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Three Essays in Applied Economics and Policy Analysis

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Contents

Chapter 1

Introduction

This dissertation consists of three essays. The first essay (chapter 2)[1] empirically investigates whether South Asian countries constitute an optimum currency area (OCA) by applying a structural vector auto-regression (SVAR) model to trace global, regional, and domestic shocks. Variance decompositions show that domestic shocks dominate regional and global shocks, which contrasts with the findings for the European Union countries, used as a basis for comparison. This paper concludes that at the present time the South Asian region as a whole does not meet the prerequisite conditions of an OCA. The loss of an autonomous monetary instrument can outweigh the benefits of a common currency.

The second essay (chapter 3) investigates the effect of extended unemployment insurance (UI) coverage in the United States in recent years on job search. The U.S. government extended UI benefits in several phases in 2008-2009, increasing the duration of the benefits to a maximum of 99 weeks, up from the regular 26 weeks. Using the American Time Use Survey (ATUS) data, I find that women are more sensitive to the extended UI benefits than men. Difference-in-differences estimation shows that the average effect of the UI extensions for women is over a 10 percentage points decline in the probability of job search. However, I do not find any statistically significant effect on men.

[1]This chapter has been revised with Robert Thornton and Alex Nikolsko-Rzhevsky, and submitted to a journal.

In the third essay (chapter 4), I study the evolution of relative wages, and quality of school teachers in the U.S. over the past half-century. I analyze the quality through the prism of a Roy (1951) model of occupational choice. The estimates imply that those selecting to be teachers are more able workers than those schools would see from random assignment. However, the ability distribution of female teachers is on the decline, while that of non-teachers has steadily been rising. I supplement the Roy model with an examination of the teachers' relative cognitive attributes (measured by standardized test scores). I find that teachers have lower average cognitive ability than that of non-teachers. And, the decline in the quality comes on the heels of the declining relative wage. I show that lower pay of female teachers than that of non-teachers is not a permanent phenomenon, but a new trend emerging from 1990 onwards. To seek explanation for the rising wage gap, I use a model of the rising demand for skills in the non-teaching sector, and find a secular demand for the skills.

Chapter 2

To Be or Not to Be: An Optimum Currency Area for South Asia?

2.1 Introduction

The South Asian Association for Regional Cooperation (SAARC), a political and economic association of eight countries founded in 1985, continues on a course toward regional integration aimed at an economic union by 2020. The launch of the South Asia Free Trade Agreement (SAFTA) in 2006, which seeks to transform the region into a free-trade area by 2016, raises the question of the possibility of adopting a common currency. The currency debate began in the political arena and news media after then Prime Minister of India Atal Behari Vajpayee delivered a speech at the 12th SAARC Summit on January 4, 2004, envisioning "an Economic Union, open borders and a common currency for the region" ("Text of PM Vajpayee's Speech", 2004). Many observers see such a union as a platform for overcoming prevalent political discontent and for focusing on closely integrating the region. Additionally, the union is perceived as a way for the region to realize economic gains from cooperation.

Indeed, formation of a common currency could bring significant economic benefits by reducing transaction costs of trading goods and services and eliminating exchange-rate risks, thereby boosting trade and investment. A shared currency also decreases relative price distortions as prices across the nations become directly comparable. Likewise, countries could see other dynamic efficiency gains through an increased productivity of capital, and they would no longer require a high volume of foreign exchange reserves to defend their currencies (Gros and Thygesen, 1999).

However, the costs may outweigh the benefits if the countries' underlying economic structures are not ripe for a monetary union. The major disadvantage stems from relinquishing an independent monetary policy. When faced with a domestic shock, countries would not be able to actively respond by increasing or decreasing their money supply, and they would have to rely entirely on fiscal policy. Additionally, joining a union implies non-trivial preparatory costs, such as converting outstanding assets into a new currency, which could reduce or even eliminate the potential benefits of a common currency.

In order to assess whether a currency union could bring a net positive economic effect, the optimum currency area (OCA) theory is used. Its criteria are laid out in the classic works of Mundell (1961), McKinnon (1963), and Kenen (1969) and include: i) labor mobility, ii) openness of the economies, iii) product diversification, and iv) fiscal integration. Notably, the traditional criteria are generally of a qualitative nature, thus failing to produce a single well-defined approach for consistently assessing the viability of a monetary union. Recent research has focused on devising empirical methodologies to quantify the OCA theory. One of the most well-known examples of these methodologies is the introduction of the Maastricht Treaty "convergence-criteria" used to evaluate the readiness of the European countries wishing to join the E.U. Agbeyegbe (2008) uses some of the Treaty's criteria to assess whether the Southern Africa Development Community is suitable for a viable monetary union. Despite some advantages, this approach is subject to vagueness in terms of interpretation and lacks a theoretical basis. Hence the criteria should be treated as necessary, but not sufficient, conditions.

A more modern and, arguably, preferable approach in the literature to operationalize the OCA theory is to assess the properties of underlying macroeconomic shocks to capture and quantify core properties of many major qualitative criteria. In particular, a single monetary policy should be effective enough to absorb symmetric region-specific disturbances across countries, lessening the relevance of an autonomous exchange-rate tool. If the shocks are asymmetric, on the other hand, other arrangements would be preferable instead, even when convergence conditions are satisfied. Indeed, while the European countries joining the Economic and Monetary Union (EMU) broadly satisfied the convergence criteria of the Maastricht Treaty, some economists believed that several countries were not subject to symmetric shocks (e.g., Salvatore, 1997). Bayoumi and Eichengreen (1992) find more idiosyncratic shocks in Europe as compared to the states in the U.S., raising doubts about the smooth functioning of the then-planned euro. Responding to the current euro zone crisis, Krugman (2012) adds that architects of the euro took asymmetric shocks as a lesser problem and that the OCA theory was not supportive of a common currency.

In order to empirically extract the shocks and study their nature for evidence of potential suitability of a monetary union in a given region, one can use the identification strategy proposed by Blanchard and Quah (1989). Bayoumi and Eichengreen (1992), who were arguably the first to adopt this methodology, apply a two-variable structural vector auto-regression (SVAR) model to investigate the underlying demand and supply shocks in Europe, and they compare the results with the U.S. findings. Buigut and Valev (2005) and Huang and Guo (2006) apply a similar approach to study the possibility of a monetary union in East Africa and East Asia, respectively. Despite the fact that there is recent strong interest in a common currency in South Asia, the only related work I am aware of is that of Saxena (2005), who applies a two-variable SVAR to identify demand and supply shocks in the region. Saxena (2005) concludes that the cost of a South Asian monetary union would be low, stating that the sizes of both types of shocks are small with a relatively rapid speed of adjustment. However, the main limitation of this and similar two-variable approaches is that they ignore the role of domestic, regional, and global shocks. A high degree of correlation in supply shocks across countries may lead researchers to justify a country's suitability for a single currency. However, instead of a domestic or a regional shock, such a correlation might be driven by a global shock. In such a scenario, an exchange-rate system of a global mechanism may be preferable to a common currency (Chow and Kim, 2003).

To overcome this drawback, I operationalize the OCA theory by explicitly estimating the contribution of global, regional, and domestic shocks to the national output through the application of a SVAR model. Symmetric exogenous shocks would imply that the countries are integrated well with the outside world and, hence, that a single currency would be suitable, or vice versa. Specifically, when regional shocks dominate each country's output, the region can embrace a single currency since all countries will be susceptible to similar disturbances. On the other hand, when country-specific shocks are prevalent, each country would be better off by having an autonomous monetary instrument to fight the heterogenous nature of economic disturbances. This methodology was first proposed by Chow and Kim (2003), who use it to calculate forecast error variance decomposition to study the suitability of a common currency in East Asia. Following their technique, Zhao and Kim (2009) examine if the CFA franc zone forms an OCA. However, there has been a paucity of research on a South Asian common currency, a gap that I hope to fill with this study.

The target of our study is the eight SAARC nations: the seven founding members, Bangladesh, Bhutan, India, the Maldives, Nepal, Pakistan, and Sri Lanka, and a new entrant, Afghanistan, which I subject to only a preliminary examination. I begin by examining some of the most common "traditional" qualitative criteria of an OCA. If countries have free labor mobility, a significant volume of intra-regional trade, similar economic structures, and fiscal integration, classical theory suggests that they could benefit from a common currency. Likewise, the Maastricht Treaty's convergence criteria are good indicators for gauging the preliminary readiness for a monetary union. However, our analysis indicates that the South Asian nations do not meet these criteria at this time. Nonetheless, a shared currency may still be justified if there is a strong correlation of macroeconomic shocks across the countries.

Hence, I then look at the symmetry of macroeconomic shocks by extracting the underlying structural global, regional, and country-specific shocks through the application of the SVAR model to the seven SAARC countries for the period from 1970 to 2011. The newly admitted eighth SAARC member, Afghanistan, is excluded from the SVAR analysis due to data availability constraints and to its unique nature as a war-ravaged economy. Because South Asia, like other regional unions, has been trying to emulate the EMU, it is appropriate to compare the results with the euro zone countries. Therefore, I choose 11 European countries that adopted the euro in the first phase in 1999 as our control group. For European countries, my main estimations are based on data from 1970 to 1998, as it would be fairer to assess the current suitability of the South Asian countries vis-a-vis the suitability of the European countries right before the launch of the euro. In my analysis, I treat India as a "center of gravity" for a common currency in South Asia, and Germany as a "center of gravity" in the euro zone, because of their dominant economic sizes in the two regions. In particular, for the South Asian region, I consider the possibility of the SAARC nations adopting the Indian currency, the rupee, as an anchor. The U.S. is used for both groups as a country responsible for global structural shocks. However, I later relax the definition of regional and global economies in the robustness checks.

The forecast error variance decomposition demonstrates that country-specific shocks account for a significant share of South Asian countries' output variability, with regional shocks playing a very minor role. Additionally, the proportion of regional shocks in the SAARC economies' variation is much smaller than that in the euro zone economies, while most of the correlations of domestic shocks are insignificant. The impulse response function analysis also shows that the economies do not respond to both regional and global shocks in a uniform manner. Since the SAARC members are on the bottom rung of the development process, it seems a far-fetched idea for them to set up a fiscal union or other mechanisms to compensate a member for any monetary loss during an economic crisis. Consequently, after taking into account the failure of both the traditional assessment criteria and modern econometric analysis to show support for a monetary union, I conclude that the adoption of a common currency in South Asia does not appear reasonable in the immediate future.

2.2 Data

I use data from four different sources. Output data for most South Asian and European countries[1] come from the World Development Indicators (WDI) published by the World Bank.[2] For the Maldives, Bhutan, and Ireland, the WDI coverage is limited; hence, I turn to the United Nations Statistics Division-National Accounts.[3] Output is defined as gross domestic product (GDP) measured in constant 2000 USD. Because quarterly GDP data is not available for South Asian economies, the data in this paper is annual, covering the time period from 1970 to 2011.[4]

In addition to output, I also collect World Bank data on remittances, inflation, public debt, budget deficits, and lending rates. Remittances refer to current transfers by migrant workers plus wages and salaries transferred by nonresident workers. The inflation rate is the yearly percentage change in the consumer price index. Debt refers to external debt owed to nonresidents repayable in foreign currency, goods, or services. Deficit is defined as

[1] Austria, Bangladesh, Belgium, Finland, France, Germany, India, Ireland, Luxembourg, Nepal, the Netherlands, Portugal, Spain, and Sri Lanka

[2] The World Bank data is available at http://databank.worldbank.org/data/home.aspx.

[3] The United Nations data is available at http://unstats.un.org/unsd/snaama/dnlList.asp.

[4] Prior to 1970, data are not available for most of the South Asian countries. Moreover, Bangladesh, one of the important economies in South Asia, became independent only in 1971.

revenue including grants minus both expenses and acquisition of nonfinancial assets. The lending rate is defined as the interest rate charged by banks to the private sector.[5] I use the Directions of Trade data from the International Monetary Fund (IMF) from the year 2002 to 2011 to calculate the trade-weighted regional and global GDPs, and intra-regional trade for all countries except Bhutan. Lastly, trade data for Bhutan are compiled from the Bhutan Trade Statistics due to its unavailability through the IMF.

2.3 Preliminary Analysis

A. Comparative Analytics

The classical OCA literature states that a monetary union works well for economies with similar structures, a high volume of trade flows, and free labor mobility. Having a similar economic structure and the same level of development indicates that countries face similar problems or economic shocks, which could in turn make a single currency more desirable. As shown in Table 1, South Asian economies possess largely similar structures in terms of their production. The service sector accounts for the largest share of GDPs in all countries, followed (with the exception of Bhutan) by agriculture. Due to the Maldives' large reliance on tourism, the service sector has a 82 percent share in its GDP. Moreover, the degree of similarity in the structures of the South Asian economies in terms of production is not far off from that of European countries (Table 2). I use the data until 1998 for the European countries as our objective is to compare the current readiness of the South Asian countries for a shared currency with the readiness of the European countries just before the launch of the euro. For many South Asian countries listed in Table 1, remittances comprise a substantial contribution to GDP with the major source for all being the Gulf region and East Asia – hence a similar source of shocks. Finally, Nepal and Bhutan have already pegged their cur-

[5]The World Bank has two separate data series - the interest rate spread (lending rate minus deposit rate) and the deposit rate. Therefore I calculate the lending rate as the interest rate spread plus the deposit rate.

rencies to India's rupee. However, due to the varying pace of economic and political reforms, these countries are in different stages of economic development. Afghanistan, Bangladesh, Bhutan, and Nepal are the least-developed countries, whereas the remaining four – India, the Maldives, Pakistan, and Sri Lanka – are categorized as developing ones. India, which accounts for around 80 percent of South Asia GDP, dominates the region, which is populated by around 1.5 billion people. Appendix Tables II and III contain information about major export commodities, and economic indicators of the South Asian countries.

An *intra-regional trade* relationship is considered to be another vital yardstick for assessing prospects for a common currency. When countries have an increasingly large volume of trade, their economic structures and conditions converge. Also, the more that countries trade, the greater the potential gains from a currency union become. For example, Alesina and Barro (2002) indicate that the countries that trade with each other in a larger volume are the ones which reap more benefits from a shared currency, due to a reduction in transactions costs. Table 3 presents shares of each SAARC member country's trade – both imports and exports – with other members based on the total trade volume from the years 2002 to 2011.[6] For example, the value 0.16 in column 3, row 1, for Afghanistan and Bangladesh indicates that Afghanistan's trade share with Bangladesh is 0.16 percent of its total foreign trade. Other than Bhutan and Nepal, for which trade flows with India make up about 78 and 58 percent of their total trade volumes, respectively, the South Asian countries are trading with each other on a very low scale. For example, India's trade share with each of the other economies in the region is less than one percent. In contrast, as shown in Table 4, the European countries trade with each other in substantially higher quantities than do the South Asian economies. However, we should keep in mind that there is a substantial amount of informal trade among countries in South Asia due to porous national borders.

The final factor I look at is *labor mobility*. The free flow of labor from struggling economies to surging economies in a currency zone is an important tool for tackling asym-

[6]For Bhutan, the time span goes from the year 2004 to 2011 due to data limitations.

metrical economic shocks. In South Asia, there is no restriction on labor mobility from Nepal and Bhutan to India. However, there are some restrictions on labor mobility in the rest of the region. Even though there are no official data to formally analyze the current trends in labor movements across the SAARC countries, one of the goals of a South Asian Economic Union coming into effect in 2020 is free labor mobility across the whole region. In Europe, labor can move freely from one country to another. In practice, however, its mobility is limited due to informal barriers, such as the limited recognition of professional skills, acquired in a home country, in other member states (Zimmermann, 2009).

B. The Maastricht Treaty

Fulfilling the convergence criteria of the Maastricht Treaty, which are laid out for European countries to join the euro, lends further support to the pursuit of a currency union. The Maastricht criteria are:

(i) The country must have an inflation rate within 1.5 percentage points above the average of the three countries with the lowest inflation rates among European members;

(ii) The country should maintain its public debt within 60 percent of its GDP;

(iii) The country must have a budget deficit not exceeding three percent of its GDP;

(iv) The country's long-term interest rate must be within two percentage points above the average inflation rate of the three countries with the lowest inflation rates;

(v) The country's currency must join the Exchange Rate Mechanism (ERM II) for two straight years before adopting the single currency.

Table 4 reports the convergence criteria with respect to the South Asian countries. Bhutan and India are very close to meeting the Treaty's inflation criterion. But the Maldives and Pakistan experienced inflation rates 5.80 and 4.89 percentage points above the average of the three-lowest inflation rates in the region. Due to data limitations, public debt in this paper refers only to the stock of external debt.[7] All countries have external debt of less than 60 percent of GDP. Half of the countries - India, the Maldives, Pakistan, and Sri Lanka - have budget deficits higher than three percent. In terms of the interest rate criterion, only Nepal appears to meet it. Bhutan has the highest interest rate of 14 percent, almost double the Treaty's standard.

To sum up, an examination of the economic structures, labor mobility, trade flows, and the Maastricht Treaty criteria seems to indicate that the South Asian nations are not well suited for a single currency.[8] Nonetheless, a shared currency may still be justifiable if for the countries macroeconomic shocks are highly correlated.

2.4 Empirical Specification

To uncover the underlying structural global, regional, and country-specific shocks, I apply the methodology of Chow and Kim (2003) that is based on the identification strategy of Blanchard and Quah (1989). Consider the following structural VAR which is stationary and stable:

$$AX_t = \gamma + A_1 X_{t-1} + \epsilon_t \tag{2.1}$$

where the vector X_t represents $[\Delta gdp_t^g,\ \Delta gdp_t^r,\ \Delta gdp_t^d]'$; i.e. the log-difference of global, regional, and domestic GDPs respectively. Each GDP depends on its own lagged values and lagged values of other remaining GDPs. Likewise, $\epsilon_t = [\epsilon_t^g,\ \epsilon_t^r,\ \epsilon_t^d]'$ is a vector of global, regional, and domestic shocks.

[7]Public debt is the sum of external (foreign) and domestic debt. However, external debt constitutes most of public debt for the South Asian countries due to the rudimentary state of the domestic debt market.

[8]One possibility for dealing with these unfavorable indicators is the establishment of a fiscal union. Countries are required to follow a set of specific fiscal guidelines under such a union, and would be compensated with the fiscal transfers during a crisis. But the formation of such a union does not seem promising in the near future in South Asia.

To explain further, the subprime mortgage crisis in the US and the subsequent 18-month Great Recession lasting until June 2009 is considered to be a global shock. Another example would be a sudden rise in oil prices. Hence, a global shock affects all world economies at once. Regional shocks, on the other hand, only affect the countries within a region, albeit in a similar fashion. Regional fluctuations in food prices may constitute a regional shock in the South Asian context, as counties consume relatively similar food items while their trade with the global market is limited. The current crisis in the euro zone would constitute a regional shock for European countries.[9] Domestic shocks that are specific to a country's economy would represent both aggregate demand and supply shocks. Monetary and fiscal policies, and changes in productivity as well as in the terms of trade, could be sources of country-specific shocks.

I assume that all countries' GDPs are subject to a combination of these three shocks. In particular, the system of equations is expressed as:

$$\Delta gdp^g = \mu_1 + \Theta_{11}(L)\epsilon_t^g + \Theta_{12}(L)\epsilon_t^r + \Theta_{13}(L)\epsilon_t^d \tag{2.2}$$

$$\Delta gdp^r = \mu_2 + \Theta_{21}(L)\epsilon_t^g + \Theta_{22}(L)\epsilon_t^r + \Theta_{23}(L)\epsilon_t^d \tag{2.3}$$

$$\Delta gdp^d = \mu_3 + \Theta_{31}(L)\epsilon_t^g + \Theta_{32}(L)\epsilon_t^r + \Theta_{33}(L)\epsilon_t^d \tag{2.4}$$

where the matrix of lag polynomials $\Theta(L) = \begin{bmatrix} \Theta_{11}(L) & \Theta_{12}(L) & \Theta_{13}(L) \\ \Theta_{21}(L) & \Theta_{22}(L) & \Theta_{23}(L) \\ \Theta_{31}(L) & \Theta_{32}(L) & \Theta_{33}(L) \end{bmatrix}$

$= \sum_{i=0}^{\infty} L^i \begin{bmatrix} {\theta_{11}}^{(i)} & {\theta_{12}}^{(i)} & {\theta_{13}}^{(i)} \\ {\theta_{21}}^{(i)} & {\theta_{22}}^{(i)} & {\theta_{23}}^{(i)} \\ {\theta_{31}}^{(i)} & {\theta_{32}}^{(i)} & {\theta_{33}}^{(i)} \end{bmatrix}$

[9] However, it is true that the euro zone problems also affect economies beyond its regional borders, including South Asia. So at least part of the shocks would be considered to be of a global nature.

To compute the structural shocks, I first rewrite the structural equation (1) in the following reduced form and then estimate it:

$$X_t = A_0^* + A^* X_{t-1} + e_t \tag{2.5}$$

where X_t is a 3×1 vector of observed variables, $A_0^* = A^{-1}\gamma$, $A^* = A^{-1}\ A_1$, and $e_t = A^{-1}\ \epsilon_t$. To uniquely estimate structural shocks from the reduced form equations, I need $3^2 = 9$ restrictions. First, I assume that the variance-covariance matrix of structural errors $D_\epsilon = \mathbb{E}(\epsilon_t \epsilon_t{}')$ is a diagonal matrix. This generates $\frac{3(3+1)}{2} = 6$ independent equations (i.e. six restrictions). Still, I need $\frac{3(3-1)}{2} = 3$ restrictions. Following Chow and Kim (2003), I therefore make the three restrictions below. These restrictions are based on the assumption that all domestic economies, both European and South Asian (with the exception of their regional centers – Germany and India) can be viewed as small open economies (SOE). In particular, I assume that:

(i) Country-specific shocks do not have any impact on the regional or global output in the long-run. The rationale is that the size of each of the individual economies is too small, relative to the size of the region and the world economy, to influence them in the long-run. For example, if the US suffers from an economic recession, it may have economic impacts in Nepal or South Asia. However, an economic recession (or boom) on Nepal will change neither income nor prices in the rest of South Asia or the US in the long-run, nor will such changes consequently affect their outputs. This implies that:

$$\sum_{i=0}^{\infty} \theta_{23}^i = \Theta_{23}(1) = 0, \text{ and } \sum_{i=0}^{\infty} \theta_{13}^i = \Theta_{13}(1) = 0 \tag{2.6}$$

(ii) Regional shocks do not have any impact on global output in the long-run. For instance, neither a positive nor negative economic shock in South Asia will have long-run implications for the US economy. This means that:

$$\sum_{i=0}^{\infty} \theta_{12}^{i} = \Theta_{12}(1) = 0 \tag{2.7}$$

The moving average representation of equation (5) takes the following form:

$$X_t = \mu + \Phi(L)e_t \tag{2.8}$$

I calculate $\Phi(1)$ = I + Φ_1 + Φ_2 + Φ_3 +....+ Φ_n as $n \longrightarrow \infty$, where $\Phi_j = A^{*j}$ $\forall j = 1, 2, 3, ..., n$ as $n \longrightarrow \infty$. In addition, Σ_e, the variance-covariance matrix of errors in the reduced-form equations, is computed. Then I estimate, Ξ, where $\Xi = \Phi(1)\ \Sigma_e\ \Phi(1)'$. Using the Cholesky decomposition of Ξ, I derive

$$\Xi = \Theta(1) I \Theta(1) \tag{2.9}$$

where $\Theta(1)$ is a lower triangular matrix. I represents an identity matrix. To extract structural shocks, I can find reduced-form errors e_t as $\epsilon_t = Ae_t$, where $A = \Theta(1)^{-1}\ \Phi(1)$.

Asymmetric country-specific shocks imply the necessity of an independent monetary policy and exchange-rate system to cope up with idiosyncratic business cycle fluctuations. As a result, a monetary union will be costly. The converse is true as well. The main focus of our analysis is on regional shocks. If regional shocks are dominant in overall fluctuations of national output, a common currency seems to be viable. Since the South Asian countries have opened up considerably over the last two decades, regional shocks are expected to play a greater role in their economies. Finally, a prevalence of global shocks would indicate that the countries' exchange rate arrangements should lean more towards a global, rather than a regional, currency (for example the U.S. dollar).

2.5 Empirical Results

In this section, I present results from the structural VAR. Similar to Chow and Kim (2003), I use U.S. GDP as a proxy for global output. Likewise, I use the Indian economy as a proxy for regional GDP for South Asia and German GDP for European countries. In the robustness checks, I explore other alternative definitions of regional and global economies.

A. Correlation of Domestic and Regional Shocks

I estimate the VAR(1) model for the seven South Asian and 11 European countries. Each specification includes the first-difference of log GDPs – domestic, regional, and global – as well as their first lags as independent variables.[10] Since my objective is to compare the current readiness of South Asia with the readiness of Europe right before the formation of a single currency, I use data from the year 1970 to 2011 for South Asia and only until 1998 for the European countries. It should be noted that the euro was launched on January 1, 1999. A uniform lag length of one is chosen for all models. The resultant models appear stable with the modulus of eigenvalues lying within the unit circle.[11]

From the reduced-form models, I recover the structural global, regional and domestic shocks according to the methodology described in Section 2.4 Symmetric and positive shocks are desirable for the prospects of a monetary union to be feasible. A negative correlation means that a negative (positive) shock in another member would produce a positive (negative) effect on the domestic economy, thus requiring different monetary policies. For instance, if Nepal suffers from a negative shock such as a decline in productivity or a power outage or increasing labor union unrest or a general wage rise, then the remaining economies will see a positive boost. It is not uncommon for firms to relocate to another country to

[10] Each detrended series has been tested for stationarity using the Dickey Fuller Generalized Least Squares (DF-GLS) test with the results presented in Appendix Table I.

[11] The results of stability tests are not reported due to space constraints. They are available upon request.

escape negative shocks in their country of operation. When firms produce perfectly substitutable goods and services and rely on the same market, a loss in one country brings gain to another country. For example, suppose Nepal and Sri Lanka are exporting garments to the US market. If garment factories in Nepal are unable to deliver on time due to local problems and increase prices due to rising production costs, the U.S. importers would switch to Sri Lanka.

Tables 6 and 7 report pairwise correlations of domestic shocks among the SAARC and European countries, respectively. The correlations among most of the countries' shocks in South Asia are statistically insignificant. Correlations between Bangladesh and Pakistan and Sri Lanka are significant at the five percent and one percent levels respectively. Likewise, Bangladesh's domestic shocks are significantly correlated with Bhutan's at the 10 percent level. By way of comparison, most of the correlations for the euro zone countries are positive and significantly different from zero. These results imply that the economies in the South Asia are affected by non-synchronized shocks with an insignificant common component, suggesting a need for an independent instrument to address and adjust output fluctuations, rather than a one-size-fits-all monetary policy.

B. Analysis of Impulse Response Functions

Through impulse response function analysis, I am trying to see how a one-time regional or global shock, such as the Great Recession or a swing in oil and food prices, affects domestic output in each country. It could be argued that, if domestic output in each country responds to outside shocks in a similar manner, then the countries are good candidates for a monetary union. Figure 1 plots the response of domestic output to regional disturbances calculated from our models for the South Asian and figure 2 for the European countries. Figure 3 plots the responses to global shocks for South Asia and figure 4 for the European countries. Since by assumption the disturbances are not correlated, we can explain responses of domestic output to regional or global shocks, holding everything else constant. In particular, I am able to measure the implied causal effect of the three shocks on each GDP.

The response of Pakistan to a regional shock appears to be largely different from the rest of the South Asian countries. In light of its entrenched "political rivalry" with India, the result is not surprising. Because of the rivalry, the countries have very low levels of trade and economic linkages, as well as cross-border movement of people. Consequently, Pakistan's economy, which is not closely linked to India's, has generated a response to the regional shock that is different from the rest. For Nepal, the response path veers off to the negative, with a positive regional shock hitting its economy negatively over about a two-year horizon. The observations for other countries show that they have a long-term positive path of response. However, the responses do vary in terms of both the magnitude and the adjustment period. On the other hand, for the European countries (with the exception of Finland), all countries respond to regional shocks in a similar way.

With regard to a global shock for the South Asian economies, the responses of Pakistan and the Maldives swing from positive to negative with different magnitudes and shapes as the forecast horizon rises. One possible reason for the Maldives' quite distinct response is that its currency is pegged to the US dollar. However, the remaining economies initially react with a negative response to a global shock. On the other hand, the European countries have almost identical shapes for the impulse response. In a nutshell, the response functions do not reflect the symmetry that would justify a single currency in South Asia.

C. Variance Decomposition

Arguably, the most important among the approaches I consider in this paper for studying the currency union is the forecast error variance decomposition. It is based on the fact that the three unexpected disturbances that I have termed as global, regional, and local shocks would be expected to produce errors in forecasting a country's output, and the respective share of each shock would signal the suitability of a particular exchange rate system. Specifically, dominant regional shocks favor a monetary union, significant domestic shocks would argue for an independent exchange rate, and a strong influence of global shocks would signal that pegging to a global currency might be a viable option. Intuitively, dominant regional shocks signal that countries within a region face similar economic problems or shocks and that a single monetary policy could be suitable to respond to them. Similarly, dominant global shocks indicate that the nature of countries' economic shocks or problems closely reflects those of the global economy. Hence, a monetary policy that works for the global economy could also work for the countries, thus justifying the viability of a currency peg. I perform the analysis using two different forecast horizons: a short-run horizon of two years and a long-run horizon of 12 years.[12] Tables 8 and 9 contain the results of the variance decomposition from my benchmark models. Each value represents the percentage of variability in two- and 12-period-ahead forecast errors in output which are attributable to each of the three structural shocks.

