). However, other studies (e.g. Slaughter (2001)) find that the impact of offshoring on wage bill share is insignificant when time

[10] their definition of inequality is the production workers' share of the total wage bill

fixed effects are included.[11]

1.3.1 What is Offshoring?

Offshoring, also referred to as "trade in tasks," is defined as conducting some portion of final good production outside the domestic border. Offshoring is commonly but incorrectly called "outsourcing," which refers to arms length production that takes place either domestically or internationally. It includes both foreign outsourcing from unrelated suppliers of intermediate goods (international arms length production) and tasks performed abroad by subsidiaries or related entities of a multinational firm (foreign direct investment). Tempest (2006) describes Mattel's production process for the many components of a Barbie doll, which takes place in the United States, Saudi Arabia, Japan, Taiwan, China, Indonesia and Malaysia, and finally is marketed and distributed back in the U.S. Automobiles and electronics are other examples of goods in which most of the manufacturing process occurs globally.

When offshoring takes the form of intermediate good production, physical goods are shipped from one country to another and counted as part of total trade volume. However, a growing portion of trade in tasks is actually in services. Accounting and tax services, radiology and other medical laboratory processes, customer service call centers, document processing, and data processing are all services that are now traded internationally. Given that much of these service products can be delivered between parties electronically, the transportation costs are close to zero.

The primary obstacle to measuring and studying offshoring in U.S. firms is that there is no official dataset or reporting process for trade in tasks. When trade in physical goods occurs between two unaffiliated firms, it is not always clear whether goods are intermediate inputs or final use commodities. The value of international transactions within a firm may be manipulated by the firm in order to avoid certain

[11] I use both time and industry fixed effects throughout my empirical analysis.

import taxes. Even without firm manipulation, the cost of importing both goods and services within the firm is much lower than importing them from an unaffiliated supplier. Finally, the fact that offshoring is widely prevalent speaks to another source of distortion: prices of international commodities are not fully arbitraged, and imported inputs are generally cheaper than domestic substitutes. Much of the trade in services is not reported officially at all, although the BEA does now collect survey data from American firms on trade in services with affiliated parties. For these reasons, it is neccessary to construct an approximate measure of offshoring.

1.3.2 Offshoring measurement

Offshoring measurement for U.S. industries is not straightforward because the U.S. does not currently compile data on offshoring by American firms. Feenstra and Hansen (1996) introduced a method for measuring offshoring in the manufacturing sector, and Amiti and Wei (2009) follow a similar technique to measure offshoring in five broad service categories. I build on these previous measures of offshoring by including both manufacturing and service industries in the analysis, using industry level input-output tables and trade data for both sectors. I define offshoring as the share of an industry's non-energy inputs that are imported. Measurement according to this definition requires both information about the use of intermediate inputs and information about import intensities of all relevant inputs. I use a combination of international trade data from the Bureau of Economic Analysis (BEA) and industry level production data obtained from BLS input-output tables. The measure of each industry's material offshoring of material production is denoted as OSM_{it} and OSS_{it} is the measured offshoring of service inputs. The intermediate goods usage data is taken from the Bureau of Economic Analysis (BEA) input output accounts, based on the 2002 benchmark tables and downloaded from the Bureau of Labor Statistics

(BLS) [12]. These tables give the breakdown of all input materials and services, by industry. The offshoring measure is defined as:

$$OS_{it} = \sum_j \left[\frac{\text{inputs}_{jit}}{\text{total non-energy inputs}_{it}}\right] * \left[\frac{\text{imports}_{jt}}{\text{production}_j + \text{imports}_j - \text{exports}_{jt}}\right]$$

For each input good or service j, the first term represents input purchases of that good (service) by the industry i during period t, as a fraction of all non-energy inputs (both material and service) for industry i at time t. The second term represents the share of good or service j that was imported nationally: total imports of good or service j, divided by total supply of j (total supply is equal to domestic production plus net imports of service. This second term is calculated at the country level for each year, since imports and exports of each input are not available by industry. It is neccessary to assume a constant share of imports in j for all industries that use j as an input. The metric can equivalently be expressed as:

$$OS_{it} = \frac{1}{Inputs_{it}} \left[\sum_j \frac{\text{inputs}_{jit} * \text{imports}_{jt}}{\text{total domestic supply}_{jt}}\right]$$

Throughout this paper I will use OSM to refer to manufacturing offshoring, and OSS to refer to service offshoring. The services that I included were (1) finance, (2) insurance, (3) telecommunications, (4) business support services,[13] and (5) computer and information services. Other major service categories (for example: educational services, transportation services) are not included because trade volumes are either equal to zero or simply unreported. The measure for OSM is a sum over 38 manufac-

[12] The data are available starting in 1993, `http://www.bls.gov/emp/ep\_data\_input\_output\_matrix.htm`.

[13] This includes business, professional, scientific and technical services. For example: legal, administrative, medical support services.

turing industry inputs. Out of the 170 final use commodities in the BEA input-output tables, I am able to construct measures of OSM and OSS for 129 industries present in the Census in 1990, 2000 and 2010. Figure 1·5 and Figure 1·6 display the box plots of these measures over the period 1993 to 2000.[14]

From the figures, one can see that both measures are increasing over time, and increasing in variance. This is particularly true of the OSS measure. The data for trade in services is limited during the 1990s, and it was neccessary to aggregate many service inputs into the five categories described above. This and the fact that service imports were very low in the 1990s produce an OSS measure that is quite small in magnitude and variance during the 1990s. In the 2010 data, the top three industries in material offshoring were metals processing, computer equipment manufacturing, and seafood production and packaging. Other industries with a high OSM measures tended to be manufacturing industries. The top three service offshoring industries included a service industry: insurance, as well as two manufacturing industries: computer equipment and pharmaceuticals.

1.4 Theoretical Framework

In order to inform the empirical analysis, I describe a simple task based model and characterize the effect of offshoring on wages within this framework.

1.4.1 Production

The factors of production are labor in the form of three types of tasks: manual (M), routine (R), or abstract (A). Total economic output is a Cobb-Douglas aggregation of the three task inputs: $Y = L_M^{\alpha} L_R^{\beta} L_A^{\gamma}$, with $\alpha + \beta + \gamma = 1$. One can think of

[14] I matched 1993 OSS and OSM measures with wage data from the 1990 Census, since the BEA data is unavailable for the year 1990.
The measure was adapted to the state level for a robustness check. In order to measure offshoring variables for a state, I calculated the weighted average of all industry level offshoring measurements, using each industry's share of gross state product for the weights.

the task-specific production $L_M, L_R,$ and L_A as intermediate good production, where overall economic output is an aggregate of these intermediate goods. Normalizing the price of the final good to 1 and assuming zero fixed costs, profit is equal to

$$L_M^{\alpha} L_R^{\beta} L_A^{\gamma} - p_M L_M - p_R L_R - p_A L_A$$

where p_k is the price of intermediate good $k \in \{M, R, A\}$. Profit maximization yields the following first order conditions:

$$FOC(L_M):\ \alpha \frac{Y}{L_M} = p_M \tag{1.1}$$

$$FOC(L_R):\ \beta \frac{Y}{L_R} = p_R \tag{1.2}$$

$$FOC(L_A):\ \gamma \frac{Y}{L_A} = p_A \tag{1.3}$$

Dividing (1.3) by (1.2) and rearranging, we can write the relative demand for abstract tasks with respect to the demand for routine tasks, which is always increasing in $\frac{p_R}{p_A}$.

$$\frac{L_A}{L_R} = \frac{\gamma p_R}{\beta p_A} \tag{1.4}$$

Similarly, the relative demand for routine tasks versus manual tasks is increasing in $\frac{p_M}{p_R}$ and can be written as:

$$\frac{L_R}{L_M} = \frac{\beta p_M}{\alpha p_R} \tag{1.5}$$

1.4.2 Workers

Labor is supplied inelastically by workers in one of the three types of task (M, R, or A). Each worker has exogeneously determined skill level z, where $z \sim G(.)$ over the interval $[0, 1]$. An individual with skill level z can produce $\phi_k(z)$ units of output, where $k \in \{M, R, A\}$. In this case, worker productivity is constant for task M, but linear and increasing in skill for tasks R and A.

$$\phi_k(z) = \begin{cases} a_M, & \text{for } k = M \\ a_R + b_R z, & \text{for } k = R \\ a_A + b_A z, & \text{for } k = A \end{cases}$$

Let $a_M > a_R > a_A$. This means that an individual with the lowest amount of skill, $z = 0$, would be the most productive in the M task, and very poor at producing the A task. Setting $0 < b_R < b_A$ means that productivity increases with skill in both the routine and the abstract tasks, but the marginal return to skill is greater in the abstract task. These assumptions on the parameters of $\phi_k(.)$ imply that for three workers with skill levels $z' < z'' < z'''$, z' will have a comparative advantage in the manual task, z'' will have a comparative advantage in the routine task, and z''' will have a comparative advantage in the abstract task.[15] Hence, in an efficient allocation of labor, the least skilled workers will perform manual tasks, the most skilled workers will perform abstract, and those workers in the middle of the skill distribution will perform the routine tasks.

Figure 1.7 illustrates that this is the equilibrium allocation of skill to tasks: for every skill level z, the worker selects the task in which she earns the highest wage. Each worker will be paid the value of her marginal product: the unit price for task k multiplied by her productivity $\phi_k(z)$.

$$w_k(z) = p_k \phi_k(z)$$

We can solve for the threshold points Z_1 and Z_2 in terms of the productivity parameters and intermediate good prices. In equilibrium, the worker with skill level $z = Z_1$

[15] In general, the assumption that $\frac{\phi_A(z)}{\phi_R(z)}$ and $\frac{\phi_M(z)}{\phi_R(z)}$ are both increasing in z is sufficient to generate this pattern of comparative advantage.

will be indifferent to working in either manual or routine tasks:

$$p_M a_M = p_R \left(a_R + b_R Z_1\right) \tag{1.6}$$

$$\implies Z_1 = \frac{p_M a_M - p_R a_R}{p_R b_R} \tag{1.7}$$

Taking the partial derivative of Z_1 with respect to p_r, we can see that $\frac{\partial Z_1}{\partial p_R} < 0$.

$$\begin{aligned} \frac{\partial Z_1}{\partial p_R} &= \frac{\partial}{\partial p_R}\left(\frac{p_M a_M - p_R a_R}{p_R b_R}\right) \\ &= \frac{-a_R(p_R b_R) - b_R(p_M a_M - p_R a_R)}{(p_R b_R)^2} \\ &= -\frac{p_M b_R a_M}{(p_R b_R)^2} < 0 \end{aligned}$$

As the price for the routine task falls, the threshold skill level between the manual and routine tasks rises. As a result, some workers will switch from the routine to the manual task. Similarly, the worker with skill level $z = Z_2$ will be indifferent to working in either routine or abstract tasks:

$$p_R \left(a_R + b_R Z_2\right) = p_A \left(a_A + b_A Z_2\right) \tag{1.8}$$

$$\implies Z_2 = \frac{p_R a_R - p_A a_A}{p_A b_A - p_R b_R} \tag{1.9}$$

The threshold level Z_2 is increasing in p_R:

$$\begin{aligned} \frac{\partial Z_2}{\partial p_r} &= \frac{\partial}{\partial p_r}\left(\frac{p_R a_R - p_A a_A}{p_A b_A - p_R b_R}\right) \\ &= \frac{a_R(p_A b_A - p_R b_R) - (p_R a_R - p_A a_A)(-b_R)}{(p_A b_A - p_R b_R)^2} \\ &= \frac{a_R p_A b_A - b_R p_A a_A}{(p_A b_A - p_R b_R)^2} \end{aligned}$$

which is > 0 if and only if

$$a_R p_A b_A > b_R p_A a_A$$
$$\frac{a_R}{b_R} > \frac{a_A}{b_A}$$

The above inequality holds by assumption ($a_R > a_A$ and $b_R < b_A$). As the global price for the routine task increases, the threshold skill level between the routine and abstract tasks rises: some workers previously performing the routine task will switch to the abstract task. Substituting the parameters for Z_1 and Z_2, we can express the length of the skill interval in which routine tasks are performed as

$$Z_2 - Z_1 = \frac{(p_M a_M - p_A a_A)\, p_R b_R + (p_R a_R - p_M a_M)\, p_A b_A}{(p_A b_A - p_R b_R)\, p_R b_R} \tag{1.10}$$

This expression is increasing in P_R: the skill interval that represents the workers engaged in the routine task will narrow as the price for routine labor falls.

1.4.3 Labor Market Clearing

Market clearing in each type of task requires that the sum of the workers' productivity in each type of task must be equal to the total factor demand. The market clearing condition for manual tasks L_M is:

$$L_M = a_R G(Z_1) \tag{1.11}$$

Since $G'(.)$ is non-negative, the share of domestic labor in the manual task will increase as Z_1 increases (equivalently, as p_R decreases).

Market clearing for routine and abstract tasks are given by:

$$L_R = a_R\,(G(Z_2) - G(Z_1)) + b_R \int_{Z_1}^{Z_2} z.g(z)\,\mathrm{d}z \tag{1.12}$$

and

$$L_A = a_A \left(G(1) - G(Z_2)\right) + b_A \int_{Z_2}^{1} z.g(z)\,\mathrm{d}z \tag{1.13}$$

We can show that L_R, the mass of domestic labor production in the routine task, is generally increasing in p_R.

$$\frac{\partial L_R}{\partial p_R} = a_R \left[G'(Z_2)\frac{\partial Z_2}{\partial p_R} - G'(Z_1)\frac{\partial Z_1}{\partial p_R}\right] + b_R \left[\frac{\partial}{\partial p_R}\int_{Z_1(p_R)}^{Z_2(p_R)} zg(z)\mathrm{d}z\right] \tag{1.14}$$

The first term in (1.14) is positive:

$$a_R \left[G'(Z_2)\frac{\partial Z_2}{\partial p_R} - G'(Z_1)\frac{\partial Z_1}{\partial p_R}\right] > 0$$

because

$$\begin{aligned} G'(z) &> 0 \\ \frac{\partial Z_2}{\partial p_R} &> 0 \\ \frac{\partial Z_1}{\partial p_R} &< 0. \end{aligned}$$

The second term is also positive. We can write this term as:

$$b_R \left[\frac{\partial}{\partial p_R}\int_{Z_1(p_R)}^{Z_2(p_R)} zg(z)\mathrm{d}z\right] = b_R \left[\frac{\partial Z_2}{\partial p_R} Z_2 g(Z_2) - \frac{\partial Z_1}{\partial p_R} Z_1 g(Z_1) + \int_{Z_1}^{Z_2} \frac{\partial}{\partial p_R}\left(zg(z)\right)\mathrm{d}z\right].$$

Since

$$\frac{\partial Z_2}{\partial p_R} > 0$$
$$\frac{\partial Z_1}{\partial p_R} < 0$$
$$Z_2 g(Z_2) > 0$$
$$Z_1 g(Z_1) > 0$$
$$\frac{\partial}{\partial p_R}(zg(z)) = 0,$$

it follows that

$$b_R \left[\frac{\partial}{\partial p_R} \int\limits_{Z_1(p_R)}^{Z_2(p_R)} zg(z)\mathrm{d}z \right] > 0$$
$$\implies \frac{\partial L_R}{\partial p_R} > 0.$$

Similarly, we can show that

$$\frac{\partial L_A}{\partial p_R} = \frac{\partial}{\partial p_R} \left[a_A \left(G(1) - G(Z_2)\right) + b_A \int\limits_{Z_2}^{1} z.g(z)\,\mathrm{d}z \right] < 0. \tag{1.15}$$

1.4.4 Offshoring in the task based framework

Offshoring occurs when firms can use foreign workers to replace more costly domestic workers. As Autor (2008) points out, certain characteristics make a specific class of occupations easier for a firm to offshore. For example, occupations requiring face to face contact (such as childcare providers, bartenders, public transportation attendants) may not require a high level of skill, but are difficult or impossible to offshore. Abstract tasks are also prohibitively difficult or costly to offshore, because these occupations require the worker to engage in a constantly changing enviroment and respond using human judgement. Assuming that routine (R) tasks are the potentially offshorable task input, access to cheap foreign labor for this task is equivalent to a decrease in the global price for R tasks: $p_R \downarrow$. As a result, some of the domestic middle task workers will be displaced by foreign workers, and switch to either the manual or the abstract task. From Equation (1.10) one can show that with a decline in p_R, $(Z_2 - Z_1)$ will decrease. Using Equation(1.12), this also means that the quantity of domestic labor employed in the routine task will fall. Furthermore, congruent with the Stolper Samuelson theorem, the relative payments to abstract task workers relative to routine workers will increase, since routine tasks are now being imported. Figure 1.8 shows the effect of this type of price shock on wages and on the allocation of workers between tasks.

In this framework, introduction of offshoring as a decline in the global price of mid-level labor implies that increased offshoring will be associated with decreased real wages for middle skilled workers, an increased 90/50 spread, as well as a decreased 50/10 spread. One could also consider the case in which routine and abstract tasks are price complements [16]: in this case a decline in the global price for routine tasks will increase the demand for abstract tasks, and we will see an increased wage level for high skill workers as in Figure 1.9.

1.5 Empirical Strategy

1.5.1 Measuring Inequality

The empirical analysis uses data from several sources. For individual level wages, I use data from the 1990 and 2000 Census, and the 2011 American Community Survey (ACS).[17] I restrict the sample to civilian individuals aged 16 to 65 who worked for

[16] for example, a CES production function with elasticity of substitution¡1

[17] Earnings from the 2011 ACS are further removed from the 2008 recession shock than earnings in the 2010 ACS.

wages for at least one week in the year prior to the survey. Using annual earnings, weeks worked during the year, and average hours per week, I construct hourly wages for each individual. For each industry in 1990, 2000, and 2011, I use the difference in log wages between the 10 percentile and the median, as well as the log gap between the median and 90th percentile wage, as measures of lower and upper tail inequality, respectively. Table 1.1 describes the data aggregated at the industry-year level.[18] The mean industry employs a little under 1 million people. It pays an annual income to its 10th percentile, median, and 90th percentile workers of roughly $7,000, $28,000, and $63,000.[19] Employees of the average industry are 15 percent foreign born, 11 percent black, 37 percent female, 22 percent college educated, and 17 percent are union members. The final dataset used in the empirical analysis has 367 observations: 121 industries in 1990, and 123 in 2000 and 2011.

1.5.2 Econometric specification

I used a fixed effects model for the baseline analysis. The empirical framework for examining the effect of offshoring on inequality is the following:

$$Y_{it} = \alpha + \beta_1 \mathrm{oss}_{it} + \beta_2 \mathrm{osm}_{it} + \gamma \mathrm{X}_{it} + \delta_i + \tau_t + e_{it}$$

where Y_{it} is the relevant outcome variable for industry i during year t, osm_{it} is offshoring of material inputs, oss_{it} is service offshoring, X_{it} includes industry characteristics: controls for female, black, and immigrant employment, college-educated share of employment, and unionization. (Observations are weighted by total industry employment, measured in persons employed.)[20]

[18] Industries are defined at the 3-digit NAICS level, although it is neccesary to further combine some of the 3-digit industries in order to harmonize data from the Census and the BEA.

[19] All dollar amounts are given in 1999 dollars.

[20] In a perfectly competitive model of the labor market, workers of equal skill levels should have identical wages across industries. However, there is plenty of empirical evidence of inter-industry frictions and resulting wage differentials; see Gibbons and Katz (1992), Abowd, Kramarz and Margolis

The dependent variables that I use include: log hourly wage at the 10th, 50th, and 90th percentiles, and the spreads between the median log wage and the 10th and 90th percentile log wages, respectively.

$$\text{spread}_{50-10,i,t} = \ln \omega_{it}^{50} - \ln \omega_{it}^{10}$$
$$\text{spread}_{90-50,i,t} = \ln \omega_{it}^{90} - \ln \omega_{it}^{50}$$

These measures represent the mid-skill premium relative to low-skill wages, and the high-skill premium relative to mid-level wages.

1.6 Results

The results for the baseline fixed effects model are displayed in Table 1.2. Columns 1, 2, and 3 use the log wage at the 10th, 50th, and 90th percentiles as the dependent variable. The outcome variable in Column 4 is the lower tail inequality: the difference between the 10th percentile and 50th percentile log wage. Column 5 uses the upper tail inequality: the difference between the median and the 90th percentile. I also include log industry employment as a dependent variable; these results are in Column 6. All specifications include a full set of year and industry fixed effects. With the exception of Column 6, observations are weighted by industry employment.

Both OSS and OSM have a significant and positive effect on wages throughout the wage distribution. Because the magnitude of these effects is substantially larger for the industries' 90th percentile wage than for the median wage, OSM and OSS also each have a significant and positive effect on the upper tail wage spread, with estimated coefficients of $\hat{\beta}_{OSS} = 1.376^{**}$ and $\hat{\beta}_{OSM} = 0.215^{**}$ (see Column 5 of Table 1.2).[21]

(1999).

[21] Robustness checks: these results are robust to various alternative specifications. I separate the sample by gender, and also into services and manufacturing. I use weekly log wages to construct

Table 1.3 interprets the results of the fixed effect regression in the context of the sample data set. During the sample period 1990-2011, industry upper tail inequality ($ln(\frac{w_{90}}{w_{50}})$ has a standard deviation of 0.1735 log points. An estimated OSS coefficient of 1.376 for the upper tail regression means that an increase in the OSS measure of 1 standard deviation is associated with an increase in upper tail wage inequality of approximately 0.011 log points, or roughly 6% of the between industry standard deviation found in the data. An OSM coefficient of 0.215 implies that a 1 standard deviation increase in material offshoring results in an increased upper tail spread of 0.02 log points, which is 12.6% of the observed industry variance.

The time series interpretation is summarized in Table 1.4. Between 1990 to 2011, the mean industry in the sample experienced an increase in services offshoring from 0.0143 to 0.0287, a difference of 0.0144. This implies an increase in upper tail wage inequality of $(1.376)(0.0144) = 0.02$ log points, which is 32% of the observed increase in the 90/50 spread for this period.[22] Similarly, the increase in material offshoring of 0.114 [23] implies an increase in the 90/50 spread of 0.025 log points: 40% of the observed rise in upper tail inequality.

In contrast to the positive wage effects, material offshoring has a negative effect on employment: Column 6 of Table 1.2 shows that the estimated coefficent for OSM is -1.236**, indicating that a 10% increase in material offshoring leads to a 12% decline in industry employment. (Due to the limited variation of the trade services data, these results are not precise enough to give any information about the effect of

the wage levels and spreads, and I remove various industry level controls (not the fixed effects). I use different definitions for the wage spreads (for example: 30th-10th percentile spread, or 90th-70th percentile spread), and do not find any discontinuities. I also use the CPS wage data as an alternative to the Census. In general these regressions have less precision, but do not contradict the results in the baseline equation.