For the European countries, the results are mixed (Table 9). The Austrian economy has the largest contribution of regional shocks, which contribute around 38 percent to both the short- and long-run variability in output. Likewise, Spain has about a 33 percent contribution of the regional shock in the short-run horizon and about 27 percent in the long run. The regional shock explains almost one-third of the variation in the Portuguese economy. France, the second largest economy in Europe, seems to be considerably influenced by Germany. Regional shocks account for around 28 percent of its economy's variation. Likewise, Belgium, Luxembourg, and the Netherlands each have about 20 percent of the variation in their economies explained by the regional shocks. On the other hand, for Finland, regional shocks seem to have a relatively smaller influence, accounting for about eight percent of fluctuations in forecast errors of its economy in the short run. This appears to match well the anecdotal evidence. Indeed, Finland is considered to be less integrated into the euro

[12] My conclusions are not sensitive to the exact choice of the forecast horizons.

zone, with five of its seven largest trading partners from outside the euro zone and Russia being its largest exporter and Sweden the largest importer ("The Finn Red Line", 2012). In addition, regional shocks play a minor role in the variation of the Irish economy, explaining less than four percent of the variation, the lowest contribution among European countries in my analysis.

The results largely agree with the current functioning of the euro-economies. Ireland is the first country to face an economic crisis after the formation of the euro. Besides, it is important to note that Ireland was among "the EU cohesion countries" - a group of countries whose economic structures were different from the rest of the European members. Likewise, regional shocks explain only around seven percent of the variation in the Italian economy. Currently, Italy is one of the few European countries facing a sovereign-debt crisis with a possibility of dropping out of the Union. The share of regional shocks in the variation of the economies of Spain and Portugal–two other troubled economies in the euro zone–is relatively higher than what we expected. However, it could be worth noting that domestic shocks are still dominant in their economies' variation, signalling their unreadiness for a shared currency. Overall, domestic shocks demonstrate limited evidence of a successful and smooth functioning of the euro. Nevertheless, the European countries seem to constitute a better fit for a union than do the South Asian economies, as Table 8 shows.

In spite of India's economic dominance in the region, it is surprising to see the low contribution of regional shocks for practically all the South Asian economies. Sri Lanka, which is an island, shows around a 14 percent contribution of regional shocks in the long-run. As the country is geographically separated from the rest of the region and had been in a civil conflict, it might indeed be not well-integrated into the region. The regional shocks' contribution to the Maldives economy is negligible, just above one percent. Because this archipelago nation is dependent on tourism and because its leading trading partners are from outside the region, its economy is almost completely unaffected by regional shocks.

In the face of its currency being pegged to the US dollar, the global shock has a minimal contribution of around four percent. This is not surprising because European and Southeast Asian countries are its leading markets for tourism as well as trade. Likewise, regional shocks explain only around 11 percent of the variation in the economy of Pakistan, whose relations with India have historically been shaky. Hence, this result is not surprising, either. The results for other countries, however, appear to be more prominent. Indeed, regional shocks play a higher role in the output variation of economies in Nepal, Bangladesh, and Bhutan in both the short-and long-run horizons, especially when compared to other South Asian economies. Regional shocks explain around 30 percent of Bangladesh's fluctuations, and around 20 and 18 percent of those of Nepal and Bhutan. One could expect regional shocks to dominate the variation in the Bhutanese and Nepalese economies as both have pegged their currencies with India and rely heavily on trade with it. Despite the currency peg, their fundamental economic structures are vastly different, since they are at different stages of economic development. The peg has long been viewed as a monetary convenience rather than as an economic or monetary necessity.

Bangladesh, on the other hand, has been subject to a greater influence of regional shocks compared to Nepal and Bhutan. First, Bangladesh is a breakaway country that still maintains close ties with India. Second, due to its climatic and geographical proximity with India, its agricultural production (rice being the principal crop) is similar to that of India. Therefore, Indian policies have direct implications on its agricultural sector, which has long been the backbone of its economy. Third, the textile industry of Bangladesh, the leading source of its foreign exchange, is in direct competition with India, another leading exporter, in the global textile market. Hence, any Indian policy or shock with regard to the textile industry has direct influence on the economy of Bangladesh.

D. Endogenous OCA Theory

An endogenous OCA theory has been gathering attention in the literature. The theory states that, even if countries are not a good candidate for a single currency ex ante, they might be well suited for it ex post. Frankel and Rose (1998), who popularized the theory, argue that once a country enters into a monetary union, trade flows will increase, which in turn could create more symmetric business cycles. This view was prevalent during the phase of the euro's design and is considered to have influenced the euro project. In their investigation of the OCA endogeneity hypothesis, Vieira and Vieira (2012) find that in the first 10 years after the introduction of the euro, core euro member countries have indeed experienced an improvement in the OCA properties.

I first estimate the forecast error variance decomposition for European countries extending the period up to the year 2011.[13] Table 10 contains the results. I then compare these results with the ones from the benchmark model that uses GDP data up to the year 1998, just before the introduction of the euro (Table 9). The contribution of regional shocks has increased for all countries (except Spain) in the post-euro phase, lending some validity to the endogenous OCA theory. For example, the contribution of regional shocks to the variation in the Austrian economy increased by around 8 percentage points. With this increment, domestic shocks are no longer dominant in its economy; instead, the role of regional shocks has become the largest. For Italy, the contribution of regional shocks increased by approximately 20 percentage points, the highest rise. However, regional shocks, notwithstanding their growing role, are still unable to dominate the euro zone economies.

[13] Due to use of yearly data in our study i do not have enough observations to investigate only the post-euro period (i.e. 1999 to 2011).

E. A Smaller Currency Union ?

Even though our results do not support the idea of a single currency in the whole of South Asia, it seems reasonable to consider the subset of Bangladesh, Bhutan, India, and Nepal. Bangladesh has one-third of its output fluctuation explained by regional shocks. This is on a par with the results for many EU countries. Bhutan and Nepal, which have historically pegged their currencies to the Indian rupee, are more susceptible to regional shocks.

Most of the trade of Bhutan and Nepal is with India. India is also the largest foreign investor in both countries. There is free labor mobility from both of these countries to India. Likewise, India is the largest trading partner of Bangladesh. In addition, these countries are politically, culturally, and geographically close to India. Therefore, they might contemplate a shared currency, with the Indian rupee as an anchor. However, as part of laying the groundwork for a common currency, these countries should first work to further liberalize trade as well as the movement of labor and set up some sort of fiscal coordination or union. To be precise, even if they are not perfect candidates for a common currency, there are some indications that they would benefit from it due to their large volume of trade and close economic linkages.

2.6 Robustness Checks

What regional and global shocks constitute may not have a unequivocal and unanimous definition. To ensure that my results are largely invariant to the definition of regional and global output, I next estimate three alternative models to calculate forecast error variance decomposition. Table 11 contains results from these models for the South Asian countries, and Table 12 reports results for the European countries.

In the first alternative model (Model I in Table 11), I define the sum of GDPs of the three-largest Asian economies as regional GDP, and that of the US, the UK and German economies as global GDP for the South Asian nations. For India, regional output is the sum of the GDPs of Japan, China, and South Korea, while for the rest of the countries it is the sum of the GDPs of Japan, China, and India. For the South Asian countries, the results for the regional shocks are close to those of the benchmark model, except for Nepal and the Maldives. The effect of the regional shocks on the output variation of Nepal declines considerably. Since Nepal shares an open border with India, along with a large volume of trade and a pegged currency, the effect of the Chinese and Japanese economies is expected to be lower than that of the Indian economy.

Likewise, for the euro-zone countries, I define the sum of GDPs of the three-largest economies as regional GDP, and the sum of those of the US, Japan, and China as global GDP. The contribution of regional shocks for Austria and Belgium changes slightly. For Italy, Luxembourg, and the Netherlands it decreases modestly as compared to the benchmark model. The Irish economy experiences an increase in the explanation of output fluctuation caused by the regional shock. This seems to be intuitive in light of Ireland's economic and geographic proximity to the U.K. Similarly, France, Portugal, and Spain see an increased role of regional shocks in the first alternative model in comparison to the benchmark model.

In the second alternative model (II), I use the same definition of regional and global GDPs as in the first one, but instead of the sum I use the weighted average of the GDPs to calculate the regional and global outputs. The results do not deviate to a large extent in this alternative specification as compared to the benchmark model.

In the third alternative model, I apply a trade-weighted GDP in the first alternative model specification. I calculate trade weight by summing both imports and exports of each country i to the rest of the world from 2002 to 2011 and by dividing the country's trade to its respective partner country j during the period by its total world trade.[14] Because of lack

[14]Consider the trade-weighted regional GDP of country i. $GDP_i^{Region} = \frac{\sum_{j=1}^{J} Trade_{ij} \times GDP_j}{\sum_{m=1}^{M} Trade_{im}}$, where $Trade_{ij}$ is country $i's$ imports plus exports between countries i and j, GDP_j is country $j's$ GDP, J is the number of major "regional" economies, and M is the total number of trading partners for country i.

of data, the trade weight for Bhutan includes slightly different years (from 2004 to 2011). For the European countries, trade data before the introduction of the euro were limited. Because trade weight is calculated using data from 2002 to 2011, I use the full sample of GDPs up to the year 2011 to calculate the forecast error variance decomposition. Thus it is more appropriate to compare these results for the European countries with those from the benchmark model that uses the data until 2011 (Table 10). For most of the European economies, the variation caused by regional shocks is close to that of the benchmark model. France, Luxembourg, and Portugal experience a modest rise in the role of regional shocks. Among the South Asian countries, the role of regional shocks in the explanation of the variation in the Maldives' economy is almost the same in this alternative model as in the benchmark model. Likewise, regional shocks change only slightly for Bhutan and Nepal. Bangladesh, Pakistan, and Sri Lanka experience a moderate decline in the explanation caused by regional shocks. Overall, the results appear to be robust in terms of the contribution of regional shocks in each economy in all three alternative models.

2.7 Conclusion

In this paper I investigate whether the South Asian countries could meet the underlying prerequisite criteria of an OCA to form a monetary union. To this end, I assess traditional OCA properties as well as the Maastricht Treaty, and I empirically operationalize OCA theory. In particular, I apply structural VAR methodology to uncover macroeconomic shocks - specifically global, regional, and local shocks. Forecast error variance decompositions suggest that the SAARC members have not yet become well-integrated into the global economy, and that regional shocks play a less important role in their output variation as compared to the E.U. Rather domestic shocks explain most of the variability in the South Asian economies. However, the results also suggest that a monetary union for Bangladesh, Bhutan, India, and

Trade-weighted global GDP, GDP_i^{Global}, is defined similarly except J is the number of "global" economies.

Nepal might be reasonable.

South Asian nations also can learn an important lesson from the experience of the euro zone. The lesson is that fiscal integration and labor mobility are crucial for sustaining a single currency, in addition to the correlation of macroeconomic shocks. Even so, in South Asia fiscal integration seems only a remote possibility so far because all of that region's countries are in the early stages of economic advancement. Still they are working towards implementing a South Asian Economic Union by 2020, which aims for free labor mobility across the region.

On the other hand, we cannot overlook political factors too, since political motivation also helped launch the euro. Feldstein (1997) stresses that the pursuit of the European Monetary Union (EMU) was fundamentally a result of political considerations, arguing that the economic effect from a single currency would be negative. It took more than four decades for European countries to reconcile their political differences and disputes and to agree upon a common currency. European countries entered into the Treaty of Rome in 1958 for economic cooperation after the the Treaty of Paris in 1951 in order to prevent war, helping to end the longstanding Franco-German rivalry. South Asia's economic transformation has been shaken and overshadowed by the geo-political rivalry between Pakistan and India, the region's two largest economies, over decades. However, the rivalry appears to have subsided over the years. Nevertheless, both India and Pakistan still must increase their efforts to end the rivalry, expeditiously embarking on the approach taken by the EU. It is possible and feasible for the SAARC to achieve a similar type of monetary integration as the E.U. The SAFTA is expected to give an impetus to regional economic integration in the years to come, bringing the countries closer to monetary cooperation. Frankel and Rose (1998) argue that increased trade relations could lead to an increased synchronization of countries' business cycles. More important, if the SAARC members are able to effectively implement their planned Economic Union by 2020, they might then see a considerable correlation of macroeconomic shocks, pushing themselves on a trajectory towards an eventual OCA.

In a nutshell, since monetary union has very serious and far-reaching economic consequences, it is always better to cautiously and thoroughly assess its readiness. Overall, the results in this paper imply that the region as a whole has a long way to go to achieve a solid economic convergence, one that would generate clear evidence of positive economic effects from a monetary union. Therefore, the countries should first expedite the process of economic union and trade liberalization. Only then should they push forward the agenda of a common currency.

Table 1: **Structure of the SAARC Economies**

	Afghanistan	Bangladesh	Bhutan	India	Maldives	Nepal	Pakistan	Sri Lanka
% share of GDP								
Agriculture	21	18	16	18	6	32	22	12
Industry	23	28	44	27	13	15	25	30
Services	57	54	40	56	82	53	53	58
Remittances	2	11	1	3	0	22	6	9
% Share of exports								
Agricultural Raw Materials	13	-	0.2	1.8	0.0003	3	2	4
Food	39	-	8	8	97	19	19	25
Manufactures	14	-	68	62	0.10	74	71	69
% Share of imports								
Agricultural Raw Materials	-	-	3	2	2	2	5	2
Food	14	-	11	4	21	15	12	13
Fuel	35	-	15	38	25	21	34	21
Manufactures	14	-	63	47	51	57	46	63

Source: The World Bank. The shares are based on data for 2011.
Note: (-) means data is not available.

Table 2: **Structure of the European Economies**

Country	% share of GDP Agriculture	Industry	Services
Austria	2	31	67
Belgium	1	28	71
Finland	3	34	62
France	3	23	73
Germany	1	31	68
Ireland	4	41	54
Italy	3	29	68
Luxembourg	1	21	78
Netherlands	3	25	72
Portugal	4	29	67
Spain	5	29	66

Source: The World Bank. The shares are based on data for 1998.

Table 3: **Intra-Regional Trade: SAARC**

Country	Afghanistan	Bangladesh	Bhutan	India	Maldives	Nepal	Pakistan	Sri Lanka
Afghanistan	-	0.16	0	7	0	0	27.14	0.012
Bangladesh	0.027	-	0.045	9.16	0.001	0.10	1.003	0.081
Bhutan	0	1.69	-	78.6	0.003	0.58	0.002	0.01
India	0.1	0.67	0.063	-	0.023	0.46	0.38	0.75
Maldives	0	0.024	0	8.8	-	0.001	0.33	0.07
Nepal	0	0.92	0.084	58.69	0.0001	-	0.105	0.04
Pakistan	2.63	0.69	0.0015	2.95	0.011	0.009	-	0.47
Sri Lanka	0.003	0.15	0	15.3263	0.394	0.00862	1.23	-

Note: The values denote each member country's trade – both imports and exports– with member countries. For example, the value 0.16 for Afghanistan and Bangladesh states that Afghanistan's trade share with Bangladesh is 0.16 percent of its total foreign trade. The share is based on the trade volume from 2002 to 2011 which is obtained from the Direction of Trade, the IMF. For Bhutan, I use the data from the Bhutan Trade Statistics, the Ministry of Finance.

Table 4: **Intra-Regional Trade: EU**

Country	Austria	Belgium	Finland	France	Germany	Ireland	Italy	Luxembourg	Netherlands	Portugal	Spain
Austria	-	1.83	0.51	3.64	37.90	0.39	7.71	0.20	2.98	0.28	1.76
Belgium	0.81	-	0.60	14.33	18.17	2.98	4.14	1.30	14.99	0.54	2.70
Finland	0.90	2.81	-	3.58	12.97	0.62	3.01	0.10	6.06	0.44	1.88
France	0.94	9.22	0.48	-	17.53	1.01	8.46	0.56	5.59	1.16	7.74
Germany	4.98	5.74	0.95	9.25	-	0.95	6.25	0.49	8.79	0.74	3.65
Ireland	0.40	10.22	0.41	5.08	7.76	-	3.11	0.12	4.35	0.37	2.69
Italy	2.46	3.44	0.51	10.68	15.12	0.75	-	0.26	4.05	0.75	5.54
Luxembourg	1.13	20.58	0.45	13.33	22.41	0.41	4.30	-	4.79	0.55	2.43
Netherlands	0.99	11.26	0.96	6.96	21.28	1.02	3.79	0.30	-	0.59	2.71
Portugal	0.63	2.96	0.53	10.03	13.68	0.72	5.11	0.19	4.38	-	29.30
Spain	0.88	3.26	0.50	15.70	13.28	1.07	8.40	0.21	4.26	5.84	-

Note: The values denote each member country's trade – both imports and exports– with member countries. For example, the value 1.83 for Austria and Belgium states that Austria's trade share with Belgium is 1.83 percent of its total foreign trade. The share is based on the trade volume from 2002 to 2011 which is obtained from the Direction of Trade, the IMF.

Table 5: **SAARC Countries and Their Preparation Relative to the Maastricht Treaty Criteria**

	Inflation rate	Deficit	Debt	Interest rate
Afghanistan	5.69	-0.61	13.68	-
Bangladesh	10.70	-0.92	24.17	13.25
Bhutan	8.85	-	59.77	14.00
India	8.86	-3.68	17.85	-
Maldives	12.83	-16.75*	47.94	10.20
Nepal	9.55	-0.99	20.95	8.00*
Pakistan	11.92	-6.48	28.63	14.42
Sri Lanka	6.72	-6.41	40.53	9.41

Source: The data are based on the year 2011. An asterisk (*) denotes that I use data for 2010 due to data unavailability for 2011. The interest rate refers to the lending rate.
Note: (-) means that data are not available.

Table 6: Correlation of Domestic Shocks: SAARC

	BA	BH	MA	NE	PA	SR
Bangladesh	1.0000					
Bhutan	0.2863*	1.0000				
	(0.1554)					
Maldives	0.1164	0.1960	1.0000			
	(0.1611)	(0.1591)				
Nepal	0.0885	-0.1613	-0.1009	1.0000		
	(0.1616)	(0.1601)	(0.1614)			
Pakistan	0.3950**	0.1934	0.0540	0.0066	1.0000	
	(0.1490)	(0.1592)	(0.1620)	(0.1622)		
Sri Lanka	0.4225***	-0.1114	0.1217	-0.0264	0.2126	1.0000
	(0.1470)	(0.1612)	(0.1610)	(0.1622)	(0.1585)	

Note: * denotes significance at the 10 percent level, * * and * * * at the five percent and one percent levels. Standard errors are in parentheses.

Table 7: Correlation of Domestic Shocks: Euro

	AU	BE	FI	FR	IR	IT	LU	NE	PO	SP
Austria	1.0000									
Belgium	0.4898 ***	1.0000								
	(0.1744)									
Finland	0.2976	0.3590*	1.0000							
	(0.1909)	(0.1867)								
France	0.5476***	0.7415***	0.2676	1.0000						
	(0.1673)	(0.1342)	(0.1927)							
Ireland	0.0615	0.0936	0.1626	-0.0783	1.0000					
	(0.1996)	(0.1991)	(0.1973)	(0.1994)						
Italy	0.2141	0.6628***	0.1953	0.6603***	-0.3566*	1.0000				
	(0.1954)	(0.1498)	(0.1961)	(0.1502)	(0.1868)					
Luxembourg	0.3630*	0.3591*	-0.0603	0.3872**	-0.2938	0.0542	1.0000			
	(0.1864)	(0.1867)	(0.1996)	(0.1844)	(0.1912)	(0.1997)				
Netherlands	0.4814**	0.6929***	-0.0274	0.3987**	0.0393	0.3375*	0.4476**	1.0000		
	(0.1753)	(0.1442)	(0.1999)	(0.1834)	(0.1998)	(0.1883)	(0.1789)			
Portugal	0.6334***	0.5482***	0.2431	0.6567***	-0.0275	0.3889**	0.3739*	0.3748*	1.0000	
	(0.1548)	(0.1673)	(0.1940)	(0.1508)	(0.1999)	(0.1843)	(0.1855)	(0.1854)		
Spain	0.6709***	0.6719***	0.2828	0.5803***	0.1210	0.2661	0.5370***	0.5062***	0.7320***	1.0000
	(0.1483)	(0.1481)	(0.1918)	(0.1629)	(0.1985)	(0.1928)	(0.1687)	(0.1725)	(0.1363)	

Note: * denotes significance at the 10 percent levels, * * and * * * at the five percent and one percent level. Standard errors are in parentheses.

Figure 1: Response of Domestic Output to a Regional Shock: SAARC

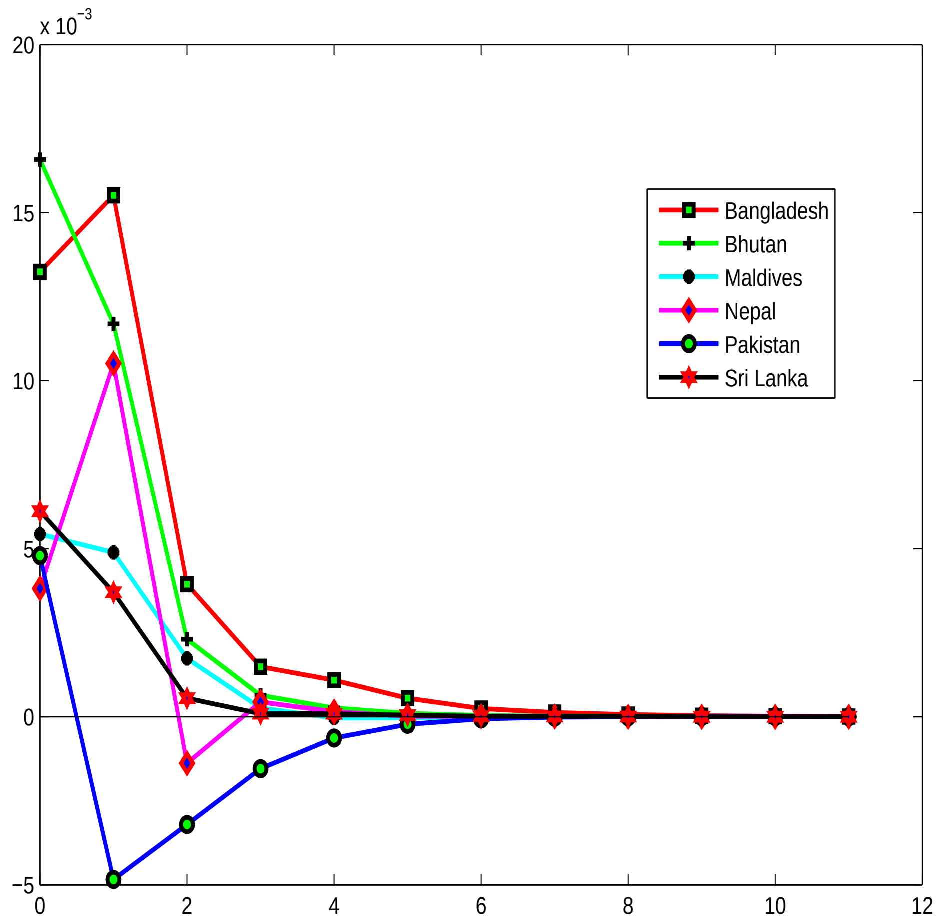


Figure 2: Response of Domestic Output to a Regional Shock: EU

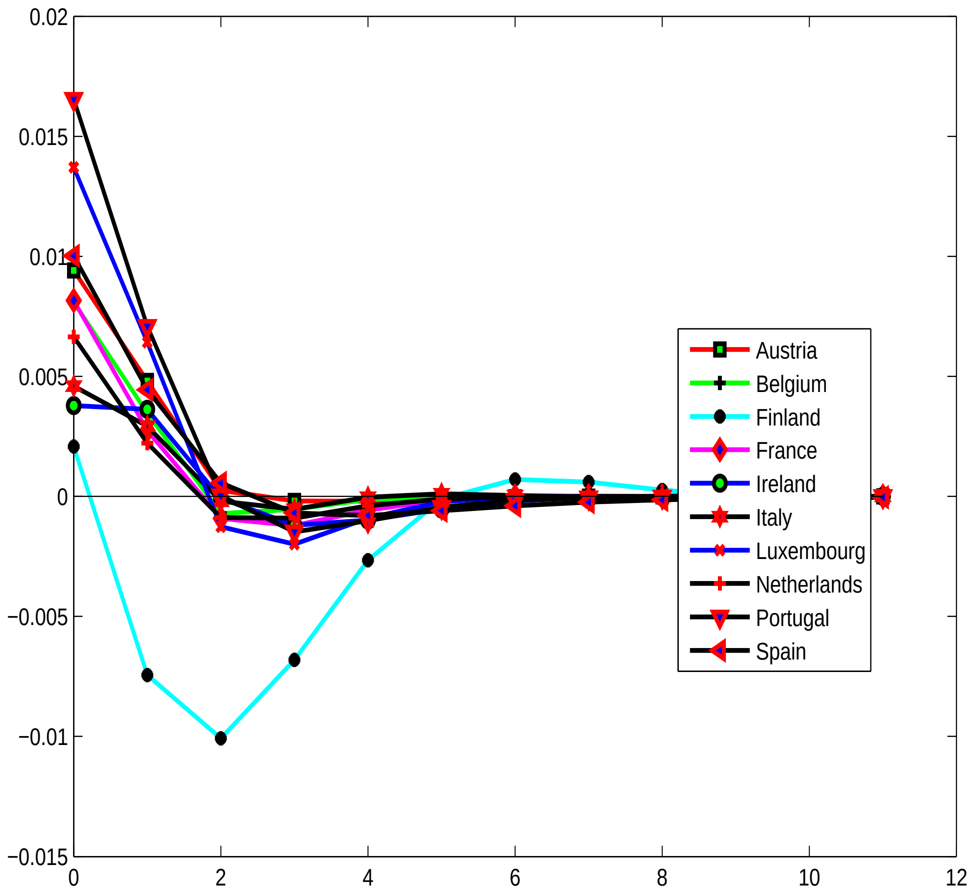


Figure 3: Response of Domestic Output to a Global Shock: SAARC

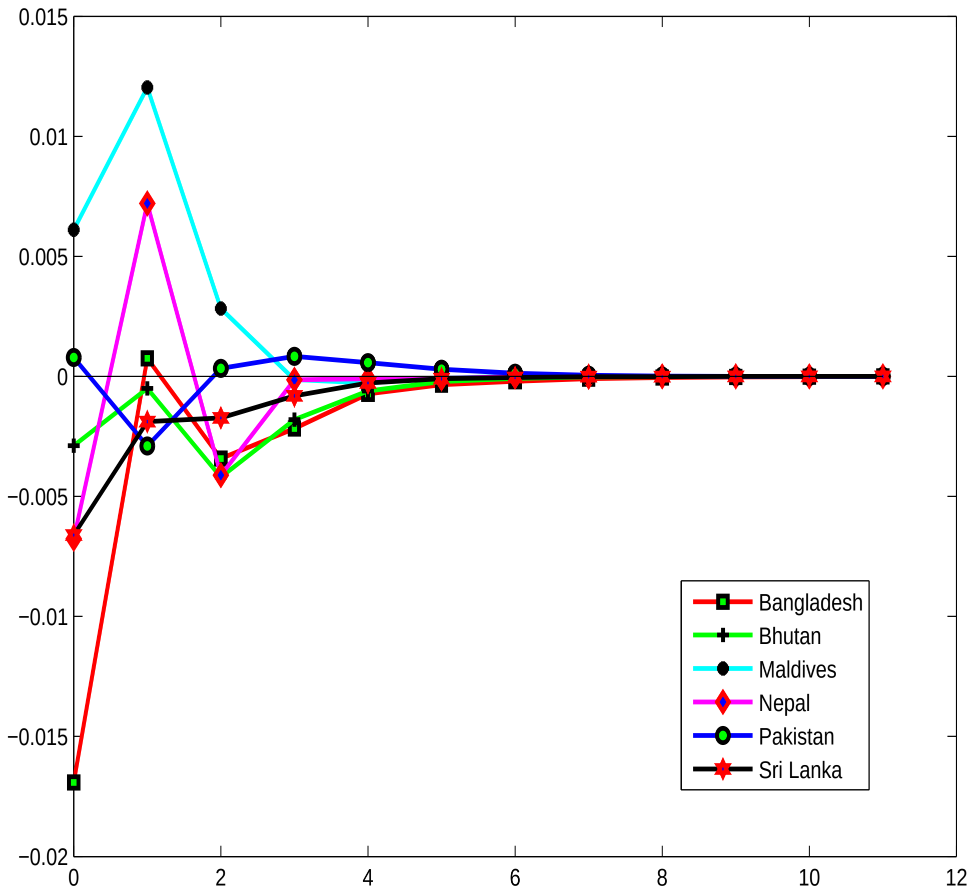


Figure 4: Response of Domestic Output to a Global Shock: EU

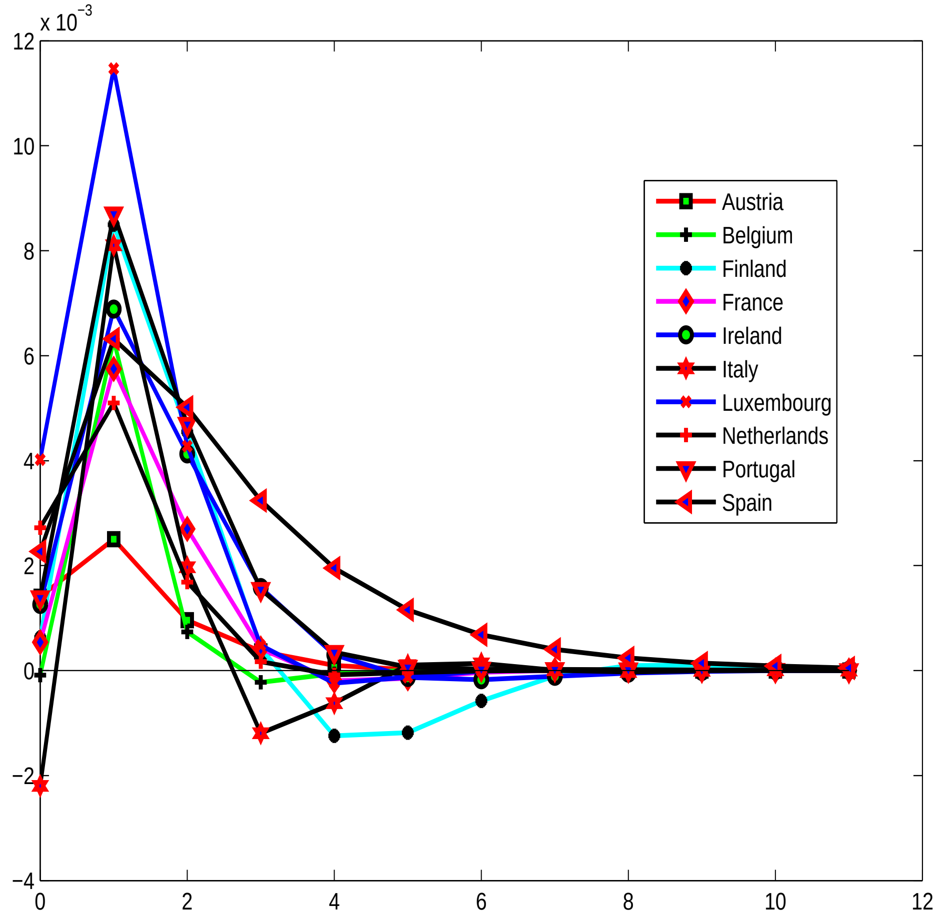


Table 8: **Variance Decompositions in the Benchmark Model : SAARC**

	Years	Global shock	Regional shock	Domestic shock
Bangladesh	2	22.51	32.63	44.86
	12	23.15	33.14	43.72
Bhutan	2	0.39	18.51	81.11
	12	1.32	18.51	80.17
Maldives	2	4.10	1.20	94.70
	12	4.26	1.27	94.47
Nepal	2	16.82	21.55	61.63
	12	19.08	21.17	59.75
Pakistan	2	2.32	11.97	85.71
	12	2.45	14.21	83.34
Sri Lanka	2	12.95	14.01	73.04
	12	13.81	13.92	72.27