[22] from Table 1.1: mean increase in 90/50 spread from 1990 to 2011 was 0.062 log points

[23] The mean industry OSM measure was 0.112 in 1990, and 0.226 in 2011.

service offshoring on employment.) Given the sample standard deviation in OSM of 0.102, this result attributes 9.5% of the standard deviation in employment to material offshoring. These data clearly indicate a tradeoff between employment and real wage levels for workers in offshoring industries.

1.6.1 Potential Mechanisms

There are three primary reasons that offshoring might have a positive effect on wages and the upper tail spread. The first standard explanation of many trade models is that offshoring is associated with more productive industries, and workers in such industries are rewarded for their relatively high marginal product with higher wages. If these wage effects are increasing in the wage rank, they would act to exacerbate the upper tail spread as well. It is important to note that this mechanism is not consistent with a competive labor market model: in a competitive model, wages are determined on a macro level by labor supply and demand and firms choose a level of production at which the marginal product of labor is equal to the market wage. [24]

However, several other authors including Grossman and Rossi-Hansberg (2008), Ottaviano et al. (2010), and Wright (2011) assume a model in which offshoring decreases production costs and increases productivity in all workers. In order to address this viewpoint, I include industry level productivity as a control in the fixed effects regression. (Productivity is defined as output per labor hour.) In Table 1.5, I include industry productivity, and find that the coefficients for wage levels and spreads are

[24] Example: CD Production ($Y = L^{\alpha}K^{1-\alpha}$)

- Profit maximization $\rightarrow$

$$\alpha L^{\alpha-1}K^{1-\alpha} = \omega$$
$$\text{productivity} = \frac{L^{\alpha}K^{1-\alpha}}{L} = \alpha^{-1}\omega$$

- Productivity $\uparrow$ because $\omega \uparrow$

very similar to those in the baseline fixed effects model. In addition, the productivity coefficients in the wage level and wage spread regresions are insignificant. From these results there is no evidence that the wage effects in Table 1.2 are driven by increased productivity. Regressing productivity on industry controls and the offshoring measures also fails to indicate that either form of offshoring has any significant effect on productivity.

Secondly, the positive wage effects could be driven by the fact that industries that offshore heavily are disproportionately replacing their low and middle skilled domestic workers with foreign workers. This explanation is supported by the large negative effect of OSM on employment, shown in Column 6 of Table 1.2. [25] In the extreme case, if the total unemployment implied by the additional offshoring came from the bottom half of the distribution, this would result in higher average wages for the new distribution of surviving workers. By construction, 10th percentile wages in an industry that has previously laid off the low skilled workers will be higher than the 10th percentile wage in an identical industry that did not undergo such layoffs.

I carry out the following bounding exercise in order to assess the extent to which the employment effects could create the illusion of higher wages throughout the wage distribution. First, for each industry in the 1990 sample, I multiply the observed change in OSM between 1990 and 2000 by the value of the OSM coefficient in the fixed effects model of log employment (approximately 1.2, Table 1.2, column 6).

$$\beta_{OSM} * \triangle \text{OSM}_{i,1990-2000} * 100\%$$

This gives the predicted percentage decrease in employment implied by the regression results in column (6) of Table 1.2. Then, I look at the case in which the full change in employment comes from the lower end of the wage distribution. For example,

[25] This negative effect of offshoring on employment contradicts the findings of Olney (2011)

suppose an industry increased OSM by 0.08 ($dOSM_{i,1990-2000} * 100 = 8\%$). The implied percentage decrease in industry i as a result of material offshoring is equal to

$$1.2 * dOSM_{i,1990-2000} * 100\% =$$
$$1.2 * 8\% = 10\%$$

where $dOSM_{i,1990-2000}$ is the change in the OSM measure between 1990 and 2000. All workers in the 1990 sample are ranked according to their hourly wages, and the lowest 10 percent of workers are eliminated. I use a similar method to truncate all industries in the 2000 sample, using the change in OSM between 2000 and 2010. The 2010 sample is unchanged for this exercise.

Table 1.6 shows the results from the bounded dataset. The coefficient for OSS is not much changed for any of the outcomes. This is in line with reasonable expectations since the datsets were not truncated on the basis of changes in the OSS. It also supports the weak correlation between OSS and OSM. However, the effects of OSM on the low level and median wage are now significantly negative, and the effect on the high level wage is statistically zero. Both the lower tail spread (column 4) and upper tail spread (column 5) regressions show a postive coefficient for OSM. The coefficient in column 5, for the upper tail spread, has increased from 0.215*** to 0.473***. So, it is possible that the negative employment effects are not only giving the offshoring industries the appearance of higher wages, but also masking the full impact on upper tail inequality. It is important to emphasize that since I cannot track which individuals are laid off between Censuses, this bounding exercise shows only what the employment effect may be doing, and it cannot provide any definitive empirical support for this mechanism. It shows only that this mechanism cannot be ruled out.

Thirdly, in keeping with the task based framework, it could be that offshoring acts as a substitute for the routine task inputs originally performed by workers in the middle of the wage distribution. When industries experience increased access to offshoring, the global price of routine task inputs drop. As a result, domestic workers see their market wage fall relative to workers in manual and abstract tasks, as depicted in Figure 1·8. This mechanism alone would explain a positive effect of offshoring on the upper tail spread, but it would not directly imply higher real wages throughout the skill distribution. Furthermore, if only routine tasks and not low skill manual tasks are offshored, we would see a negative effect of offshoring on the 50/10 spread.

Some authors (for example, Acemoglu et al. (2011)) have proposed that offshoring operates like an abstract task enhancing technological shock (see Figure 1·9). For example, if offshoring is complementary to the highly complex task, and substitutable with routine occupations, increased offshoring would produce an increased wage gap between these two categories and explain the positive wage effects seen at the 90th percentile level. The observable implications are similar if routine and abstract tasks are p-complements. Nonetheless, without an overall increase in worker productivity, this still does not explain the positive wage effects at the 10th and 50th percentiles.

In order to investigate this task based model as a potential explanation, I use data on task characteristics from the O*NET database.[26] The O*NET dataset contains various measures of task characteristics associated with several hundred different occupations. I start with a rough partition that classifies all of occupations as being either routine, manual or abstract, then refine these classifications into six different measurements. Following the practice of Autor Levy Murnane (2003), Autor and Dorn (2012 wp) and Autor Katz and Kearney (2006), the refined measures are

[26] The Occupational Informational Network, or O*NET, is a database produced jointly by the US Deparment of Labor and the Employment and Traning Administration. It is available online at http://www.onetcenter.org/.

organized along two broad dimensions: (i) routine versus non-routine, and (ii) cognitive versus manual. Non-routine tasks are further described as either analytic or interpersonal. Additionally, non-routine occupations could be either physical (truck drivers, fire fighters) or cognitive (lawyers, teachers) in nature. Table 1.7 gives descriptions and examples for each of the six measures: non-routine cognitive analytic, non-routine cognitive personal, routine cognitive, routine manual, non-routine manual physical, non-routine manual personal. Examples of non-routine cognitive analytic occupations are physicians, mathematicians, and economists. Examples of Routine Cognitive occupations include switchboard operators and call center workers.

These measures are normalized across the occupations that appear in the 1990 Census, which serves as my base year. I assigned each occupation in my dataset a binary score for each of these nine measures, equal to 1 if the occupation's score was above the mean occupation score in the 1990 sample. For example, in 1990, the (weighted[27]) mean routine cognitive score for all ocupations was equal to -.0771. So, an occupation in any year is classified as Routine Cognitive (RCog=1) if it has a routine cognitive score greater than -.0771. Then, industries are described by the fraction of occupations in each of the six main categories. This means that an occupation has a binary variable in each of the three course categories, and each of the six finer categories, and each industry has nine corresponding continuous variables that vary between zero and one.

To summarize the relationships between these task measures and offshoring, I regressed service and material offshoring on the lagged industry level measures. Lagging the occupational composition reduces the potential for endogeneity, assuming that current offshoring does not affect past industry composition. Table 1.8 shows the results from regressing OSS on the three coarse categories in Column (1), and the results from regressing OSM on the three coarse categories in Column (2). It is

[27]weighted by the occupation's 1990 population

clear that there are fundamental differences between the two different forms of offshoring. OSS increases with the share of routine jobs and decreases with the share of manual jobs. This is consistent with the notion that the routine tasks are highly offshorable, while manual tasks require a proximate worker and are harder to move overseas. However, Column (2) shows that material offshoring decreases with routine jobs and increases with the share of abstract tasks.

Since the latter result appears to contradict the assumptions of the task based model, I re-estimate the two equations using the finer task descriptions. The estimated coefficients for the finer measures are given in Columns (3) and (4) of Table 1.8. With respect to service offshoring, the positive effect of routine tasks in Column (1) is supported by the positive effect of Routine Cognitive tasks in Column (3). The negative effect of manual tasks on OSS is also confirmed, since the variables nonroutine manual physical and nonroutine manual personal also have negative signs. The material offshoring measure is less straightforward. Both types of routine task measures–cognitive and manual–have negative signs, although only the former effect is statistically significant. But the coarse abstract measure is divided into Nonroutine Cognitive Analytical and Personal. While both these measures have a positive effect on OSM, neither is significant.

Finally, I run the baseline fixed effects regression including all original control variables in addition to the 10 year lagged fraction of occupations in the industry that are in each of the three coarse categories, followed by the six finer measures.[28] Tables 1.9 and 1.10 show that including these lagged occupation shares does change the estimated effect of the OSM measure and OSS meausures. For a given occupational composition, an industry will see larger effect on upper tail inequality from OSS and a slightly smaller but still positive effect from OSM.

[28]Using current occupation shares does not change the offshoring coefficients from those seen in the baseline regression; moreover current offshoring measures appear uncorrelated with current industry composition

1.7 Conclusion

In this paper, I examine the impact of offshoring on wage convexification through the framework of a task based model. In particular, I look for evidence to support the hypothesis that offshoring decreases relative wages of middle skilled workers because these workers perform highly routine tasks. I use industry level measures of offshoring and aggregate individual wage data to construct industry measures of upper and lower tail inequality. I find that offshoring significantly increases wage levels at each point in the earnings distribution and also increases the 90/50 spread.

Of the three mechanisms that I consider, both a productivity effect and selection are consistent with the positive wage effects. I show that the positive wage effects could be fully explained by selection, and this explanation is plausible because the increased wages in offshoring industries are accompanied by a large decrease in employment. However there is no empirical evidence of productivity enhancement. In other words, elevated wages in highly offshored industries are most likely due solely to the fact that domestic positions for low paid, low skilled workers are being eliminated. The positive effect of service offshoring on the 90/50 spread is magnified when lagged occupational composition is controlled for, while the positive effect of material offshoring is dampened. This study provides support for the hypothesis that offshoring is directly increasing inequality in the upper half of the wage distribution, but also shows that positive wage effects of offshoring are due to selection in layoffs. The results shown in this paper indicate that offshoring acts as a substitute for domestic workers in routine service occupations.

Abowd, John M., Francis Kramarz and David N. Margolis. 1999. "High Wage Workers and High Wage Firms." *Econometrica* 67(2): 251-333.

Acemoglu, Daron. 2002. "Technical Change, Inequality and the Labor Market." *Journal of Economic Literature* 40(1): 7-72.

Acemoglu, Daron and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." *Handbook of Labor Economics* 4(2): 1043-1171.

Autor, David and David Dorn. 2012. "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market." *American Economic Review* forthcoming.

Autor, David and Lawrence Katz. 1999. "Changes in the Wage Structure and Earnings Inequality." *Handbook of Labor Economics* 3(1): 1463-155.

Autor, David, Lawrence Katz and Melissa Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics* 90(2): 300-323.

—. 2006. "The Polarization of the U.S. Labor Market." *American Economic Review Papers and Proceedings* 96(2): 189-194.

Autor, David, Lawrence Katz and Alan Krueger. 1999. "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics* 113(4): 1169-1213.

Autor, David, Frank Levy and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118(4): 1279-1333.

Autor, David, Alan Manning and Christopher L. Smith. 2010. "The Contribution of the Minimum Wage to U.S. Wage Inequality over Three Decades: A Reassessment." NBER Working Paper no. 16533.

Amiti, Mary and Shang-Jin Wei. 2005. "Fear of Service Outsourcing: Is it Justified?" *Economic Policy* 20(42): 308-347.

—. 2009. "Service Offshoring and Productivity: Evidence from the US." *The World Economy* 32(2): 203-220.

Blinder, Alan. 2007. "How Many U.S. Jobs Might Be Offshorable?" CEPS Working Paper no. 142.

Card, David and John E. Dinardo. 2002. “Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles.” *Journal of Labor Economics* 20(4): 733-783.

Crinó, Rosario. 2010. “Service Offshoring and White-Collar Employment.” *The Review of Economic Studies* 77(2): 595-632.

Dinardo, John, Nicole M. Fortin and Thomas Lemieux. 1996. “Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach.” *Econometrica* 64(5): 1001-1044.

Feenstra, Robert and Gordon Hanson. 1996. “Globalization, Outsourcing, and Wage Inequality.” *The American Economic Review* 86(2): 240-245.

—. 1999. “The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States.” *The Quarterly Journal of Economics* 114(3): 907-940.

—. 2003. “Global Production Sharing and Rising Inequality: A Survey of Trade and Wages.” *Handbook of International Trade* 3: 146.

Fernández, Raquel, Alessandra Fogli, and Claudia Olivetti. 2004. “Mothers and Sons: Preference Formation and Female Labor Force Dynamics.” *The Quarterly Journal of Economics* 119(4): 1249-1299.

Firpo, Sergio, Nicole M. Fortin and Thomas Lemieux. 2011. “Occupational Tasks and Changes in the Wage Structure.” IZA Discussion Paper no. 5542.

Goos, Maarten and Alan Manning. 2007. “Lousy and Lovely Jobs: the Rising Polarization of Work in Britain.” *The Review of Economics and Statistics* 89(1): 118-133.

Goos, Maarten, Alan Manning and Anna Salomons. 2011. “Explaining Job Polarization: The Roles of Technology, Offshoring and Institutions.” CES Discussion Series Paper no. 11.34.

Grossman, Gene and Esteban Rossi-Hansberg. 2006. “The Rise of Offshoring: Its Not Wine for Cloth Anymore.” FRB Kansas City Working Paper.

—. 2008. “Trading Tasks: A Simple Theory of Offshoring.” *The American Economic Review* 98(5): 1978-1997.

Heckman, James J. and V. Joseph Hotz. 1986. “An Investigation of the Labor

Market Earnings of Panamanian Males: Evaluating the Sources of Inequality." *The Journal of Human Resources* 21(4): 507-542.

Katz, Lawrence and Lawrence Summers. 1989. "Can Interindustry Wage Differentials Justify Strategic Trade Policy?" In *Trade Policies for International Competitiveness,* edited by Robert C. Feenstra, 85-124. Chicago: University of Chicago Press.

Lee, David S. 1999. "Wage Inequality in the United States During the 1980s : Rising Dispersion or Falling Minimum Wage?" *The Quarterly Journal of Economics* 114(3): 977-1023.

Lee, Chul-In and Gary Solon. 2006. "Trends in Intergenerational Income Mobility." NBER Working Paper No. 12007.

Lemieux, Thomas. 2006. "Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill?" *The American Economic Review* 96(3): 461-498.

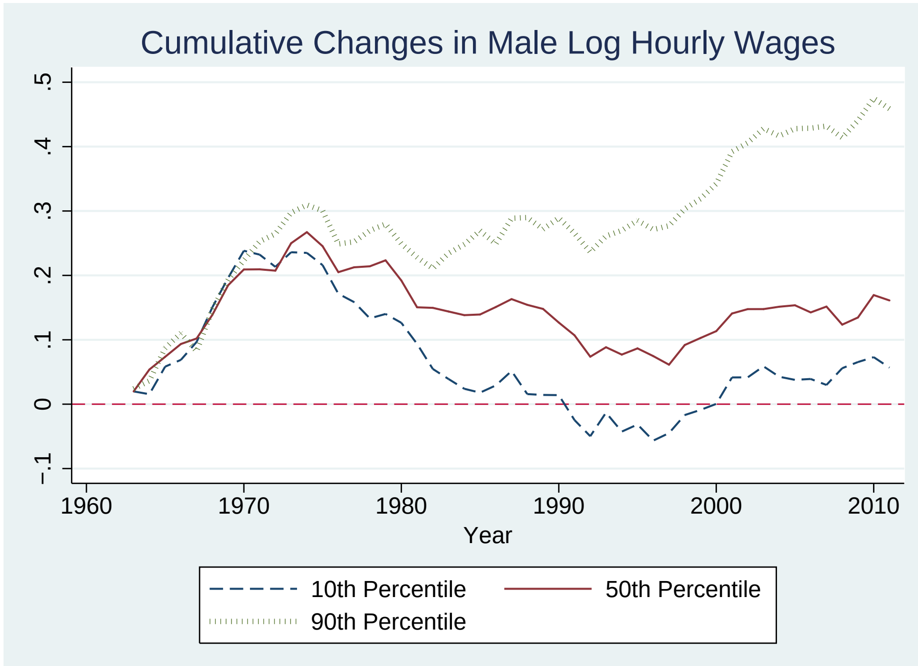
Olney, William W. 2011. "Offshoring, Immigration, and the Native Wage Distribution." Williams College Working Paper.

Ottaviano, Gianmarco, Giovanni Peri and Greg C. Wright. 2010. "Immigration, Offshoring and American Jobs." NBER Working Paper no. 16439.

Slaughter, Matthew. 2001. "International Trade and Labor Demand Elasticities. *Journal of International Economics* 54(1): 27-56.

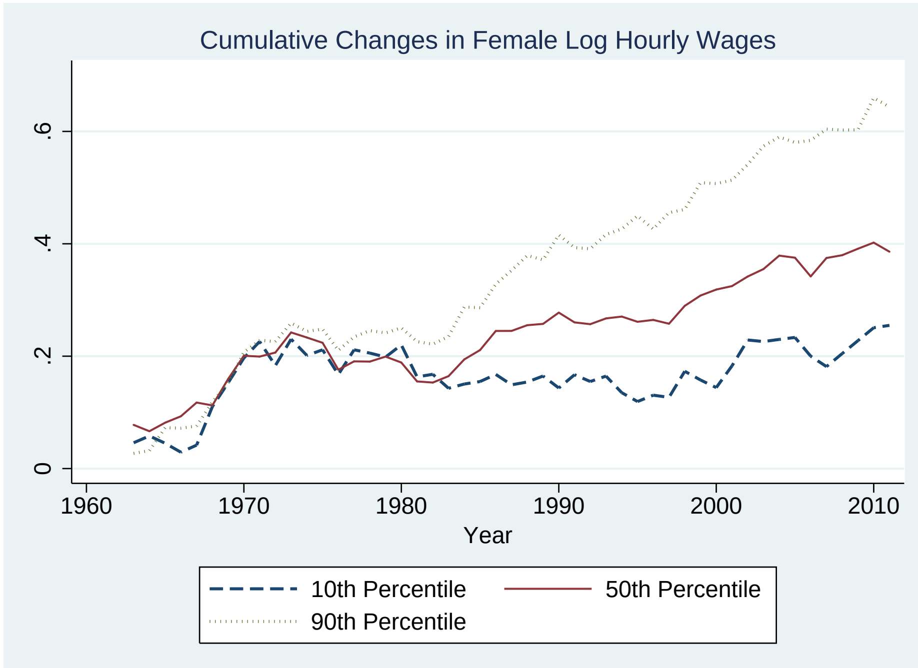
Wright, Greg C. 2011. "Revisiting the Employment Impact of Offshoring." Job Market Paper.