Table 9: **Variance Decompositions in the Benchmark Model: EU**

	Years	Global shock	Regional shock	Domestic shock
Austria	2	2.84	38.50	58.66
	12	3.19	38.35	58.46
Belgium	2	10.73	20.97	68.30
	12	10.83	21.07	68.11
Finland	2	10.33	8.49	81.18
	12	10.49	23.39	66.11
France	2	12.79	28.42	58.79
	12	15.08	28.32	56.61
Ireland	2	6.78	3.78	89.43
	12	9.01	3.95	87.04
Italy	2	17.52	7.37	75.11
	12	18.13	7.14	74.74
Luxembourg	2	12.84	19.93	67.23
	12	14.14	20.04	65.82
Netherlands	2	14.32	21.04	64.64
	12	15.24	21.37	63.39
Portugal	2	7.68	32.00	60.33
	12	9.79	31.35	58.86
Spain	2	12.53	33.36	54.12
	12	18.81	26.52	54.66

Table 10: **Variance Decompositions for Full Sample from 1970 to 2011: EU**

	Years	Global shock	Regional shock	Domestic shock
Austria	2	12.04	46.38	41.58
	12	13.37	45.96	40.67
Belgium	2	15.80	30.66	53.54
	12	16.34	31.19	52.47
Finland	2	18.56	16.09	65.35
	12	20.28	24.13	55.58
France	2	24.33	40.35	35.32
	12	28.97	38.73	32.30
Ireland	2	36.05	5.86	58.09
	12	42.16	6.17	51.67
Italy	2	20.76	26.66	52.58
	12	22.75	27.04	50.21
Luxembourg	2	19.95	24.73	55.32
	12	22.79	25.12	52.09
Netherlands	2	24.08	27.41	48.51
	12	26.64	27.51	45.85
Portugal	2	17.37	37.76	44.87
	12	23.12	34.33	42.55
Spain	2	30.47	22.95	46.58
	12	43.46	17.10	39.44

Table 11: **Variance Decompositions in the Alternative Models: SAARC**

		Model(I)			Model(II)			Model(III)		
	Years	GS	RS	DS	GS	RS	DS	GS	RS	DS
Bangaldesh	2	9.5	33.1	57.4	6.9	49.1	44.0	10.6	17.0	72.4
	12	9.6	33.4	57.0	6.9	49.1	43.9	11.9	19.4	68.7
Bhutan	2	0.6	17.0	82.4	3.2	7.7	89.1	0.4	22.8	76.8
	12	0.7	17.1	82.2	3.2	7.9	88.9	1.5	22.6	75.9
India	2	6.7	11.0	82.3	5.6	16.7	77.7	6.7	14.6	78.7
	12	7.0	11.5	81.5	5.7	18.7	75.6	7.7	14.5	77.9
Maldives	2	2.9	9.0	88.1	3.1	2.3	94.6	3.5	9.8	86.8
	12	3.1	9.1	87.8	3.3	2.5	94.2	3.6	9.8	86.6
Nepal	2	8.8	0.5	90.7	18.3	3.2	78.5	12.4	18.9	68.6
	12	8.9	0.5	90.6	18.1	4.1	77.7	14.5	18.6	66.9
Pakistan	2	0.3	17.2	82.5	0.8	10.9	88.2	0.2	5.0	94.8
	12	0.6	17.9	81.5	1.1	14.8	84.1	0.3	5.0	94.7
Sri Lanka	2	10.1	7.5	82.4	7.7	16.4	75.9	10.7	1.2	88.1
	12	10.7	7.5	81.8	7.9	17.1	75.0	11.4	1.3	87.3

Note: GS denotes global shock, RS regional shock, and DS domestic shock.

Table 12: **Variance Decompositions in the Alternative Models: EU**

	Years	Model(I)			Model(II)			Model(III)		
		GS	RS	DS	GS	RS	DS	GS	RS	DS
Austria	2	13.4	41.5	45.1	10.2	40.8	49.0	14.3	46.9	38.7
	12	17.0	40.2	42.8	12.4	39.9	47.7	15.3	46.8	38.0
Belgium	2	25.0	20.5	54.5	15.5	22.4	62.1	20.6	36.3	43.2
	12	25.5	21.1	53.4	16.0	22.7	61.3	20.8	36.7	42.5
Finalnd	2	14.9	4.2	80.9	16.6	4.1	79.3	18.8	14.3	66.9
	12	15.3	4.3	80.5	16.3	8.3	75.4	18.4	18.9	62.7
France	2	37.3	37.7	25.1	25.6	27.3	47.1	29.7	50.3	20.0
	12	38.4	37.0	24.6	27.2	27.1	45.7	32.1	48.3	19.6
Germany	2	26.2	3.9	69.9	12.6	1.7	85.7	10.3	2.4	87.2
	12	26.2	4.6	69.2	12.8	2.0	85.2	10.6	2.5	86.9
Ireland	2	0.2	14.5	85.3	5.2	3.4	91.3	38.9	7.8	53.3
	12	2.3	15.7	82.1	7.2	3.4	89.4	42.7	7.0	50.3
Italy	2	33.8	1.9	64.3	23.1	4.8	72.1	19.7	34.3	46.0
	12	34.0	1.9	64.1	23.5	4.7	71.8	20.7	34.3	45.0
Luxemburg	2	32.3	12.1	55.6	18.2	21.3	60.6	10.3	42.4	47.3
	12	33.4	12.3	54.3	19.5	21.1	59.4	12.7	41.6	45.7
Netherlands	2	19.7	9.8	70.6	20.5	9.1	70.4	25.3	23.2	51.5
	12	22.0	9.6	68.3	21.7	9.1	69.2	26.5	23.4	50.1
Portugal	2	23.1	49.7	27.2	16.4	52.9	30.7	22.8	54.9	22.3
	12	24.3	48.8	27.0	17.9	51.6	30.5	25.3	50.4	24.3
Spain	2	31.8	52.0	16.2	27.9	44.8	27.3	37.6	46.6	15.8
	12	36.4	46.6	17.0	31.9	39.1	29.0	43.0	37.2	19.8

Note: GS denotes global shock, RS regional shock, and DS domestic shock.

Appendix

Table I: **Unit Root Test**

Country	Dickey-Fuller Generalized Least Squares Test
Bangladesh	-3.77***
Bhutan	-3.89***
India	-5.40***
Maldives	-4.55***
Nepal	-4.89***
Pakistan	-2.22
Sri Lanka	-3.00*
Austria	-3.79***
Belgium	-3.62**
Finland	-3.78***
France	-3.52**
Germany	-3.73**
Ireland	-2.45
Italy	-4.95***
Luxembourg	-3.0
Netherlands	-3.18*
Portugal	-3.82***
Spain	-2.52
US	-4.52***

Note: The test is conducted using three lags for all variables, using data from 1970 to 1998 for European counties, and to 2011 for the rest. The reported test results are for the first lag. The null hypothesis is that variables have unit root. * denotes the rejection of the null hypothesis at the 10 percent significance level, * * and * * * denote the five percent and one percent significance levels respectively.

Table II: **Major Export Commodities**

Country	Principal Exports
Afghanistan	opium, fruits and nuts, handwoven carpets, wool, cotton, hides and pelts, precious and semiprecious gems
Bangladesh	garments, knitwear, agricultural products, frozen food (fish and seafood), jute and jute goods, leather
Bhutan	electricity (to India), ferrosilicon, cement, calcium carbide, copper wire, manganese, vegetable oil
India	petroleum products, precious stones, machinery, iron and steel, chemicals, vehicles, apparel
Maldives	fish
Nepal	clothing, pulses, carpets, textiles, juice, pashima, jute goods
Pakistan	textiles, rice, leather goods, sports goods, chemicals, manufactures, carpets and rugs
Sri Lanka	textiles and apparel, tea and spices; rubber smanufactures; precious stones; coconut products, fish

Source: The World Factbook, Central Intelligence Agency, US.

Table III: **Major Economic Indicators**

	Population	GDP Size	GDP Growth	GDP Per Capita	Tax Revenue	Trade	FDI
Afghanistan	35.3	19.2	5.7	1138.9	8.7	81.5	0.4
Bangladesh	150.5	111.9	6.7	1776.9	10.0	54.5	0.7
Bhutan	0.7	1.7	5.6	5845.6	-	92.4	0.9
India	1241.5	1872.8	6.3	3650.2	10.4	54.2	1.7
Maldives	0.3	2.1	7.5	8871.3	-	224.0	13.7
Nepal	30.5	18.9	3.9	1252.1	13.2	41.7	0.5
Pakistan	176.7	210.2	3.0	2744.8	9.3	33.4	0.6
Sri Lanka	20.9	59.2	8.3	5581.7	12.4	60.7	1.6

Source: The World Bank. The data is based on the year 2011. Population is reported in millions. GDP size is measured in billions (current US$). GDP growth is the annual percentage growth rate of GDP at market prices. GDP per capital based on purchasing power parity is measured in the current US dollar. Tax revenue, trade, and foreign direct investment (FDI) are specified as their ratio to GDP.
Note: (-) means data is not available.

Chapter 3

Extended Unemployment Insurance and Job Search: Evidence from Time Use Data

3.1 Introduction

The United States government extended the duration of unemployment insurance (UI) benefits in several phases from mid-2008 to late 2009, raising the duration up to 99 weeks from the regular 26 weeks. The extensions, billed as the most generous in U.S. history, were targeted at financially helping job losers smooth their consumption in a period of severe unemployment resulting from the Great Recession of 2007-09. However, the government's move to extend benefits stirred a debate over the disincentive effect on recipients' labor supply, which could contribute to a higher unemployment rate. For instance, in an op-ed, Barro (2010) argues that in the absence of extended UI coverage, the U.S. unemployment rate would have been 6.8 percent in June 2010, instead of the actual rate of 9.5 percent. On the other hand, the administration has argued that UI extensions have had no impact on the persistently high unemployment rate, which is viewed as caused by the severe downturn and sluggish recovery associated with the Great Recession.

Establishing the causal link between the UI benefits extension and the unemployment rate is inherently difficult because of the endogenous nature of the insurance program. In theory, the disincentive effect of an expansion in UI benefits impacts the unemployment rate through two direct channels: discouraging job search behavior of unemployed individuals and increasing their reservation wage (i.e., decreasing their job-acceptance rate). Indirectly, there are at least four additional channels through which extended UI benefits could affect the unemployment rate both in the short run and long run. First, the coverage can increase consumption of goods and services, thus edging up overall output and the employment rate in the short run. The Congressional Budget Office (CBO) estimates that one dollar spent on extended UI benefits can create a multiplier effect of $1.10 in the economy. Second, it entails "crowd-out" effect in the short run, which is the effect of the receipt of UI benefits by a family member on the labor supply by other family members. Cullen and Gruber (2000) find that wives' hours of labor supply could go up by about 30 percent during the period of their husbands' unemployment if the latter did not have access to UI benefits. Likewise, in the long run, unemployment insurance could help better match workers and firms, thus increasing output and, consequently, employment in the economy (Acemoglu and Shimer 2000). With benefits, an unemployed individual could afford to search and wait for a better-suited, higher-paid and higher-productivity job. Finally, the disincentive effect of UI benefits may lengthen the duration of unemployment, deteriorating their skills for future jobs, thus decreasing productivity in the economy and increasing unemployment in the long run.

The direct and indirect disincentive effects require a general equilibrium analysis to quantify the link between the UI program and unemployment rate as well as unemployment spells. Therefore, in an empirical investigation of the unemployment insurance program, evaluating its effect on the key variables such as job search and reservation wage, seems to be more reasonable strategy. Yet there is a paucity of research studying the effects of recent UI extensions on the two key variables. Krueger and Mueller (2010) study the effect of regular UI benefits on job search intensity of unemployed individuals in the U.S. from 2003 to 2007. One of their findings is that the generosity of unemployment insurance negatively impacts job search activity among the unemployed (estimated elasticities range from -1.6 to - 2.2). Econometric methodology and research question in this paper differ somewhat from Krueger and Mueller (2010). Particularly, in this paper I attempt to estimate the causal effect of the expansions in UI coverage during the Great Recession of 2007-2009 and its aftermath, on job search behavior of the unemployed.

In line with the labor supply literature, I focus on the effects on women and men separately. Women's labor supply is considered to be more elastic than men's. For example, Alesina, Ichino and Karabarbounis (2011) argue for gender-based taxation because men are less responsive to market wages and compensation. They argue that because of historical, social and cultural reasons, men derive more utility from participating in the labor market even while market compensation is low. However, it is socially acceptable for women to fully engage in home production. The intuition of Alesina, Ichino and Karabarbounis (2011) is equally valid in the UI system. Unemployment benefits could induce women to abandon the labor market in favor of home production.

This paper's objective is to focus on just one "channel," where UI extension can be treated as plausibly exogenous. In my research design, I assume that eligibility for UI is not affected by search activity. I use the American Time Use Survey (ATUS) data, as it provides information about job search activities of unemployed individuals. This paper's identification strategy uses unemployed persons eligible for UI benefits as a treatment group and those ineligible as a control group (e.g., Farber and Valletta, 2013; Rothstein, 2011; Krueger and Mueller, 2010). I use two supplementary empirical approaches to investigate the disincentive effect of extended UI benefits. I first estimate the effect of the weekly average UI benefits on job search intensity (an amount of time spent on job search activities on a given diary day) for the eligible group relative to the ineligible group by year from April 2004 to 2011. My goal is to assess whether the average dollar amount of the weekly UI benefits affect the job search intensity differently in the post-extension period.

Second, I employ the difference-in-differences (DD) method, since the extensions in 2008-2009 could be treated as a natural experiment or pseudo-experiment. Before proceeding to the actual estimation, I test if the control group could serve as a true counterfactual, so that the proposed DD methodology is a statistically valid approach. The post-treatment sample consists of the period 2010-2011. Even though the UI extension began in June 2008, Congress successively revised and introduced new tiers of extensions with different features and benefits until November 2009 (see Section II for details). More importantly, the extensions were still intact through 2010 and 2011 (and continued into 2013, albeit with some changes made in 2012). At the time of writing, the latest year of data available from the ATUS is 2011. I choose the period before June 2008, specifically from April 2004 to May 2008, as the pre-treatment period. Prior to March 2004, another moderately extended UI coverage–Temporary Extended Unemployment Compensation (TUEC)–was in effect. As UI coverage was extended during recessions in the past, the unemployed might have anticipated an extension in UI coverage, especially after the beginning of recession (December 2007) and might subsequently have reduced job search efforts. To overcome this anticipation effect, I also estimate models using pre-treatment period only until December 2007. It is worth mentioning that even though the potential duration of benefits has been extended, the replacement rate (ratio of the UI benefits relative to previous earnings) has been left unchanged. Therefore, the recipient received the weekly dollar amount of the extended benefits equal to the regular benefit amount.

To preview the results, I find women are more responsive to the extended UI benefits (the effect for women is negative and statistically significant) than men. The average effect of the extensions of UI coverage on job search behavior of unemployed women is over a 10 percentage point decline in the probability of job search. I find that the probability of unemployed men searching for a job decreases by one percentage point; however, it is not statistically significant. I apply a placebo test to check whether the model is capturing actual treatment effects, not the pre-existing differential trends between treatment and comparison units.

This paper is related to the literature empirically investigating the disincentive effect of UI benefits. The majority of the literature that is focused on the effect of UI benefits on unemployment durations or exits (e.g., Katz and Meyer, 1990; Meyer, 1990; Card and Levine, 2000; Jurajda and Tannery, 2003) shows a wide range of disincentive effects. Furthermore, this paper complements a strand of the literature that looks at the disincentive effect of extended benefits associated with the Great Recession on unemployment rates. Rothstein (2011), along with examining the effect of UI extensions on unemployment exits and durations, investigates the effect on the unemployment rate, and finds a small effect of about a 0.1 to 0.5 percentage point increase in the unemployment rate. Farber and Valletta (2013) apply a similar approach to Rothstein (2011), and their estimates show a statistically significant and small increase in unemployment duration, and around a 0.4 percentage point rise in the unemployment rate. Fujita (2011) and Mazumder (2011) employ a simulation approach, based on the estimated parameters in the previous research, to measure the disincentive effect of UI on unemployment rates. They find that extended UI benefits contributed to around a 0.8 to 1.2 percentage point increase in the unemployment rate. Using a structural calibrated model, Nakajima (2012) finds that UI extensions of 2008-2009 caused the unemployment rate to increase by 1.4 percentage points, accounting for about 29 percent of the total unemployment rate increase in the US between 2005-2007 and 2009-2011. This paper contributes to this literature by looking at the effect of extended UI benefits on job search behavior, a key variable affected by the UI program.

This paper is also related to a growing literature studying the job search effort of the unemployed. Aguiar, Hurst and Karabarbounis (2013), who study how individuals utilize their lost work hours during the recent recession in the U.S., find that around two to six percent of the lost market work hours were devoted to job search. Likewise, DeLoach and Kurt (2013), Gomme and Lkhagvasuren (2013), and Mukoyama, Patterson and Sahin (2014) study the job search behavior over the business cycles using the ATUS data. Though not a primary objective of this paper, its results have implications for understanding the prediction of the standard search and matching model. For instance, Shimer (2005) finds that the textbook search and matching model is unable to account for the observed volatility of the labor market tightness, defined as the vacancy to unemployment ratio. The volatility might be affected by fluctuations in job search behavior over the business cycle due to changes in generosity of unemployment benefits. Note that the U.S. government has historically extended the unemployment insurance during periods of economic downturn.

The remainder of this paper proceeds as follows. Section II offers a brief description of the unemployment insurance system in the U.S. Section III describes data and presents basic estimates. I design a difference-in-differences specification in Section IV. Section V presents results, and Section VI includes placebo tests and further robustness checks. Section VII presents its conclusions.

3.2 Background on Unemployment Insurance Extensions

Established under the Social Security Act of 1935 as a joint federal-state program, the unemployment insurance (UI) system provides temporary financial support to workers who lose lobs. The UI aims to ease financial hardships of the unemployed and facilitate their job search behavior. Normally, states set the parameters of the regular UI benefits, including the maximum and minimum amount of the benefits, the potential duration of the benefits, and eligibility criteria. The duration of availability is typically 26 weeks in most states[1] during normal economic periods. The weekly benefit amount varies from state to sate. In 2011, an average worker received around $300 a week nationwide, replacing almost half of his or her previous earnings. To receive benefits, workers must lose their job through no fault of their own, must have a certain amount of previous earnings, and must actively search for work. Generally, new entrants and re-entrants into the labor force as well as those who voluntarily leave jobs or are fired for a cause like misconduct are not eligible for the benefits. According to Krueger and Meyer (2002), about 40 percent of all unemployed individuals (both eligible and ineligible) qualify for and receive UI benefits.

One important aspect of the U.S. unemployment insurance system is that the government has historically extended the duration of UI benefits during periods of economic downturn through two channels. Since 1970, Extended Benefits (EB), a joint federal-state program, has provided an additional 13 and 20 weeks of benefits in states exceeding the unemployment rate of 6.5 percent and 8 percent, respectively. On top of that, the federal government has extended the duration of UI coverage on a temporary basis to the unemployed during recessions or periods of severe unemployment. So far Congress has activated such temporary programs eight times - 1958, 1961, 1971, 1974, 1982, 1991, 2002, and 2008 (see Whittaker and Isaacs, 2013).

As part of its response to severe unemployment brought about by the Great Recession, Congress enacted the Emergency Unemployment Compensation (EUC) program in June 2008 (see Appendix Table A1). In the beginning, the EUC offered an additional 13 weeks of benefits to the unemployed who exhausted their regular benefits. Congress expanded the duration of EUC benefits in successive phases until November 2009, increasing the duration of the benefits under the EUC up to 53 weeks. There are four tiers of EUC. EUC Tiers

[1] In Missouri and South Carolina, regular UI benefits are available for 20 weeks, and in Arkansas for 25 weeks (see "Council of Economic Advisors").

I and II offer an additional 20-weeks and 14-weeks of compensation for the unemployed in all states irrespective of unemployment rates. However, the remaining two tiers are based on unemployment rates. EUC Tier III provides benefits for a further 13 weeks in states where the unemployment rate exceeds six percent. EUC Tier IV is implemented in states exceeding 8.5 percent unemployment and offers an additional six weeks of benefits. In total, an unemployed individual in 2010 and 2011 was able to receive UI benefits as long as 99 weeks (26 weeks under the standard UI, 20 weeks under the EB and 53 weeks under the EUC). These unprecedented extensions have been called the most generous in U.S. history (e.g., Barro, 2010).

3.3 Data and Basic Estimates

This paper draws its main data from the American Time Use Survey (ATUS) as it is the only nationally representative survey that contains information about job search activity. This information enables me to directly investigate the effect of unemployment insurance on job search behavior. The U.S. Census Bureau conducts the ATUS, which is sponsored by the Bureau of Labor Statistics. The ATUS selects respondents from the outgoing sample of the Current Population Survey (CPS). Individuals aged 16 or above are surveyed in the ATUS, two to five months after their final CPS interview; about 71 percent after three months. Individuals are asked to report their detailed activities on the basis of their previous day's time use diary. One of the several activities reported in the ATUS is the amount of time spent on job search. Job search includes making contacts to employers, looking at and responding to job advertisements, filling out applications, and traveling to job interviews. A complete list of activities used as job search in this paper are given in Table A2 in Appendix B.

I limit the data to unemployed individuals between ages 25 to 64 years in the main estimations since this group has a strong participation in, and inclination toward, the labor market.[2] This paper's choice of a lower-bound age restriction follows Blau and Kahn (2007), and Cullen and Gruber (2000), in order to avoid complications related to choices of schooling versus market work by young people. According to Mulligans (2012), more than 75 percent of unemployed youths between ages of 16 to 24 years do not receive UI benefits. Upon reaching 65, an individual's labor market behavior may change due to eligibility for social security and medicare benefits. I use data from April 2004 to 2011. The ATUS began collecting data in 2003. Its 2003 survey consists of around 20,000 respondents. Since 2004, the number of respondents has decreased to approximately 13,000 each year. The sample (which excludes individuals who are employed, are out of the labor force or aged below 25 and above 64) includes 3,259 unemployed persons. The data are repeated cross-sections.

The definition of an unemployed person in the ATUS is the same as in the CPS. The definition includes those aged 16 years and older who are unemployed, but available for work in the reference week and who have actively been searching for work in the past four weeks. Search rule is exempted for those individuals who are expecting to be recalled to a job. (These individuals are still considered unemployed even if they have not looked for work in the past four weeks prior to the survey.)

The ATUS does not contain any explicit information about eligibility and ineligibility for UI benefits, nor does it have any information on whether eligible individuals indeed claim the benefits. However, the data contain information about individuals' reasons for unemployment. Using these reasons for unemployment, I follow the classification strategy of Krueger and Mueller (2010) to infer an individuals' eligibility for UI benefits. In recent years, this strategy of classification has become popular in the literature (e.g., Farber and Valletta, 2013; Rothstein, 2011). I first divide unemployed persons into four categories: i) job losers, ii) those expecting a recall from their previous employer, iii) voluntary job leavers, and iv) new entrants and re-entrants into the labor force. Then, I categorize: i) job losers as well as ii) those expecting a recall from the previous employer as eligible for UI benefits,

[2] Nonetheless I separately estimate effects of the UI extensions for youths between ages of 16 to 24 years.

and iii) voluntary job leavers as well as iv) re- or new entrants into the labor force as the ineligible group. More specifically, each category is defined in the following way:

(i) Job losers: This category includes persons who reported in the CPS interview that they were on layoff, or that they had become unemployed due to the ending of a temporary job, and are still unemployed in the ATUS interview. It also includes those who reported in the CPS that they are employed, but are unemployed in the ATUS interview. It could be recalled that CPS data were collected two to five months prior to the ATUS.

(ii) Expecting a recall: This category consists of unemployed persons who indicate in the ATUS interview that they are expecting a recall for work from their previous employer.

(iii) Voluntary job leavers: This category includes those who reported in the CPS that they quit their job, and are unemployed in the ATUS. It is worth mentioning that the ATUS questionnaire does not include any information about job quitters, so I turn to the CPS data to identify them.

(iv) Re- and new entrants: This category includes those persons who reported in the CPS that they are out of the labor force, but who are unemployed at the time of the ATUS interview. It also includes those who reported in the CPS interview that they are re-entrants or new entrants in the labor force and are still unemployed at the time of the ATUS.

Presumably, my classification strategy has some flaws since I am unable to observe if eligible persons actually receive UI benefits. One of the flaws in my classification is related to re- and new entrants into the labor force. In my classification strategy, those who are re- and new entrants or those who are out of the labor force at the time of the CPS interview but are unemployed in the ATUS interview are categorized as ineligible. However, it is possible for some of them to have found a job and become unemployed again during the period between the CPS and ATUS interviews. So, it is possible for me to classify a person as ineligible on the basis of the CPS data where he/she in fact became eligible in the months between the CPS and ATUS survey. However, I could not verify this possibility in the ATUS data. This classification error is expected to create a downward bias in the estimation of the parameter of my interest, thus underestimating the true effect of UI extensions. Likewise, I am unable to observe if eligible individuals actually receive benefits. Those unemployed who are not actually collecting unemployment benefits might have a higher participation rate in job search (if the theory that UI benefits discourage job search is to be believed). Excluding them from the eligible group decreases the overall mean of job search of that group, which in turn increases absolute magnitude of UI effect. To sum up, these errors are likely to create a downward bias in my estimates.

A. Preliminary Analytics

In this subsection, I attempt to calculate both the probability and intensity of job search across groups before and after the extensions of UI benefits, using the data from April 2004 to May 2008, and 2010 to 2011. Table 1 contains job search participation rates in pre- and post-treatment periods across treatment and control groups. I define the participation rate (i.e., the probability of participation) as the share of unemployed individuals in the sample who spend time in job search on the surveyed day.

The calculations in Table 3, which are DD estimates without any control variables, show that UI coverage expansions decreases the job search probability of the unemployed women eligible for UI benefits by around seven percentage points, relative to those ineligible women. Likewise, the average effect of UI extensions for men is around a three percentage points decline in the probability of job search. If the treatment (the extensions of UI coverage) were completely random, this estimate would be the implied causal effect. However, the estimates might be driven by observed or unobserved individual characteristics, instead of being the effect of the extended UI coverage. I then attempt to understand if there is any change in the composition of the control group between pre- and post-treatment periods, to raise the group's job search outcome in a larger proportion than that of the treatment group. For this purpose, I look at the observed characteristics between the pre- and post-treatment period. Table 2 contains observed characteristics of each group before and after the treatment (Panel A for women and Panel B for men). The characteristics of each group mostly seem similar between pre- and post-treatment periods. The only noticeable changes are a shift to more educated/experienced women in the treatment group after the recession. But, the big shift in job search is for the control group, not the treatment group. Nonetheless, we cannot deny a possibility that unobserved characteristics might be different between pre- and post-treatment periods, but we cannot verify it. (In this event, the conditional independence assumption could be violated.)

On the other hand, it could be argued that as the job arrival rate is lower during the period of economic slack (the post-treatment period), both groups are required to put extra search efforts to achieve the same level of success as in the normal economic times (pre-treatment period). Hence, those ineligible for unemployment benefits sped up their efforts in the post-treatment period, while those eligible did not speed up due to the generous benefits. This might have led to a slower growth of job search by the treatment group.

Table 3 presents the probabilities of job search over the subgroups of unemployed individuals across gender on a given diary day before and after the UI expansions. On average, around 16 percent of the total unemployed women engaged in job search (i.e., had greater than zero-minute job search) before the extensions of UI coverage, in comparison to 22 percent after the extensions. In all sub-categories, the participation of women in job search in the post-extension period is higher than pre-extension period. Likewise, the proportion of unemployed men engaging in job search was 28 percent after the extensions, up from 26 percent before the extensions. Among the sub-categories of unemployed men, all except Hispanic and other groups have a higher proportion of job-search in the post-extension period than the pre-extension period.

Table 4 reports job search intensity (i.e., the total amount of time an individual spends looking for a job on a given diary day). Except quitters, there has been an increase in job search activity for women by their types of unemployment and race in the post-extension period as compared to the pre-extension period. Among unemployed men, quitters, Hispanic and those in the category of other race has decreased job-search intensity in the post-treatment period.

Overall, these preliminary analytics show that job search activity has mostly increased across groups, including treatment and control groups, in the post-treatment period as compared to the pre-treatment period. Furthermore, those eligible for UI benefits had higher probability and intensity of job search in the pre-treatment period, in comparison to those ineligible. However, growths in both the probability and intensity of job search between pre- and post-extension periods for the eligible group were considerably slower than that of the ineligible group.