Figure 1·1: Evolution of Hourly Wages (Men)



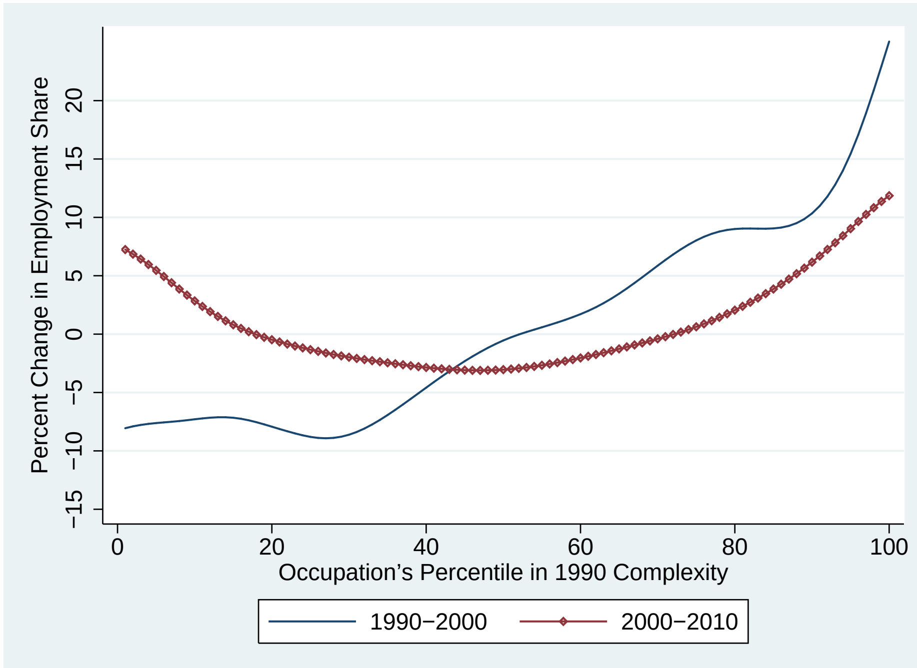
Data from Current Population Survey MORG, available at www.nber.org

Figure 1·2: Evolution of Hourly Wages (Women)



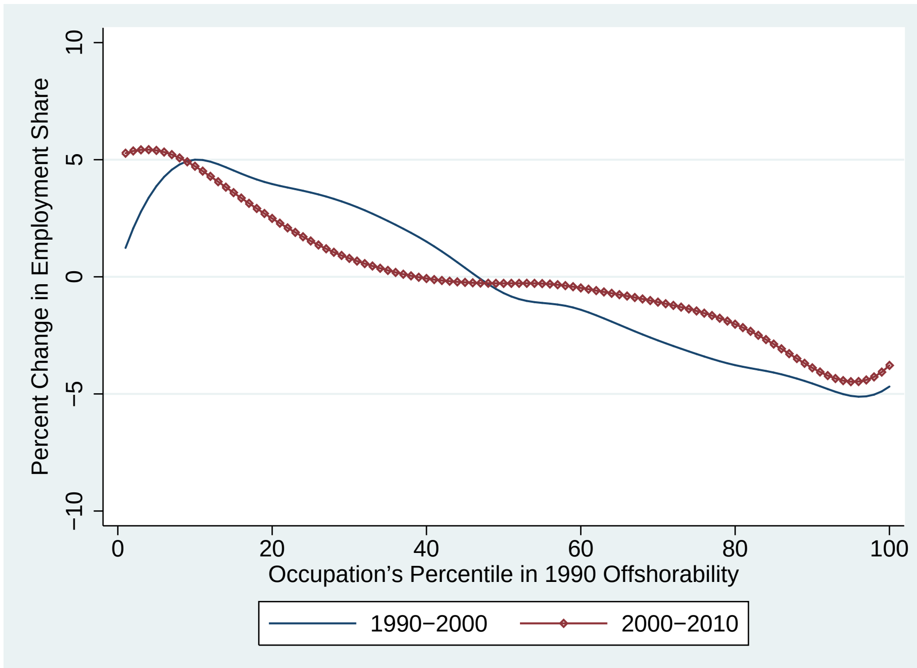
Data from Current Population Survey MORG, available at www.nber.org

Figure 1·3: Changes in Employment Shares by Complexity



Data from US Census, available at usa.ipums.org

Figure 1·4: Changes in Employment Shares by Offshorability



Data from US Census, available at usa.ipums.org

Figure 1·5: Offshoring of Material Inputs

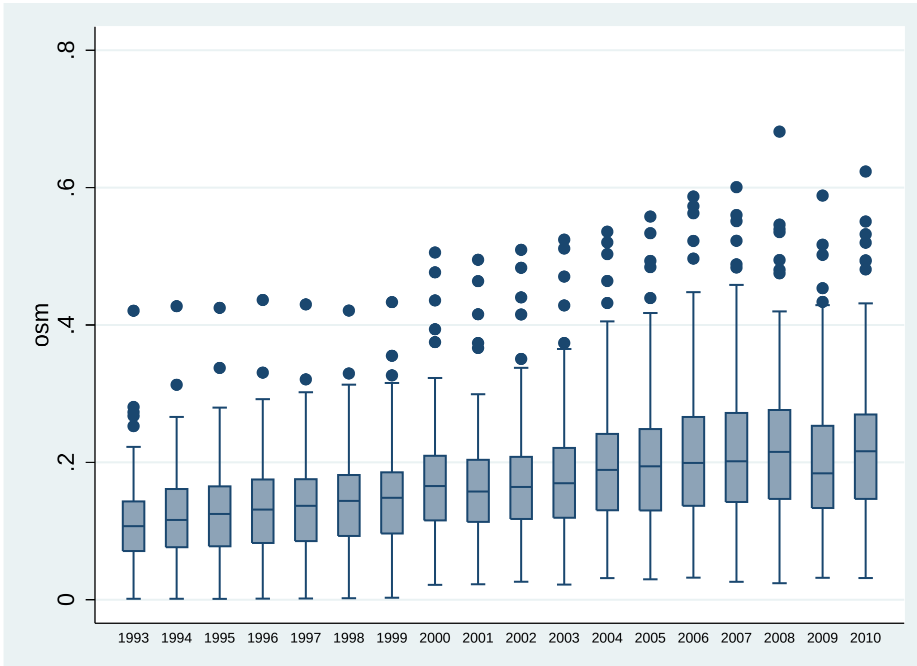


Figure 1·6: Offshoring of Service Inputs

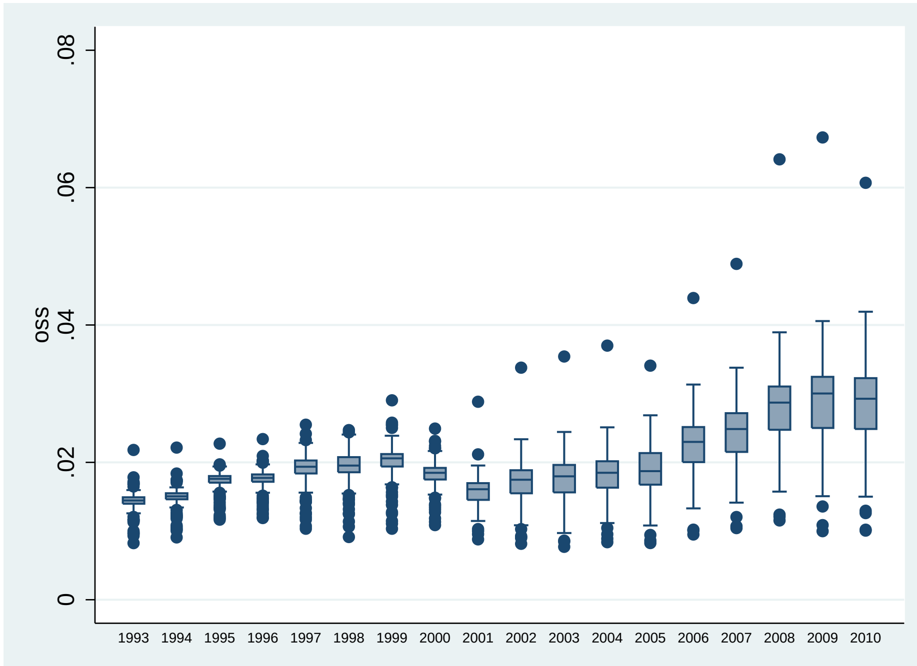


Figure 1·7: Wage Schedule for Efficient Task Allocation

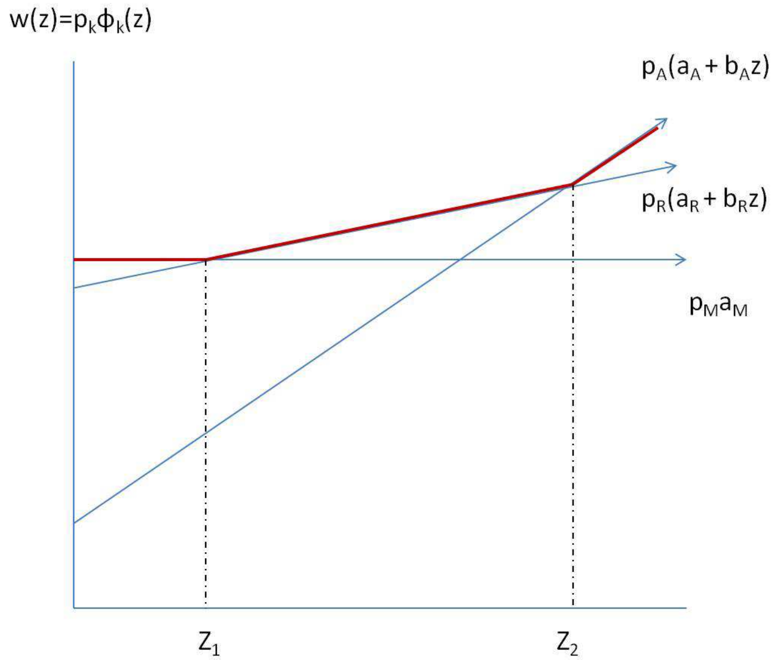


Figure 1·8: Decline in the Global Price for Routine Tasks

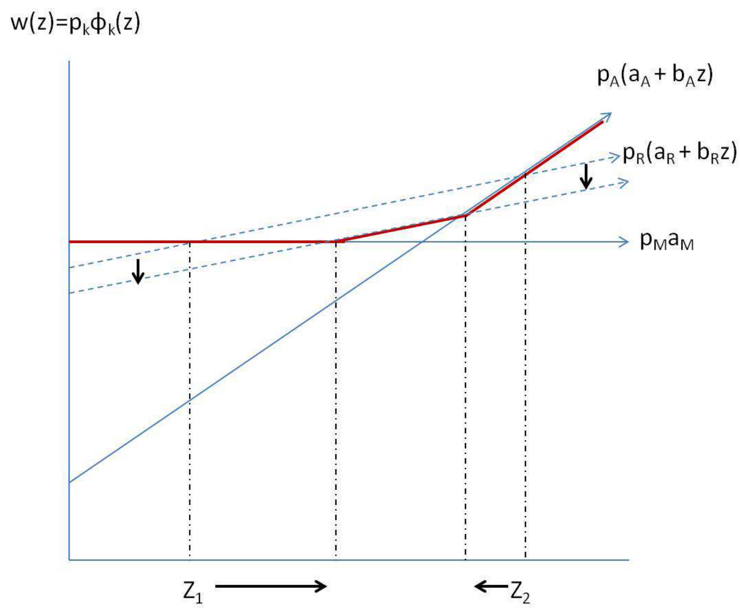


Figure 1·9: Abstract Task Enhancing Technology

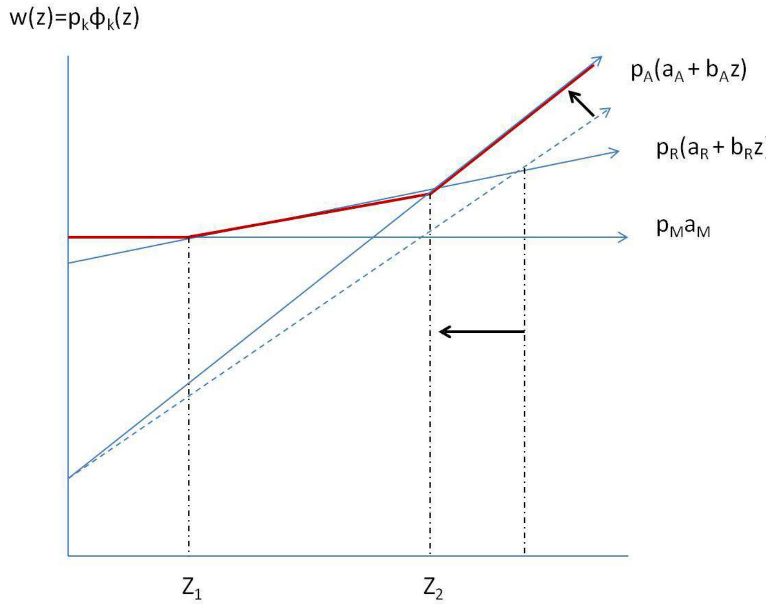


Table 1.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Industry Size					
Industry Employment (millions)	0.987	1.987	0.0097	16.9	367
Industry Log Employment	12.868	1.322	9.178	16.645	367
Income (2000 dollars)					
10th Percentile Annual	7,469.88	4,707.80	776.56	31,000	367
Median Annual	27,615.18	10,118.53	6,986.45	58,241.70	367
90th Percentile Annual	63,085.57	22,375.95	21,496.77	226,754.4	367
10th Percentile (Hourly) LWage	1.789	0.303	1.055	2.680	367
Median Hourly LWage	2.605	0.290	1.896	3.288	367
90th Percentile LWage	3.380	0.283	2.741	4.582	367
Lower Tail Spread	0.8157	0.1250	0.4853	1.2646	367
Upper Tail Spread	0.7749	0.1719	0.2877	1.5307	367
d90/50 1990-2000	0.05472	0.1218	-0.2559	0.5051	127
d90/50 2000-2011	0.0072	0.1109	-0.4910	0.3288	129
Other Industry Characteristics					
Foreign Born	0.1350	0.0848	0.0000	0.5212	367
Black	0.1046	0.0507	0.0000	0.2870	367
Female	0.3697	0.2007	0.0584	0.9490	367
College Degree	0.2213	0.1529	0.00	0.7269	367
Union	0.1218	0.1159	0.00	0.6712	367
Offshoring Measures					
Material Offshoring	0.1706	0.1017	0.0014	0.6235	367
ΔOSM 1990-2000	0.0590	0.0609	0.0021	0.4914	126
ΔOSM 2000-2011	0.0558	0.0433	-0.0124	0.2484	128
Service Offshoring	0.0206	0.0076	0.0082	0.0607	367
ΔOSS 1990-2000	0.0039	0.0018	-0.0056	0.0103	126
ΔOSS 2000-2011	0.0105	0.0059	-.0017	0.0376	128

Table 1.2: Labor Market Outcomes
Industry Wages, Inequality and Employment

VARIABLES	(1) 10th Pctle Wage	(2) Med. Wage	(3) 90th Pctle Wage	(4) 50/10 Sprd	(5) 90/50 Sprd	(6) Log Emp
Service Offshoring	1.976**	2.127***	3.503***	0.151	1.376**	4.239
	(0.914)	(0.706)	(0.992)	(0.684)	(0.676)	(7.218)
Material Offshoring	0.496***	0.340***	0.555***	-0.156	0.215**	-1.236**
	(0.128)	(0.0989)	(0.139)	(0.0958)	(0.0947)	(0.592)
Black	-0.131	-0.00512	-0.0759	0.126	-0.0708	1.529
	(0.271)	(0.210)	(0.294)	(0.203)	(0.201)	(1.167)
Female Share	-0.0302	-0.423***	-0.718***	-0.393***	-0.295***	-0.179
	(0.142)	(0.109)	(0.154)	(0.106)	(0.105)	(0.670)
Foreign Born	0.0141	0.0586	0.0709	0.0444	0.0123	-1.022
	(0.199)	(0.154)	(0.216)	(0.149)	(0.147)	(0.815)
Share Union	0.262*	0.369***	0.0493	0.107	-0.319***	1.579**
	(0.135)	(0.104)	(0.147)	(0.101)	(0.0999)	(0.680)
Share with BA	0.338***	0.497***	0.614***	0.159*	0.116	0.620
	(0.112)	(0.0867)	(0.122)	(0.0841)	(0.0831)	(0.516)
Observations	367	367	367	367	367	367
Adjusted R^2	0.963	0.978	0.957	0.828	0.917	0.901

All regressions include year and industry fixed effects
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.3: Contextual Interpretation of OSS and OSM Coefficients

	(1) 10th Pct. Wage	(2) Med. Wage	(3) 90th Pct. Wage	(4) 50/10	(5) 90/50	(6) Ln Emp
Dep. Var. SD	0.3116	0.2959	0.290	0.128	0.1735	1.319
β_{OSS}	1.976**	2.127***	3.503***	0.151	1.376***	4.239
% exp. by 1SD $\uparrow$ OSS	4.83%	5.48%	9.20%	–	6.04%	–
β_{OSM}	0.496***	0.340***	0.555***	-0.156	0.215**	-1.236**
% exp. by 1SD $\uparrow$ OSM	16.18%	11.68%	19.46%	–	12.60%	-9.53%

OSS SD=0.008, OSM SD=0.102

Table 1.4: Effect on Upper Tail Inequality

S hare of 90/50 Increase Explained by Offshoring (Mean Industry 1990-2011)					
	$\Delta_{1990-2011}$ OS	β	$\Delta_{1990-2011} * \beta$	$\Delta_{1990-2011}$ Ineq.	$\frac{\Delta\text{Predicted}}{\Delta\text{Observed}}$
OSS	0.0144	1.376	0.0199	0.062	0.32
OSM	0.1151	0.215	0.0247	0.062	0.40

Table 1.5: Industry Wages and Inequality Controlling for Productivity

VARIABLES	(1) 10th Pct. Wage	(2) Med. Wage	(3) 90th Pct. Wage	(4) 50/10 Spread	(5) 90/50 Spread	(6) Log Emp
Service Offshoring	1.974**	2.023***	3.512***	0.0493	1.489**	4.162
	(0.790)	(0.683)	(0.970)	(0.622)	(0.673)	(5.451)
Material Offshoring	0.332***	0.280***	0.505***	-0.0521	0.225**	-0.904**
	(0.111)	(0.0961)	(0.136)	(0.0876)	(0.0947)	(0.449)
Black	-0.214	-0.00810	-0.0818	0.206	-0.0737	1.567*
	(0.231)	(0.200)	(0.283)	(0.182)	(0.197)	(0.875)
Female Share	-0.0596	-0.448***	-0.713***	-0.388***	-0.265**	0.417
	(0.126)	(0.109)	(0.154)	(0.0989)	(0.107)	(0.518)
Foreign Born	-0.123	-0.00685	0.0286	0.117	0.0354	0.322
	(0.167)	(0.145)	(0.206)	(0.132)	(0.143)	(0.616)
Share Union	0.281**	0.382***	0.00863	0.101	-0.374***	1.677***
	(0.117)	(0.101)	(0.143)	(0.0920)	(0.0995)	(0.512)
Share with BA	0.411***	0.501***	0.562***	0.0908	0.0604	0.795**
	(0.0970)	(0.0838)	(0.119)	(0.0764)	(0.0826)	(0.387)
Productivity	11.80	25.50	55.95	13.70	30.45	-1,697***
	(44.50)	(38.47)	(54.61)	(35.05)	(37.90)	(129.2)
Observations	367	367	367	367	367	367
Adjusted R^2	0.971	0.980	0.958	0.837	0.917	0.943

All regressions include year and industry fixed effects
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.6: Industry Wages and Inequality: Bounding Experiment

VARIABLES	(1) 10th Percentile Wage	(2) Median Wage	(3) 90th Percentile Wage	(4) 50/10 Spread	(5) 90/50 Spread
Service Offshoring	2.643**	2.179***	3.597***	-0.464	1.418**
	(1.039)	(0.729)	(1.010)	(0.749)	(0.654)
Material Offshoring	-1.459***	-0.379***	0.0934	1.080***	0.473***
	(0.146)	(0.103)	(0.142)	(0.105)	(0.0920)
Black	0.126	-0.000518	-0.0558	-0.127	-0.0553
	(0.304)	(0.213)	(0.295)	(0.219)	(0.191)
Female Share	-0.217	-0.511***	-0.741***	-0.294**	-0.231**
	(0.165)	(0.116)	(0.160)	(0.119)	(0.104)
Foreign Born	-0.245	-0.0107	0.0293	0.234	0.0400
	(0.219)	(0.154)	(0.213)	(0.158)	(0.138)
Share union members	0.401***	0.390***	-0.0388	-0.0110	-0.429***
	(0.154)	(0.108)	(0.149)	(0.111)	(0.0968)
Share with BA	0.670***	0.621***	0.615***	-0.0497	-0.00536
	(0.127)	(0.0894)	(0.124)	(0.0918)	(0.0803)
Observations	367	367	367	367	367
Adjusted R^2	0.960	0.977	0.956	0.875	0.926

All regressions include year and industry fixed effects
Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
The data for these regressions were truncated by eliminating individual workers according to the predicted change in employment from the results in Table 1.2, Column (7), and the observed change in the industry's measure of material offshoring. For the purposes of this exercise,the least paid workers in the sample are assumed to the be first laid off. The 1990 observations were adjusted based on the change in offshoring between 1990 and 2011, and the 2000 observations were adjusted based on the change between 2000 and 2011. See Section 1.6.1 for details.

Table 1.7: Description and Examples of Task Measures

Task Measure	**Description**	**Examples of Tasks or Occupations with a high score**
1. Non-routine cognitive analytic	Mathematical or complex problem solving ability	Engineer, Physician, Economist, Mathematician
2. Non-routine cognitive personal	Ability to direct, control and plan projects or activities	Managers, Teachers, Attorneys
3. Routine cognitive	Requires ability to precisely attain limits or standards	Navigation, maintain records or measurements, switchboard operater, call center worker
4. Routine manual	Ability for small object manipulation	Cooking and baking by recipes, assembly line worker, packing objects for storage or shipping
5. Non-routine manual physical	Hand-eye-foot coordination	Bus driver, Gardener, Janitor, Pilot, Cattle rancher, Farmer
6. Non-routine manual personal	Adaptability and interactive ability in physical tasks	Hairdresser, Aesthetician, Daycare provider, Massage Therapist

Task measures and descriptions are from Autor et al.

Table 1.8: The Determinants of Industry Offshoring

VARIABLES	(1) Service Offshoring	(2) Material Offshoring	(3) Service Offshoring	(4) Material Offshoring
Routine Cognitive L10			0.0215**	-0.204***
			(0.0108)	(0.0769)
Routine Manual L10			0.00682	-0.0186
			(0.00942)	(0.0668)
Nonrout. Cognitive Analytical L10			0.0125*	0.0298
			(0.00701)	(0.0497)
Nonrout. Cognitive Personal L10			-0.0166*	0.0734
			(0.00893)	(0.0634)
Nonrout. Manual Physical L10			-0.0287***	-0.0173
			(0.0105)	(0.0747)
Nonrout. Manual Personal L10			-0.0342***	0.0469
			(0.0103)	(0.0729)
Routine L10	0.0344***	-0.166**		
	(0.00987)	(0.0720)		
Manual L10	-0.0616***	-0.0534		
	(0.0141)	(0.103)		
Abstract L10	0.00396	0.0791**		
	(0.00440)	(0.0321)		
Observations	367	367	367	367
Adjusted R^2	0.713	0.869	0.701	0.871

All regressions include year and industry fixed effects
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.9: Controlling for Coarse Composition L10

VARIABLES	(1) 10th Percentile Wage	(2) Median Wage	(3) 90th Percentile Wage	(4) 50/10 Spread	(5) 90/50 Spread	(6) Log Emp
Service Offshoring	1.546	2.070***	4.332***	0.524	2.262***	4.235
	(0.981)	(0.757)	(1.059)	(0.736)	(0.712)	(7.358)
Material Offshoring	0.531***	0.370***	0.557***	-0.160	0.186*	-1.206**
	(0.131)	(0.101)	(0.141)	(0.0981)	(0.0949)	(0.597)
Routine share L10	0.112	0.00873	-0.276	-0.104	-0.285**	1.071
	(0.164)	(0.126)	(0.176)	(0.123)	(0.119)	(0.804)
Abstract share L10	-0.0913	-0.105*	-0.0863	-0.0140	0.0190	0.252
	(0.0700)	(0.0540)	(0.0756)	(0.0525)	(0.0508)	(0.501)
Manual share L10	-0.202	-0.0246	0.353	0.178	0.377**	0.516
	(0.222)	(0.171)	(0.239)	(0.166)	(0.161)	(1.130)
Observations	367	367	367	367	367	367
Adjusted R^2	0.963	0.978	0.957	0.827	0.920	0.900

All regressions include year and industry fixed effects
Other controls: foreign born/female/black/college educated/unionized shares of industry
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.10: Controlling for Fine Composition L10

VARIABLES	(1) 10th Percentile Wage	(2) Median Wage	(3) 90th Percentile Wage	(4) 50/10 Spread	(5) 90/50 Spread	(6) Log Emp
Service Offshoring	1.661*	2.173***	4.219***	0.512	2.046***	3.191
	(0.937)	(0.733)	(1.029)	(0.717)	(0.709)	(7.335)
Material Offshoring	0.587***	0.398***	0.573***	-0.189*	0.175*	-1.092*
	(0.128)	(0.100)	(0.141)	(0.0981)	(0.0971)	(0.598)
Routine Cognitive share L10	0.593***	0.281**	0.184	-0.312**	-0.0964	1.235*
	(0.157)	(0.123)	(0.172)	(0.120)	(0.119)	(0.679)
Routine Manual share L10	-0.300**	-0.287**	-0.428***	0.0129	-0.141	1.124
	(0.142)	(0.111)	(0.156)	(0.109)	(0.108)	(0.831)
Nonrout. Cognitive Analytic share L10	-0.0348	-0.0830	-0.0467	-0.0482	0.0363	-0.00521
	(0.101)	(0.0787)	(0.111)	(0.0770)	(0.0762)	(0.569)
Nonrout. Cognitive Personal share L10	-0.143	-0.0435	-0.0554	0.0993	-0.0120	0.594
	(0.125)	(0.0980)	(0.138)	(0.0959)	(0.0948)	(0.840)
Nonrout. Manual Physical share L10	-0.219	0.0418	0.196	0.261**	0.155	0.392
	(0.154)	(0.120)	(0.169)	(0.118)	(0.116)	(0.860)
Nonrout. Manual Personal share L10	-0.0980	-0.0419	0.196	0.0560	0.238**	0.195
	(0.148)	(0.116)	(0.163)	(0.114)	(0.112)	(0.932)
Observations	367	367	367	367	367	367
Adjusted R^2	0.965	0.979	0.958	0.831	0.918	0.902

All regressions include year and industry fixed effects
Other controls: foreign born/female/black/college educated/unionized shares of industry
Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Chapter 2

The Role of Gender in Income Mobility

2.1 Introduction

Previous studies of intergenerational income mobility in the United States have focused primarily on the transmission of earnings from fathers to sons. However, thanks to the increase in female labor force participation throughout the last several decades, combined with the new availability of longitudinal, multi-generational data, it is now possible to include both mothers and daughters in this analysis. This allows researchers to know whether the effect of maternal earnings is separate and distinct from the effect of the father's earnings. Furthermore, we can investigate whether the effect of either parent on the child's income varies with the gender of the child.