3.4 Difference-in-Differences Estimates for Job Search Probability

My goal in this section is to assess the effect of UI extensions on job search behavior during the Great Recession and its aftermath. As the extensions could be seen as a pseudo-experiment, I apply a difference-in-differences (DD) regression, which is very popular in the literature to measure the policy effect or intervention. I use the period from March 2004 to May 2008 as the pre-treatment period and 2010-2011 as the post-treatment period. One of the major issues in DD analysis is whether the control units in a study can truly serve as the counterfactual of the treatment units. If there are systematic differences between the comparison and treatment units, the estimates from the DD approach may reflect results of their differences, not the policy effect (treatment). This is true even if the unconfoundedness assumption still holds in the regression. One indirect way of testing such a systematic difference is to test if there is a sufficient overlap in the covariates between treatment and control units. For this purpose, one may think of an conventional approach which is to use a t-test:

$$t = \frac{\bar{X_1} - \bar{X_0}}{\sqrt{\frac{S_0^2}{N_0} + \frac{S_1^2}{N_1}}}. \quad (3)$$

However, the major drawback with this test is that it is very sensitive to sample size, and it tends to over-reject the null hypothesis when the sample size increases. To address this limitation, Imbens and Wooldridge (2009) suggest using a normalized difference (which is also scale-invariant), where the difference is:

$$\Delta X = \frac{\bar{X_1} - \bar{X_0}}{\sqrt{S_0^2 + S_1^2}}. \quad (4)$$

The authors also suggest that researchers can use the threshold of one-quarter normalized difference as a rule of thumb. Exceeding this specified threshold implies that covariates are different between control and treatment units. In Tables 5 and 6, I report normalized differences for each individual-specific covariates used in the DD model for women and men respectively. The differences are calculated for the control and treatment groups during pre- and post-treatment periods, separately. Almost all of the differences are less than one-quarter. (For women, only one variable–a dummy variable for the white–is slightly higher than one-quarter, and for men, age variables slightly exceed this threshold.) Overall, this suggests that individual characteristics are not systematically different by the treatment status. Therefore, the difference-in-differences estimator could be seen as a plausible empirical strategy.

As many respondents in the sample are not participating in job search (i.e., they have zero-search) on a given diary day, I am interested in looking at the impact of the UI benefits on the probability of their decision to participate in the job search activity. (In an alternative specification and robustness check later, I actually look at the effect on job search intensity using the DD method in the form of equation [5] below.) It is important to note that the probability of job search in this paper could be viewed as the probability of sampling an individual who spends a positive amount of time in job search activities. It is true that to be counted as unemployed in the CPS data, an individual should have at least one active job search in the last four weeks preceding the surveyed date. Note that respondents in the ATUS data are drawn from the CPS's respondents, and the ATUS follows the CPS's definition of unemployment. In the CPS (and the ATUS), active job search refers to an activity which could land an individual on a job without any additional work. Otherwise, an activity is called passive, which is not enough for an individual to be categorized as an unemployed. For example, looking at an ad on newspaper is a passive activity. However, in the definition of job search in this paper, both active and passive activities are included. I have listed a complete list of job search activities in Appendix A.

One of the shortcomings of time diary data is that we can observe a respondent's activities only on a particular day. Hence, it is possible that the respondent might have spent time looking for a job on other days. Nonetheless, sampling an individual with positive amount of time devoted to job search could be a close proxy to the job search probability of the individual. The intensity with which a job seeker pursues a position should be positively correlated with the probability to have a positive amount of job search on a random day of the survey. For instance, if an individual has only one active job search in the past four weeks, and is categorized as unemployed, it is very likely that we observe zero job search probability on the surveyed day. On a given surveyed day, around 18.38 percent unemployed women have greater than zero job search activities (i.e., around 81.62 have zero job search). Likewise, around 26.94 percent unemployed men have greater than zero job search activities. Table 3 contains further details on how many respondents have job search activities greater than zero on a diary day, by the type of unemployment before and after the treatment. Note that the probability of the participation represents the share of unemployed individuals in the sample who have a greater than zero job search on a given diary day.

One advantage of using the binary dependent variable (probability of job search instead of job search intensity) is that it is less prone to measurement error. The reason is that it is easier for individuals to remember whether they looked for a job on a given diary day, rather than recalling the amount of time they spent looking for a job. Specifically, I estimate the logit DD model below on repeated cross-sectional data to measure the causal effects of UI extensions on job search decision.

$$Pr[y_{i(t,s)} = 1 | Post_t, Treat_i, x_{i(t,s)}] =$$
$$\Lambda[\alpha + \beta_1 Post_t + \beta_2 Treat_i + \delta Post_t * Treat_i + \lambda Trend_t + \theta' x_{i(t,s)}$$
$$+\gamma_3 AWB_s + \gamma_1 un\_rate_s + \gamma_2 un\_dur_i + \gamma_5 \widehat{ln(w)}_{i(t,s)} + \gamma_4 stateresid_s], \qquad (5)$$

where i = 1, 2, 3, ...N denotes individuals, and s represents state. The outcome variable, $y_{i(t,s)}$, is an indicator variable equal to 1 if an individual participates in job search; otherwise 0. $\Lambda(.)$ is the logistic cumulative distribution function. The variable $Post_t$ is a dichotomous variable which equals 1 if it is the post-extension period. The variable $Treat_i$ is a dummy variable, equal to 1 if an individual is eligible for UI benefits. The variable $Post_t * Treat_i$ is the variable of interest (its coefficient is the treatment effect). The treatment and control groups have the same linear time trend. (In a later robustness check, instead of time trend I use a year fixed-effect model, and also use a quadratic time trend.) $x_{i(t,s)}$ is a vector of individual characteristics, including age, age-squared, level of education, race, sex, presence of child in house, and marital status.[3] The variable AWB_s is average weekly UI benefits (which represents the average dollar amount of benefits received by a recipient per week, calculated by month and state).[4] I also include other control variables described

[3]The variable partner represents martial status, which includes both the married and individuals cohabiting with a partner as a non-reference group.

[4]I collect average weekly unemployment benefits from Department of Labor Employment and Training Administration (`http://workforcesecurity.doleta.gov/unemploy/claimssum.asp`).

below.

The unemployment rate (un_rate_s): One of the major factors that might influence an individual's job search behavior is a perception about the macroeconomic environment. Unemployed individuals may not look for jobs during a period of severe unemployment if they perceive that jobs may not be available and that the marginal cost of job search will be higher than the expected payoff. Conversely, it could be argued that an individual needs to put extra time and effort to find a job in a period of mass unemployment due to a decline in jobs arrival rate. And, the literature is not conclusive about the cyclical property of job search behavior. DeLoach and Kurt (2013), and Gomme and Lkhagvasuren (2013) find job search behavior to be pro-cyclical (unemployed decrease search efforts during the labor market slack), while Mukoyama, Patterson and Sahin (2014) shows that the aggregate job search effort is countercyclical. To capture the potential change in an individual's job search behavior, I control for the monthly unemployment rate by state.[5] In the ATUS data, I can observe the month of interview of the respondents, so I am able to match the interview month with the monthly unemployment rate.

The unemployment duration (un_dur_i): The canonical model of Mortensen (1977) predicts that unemployed individuals ineligible for UI benefits put constant effort toward job search irrespective of their unemployment duration, while eligible ones speed up their search effort when their benefits are about to expire. Therefore, controlling for unemployment duration is essential. However, the ATUS data do not include the unemployment duration of individuals. As in Krueger and Mueller (2010), I use the duration reported by unemployed individuals in the CPS interviews. I then add the number of weeks between their CPS and ATUS interview to the duration reported in the CPS. However, for the respondents who are not unemployed in the CPS interview but are in the ATUS, I am not able to observe their duration. Therefore, I impute a proxy duration for them, which is half of the weeks between

[5] I compile monthly state unemployment rates from the Bureau of Labor Statistics. The data can be downloaded at `http://www.bls.gov/schedule/archives/laus_nr.htm#2003`.

the CPS and ATUS interviews.

Potential wage ($\widehat{ln(w)}_{i(t,s)}$): Potential wage is believed to influence an unemployed individual's behavior. For those unemployed persons who expect a higher wage in the labor market, unemployment benefits might have minimal effects as their opportunity cost of staying unemployed would be high. For the low earnings group, the weekly benefits can replace a significant portion of their potential earnings, encouraging them to substitute their labor with leisure. However, the data do not contain information about previous earnings of the unemployed, even if they have work history. To deal with this wage issue, I estimate a predicted wage for each individual. First I use the Current Population Survey's (CPS) Outgoing Rotation Group data and estimate the following state-fixed effect model separately for each year [6] for log-wage:

$$log(w_{i,s}) = \varrho + \upsilon x\prime_{i,s} + dummy_s + \epsilon_{i,s}, \qquad (2)$$

where x_{is} is a vector of individual characteristics, which include the level of education, age, age-squared, gender, marital status, and presence of children. I also use state dummies. Then, on the basis of estimated parameters from equation (2) for a particular year, I predict expected log-wage for each respondent in the ATUS for that year.[7]

Distribution of the potential wage offer ($stateresid_s$) : Another determinant of job search is the potential wage offer distribution. The rationale behind this is that the more dispersed the distribution is, the more time individuals spend looking for a job as they try to get the best possible wage. As a proxy for the potential wage-offer distribution, I use residual wage dispersion calculated as the standard deviation of the residual ($\epsilon_{i,s}$) from wage

[6] I use the Central for Economic and Policy Research (CEPR) version of the CPS data. This data adjusts for over-time earnings, tips and commissions. Output results from this estimation are omitted due to space constraints.

[7] Because each year I run a separate regression, the number of observations vary by the year. In 2004, the number of observations is 108,752. The number includes 108,228 in 2005, 107,085 in 2006, 106,314 in 2007, 104,910 in 2008, 139,326 in 2010, and 137,828 in 2011.

equation (2) for each state and year (see Krueger and Mueller, 2010).

For the non-linear DD model, the interpretation of the policy parameter, δ, is different from the case of a linear regression. The average treatment effect on the treated (ATT) equals the differences in the two cross differences (e.g., Eissa and Liebman 1996, Puhani 2012). Let τ be the effect:

$$\begin{aligned}\tau = \Lambda[\alpha + \beta_1 Post_t + \beta_2 Treat_i + \delta Post_t * Treat_i + \gamma_1 Trend_t + Z'_{i(t,s)}\theta] \\ -\Lambda[\alpha + \beta_1 Post_t + \beta_2 Treat_i + \gamma_1 Trend_t + Z'_{i(t,s)}\theta], \qquad (6)\end{aligned}$$

where $Z_{i(t,s)}$ is a vector of all control variables used in regression (5). Bertrand, Duflo and Mullainathan (2004) show that the conventional DD standard errors are severely understated due to serial correlation. As suggested by the authors to correct for possible serial correlation, I calculate the variance-covariance matrix of errors, clustering at the state level, from the regression of equation (5).[8] Then, I apply the Delta Method to calculate standard errors for estimates.

3.5 Results

In this section I present results from a variety of specifications of difference-in-differences (DD) estimation based on equation (5) to explore the causal effect of the recent UI extensions on job search behavior across gender. The focus of this paper on gender differences in the impact of the extensions in UI benefits is in line with the labor supply literature.

I estimate four-baseline nonlinear DD models for men and women separately; the results are presented in Table 7 and 8. The first three models include same control group,

[8]Indeed, clustered standard errors in this paper are slightly higher than the conventional robust standard errors, supporting Bertrand, Duflo and Mullainathan's (2004) argument.

but slightly different treatment groups. The first model consists of the full sample (all individuals eligible for UI benefits as treatment group). In the second and third models I attempt to exclude those eligible unemployed persons, who are perceived to have exhausted their UI coverage. In the pre-treatment period, UI benefits were usually available for 26 weeks. Therefore, I exclude those eligible individuals having the duration of unemployment more than 26 weeks in the pre-treatment time (from the treatment group). In the second model, I exclude all individuals who are unemployed more than 99 weeks in 2010 and 2011 (from the treatment group), as they were eligible for UI benefits up to 99 weeks. In the third model, I exclude all eligible individuals who are unemployed more than 60 weeks in the post-treatment period (for the reasons explained in the earlier Section).

In model 4, I exclude those unemployed persons who are on temporary layoff and expecting a recall from their previous employer (from both the control and treatment group), and those who voluntarily left the job (from the control group). It is expected that these people behave quite differently from the average labor market participant. The sample then consists of individuals who are on layoff through no fault of their own as eligible (treatment) group, and re- or new entrants in the labor force as ineligible (control) group.

In all these models, I find consistently close results (Table 7) for women. I get positive and significant effect of the eligibility status (i.e. the variable eligible) on job search behavior. One of the potential reasons for having higher job search probability for eligible group could be the requirement of job search to collect UI benefits. And, it is possible that eligible individuals might have kept up looking for a job; however, they might have refused to take up job offers, increasing reservation wage and extending the duration of unemployment (another disincentive effect of UI benefits which I do not explore here). Another possibility for the higher probability of job search by the eligible group than the ineligible group could be the result of the initial differences in job search behavior. It could be noted that the eligible group mostly consists of those who are laid off from work, and the ineligible group consists of re- or new entrants in the labor force. Arguably, a layoff can be considered as a shock to the worker. In light of the shock, the laid-off worker could be in greater need of a job to smooth or maintain consumption than that of a re- or new entrant who can have a relatively longer period to adjust for consumption. Nonetheless, this variable does not represent the effect of UI extensions.

The interaction term between eligibility and post-treatment period (referred as $Treat_i \times Post_t$) is the variable of interest as its coefficient is the implied causal effect of treatment (extensions of UI benefits). In the technical language of program evaluation, the coefficient is termed as average treatment effect on the treated (ATT). The average effect of the UI extensions in 2010 and 2011 is over 10 percentage points decline in the probability that an eligible unemployed woman searches a job. It is statistically significant at the five percent level in the first and third model, and at the one percent level in the second and fourth models. This represents around a 56 percent of the average predicted probability of job search (i.e., the ratio of the effect to $\bar{\hat{p}}$). I find around a one percentage point decline in the probability of job search for men (Table 8). However, it is not statistically significant.

A. The Effect of UI Extension on Youths

In this subsection, I attempt to evaluate the effect of UI extensions on youths between ages of 16 to 24 years by gender. Unemployment benefits are expected to have very minimal impact on this group's labor market decision, since over 75 percent of unemployed youths do not receive unemployment benefits (see Mulligans 2012). First, most youths either enroll in schools and colleges, or are planning to enroll. Second, many might not have sufficient work history to be eligible for UI benefits. Third, as they are in the early phases of their career, finding a job and gaining work experience could be a priority, instead of being dependent on the social safety net. As expected, the effects are not statistically different from zero.[9]

[9] To save some space, I do not report the results and are available upon request.

B. Anticipation Effects

It is worth considering if the results are clouded by anticipation effects. Historically, unemployment benefits have been extended during recessions. With the advent of the Great Recession in December 2007, the unemployed individuals eligible for UI coverage might have anticipated the extension of UI benefits in the near future. Thus, I attempt to take anticipation effects into account. I exclude 2008-data from the pre-treatment period (include only from March 2004 to 2007), and estimate the two models for women.[10] The first regression includes the full sample, while the second excludes those individuals expecting a recall from their previous employer, quitters, and those eligible individuals who are supposed to have exhausted UI benefits (those having remained unemployed more than 26 weeks in pre-treatment period and 60 weeks in the post-treatment period). Table 9 reports the results. I find consistently close results to the baseline specification. The average effect of the UI extensions is a decline of job search in the range of 10 to 13 percentage points, and statistically significant at the five percent level in the first model, and at the one percent level in the second model.

3.6 Robustness Check

A. Placebo Test

I apply two placebo tests to further explore if the results are robust, not spurious, and to justify the validity of difference-in-differences (DD) methodology in this paper. One of the most important assumption in DD regression is a common trend (i.e. in the absence of treatment, the treatment group would evolve in the similar fashion as control group). The placebo tests complement the normalized-differences test used in Section IV to gauge the

[10] I do not report estimation for men as I do not find statistically significant effects on the baseline specification for them.

common trend assumption. If the results in the baseline model were not the true policy effect, rather the reflection of the underlying structural differences between treatment and control units, I should expect statistically significant estimates in the model with only pre-treatment period data.

I carry out two placebo tests using the data from the pre-treatment period. First, I use all pre-treatment data from April 2004 to May 2008, during which no federal emergency unemployment compensation program was introduced. I divide the data into two periods (from April 2004 to 2005 as the pre-treatment period, and from 2006 to May 2008 as the post-treatment period). Second, I extend the placebo test by changing the treatment periods. I use data from April 2004 to 2005 as the pre-treatment period, and 2006 and 2007 as the post-treatment period, excluding 2008. I run the logit difference-in-differences regression with the same specification as in equation (5). Unemployed individuals eligible for UI benefits represent the treatment group, and ineligible individuals are the control group, the same definition as in the main baseline DD model. My variable of interest is the interaction between the variables eligibility and post-treatment period (denoted as $Treat_i \times Post_t$), as in the baseline model.

I run two regressions for each placebo test. First regression includes the full sample. Second regression excludes those who are supposed to exhaust UI benefits from the treatment group (those unemployed longer than 26 weeks), those expecting a recall from the past employer, and quitters. Results from the placebo tests are reported in Table 10 for women. (I do not report results for men as I do not find any effect in the main estimations.) The variable of interest ($Treat_i \times Post_t$) is not statistically different from zero in both specifications. To save space, I do not include estimates of controlled variables. To sum up, the placebo tests further validate the findings for the effects of UI extensions on the probability of job search in the baseline DD regression.

B. Effect on Job Search Intensity

In this subsection, I attempt to measure the effect of UI extensions in terms of job search intensity. First, I run the ordinary least squares (OLS) model for equation (5) (linear DD regression) with the amount of job search as the dependent variable. I exclude those who are expecting a recall from their past work, quitters, and those who are supposed to use up their UI benefits (those having remained unemployed more than 26 weeks in the pre-treatment period and 60 weeks in the post-treatment period). Table 11 reports results. The average effect is around 30 minutes decline in job search intensity on a given diary day. The estimate is significant at the five percent level without clustering. With clustering, the estimate is significant at the 10 percent level.

Additionally, I employ a Tobit difference-in-differences model, as job search intensity is highly skewed because most respondents in the survey have zero search (almost 80 percent). The OLS method does not work in extremely skewed data due to the violation of the normality assumption. Table 11 shows results from the Tobit difference-in-differences model. The model is left-censored (censored below zero). I find a negative and statistically significant (at the five percent level) effect.

C. Further Sensitivity Analysis

In this subsection I provide results from additional robustness exercises (see Table 12). First, I estimate a logit difference-in-differences regression using year fixed-effects instead of time trend. I normalize 2004 and the first year of the post-treatment period 2010 to zero to avoid the dummy variable trap. Second, I allow for quadratic time-effect. Third, I exclude unemployed women aged 55 and above from the data and estimate the model, to ensure that results are not driven by matters related to retirement. It is expected that those people who are close to retirement react to the labor market differently. As reported in Table 12, all results from these alternative specifications are close to those from the preferred baseline specification.

3.7 Conclusion

In this paper, I investigate the effects of unemployment insurance (UI) extensions on job search, using data from the American Time Use Survey (ATUS). The government made successive decisions about the extensions of UI coverage from June 2008 to November 2009, raising the duration of benefits to as many as 99 weeks. The extensions that are termed as the most generous in history were continued into 2011. In the research design of this paper, I use unemployed persons eligible for UI benefits as the treatment group and the ineligible as the control group. I use two supplementary empirical strategies to assess the disincentive effect of extended UI benefits coverage.

First, I investigate the differences in the effect of the average weekly UI benefits in job search intensity of the eligible individuals between the post-treatment and pre-treatment period, relative to the ineligible. Second, I apply a difference-in-differences estimator, as the extensions provide a pseudo-experiment. I focus on gender differences in the effect of UI extensions. Both strategies provide a negative and statistically significant effect on women, but for men the estimate is not statistically different from zero. The average treatment effect for women is around a 10 percentage point decline in a job search probability.

Some caveats apply to this study. Presumably, there have been some classification errors when it comes to classifying unemployed workers into eligible (for UI benefits) and ineligible groups. On top of that, I use eligible workers as the treatment group. In practice, a moderate portion of the eligible workers do not claim benefits (which makes it inappropriate to put them into treatment group). Both of these limitations will likely cause the results to be underestimated (i.e., downward bias). If the ATUS begins collecting information about

UI benefits received by individuals, more precise evaluation of the UI benefits system will be possible.

Table 1: Difference-in-Differences (DD) Estimates without Control Variables

	Women			Men		
	Control	Treatment	Difference	Control	Treatment	Difference
Before	0.108	0.205	0.096	0.209	0.275	0.066
	(0.023)	(0.027)	(0.036)	(0.044)	(0.031)	(0.054)
After	0.204	0.227	0.023	0.256	0.291	0.035
	(0.032)	(0.033)	(0.046)	(0.050)	(0.028)	(0.057)
DD			- 0.073			- 0.031
			(0.058)			(0.079)

Notes: The estimates are the average job search probabilities. Standard errors are reported in parentheses. These are calculated using the American Time Use Survey (ATUS) data from April 2004 to May 2008 (before treatment), and from 2010 to 2011 (after treatment), and applying survey weights.

Table 2: Characteristics of Individuals by Group

	Control		Treatment	
	Before	After	Before	After
Panel A: Women				
Less than HS	0.216	0.205	0.170	0.093
High School	0.526	0.541	0.522	0.493
Bachelor's Degree	0.199	0.195	0.232	0.322
Master's Degree/PhD	0.055	0.058	0.074	0.092
Age	39.564	39.488	41.622	44.119
Child Dummy	0.645	0.608	0.530	0.465
Married	0.615	0.588	0.608	0.550
White	0.455	0.462	0.657	0.573
Black	0.235	0.220	0.139	0.202
Hispanic	0.220	0.259	0.158	0.164
Others	0.091	0.059	0.045	0.061
Unemployment Duration	8.055	15.269	7.07	23.248
Observations	375	293	377	341
	Control		Treatment	
	Before	After	Before	After
Panel B: Men				
Less than HS	0.173	0.219	0.121	0.176
High School	0.553	0.547	0.593	0.553
Bachelor's Degree	0.237	0.185	0.201	0.204
Master's Degree/PhD	0.0295	0.032	0.071	0.062
Age	43.765	42.022	42.878	43.299
Child Dummy	0.405	0.327	0.376	0.414
Married	0.519	0.499	0.597	0.574
White	0.475	0.540	0.577	0.591
Black	0.310	0.292	0.200	0.187
Hispanic	0.126	0.127	0.160	0.177
Others	0.089	0.041	0.063	0.045
Unemployment Duration	9.397	11.543	7.107	25.401
Observations	154	143	359	410

Note: The estimates are calculated using the American Time Use Survey (ATUS) data from April 2004 to May 2008 (before treatment), and from 2010 to 2011 (after treatment).

Table 3: **Probability of Job Search by Group**

	Women				Men			
	Before		After		Before		After	
	Prob.	N	Prob.	N	Prob.	N	Prob.	N
All unemployed individuals	0.16	752	0.22	634	0.26	513	0.28	553
By types of unemployment								
Job losers	0.20	377	0.23	341	0.28	359	0.29	410
Quitters	0.23	27	0.26	16	0.22	19	0.48	11
New- or re-entrants	0.10	348	0.20	277	0.21	135	0.24	132
Job search by race								
White	0.18	433	0.22	318	0.25	288	0.31	301
Black	0.16	141	0.22	150	0.26	109	0.35	132
Hispanic	0.10	145	0.19	130	0.24	80	0.12	93
Others	0.16	33	0.24	36	0.36	36	0.23	27

Note: Job search probabilities are calculated using the American Time Use Survey (ATUS) data from April 2004 to May 2008 (before), and from 2010 to 2011 (after), and applying survey weights.

Table 4: **Job Search Intensity by Group**

	Women				Men			
	Before		After		Before		After	
	Intens.	N	Intens.	N	Intens.	N	Intens.	N
All unemployed individuals	20.90	752	35.37	634	50.82	513	51.68	553
By types of unemployment								
Job losers	31.19	377	36.04	341	54.12	359	56.58	410
Quitters	37.61	27	23.41	16	77.30	19	36.97	11
New- or re-entrants	8.78	348	35.26	277	37.94	135	38.98	132
Job search by race								
White	25.10	433	38.20	318	51.25	288	58.91	301
Black	14.79	141	37.50	150	44.44	109	60.84	132
Hispanic	14.50	145	27.22	130	46.75	80	20.58	93
Others	21.25	33	31.11	36	77.23	36	27.66	27

Notes: Job search intensity is calculated using the American Time Use Survey (ATUS) data from April 2004 to May 2008 (before), and from 2010 to 2011 (after), and applying survey weights. The intensity is measured as the number of minutes spent on job search on a given diary day.

Table 5: Normalized Differences: Women

Variables	Treat. Group Mean	Treat. Group SD	Cont. Group Mean	Cont. Group SD	Difference
Panel A: During the Pre-Treatment Period					
Less than HS	0.170	0.376	0.216	0.412	-0.084
High School	0.522	0.500	0.526	0.500	-0.005
Bachelor's Degree	0.232	0.423	0.200	0.400	0.056
Masters Degree	0.074	0.262	0.055	0.228	0.056
Ph.D.	0.002	0.043	0.004	0.060	-0.025
Age	41.622	10.119	39.489	9.997	0.150
Age squared	1834.525	866.403	1659.023	849.321	0.145
Child dummy	0.530	0.500	0.645	0.479	-0.166
Partner	0.608	0.489	0.615	0.487	-0.010
White	0.657	0.475	0.455	0.499	0.294
Black	0.140	0.347	0.235	0.424	-0.174
Hispanic	0.159	0.366	0.220	0.415	-0.110
Other	0.045	0.207	0.091	0.288	-0.131
N	377		374		

Variables	Treat. Group Mean	Treat. Group SD	Cont. Group Mean	Cont. Group SD	Difference
Panel B: During the Post-Treatment Period					
Less than HS	0.093	0.290	0.205	0.404	-0.225
High School	0.493	0.501	0.541	0.499	-0.067
Bachelor's Degree	0.322	0.468	0.195	0.397	0.206
Masters Degree	0.092	0.290	0.058	0.234	0.092
Ph.D.	0	0	0.001	0.030	-0.030
Age	44.119	10.984	39.537	10.247	0.305
Age squared	2066.757	965.846	1667.844	845.857	0.311
Child dummy	0.465	0.500	0.608	0.489	-0.204
Partner	0.550	0.498	0.588	0.493	-0.054
White	0.573	0.495	0.462	0.499	0.158
Black	0.202	0.402	0.220	0.415	-0.032
Hispanic	0.164	0.371	0.259	0.439	-0.165
Other	0.061	0.239	0.059	0.235	0.006
N	341		293		

Note: The estimates are calculated using the American Time Use Survey (ATUS) data from April 2004 to May 2008, and from 2010 to 2011, and applying survey weights.

Table 6: **Normalized Differences: Men**

Variables	Treat. Group Mean	Treat. Group SD	Cont. Group Mean	Cont. Group SD	Difference
Panel A: During the Pre-Treatment Period					
Less than HS	0.121	0.326	0.173	0.379	-0.104
High School	0.593	0.492	0.553	0.499	0.057
Bachelor's Degree	0.201	0.401	0.237	0.427	-0.062
Masters Degree	0.071	0.258	0.030	0.170	0.135
Ph.D.	0.013	0.115	0.007	0.086	0.042
Age	42.878	10.272	43.765	11.876	-0.057
Age squared	1943.707	891.635	2055.520	1040.115	-0.082
Child dummy	0.376	0.485	0.405	0.493	-0.042
Partner	0.597	0.491	0.519	0.501	0.111
White	0.577	0.495	0.475	0.501	0.144
Black	0.200	0.401	0.310	0.464	-0.179
Hispanic	0.160	0.367	0.126	0.333	0.069
Other	0.063	0.243	0.089	0.286	-0.070
N	359		154		

Variables	Treat. Group Mean	Treat. Group SD	Cont. Group Mean	Cont. Group SD	Difference
Panel B: During the Post-Treatment Period					
Less than HS	0.176	0.381	0.219	0.415	-0.077
High School	0.553	0.498	0.547	0.500	0.008
Bachelor's Degree	0.204	0.404	0.185	0.390	0.034
Masters Degree	0.062	0.242	0.032	0.177	0.101
Ph.D.	0.005	0.072	0.017	0.128	-0.077
Age	43.299	11.568	42.022	11.119	0.080
Age squared	2008.297	1004.439	1888.653	964.058	0.086
Child dummy	0.414	0.493	0.327	0.471	0.127
Partner	0.574	0.495	0.499	0.502	0.107
White	0.591	0.492	0.540	0.500	0.072
Black	0.187	0.390	0.292	0.457	-0.177
Hispanic	0.177	0.383	0.127	0.334	0.100
Other	0.045	0.208	0.041	0.199	0.016
N	410		143		

Note: The estimates are calculated using the American Time Use Survey (ATUS) data from April 2004 to May 2008, and from 2010 to 2011, and applying survey weights.

Table 7: **Results from Nonlinear Difference-in-Differences Models: Women**

Variables	Full Sample (1)	Unemp. Dur.$\leq$ 99 Weeks (2)	Unemp. Dur.$\leq$60 Weeks (3)	W/0 Indivs. Expecting a Recall and Quitters (4)
Treat	0.0983***	0.104***	0.106***	0.153***
	(0.0299)	(0.0310)	(0.0312)	(0.0314)
Post	0.0652	0.0613	0.0687	0.0612
	(0.0718)	(0.0754)	(0.0774)	(0.0784)
Treat×Post	-0.107**	-0.117***	-0.113**	-0.132***
	(0.0457)	(0.0437)	(0.0453)	(0.0494)
Time	0.0221	0.0214	0.0196	0.0238
	(0.0163)	(0.0170)	(0.0168)	(0.0186)
High School	0.0577	0.0571	0.0634	0.0583
	(0.0438)	(0.0428)	(0.0450)	(0.0570)
Bachelor's Degree	-0.0551	-0.0830	-0.0735	-0.0319
	(0.0894)	(0.0827)	(0.0851)	(0.122)
Master's Degree	-0.0209	-0.0514	-0.0563	0.000587
	(0.130)	(0.112)	(0.107)	(0.200)
Age	0.00153	-0.00201	0.0000694	-0.00182
	(0.0125)	(0.0129)	(0.0141)	(0.0152)
Age squared	-0.0000393	-0.00000228	-0.0000294	0.00000957
	(0.000141)	(0.000146)	(0.000163)	(0.000171)
Child Dummy	-0.0375	-0.0459	-0.0498	-0.0337
	(0.0363)	(0.0366)	(0.0362)	(0.0452)
Partner	-0.0703**	-0.0804***	-0.0757***	-0.0447
	(0.0283)	(0.0277)	(0.0263)	(0.0337)
Black	-0.00141	-0.000699	0.00259	-0.00790
	(0.0382)	(0.0377)	(0.0360)	(0.0431)
Hispanic	0.0308	0.0421*	0.0475**	0.0161
	(0.0242)	(0.0231)	(0.0240)	(0.0246)

Table 7 Continued ....

	(1)	(2)	(3)	(4)
Other	0.00411	0.0233	0.0299	-0.0600
	(0.0680)	(0.0709)	(0.0734)	(0.0586)
Predict wage	0.344**	0.388**	0.374**	0.339*
	(0.148)	(0.151)	(0.150)	(0.190)
State residual	-0.485	-0.473	-0.584	-0.558
	(0.612)	(0.609)	(0.648)	(0.733)
Unemploy rate	-0.00481	-0.00298	-0.00293	0.000502
	(0.00764)	(0.00787)	(0.00823)	(0.00887)
Avg. Weekly UIB	-0.000903***	-0.00105***	-0.00103***	-0.00102***
	(0.000324)	(0.000329)	(0.000338)	(0.000386)
Unemploy Duration	0.000628	0.000578	0.000588	0.000256
	(0.000635)	(0.000638)	(0.000676)	(0.000713)
N	1386	1345	1308	1192

Notes: Standard errors are reported in parentheses, which are calculated using the Delta Method. Errors are clustered at the state level. *** denotes the significance at the one percent level, ** at the five percent level, and * at the ten percent level.

The regression (1) consists of all unemployed persons. (2) excludes individuals eligible for UI benefits who are unemployed more than 26 weeks in the period between April 2004 and May 2008 and more than 99 weeks in the period between 2010 and 2011. (3) excludes individuals eligible for UI benefits who are unemployed more than 26 weeks in the period between April 2004 and May 2008 and more than 60 weeks in the period between 2010 and 2011. (4) excludes those who voluntarily leave jobs and who are on a temporary layoff expecting a recall from the past employer.

Table 8: **Results from Baseline Nonlinear Difference-in-Difference Models: Men**

Variables	Full Sample (1)	Unemp. Dur.$\leq$ 99 Weeks (2)	Unemp. Dur.$\leq$60 Weeks (3)	W/0 Indivs. Expecting a Recall and Quitters (4)
Treat	0.0501	0.0376	0.0350	0.108*
	(0.0573)	(0.0563)	(0.0564)	(0.0624)
Post	-0.0239	-0.0258	-0.0304	-0.0741
	(0.0827)	(0.0750)	(0.0760)	(0.106)
Treat$\times$Post	-0.0116	0.00677	-0.00575	-0.0148
	(0.0842)	(0.0821)	(0.0840)	(0.0922)
Time	0.0257	0.0253	0.0215	0.0364
	(0.0176)	(0.0170)	(0.0160)	(0.0235)
High School	0.0972	0.105	0.153*	0.106
	(0.102)	(0.104)	(0.0915)	(0.113)
Bachelor's Degree	0.270	0.304	0.380*	0.299
	(0.233)	(0.238)	(0.204)	(0.244)
Master's Degree	0.448*	0.455*	0.535***	0.469*
	(0.249)	(0.261)	(0.198)	(0.243)
Ph.D	0.0590	0.138	0.252	0.222
	(0.410)	(0.461)	(0.473)	(0.456)
Age	0.0414***	0.0453***	0.0445***	0.0533***
	(0.0151)	(0.0148)	(0.0138)	(0.0188)
Age squared	-0.000451***	-0.000499***	-0.000480***	-0.000583***
	(0.000168)	(0.000165)	(0.000154)	(0.000204)
Child Dummy	0.0635	0.0465	0.0516	0.0718
	(0.0620)	(0.0616)	(0.0583)	(0.0676)
Partner	-0.0457	-0.0326	-0.0288	-0.0474
	(0.0560)	(0.0537)	(0.0520)	(0.0636)
Black	0.0343	0.0360	0.0265	0.00922
	(0.0330)	(0.0335)	(0.0355)	(0.0341)
Hispanic	-0.0875**	-0.0973**	-0.0882**	-0.0800*
	(0.0364)	(0.0406)	(0.0423)	(0.0473)

Table 8 Continued ....

	(1)	(2)	(3)	(4)
Other	0.00464	-0.000914	0.00736	0.00710
	(0.0852)	(0.0826)	(0.0837)	(0.0995)
Predict wage	-0.191	-0.230	-0.295	-0.275
	(0.248)	(0.248)	(0.231)	(0.284)
State residual	0.896	0.867	1.069	0.771
	(0.718)	(0.695)	(0.719)	(0.764)
Unemploy rate	-0.0111	-0.0113	-0.00662	-0.0130
	(0.0103)	(0.0101)	(0.0116)	(0.0128)
Avg. Weekly UIB	0.000688	0.000714	0.000558	0.000646
	(0.000471)	(0.000503)	(0.000487)	(0.000523)
Unemploy Duration	-0.000188	-0.000644	-0.00126	-0.000925
	(0.000636)	(0.000818)	(0.000892)	(0.000795)
N	1066	1009	968	856

Notes: Standard errors are reported in parentheses, which are calculated using the Delta Method. Errors are clustered at the state level. *** denotes the significance at the one percent level, ** at the five percent level, and * at the ten percent level.

The regression (1) consists of all unemployed persons. (2) excludes individuals eligible for UI benefits who are unemployed more than 26 weeks in the period between April 2004 and May 2008 and more than 99 weeks in the period between 2010 and 2011. (3) excludes individuals eligible for UI benefits who are unemployed more than 26 weeks in the period between April 2004 and May 2008 and more than 60 weeks in the period between 2010 and 2011. (4) excludes those who voluntarily leave jobs and who are on a temporary layoff expecting a recall from the past employer.

Table 9: **Anticipation Effects: Women**

	Full Sample	W/0 Unemp. Dur. >60, Indivs. Expecting a Recall and Quitters
Variables	(1)	(2)
Treat	0.0951***	0.163***
	(0.0313)	(0.0364)
Post	0.118	0.142
	(0.0942)	(0.102)
Treat×Post	-0.104**	-0.138***
	(0.0481)	(0.0504)
Time	0.0106	0.00444
	(0.0189)	(0.0215)
N	1312	1052

Notes: Standard errors are reported in parentheses, which are calculated using the Delta Method. Errors are clustered at the state level. *** denotes the significance at the one percent level, ** at the five percent level, and * at the ten percent level.

The regression (1) consists of all unemployed persons. (2) excludes individuals eligible for UI benefits who are unemployed more than 26 weeks in the period between April 2004 and 2007 and more than 60 weeks in the period between 2010 and 2011, and those who voluntarily leave jobs and who are on a temporary layoff expecting a recall from the past employer.

Table 10: **Placebo Test**

	April 2004 to May 2008		April 2004 to 2007	
	Full Sample	Sub-sample	Full Sample	Sub-sample
Variables	(1)	(2)	(3)	(4)
Treat	0.126**	0.223***	0.121**	0.212***
	(0.0525)	(0.0618)	(0.0493)	(0.0582)
Post	-0.0104	0.0213	0.00828	0.0399
	(0.0597)	(0.0537)	(0.0529)	(0.0598)
Treat×Post	-0.0502	-0.0835	-0.0576	-0.0902
	(0.0632)	(0.0651)	(0.0655)	(0.0690)
Time	0.0348	0.0302	0.0166	0.00618
	(0.0243)	(0.0266)	(0.0337)	(0.0400)
N	752	594	678	530

Notes: Standard errors are reported in parentheses, which are calculated using the Delta Method. Errors are clustered at the state level. *** denotes the significance at the one percent level, ** at the five percent level, and * at the ten percent level. Subsample (referring to models 2 and 4) means excluding unemployed individuals expecting a recall from their past employer, quitters, and those having more than 26 weeks of unemployment duration.

Table 11: **DD Estimates of Job Search Intensity**

Variables	OLS (1)	Tobit (2)
Treat	28.86	161.2
	(7.459)***	(35.28)***
	[7.756]***	[39.53]***
Post	23.38	84.58
	(20.10)	(73.57)
	[17.38]	[79.45]
Treat×Post	-30.63	-167.4
	(17.37)*	(69.25) **
	[13.83]**	[57.75] ***
Time	2.778	17.57
	(3.048)	(15.97)
	[2.929]	[14.30]
N	1116	1116

Notes: Standard errors for Tobit model are calculated using the Delta Method. Errors reported in parentheses are clustered at the state level, while errors reported in square brackets are calculated without clustering. *** denotes the significance at the one percent level, ** at the five percent level, and * at the ten percent level.

Table 12: **Further Robustness Checks**

	Women		
Variables	Year Fixed-effects	Quadratic Trend	W/O > 55 Years
Treat	0.173***	0.166***	0.157***
	(0.0352)	(0.0335)	(0.0422)
Post	0.158**	0.0403	0.102
	(0.0728)	(0.101)	(0.0993)
Treat×Post	-0.143***	-0.138***	-0.129**
	(0.0475)	(0.0479)	(0.0508)
N	1116	1116	984

Notes: Standard errors are reported in parentheses, which are calculated using the Delta Method. Errors are clustered at the state level. *** denotes the significance at the one percent level, ** at the five percent level, and * at the ten percent level.

Appendices

Appendix A

Table A1: **Maximum Weeks of Benefits**

	Weeks	Eligible States
UI	20-26	all
EUC Tier 1	20	all
EUC Tier 2	14	all
EUC Tier 3	13	states with unemployment rate greater than six percent
EUC Tier 4	6	states with unemployment rate greater than 8.5 percent
EB Option 1	13	states with unemployment rate greater than 6.5 percent
EB Option 2	20	states with unemployment rate greater than 8.0 percent

Notes: UI benefits are available for 20 weeks in Missouri and South Carolina. In Arkansas, the benefits are available for 25 weeks.
Source: Council of Economic Advisors, December 2011. Retrieved February 2013, from `http://www.whitehouse.gov/sites/default/files/ui_report_final.pdf`

Appendix B

I derive job search activities from the American Time Use Survey Activity Coding Lexicon. All activities are coded in a three-tiered classification system. The first-tier category includes major activities, while the second tier includes subcategory of the first tier, and the third tier includes subcategory of the second tier. Table A2 presents detailed codes and search activities in the ATUS 2011 that are used in this paper.

Table A2: Description of the ATUS Lexicon Codes and Activities

Codes	Job Search Activities
050401	
	Contacting employer
	Sending resumes to employers
	Placing or answering ads
	Researching details about a job
	Asking about job openings
	Researching an employer
	Submitting applications
050403	
	Interviewing by phone or in person preparing for interview
	Scheduling or canceling interview (for self)
	Preparing for interview
050404	
	Waiting associated with job search or interview
050405	
	Security procedures related to job search or interviewing
050499	
	Job search and interviewing, not elsewhere specified
180504	
	Travel related to job search and interviewing

Chapter 4

Relative Wages, Self-Selection, and Quality of School Teachers: 1964-2013

4.1 Introduction

Debates regarding the quality of U.S. elementary and secondary schools have intensified over recent years.[1] Teachers have always remained in the center of school-quality discussions, as the literature has reached a broad conclusion that teachers are the singularly most crucial input in education production (i.e., improving the human capital or the quality of students).[2] However, documenting teacher quality over time has proven difficult owing particulary to two challenges. First, the literature has been unable to settle the issue of what constitutes the most important attribute of teacher quality (cognitive attributes, experience, education level, or other non-cognitive traits like passion, creativity, and so on). Second, time-series

[1]Recent (under)performance in international tests by U.S. students has been used as an evidence of "subpar" school performance. In the 2012 Program for International Student Assessment (PISA) tests (the standardized international tests taken by 15-year-olds in math, science, and reading), the U.S. ranked in the middle or below the average of the Organization for Economic Co-operation and Development (OECD) countries. The U.S. ranked 27th in math, 20th in science, and 17th in reading. Education Secretary Arne Duncan reacted to the PISA scores of U.S. students as "a picture of educational stagnation." Duncan's remark is available at http://www.ed.gov/news/speeches/threat-educational-stagnation-and-complacency.

[2]E.g., Hanushek, 1992; Sanders and Rivers, 1996; Chetty et al., 2011; and Hanushek, 2011.

data measuring teacher quality over time are not available.

Trying to overcome these challenges, I examine the distribution of long-term teacher ability through the lens of a Roy (1951) model of occupational choice. Additionally, I supplement the Roy model by analyzing the evolution of teacher characteristics over time from other dimensions. Specifically, I focus on long-term relative wages of teachers, an increasing demand for skills in the non-teaching market, and cognitive attributes; all of them could collectively help us to understand educational outcomes. The focus of this study is female teachers, as they make up around 75 percent of the total teacher population. Regardless, I separately carry out most of the estimates for male teachers as well.

I begin the analysis by comparing teachers' wages with the rest of the occupations from 1964 to 2013, using the Current Population Survey (CPS) data. An increasing debate over the inability of schools to attract promising and high-ability candidates to the teaching profession is rooted in the hypothesis of lower wages.[3] The ordinary least squares (OLS) regressions show that the relative annual wages of women in teaching began to fall behind the non-teaching sector after 1990.[4] Note that both women's labor supply and wage inequality on the back of skill biased technology changes began to rise since 1980s. However, male teachers have always been earning less than their counterparts in other sectors. I also emphasize wage differences of top-earners in the teaching versus non-teaching sector. High-ability college graduates tend to choose sectors that have higher growth prospects of wages, which could be reflected by top-earners' salary. I use a newly developed approach, the recentered influence function (RIF) regression approach of Firpo, Fortin and Lemieux (2009), to estimate the distributional difference. The wage gap at the 90th percentile of the distribution is still sharper than the average gap. For female teachers, compensations at this distribution were six percent less in 1964, which widened to around 43 percent in 2013. For male teachers, the gap almost doubled during 1964-2013.

[3]Some researchers use relative wage as a proxy for teacher quality (e.g., Lakdawalla, 2006).

[4]I also estimate the regression using hourly wage and the trend is the same.

Next, I explore the proximate causes of the wage gap between teachers and non-teachers. As a first step, I use the Blinder-Oaxaca decomposition, developed by Oaxaca (1973), and Blinder (1973). The objective is to assess whether wage differences between teachers and other professionals are due to observed characteristics such as education, wage, sex and race or to unobserved factors which could be institutional differences in wage setting or premiums for working in the non-teaching sector. Estimations show that female teachers were able to collect some sort of premiums in the 1970s. However, the trend reverses after 1980, with female non-teachers being able to reap additional benefits or collect a premium. For males, non-teachers have always earned a wage premium. Above all, the observed characteristics cannot explain the wage gap.

Second, to understand why teachers are paid less than that of non-teachers for the same characteristics (as shown by the decomposition), I apply a constant elasticity of substitution (CES) framework to analyze the growing demand for skills in the non-teaching sector. This examination is important in view of Baumol's (1967) observation that technological changes have little effect on increasing productivity in the education industry, while having a larger effect in other sectors. If Baumol (1967) is right, then the relatively higher rise in productivity in the non-teaching sector should increase the demand and relative wage of non-teachers. I follow the approach of Katz and Murphy (1992), and Autor, Katz and Kearney (2008), who apply the framework to study the demand for skills in the economy as a whole. I find a positive and statistically significant trend of demand for skills over years. In other words, there is a shift in relative demand for non-teachers, causing non-teachers' relative wage to grow faster. Third, I use a simple approach to estimate the influence of unions on teacher pay in the 1990s and 2000s. Calculations show that being a union member in teaching has a lower wage premium than in non-teaching sectors.

In light of the wage gap and the demand for skills in the economy, I next measure the distribution of unobserved ability in the teaching sector over time through the prism of a Roy

(1951) model of occupational choice. This is in response to the literature in the economics of education which suggests that unobservable qualities are more important than observable ones to influence student performance. For instance, Aaronson, Barrow and Sander (2007), using matched student-teacher administrative data from Chicago public high schools, show that observed characteristics of teachers could explain only a little about quality. I use evidence of self-selection of workers into teaching as a basis for unobserved ability. The idea is that individuals with a higher unobserved quality self-select themselves into a sector that has a higher variance of wage, where the likelihood of getting higher prices for their skills increases. Note that individuals have different skills and aptitudes suited to and valued by occupations differently. For example, skill or ability that makes an individual a great teacher might not be useful to be a lawyer. Hence, individuals sort themselves into an occupation where their skills are valued most. From the perspective of schools, the evidence of positive selection is considered to be good, because it suggests that those who join teaching are better able workers than those teachers that schools would see if individuals were randomly assigned to teaching.

Results show that females have a positive selection into teaching and negative selection into the non-teaching sector before 2000. After 2000, there has been a positive selection into both sectors, which imply that they began to select a profession on the basis of their comparative advantage. However, the magnitude of the selection variable has largely been declining for teachers, and steadily been increasing for non-teachers. These suggest that the relative strength of self-selection into teaching, and consequently teacher ability, is on the decline over time.

As a final yardstick to analyze teaching quality, I document the relative cognitive ability of teachers. (This is viewed as the supplement to the Roy model.) I use four cohorts of National Longitudinal Survey (NLS), specifically NLS of Youth 1997, NLS of Youth 1979, NLS of Young Women and Mature Women, NLS of Young Men and Older Men. I document the standardized test scores and math ability of teachers versus non-teachers in high school to measure quality. By these yardsticks, I find teachers have lower quality than non-teachers.

This paper contributes to several strands of the literature. The estimates of the Roy model could be viewed as documentation of unobserved quality of teachers over time. Even though unobserved teacher attributes are found to be more important than observed ones, including cognitive ability and experience, there is a paucity of literature documenting unobserved quality of teachers over time (see Autor, 2009, p. 11, for importance and absence of the literature looking at the self-selection). Instead, Bacolod (2007) limits Roy's (1951) model mainly to a framework to organize discussion about occupational choice in teaching. Furthermore, the evidence of self-selection in this paper is very important from the perspective of policy makers or school districts. The declining magnitude of the self-selection variable suggests that rigid salary schedules of school districts might have driven away highly able individuals from teaching. Hence, schools may want to increase the variance of wages to attract better teachers. The implication of this paper's finding is also related to the literature studying the policies to improve teacher quality (e.g., Rothstein, 2012).

This paper adds to the literature of a growing demand for skills in the non-teaching sector. Stoddard (2003) and Lakdawalla (2006) consider the rising price of skills in the non-teaching sector for falling quality of teachers. However, they essentially use the relative wage as a proxy for quality. This paper's estimates of demand for skills shed

light on why able workers shift from teaching to non-teaching. My approach to investigate the wage gap in the upper-tail distribution is new in the literature. This paper also contributes to the limited literature using standardized test scores to gauge the quality of teachers.

The rest of the paper is organized as follows. Section II documents the trend of school teachers' wages, including the conditional mean wage and upper-tail wage comparisons. I look at main proximate causes of the wage gap in Section III. Section IV builds a Roy Model to present the evidence of self-selection of teachers. Section V documents evidence of the distribution of cognitive quality over time. Section VI concludes.

4.2 Data and Wage Structure

In this section, I describe data sources, and the evolution of the relative wages of teachers in the U.S. I think that understanding the relative wages is a good starting point for understanding teacher quality since, in the literature, the relative wage is used as a proxy for quality. It is also a major complaint of school officials for their inability to attract the best candidates in teaching. Then, in later sections, I seek sources of the wage gap and investigate its implications for teacher quality.

4.2.1 Data

The main data for this paper are drawn from the March Current Population Surveys (CPS) from survey years 1964 to 2013.[5] The Census Bureau began issuing the CPS data in March 1962. However, the March 1963 survey lacks information about education. I limit data to individuals age 25-65 and working full time, using the Census Bureau's definition of 35 hours of work a week. I exclude ages below 25 to avoid the issues related to youth unemployment and early career choices.[6] Furthermore, as in Manski (1987), Dolton (1990), and Dolton and Makepeace (1993), I restrict the data to individuals with a bachelor's degree (16-years of education) or above. The goal is to get a comparison group that is similar to teachers and to avoid the estimates being distorted due to the comparison of two different groups. Note that the teaching profession generally requires a four-year-college degree and a full-time workload. In the CPS data, I identify teachers using three-digit census occupation codes

[5] I extract data from the Integrated Public Use Microdata Series (IPUMS).

[6] I also estimate only using individuals age 25-54, a prime-age working group. And, results are qualitatively similar.

before 2003 and four-digit occupation codes thereafter (See Appendix for details). Teachers, in this paper, refer to both public and private school teachers, and include kindergarten, elementary, and secondary school teachers. I use the 1999 Consumer Price Index for All Urban Consumers (CPI-U) to convert wages into real values in terms of 1999 dollars. I also use the appropriate CPS survey weights to create the entire distribution of my variables of interest.

Additionally, I obtain cognitive quality data from the four cohorts from the National Longitudinal Survey (NLS), specifically NLS of Youth 1997, NLS of Youth 1979, NLS of Young Women and Mature Women, NLS of Young Men and Older Men. These cohorts entail widely used measures of cognitive attributes, and the cohorts are surveyed at different points in time, which enable me to analyze teacher cognitive skills over time. Details of data description and construction are provided in the Appendix.

4.2.2 Trend over Half a Century

In this subsection, I document the evolution of wages of teachers versus non-teaching workers in the U.S from 1964 to 2013. Wages are measured in constant 1999 dollars. Figure 1 plots unconditional average annual log wages of teachers against all workers in non-teaching professions by gender. Female teachers earned more than their counterparts in non-teaching sectors until the mid-90s (Panel A of Figure 1). Thereafter, the trend reverses, and the gap continues to rise, except for a short period around the financial crisis of 2007-08. The average relative wage has historically been lower for male teachers (Panel B of Figure 1). I also plot the hourly wage for female and male teachers in Figure 2, and it is consistent with the annual wage.

Teaching versus Finance and Engineering

I also compare teachers' salaries against workers in finance and engineering, as it is widely believed that these two professions have become more lucrative for high-aptitude individuals in recent periods.[7] Hence, I think that it is important to compare teacher pay with that of the pay in these two professions. This could, to some extent, help us understand the implication of the compensation for luring individuals with top quality into teaching. Figure 3 contains the annual log wages of teachers versus those in finance and engineering. Before 1980, female teachers earned more than those working in finance (Panel A of Figure 3). Females in finance began to catch up with teachers since 1980, and the gap began to widen after mid-90s. This finding relates to Philippon and Reshef's (2012), which shows that finance became a high wage sector after 1985. Female engineers have always fared better than teachers. On the other hand, male teachers' wages were lower than that of the wages of engineers and those in finance since the beginning of the sample, with the gap widening markedly after the mid-90s (Panel B of Figure 3).

4.2.3 OLS Estimates

Next, I proceed to estimate the relative wages of teachers, accounting for different demographic dimensions, education, and unobserved factors. I fit ordinary least squares (OLS) regressions for women and men separately for each year's survey data from 1964-2013. In particular, I estimate the regression in the following form, (which is also called state-fixed effect regression):

$$y_{i,t} = \alpha + \beta X_{i,t} + T_i + \lambda_s + \epsilon_{i,t}, \tag{4.1}$$

[7] Philippon and Reshef (2012) find that finance became high wage and skill intensive sector after 1985. This finding could have direct implication in the allocation of talent in other sectors, including teaching.

where T_i is a dummy variable for teachers, λ_s is a vector of state-fixed effects, $X_{i,t}$ are demographic variables such as education,[8] sex, age, age-squared, race, marital status, and the metropolitan residence.[9] The dependent variable is the annual log wage. I plot the coefficient of the teacher dummy for each year in Figure 4. These coefficients appear to confirm the pattern of Figure 1. Women teachers' relative earnings began to fall around the mid-70s, and became negative after the early 1990s (Panel A of Figure 4). It should be noted that skill-biased technological changes, among other factors, accelerated U.S. wage inequality since the 1980s. The wage gap became the largest right before the financial crisis of 2007-08. Additionally, the persistent higher teacher pay before the early 1990s is attributed to massive hirings of teachers in the 1960s and 1970s to meet educational needs of the baby boom cohorts and subsequent rise in teacher-student ratio. As Flyer and Rosen (1997) argue, in the 1980s, on the back of the early hirings, the experience of women teachers rose substantially, an important factor for higher wages. For men, the estimated effect of being a teacher is consistently negative (Panel B of Figure 4). The earnings gap continues to widen. I also estimate equation (4.1), replacing the dependent variable with log hourly wages. Figure 5 graphs the estimated coefficients. The message coming from these estimates is consistent with that of those from the log annual wages.

A few studies have analyzed the relative wages of teachers, and their findings reach a consensus conclusion of decline in teacher pay (see Podgursky, 2011 for the review). Hanushek and Rivkin (1997) calculate, from the U.S. census data, the proportion of college graduates who earn less than teachers. Likewise, Lakdawalla (2006), and Stoddard (2003) use teacher earnings relative to non-teaching graduates as a proxy for measuring quality. Allegretto, Corcoran and Mishel (2004), using the CPS Outgoing Rotation Group data, find that teachers' wages are around 14 percent lower than those of workers in comparable occupations to teachers. The estimate of Taylor (2008), which uses the U.S. 2000 census data,

[8] Education is divided into two categories: a four-year college degree and an advanced degree(an master's degree or beyond).

[9] I use a separate dummy variable for the central metropolitan, and outer metropolitan.

shows the average teacher's wage (relative to the comparable occupations) is around four percent lower. This paper's estimates, coming from the March CPS data and covering a long time span, are helpful in visualizing "turning points" in teacher salary. As I have shown, lower teacher salary is not a permanent phenomenon, particularly for women teachers, but a relatively new trend emerging from increasing outside opportunities of women. Overall, female teachers earned around 10-20 percent more than other comparable females workers (college-graduated workers) in the '70s, and around 10 percent more in the '80s, and earned around 10 percent less in the '90s. Likewise, they continue to earn less in the 2000s (around 10-15 percent).

4.2.4 Recentered Influence Function Estimates for Top Earners

In this subsection, I investigate the wage distribution of teachers in the upper-tail, relative to non-teachers. This study of distributional wage differences is new in the literature of economics of education. The focus on central tendency of wage (i.e, the mean wage) could miss an important element of occupational choice: Many well-qualified people could still choose a low-paying job if they see a tremendous prospect of salary growth. Particularly, if top-earners in other sectors earn more money, recent graduates may follow these professions in hopes of future career growth. Quantile regression has become popular in the study of distributional wage gaps between two groups.[10] As in Boudarbat and Lemieux (2014), I use the unconditional quantile regression(UQR) method of Firpo, Fortin and Lemieux (2009), operationalized as Recentered Influence Function (RIF henceforth). The RIF approach improves the conditional quantiles regression (developed by Koenker and Bassett, 1978). The main shortcoming of the conditional quantile regression is that the estimates of the effect of explanatory variables on the mean of outcome variable are not consistent. In other words, the expectation of conditional quantiles regression at a particular quartile does not equal

[10]Mueller (1998) uses quantile regression to investigate wage differences in Canada. Melly (2005) applies such an approach in German context.

the unconditional expectation of the quartile. To further clarify, conditional expectation of the OLS regression average up to the unconditional expectation due to the law of large numbers but this is no longer true with the quantile estimator, (i.e., $E_X E(Y|X) = E(Y)$, but $E_X E(Y^{\tau}|X) \neq E(Y\tau)$). To operationalize the UQR, Firpo, Fortin and Lemieux (2009) show that the dependent variable (which is annual log wage in this paper) can be replaced by the RIF. The RIF for the τth quantile q_{τ} is defined as:

$$RIF(W_{i,t}, q_{(\tau)}) = \frac{q_{(\tau)} + [\mathbb{1}(W_{i,t} \geq q_{(\tau)}) - (1-\tau)]}{f(q_{(\tau)})}, \tag{4.2}$$

where $\mathbb{1}(.)$ is an indictor function equal to 1 if $W_{i,t} \geq q_{(\tau)}$, and $f(.)$ is a density of the marginal distribution of wage. Then, the RIF regression is:

$$RIF(W_{i,t}, q_{(\tau)}) = \beta T_i + X_{i,t}\gamma + e_{i,t} \tag{4.3}$$

where T_i is a dummy variable for teachers, and $X_{i,t}$ is a vector of the same control variables used in the OLS regression above.

I run the RIF regression (equation 4.3) at the 90th percentiles from 1964-2013 for men and women separately to capture wage differences between top earners in the teaching and non-teaching sectors. I plot the coefficients of β from the regression for each year in Figure 6. I also fit the RIF regression in the 10th percentile to see how trends differ at the top- and bottom-tails. A simple picture that emerges from the quartile estimations is that the wage gap between teachers and non-teachers in the upper-tail (90th percentile) grew much faster than in the lower-tail (10th percentile) or in mean. In the early 1970s, women teachers earned around 7 percent less than non-teachers at the wage distribution of 90th percentile (Panel A of Figure 6). However, the gap widened to above 43 percent in 2013. For male teachers, the wage gap grew more slowly than female teachers (Panel B of Figure 6). In 2013, the gap between teachers and non teachers at the 90th percentile was twice what it was in 1964. I also estimate the conditional quantile regression as a robustness check and Figure 7 plots the estimates. The message from it is same as the RIF regression.