The goal of this paper is to examine the role of gender in income mobility. Specifically, it measures the difference in the degree of income mobility experienced by daughters versus sons, as well as the relevance of maternal versus paternal earnings to income mobility. This is an important topic because it can help to illuminate the mechanism of intergenerational income transmission. A parent's and child's lifetime incomes are correlated for at least three reasons: 1) genetic transmission of earning ability, 2) direct transmission of income through bequeathment or investment in the child's human capital, or 3) through assortative matching in marriage. Assortative matching in either generation can impact the child's income. First of all, the parent's income is correlated with the genes and wealth of his/her spouse, which will then be positively correlated with the child's income. Secondly, the parent's income can improve the marriage market for the child through various channels. For example, having wealthy parents is likely to give the child access to higher socioeconomic circles (exposure to higher quality potential matches), and is also likely to result in greater human capital investment (making the child more attractive to others).

A different magnitude of elasticity with respect to maternal income compared to paternal income indicates that investment in children's human capital may be tied to the allocation of earnings within a household. If this investment is the most important mechanism for income transmission, we would expect a larger elasticity with respect to the parent who prefers higher levels of investment. Previous studies have suggested this parent is the mother; for example, see Currie and Moretti (2003). Furthermore, if the income of the same-sex parent has a larger impact, this could reflect the importance of labor force attachment. Daughters who grow up with high income earning mothers may feel more incentive to pursue higher earning careers themselves.

Assortative matching in the marriage market and differences in labor supply between men and women are the main reasons income elasticities may differ for sons and daughters.[1] On average, women are still less likely to work then men. With assortative matching, women with high earning fathers tend to marry men who also have high earning fathers. The established high level of income elasticity between fathers and sons means that these women will have high earning husbands. If married couples have negative cross price labor supply elasticities, these women will be less likely to participate in the labor force, and more likely to work fewer hours. As a result, their wages will be lower. Additionally, assortative matching combined with intergenerational patterns of labor supply will impact the household's intergenerational income elasticity (IGE). Fernandez, Fogli and Olivetti (2004) find that women with working mothers in law have higher labor supply than women whose husbands'

[1]See Raaum et al. (2007)

mothers did not work. This underscores the benefit of isolating the effects of elasticity with respect to maternal income.

I use data from the Children of the NLSY97 (NLSY97 C/YA) to estimate income elasticity with respect to parental earnings. This is a panel dataset, which allows for some control of the bias due to measurement error in permanent income of both the parents and their children. Within the NLSY97 C/YA sample, the estimated elasticity of income with respect to paternal income is around 0.33 for sons, and 0.163 for daughters. The effect of maternal income was not significant for sons, and 0.15 for daughters. However, in pooled regressions of sons and daughters there is no evidence that the IGE depends on the child's gender. In addition, non-linear least squares estimation implies that IGE with respect to maternal income is significant but roughly one half the magnitude of IGE with respect to paternal earnings.

In Section 2 I briefly describe the existing literature in this research area, concentrating primarily on the U.S. studies. Section 3 discusses the features of the NLSY data. In Section 4, I present the empirical model and estimation results, and Section 5 concludes the paper.

2.2 Previous Studies

The most conspicuous weakness in the empirical research on income mobility is the exclusion of women. Solon (1999) summarizes major studies that have been done on income mobility in the United States, and lists 15 papers that focus solely on the incomes of fathers and sons, and only four that examine the level of mobility for daughters. Of these four that include the daughter's income as an outcome variable, Altonji and Dunn (1991) and Peters (1992) use NLS data, as I did[2]. On average, the more recent literature suggests an elasticity for American sons around 0.4, and

[2]Both papers estimated a higher level of mobility than my results show.

around 0.3 for American daughters[3]. None of these studies isolated the influence of maternal income. More recently, work by Jantti et al. (2006) find that the elasticity for daughters' earnings with respect to fathers' are smaller than the corresponding elasticity for sons' earnings. However, they do not separately control for the effect of maternal earnings.

The elasticity estimates tend to increase in size with the date of publication. This does not necessarily implicate an increasing elasticity over time. Rather, the empirical approach to this question has evolved over time to include more refined controls for omitted variables and measurement error. Most of the empirical studies from the 1970s and 1980s estimated an intergenerational elasticity in the United States around 0.2, for example: Behrman and Taubman (1985); Sewell and Hauser (1975), Becker and Tomes (1986). However, Chadwick and Solon (2002) show that measurement error in the wage data results in a downward bias on the elasticity estimates, that is, an overstatement of income mobility. Chadwick and Solon use the parents' ages to instrument for earnings as a method of controlling the measurement error bias. They examine the relationship between the parents combined earnings, and the total earnings of their daughter and son in law. Using data from the PSID, they estimate that intergenerational elasticity of household income is around 0.4[4].

Chadwick and Solon, along with other studies (Mazumder (2005), for example) have also addressed the need to control for measurement error in the child's permanent income[5]. Mayer and Lopoo (2004, 2005) include only children aged 30 in their analysis to try to control for this bias. Lee and Solon (2006) address the measurement error by including extensive controls for both the child's age and birth cohort, as well as controls for the interaction of the child's age with the parental income.

[3] This is an imperfect comparison, since the econometric specifications are not identical across authors.

[4] Solon (1992) found a comparable measure when linking the generations via sons.

[5] I will discuss this issue further in Section 4.

Mazumder (2005) includes similar age controls, but also addresses the problem of top-coded income data (the highest values are censored to protect individual privacy) and incorporates a very long term average for paternal income over a period of 16 years.

Mazumder's study suggests that even Solon et al. estimates were biased downwards: he estimates father-son elasticity to be 0.613, and father-daughter elasticity slightly lower at 0.57. It should be noted that since earnings shocks are persistent, even multi-year averages are imperfect measures of permanent income. Mazumder considers family income to be a better measure of permanent income than paternal earnings alone when only a few years of earnings data is available for the individual. Of course, this precludes the possibility of measuring the relative importance of the father's earnings versus the mother's.

I was unable to find a study that included maternal income separately from paternal income, although several summed the two and used total household income as an explanatory variable (for example, Chadwick and Solon (2000) and Ermisch et al. (2006)). However, assortative matching in the marriage market means that should a mother's income affect her child's income mobility, omitting the maternal income will bias the estimate of child-father elasticity (see Lam and Schoeni (1993) or Behrman and Rosenzweig (2002)).

2.3 Data

My analysis uses data from the National Longitudinal Survey of Youth 1979 (NLSY79), and from the NLSY79 Children and Young Adults (NLSY79 C/YA). Each respondent in the C/YA survey is the biological child of a woman in the original NLSY79. For the NLSY79 C/YA, children aged 15 and older were interviewed biennially until 2008 (the latest available data), and the survey includes detailed questions about labor force experiences. Since it is possible to link the data for children in the NLSY79 C/YA to women and their spouses in the NLSY79, these two sources allowed me to construct a bi-generational dataset with earnings information for the mother (respondent in the NLSY79), father (respondent's spouse), and child(ren) (in the NLSY79 C/YA).

I restricted the sample to children at least 25 years old in 2010, who reported annual income for at least one year between 1994 and 2010, and had mothers in the NLSY79 who were married exactly once. Only earnings reported after the age of 25 was used to construct the children's permanent income measures.[6] There were 735 children (337 males and 398 females) that met these requirements and also had parents with reported annual income.

Table 3.1 describes the characteristics of the restricted sample, including the ages of each of the family members during their recorded earning years. The actual ages of the children ranged from 25 to 40 in 2010, and the mean annual income after age 25 was $19,777 for men and $15,490 for women. (All income values are in year 2000 dollars.) The mothers in this sample had an earnings distribution substantially below the fathers. The income data for both children and parents shown in Table 3.1 is measure of average real income. This measure is described in greater detail in Section 4.

Tables 2 and 3 give the basic correlation coefficients for income and education of the parents and children.[7] The correlation between the log income of the father and the log income of the child is 0.22 and the correlation between the father's and child's is 0.28. The correlation for child's and mother's income is considerable smaller: 0.14.

[6]Individuals over the age of 25, despite being far from the peak of their earnings life-cycle, still have earnings that are much more representative of their lifetime permanent income than measures of current income from their late teens or very early twenties.

[7]The income correlation coefficient ρ is related to IGE β by the following expression:

$$\rho = (\sigma_0/\sigma_1)\,\beta$$

where σ_0 is the standard deviation of the initial generation's income and σ_1 is the standard deviation of the child's generation's income.

However, the schooling correlations are fairly equal for the two parents: 0.28 for the child-father, and 0.29 for the child mother. There is evidence of assortative matching in the parent generation: the correlation of husbands' and wives' years of schooling is 0.33, and the correlation between husbands' and wives' log permanent income is around 0.3.

2.4 Econometric Model and Results

Suppose each family unit i has a single decision maker (the parent). This parent's permanent income partly determines each child's income via the parent's decision to invest in the child's human capital[8].

Following the statistical model of Solon (1992), the lifetime permanent income of child j from family i can be decomposed as[9]

$$y_{ij} = a_i + b_{ij}$$

[8] Simplified from Becker and Tomes (1979). A parent solves the problem:

$$\begin{aligned}
&\max(U_i) = \alpha C_0 + (1-\alpha)y_1 \\
&\text{subject to the budget constraint} y_0 = C_0 + I_0 \\
&\text{where} C_0 = \text{parental consumption} \\
&I_0 = \text{parent's investment in child's human capital} \\
&y_0 = \text{parental income} \\
&y_1 = \text{child's income.}
\end{aligned}$$

The technology translating the investment I_0 into the child's permanent income y_1 is:

$$y_1 = (1+r)I_0 + E_1$$

where r is the rate of return on the child's human capital, and E_1 represents all other determinants of the child's income. The first order condition for the parent's problem implies the optimal investment is:

$$I_0 = \alpha y_0 - \frac{(1-\alpha)E_1}{(1+r)}$$

which implies the following relationship between the parent's and child's permanent income:

$$y_1 = \beta y_0 + \alpha E_1$$

where $\beta = \alpha(1-r)$. The interpretation of β is the intergenerational income elasticity.

[9] Expressing these variables as deviations from the mean allows us to suppress the intercept term.

where a_i represents the fixed effect for family i, and b_{ij} is the idiosyncratic component for child ij. a_i, the family background effect, can be written as a sum of βX_i: the effect of parental income, and z_i: the influence of all family background factors orthogonal to parental income. That is:

$$a_i = \beta X_i + z_i$$

where z_i is uncorrelated to a_i, and therefore uncorrelated to y_{ij}. Hence the expression for the child's permanent income becomes

$$y_{ij} = \beta X_i + z_i + b_{ij} = \beta X_i + u_{ij}$$

(where $u_{ij} = z_i + b_{ij}$). If this is the correct specification, OLS will yield a consistent estimator for β. When we use log income, β represents the elasticity of y_{ij} with respect to X_i. However, obviously we cannot perfectly observe permanent income. If instead of permanent income we use current income $y_{ijt} = y_{ij} + \mu_{ijt}$, where μ_{ijt} is the idiosyncratic income shock in year t, it is simple to show that

$$\text{plim}(\hat{\beta}_{OLS}) = \beta - \frac{Var(\mu_{ij0})}{E(y_{ij}^2} < \beta$$

To approximate permanent parental income with minimal measurement error, I used a simple average of reported annual income over the period 1979 to 2008, denoted as Y_{i0}. For the parent with reported income in a total of T years (not consecutive, in general), this is defined as

$$Y_{i0} = \frac{1}{T}\{\sum_t Y_{i0t}\}$$

where Y_{i0t} is the annual income of the parent to child i in year t. I will use y_{i0} to denote $\log(Y_{i0})$. Since the current income values used to generate Y_{i0} for each parent are not reported at a common level of age and experience, it is neccessary to control for the ages of the individual at the time of the reported annual income. Following Lee and Solon, I included controls for a quadratic in parental age A_i. I defined the age control as

$$A_{i0} = \frac{1}{T}\{\sum_t Age_{i0t}\}$$

for each t used in the Y_{i0} measure, and where Age_{i0t} is the age of the parent to individual i in year t. Although Lee and Solon included a full quartic in parental age, I did not find a marginal benefit of any higher order terms beyond A_{i0}^2.

In addition to the measurement error in the parental income, it was also necessary to control for the measurement error due to observing current rather than permanent income for the children. While measurement error in the left hand side variable generally does not affect the consistency of the OLS estimator, this measurement error is clearly correlated with the observed current income and therefore will bias the estimate. At the earliest years of the child's life cycle, current income is smaller than permanent income. As the child gains experience, the difference between current and permanent income diminishes. Reville (1995) found that because of this measurement error, estimates for intergenerational elasticity are much lower when the children's income data is collected early in the life cycle[10]. A lower measured correlation between the earnings of parents and children implies a higher degree of income mobility. To control for the fact that a large fraction of my data for the children's earnins was measured early in the life cycle, I included a control for a quadratic in the child's age for every year. Additionally, the size of the NLS database allowed me to restrict observations to only those children aged 25 years and older. This provided some guarantee that the children beyond past the earliest years of their earnings life cycle. Even after this age restriction, the sample retained over 4,000 individuals. I also included an interaction terms between the child's age and the parental income. This variable captures the fact that the effect of parental income grows more relevant as

[10]I was not able to access a full copy of this unpublished study, but came across references to it in multiple papers.

the child reaches the peak earning years of the life cycle[11]. These controls fall short of a perfect solution. As Mazumder remarks (2005), "...There is no simple way to deal with measurement error problem for the dependent variable, given the lack of direct survey data on the children in their adult years" (p. 243).

Finally, we need to consider the possibility of assortative matching in the marriage market. There may be a positive correlation between the ability endowments of husbands and wives, implying a correlation between spouses' earnings. This is in fact the case for the NLS dataset, as we can see from Table 2. If maternal income influences the decision of how much to invest in the child's human capital, then it will also help determine the child's income. Then, omitting the maternal earnings as an explanatory variable for y_{it} will bias the estimated effect of the father's log earnings. Since the allocation, not only the total, of parental earnings may be important, I estimate a non-linear model . The relative sizes of the father-child and mother-child elasticities will reflect the relative importance of the two spouses in the investment decision. This of course may lead to some selection issues: the sample is made up of children who worked, and had parents who both participated in the labor force at some point.

2.4.1 Combined Parental Income

To establish a baseline measure of IGE for this sample, I used the pooled sample of both male and female children and regress the child's log permanent income on their parents' log permanent income. I included controls for the age of both the child and father. In addition to a child gender dummy variable, I included an interaction of

[11]I only included this interaction term for the father's income. Including an interaction term for maternal income and the child's age produced an insignificant parameter estimate for this variable, probably due to the fairly high correlation of age between spouses.

this variable with the parental income.

$$y_{i1} = \alpha + \beta y_{i0} + \beta_1 A_{i0} + \beta_2 A_{i0}^2 + \gamma_1 A_{i1} + \gamma_2 A_{i1}^2 +$$
$$\gamma_3 daughter + \gamma_4 (daughter) * (y_{i0}) + \varepsilon_i$$

where y_{i1} is the child's current log income in year t, A_{i1} controls for the age of the child, y_{i0} is the log income measure for the parents (an average of all reported joint annual income). $daughter = 1$ if the child is female. The purpose of this specification is to look for evidence of a different elasticity for sons versus daughters. While the first *daughter* dummy variable simply expresses the difference in means between males and females, if the interaction term is significant and positive (negative), it implies that at any level of a daughter's income, her father's permanent income has a greater (lesser) influence on her income than it would have on her brother.

Table 2.4 shows the relevant results for the pooled OLS. The estimate of the IGE is 0.361 in the full specification (Column 3). This regression includes the daughter dummy and interaction term. The parameter on the interaction term *daughter*log parental income* is negative but statistically insignificant. In this specification there is no evidence that the gender of the child significantly affects the elasticity with respect to the joint parental income.

2.4.2 Maternal versus Paternal Income

Table 2.5 shows the results the OLS regression of the child's income on father's (Columns 1 and 3) and mother's income (Columns 2 and 4). Using the individual parent's incomes rather than their total income yields much smaller IGE estimates than those given in Table 2.4, only about 0.19 for paternal income, and 0.17 for maternal income. This is expected: as mentioned above, assortative matching between parents means that including only one parent's income will bias the IGE results downwards. Next, to measure the relative effects of the two parents' incomes, I estimate the following non-linear model:

$$\begin{aligned} y_{i1} =& \alpha + \beta_0 \left(y_{iFa} + \beta_1 y_{iMo} \right) + \gamma_1 A_{i0} + \gamma_2 A_{i0}^2 \\ &+ \gamma_3 A_{i1} + \gamma_2 A_{i1}^2 \varepsilon_i \end{aligned}$$

Where y_{iFa} is the father's log income, and y_{iMo} is the mother's log income. A_{i1} and A_{i0} are the control variables for the child's and father's age at the time of the income, as in the OLS models. The results in Table 2.6 show the results. In Columns 1-4, the mother's income is not significant because the sample size is too small. However the results in Column (5) are for the pooled sample, and yield significant estimates for the income of each parent: $\hat{\beta}_0$ is equal to 0.238, and $\hat{\beta}_1$ is equal to 0.491, indicating the maternal IGE is roughly half the magnitude of the paternal IGE.

Lastly, I separated the sample into sons and daughters and ran the regression on each gender group individually. Table 2.7 shows the results: although the IGE for sons is slightly larger than the IGE for daughters, it is a very small difference (0.307 for daughters and 0.361 for sons). This confirms the result for the pooled regression including the female control, which showed that the female interaction with parental income was not significant (for comparison, the results of this model is shown again in Column (5) of Table 2.7).

2.5 Conclusion

As a result of this analysis, I was able to estimate both the total magnitude of the intergenerational elasticity of income, as well as to provide a decomposition of this elasticity into paternal and maternal effects. Specifically, I found that maternal income has a lesser effect that paternal income, but still a significant one: elasticity attributable to the mother's income is about one half the magnitude of the portion due to the father's income. However, the gender of the child does not change the IGE results much in either the pooled or separated OLS regressions. These results suggest that differences in labor force participation are still driving much of the gender differences in measured IGE. In order to add to the study, it would be useful to control for the abiity of the child's mother, which is measured by her AFQT score in the NLSY79. This would be a way to estimate the fraction of IGE due to genetics.

Altonji, Joseph G. and Thomas A. Dunn. 1991. "Relationships Among the Family Incomes and Labor Market Outcomes of Relatives." NBER Working Paper no. 3724.
Baker, Michael and Gary Solon. 2003. "Earnings Dynamics and Inequality among Canadian Men, 1976-1992: Evidence from Longitudinal Income Tax Records." *Journal of Labor Economics* 21(2): 267-288.

Becker, Gary and Nigel Tomes. 1979. "An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility." *The Journal of Political Economy* 86(6): 1153-1189.

Behrman, Jere R. and Mark R. Rosenzweig. 2002. "Does Increasing Women's Schooling Raise the Schooling of the Next Generation?" *The American Economic Review* 92(1): 323-334.

Behrman, Jere R. and Paul Taubman. 1985. "Intergenerational Earnings Mobility in the United States: Some Estimates and a Test of Becker's Intergenerational Endowments Model." *The Review of Economics and Statistics* 67(1): 144-51.

Chadwick, Laura and Gary Solon. 2002. "Intergenerational Income Mobility Among Daughters." *The American Economic Review* 92(1): 335-344.

Chiappori, Pierre-Andre, Murat Iyigun, and Yoram Weiss. 2009. "Investment in Schooling and the Marriage Market." *The American Economic Review* 99(5): 1689-1713.

Currie, Janet, and Enrico Moretti. 2003. "Mother's Education and the Intergenerational Transmission of Human Capital: Evidence from College Openings." *The Quarterly Journal of Economics* 118(4): 1495-1532.

Ermisch, John, Marco Francesconi, and Thomas Siedler. 2006. "Intergenerational Mobility and Marital Sorting." *The Economic Journal* 116(513): 659-679.

Fernández, Raquel, Alessandra Fogli, and Claudia Olivetti. 2004. "Mothers and Sons: Preference Formation and Female Labor Force Dynamics." *The Quarterly Journal of Economics* 119(4): 1249-1299.

Hauser, Robert M. and William H. Sewell. 1975. *Education, Occupation and Earnings: Achievement in the Early Career.* New York: Academic Press.

Heckman, James J. and V. Joseph Hotz. 1986. "An Investigation of the Labor Market Earnings of Panamanian Males: Evaluating the Sources of Inequality." *The Journal of Human Resources* 21(4): 507-542.

Jantti, Markus, Bernt Bratsberg, Knut Roed, Oddbjorn Raaum, Robin Naylor, Eva Osterbacka, Anders Bjorklund, and Tor Eriksson (2006). "American Exceptionalism in a New Light: a Comparison of Intergenerational Earnings Mobility in the Nordic Countries, the United Kingdom and the United States." IZA Discussion Paper no. 1938.

Lam, David and Robert F. Schoeni. 1993. "Effects of Family Background on Earnings and Returns to Schooling: Evidence from Brazil." *Journal of Political Economy* 101(4): 710-740.

Lee, Chul-In and Gary Solon. 2006. "Trends in Intergenerational Income Mobility." NBER Working Paper No. 12007.

Levine, David I. and Bhashkar Mazumder. 2002. "Choosing the Right Parents: Changes in the Intergenerational Transmission of Inequality–Between 1980 and the Early 1990s." FRB Chicago Working Paper no. 2002-08.