4.3 Proximate Causes of Wage Gap

After showing the declining relative wages in an earlier section, I, in this section, turn to examine the causes behind the teacher-nonteacher wage gap. First, I use the Blinder-Oaxaca decomposition to analyze whether the wage gap could be explained by the differences in the distribution of observable characteristics between teachers and non-teachers. However, observed characteristics couldn't explain the entire wage gap. In the next step, I analyze the gap using a simple demand and supply framework in the competitive labor market. The objective of this framework is to understand if there is a secular increase in demand for non-teaching jobs, raising their earnings relatively faster than that of teachers. Third, I look at the role of declining union influence, and at the monopsony power of school districts.

4.3.1 Blinder-Oaxaca Decomposition

In this subsection, I identify the role of "explained" and "unexplained" components to explain the differences between teachers and non-teachers wages. When the wage gap cannot be explained by observed characteristics, it has implications for allocations of skills. This is because the non-teaching sector has a more favorable wage setting system to its workers than that of teaching. The most popular methodology in the literature for such a study is the Blinder-Oaxaca decomposition, developed by Oaxaca (1973), and Blinder (1973). The technique has widely been used in labor economics in different contexts (e.g., wage differences between the black and the white, men and women, public and private sector workers, unions and non-unions, older and younger workers).

In this paper's setting, the "explained" component includes education, wage, race, and the state of residence (the same variables used equation 4.1). And, the "unexplained" component could be interpreted as a premium of working in the non-teaching sector, institutional differences in wage setting or institutional arrangement of school system that rewards teachers with higher wages. (Schools might have salary schedules that pay higher or lower wages to a teacher than he/she could get in the non-teaching sector. For example, unions in schools could put pressure on school districts to set higher wage.) I estimate the following Blinder-Oaxaca decomposition:

$$\Delta_{wage} = \underbrace{[E(X_{tc})'(\beta_{tc} - \beta_{ntc}) + [E(X_{tc}) - E(X_{ntc})]'(\beta_{tc} - \beta_{ntc})}_{\text{Unexplained}} + \underbrace{[E(X_{tc}) - E(X_{tc})]'\beta_{tc}}_{\text{Explained}} \tag{4.4}$$

I pool six years of CPS data over time into eight single cross-sectional datasets (i.e.,1964-1969, 1970-1975, 1976-1981, 1982-1987, 1988-1993, 1994-1999, 2000-2005, 2006-2013).[11] It is not uncommon in empirical analysis to pool the CPS data for reasons of making datasets richer, and of convenience. In my case, the pooling is more of a convenience of presenting results. Since my purpose is to present the patterns over time, pooling for the particular number of years does not alter the story. I also add time dummies in the estimation. I construct the decomposition separately for male and female. Table 1 contains results for women and Table 2 for men. Recall that until 1991, the mean log wage of women teachers is greater than non-teachers (see Figure 1). From 1964-75, the estimate of non-teacher women's "explained" component is positive and unexplained component negative. Specifically, the observed characteristics cannot explain why non-teachers were paid around 0.16 log points less. This suggests that women teachers were able to reap some sort of premium (because of favorable salary schedules of school districts or greater discrimination outside teaching).

[11] The last dataset has more than six years as the total number of years cannot be evenly divided by six. Though the choice of six years is random, changing years does not alter the pattern of my results.

Note that in the 1960s and early 1970s, teacher union's influence was on the rise. From 1975-93, both explained and unexplained components are negative. This means that non-teachers should be paid 0.01-0.03 log points less based on observed characteristics. (Put differently, teachers should be paid 0.01-0.03 log points more given their observed characteristics.) Still, the model cannot explain why non-teachers are paid around 0.09-0.2 log points less. As mentioned above, this could be a premium of working in schools. However, after 1991, the trend reverses, with the estimate of the "unexplained" component being positive. This implies that non-teachers are able to collect a wage premium (due to higher wage setting in the non-teaching sector or restricted salary schedules of school districts). The recent pattern that women teachers are not paid as much as their counterparts with the same characteristics has implications for quality issue, which I will explore in later sections.

As contained in Table 2, the unexplained component for men has always been positive, which suggests that non-teachers are getting a wage premium (or a higher wage which cannot be explained by observed characteristics).

4.3.2 Demand for Skills

If observed characteristics cannot explain the wage gap, then what could be the other plausible reasons? One strong possibility is that the demand for skills in the non-teaching sector has risen at a quicker pace than in teaching. This hypothesis is in line with Baumol (1967), who notes that economic forces like technological changes raise worker productivity differently across sectors, and views teaching as a sector where productivity per worker remains relatively constant. If this is true, quicker productivity increases in the non-teaching sector has increased the sector's relative wage.

Furthermore, it could be noted that shifts in demand and supply of teachers also affect the relative wage. The teacher-student ratio has declined over time. (It was 13.59 [per hundred students] in 2010 compared with 21.10 in 1972). Note that during that period, number of students has increased, which has in turn increased the demand for teachers. On the supply side, it is well documented that women's labor force participation and education level increased over the years. For instance, the fraction of women with a four-year college-degree increased three times between 1964 and 2000 (see Corcoran, Evans and Schwab, 2004). In this paper, I focus on the relative demand for non-teachers. Specifically, I use a constant elasticity of substitution (CES) production function to study the growing demand for skills in the non-teaching sector, which could explain the declining relative wages of teachers.

My analysis follows a growing literature in rising demand for and price of skills in the U.S. economy.[12] A central message coming from this literature is that there has been a secular growth in the demand for skills (college-educated workers) since 1960. This has direct implications for teaching. When the demand for skills in the non-teaching sector rises, pushing wages up, the wage gap between teachers and non-teachers is bound to increase. Ceteris paribus, schools should afford to pay higher wages to get the same-skilled person. Otherwise, with the same level of salary spending, they end up having a lower-skilled worker. Drawing insight from this literature, Lakdawalla (2006) uses a theoretical framework to explain why a rise in the demand for skills (consequently the price) in the non-teaching sector induces schools to replace skilled teachers with unskilled ones. Similarly, Stoddard (2003) argues that the rise in the skill price for women and fall in teacher-student ratio lead schools to hire low quality teachers. Both Lakdawalla (2006) and Stoddard (2003) essentially use relative wages to measure increasing prices of skills in non-teaching sector. I use a different approach to test this hypothesis

To proceed with an empirical approach to measure the effect of increasing price of skills in the non-teaching sector, I use a simple conceptual framework, following the approach of Katz and Murphy (1992) and Autor, Katz and Kearney (2008). Philippon and Reshef (2012) build on this approach to study the relative demand in finance. Let's consider two

[12]See Katz and Murphy, 1992; Autor, Katz and Krueger, 1998; Acemoglu, 2002; Autor, Katz and Kearney, 2008, for detailed review.

types of workers, non-teachers and teachers with high human capital and moderate or low human capital, respectively, in a closed economy. The aggregate production in the economy takes the following form:

$$Y = \left[\theta(a_t N_{ntc})^{\frac{\sigma-1}{\sigma}} + (1-\theta)(b_t N_{tc})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{1-\sigma}}, \tag{4.5}$$

where N_{ntc} and N_{tc} are the number of non-teachers and teachers respectively, and σ, the aggregate elasticity of substitution, is assumed to be greater than one.[13] a_t and b_t are parameters measuring productivity. If changes in technology equally support production of education and non-education goods, a_t and b_t change in a similar fashion (i.e., will have the same growth rates). As Baumol (1967) suggests, technological changes have disproportionally favored non-teachers to increase productivity. For example, with the availability of new technology and software, a worker in finance is able to produce more tasks now than decades ago, say in the 1960s. (He/she is able to execute more transactions through computer, quickly analyze big data and so on.) However, teaching methodology or approach, especially until high school, has remained the same for a long time. Hence, teacher output has not increased considerably due to technological changes.

In order to connect this theoretical concept with the empirical estimation, I, following the literature, assume that the labor market is perfectly competitive. So workers are paid equal to their marginal products. After solving for cost minimization problem for equation (4.5) and some algebraic steps, I get

$$ln\omega = \frac{\sigma-1}{\sigma} ln(\frac{a_t}{b_t}) - \frac{1}{\sigma} ln(\frac{N_{ntc}}{N_{tc}}), \tag{4.6}$$

where $ln\omega = ln(\frac{W_{ntc}}{W_{tc}})$. To proceed to estimate equation (4.6), I assume that relative wages of teachers to non-teachers and the ratio of supply varies by year, and σ is time-invariant.

[13]Actually, we find σ greater than one in the empirical estimation later. In the literature too, σ is found to be greater than one. See for Katz and Murphy, 1992, and Autor, Katz and Krueger, 1998, for review.

And I estimate the following regression:

$$ln\omega = \eta_0 + \beta_1 t - \beta_2 \eta + \epsilon_t \tag{4.7}$$

where η is $ln(\frac{N_{ntc}}{N_{tc}})$, and its parameter β_2 estimates $\frac{1}{\sigma}$, and the parameter of time trend β_1 estimates wage premium or demand for skills in the non-teaching sector. And, my hypothesis is that $\frac{dln(\frac{a_t}{b_t})}{dt} > 0$. In words, the relative productivity of non-teachers is on the rise due to the relative increase in skill-augmenting technology. More importantly, $\frac{dln(\frac{a_t}{b_t})}{dt} > 0$ is positive when $\sigma > 1$, which in turn indicates the shift in the demand for non-teachers to the right and up.

I estimate equation (4.7), using the CPS data from 1964-2013 for men and women separately. To estimate it, I aggregate wages by year. This gives me 50 observations. I use a linear time trend, t, and estimate its coefficient β_1. Table 3 contains the results. I find a positive and statistically significant value of β_1 (and σ in the range of 1.11-1.62), showing increased demand for skills in the non-teaching sector and the relative productivity of non-teachers has been increasing. The increase in the productivity of workers in the non-teaching sector should increase the price of their skills, and hence the relative wages of non-teachers. The results are consistent with Baumol's (1967) view that education is a "relatively constant productivity industry." The rising demand and price of skills in the non-teaching sector should have implications for allocation of talents between teaching and non-teaching sectors. And, I use a Roy (1951) Model of occupational choice in Section V to understand the distribution of skills over time.

4.3.3 Unions and Monopsony

Next, I analyze the influence of union or collective bargaining and monopsony power of schools[14] in the relative wages of teachers. After the steady rise of teachers' unions in the 1960s and 1970s, researchers have been trying to estimate the contribution of unionization or collective bargaining on teacher salary; mostly they find positive effects (e.g., Baugh and Stone, 1982; Ballou and Podgursky, 2002). Hoxby (1996), a more comprehensive and widely cited paper in teacher unionization, finds that unionization leads to over 9 percent increase in per student spending; most of which goes to teacher pay. Lovenheim (2009), which contradicts Hoxby's findings, shows little effect of unionization on teachers' wages. Likewise, West and Mykerezi (2011) find that unionization increases the starting salary of teachers by approximately four percent.

I use two simple approaches to look at the effect of unionization on teachers' relative pay. First, I run the regression similar to the wage equation (4.1) adding a dichotomous variable of union membership and its interaction with teacher.[15] The interaction variable measures the relative influence of union coverage on teachers' wages to non-teachers'. Unfortunately, the CPS data do not contain information on union membership prior to 1990, limiting the estimation to the period thereafter. Since my goal is to shed light on the overall effect, rather than the yearly effect of unionization, I divide the data into two sets: 1990-2000, and 2001-2013, and run two regressions for each gender. I also include year-fixed effects in the regression model.

Table 4 contains results for both female and male teachers. If an individual were a female teacher and had union coverage, the wage was around five percent less in the '90s, as compared to the wage of a union-member woman non-teacher. Likewise, a union-member woman-teacher has a lower wage than a non-teacher union-member in 2000s. However, the

[14]Clearly, it is beyond the scope of this paper to quantify the casual effect of union and monopsony power in teacher wage.

[15]Union membership variable also includes non-members if they are covered by union.

effect is not statistically different from zero. For men, I do not find any statistically significant effect of being a union member and teacher. Note that being a union member has a positive effect on wage for both men and women. Nonetheless, the coefficients are negative. Overall, the message is that teachers are not getting any positive effect of union coverage compared to non-teachers in recent decades.

Second, I look at the wage distribution of teachers at the 10th percentile. Unionization increases across-the-board salary schedules, even though it compresses the variation of salary (e.g., Hoxby and Leigh, 2004). Hence, those at the lower distribution are expected to have more stable salaries. I use the estimates derived above (using both the RIF and conditional quantile regressions). As shown in Figures 6-7, teachers' salary at the 10th percentile distribution is more stable than at the 90th percentile. This should be read with caution, however. (Even though it sheds some light on the power of union, it is hard to entirely credit the distribution of wage at the lower-tail to unions.) Taken both approaches together, it suggests that even though unionization in teaching has favored those at the lower distribution, it does not have any effect in raising a teacher's wage higher than a non-teacher.

Furthermore, monopsony power in school districts might have pulled teacher salary down. For instance, Ransom and Sims (2010), who find a significant presence of monopsony power in public school districts in Missouri, suggest that teachers' salaries could be lower by around 27 percent, compared to the salary they could have otherwise earned in the absence of monopsony power of school districts.

4.4 Roy Model of Self-Selection

In view of the evidence of the falling relative wage of teachers and rising demand for non-teaching jobs in Section III, I next explore the distribution of teachers' skill over time through the prism of a Roy (1951) model of occupational choice. It is worth mentioning that various observers have hypothesized that rising job opportunities coupled with rising earnings outside of teaching have decreased teacher quality. However, there is little evidence of testing this hypothesis due to lack of time-series data, as recognized by Corcoran, Evans and Schwab (2004). Autor (2009) observes that wages in the teaching profession have turned out to be be "a higher floor and lower ceiling" for women due to expanded outside opportunities.[16]I use a two-sector Roy model to overcome this data issue and shed light on ability through self-selection. Going by Autor's (2009) observation, the Roy model should predict a declining or changing (from positive to negative) trend of self-selection into teaching.

The framework of the Roy model has been widely used in modelling choices, including occupation, and education. Willis and Rosen (1979), Heckman and Sedlacek (1985, 1990), Heckman and Honore (1990) formalized and expanded the Roy model. Borjas (1987) applies the Roy model to study the self-selection and earnings of Mexican immigrants in the U.S. Gould (2002) uses Roy model to understand how changing prices of skills over time have altered the wage inequality in the U.S. Bacolod (2007) draws theoretical insight of a Roy (1951) model from Borjas (1987) to explain the distribution of teachers' quality prior to 1990. I significantly extend Bacolod (2007), with this paper's objective, framework, and findings having different implications.[17] In particular, the contribution of this paper is to apply the framework of a Roy (1951) model to provide the evidence of self-selection over time to illustrate how changing prices of women's skills in the non-teaching sector have changed the distribution of teacher ability. Rather, the concept of this paper is in spirit closer to Correa, Parro and Reyes (2014), who apply the Roy model to provide the evidence of self-selection of teachers into public schools in Chile.

In spirit of Roy (1951), I assume that individuals make optimizing decisions about their career choice. Note that optimizing career choice is equivalent to optimizing wage.

[16]Hoxby and Leigh (2004) shows that compression of wages by union is a leading cause for decline in teacher quality measured by SAT scores.

[17]Bacolod (2007), in a footnote, briefly mentions that the estimates of the Roy model's parameters (estimated using the census data until 1990) are negative, implying that there is absolute selection of women into non-teaching.

The decision stems from the fact that individuals are endowed with certain, different skills and they choose a market to work, where their skills fetch higher earnings. Prices of skills vary across markets and over time, thereby altering the distribution of the relative skills across markets. To illustrate the ability of teachers over time, I assume that the economy constitutes two market sectors (teaching and non-teaching), and workers are multi-skilled, but can work in only either one of them. (They cannot work in both sectors at one time.)

To view how the distribution of teacher ability can be changed over time due to the rise in price of skills in the non-teaching sector, let's consider a simple example of an occupational choice of a talented woman named Kelly. Suppose she is good at trading financial products, and is also capable of teaching; this brings a choice between two occupations: finance and teaching. It is indeed true that if she becomes a teacher, she can teach in more effective way than an average teacher. Also, let's suppose that initially there is not a big salary difference between teaching and finance. This could initially make her almost indifferent to joining teaching or finance. And with new technological changes, say the development of high-frequency trading system, she now can trade financial products in a quicker speed and greater amount. Her skill now can significantly improve a firm's revenue, promoting it to provide a very high level of compensation. On the other hand, technological change will not help her to increase education production by much, since the teaching methodology has remained virtually same over time. For instance, even though classes are equipped with computer or other technological devices, she cannot teach several classes at one time. Above all, somewhat rigid salary schedules do not leave much room to pay her markedly higher salary than the rest of her peers. As a result, her optimum career choice will clearly be finance.

To formalize the concept of the Roy model, let tc and ntc represent teaching and non-teaching sectors, respectively. Building on Heckman and Sedlacek (1985), I assume that a representative agent has an N-vector of skills S, which are used to produce an amount of task $T_i(S)$, where $i \in (tc, ntc)$. Prices of tasks are are denoted as π_{tc} and π_{ntc}, respectively. The task function $T_i(S)$ maps a worker's ability or skills onto tasks the worker can perform in sector i, where $i \in (tc, ntc)$. For example, the task function maps from an individual's passion, creativity, efficiency, knowledge, dedication, and motivation onto the individual's teaching ability or task. Workers are paid equivalent to the total price of their tasks, i.e, $w_i = T_i(S) \times \pi_{tc}$. Hence, the log wages in the teaching and non-teaching sectors are

$$lnW_{tc} = ln\pi_{tc} + lnT_{tc}(S) \tag{4.8}$$

$$lnW_{ntc} = ln\pi_{ntc} + lnT_{ntc}(S) \tag{4.9}$$

Workers are heterogenous in their preferences and ability or skill to execute tasks. To maximize income, a representative worker chooses the sector having the higher wage return to skill, i.e, $T_{tc}(S)\pi_{tc} > T_{ntc}(S)\pi_{ntc}$. Following Roy (1951), I assume that log of tasks (lnT_{tc}, lnT_{ntc}) are normally distributed with mean (μ_{tc}, μ_{ntc}) and covariance matrix Σ. The task function $T_{tc}(S)$ contains both observed characteristics or skills $(X\beta)$, and unobserved vector (η) with $\mathbb{E}(\eta) = 0$. I then describe the wage equations as

$$lnW_{tc,i} = ln\pi_{tc,i} + lnT_{tc,i} = ln\pi_{tc,i} + X\beta_{tc,i} + \eta_{tc,i} = \alpha_{tc,i} + X\beta_{tc,i} + \eta_{tc,i} \tag{4.10}$$

$$lnW_{ntc,i} = ln\pi_{ntc,i} + lnT_{ntc,i} = ln\pi_{ntc,i} + X\beta_{ntc,i} + \eta_{ntc,i} = \alpha_{ntc,i} + X\beta_{ntc,i} + \eta_{ntc,i} \tag{4.11}$$

where η_{tc} and η_{ntc} are normally distributed random errors with mean zero and the standard variance-covariance matrix of bivariate normal distribution.

Above, I derive the population distribution of wages and abilities in the teaching and non-teaching sectors. The wages and abilities derived above would be true if individuals were randomly assigned to teaching and non-teaching sectors. However, in real life, rational individuals self-select into an occupation on the basis of their observed and unobserved skills and preferences. Then, the next question is who decides to become a teacher? A worker decides to join teaching if $lnW_{tc} > lnW_{ntc}$, and the probability of going into teaching is $Pr(tc) = Pr(lnW_{tc} > lnW_{ntc}) = \Phi(c_{tc})$. Note that $\Phi(.)$ is the standard cumulative distribution function for a normal variable.

In view of an individual's decision to select either one of the sectors, it is necessary to account for the self-selection issue (see Heckman 1976, 1979) to characterize the distribution of wages and abilities within the teaching or non-teaching sector. Before proceeding for the derivation of wages and abilities, let $\zeta = \epsilon_{tc} - \epsilon_{ntc}$, then $\sigma_\zeta = \sqrt{Var(\epsilon_{tc} - \epsilon_{ntc})} = \sqrt{\sigma_{tc}^2 + \sigma_{ntc}^2 - 2\sigma_{ntc,tc}}$. The observed log wages in teaching sector is

$$\begin{aligned} \mathbb{E}(lnW_{tc}|X_{tc}, T = 1) &= \mathbb{E}(\alpha_{tc} + X\beta_{tc} + \eta_{tc}|lnW_{tc} > lnW_{ntc}) \\ &= \alpha_{tc} + X\beta_{tc} + \frac{\sigma_{tc}^2 - \sigma_{tc,ntc}}{\sigma_\zeta}\lambda(c) \end{aligned} \tag{4.12}$$

,where $\lambda(c)$ is $\frac{\phi(c)}{\Phi(c)}$, and $c = \frac{\alpha_{tc}+X\beta_{tc}-\alpha_{tc}-X\beta_{tc}}{\sigma_\zeta}$. In the similar approach, the mean of the observed log wages in non-teaching sector is

$$\begin{aligned} \mathbb{E}(lnW_{ntc}|X_{ntc,i}, T = 0) &= \mathbb{E}(\alpha_{ntc} + X\beta_{ntc} + \eta_{ntc}|lnW_{tc} < lnW_{ntc}) \\ &= \alpha_{ntc} + X\beta_{ntc} + \frac{\sigma_{ntc}^2 - \sigma_{ntc,tc}}{\sigma_\zeta}\lambda(-c), \end{aligned} \tag{4.13}$$

where $\lambda(-c)$ is $\frac{\phi(c)}{1-\Phi(c)}$. In equations 4.12-4.13, $\lambda(.)$ is referred to as the so-called inverse-mill ratio, and it is always positive and decreasing function of c.

Now, the interest is in knowing the sign and magnitude of the coefficients of the so-called inverse-mill ratios to understand the distribution of skills within each sector. These coefficients are jointly determined by the variance of the ability within each sector and the covariance of abilities across teaching and non-teaching. Note that as mentioned earlier, to maximize utility (which is equivalent to wage maximization), workers choose professions according to their tastes and skills. Different professions require different skills. For example, a worker who is very good at teaching may not be a good engineer or finance worker. Thus, a worker who is good at teaching becomes a teacher, and good at finance works in the finance industry. If the worker has very high teaching skill and very low finance skill, then covariance between teaching and finance skill is low. On the other hand, when both sectors require the same general skills, there will not be any selection issue. This is because the nature the work becomes “anybody-can-do” type.

In terms of the signs of both coefficients $\lambda(.)$ in equations 4.12-4.13, we can have three possibilities: (i) the coefficients are positive in both equations; (i) the coefficient is positive in teachers' wage equation and negative in non-teachers; and (iii) the coefficient is positive in non-teachers' wage equation and negative in teachers. However, it is not possible to have negative coefficients in both the equations, as shown in Heckman and Sedlacek (1985). To see why both coefficients cannot be negative, let's look at it from mathematical perspective. The coefficient of the inverse mills ratio in the teaching sector is $\frac{{\sigma_{tc}}^2-\sigma_{tc,ntc}}{\sigma_\zeta}$, and the non-teaching sector is $\frac{{\sigma_{tc}}^2-\sigma_{tc,ntc}}{\sigma_\zeta}$. By definition of the positive semi-definite covariance matrix Σ, we should have either ${\sigma_{tc}}^2 - \sigma_{tc,ntc} > 0$ or ${\sigma_{ntc}}^2 - \sigma_{tc,ntc} > 0$. Hence, getting negative coefficients in both equations is not a mathematical possibility.

First, let's discuss what the evidence of positive-selection (the positive coefficients) means. If the coefficients of the inverse-mills ratio are positive in both equations, the skill or ability of the workers in both sectors is higher than that of the average population skill of a randomly assigned economy (i.e., the average ability of workers when they are randomly assigned to each sector). For instance, in equation 4.12, the coefficient of $\lambda(.)$, $\frac{\sigma_{tc}^2-\sigma_{tc,ntc}}{\sigma_\zeta}$, is positive, only when $\sigma_{tc}^2 > \sigma_{tc,ntc}$ (since σ_ζ is always positive). This suggests that the distribution of an individual's teaching ability (measured by σ_{tc}^2) is higher than the covariance of her ability between teaching and non-teaching. The same interpretation could be given to the positive coefficient in equation 4.13. Positive coefficients in both equations imply that workers have selected each sector on the basis of their comparative advantage. Put differently, those who have a lower opportunity cost in teaching (higher relative value of their skills) become teachers, and those who have a lower opportunity cost in non-teaching become non-teachers.

Furthermore, the Roy model helps to understand how changes in the price of skills in the non-teaching sector alters the distribution of ability in the teaching sector. In the spirit of Heckman and Honore (1990), it could be shown that an increase (a decrease) in the price of skills in non-teaching sector leads to a decrease (an increase) in the distribution of ability in the teaching sector.[18] Suppose that advancement in technology disproportionally favors to the non-teaching sector, increasing prices of skills in that sector, then individuals with higher than the average population skill in teaching sector switches to the non-teaching sector. For this to happen, there should be sufficient correlation between individuals' ability to perform both teaching and non-teaching tasks.

Results

I estimate the conditional average wage equations for both sectors above, applying Heckman's two-step estimator and using the repeated cross-section data from the CPS survey years 1968-2013.[19] First, I estimate a Probit model for calculating the probability that an individual chooses teaching given observed characteristics and calculate the inverse-mill ratios. Then, I estimate the wage equations 4.12-4.13, using the inverse-mill ratio as a control variable. In the literature, this econometric procedure is also known as a control function. To identify

[18]Note that from equation (14), $lnW_{tc} = ln\pi_{tc} + lnT_{tc}(S)$. And, let's assume that task function is linear in skill, i.e. $T_{tc}(S) = S_{tc}$. Then, replacing log wage in equation (4.12) ($lnW_{tc} = ln\pi_{tc} + S_{tc}$), and taking derivative with respect to $ln\pi_{ntc}$ (the price of skills in the non-teaching sector), I get

$$\frac{\partial \mathbb{E}(lnW_{tc}|lnW_{tc} > lnW_{ntc})}{\partial ln\pi_{ntc}} = \frac{\partial ln\pi_{tc} + S_{tc} + \frac{\sigma_{tc}^2 - \sigma_{tc,ntc}}{\sigma_\zeta}\lambda(c)}{\partial ln\pi_{ntc}} = -\frac{\sigma_{tc}^2 - \sigma_{tc,ntc}}{\sigma_\zeta}{\sigma_\zeta}^2\lambda'(c)$$

Consider the right term. σ_{tc}^2 is always positive. $\lambda'(c)$ is positive too. Hence, as long as $\sigma_{tc,ntc}$ is positive (which happens when there is a positive correlation between teaching and non-teaching skills), the whole term is negative.

[19]I exclude the survey years 1964-67, during which there is no information about children. As mentioned below, the number of children has been used as one of the variables for exclusion restriction.

the coefficients in the wage equation, it is expected to have at least one exclusion restriction, i.e., a variable that affects the probability of becoming teachers, but does not directly affect wage. (However, French and Taber [2011] point out that the exclusion restriction is not required as identification is possible through the functional form with the inverse-mill ratio being a non-linear function.) Following the literature, I exclude number of children and marital status of women from the wage equation. The argument is that these variables could influence a woman's selection into a profession. However, they are not expected to directly influence wages. Flyer and Rosen (1997) point out that the main attraction of women into teaching is non-depreciation of their wage when they return to work after longer leaves, especially maternal leaves. Also, it is well documented in the literature that female teachers have more children than non-teachers. Mulligan and Rubinstein (2008) use the same variables to satisfy the exclusion restriction when they use the Roy model to study self-selection of women into full-time work. Likewise, Gould (2002), who applies the Roy model to examine the self-selection of individuals into an occupation on the basis of their comparative advantage and the effect on wage inequality, use the marital status for the exclusion restriction. I also use only the number of children for the exclusion restriction, and the results are qualitatively similar. I limit the sample to women, as I do not have any variable for the exclusion restriction for men, and the teaching profession is dominated by women.

For reasons explained in an earlier section, I pool six-year data into eight single cross-sectional datasets (1968-1973, 1974-1979, 1980-1985, 1996-1991, 1992-1997, 1998-2003, 2004-2009, 2010-2013). Results are reported in Table 5. As a clarification on the interpretation of the results, it is important to note that interest does not lie in interpreting the coefficients of inverse-mill ratios as their effects on log wage. (The goal is not limited to getting the consistent estimates to predict wage.) Rather, I am using the coefficients to illustrate the distribution of ability of teachers through the evidence of self-selection. It could be recalled that the coefficient, for instance in the teacher's wage equation, entails the variance of ability in teaching and covariance of the ability between teaching and non-teaching. We could expect declining covariance of ability between teaching and non-teaching jobs over time, as jobs have increasingly been specialized. For instance, in earlier decades, it could have been easier for a college graduate becoming a teacher to know or learn banking skills as banks were much more focused on traditional roles such as lending and borrowing in earlier days. However, over the years, the banking system has become highly specialized with inventing new banking products, which are very hard for outsiders to understand.

There is positive selection of women into teaching before 2000, and negative selection into the non-teaching sector. This implies that women have an absolute advantage in teaching. Their skills have higher prices in teaching than the non-teaching sector. In other words, their ability is suited more to teaching. However, after 2000, there has been positive selection into both sectors, which implies that women began to select on the basis of their comparative advantage. This also indicates the possibility of declining correlation between their abilities to teach and to perform non-teaching jobs.

Another key insight that emerges from the results is that the magnitude and strength of statistical significance of negative selection into the non-teaching sector constantly declined, eventually turning into positive selection. And, the positive selection has then become stronger over time. For instance, the selection coefficient for the non-teaching sector for 1968 to 1973 was -1.8, which declined (in terms of absolute magnitude) to -0.17 for 1998-2003. After 2004, the coefficient became positive, and increased to 0.35 in the period for 2010-2013. However, the positive selection into teaching was increasing until the mid-'80s. Then, it has largely declined over time, except the periods of 1998-2003 and 2010-2013. For example, the selection coefficient was 0.095 in the period 1968-1973, increased to 0.473 in 1980-1985, and declined to 0.315 in 20004-09. Taken together, these suggest that prices of skills have risen in the non-teaching sector over years, and the pool of talented women who crowded in teaching earlier has begun to fade, with able women selecting the non-teaching sector, rather than teaching. Furthermore, I estimate the Roy model, excluding those aged above 54 to avoid issues related to retirement, and the message is consistent (Table 6).