Mayer, Susan E. and Lopoo, Leonard M. 2004. "What Do Trends in the Intergenerational Economic Mobility of Sons and Daughters in the United States Mean?" In *Generational Income Mobility in North America and Europe,* edited by Miles Corak, 90-121. Cambridge: Cambridge University Press.

—. 2005. "Has the Intergenerational Transmission of Economic Status Changed?" *Journal of Human Resources* 40(1): 169-85.

Mazumder, Bhashkar. 2005. "Fortunate Sons: New Estimates of Intergenerational Mobility in the United States Using Social Security Earnings Data." *The Review of Economics and Statistics* 87(2): 235-255.

Peters, H. Elizabeth. 1992. "Patterns of Intergenerational Mobility in Income and Earnings." *Review of Economics and Statistics* 74(3): 456-466.

Raaum, Oddbjørn et al. 2007. "Marital sorting, household labor supply, and intergenerational earnings mobility across countries." *The BE Journal of Economic Analysis & Policy* 7(2).

Reville, Robert T. 1995. "Intertemporal and Life Cycle Variation in Measured Intergenerational Income Mobility." Unpublished.

Slaughter, Matthew. 2001. "International Trade and Labor Demand Elasticities. *Journal of International Economics* 54(1): 27-56.

Solon, Gary. 1992. "Intergenerational Income Mobility in the United States." *The American Economic Review* 82(3): 393-408.

—. 1999. "Intergenerational Mobility in the Labor Market." *Handbook of Labor Economics* 3(1): 1761-1800.

—. 2004. "A Model of Intergenerational Mobility Variation over Time and Place," In *Generational Income Mobility in North America and Europe,* edited by Miles Corak, 38-47. Cambridge: Cambridge University Press.

—. 2013. "Theoretical Models of Inequality Transmission Across Multiple Generations." NBER Working Paper no. 18790.

Table 2.1: Summary statistics: Means

Children of the NLSY79, age 25+

	Men	**Women**
Year of Birth	1980.6	1980.8
Age (time of income)	27.26	27.19
Permanent Income	19,776.60	15,490.31
G2 HH income	25,761.24	25,728.96
Mother's income	11,189.60	11,668.17
Father's income	24,328.68	22,663.79
Mother's age (time of income)	31.45	30.65
Father's age (time of income)	33.94	32.59
Highest grade	12.42	13.06
Mother's highest grade	12.41	12.67
Father's highest grade	12.15	12.13
Female	0	1
N	337	398

All income amounts are in 2000 dollars

Table 2.2: Permanent Income Correlation Coefficients

	Child's Log Income	Father's Log Income	Mother's Log Income
Child's Log Income	1		
Father's Log Income	0.2215	1	
Mother's Log Income	0.1363	0.295	1

Table 2.3: Schooling Correlation Coefficients

	Child's Schooling	Father's Schooling	Mother's Schooling	HH1 permanent inc.
Child's Schooling	1			
Father's Schooling	0.2791	1		
Mother's Schooling	0.2915	0.3308	1	
HH1 permanent inc.	0.3258	0.3307	0.2989	1

HH1 is the child's parental home.

Table 2.4: Combined Parental Income OLS

VARIABLES	(1) Child's Log Income	(2)	(3)
Parental log income	0.321***	0.345***	0.361***
	(0.0576)	(0.0628)	(0.0883)
Child Age		1.573**	1.712**
		(0.731)	(0.726)
Child Age squared		-0.0282**	-0.0308**
		(0.0132)	(0.0131)
Dad Age		-0.0169	-0.0153
		(0.0348)	(0.0346)
Dad Age squared		0.000129	9.84e-05
		(0.000451)	(0.000448)
female			0.0683
			(1.185)
Female*Parental Inc			-0.0348
			(0.115)
Observations	572	572	572
Adjusted R^2	0.050	0.054	0.069

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Maternal vs Paternal Income (OLS)

VARIABLES	(1)	(2)	(3)	(4)
	Child's Log Income			
Dad's permanent log income	0.182***		0.189***	
	(0.0489)		(0.0514)	
Mom's permanent log income		0.161***		0.165***
		(0.0400)		(0.0442)
Child Age			1.460**	1.631**
			(0.718)	(0.769)
Child Age squared			-0.0262**	-0.0293**
			(0.0130)	(0.0139)
Dad Age			0.00622	-0.00706
			(0.0362)	(0.0379)
Dad Age squared			-0.000153	3.31e-05
			(0.000482)	(0.000498)
Observations	582	579	582	550
Adjusted R^2	0.022	0.026	0.023	0.025

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: Maternal vs Paternal Income Allocation (NLLS)

VARIABLES	(1) sons	(2) daughters	(3) sons	(4) daughters	(5) all
Dad's permanent log income	0.290***	0.160*	0.329***	0.163*	0.238***
	(0.0950)	(0.0856)	(0.0967)	(0.0866)	(0.0649)
Mom's permanent log income	0.192	0.780	0.263	0.891	0.491*
	(0.232)	(0.639)	(0.217)	(0.691)	(0.255)
chAGE			1.887**	1.497	1.540**
			(0.870)	(1.470)	(0.747)
chAGE2			-0.0337**	-0.0263	-0.0273**
			(0.0156)	(0.0267)	(0.0135)
dadAGE			-0.0253	-0.0712	-0.0450
			(0.0632)	(0.0582)	(0.0430)
dadAGE2			4.04e-05	0.000995	0.000495
			(0.000849)	(0.000776)	(0.000576)
Observations	254	282	254	282	536
Adjusted R^2	0.042	0.035	0.072	0.035	0.045

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.7: Sons versus Daughters (OLS) II

VARIABLES	(1) sons	(2) daughters	(3) sons	(4) daughters	(5) all
Parental log income	0.334***	0.304***	0.384***	0.307***	0.361***
	(0.0829)	(0.0791)	(0.0903)	(0.0861)	(0.0883)
Child Age			1.874**	1.290	1.712**
			(0.877)	(1.309)	(0.726)
Child Age squared			-0.0337**	-0.0230	-0.0308**
			(0.0157)	(0.0237)	(0.0131)
Dad Age			-0.0213	-0.0449	-0.0153
			(0.0453)	(0.0567)	(0.0346)
Dad Age squared			4.86e-05	0.000653	9.84e-05
			(0.000569)	(0.000764)	(0.000448)
female					0.0683
					(1.185)
fem_F1inc					-0.0348
					(0.115)
Constant	6.258***	6.294***	-19.54	-11.01	-17.36*
	(0.855)	(0.815)	(12.31)	(17.95)	(10.12)
Observations	272	300	272	300	572
Adjusted R^2	0.053	0.044	0.076	0.037	0.069

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 3

Examination of the Expansion in the College Gender Gap

3.1 Introduction

The widening college gender gap in the United States and other developed economies is a puzzle that continues to draw attention in both the media and academic research, but has yet to be adequately explained. Why are college completion rates for men continuing to fall relative to those of women? Not only is the male rate failing to keep pace with the female rate, but among certain ethnic groups (Blacks and Latinos) they have stagnated and may even be going down. This is occurring in spite of the increasing returns to college education, and the indisputable evidence that the lack of a college education is linked to many negative economic outcomes, including poorer health, lower wealth, and worse marital outcomes.

This paper asks the following questions:

1. Have men fallen behind in their average attainment for these obervable characteristics? Could decreasing grades and standardized test scores explain the drop in male college attendance? Are men taking easier courses in high school than women are?

2. How does the relative importance of explanatory factors differ for men versus women? Specifically, I will focus on the categories of high school academic performance, aptitude, and family background. For example: having a single

mother may be more harmful to men than women. Taking advanced math classes in high school may be much more useful for women than men.

3. Has the effect of any of these proximate factors changed over time? For example, it is possible that women have always had an advantage in high school GPA, but that the effect of high school GPA has increased between 1980 and 1990.

3.1.1 Background

The literature on this topic primarily highlights the reversal and dramatic growth of the U.S. college gender gap over the course of the last century. During the period between 1900 and 1930, the ratio of male to female college graduates was actually at parity, as documented by Goldin (1995) and Goldin, Katz, and Kuziemko (2006). In the 1930s male enrollments began to increase relative to female enrollments, and GI Bills following WWII and the Korean War accelerated this trend. According to data from the US Census, among those aged 25-29, the M/F college graduate ratio peaked around 1952 at 2.1. At this time the college graduation rate for young men was more than double the rate for young women (13.8% versus 6.7%; see Figure 3·1). However, female college attendance began catching up in the 1950s, and college enrollment of the two genders returned to parity around 1980. Since then, the college gender gap has reversed dramatically. In 2011, 28.4% of young men in this age group had completed college, compared with a rate of 36.1% for women. About 58% of new college graduates are women.

Goldin et al. demonstrate that women's aptitude scores and high school performance in the 1950s and 1960s were much closer to men than their lagging college attendance rates would imply. Changes in the women's labor market accelerated in the 1970s (related to changes in the marriage market, birth control, and cultural norms) and expanded career opportunites for women, thereby increasing the financial returns to women of attending college. In the early 1970s, the typical female college graduate was married within a year of receiving her degree, and had only a 40.5% chance of participating in the labor force after marriage[1]. Since that time, women's median age at marriage has been increasing, from 21 years in 1970 to 26 years in 2010, as has the median age of first childbirth for college educated women. This means that women are more likely to work after college. Additionally, they are more likely to continue working after being married: the participation rate of married women was 50% in 1980 and over 60% in 2000.

In light of these dynamics, the convergence in college attendance rates for men and women that occured from the 1950s to the 1980s is not excessively surprising. What is remarkable is that women have moved beyond equality with men, and in the current graduating college class the ratio of women to men is nearly 1.4. While it is true that women without a BA are more likely to live in poverty than high school degree bearing men[2], there is no clear evidence that the lifetime economic returns of a bachelor's degree are higher for women than for men[3]. When measured as the mean wage of a college graduate over a high school graduate, the college premium is still higher for men than for women.

3.1.2 Possible explanations for the growing gap

Both the increasing college graduation rate of young women, as well as the lagging and subsequently decreasing college graduation rate for young men act to exacerbate

[1]Data from the U.S. Census. The participation rate for married men at this time was 86.1%. It has since fallen to about 75.8%.

[2]See Chiappori, Iyigun and Weiss (2009). This is due in part to the better marriage prospects for women, and the fact that women without a college degree are more likely to be single mothers. DiPrete and Buchmann (2005, 2006) point to the important role education plays as insurance against poverty, in particular for young women. Completing college reduces poverty for women through higher wages, of course, but also by diminishing the risk for single motherhood as well as the risk of divorce.

[3]However, Dougherty (2005) points out that most U.S. studies do find higher returns to years of schooling for women then for men.

the male disadvantage in the college gender gap. It is not obvious why male college rates have fallen so far behind those for women, although a few reasons have been discussed. Recent research by Dwyer et al. (2012) has suggested that men are less willing than women to incur debt in order to finish college. This is consistent with the fact that the female to male college ratio is much more extreme for low socioeconomic status students, who are more likely to rely on financing to complete college. Since the college gender gap is especially severe among poor and minority households, it could be that the expected financial rewards to college differ depending on socieconomic status. Studies by Altonji and Dunn (1996) find no difference in returns to schooling by family background, and Barrow and Rouse (2005) find that returns to schooling are relatively constant across race and ethnicity. However, these studies do not specifically measure the returns to college.

Another possible explanation for the male disadvantage is a higher rate of behavioral disorders in young men than in young women. Heckman and Rubinstein (2001) show that early childhood traits and behaviors have significant effects on economic outcomes in adulthood, specifically in attaining a high school diploma over a GED, and for wages. Bertrand and Pan (2011) point out that behavioral problems in high school boys are associated with a decreased likelihood of completing high school and subsequently a decreased likelihood of attending college. Another study by Turner (2004) suggests that people with a GED may lack the committment to complete college.

Male high school students continue to outperform females on standardized tests (particularly in math). They also have not significantly changed their class percentile rankings (see Figures 3·2 and 3·3), or levels of college preparedness measured by the number of advanced classes taken in high school, etc. However, behavioral factors may be preventing men from succeeding in college, working through some additional mechanism besides high school academic success.

Family background might also be part of the explanation. The share of all children living with only one parent rose from 20% in 1979 to 29% in 1997[4]. There is some evidence that single mothers spend less time engaging with their male children than their female children. If these differences in parenting affect college success, or if growing up with a single mother adversely affects boys more than girls, the increase in single motherhood would result in a widening of the college gender gap. McLanahan and Sandefur (1994) argue that children of single mothers perform worse on standardized tests and complete less education than children raised by two parents. Hetherington et al. (1998) and Elwood and Jencks (2004) point out that the negative outcomes associated with single mothers are hard to disentangle from the correlated effects of poverty, addiction, lack of stability, and others.

Collectively, the existing studies point to a wide range of potential explanations for the increase in the college gender gap. The contribution of this paper is to estimate the relative importance for college success of three types of explanatory factors: family background, school performance, and natural ability. I use data from two comparable samples in the National Longitudinal Survey (NLSY79 and NLSY97) and decompose the college gender gaps for each sample, as well as the change in this gap over the two periods. The rest of this paper is organized as follows. Section 3.2 explains the empirical strategy, section 3.3 describes the data, section 3.4 discusses the results, and section 3.5 concludes.

3.2 Empirical Strategy

In order to answer questions 1 and 2, regarding changes in attributes versus changes in returns, I implement an Oaxaca-Blinder decomposition of the education gaps (see Oaxaca (1973), Blinder (1973)). This decomposition separates two types of changes

[4]Data from CPS, in Ellwood and Jencks (2004).

that could account for why the gender gap increased between the 1979 and 1997 NLSY samples. Firstly, women may have disproportionately improved their average levels of attainment in their observable characteristics, such as high school rank, mathematical ability, or standardized test scores. Secondly, the relative importance attributed to these characteristics may have changed over time so that certain achievements now favor women more then men. College entrance and completion for men and women, Y_{Mi} and Y_{Fi}, can be expressed as:

$$Y_{Mi} = \beta_M X_{Mi} + \epsilon_{iM}$$

$$Y_{Fi} = \beta_F X_{Fi} + \epsilon_{iF}$$

Where X_M and X_Y are vectors of explanatory variables from three categories: academic factors, aptitude, and family background.

The gender gap can therefore be expressed as the difference between the mean values of Y for men and women:

$$\overline{Y}_M - \overline{Y}_F = \hat{\beta}_M(\overline{X}_M - \overline{X}_F) + (\hat{\beta}_M - \hat{\beta}_F)\overline{X}_F$$

Where $\bar{Y}_M$ and $\bar{Y}_F$ are the average completion rates for men and women, respectively. We can measure the difference in mean education outcomes for both the NLSY79 and NLSY97, and estimate the contribution from each of the two terms on the right hand side. Estimation of $\hat{\beta}_M(\overline{X}_M - \overline{X}_F)$ gives the explained component: the contribution of differences in attributes between men and women. The value of $(\hat{\beta}_M - \hat{\beta}_F)\overline{X}_F$ is the unexplained portion: the amount of the gap due to differences in returns to men and women.[5]

To look more closely at differences in returns for men and women, I also test for significance of interaction terms between explanatory variable and a *Female* indicator.

[5]There are two ways to weight the explained and unexplained components. See Appendix B for the alternative weighting.

From:

$$Y_{it} = \beta_{0t} + \beta_{1t}X_{it} + \beta_{2t}FEM_{it} + \beta_{3t}FEM_{it} * X_{it} + \epsilon_{it}$$

Test:

$$H_0 : \hat{\beta}_{3t} = 0$$

for t=1979, 1997.

To address question 3: with respect to the expansion of the female advantage over time (or, equivalently, the increasingly negative value of $Y_M - Y_F$), the change is due to both changes in relative male and female attributes (changes in $X_M - X_F$) as well as an adjustment in the relative importance of the explanatory variables (changes in $\beta_M - \beta_F$ over time). The decomposition of the gap expansion between time t=0 and t=T can be written as:[6]

$$\begin{aligned}
\left(\bar{Y}_{M1} - \bar{Y}_{F1}\right) - \left(\bar{Y}_{M0} - \bar{Y}_{F0}\right) = \hat{\beta}_{F0}\left[\left(\bar{X}_{M1} - \bar{X}_{F1}\right) - \left(\bar{X}_{M0} - \bar{X}_{F0}\right)\right] \\
+ \left(\hat{\beta}_{M0} - \hat{\beta}_{F0}\right)\left(\bar{X}_{M1} - \bar{X}_{M0}\right) \\
+ \left(\hat{\beta}_{F1} - \hat{\beta}_{F0}\right)\left(\bar{X}_{M1} - \bar{X}_{F1}\right) \\
+ \left[(\hat{\beta}_{M1} - \hat{\beta}_{F1}) - (\hat{\beta}_{M0} - \hat{\beta}_{F0})\right]\bar{X}_{M1}
\end{aligned}$$

This framework separates the change in the college gender gap that is due to a shifting relationship between the explanatory variables and college completion from the change that is arising because women's endowments in the explanatory variables are increasing relative to men. The contribution to the increased gap of the change in women's relative endowments is equal to the first term in the above equation, $\hat{\beta}_{F0}\left[\left(\bar{X}_{M1} - \bar{X}_{F1}\right) - \left(\bar{X}_{M0} - \bar{X}_{F0}\right)\right]$. The fourth term of the decomposition, $\left[(\hat{\beta}_{M1} - \hat{\beta}_{F1}) - (\hat{\beta}_{M0} - \hat{\beta}_{F0})\right]\bar{X}_{M1}$, is the component due to the change in relative

[6] As above, there are several different ways to decompose the increase in the gap. See Appendix B.

coefficients.[7]

We can also check whether or not coefficients have changed over time for men and/or for women by pooling together the NLSY79 (Sample 1) and NLSY97 (Sample 2) and estimating the following relationship. *SAMP2* is an indicator for the NLSY97 sample, and *FEM* is the Female dummy.

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 \mathrm{FEM}_i + \beta 3\left(FEM_i * X_i\right) + \beta_4 SAMP2_i +$$
$$\beta_5\left(SAMP2_i * X_i\right) + \beta_6\left(SAMP2_i * FEM_i\right) + \beta_7\left(SAMP2_i * FEM_i * X_i\right) + \epsilon_i$$

(a) To check if coefficients have changed for men over time, test

$$H_0 : \hat{\beta}_5 = 0$$

(b) To test for any change in coefficients for women:

$$H_0 : \hat{\beta}_5 + \hat{\beta}_7 = 0$$

3.3 Data

The data comes from the NLSY79 and NLSY97. The individuals in the sample are natural citizens, civilians in adulthood, who answered questions about their completed education at age 19 and age 25, and for whom there is household income data available for at least one year during which they were living with their parent(s) and aged 14-17.[8] Those from the NLSY79 were born between 1960 and 1964, and those from the NLSY97 were born between 1980 and 1984. Table 3.1 breaks down the summary means for men and women in the two surveys, along with gender differences and

[7]The cross terms (the second and third terms of this decomposition) change slightly depending on which decomposition is used. They account for the fact that relative attributes and relative returns to attributes are changing simultaneously. In this case, the second term is equal to the initial male premium multiplied by the absolute increase in male attributes. The third term is equal to the increased returns to females multiplied by the final male advantage in observable attributes. See Appendix B for alternative cross term forms.

[8]See Appendix A for an accounting of the sample size resulting from the data requirements.

the difference in differences. The table shows a statistically significant change in the college gender gap, but the only explanatory characteristics that have statistically significant changes in the male-female difference are the high school courses: the numbers of math, science and foreign language courses taken in high school.

The independent variables used as regressors include demographic controls (dummy variables for female, black, hispanic, birth year, and three of four U.S. regions, year of birth dummy variables), family background (parental log average income in 2000 dollars, education dummies for both parents, mother's age at first birth and at youth's birth, and a control for growing up with a single mother), academic performance in high school (a cubic in class percentile, the number of math, foreign language, and science courses completed), and aptitude (normalized percentile scores in the AFQT exam)[9]. To gauge the gender differences in the contribution of each control variable, a full set of interactions of *FEM* with each regressor is included.

The rates of college entry and college completion are heterogeneous across the income distribution. Table 3.2 summarizes rates of educational attainment across income quartiles for both the NLSY79 and the NLSY97 samples. The income quartiles are calculated using the average real household income (parental income in 2000 dollars) while the youth was between the ages of 14 and 17 and living in her parental home. If the household income was not reported for one (or more) of these years, the average is based on all available years. Percentiles are created using the baseline cross sectional weights to approximate the national income distribution.

The top panel of Table 3.2 displays the rates for the NSLY79 sample, made up

[9]Class percentile note: In the 1979 sample, class rank and class size are both available, so each individual's true class percentile can be calculated. However in the 1997 sample, only categorical data is available for class size: class size is given as up to 100, 101-220, 223-330, 331-470, and larger than 470. In order to create comparable measures of class rank across the two samples, I created a categorical class size measure for the early sample, and defined a measure of approximate class percentile for both samples as 1-(the raw class rank/upper bound of class size category). Then I used the within-sample percentile of the approximate measure as my the class rank measurement.

of individuals from birth cohorts 1960-1964. The bottom panel is for the sample from the NLSY97, born in 1980 to 1984. Following the method used by Bailey and Dynarski (2011), college entrance is defined as attempting at least 13 years of school by age 19, and the college graduation rate is defined as the share of the sample that has completed 16 years of school by age 25. For reference, the rate of high school graduation, defined as completing 12 years of school by age 19, is also included. The college entrance and college completion rates increased across income quartiles between the earlier and later sample. The slope of both these rates is steeper in the later cohort, indicating an increased relationship between income and higher education.

Table 3.3 shows the education rates for all men and all women in each respective sample, and the female to male ratio is calculated for each measure. These ratios are plotted in Figure 3·4. The data from the NLSY show similar high school graduation rates for men relative to women in the 1979 and 1997 samples.[10] The high school graduation rates are quite stable for both men and women, as is the female to male ratio of this rate. Although the female to male ratio for college entrance declined slightly between the 1979 sample and the 1997 sample, the college completion ratio increased from 1.06 to 1.48. These statistics echo the pattern described by Goldin, Katz and Kuziemko (2006).

Figure 3·4 plots the female to male college graduation ratio for each income quartile in the two samples. The female to male college ratios in the earlier sample (NLSY79) do not show a clear monotonic trend, but these ratios are decreasing in income for the more recent sample (NLSY97). In particular, quartiles 1 and 2 are

[10] Heckman and LaFontaine (2010) estimate the "true" high school graduation rate for the NLSY samples by imputing GED rates and argue that after this adjustment there is an observable gender gap in high school graduation rates. They estimate that roughly half of the increase in the college attendance gender gap can be explained by increases in males who drop out of high school, or who receive GEDs rather than high school diplomas. Nevertheless, this is not portrayed as a causal relationship: the factors that result in a GED also result in lower college graduation rates.

the most extreme at 1.61 and 1.81. Both the college entrance ratio and college completion ratio are lowest for individuals in the fourth quartile in the NLSY97. This figure suggests that income may have an impact on the recent expansion of the college gender gap.

Ability measures, course choice and high school grades are likely to be correlated with the student's gender. Additionally, it is possible that household income and household structure are not independent of gender: girls may be more likely to live with single mothers, and as a result be more likely to live in a low income household. The gender gap could be affected by male-female differences in the average quantities of these characteristics, as well as by differences in coefficients. However, certain other factors, such as parental education, should not be correlated with gender. These factors can only contribute to the gender gap if their effects on education are greater for women than for men (or vice versa).

Table 3.4 shows that in the NLSY97 sample, both poverty and having a single mother for a parent are associated with a lower college enrollment male to female ratio. In Table 3.4, the income levels of 1979 single mother households are more or less comparable to households below the median. We can see in the upper panel that male students with a single mother do not appear to be at a disadvantage compared to male students from the comparable income group. Rather, the female to male ratio for high school graduation, college entrance, and college graduation are all more extreme in the low income group than in the single mother group. However, the single mother group in the NLSY97 has higher male to femle education ratio than the comparison group (households from the lower three income quartiles[11]). In particular, the college entrance ratio for 1997 single mom households is 1.37, compared to the low income

[11]In the NLSY 1979, average income for the single mother households was \$29,502, and mean income for families below the median was \$31,541. In the 1997 sample, mean income in single mother families was 35,658 in 2000 dollars, and the mean for families below the 75th percentile was \$35,467. All monetary amounts are in 2000 dollars.

ratio of 1.35. The 1997 single mom college graduation ratio is 1.71, considerably higher than the low income ratio, 1.57.

3.4 Empirical Results

Table 3.5 displays the decomposition of the 1979 and 1997 gaps into attributes and coefficients. In the 1979 sample, we observe a significant gender gap in College Entrance: men are 8.8 percentage points below women. None of this gap is explained by a female advantage in characteristics; it is all unexplained, or due to gender differences in returns to the characteristics on college entrance. The gap for College Entrance in the 1997 sample is wider (men are at at 12.2 point disadvantage). However, now there is a portion of this gap due to higher attributes in women than men. The share of the 12.2 point gap eplained by the female characteristics is 40.2%. For College Graduation, the 1979 gap is close to zero (men have a college graduation rate that is 1.6 percentage points higher than women). The observable characteristics actually predict a slight advantage to women of 2.5 percentage points. As a result, a male advantage of 4.06 points is attributed to the gender difference in coefficients. However, the college graduation gap is 12.9 percentage points in the 1997 sample. Of the 12.9 points, 6.6 points are due to differences in characteristics, and 6.4 points are due differences in returns that favor women. This is in sharp contrast to the 1979 sample, in which the differences in returns favored men.

Table 3.6 addresses question 3: How much of the *increase* in the college gender gap is due to observable characteristics? Terms 1-4 reflect the terms of the gap expansion decomposition. Term 1 indicates that 6.8 of the 13 point gap (46.7%) is due to the change over time in the gender gap in returns, $\beta_M - \beta_F$. Term 4 indicates that 5.7 of the 13 point gap (44%) is due to the change over time in the gender gap in characteristics, $X_M - X_F$.

The table also breaks down the explained and unexplained components into four groups of variables: family background, school performance, ability, and group fixed effects. Family background includes the parents' socioeconomic factors, race, and household structure (having a single mother). Family background is a negligible portion of the explained component, but it dominates the unexplained portion. This means that the effect of family background is disproportionately hurting the college graduation rates of men. School performance (class rank and high school courses) is the majority (2/3) of the explained increase in the gender gap. Notice that the school performance portion of the unexplained term actually acts against the female advantage. If the returns to school performance with respect to college were equal for men and women, all else equal, the college gender gap would expand even further.

The effect of ability (measured as the normalized AFQT score) is very tiny in the unexplained component (i.e. relative effects of ability are not driving the gender gap), but about 30% of the explained component. This result is somewhat ambiguous. The direct interpretation is that women have increased their relative AFQT scores relative to men (shown in the last row of Table 3.1), and this has contributed to widening the college gap (about 1.75 percentage points of the total 14.5 percentage point increase). However, since the AFQT is supposed to reflect natural ability, changes in the relative scores of men and women are more likely to reflect changes in the gender bias of the testing methodology. It is possible these changes are correlated with new gender biases that also affect college success, but that conclusion is beyond the scope of this study.

Table 3.7 shows the the F-test results for joint significance of the set of controls interacted with the female indicator.[12] In both samples, we see that there is no evidence of a significant gender difference in the coefficients with respect to college entrance. However, there is evidence that coefficients between men and women differ

[12]The full regression results for all the F-tests are displayed in Appendix C.

with respect to college graduation. This is an interesting result because it suggests that men and women have similar intentions or expectations when they enroll in college, but for some reason the men have a more difficult time completing college.

Table 3.8 tests the change in coefficients over time for men and women. From the top half of the panel, the F-test indicates stable coefficients over time for men, but the coefficients have changed significantly for women with respect to both high school graduation and college graduation. This means that the unexplained portion of the increased college gap (Term 4 in Table 3.5) is coming from changes in the female parameters rather than the male parameters.

3.5 Conclusion

The decomposition results in this study show that female characteristics do predict some advantage for women in college graduation rates, and even predicted a small advantage in the earlier sample (NLSY79). However, the observable characteristics do not explain the full gap in the NLSY97 sample, or the increased size of the gap between the 1979 and 1997 samples. In the NLSY97, there is a substantial female advantage in college graduation. Roughly half of the observed college graduation gender gap in the NLSY97 is due to advantages in women's characteristics, and roughly half is "unexplained" (due to gender differences in the coefficients). With respect to the increase in the gender gap, 40% can be attributed to changes in the relative endowments of women, and 47% is due to changes in relative returns to these endowments.

Overall there is some evidence that poverty or household structure affects adolescent boys more than girls, and that this differential effect has contributed to the growth of the college gender gap. By breaking down the explained and unexplained portion of the increased gender gap, the results indicate that the male coefficient effect of family background is huge in comparison to all the other variables.

The results from this study are clearly not enough to conclude a causal relationships between family background and college success. There are certainly cultural or other unobserval factors that impact both family background and college graduation. However, these findings do have useful public policy implications. The fact that family background is potentially a strong predictor this gap means that policies aimed at helping men succeed in college would be the most effective if they targeted men from lower income, lower educated, or single mother households. Secondly, these results show that policies aimed only at encouraging men to enroll in college will not address the additional imbalance that occurs between enrollment and graduation. For example, in addition to increasing access to college financing, policy makers should encourage more work-study opportunities and make it easier to refinance student loans.

Bailey, Martha J., and Susan M. Dynarski. 2011. “Gains and Gaps: Changing Inequality in US College Entry and Completion.” NBER Working Paper no. 17633.

Barrow, Lisa, and Cecilia Elena Rouse. 2005. “Do Returns to Schooling Differ by Race and Ethnicity?” *The American Economic Review* 95(2): 83-87.

Bertrand, Marianne and Jessica Pan. 2011. “The Trouble with Boys: Social Influences and the Gender Gap in Disruptive Behavior.” NBER Working Paper no. 17541.

Buchmann, Claudia, and Thomas A. DiPrete. 2005. “The Growing Female Advantage in College Completion: The Role of Family Background and Academic Achievement.” *American Sociological Review* 71(4):5 15-541.

Cameron, Stephen V., and James J. Heckman. 2001. “The Dynamics of Educational Attainment for Black, Hispanic, and White Males.” *Journal of Political Economy* 109(3): 455-499.

Card, David, and Thomas Lemieux. 2001. “Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis.” *The Quarterly Journal of Economics* 116(2): 705-746.

Chiappori, Pierre-Andre, Murat Iyigun, and Yoram Weiss. 2009. “Investment in Schooling and the Marriage Market.” *The American Economic Review* 99(5): 1689-1713.

DiPrete, Thomas A., and Claudia Buchmann. 2006. “Gender-Specific Trends in the Value of Education and the Emerging Gender Gap in College Completion.” *Demography* 43(1): 1-24.

Dougherty, Christopher. 2005. “Why are the Returns to Schooling Higher for Women than for Men?” *Journal of Human Resources* 40(4): 969-988.

Dwyer, Rachel E., Randy Hodson, and Laura McCloud. 2012. “Gender, Debt, and Dropping Out of College.” *Gender & Society* doi:10.1177/0891243212464906.

Elwood, D. T., and Christopher Jencks. 2004.“The Uneven Spread of Single-Parent Families: What Do We Know? Where Do We Look for Answers?” *Social Inequality,* edited by K. M. Neckerman, 3-78. New York: Russell Sage Foundation.

Goldin, Claudia. 1995. “Career and Family: College Women Look to the Past.” NBER Working Paper no. 5188.

Goldin, Claudia, Lawrence F. Katz, and Ilyana Kuziemko. 2006. "The Homecoming of American College Women: The Reversal of the College Gender Gap." NBER Working Paper, no. 12139.

Heckman, James J. and Paul A. LaFontaine. 2010. "The American High School Graduation Rate: Trends and Levels." *The Review of Economics and Statistics* 92(2): 244-262.

Heckman, James J. and Yona Rubinstein. 2001. "The Importance of Noncognitive Skills: Lessons from the GED Testing Program." *The American Economic Review* 91(2): 145-149.

Hetherington, E. Mavis, Margaret Bridges, and Glendessa M. Insabella. 1998. "What Matters? What Does Not?" *American Psychologist* 53(2): 167-184.

Jacob, Brian A. 2002. "Where the Boys Aren't: Non-cognitive Skills, Returns to School and the Gender Gap in Higher Education." *Economics of Education Review* 21(6): 589-598.

Kearney, Melissa Schettini, and Phillip B. Levine. 2011. "Income Inequality and Early Non-Marital Childbearing: An Economic Exploration of the 'Culture of Despair'." NBER Working Paper no. 17157.

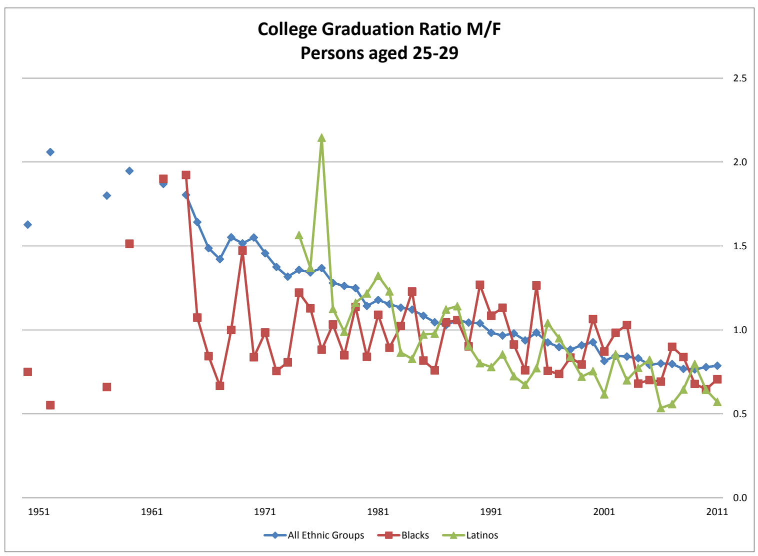
Lam, David and Robert F. Schoeni. 1993. "Effects of Family Background on Earnings and Returns to Schooling: Evidence from Brazil." *Journal of Political Economy* 101(4): 710-740.

Lang, Kevin and Michael Manove. 2011. "Education and Labor Market Discrimination." *American Economic Review* 101(4): 1467-96.

Olivetti, Claudia and Barbara Petrongolo. 2008. "Unequal Pay or Unequal Employment? A Cross-Country Analysis of Gender Gaps." *Journal of Labor Economics* 26(4): 621-654.

Turner, Sarah. 2007. "Going to College and Finishing College. Explaining Different Educational Outcomes." In *College Choices: The Economics of Where to Go, When to Go, and How to Pay for It,* edited by Caroline Hoxby, 13-62. Chicago: University of Chicago Press.

Figure 3·1: Decreasing M/F BA Ratio



Source: 1947, and 1952 to 2002 March Current Population Survey, 2003 to 2011 Annual Social and Economic Supplement to the Current Population Survey (noninstitutionalized population, excluding members of the Armed Forces (living in barracks).

Figure 3·2: NLSY79: Gender Composition of Class Rank Quartiles

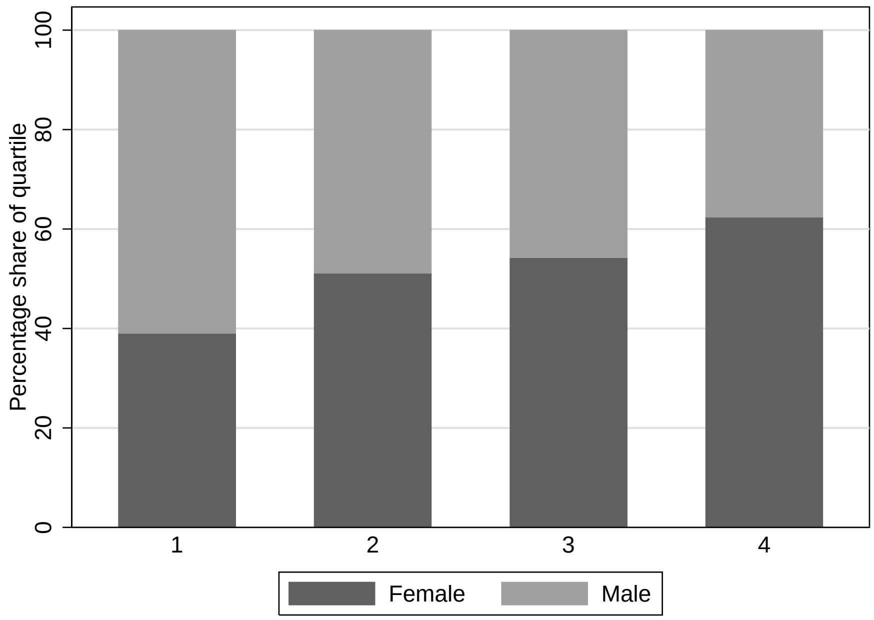


Figure 3·3: NLSY97: Gender Composition of Class Rank Quartiles

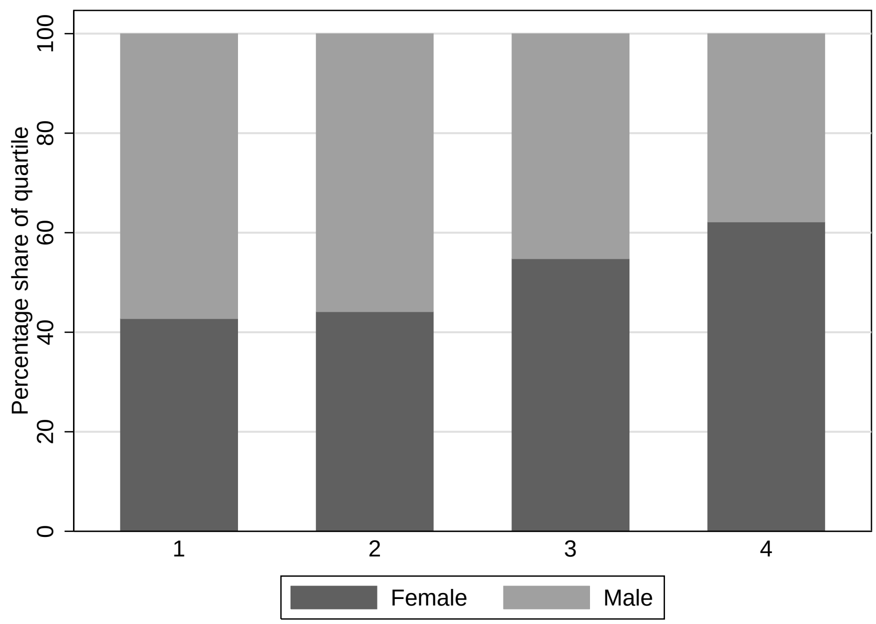


Figure 3·4: Female to Male Ratio by Income

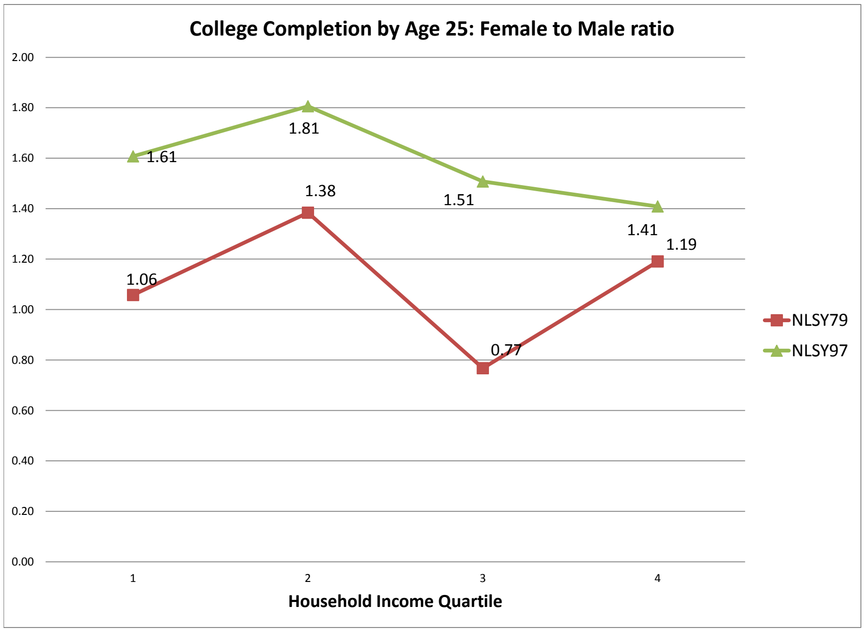


Table 3.1: Summary of Differences: Means

	1979			1997			
	Women	**Men**	**W-M**	**Women**	**Men**	**W-M**	**△W-M**
HS Grad 19	0.8503	0.7733	0.0770***	0.8207029	0.7623556	0.0583***	-0.0186
			(0.0137)			(0.0114)	(0.0174)
College Entrance 19	0.3863	0.2952	0.0912***	0.5750415	0.4573462	0.118***	0.0265
			(0.0166)			(0.0139)	(0.0212)
BA grad 25	0.1952	0.1847	0.0104	0.3321611	0.224132	0.108***	0.0976***
			(0.0138)			(0.0125)	(0.0184)
Parental net income	54,209	55,330	-1,120	58,443.94	59,224.11	-780.2	340.1
			(1,105)			(1,395)	(1,825)
mom HS	0.6424	0.6684	-0.0259	0.8141841	0.8203971	-0.00621	0.0197
			(0.0167)			(0.0108)	(0.0190)
mom BA	0.0967	0.0909	0.00585	0.2208882	0.2358321	-0.0149	-0.0208
			(0.0102)			(0.0118)	(0.0158)
dad HS	0.6061	0.6187	-0.0126	0.7368904	0.7558206	-0.0189	-0.00637
			(0.0171)			(0.0122)	(0.0203)
dad BA	0.1558	0.1646	-0.00875	0.2259308	0.2337458	-0.00781	0.000932
			(0.0129)			(0.0118)	(0.0173)
mom age 1st birth	21.7831	21.9301	-0.147	23.26407	23.31295	-0.0489	0.0982
			(0.169)			(0.136)	(0.211)
mom age youth's birth	25.8924	25.9305	-0.0381	25.41374	25.75927	-0.346**	-0.307
			(0.234)			(0.148)	(0.262)
Single mom	0.1384	0.1309	0.00750	0.3999897	0.364958	0.0350**	0.0275
			(0.0120)			(0.0136)	(0.0184)
Class pctile	0.5478	0.4494	0.0984***	0.5452445	0.4535146	0.0917***	-0.00668
			(0.0129)			(0.0110)	(0.0167)
# math	1.9585	2.2065	-0.248***	4.510813	4.345821	0.165*	0.413***
			(0.0511)			(0.0921)	(0.111)
# foreign language	0.7842	0.5806	0.204***	2.395279	1.766844	0.628***	0.425***
			(0.0375)			(0.0659)	(0.0800)
# science	1.7218	1.8237	-0.102**	3.945449	3.793721	0.152*	0.254**
			(0.0495)			(0.0845)	(0.103)
AFQT age pctile	50.6300	49.8994	0.731	53.59627	51.92472	1.672*	0.941
			(1.037)			(0.881)	(1.346)

Standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

Table 3.2: Education by Parental Income Quartile

NLSY79: Birth Cohorts 1960-1964

Quartile	HS Graduate	College Entrance	BA Graduate
1	64.26%	19.91%	6.63%
2	80.70%	27.17%	14.43%
3	87.12%	36.65%	18.53%
4	92.01%	53.96%	38.45%

NLSY97: Birth Cohorts 1980-1984

Quartile	HS Graduate	College Entrance	BA Graduate
1	59.72%	26.97%	9.41%
2	77.75%	44.56%	20.01%
3	87.91%	61.89%	34.49%
4	92.58%	75.03%	48.99%

Source: NLSY79 and NLSY97. Sample includes all natural citizens who responded to questions about their completed education at age 19 and age 25. High School Graduates are those whocompleted at least 12 grades of school by age 19. College entrance is defined as attempting at least 13 years of school by age 19. The BA rate is the share of the sample completing at least 16 years of school by age 25.

Table 3.3: Education by Gender

NLSY79: Birth Cohorts 1960-1964

	HS Graduate	College Entrance	BA Graduate
Men	77.33%	29.52%	18.47%
Women	85.03%	38.63%	19.52%
F/M Ratio	1.10	1.31	1.06

NLSY97: Birth Cohorts 1980-1984

	HS Graduate	College Entrance	BA Graduate
Men	76.24%	45.73%	22.41%
Women	82.07%	57.50%	33.22%
F/M Ratio	1.08	1.26	1.48

Source: NLSY79 and NLSY97. See Table 1.