4.5 Cognitive Quality

In this section, as a final yardstick to determine if the falling relative wages of teachers has led to a decline in quality, I use the relative cognitive attributes. As discussed above, teacher quality is hard to measure as it entails several dimensions of an individual's unobserved attributes such as patience, a sense of humor, learning attitude, communication skills, enthusiasm and observed cognitive skills. More important, the literature is yet to reach a conclusion about what constitutes the most important aspect of teacher quality. So I think it is important to look at teacher quality from different dimensions. The focus on relative cognitive ability could be viewed as a supplement to the Roy model that I developed in Section IV. The Roy (1951) model is helpful in assessing the unobserved teacher ability.

A growing literature has used the cognitive attributes of teachers to study the relationship between teacher quality and student achievement.[20] However, the literature is not straightforward on the link between cognitive ability and teacher quality. Therefore, it is hard to justify that cognitive attributes are a reasonable predictor of teacher quality. Nonetheless, I think it is still important to examine cognitive attributes as they may reflect at least some aspect of teacher quality.

I use verbal and math ability of teachers in high school, ASVAB, AFQT and IQ scores as a proxy for cognitive skills (see Appendix for details about these variables). These scores have increasingly been used in the literature (see Corcoran, Evans and Schwab, 2004; Bacolod, 2007; Cameron and Heckman, 1998; Heckman, 1995). The majority of the literature has focused on cross-sectional studies of cognitive abilities. A notable exception includes

[20] Ehrenberg, Goldhaber and Brewer (1995) use verbal aptitude score, Ballou and Podgursky (2002), and Weaver (1983) use SAT score. Hanushek and Pace (1995)also use either ACT or SAT scores.

Corcoran, Evans and Schwab (2004) and Bacolod (2007). Using five longitudinal surveys from five different sources covering different points of time (mostly capturing the period from 1957 to 1992), Corcoran, Evans and Schwab (2004) show a decline in the probability of high-quality women joining teaching over time. As in Bacolod (2007), I use three cohorts of the National Longitudinal Survey (NLS), specifically NLS of Youth 1979, NLS of Young Women and Mature Women, NLS of Young Men and Older Men. Additionally, I supplement these with the latest cohort, the NLS of Youth 1997. She shows that the fraction of female and white male teachers who score above the 80th percentile has markedly declined over time. A key difference from Bacolod (2007) is some of my estimation approaches (described below) along with the latest cohort of data, and the sample selection. In particular, she chooses to include all teachers with an associate degree in the estimation. Schools normally require a four-year college degree to be a teacher. And, those with an associate degree could be a substitute, part-time teacher or support staff. Second, and more importantly, her comparison group is essentially professional, which include college professors or doctors. Expectedly, college professors could be better qualified than school teachers. As in the literature, I exclude all those with less than a bachelor's degree, and compare teachers with all non-teachers. To reflect the early-career occupational choices, I define an individual as a teacher if he/she has ever mentioned teacher as a primary occupation in the survey between the age of 21 and 31.[21]

I go on to assess the quality from three approaches. First, I directly calculate the average distribution of teachers' cognitive attributes versus non-teachers. Second, I calculate the percentage of teachers in each cohort that have test scores at the upper quartile (80th percentile), as the debate has focused on attracting teachers from the upper tail of the quality distribution. Third, I calculate the estimated probability of an individual entering teaching by quintile, using the following logit regression.[22]

[21] For the cohort of NLS Mature Women, I use their age of the first interview, which ranges from 30-44 years.

[22] Our concept is same to Corcoran, Evans and Schwab (2004) who use logit model to estimate the likelihood

$$Pr(y_i = tc|x_i) = \alpha + Q_i + X_i\beta + \epsilon_i, \quad (4.14)$$

where Q_i is an IQ score, and X_i contains control variables described below. It would have been ideal to have time-series data to measure the quality of teachers over time. However, such data are not available. As the NLS have four cohorts targeted at different age groups in different points of time, it could still be valuable to assess the quality of teachers over time.

I present the descriptive statistics in Table 8 for women and Table 9 for men. I standardize the ability variables.[23] Two messages stand out from the descriptive statistics for women. First, the average quality of female teachers is lower than their counterparts. Second, there is no secular decline in teacher quality, as generally perceived.

The average quality of female teachers in the NLS of mature women representing the birth cohorts of 1923-1937 (ages 30-44 in 1967) is close to non-teachers. As contained in Table 8, the self-reported high school English ability of teachers from the cohort of the NLS of mature women is almost the same as non-teachers. However, in the same cohort, math ability is marginally lower. Similarly, in the cohort of the NLS of Young Woman (representing birth cohort of 1944-1954), the average IQ score of female teachers is lower. So is the average AFQT score in the cohort of the NLS79 (representing birth cohort of 1957-1964). Also, the average ability in the latest cohort, NLS97 (representing the birth cohort of 1980-1984) is lower. On change in teacher quality over time, the teacher/non-teacher gap increased from the birth cohort of 1944-1954 (NLS Young Woman) to the birth cohort of 1957-1964 (NLS79), rising from 0.11 standard deviations to 0.17 standard deviations. However, the gap decreased to 0.091 standard deviations in the cohort of 1980-1984 (NLS 97).

of teaching.

[23] ability_std = $\frac{ability - \overline{ability}}{\hat{\sigma}_{ability}}$

As contained in Table 9, for male teachers, the average quality seems to be higher than that of non-teachers in the latest cohort (NLS 97). However, the relative average quality of male teachers was lower in both the older cohorts (NLS of Young Men, and NLS 79). Corcoran, Evans and Schwab (2004), using five different longitudinal data sources (different from this paper's), find an increase in the cognitive attributes of male teachers. Additionally, I plot the entire distribution of ability. Figures 8-9 contain the kernel density of cognitive skill (teachers versus non-teachers) for female and male separately. In all cohorts except for women in the NLS 97, non-teachers have slightly higher density of cognitive attributes in the upper-tail.

I also calculate the proportion of teachers, whose test scores are in the top quintile. Table 10 contains the calculations. For the female teachers, there is a very small decline between the cohorts of NLS Young and NLS79, and a negligible rise between the cohorts of NLS79 and NLS97. For male teachers, the proportion is slightly increasing over time. I could not find a big decline for teachers and rise for non-teachers that Bacolod (2007) gets, using the same data set. The differences might have arisen from Bacolod's (2007) sample choice described above. My results are rather close to Corcoran, Evans and Schwab (2004), which documents a small decline over time for female teachers and increase for male teachers using different data sources than this paper's.

I estimate equation (4.14) separately for each cohort to see the ranking of cognitive attributes on the propensity to be a teacher.[24] Then, I calculate the predicted probability of an individual entering teaching by quintile. Table 11 presents results. There has been a secular decline in the predicted probability of becoming teachers for women from the distribution of the top 20 percentile. In all quintiles, there is a decline in the propensity to become a teacher for women between the cohorts of NLS Young and NLS 79. This

[24] To make results comparable across cohorts, I try to use the same independent variables, which are age, age-squared, race, education, region, marital status and trend along with cognitive ability variable in each estimation. The choice of the limited covariates is due to the data constraint. My approach is similar to Corcoran, Evans and Schwab (2004) who use only age and race.

result reflects the fact that the number of college-graduate females considerably increased during that period, while outside teaching opportunities increased along with a decline in the labor market discrimination against women. However, there is a rise in the propensity in all quintiles, except in the bottom and second-top, between NLS 79 and NLS 97. For men, there is a decline in the average predicted probability of becoming a teacher between NLS Young and NLS 79 in all quintiles; however, an increase between NLS 79 and NLS 97.

4.6 Conclusion

The objective of this paper is to examine the evolution of the relative wages and quality of school teachers in the U.S. over the past half-century. My analysis looks at teachers' attributes from different dimensions over time. And, I focus on female teachers as over 75 percent of school teachers in the U.S. are women.

First, I begin looking at the relative wage of teachers. The relative lower wage for female teachers was not a permanent phenomenon, rather a new one emerging especially after 1990. But for male teachers, compensation has always been lower than that of non-teachers. The wage gap of top earners at the 90th percentile is still steeper. For instance, the gap for women that was around six percent in the mid-1960s increased to over 40 percent in the late 2010s. The wage gap of top earners could discourage able college-graduates to join teaching due to better prospects of salary growth in the non-teaching sector.

In order to explore what explains the declining relative wage, I use a constant elasticity of substitution (CES) framework to examine the growing demand for skills in the non-teaching sector. I find a positive and statistically significant trend of demand for skills in the non-teaching sector over time, which could in turn raise the wage of non-teachers, thus widening the wage gap. Furthermore, such a secular increase in demand for skills should have implications for teacher quality. Hence, I next use a Roy (1951) model of occupational choice to explore teacher quality. A key insight that emerges from the estimates of the Roy model is that the ability of women in non-teaching sectors has steadily risen over the years; and somewhat declining in teaching. The estimates of the Roy model have some important policy implications. An effective approach to attract able women into teaching could be to increase the variation of salary. The current "rigid salary schedules" might not be helpful to deservingly compensate the talented pool of teachers.

To supplement the Roy model's estimates, I analyze the relative cognitive attributes. For this purpose, I use the standardized test scores as a proxy for cognitive ability, which are obtained using data from four different cohorts of the National Longitudinal Survey (NLS). I find that teachers' average cognitive ability is lower than that of non-teachers.

Appendix A: Data Source

A.1 Current Population Survey

I use the March Current Population Survey (CPS) from the sample years 1964 to 2013, which cover the actual years 1963 to 2012. The current CPS survey contains information from the preceding year. For instance, the 2013 March CPS data refers to the data from the calender year 2012. Throughout this paper, the year refers to the survey year, not the actual calender year from which data are drawn. The CPS, conducted jointly by the U.S. Census Bureau and the Bureau of Labor Statistics, is a monthly survey of 50,000 households. About 60,000 households are eligible for the CPS interview. I use the the March sample of the CPS, as it provides rich individual's demographic and income information, and it has widely been used in the empirical works.

Education

The CPS changed the definition of education variable in 1992, prior to which education was reported as the number of years. Since 1992, the education variable is reported in categories of their diploma or degree (e.g, bachelor's degree, master's degree, professional degree and doctorate degree). In order to make the reporting of education variable comparable before and after the change, I translate the number of education reported before 1992 into the categories of degree. I use 16- and 17-years of education as equivalent to a four-year college degree, and 18-years of education or above as an advanced degree. As mentioned in the text, our estimation exclude those less than a college degree. Hence, I do not need to worry about the redefinition below 16-years of education.

Occupation

Occupation refers to as the individual's primary occupation during the previous calendar year. (Note that wage refers to the total wage and salary during the previous calendar year.) For those holding multiple jobs during the preceding year, the CPS uses the occupation in which the individual worked longest. We use three-digits census occupation codes to identify teachers during 1964-2002, and four-digits census occupation codes since 2003.

A.2 National Longitudinal Survey

I obtain cognitive attributes data from four cohorts of the National Longitudinal Survey (NLS). The NLS is a nationally representative set of surveys that collect information about labor market activities. The Bureau of Labor Statistics (BLS) conducts the NLS. A distinct advantage of this data is its gathering of ability variables. Each cohort is a longitudinal survey. In this paper, I use four cohorts–National Longitudinal Survey of Youth 1997 (NLSY97), National Longitudinal Survey of Youth 1979 (NLSY79), National Longitudinal Surveys of Young Women and Mature Women (NLSW), and National Longitudinal Surveys of Young Men and Older Men (NLSM). I use the publicly available version of the data. I provide a brief introduction of each survey below.

NLSY97: The NLSY97 cohort is a nationally representative survey of 8,984 youths. At the time of the first interview in 1997, respondents were ages 12-17 years (birth cohort of 1980-1984). So far, they have been interviewed 15 times on an annual basis. The latest survey (at the time of writing) is 2011. I use the data from all 15 surveys 1997-2011.

NLSY79: The original sample size of the NLSY79 Cohort is 12,686 young men and women. In the first survey of 1979, respondents were aged 14-22 years (birth cohort of 1957-1964). The individuals were interviewed on an annual basis until 1994. Since then, they have been interviewed biennially.

NLSW: It has two groups (Mature Women and Young Women). The Mature Womens cohort includes 5,083 women aged 30-44 years (birth cohort of 1922-1937) in the first survey of 1967. These women were in their early- or mid-career at the time of the first interview. And, they could be representative of teachers quality in 1950s and 1960s. The Young Womens cohort includes 5,159. The respondents were aged 14-24 years (birth cohort of 1943-1953) at the first interview of 1968, and they were followed up until 2003. However, I only follow up individuals when they were aged 21-31 years.

NLSM: The Young Mens cohort had 5,225 men aged 14-24 years (birth cohort of 1941-1952) in their first interview of 1966. The survey was discontinued in 1981.

Variables Construction

i) **Cognitive Attributes:** There is not a consistent measure of cognitive skill across cohorts. However, except the NLS of Mature Women, all cohorts include IQ information (albeit measured slight differently) making it largely comparable across the cohorts. For the NLS of Mature Women, we use the self-reported math and English performance as a measure of cognitive ability. The survey asked respondents how well they did in math and English in high school. They rated their performance on the scale of 1-5.

NLS of Young Women/Young Men

The IQ score is referred to a composite score created by combining scholastic or aptitude tests. The tests are the Otis/Beta/Gamma, the California Test of Mental Maturity, and the Lorge-Thorndike Intelligence Test, as well as the PSAT, SAT, and ACT college entrance examinations.

NLS of 79

As a proxy for IQ, we use Armed Forces Qualifying Test (AFQT) scores which are calculated from the variable ASVAB, which refers to Armed Services Vocational Aptitude Battery test. Some 11,914 of the 12,686 NLS79 respondents were selected to participate in the ASVAB test in 1980. It tests respondents knowledge and skill in 10 areas (general science, arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations, coding speed, auto and shop information, mathematics knowledge, mechanical comprehension, and electronics information). The scores were renormed twice in 1989 (named AFQT-2) and 2006 (named AFQT-3). I use the AFQT-3.

NLS of 97

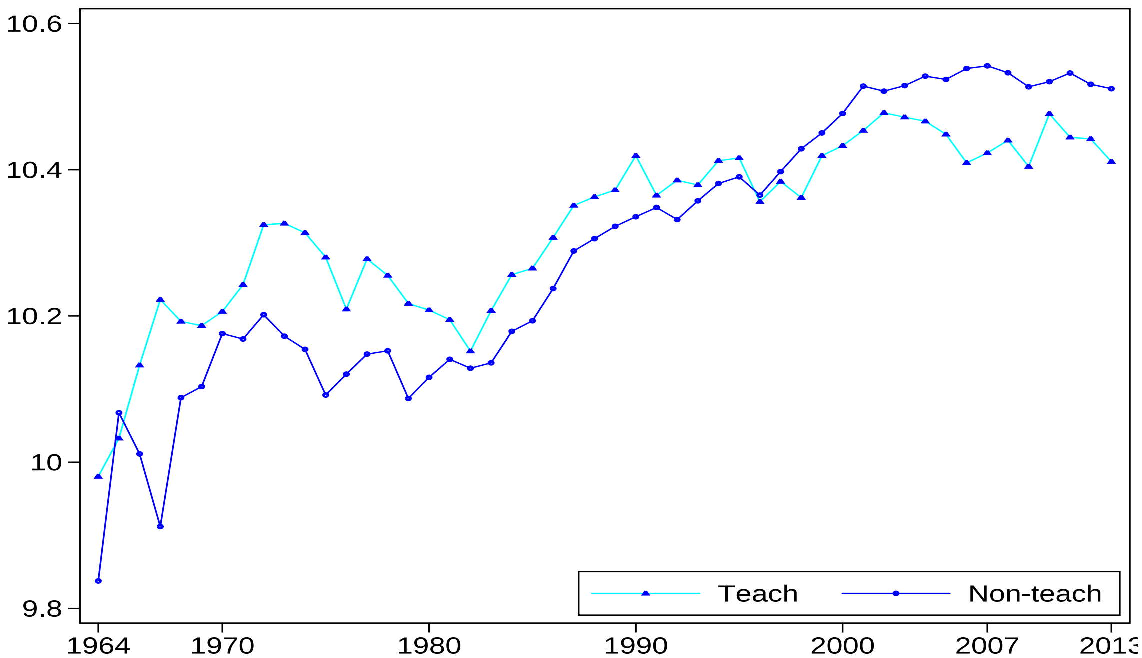
For the NLS97 cohorts, I use the Armed Services Vocational Aptitude Battery test, which is designated as ASVAB_MATH_VERBAL_SCORE_PCT in the NLS97 survey. The test measures respondent's knowledge and skills in areas of arithmetic reasoning, electronics information, numerical operations, assembling objects, general science, paragraph comprehension, auto information, mathematics knowledge, shop information, coding speed, mechanical comprehension word knowledge. Importantly, this variable is similar to the 1979 AFQT score.

ii) **Teacher:** In all cohorts, teacher is defined as the one who has mentioned his/her main job as a teacher in any survey year. The NLS documents occupations according to the census 3-digit codes. I use the three-digit census 1960-, 1970-, 1990-, and 2000 codes.

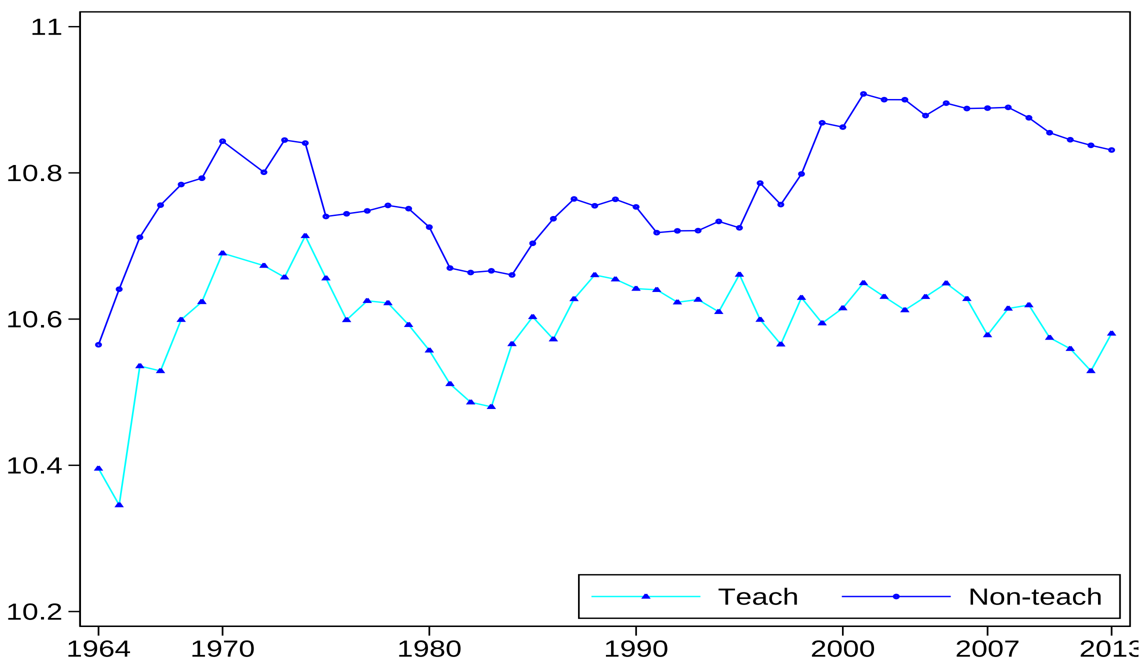
iii) **Education:** Education is documented differently in each cohort. Hence, I describe here how I calculate the level of education. I use 16- or 17-years of education as a bachelors degree, and 18-years of education or above as an advanced degree (an master's degree or beyond). Identifying education level in the NLS97 is straightforward. The cohort includes a cumulative variable that documents the highest degree ever received by respondents regardless of the survey year.

For the cohort of NLS79, education is defined in terms of number of years before 1987 and from then onwards it is categorized in terms of degree. First I use the first interviews education (the survey 1979) and update education information each survey until 1986. (Each survey asks the highest level of education.) Then I convert the number of years of education into degrees (12 or 13 years of education as a high school, 14- or 15- years of education as an associate degree, 16- or 17-years of education as a bachelors degree, and 18-years or above as a graduate degree). The goal is to link education information though 1986 to 1987 when the NLS begin asking the highest degree received. Then, I update education degree using education information in each survey.

Figure 1: Mean Annual Log Wages of Teachers versus Non-teachers



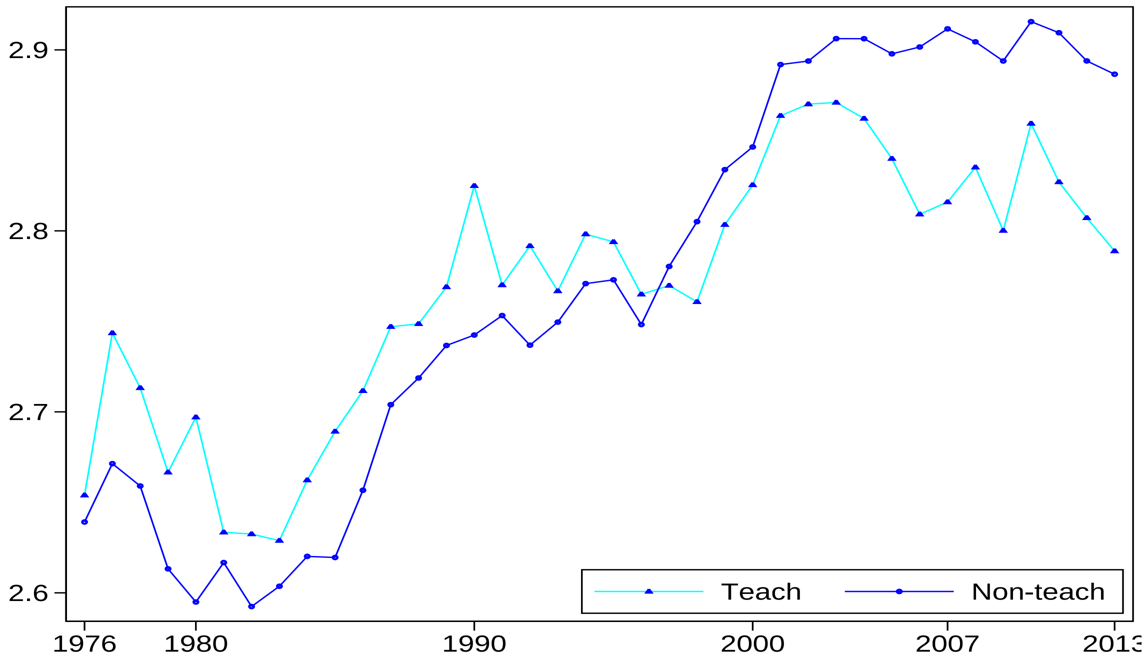
(a) Women



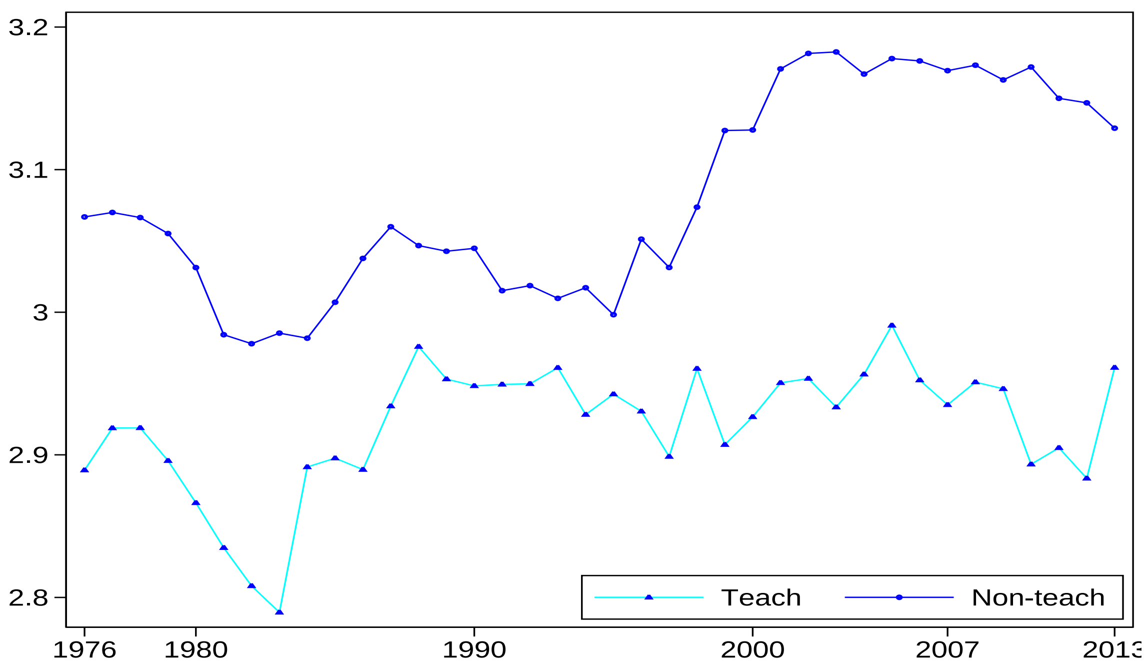
(b) Men

Note: Mean annual log wages are calculated using the CPS data, covering years 1964-2013.

Figure 2: Mean Hourly Wages of Teachers versus Non-teachers



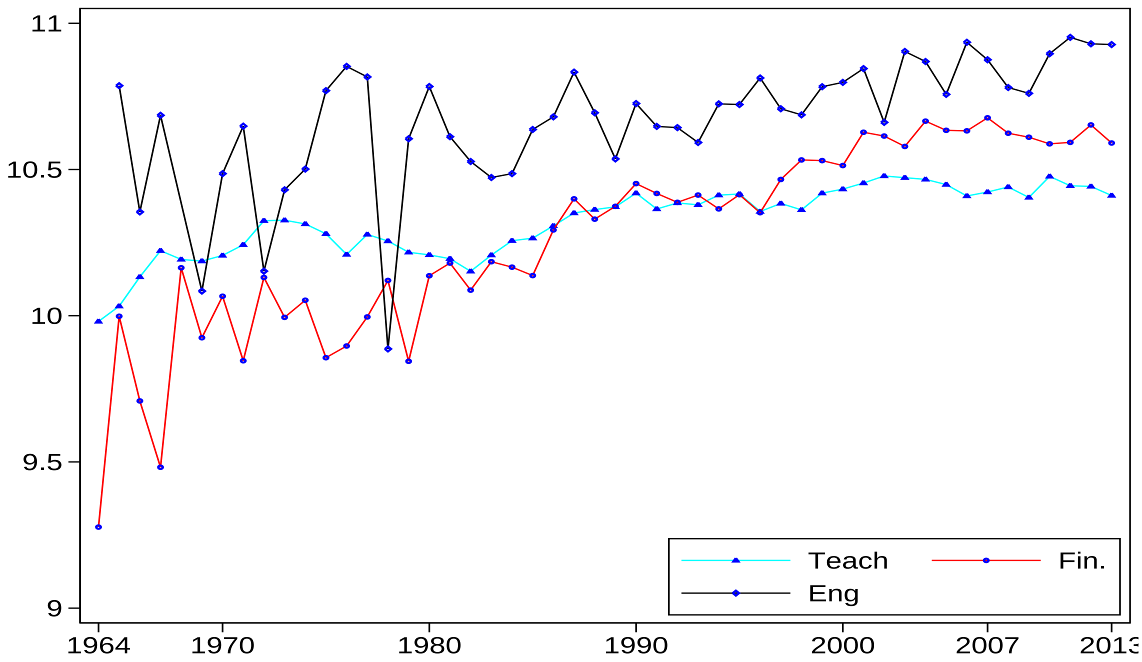
(a) Women



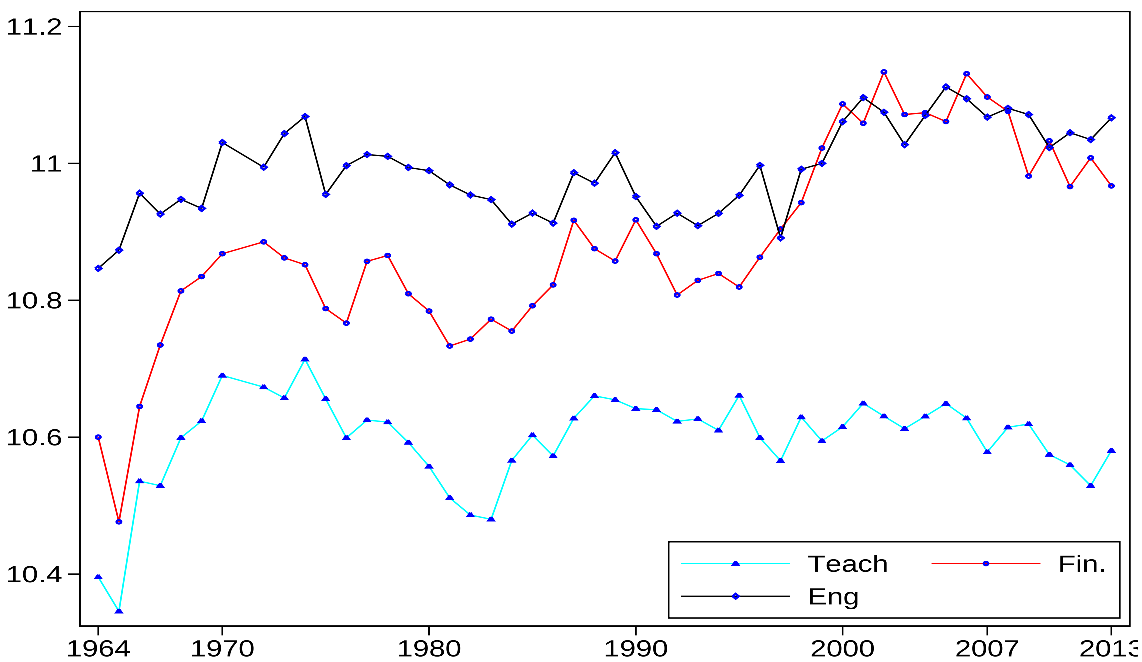
(b) Men

Notes: Mean hourly log wages are calculated using the CPS data, covering years 1976-2013. Prior to 1976, the CPS data do not contain information about the number of hours worked.

Figure 3: Teaching versus Finance and Engineering



(a) Women



(b) Men

Note: Mean annual log wages are calculated using the CPS data, covering years 1964-2013.

Figure 4: OLS Estimates for Annual Wages

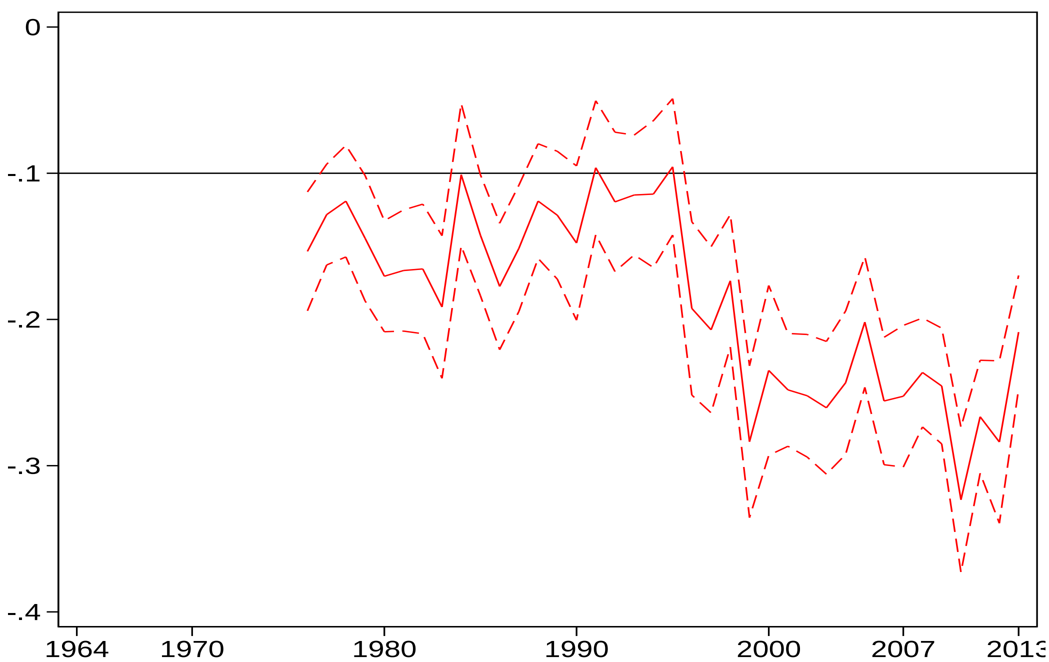
(a) Women

(b) Men

Notes: Using the CPS data from 1964-2013, I estimate the ordinary least squares (OLS) regression for each year with annual log wage as a dependent variable, and plot the coefficients of the dummy variable for teachers.

Figure 5: OLS Estimates for Hourly Wages

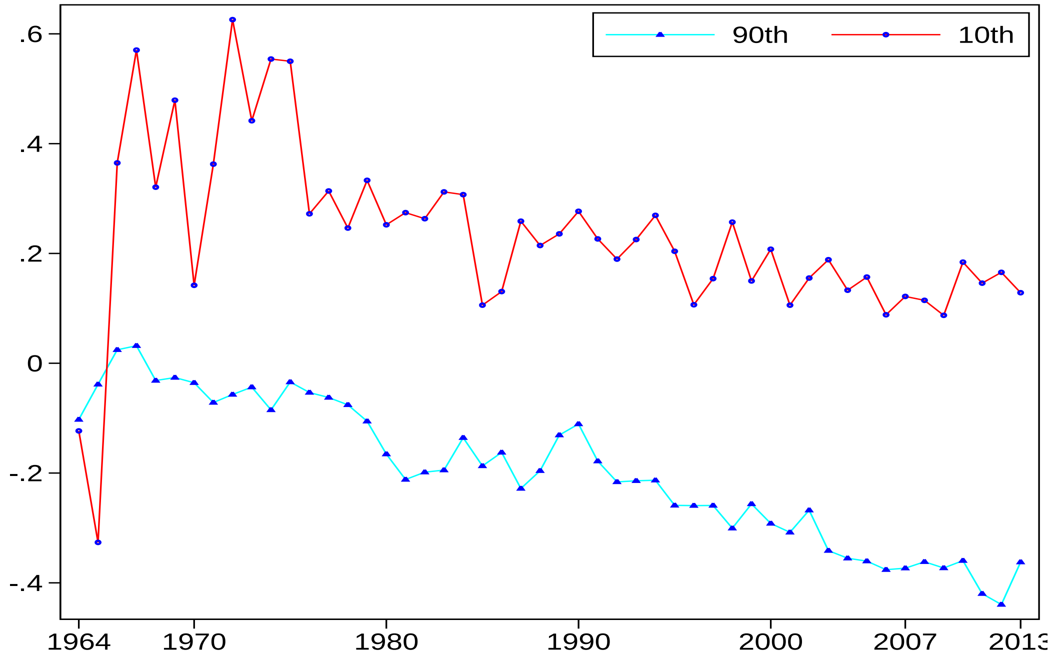
(a) Women



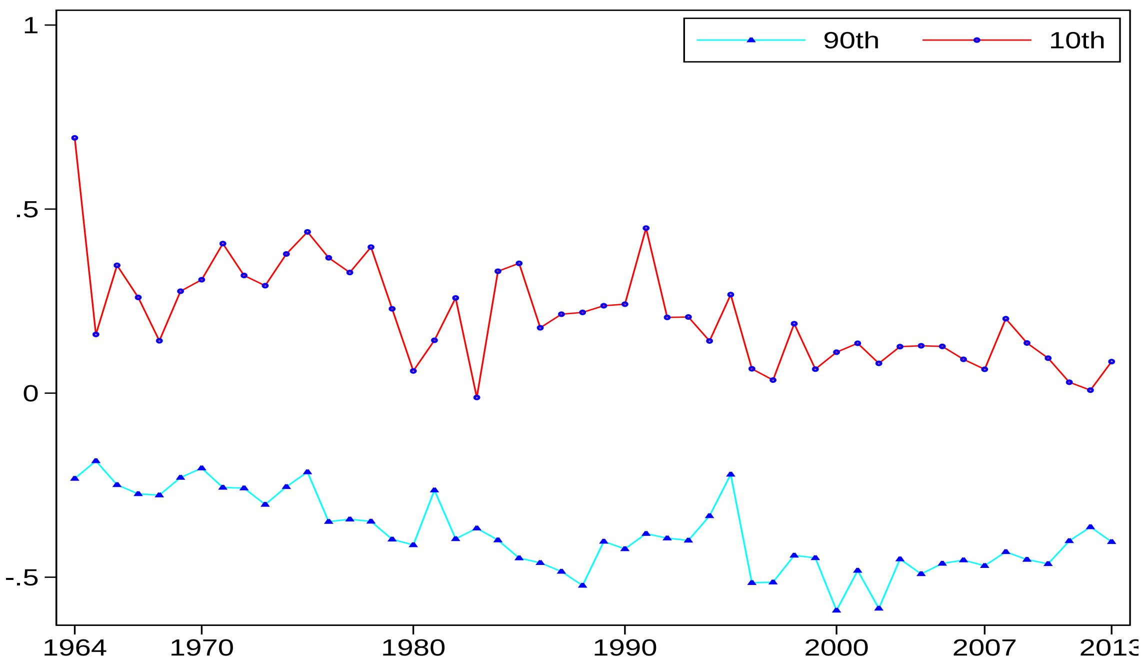
(b) Men

Note: Using the CPS data from 1964-2013, I estimate the ordinary least squares (OLS) regression for each year with hourly log wage as a dependent variable, and plot the coefficients of the dummy variable for teachers.

Figure 6: Annual Wage Distributions at the 10th and 90th Percentiles: RIF Regression



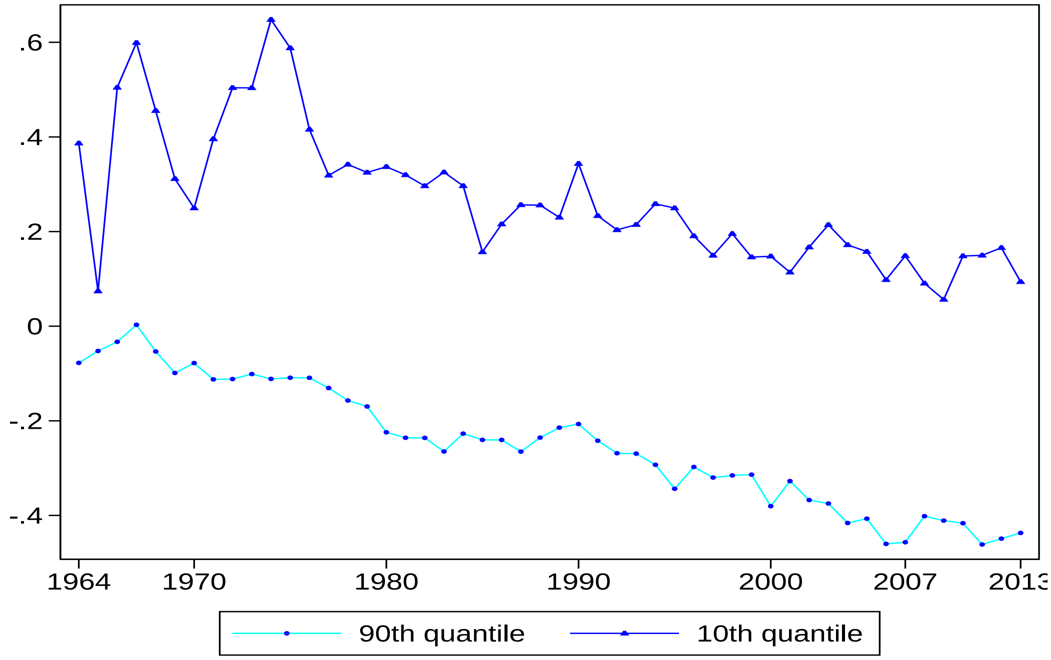
(a) Women



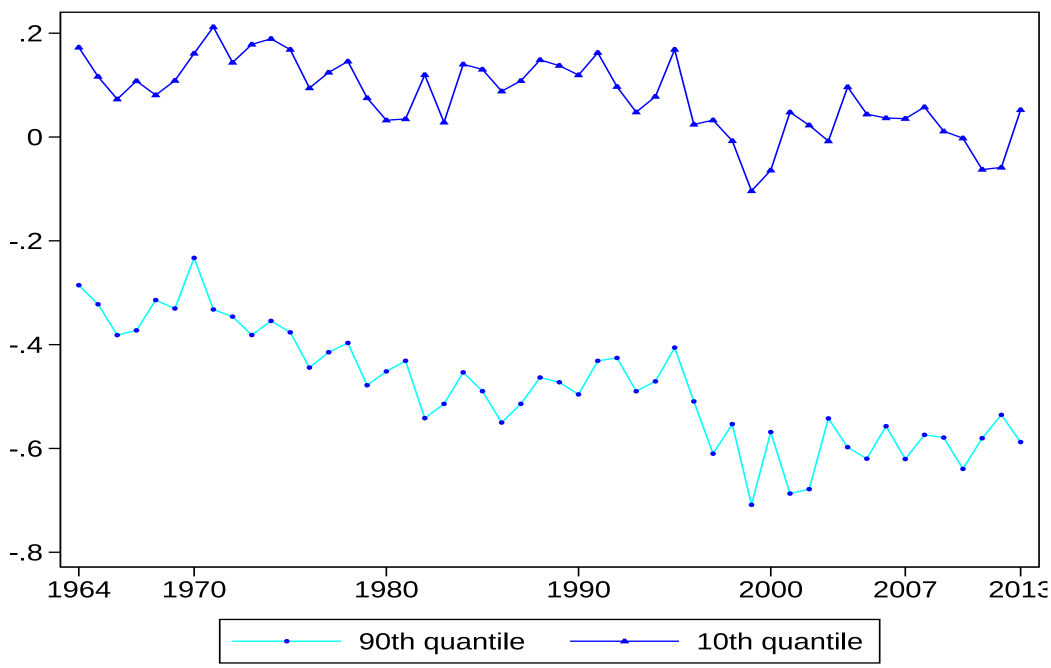
(b) Men

Notes: Using the CPS data from 1964-2013, I estimate the recentered influence function (RIF) regression to calcualte the annual log wage differentials of teachers versus non-teachers at the 10th and 90th percentiles. The coefficients are estimated for each year separately for men and women.

Figure 7: Annual Wage Distributions at the 10th and 90th Percentiles



(a) Women



(b) Men

Notes: Using the CPS data from 1964-2013, I estimate the conditional quantile regression to get the annual log wage differentials of teachers versus non-teachers at the 10th and 90th percentiles. The coefficients are estimated for each year separately for men and women.

Table 1: **Oxcana-Blinder Decomposition: Female**

Period	Mean Log wage of Non-Teachers (1)	Mean Log Wage of Teachers (2)	Differences (3)	Explained (4)	Unexplained (5)
1964-1969	9.96***	10.093***	-0.133***	0.028**	-0.161***
	(0.025)	(0.018)	(0.031)	(0.014)	(0.032)
1970-1975	10.156***	10.284***	-0.128***	0.032***	-0.161***
	(0.012)	(0.009)	(0.015)	(0.006)	(0.015)
1976-1981	10.127***	10.226***	-0.099***	-0.001	-0.098***
	(0.009)	(0.009)	(0.012)	(0.005)	(0.013)
1982-1987	10.202***	10.259***	-0.057***	-0.035***	-0.021*
	(0.007)	(0.008)	(0.01)	(0.005)	(0.011)
1988-1993	10.335***	10.381***	-0.046***	-0.029***	-0.017*
	(0.005)	(0.007)	(0.009)	(0.004)	(0.009)
1994-1999	10.404***	10.392***	0.012	-0.032***	0.044***
	(0.005)	(0.007)	(0.009)	(0.004)	(0.009)
2000-2005	10.511***	10.459***	0.053***	-0.041***	0.094***
	(0.004)	(0.006)	(0.007)	(0.003)	(0.007)
2006-2013	10.525***	10.431***	0.094***	-0.047***	0.14***
	(0.003)	(0.005)	(0.006)	(0.003)	(0.006)

Notes: Entries in the table are calculated using the Oxcana-Blinder Decomposition. Standard errors are reported in parentheses.
$***$ Significant at the 1 percent level.
$**$ Significant at the 5 percent level.
$*$ Significant at the 10 percent level.

Table 2: **Oxcana-Blinder Decomposition: Male**

Period	Mean Log wage of Non-Teachers (1)	Mean Log wage of Teachers (2)	Differences (3)	Explained (4)	Unexplained (5)
1964-1969	10.672***	10.451***	0.221***	0.139***	0.082***
	(0.009)	(0.023)	(0.024)	(0.015)	(0.02)
1970-1975	10.814***	10.684***	0.13***	0.06***	0.07***
	(0.005)	(0.008)	(0.009)	(0.007)	(0.009)
1976-1981	10.73***	10.584***	0.146***	-0.006	0.152***
	(0.005)	(0.008)	(0.009)	(0.006)	(0.009)
1982-1987	10.702***	10.555***	0.147***	-0.033***	0.179***
	(0.005)	(0.009)	(0.01)	(0.006)	(0.01)
1988-1993	10.738***	10.642***	0.096***	-0.062***	0.158***
	(0.004)	(0.009)	(0.01)	(0.006)	(0.01)
1994-1999	10.78***	10.611***	0.169***	-0.064***	0.233***
	(0.004)	(0.011)	(0.012)	(0.007)	(0.011)
2000-2005	10.891***	10.632***	0.259***	-0.029***	0.288***
	(0.004)	(0.01)	(0.011)	(0.006)	(0.01)
2006-2013	10.863***	10.585***	0.278***	-0.034***	0.312***
	(0.003)	(0.008)	(0.009)	(0.005)	(0.009)

Notes: Entries in the table are calculated using the Oxcana-Blinder Decomposition. Standard errors are reported in parentheses.
∗ ∗ ∗ Significant at the 1 percent level.
∗∗ Significant at the 5 percent level.
∗ Significant at the 10 percent level.

Table 3: **Regression Models for Demand for Skills**

Variables	Men	Women
Time trend	0.006763***	0.009337***
	0.0016704	0.0009593
NTC/TC relative supply	-0.8615522***	-0.9062199***
	0.08504	0.0235503
Constant	0.4716475***	-0.0870002***
	0.1643658	0.0107792
Observations	50	50
R-squared	0.9586	0.9973

Notes: The estimates are calculated aggregating the CPS data from 1964-2013. Standard errors are reported in parentheses.
∗ ∗ ∗ Significant at the 1 percent level.
∗∗ Significant at the 5 percent level.
∗ Significant at the 10 percent level.

Table 4: **The Effect of Union on Teacher Pay**

	Women		Men	
	1990-00	2001-13	1990-0 0	2001-13
Union Teacher	-0.050***	-0.025	-0.025	-0.001
	(0.012)	(0.013)	(0.019)	(0.017)
Union	0.076***	0.053***	0.042***	0.021***
	(0.008)	(0.007)	(0.009)	(0.006)
Teacher	-0.021*	-0.122***	-0.210***	-0.304***
	(0.010)	(0.010)	(0.015)	(0.009)
Metro Outskirts	0.153***	0.143***	0.200***	0.179***
	(0.013)	(0.012)	(0.019)	(0.016)
Metro Central	0.117***	0.132***	0.112***	0.132***
	(0.013)	(0.010)	(0.019)	(0.016)
Age	0.074***	0.067***	0.091***	0.091***
	(0.003)	(0.002)	(0.003)	(0.003)
Age-squared	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Black	-0.057***	-0.083***	-0.221***	-0.246***
	(0.013)	(0.008)	(0.014)	(0.012)
Other Race	-0.114	-0.069*	-0.223***	-0.140***
	(0.079)	(0.028)	(0.041)	(0.038)
Const	8.437***	8.690***	8.177***	8.472***
	(0.060)	(0.044)	(0.062)	(0.061)
N	63106	142464	87725	172282
R^2	0.081	0.085	0.137	0.135

Notes: The estimates are calculated using the Ordinary Least Squares (OLS) regression. Standard errors are reported in parentheses.
$***$ Significant at the 1 percent level.
$**$ Significant at the 5 percent level.
$*$ Significant at the 10 percent level.

Table 5: **Roy Model**

	Teacher		Non-teachers	
Period	Selection Coeff.	N	Selection Coeff.	N
1968-1973	0.095		-1.837	
	(0.149)		(0.179)	
	[0.636]		[-10.286]	
1974-1979	0.377		-1.065	
	(0.102)		0.115	
	[3.686]		[-9.22]	
1980-1985	0.473		-0.811	
	(0.066)		(0.094)	
	[7.127]		[-8.639]	
1986-1991	0.416		-0.605	
	(0.057)		(0.075)	
	[7.324]		[-8.062]	
1992-1997	0.333		-0.352	
	(0.055)		(0.078)	
	[6.069]		[-4.483]	
1998-2003	0.45		-0.173	
	(0.054)		(0.074)	
	[8.264]		[-2.33]	
2004-2009	0.315		0.14	
	(0.046)		(0.063)	
	[6.8]		[2.219]	
2010-2013	0.348		0.356	
	(0.077)		(0.096)	
	[4.52]		[3.69]	

Notes: The parameters of Roy Model are estimated, using the CPS data. Standard errors are reported in parentheses, and t-values are in brackets.

Table 6: **Roy Model: Aged 25-54 years**

	Teacher		Non-teachers	
Period	Selection Coeff.	N	Selection Coeff.	N
1968-1973	0.25		-2.078	
	(0.181)		(0.209)	
	[1.385]		[-9.928]	
1974-1979	0.499		-1.207	
	(0.117)		(0.125)	
	[4.252]		[-9.68]	
1980-1985	0.502		-0.803	
	(0.068)		(0.096)	
	[7.392]		[-8.329]	
1986-1991	0.411		-0.63	
	(0.055)		(0.075)	
	[7.474]		[-8.42]	
1992-1997	0.326		-0.389	
	(0.053)		(0.075)	
	[6.207]		[-5.193]	
1998-2003	0.423		-0.155	
	(0.053)		(0.071)	
	[7.947]		[-2.173]	
2004-2009	0.326		0.095	
	(0.044)		(0.063)	
	[7.364]		[1.51]	
2010-2013	0.341		0.347	
	(0.083)		(0.101)	
	[4.1]		[3.448]	

Notes: The parameters of Roy Model are estimated, using the CPS data. Standard errors are reported in parentheses, and t-values are in brackets.

Table 7: **Descriptive Statistics**

	NLS97	NLS79	NLS Young Women	NLS Young Men	NLS Mature Women
N	8984	12686	5159	5225	5083
Birth Year Range	1980-1984	1957-1964	1944-1954	1942-1952	1922-1937
Teacher	821 (9.14)	473(3.7)	752(14.58)	256(4.9)	209(4.1)
Sex:					
Female	4,385	6,283	5159	-	5083
Male	4,599	6,403	-	5225	-
Race:					
White	5,232	8,059	3,638	3,734	3,606
Black	2,388	1,252	1,459	1,438	1,390
Others	1,364	3,375	62	53	87
Education:					
High School or less:	6,204	6,504	3,018	4,057	4,394
Associate/Junior College	606	1,021	212	171	293
Bachelor's Degree	1,691	1,637	570	624	340
Beyond Bachelor's Degree	456	1,205	389	373	56

Sources: National Longitudinal Survey of Youth 1997 (NLSY97), National Longitudinal Survey of Youth 1979 (NLSY79), National Longitudinal Surveys of Young Women and Mature Women (NLSW), and National Longitudinal Surveys of Young Men and Older Men.

Table 8: **Distribution of Average Cognitive Skills: Women**

Cohort	Variable	Teacher	N	Non-teachers	N
NLS of Mature Women					
	Math Performance	3.91	138	4.07	155
	English Performance	4.303	164	4.304	192
NLS of Young Women					
	IQ score	0.078	243	0.188	467
NLS79					
	AFQT	0.0961	48	0.2643	831
NLS79					
	ASVAB	0.0632	271	0.1543	469

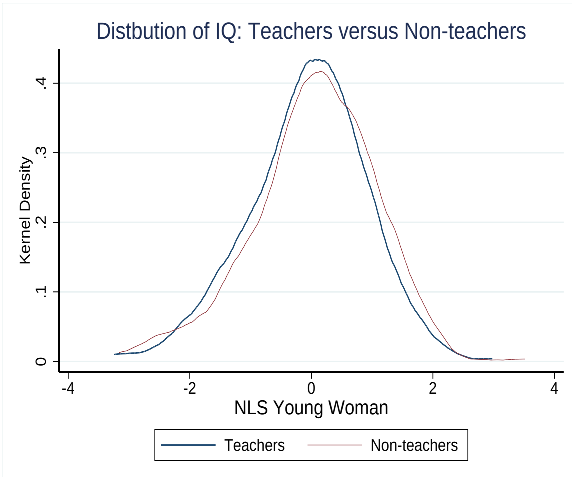
Notes: Math and English performances are self-reported on a scale, 1-5. IQ, AFQT, and ASVAB variables are standardized.

Table 9: **Distribution of Average Cognitive Skills: Men**

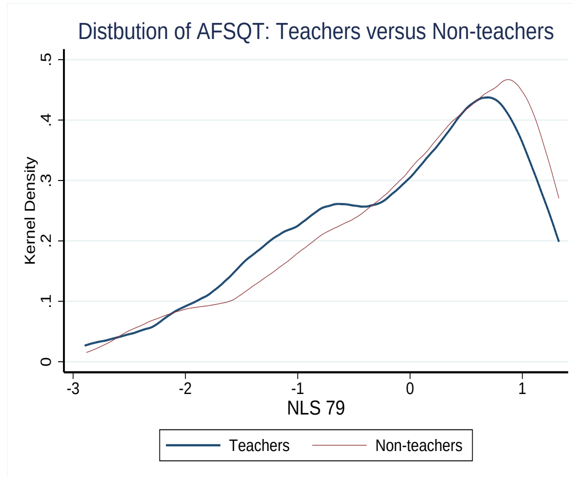
Cohort	Variable	Teacher	N	Non-teachers	N
NLS of Young Men					
	IQ score	0.0726	162	0.0929	1591
NLS79					
	AFQT	0.132	15	0.167	934
NLS97					
	ASVAB	0.238	106	0.0828	423

Notes: Math and English performances are self-reported on a scale, 1-5. IQ, AFQT, and ASVAB variables are standardized.

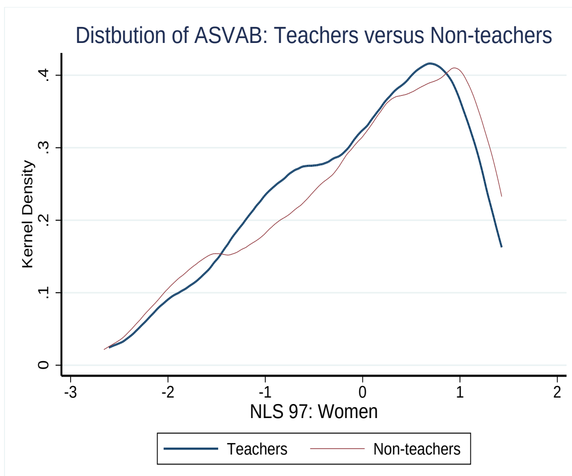
Figure 8: Distribution of IQ: Women



(a) Birth Cohort: 1944-1954



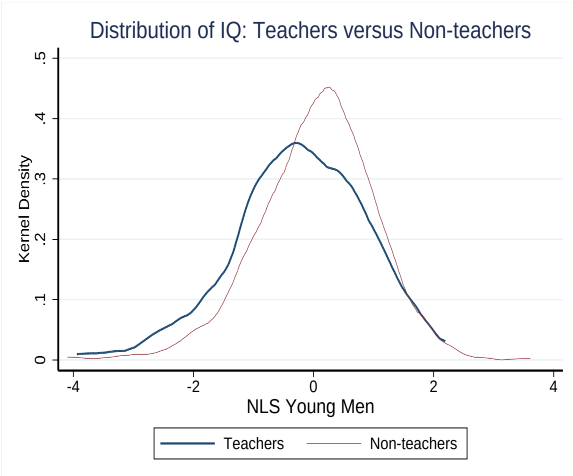
(b) Birth Cohort: 1957-1964



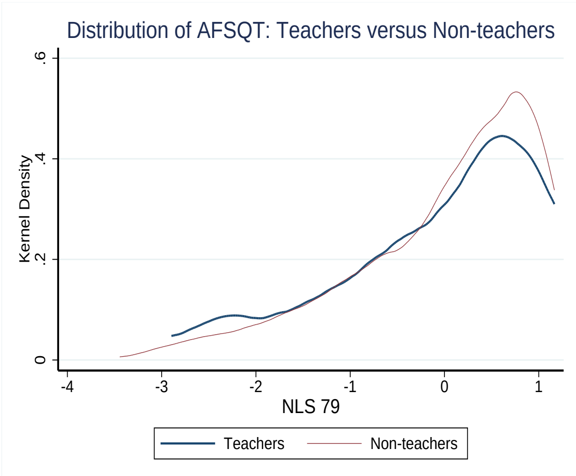
(c) Birth Cohort: 1980-1984

Note: Kernel density estimators are calculated using the default bandwidth.

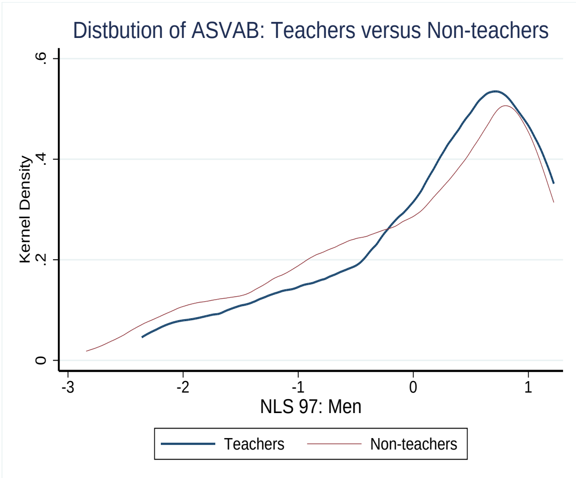
Figure 9: Distribution of IQ: Men



(a) Birth Cohort: 1942-1952



(b) Birth Cohort: 1957-1964



(c) Birth Cohort: 1980-1984

Note: Kernel density estimators are calculated using the default bandwidth.

Table 10: **Proportion of Teachers in the Top Quintile of Quality Distribution**

	Women		Men	
	Teacher	Non-teacher	Teacher	Non-teacher
NLS Young	0.166	0.227	0.162	0.205
NLS79	0.153	0.216	0.211	0.198
NLS97	0.158	0.215	0.220	0.196

Notes: The entries refer to the proportion of teachers whose IQ distribution is in the 1st quintile (the top 20th percentile).

Table 11: **Predicted Probabilities**

	(1)	(2)	(3)	(4)	(5)
Women					
NLS Young	0.490	0.458	0.497	0.443	0.390
NLS79	0.352	0.282	0.235	0.276	0.208
NLS97	0.277	0.332	0.259	0.267	0.215
Men					
NLS Young	0.234	0.216	0.198	0.146	0.160
NLS79	0.121	0.094	0.080	0.093	0.116
NLS97	0.144	0.116	0.154	0.182	0.172

Notes: (5) refers to the top 20 percentile (1st quintile), and (1) refers to the bottom 20 percentile (5th quintile)

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RESUBMITTED PAPERS

"To Be or Not to Be: An Optimum Currency Area for South Asia?" with (Alex Nikolsko-Rzhevskyy and Robert Thornton), Revised and Resubmitted to *Journal of Policy Modeling*

"Impact of the Minimum Wage on Youth Labor Markets" with (Thomas Hyclak and Shanshan Liu), Revised and Resubmitted to *LABOUR*

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