Table 3.4: Education by Household Structure and Gender

NLSY79: Birth Cohorts 1960-1964

	Single Mom	HS Graduate	College Entrance	BA Graduate
Men	0	78.8%	30.3%	19.1%
Women	0	86.9%	39.6%	20.9%
F/M ratio	0	1.10	1.31	1.09
Men	1	67.7%	24.5%	14.4%
Women	1	73.1%	32.7%	11.0%
F/M ratio	1	1.08	1.33	0.77
Income below median		HS Graduate	College Entrance	BA Graduate
Men		69.0%	17.7%	9.6%
Women		77.5%	30.4%	12.1%
F/M ratio		1.12	1.72	1.26

NLSY79: Birth Cohorts 1980-1984

	Single Mom	HS Graduate	College Entrance	BA Graduate
Men	0	84.2%	54.1%	29.1%
Women	0	88.9%	67.3%	43.1%
F/M ratio	0	1.06	1.24	1.48
Men	1	62.4%	31.2%	10.8%
Women	1	71.8%	42.7%	18.4%
F/M ratio	1	1.15	1.37	1.71
	Income below 75th Pct.	HS Graduate	College Entrance	BA Graduate
Men		71.7%	37.8%	16.5%
Women		78.2%	50.8%	25.9%
F/M ratio		1.09	1.35	1.57

Table 3.5: Decomposition I of College Gender Gap

NLSY79

	HS Grad	College Entrance	College Grad
Group 1 (Males)	0.945***	0.397***	0.279***
	(0.00812)	(0.0174)	(0.0159)
Group 2 (Females)	0.967***	0.485***	0.263***
	(0.00596)	(0.0165)	(0.0146)
Difference	-0.0219**	-0.0880***	0.0160
	(0.0101)	(0.0240)	(0.0216)
Explained	0.000802	0.00211	-0.0246
	(0.00668)	(0.0165)	(0.0160)
Unexplained	-0.0227**	-0.0901***	0.0406**
	(0.0115)	(0.0237)	(0.0201)
Obs.	1,734	1,734	1,734

NLSY97

	HS Grad age 19	College Entrance age 19	College Grad age 25
Group 1 (Males)	0.924***	0.603***	0.307***
	(0.00816)	(0.0150)	(0.0142)
Group (Females)	0.940***	0.725***	0.436***
	(0.00696)	(0.0131)	(0.0146)
Difference	-0.0166	-0.122***	-0.129***
	(0.0107)	(0.0200)	(0.0203)
Explained	-0.00469	-0.0530***	-0.0611***
	(0.00610)	(0.0134)	(0.0137)
Unexplained	-0.0119	-0.0690***	-0.0683***
	(0.0108)	(0.0183)	(0.0172)
Obs.	2,245	2,245	2,245

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Decomposition of Change in College Gender Gap

College Graduate by age 25		
	NLSY 1979	NLSY 1979
Group 1 (Males)	0.2785	0.3066
Group 2 (Females)	0.2625	0.4361
Difference (M-F)	0.0160	-0.1295
$\triangle$ Difference		-0.1454
Explained: $\hat{\beta}_{F0}\left[\left(\bar{X}_{M1}-\bar{X}_{F1}\right)-\left(\bar{X}_{M0}-\bar{X}_{F0}\right)\right]$		-0.05713***
		(0.00851)
Term 2: $\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right)\left(\bar{X}_{M1}-\bar{X}_{M0}\right)$		-0.0140
		(0.06441)
Term 3: $\left(\bar{X}_{M1}-\bar{X}_{F1}\right)\left(\hat{\beta}_{F1}-\hat{\beta}_{F0}\right)$		-0.0067
		(0.01255)
Unexplained: $\bar{X}_{M1}\left[(\hat{\beta}_{M1}-\hat{\beta}_{F1})-(\hat{\beta}_{M0}-\hat{\beta}_{F0})\right]$		-0.0568
		(0.07117)
Breakdown of Explained		
Family Background		-0.00327
School Performance		-0.03783
Ability (AFQT)		-0.01753
Group fixed effects		0.00150
Breakdown of Unexplained		
Family Background		-0.63124
School Performance		0.05772
Ability (AFQT)		-0.00252
Group fixed effects		0.5192

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.7: Comparison of Male and Female Coefficients

Test for Male-Female difference in NLSY79			
	HS Grad	College Entrance	College Grad
F-test(20, 1692)	1.71	0.92	2.20
Prob > F	0.0262	0.5570	0.0017
Obs.	1,734	1,734	1,734
Test for Male-Female difference in NLSY97			
	HS Grad	College Entrance	College Grad
F-test(20, 2202)	1.92	1.98	1.34
Prob > F	0.0084	0.0058	0.1417
Obs.	2,242	2,242	2,242

Table 3.8: Comparison of NLSY79 and NLSY97

Have coefficients changed over time for males?			
	HS Grad	College Entrance	College Grad
F-test(20, 3896)	0.0955	0.0379	0.0445
Prob > F	1.0	1.0	1.0
Have coefficients changed over time for females?			
	HS Grad	College Entrance	College Grad
F-test(39, 3896)	2.057	0.980	1.375
Prob > F	0.000128	0.506	0.0609
Obs.	3,979	3,979	3,979

Appendix A: Data Appendix

Table A-1 lists the required restrictions for the dataset, and accounts for the sample size used in the empirical analysis.

Table A-1: Sample Size Tabulation

	NLSY79	**Men 79**	**Women 79**	**NLSY97**	**Men 97**	**Women 97**
Full sample	12,686	6,403	6,283	8,984	4,599	4,385
sample weight >0	5,710	2,800	2,910	8,984	4,599	4,385
Parental income*	4,453	2,287	2,166	7,138	3,637	3,501
Birth year**	3,404	1,738	2,666	7,138	3,637	3,501
Education at ages 19 and 25 known	3,380	1,728	1,652	6,035	3,016	3,019
US citizen	3,240	1,655	1,585	5,084	2,545	2,539
Class rank percentile available	1,948	929	1,019	2,707	1,310	1,397
Mother's age at first/youth's birth	1,777	827	950	2,567	1,237	1,330
AFQT available	1,734	808	926	2,257	1,076	1,181
Log income available***	1,734	808	926	2,245	1,070	1,175

*HH income available for at least one year while R living in parental home

**Birth year during 1960-64 (NLSY79), or 1980-84 (NLSY97)

***Need family income >0

Appendix B: Alternative Decompositions

For the basic decomposition of the college gender gap, Basic I refers to:

$$\bar{Y}_{Mt} - \bar{Y}_{Ft} = \hat{\beta}_{Mt}\left(\bar{X}_{Mt} - \bar{X}_{Ft}\right) + \bar{X}_{Ft}\left(\hat{\beta}_{Mt} - \hat{\beta}_{Ft}\right)$$

The alternative weighting of the explained and unexplained components is the following, referred to as Basic II.

$$\bar{Y}_{Mt} - \bar{Y}_{Ft} = \hat{\beta}_{Ft}\left(\bar{X}_{Mt} - \bar{X}_{Ft}\right) + \bar{X}_{Mt}\left(\hat{\beta}_{Mt} - \hat{\beta}_{Ft}\right)$$

The estimates for the Basic II are given in Table B-1. A comparison of the upper panels of Table 3.5 and B-1 show that the choice of weights can change the results quite a bit. In particular, Table refoaxaca2 indicates that in the NLSY79, both characteristics and coefficients act to increase the male advantage. However, these estimates are not statistically significant. The Basic II weighting did not much alter the results for college graduation in the NLSY97 panel. The lower panel of Table B-1 shows a fairly even contribution of characteristics and coefficients to the female advantage in college graduation. The share of the gender gap attributed to coefficients is slightly greater when using Basic II than Basic I.

Similarly, the decomposition of the difference in differences can also be weighted in various ways. The starting point for the decomposition uses either Basic I or Basic II for the terms $\left(\bar{Y}_{M1} - \bar{Y}_{F1}\right)$ and $\left(\bar{Y}_{M0} - \bar{Y}_{F0}\right)$. Then, the basic structure of the decomposition depends on which intermediate terms are grouped together. The basic structure will be either: Structure I:

$$\begin{aligned}\left(\bar{Y}_{M1}-\bar{Y}_{F1}\right)-\left(\bar{Y}_{M0}-\bar{Y}_{F0}\right) &= A\left[\left(\bar{X}_{M1}-\bar{X}_{F1}\right)-\left(\bar{X}_{M0}-\bar{X}_{F0}\right)\right]\\ &+ B\left(\bar{X}_{M1}-\bar{X}_{F1}\right)\\ &+ C\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right)\\ &+ D\left[\left(\hat{\beta}_{M1}-\hat{\beta}_{F1}\right)-\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right)\right]\end{aligned}$$

or Structure II:

$$\begin{aligned}\left(\bar{Y}_{M1}-\bar{Y}_{F1}\right)-\left(\bar{Y}_{M0}-\bar{Y}_{F0}\right) &= A\left[\left(\bar{X}_{M1}-\bar{X}_{F1}\right)-\left(\bar{X}_{M0}-\bar{X}_{F0}\right)\right]\\ &+ B\left(\bar{X}_{M0}-\bar{X}_{F0}\right)\\ &+ C\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right)\\ &+ D\left[\left(\hat{\beta}_{M1}-\hat{\beta}_{F1}\right)-\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right)\right]\end{aligned}$$

Using Structure I and Basic I, the decomposition is written as:

1.

$$\begin{aligned}\left(\bar{Y}_{M1}-\bar{Y}_{F1}\right)-\left(\bar{Y}_{M0}-\bar{Y}_{F0}\right) &= \hat{\beta}_{M0}\left[\left(\bar{X}_{M1}-\bar{X}_{F1}\right)-\left(\bar{X}_{M0}-\bar{X}_{F0}\right)\right]\\ &+ \left(\hat{\beta}_{M1}-\hat{\beta}_{F0}\right)\left(\bar{X}_{M0}-\bar{X}_{F0}\right)\\ &+ \left(\bar{X}_{F1}-\bar{X}_{M0}\right)\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right)\\ &+ \bar{X}_{F1}\left[\left(\hat{\beta}_{M1}-\hat{\beta}_{F1}\right)-\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right)\right]\end{aligned}$$

Using Structure I and Basic II:

2.

$$\begin{aligned}\left(\bar{Y}_{M1}-\bar{Y}_{F1}\right)-\left(\bar{Y}_{M0}-\bar{Y}_{F0}\right) &= \hat{\beta}_{F1}\left[\left(\bar{X}_{M1}-\bar{X}_{F1}\right)-\left(\bar{X}_{M0}-\bar{X}_{F0}\right)\right] \\ &+ \left(\hat{\beta}_{F1}-\hat{\beta}_{M0}\right)\left(\bar{X}_{M0}-\bar{X}_{F0}\right) \\ &+ \left(\bar{X}_{M1}-\bar{X}_{F0}\right)\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right) \\ &+ \bar{X}_{M1}\left[\left(\hat{\beta}_{M1}-\hat{\beta}_{F1}\right)-\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right)\right]\end{aligned}$$

Using Structure II and Basic II:

3.

$$\begin{aligned}\left(\bar{Y}_{M1}-\bar{Y}_{F1}\right)-\left(\bar{Y}_{M0}-\bar{Y}_{F0}\right) &= \hat{\beta}_{M1}\left[\left(\bar{X}_{M1}-\bar{X}_{F1}\right)-\left(\bar{X}_{M0}-\bar{X}_{F0}\right)\right] \\ &+ \left(\hat{\beta}_{M1}-\hat{\beta}_{M0}\right)\left(\bar{X}_{M0}-\bar{X}_{F0}\right) \\ &+ \left(\bar{X}_{F1}-\bar{X}_{F0}\right)\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right) \\ &+ \bar{X}_{F1}\left[\left(\hat{\beta}_{M1}-\hat{\beta}_{F1}\right)-\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right)\right]\end{aligned}$$

Using Structure II and Basic II:

4.

$$\begin{aligned}\left(\bar{Y}_{M1}-\bar{Y}_{F1}\right)-\left(\bar{Y}_{M0}-\bar{Y}_{F0}\right) &= \hat{\beta}_{F1}\left[\left(\bar{X}_{M1}-\bar{X}_{F1}\right)-\left(\bar{X}_{M0}-\bar{X}_{F0}\right)\right] \\ &+ \left(\hat{\beta}_{F1}-\hat{\beta}_{F0}\right)\left(\bar{X}_{M0}-\bar{X}_{F0}\right) \\ &+ \left(\bar{X}_{M1}-\bar{X}_{M0}\right)\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right) \\ &+ \bar{X}_{M1}\left[\left(\hat{\beta}_{M1}-\hat{\beta}_{F1}\right)-\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right)\right]\end{aligned}$$

Notice that we could write eight additional versions of the decomposition by using Basic I and Basic II together, but the benefit of this method is not clear. In every possible decomposition, the explained term is always

$$A\left[\left(\bar{X}_{M1}-\bar{X}_{F1}\right)-\left(\bar{X}_{M0}-\bar{X}_{F0}\right)\right]$$

and the unexplained term is always

$$D\left[\left(\hat{\beta}_{M1}-\hat{\beta}_{F1}\right)-\left(\hat{\beta}_{M0}-\hat{\beta}_{F0}\right)\right].$$

The cross terms in each expression (weighted by B and C) are for accounting purposes, and represent the fact that attributes and returns are changing simultaneously for both groups.

Table B-1: Decomposition II of College Gender Gap

NLSY79

	HS Grad age 19	College Entrance age 19	College Grad age 25
Group 1 (Males)	0.945***	0.397***	0.279***
	(0.00812)	(0.0174)	(0.0159)
Group 2 (Females)	0.967***	0.485***	0.263***
	(0.00596)	(0.0165)	(0.0146)
Difference	-0.0219**	-0.0880***	0.0160
	(0.0101)	(0.0240)	(0.0216)
Explained	-0.00391	0.0195	0.00312
	(0.00493)	(0.0167)	(0.0156)
Unexplained	-0.0180*	-0.107***	0.0129
	(0.0109)	(0.0237)	(0.0199)
Obs.	1,734	1,734	1,734

NLSY97

	HS Grad age 19	College Entrance age 19	College Grad age 25
Group 1 (Males)	0.924***	0.603***	0.307***
	(0.00816)	(0.0150)	(0.0142)
Group (Females)	0.940***	0.725***	0.436***
	(0.00696)	(0.0131)	(0.0146)
Difference	-0.0166	-0.122***	-0.129***
	(0.0107)	(0.0200)	(0.0203)
Explained	-0.00942*	-0.0532***	-0.0567***
	(0.0108)	(0.0202)	(0.0186)
Unexplained	-0.00719	-0.0688***	-0.0728***
	(0.0107)	(0.0180)	(0.0174)
Obs.	2,245	2,245	2,245

Appendix C: Additional regressions

The set of Tables C-1 to C-6 show the results for OLS regressions of the full set of explanatory variables on high school completion, college entrance, and college completion. These regressions check for gender differences in the effects of individual characteristics by comparing the regression coefficients for men and women. The three columns in each of the Tables C-1 to C-6 represent the coefficients for (1) only women, (2) only men, (3) the female interaction term coefficients from the full sample.

Table C-1: High School Gender Gap in Cohort 1 NLSY79

NLSY79 HSGRAD

VARIABLES	(1) F	(2) M	(3) $\beta_F - \beta_M$
black	0.00536	-0.0165	0.0219
	(0.0225)	(0.0309)	(0.0375)
hispanic	-0.0641**	0.0199	-0.0840*
	(0.0293)	(0.0402)	(0.0488)
Parents' log income	0.0130	0.00665	0.00637
	(0.0124)	(0.0168)	(0.0205)
classpctile	0.189	1.076***	-0.887***
	(0.225)	(0.253)	(0.340)
classpct_2	-0.101	-2.113***	2.012***
	(0.497)	(0.603)	(0.778)
classpct_3	-0.00817	1.222***	-1.231**
	(0.317)	(0.406)	(0.510)
# of HS math courses	0.00214	0.00562	-0.00348
	(0.00585)	(0.00672)	(0.00893)
# of HS for. language courses	0.00347	0.00509	-0.00162
	(0.00603)	(0.00829)	(0.0101)
# of HS science courses	0.00149	-0.000242	0.00173
	(0.00534)	(0.00649)	(0.00837)
AFQT	0.00395	0.0369***	-0.0329**
	(0.0101)	(0.0116)	(0.0154)
mom_HS	0.00414	0.0563**	-0.0522**
	(0.0156)	(0.0219)	(0.0264)
mom_BA	-0.0121	-0.0419	0.0299
	(0.0212)	(0.0277)	(0.0344)
dad_HS	0.0219	-0.0332	0.0551**
	(0.0145)	(0.0206)	(0.0247)
dad_BA	-0.000306	-0.0187	0.0183
	(0.0183)	(0.0223)	(0.0287)
Mother's Age FB	3.35e-05	0.000236	-0.000202
	(0.00173)	(0.00242)	(0.00292)
Mother's Age YB	-0.000935	0.00127	-0.00221
	(0.00120)	(0.00171)	(0.00204)
singmom	-0.0325	0.0210	-0.0535
	(0.0214)	(0.0279)	(0.0347)
female			0.0931
			(0.230)
Constant	0.778***	0.684***	0.684***
	(0.141)	(0.186)	(0.167)
Observations	926	808	1,734
Adjusted R^2	0.038	0.087	0.069

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Region and year dummy coefficients not shown.

Table C-2: College Entrance Gender Gap in Cohort 1 NLSY79

NLSY79 ENTER

VARIABLES	(1) F	(2) M	(3) $\beta_F - \beta_M$
black	0.164***	0.234***	-0.0699
	(0.0556)	(0.0599)	(0.0818)
hispanic	0.0949	0.0539	0.0411
	(0.0725)	(0.0780)	(0.107)
Parents' log income	-0.0289	0.0456	-0.0744*
	(0.0306)	(0.0327)	(0.0448)
classpctile	0.231	0.161	0.0701
	(0.557)	(0.491)	(0.743)
classpct_2	-0.558	0.130	-0.688
	(1.230)	(1.171)	(1.699)
classpct_3	0.505	-0.0688	0.573
	(0.784)	(0.789)	(1.113)
# of HS math courses	0.0263*	0.0148	0.0115
	(0.0145)	(0.0130)	(0.0195)
# of HS for. language courses	0.0334**	0.0400**	-0.00663
	(0.0149)	(0.0161)	(0.0220)
# of HS science courses	0.0115	-0.00329	0.0148
	(0.0132)	(0.0126)	(0.0183)
AFQT	0.144***	0.128***	0.0161
	(0.0249)	(0.0225)	(0.0335)
mom_HS	0.158***	0.0822*	0.0760
	(0.0387)	(0.0425)	(0.0575)
mom_BA	0.0595	0.0369	0.0226
	(0.0524)	(0.0538)	(0.0751)
dad_HS	0.0535	0.0500	0.00353
	(0.0359)	(0.0400)	(0.0538)
dad_BA	0.0844*	0.0944**	-0.0100
	(0.0453)	(0.0433)	(0.0627)
Mother's Age FB	0.00482	0.0119**	-0.00703
	(0.00429)	(0.00470)	(0.00637)
Mother's Age YB	0.00259	-0.00584*	0.00843*
	(0.00297)	(0.00331)	(0.00446)
singmom	0.0184	-0.000916	0.0194
	(0.0530)	(0.0541)	(0.0758)
female			0.649
			(0.503)
Constant	0.158	-0.490	-0.490
	(0.348)	(0.362)	(0.366)
Observations	926	808	1,734
Adjusted R^2	0.239	0.251	0.250

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Region and year dummy coefficients not shown.

Table C-3: BA Gender Gap in Cohort 1 NLSY79

NLSY79 BAGRAD

VARIABLES	(1) F	(2) M	(3) $\beta_F - \beta_M$
black	0.00821	0.0661	-0.0579
	(0.0454)	(0.0505)	(0.0678)
hispanic	0.00950	-0.0695	0.0790
	(0.0591)	(0.0657)	(0.0883)
Parents' log income	-0.00459	0.0524*	-0.0569
	(0.0250)	(0.0276)	(0.0372)
classpctile	0.511	-0.168	0.679
	(0.455)	(0.414)	(0.615)
classpct_2	-1.582	0.0281	-1.610
	(1.004)	(0.988)	(1.408)
classpct_3	1.499**	0.593	0.907
	(0.640)	(0.665)	(0.923)
# of HS math courses	0.0365***	0.0186*	0.0179
	(0.0118)	(0.0110)	(0.0162)
# of HS for. language courses	0.0331***	0.0719***	-0.0388**
	(0.0122)	(0.0136)	(0.0182)
# of HS science courses	0.00913	0.00758	0.00155
	(0.0108)	(0.0106)	(0.0151)
AFQT	0.0831***	0.0819***	0.00119
	(0.0203)	(0.0189)	(0.0278)
mom_HS	0.0780**	0.0862**	-0.00820
	(0.0316)	(0.0358)	(0.0477)
mom_BA	0.120***	0.00895	0.111*
	(0.0427)	(0.0454)	(0.0623)
dad_HS	0.0225	0.00576	0.0167
	(0.0293)	(0.0337)	(0.0446)
dad_BA	0.0844**	0.0917**	-0.00727
	(0.0370)	(0.0365)	(0.0520)
Mother's Age FB	0.00927***	0.00668*	0.00259
	(0.00350)	(0.00396)	(0.00528)
Mother's Age YB	0.00232	-0.00120	0.00352
	(0.00243)	(0.00279)	(0.00369)
singmom	0.00397	0.0219	-0.0179
	(0.0433)	(0.0456)	(0.0628)
female			0.440
			(0.416)
Constant	-0.373	-0.814***	-0.814***
	(0.284)	(0.305)	(0.303)
Observations	926	808	1,734
Adjusted R^2	0.346	0.365	0.355

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Region and year dummy coefficients not shown.

Table C-4: High School Gender Gap in Cohort 2 NLSY97

	NLSY97 HSGRAD		
	(1)	(2)	(3)
VARIABLES	F	M	$\beta_F - \beta_M$
black	0.0206	-0.00164	0.0223
	(0.0225)	(0.0282)	(0.0358)
hispanic	-0.0244	-0.0582*	0.0338
	(0.0270)	(0.0298)	(0.0402)
Parents' log income	0.0197**	0.0231**	-0.00345
	(0.00914)	(0.0113)	(0.0144)
classpctile	0.263	0.790***	-0.527
	(0.237)	(0.254)	(0.348)
classpct_2	-0.174	-1.307**	1.133*
	(0.532)	(0.602)	(0.801)
classpct_3	-0.107	0.593	-0.699
	(0.342)	(0.400)	(0.524)
# of HS math courses	0.00893**	0.0135***	-0.00453
	(0.00409)	(0.00481)	(0.00628)
# of HS for. language courses	0.00939**	0.00584	0.00355
	(0.00370)	(0.00411)	(0.00553)
# of HS science courses	-0.00103	-0.00699	0.00597
	(0.00408)	(0.00475)	(0.00623)
AFQT	0.0470***	0.0487***	-0.00165
	(0.0101)	(0.0108)	(0.0148)
mom_HS	0.0592***	0.108***	-0.0492
	(0.0227)	(0.0273)	(0.0353)
mom_BA	0.0202	-0.0275	0.0477*
	(0.0172)	(0.0195)	(0.0259)
dad_HS	0.0770***	0.0390*	0.0380
	(0.0189)	(0.0229)	(0.0295)
dad_BA	-0.0129	-0.0103	-0.00258
	(0.0172)	(0.0205)	(0.0266)
Mother's Age FB	-0.000916	-0.00106	0.000147
	(0.00225)	(0.00253)	(0.00338)
Mother's Age YB	0.000592	0.00356*	-0.00297
	(0.00197)	(0.00218)	(0.00293)
singmom	0.00485	-0.0551***	0.0599**
	(0.0150)	(0.0182)	(0.0234)
female			0.124
			(0.171)
Constant	0.448***	0.324**	0.324**
	(0.109)	(0.133)	(0.126)
Observations	1,173	1,072	2,245
Adjusted R^2	0.135	0.160	0.149

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Region and year dummy coefficients not shown.

Table C-5: College Entrance Gender Gap in Cohort 2 NLSY97

	NLSY97 ENTER		
	(1)	(2)	(3)
VARIABLES	F	M	$\beta_F - \beta_M$
black	0.131***	0.0619	0.0692
	(0.0381)	(0.0476)	(0.0605)
hispanic	-0.0994**	-0.0367	-0.0628
	(0.0457)	(0.0503)	(0.0678)
Parents' log income	0.0603***	0.0400**	0.0203
	(0.0155)	(0.0190)	(0.0243)
classpctile	-0.132	0.987**	-1.119*
	(0.402)	(0.428)	(0.588)
classpct_2	1.496*	-0.645	2.141
	(0.902)	(1.015)	(1.353)
classpct_3	-1.193**	0.0652	-1.258
	(0.580)	(0.674)	(0.885)
# of HS math courses	0.00510	0.00234	0.00276
	(0.00692)	(0.00810)	(0.0106)
# of HS for. language courses	0.0274***	0.0245***	0.00294
	(0.00628)	(0.00693)	(0.00933)
# of HS science courses	0.0113	0.00240	0.00886
	(0.00692)	(0.00800)	(0.0105)
AFQT	0.0988***	0.0707***	0.0281
	(0.0171)	(0.0182)	(0.0250)
mom_HS	0.0830**	0.0835*	-0.000499
	(0.0384)	(0.0460)	(0.0596)
mom_BA	-0.0273	0.0808**	-0.108**
	(0.0291)	(0.0329)	(0.0438)
dad_HS	0.0982***	0.0171	0.0811
	(0.0320)	(0.0386)	(0.0498)
dad_BA	0.0140	0.0991***	-0.0852*
	(0.0291)	(0.0346)	(0.0449)
Mother's Age FB	0.00261	0.00694	-0.00433
	(0.00381)	(0.00427)	(0.00571)
Mother's Age YB	0.00118	0.000646	0.000529
	(0.00334)	(0.00367)	(0.00495)
singmom	-0.0190	-0.0201	0.00118
	(0.0254)	(0.0306)	(0.0395)
female			0.0636
			(0.289)
Constant	-0.516***	-0.580**	-0.580***
	(0.184)	(0.225)	(0.213)
Observations	1,173	1,072	2,245
Adjusted R^2	0.303	0.299	0.312

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Region and year dummy coefficients not shown.

Table C-6: BA Gender Gap in Cohort 2 NLSY97

	NLSY97 BAGRAD		
	(1)	(2)	(3)
VARIABLES	F	M	$\beta_F - \beta_M$
black	0.0574	0.0320	0.0254
	(0.0405)	(0.0415)	(0.0584)
hispanic	-0.0911*	-0.0944**	0.00331
	(0.0486)	(0.0438)	(0.0655)
Parents' log income	0.0461***	0.0329**	0.0131
	(0.0234)	(0.0165)	(0.0173)
classpctile	-0.668	0.0794	-0.747
	(0.427)	(0.373)	(0.567)
classpct_2	2.277**	0.313	1.964
	(0.957)	(0.884)	(1.306)
classpct_3	-1.243**	0.247	-1.490*
	(0.615)	(0.587)	(0.854)
# of HS math courses	-0.00247	0.00964	-0.0121
	(0.00735)	(0.00706)	(0.0102)
# of HS for. language courses	0.0285***	0.0167***	0.0117
	(0.00666)	(0.00604)	(0.00901)
# of HS science courses	0.00731	0.00445	0.00286
	(0.00735)	(0.00697)	(0.0102)
AFQT	0.0629***	0.0448***	0.0181
	(0.0182)	(0.0158)	(0.0241)
mom_HS	-0.0490	0.0812**	-0.130**
	(0.0408)	(0.0401)	(0.0575)
mom_BA	0.151***	0.113***	0.0379
	(0.0309)	(0.0287)	(0.0422)
dad_HS	0.0875**	-0.0164	0.104*
	(0.0339)	(0.0336)	(0.0480)
dad_BA	0.0524*	0.0890***	-0.0366
	(0.0309)	(0.0302)	(0.0434)
Mother's Age FB	-0.000714	0.00392	-0.00463
	(0.00405)	(0.00372)	(0.00551)
Mother's Age YB	0.00721**	-0.00126	0.00846*
	(0.00355)	(0.00320)	(0.00478)
singmom	-0.0427	-0.0551**	0.0123
	(0.0270)	(0.0267)	(0.0381)
female			-0.0433
			(0.279)
Constant	-0.615***	-0.572***	-0.572***
	(0.196)	(0.196)	(0.205)
Observations	1,173	1,072	2,245
Adjusted R^2	0.362	0.400	0.390

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Region and year dummy coefficients not shown.

Bibliography

Abowd, John M., Francis Kramarz and David N. Margolis. 1999. “High Wage Workers and High Wage Firms.” *Econometrica* 67(2): 251-333.

Acemoglu, Daron. 2002. “Technical Change, Inequality and the Labor Market.” *Journal of Economic Literature* 40(1): 7-72.

Acemoglu, Daron and David Autor. 2011. “Skills, Tasks and Technologies: Implications for Employment and Earnings.” *Handbook of Labor Economics* 4(2): 1043-1171.

Autor, David and David Dorn. 2012. “The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market.” *American Economic Review* forthcoming.

Autor, David and Lawrence Katz. 1999. “Changes in the Wage Structure and Earnings Inequality.” *Handbook of Labor Economics* 3(1): 1463-155.

Autor, David, Lawrence Katz and Melissa Kearney. 2008. “Trends in U.S. Wage Inequality: Revising the Revisionists.” *Review of Economics and Statistics* 90(2): 300-323.

—. 2006. “The Polarization of the U.S. Labor Market.” *American Economic Review Papers and Proceedings* 96(2): 189-194.

Autor, David, Lawrence Katz and Alan Krueger. 1999. “Computing Inequality: Have Computers Changed the Labor Market?” *Quarterly Journal of Economics* 113(4): 1169-1213.

Autor, David, Frank Levy and Richard J. Murnane. 2003. “The Skill Content of Recent Technological Change: An Empirical Exploration.” *Quarterly Journal of Economics* 118(4): 1279-1333.

Autor, David, Alan Manning and Christopher L. Smith. 2010. “The Contribution of the Minimum Wage to U.S. Wage Inequality over Three Decades: A Reassessment.” NBER Working Paper no. 16533.

Altonji, Joseph G. and Thomas A. Dunn. 1991. “Relationships Among the Family Incomes and Labor Market Outcomes of Relatives." NBER Working Paper no. 3724. Amiti, Mary and Shang-Jin Wei. 2005. "Fear of Service Outsourcing: Is it Justified?" *Economic Policy* 20(42): 308-347.

—. 2009. "Service Offshoring and Productivity: Evidence from the US." *The World Economy* 32(2): 203-220.

Baker, Michael and Gary Solon. 2003. "Earnings Dynamics and Inequality among Canadian Men, 1976-1992: Evidence from Longitudinal Income Tax Records." *Journal of Labor Economics* 21(2): 267-288.

Bailey, Martha J., and Susan M. Dynarski. 2011. "Gains and Gaps: Changing Inequality in US College Entry and Completion." NBER Working Paper no. 17633.

Barrow, Lisa, and Cecilia Elena Rouse. 2005. "Do Returns to Schooling Differ by Race and Ethnicity?" *The American Economic Review* 95(2): 83-87.

Belley, Philippe and Lance Lochner. 2007. "The Changing Role of Family Income and Ability in Determining Educational Achievement." *Journal of Human Capital* 1(1): 37-89.

Becker, Gary. 1973. "A Theory of Marriage: Part I." *Journal of Political Economy* 8(4): 813-846.

Becker, Gary. 1991. *A Treatise on the Family.* Cambridge: Harvard University Press.

Becker, Gary and Nigel Tomes. 1979. "An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility." *The Journal of Political Economy* 86(6): 1153-1189.

Behrman, Jere R. and Mark R. Rosenzweig. 2002. "Does Increasing Women's Schooling Raise the Schooling of the Next Generation?" *The American Economic Review* 92(1): 323-334.

Behrman, Jere R. and Paul Taubman. 1985. "Intergenerational Earnings Mobility in the United States: Some Estimates and a Test of Becker's Intergenerational Endowments Model." *The Review of Economics and Statistics* 67(1): 144-51.

Bertrand, Marianne and Jessica Pan. 2011. "The Trouble with Boys: Social Influences and the Gender Gap in Disruptive Behavior." NBER Working Paper no. 17541.

Black, Sandra E. and Paul J. Devereux. 2010. "Recent Developments in Intergenerational Mobility." NBER Working Paper no. 15889.

Blau, Francine D. 1998. "Trends in the Economic Well-Being of Women." *Journal of Economic Literature* 36(1): 112-165.

Blau, Francine D., Lawrence M. Kahn and Jane Waldfogel. 2000. "Understanding Young Women's Marriage Decisions: The Role of Labor and Marriage Market Conditions." *Industrial and Labor Relations Review* 53(4): 624-647.

Blinder, Alan. 2007. "How Many U.S. Jobs Might Be Offshorable?" CEPS Working Paper no. 142.

Borjas, George J., Stephen G. Bronars, and Stephen J. Trejo. 1992. "Self-Selection and Internal Migration in the United States." *Journal of Urban Economics* 32(2): 159-85.

Buchmann, Claudia, and Thomas A. DiPrete. 2005. "The Growing Female Advantage in College Completion: The Role of Family Background and Academic Achievement." *American Sociological Review* 71(4):5 15-541.

Cameron, Stephen V., and James J. Heckman. 2001. "The Dynamics of Educational Attainment for Black, Hispanic, and White Males." *Journal of Political Economy* 109(3): 455-499.

Card, David and John E. Dinardo. 2002. "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles." *Journal of Labor Economics* 20(4): 733-783.

Card, David, and Thomas Lemieux. 2001. "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis." *The Quarterly Journal of Economics* 116(2): 705-746.

Chadwick, Laura and Gary Solon. 2002. "Intergenerational Income Mobility Among Daughters." *The American Economic Review* 92(1): 335-344.

Chiappori, Pierre-Andre, Murat Iyigun, and Yoram Weiss. 2009. "Investment in Schooling and the Marriage Market." *The American Economic Review* 99(5): 1689-1713.

Crinó, Rosario. 2010. "Service Offshoring and White-Collar Employment." *The Review of Economic Studies* 77(2): 595-632.

Currie, Janet, and Enrico Moretti. 2003. "Mother's Education and the Intergenerational Transmission of Human Capital: Evidence from College Openings." *The Quarterly Journal of Economics* 118(4): 1495-1532.

Ermisch, John, Marco Francesconi, and Thomas Siedler. 2006. "Intergenerational Mobility and Marital Sorting." *The Economic Journal* 116(513): 659-679.

Dinardo, John, Nicole M. Fortin and Thomas Lemieux. 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach." *Econometrica* 64(5): 1001-1044.

DiPrete, Thomas A., and Claudia Buchmann. 2006. "Gender-Specific Trends in the Value of Education and the Emerging Gender Gap in College Completion." *Demography* 43(1): 1-24.

Dougherty, Christopher. 2005. "Why are the Returns to Schooling Higher for Women than for Men?" *Journal of Human Resources* 40(4): 969-988.

Dwyer, Rachel E., Randy Hodson, and Laura McCloud. 2012. "Gender, Debt, and Dropping Out of College." *Gender & Society* doi:10.1177/0891243212464906.

Elwood, D. T., and Christopher Jencks. 2004."The Uneven Spread of Single-Parent Families: What Do We Know? Where Do We Look for Answers?" *Social Inequality,* edited by K. M. Neckerman, 3-78. New York: Russell Sage Foundation.

Feenstra, Robert and Gordon Hanson. 1996. "Globalization, Outsourcing, and Wage Inequality." *The American Economic Review* 86(2): 240-245.

—. 1999. "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States." *The Quarterly Journal of Economics* 114(3): 907-940.

—. 2003. "Global Production Sharing and Rising Inequality: A Survey of Trade and Wages." *Handbook of International Trade* 3: 146.

Fernández, Raquel, Alessandra Fogli, and Claudia Olivetti. 2004. "Mothers and Sons: Preference Formation and Female Labor Force Dynamics." *The Quarterly Journal of Economics* 119(4): 1249-1299.

Firpo, Sergio, Nicole M. Fortin and Thomas Lemieux. 2011. "Occupational Tasks and Changes in the Wage Structure." IZA Discussion Paper no. 5542.

Gibbons, Robert and Lawrence Katz. 1992. "Does Unmeasured Ability Explain

Inter-Industry Wage Differentials?" *The Review of Economic Studies* 59(3): 515-535.

Goldin, Claudia. 1977. "Female Labor Force Participation: The Origin of Black and White Differences, 1870 and 1880." *Journal of Economic History* 37(1): 87-108.

—. 1984. "The Historical Evolution of Female Earnings Functions and Occupations." *Explorations in Economic History* 21: 1-27.

—. 1995. "Career and Family: College Women Look to the Past." NBER Working Paper no. 5188.

Goldin, Claudia, Lawrence F. Katz, and Ilyana Kuziemko. 2006. "The Homecoming of American College Women: The Reversal of the College Gender Gap." NBER Working Paper, no. 12139.

Goos, Maarten and Alan Manning. 2007. "Lousy and Lovely Jobs: the Rising Polarization of Work in Britain." *The Review of Economics and Statistics* 89(1): 118-133.

Goos, Maarten, Alan Manning and Anna Salomons. 2011. "Explaining Job Polarization: The Roles of Technology, Offshoring and Institutions." CES Discussion Series Paper no. 11.34.

Grossman, Gene and Esteban Rossi-Hansberg. 2006. "The Rise of Offshoring: Its Not Wine for Cloth Anymore." FRB Kansas City Working Paper.

—. 2008. "Trading Tasks: A Simple Theory of Offshoring." *The American Economic Review* 98(5): 1978-1997.

Hauser, Robert M. and William H. Sewell. 1975. *Education, Occupation and Earnings: Achievement in the Early Career.* New York: Academic Press.

Heckman, James J. and Paul A. LaFontaine. 2010. "The American High School Graduation Rate: Trends and Levels." *The Review of Economics and Statistics* 92(2): 244-262.

Heckman, James J. and Yona Rubinstein. 2001. "The Importance of Noncognitive Skills: Lessons from the GED Testing Program." *The American Economic Review* 91(2): 145-149.

Heckman, James J. and V. Joseph Hotz. 1986. "An Investigation of the Labor Market Earnings of Panamanian Males: Evaluating the Sources of Inequality." *The Journal of Human Resources* 21(4): 507-542.

Hetherington, E. Mavis, Margaret Bridges, and Glendessa M. Insabella. 1998. "What Matters? What Does Not?" *American Psychologist* 53(2): 167-184.

Jacob, Brian A. 2002. "Where the Boys Aren't: Non-cognitive Skills, Returns to School and the Gender Gap in Higher Education." *Economics of Education Review* 21(6): 589-598.

Jantti, Markus, Bernt Bratsberg, Knut Roed, Oddbjorn Raaum, Robin Naylor, Eva Osterbacka, Anders Bjorklund, and Tor Eriksson (2006). "American Exceptionalism in a New Light: a Comparison of Intergenerational Earnings Mobility in the Nordic Countries, the United Kingdom and the United States." IZA Discussion Paper no. 1938.

Kearney, Melissa Schettini, and Phillip B. Levine. 2011. "Income Inequality and Early Non-Marital Childbearing: An Economic Exploration of the 'Culture of Despair'." NBER Working Paper no. 17157.

Katz, Lawrence and Lawrence Summers. 1989. "Can Interindustry Wage Differentials Justify Strategic Trade Policy?" In *Trade Policies for International Competitiveness,* edited by Robert C. Feenstra, 85-124. Chicago: University of Chicago Press.

Lam, David and Robert F. Schoeni. 1993. "Effects of Family Background on Earnings and Returns to Schooling: Evidence from Brazil." *Journal of Political Economy* 101(4): 710-740.

Lang, Kevin and Michael Manove. 2011. "Education and Labor Market Discrimination." *American Economic Review* 101(4): 1467-96.

Lee, David S. 1999. "Wage Inequality in the United States During the 1980s : Rising Dispersion or Falling Minimum Wage?" *The Quarterly Journal of Economics* 114(3): 977-1023.

Lee, Chul-In and Gary Solon. 2006. "Trends in Intergenerational Income Mobility." NBER Working Paper No. 12007.

Lemieux, Thomas. 2006. "Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill?" *The American Economic Review* 96(3): 461-498.

Levine, David I. and Bhashkar Mazumder. 2002. "Choosing the Right Parents: Changes in the Intergenerational Transmission of Inequality–Between 1980 and the

Early 1990s." FRB Chicago Working Paper no. 2002-08.

Loughran, David. 2002. "The Effect of Male Wage Inequality on Female Age at First Marriage." *Review of Economics and Statistics* 84(2): 237-250.

Mayer, Susan E. and Lopoo, Leonard M. 2004. "What Do Trends in the Intergenerational Economic Mobility of Sons and Daughters in the United States Mean?" In *Generational Income Mobility in North America and Europe,* edited by Miles Corak, 90-121. Cambridge: Cambridge University Press.

—. 2005. "Has the Intergenerational Transmission of Economic Status Changed?" *Journal of Human Resources* 40(1): 169-85.

Mazumder, Bhashkar. 2005. "Fortunate Sons: New Estimates of Intergenerational Mobility in the United States Using Social Security Earnings Data." *The Review of Economics and Statistics* 87(2): 235-255.

Mortenson, Dale T. 1986. "Job Search and Labor Market Analysis." *Handbook of Labor Economics* 2: 849-920.

Olivetti, Claudia and Barbara Petrongolo. 2008. "Unequal Pay or Unequal Employment? A Cross-Country Analysis of Gender Gaps." *Journal of Labor Economics* 26(4): 621-654.

Olney, William W. 2011. "Offshoring, Immigration, and the Native Wage Distribution." Williams College Working Paper.

Ottaviano, Gianmarco, Giovanni Peri and Greg C. Wright. 2010. "Immigration, Offshoring and American Jobs." NBER Working Paper no. 16439.

Peters, H. Elizabeth. 1992. "Patterns of Intergenerational Mobility in Income and Earnings." *Review of Economics and Statistics* 74(3): 456-466.

Raaum, Oddbjørn et al. 2007. "Marital sorting, household labor supply, and intergenerational earnings mobility across countries." *The BE Journal of Economic Analysis & Policy* 7(2).

Reville, Robert T. 1995. "Intertemporal and Life Cycle Variation in Measured Intergenerational Income Mobility." Unpublished.

Slaughter, Matthew. 2001. "International Trade and Labor Demand Elasticities. *Journal of International Economics* 54(1): 27-56.

Solon, Gary. 1992. "Intergenerational Income Mobility in the United States." *The American Economic Review* 82(3): 393-408.

—. 1999. "Intergenerational Mobility in the Labor Market." *Handbook of Labor Economics* 3(1): 1761-1800.

—. 2004. "A Model of Intergenerational Mobility Variation over Time and Place," In *Generational Income Mobility in North America and Europe,* edited by Miles Corak, 38-47. Cambridge: Cambridge University Press.

—. 2013. "Theoretical Models of Inequality Transmission Across Multiple Generations." NBER Working Paper no. 18790.

Turner, Sarah. 2007. "Going to College and Finishing College. Explaining Different Educational Outcomes." In *College Choices: The Economics of Where to Go, When to Go, and How to Pay for It,* edited by Caroline Hoxby, 13-62. Chicago: University of Chicago Press.

Wright, Greg C. 2011. "Revisiting the Employment Impact of Offshoring." Job Market Paper.

Curriculum Vitae

Sarah Anne Kroeger

b. 1981
Department of Economics
Boston University
270 Bay State Road, Boston MA 02215 Phone: 617-981-0237
Email: skroeger@bu.edu
Web: http://people.bu.edu/skroeger

Education

Ph.D. Economics, Boston University, 2013

Dissertation title: *Essays on the Economics of Inequality*

Main Advisor: Daniele Paserman

B.A. Economics, College of William & Mary, 2003

M.A. Economics, Boston University, 2007

Fields of Interest

Labor Economics, Economics of Education, Applied Microeconomics

Teaching Experience

Instructor: Economics of the Labor Market, Boston University, Summer 2013

Instructor: Economics of Money & Banking, Boston University, Summer 2011

Instructor: Environmental Economics, Boston University, Summer 2010

Head Teaching Fellow: Principles of Macroeconomics, BU, Fall 2011 and Fall 2012

Teaching Fellow: Principles of Macroeconomics, Boston University, Spring 2010 and Spring 2012

Teaching Fellow: Principles of Microeconomics, Boston University, Fall 2009 and Fall 2010

Teaching Assistant, Economics of Management Decisions (MBA course), Graduate School of Management, Boston University, Summer 2009

Other Research Experience and Employment

Research Assistant to Professor Kehinde Ajayi, Boston University, Spring 2013

Research Assistant to Professor Shulamit Kahn, Boston University School of Management, Spring 2011

Wellington Management Company, Associate/Economic Analyst, Boston MA, 2007-2008

Research Assistant to Professor Karen Jacobsen, Tufts University, Summer 2007

Federal Deposit Insurance Corporation, Economic Research Assistant, Washington DC, 2003-2006

Grants, Fellowships, and Awards

Outstanding Teaching Fellow Award, Graduate School of Arts and Sciences, Boston University, 2013

Teaching Fellowship, Boston University, Fall 2009-Fall 2010, Fall 2011-Fall 2012

First Year Fellowship, Boston University, Fall 2008 and Spring 2009

Monroe Fellowship, College of William & Mary, 1999

Working Papers

"The Contribution of Offshoring to the Convexification of the U.S. Wage Distribution," November 2012

"The Role of Gender in Income Mobility: Evidence from the NLSY79," October 2010, updated May 2013

"Exploring the Expansion of the College Gender Gap," May 2013

Works in Progress

"Assisted Reproductive Technology and Women's Choice to Pursue Professional Degrees," (joint with Giulia La Mattina)

Conferences and Invited Seminar Presentations

2013	University of South Carolina; University of Wisconsin-Milwaukee; University of Calgary; U.S. Bureau of the Census; FDIC Division of Insurance and Research
2012	Workshop on Inequality and Macroeconomic Performance, Sciences-Po; Conference on Inequality, Skills and Globalization (presenter), University of Lille 1