4-2019

Analyzing Unemployment, Education-Occupation Mismatch, and Immigrant's Participation in the US Labor Market

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by

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A dissertation submitted to the Graduate College
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
Economics
Western Michigan University
April 2019

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ACKNOWLEDGEMENTS

First, I would like to acknowledge the influence of the three professors I worked with: Dr. Wei-Chiao Huang, Dr. Matthew Higgins, and Dr. Kevin Corder from Western Michigan University. Their support of academic work in setting up theoretical and analytical work inspired me to pursue the subject, and ultimately led to the work contained in this dissertation.

Second, I would like to thank the people who supported me in my academic journey. Special thanks to my fellow graduate students from Iraq and from other countries. My appreciation and thanks go to the Higher Committee for Education Development in Iraq (HCED) for sponsoring my studies.

Finally, I would like to thank my wife, Nawres Alwaely and my kids (Ali, Tiba, Umniyah, Mariam, and Yousef) for having the patience and supporting me to get my degree.

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Western Michigan University, 2019

Analyzing the factors that determine any labor market's outcomes is important. That is because the results of these analyses can help policy makers to adopt effective labor market policies, and thus achieve the best outcomes of that labor market. In this study, I analyze three important factors: unemployment, education-occupation mismatch, and immigrants' participation in the US labor market.

First, I analyze the problem of slow decline in the rate of U.S. unemployment after the last recessions. In this chapter, I examine whether the slow movement in U.S. unemployment is due to cyclical or structural factors. I contribute to the literature by using a FAVAR approach to investigate the relative contribution of cyclical and structural factors in U.S. unemployment.

The results show that the cyclical factors (GDP growth and vacancy) can explain about 60% of the forecast error variance of unemployment. The structural factors can explain about 16%. About 20% of unemployment is not explained through these results; this percentage of unemployment could be due to the increase in frictional unemployment. These results, in general, indicate that cyclical factors have more contribution than structural factors in the movement of the U.S. unemployment, which is in line with the literature. However, the results indicate that the FAVAR approach can provide better results by reducing the estimation bias.

Next, I examine the effect of business cycles on the Education-Occupation relationship in the US labor market. I also investigate and analyze the factors that lead to Education-Occupation mismatch problem in the US labor market. The results of this chapter indicate that Education-Occupation mismatch exists in the US labor market. The results also indicate that the business cycles can affect the Education-Occupation relationship in the US labor market.

Finally, I study immigrants' participation in the US labor market. This is important because some immigrant workers can benefit the labor market, while others can create problems (e.g. costs). Therefore, it is necessary to formulate economic policies that help in managing and balancing the benefits and costs of immigrants' participation in the US labor market.

The main goal of this chapter is to identifies the policies' targets (immigrant groups that are more likely to participate in the US labor market than other immigrant groups). Identifying the policies' targets can be used as starting point of adopting effective economic policies.

The results show that there are 62 groups of immigrants in the sample from different areas around the world. The results indicate that being from the West Indies, Philippines, and Africa increase the probability of participation in the US labor force relative to US workers. The increase in the probabilities of participation of individuals from these areas are the highest relative to the probabilities of participation of other immigrants groups in the sample.

Therefore, immigrants from the West Indies, Philippines, and Africa are identified as policy targets, and we may place more focus on immigrants from these areas when adopt economic policies. In addition, we may also focus on immigrant groups that have a high number of immigrants in the US, even though their probabilities of participation are not the highest.

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CHAPTER I

THE RELATIVE CONTRIBUTION OF CYCLICAL AND STRUCTURAL FACTORS IN THE U.S. UNEMPLOYMENT: EVIDENCE FROM A (FAVAR)

1.1 Introduction

The slow decline in the U.S. unemployment rate after the 2007-2009 recession has been the concern of researchers and policy makers. Sala et al (2012), Chen (2011), and others indicated that the rate of unemployment was still high in the U.S. even after the recovery period of the last recessions. Researchers have been trying to identify whether the factors that led to the slow decline in the U.S. unemployment rate are structural or cyclical. In this paper, I investigate the relative contribution of two main sources (cyclical and structural) in the U.S. unemployment.

The first source is related to the cyclical factors and lead to what is called (cyclical unemployment). The second source is related to the structural factors and lead to what is called (structural unemployment). Some studies consider frictional unemployment as another source, but it can be part of structural unemployment, (Lindbeck, 1999).

Structural unemployment is the part of unemployment that caused by structural changes including the changes in institutional framework, technological changes, changes in legislations and political changes. Cyclical unemployment is the part of unemployment that is caused by losing jobs due to economic downturns, Aysun (2014). The cyclical unemployment is connected to the changes in economic stimulative policies, (Diamond, 2013)

All the studies in the literature agreed that unemployment in the U.S is due to both cyclical factors and structural factors. However, many researches have been working on measuring the relative contribution of each type of factor in explaining the movement in unemployment. In this paper, I differ from the literature by using a factor augmented vector auto regression model (FAVAR) introduced by Bernanke et al (2005). I use a FAVAR to identify the relative contribution of each type of factor in explaining the movement in unemployment in the U.S.

What motivates me to use FAVAR is that past studies in this area may suffer from potential identification problems. The existence of identification problems in such studies can lead to biased results as showed by Bernanke et al (2005). Bernanke et al (2005) indicated three potential problems when using the standard VAR approach. First, some information may not be reflected in the model (measurement error in the model variables). Second, the choice of the data series to represent an economic concept is often arbitrary to some degree. Third, results can be observed only for the small subset of the variables which the researcher included in the model.

By examining some of studies in this area we can see that all the three potential problems may exist especially when identifying the structural factors. For example, Chen et al (2001) used only dispersion of industry-level stock returns as a structural factor. Sala et al (2012) used wage rigidity and a construct measure for matching efficiency as structural factors. Maidorn (2003) tested the effects of shocks to productivity, demand, wages and labor supply as structural shocks on unemployment. From these examples, I can see that researchers only consider a few structural variables and miss the others. Researchers sometimes construct proxies using different methods which can lead to measurement error. Furthermore, researchers choose structural variables that represent few structural changes in the economy. As a result, past studies may suffer from an identification problem and have biased results.

To solve the identification problem when it exists, Bernanke et al (2005) suggested using a factor augmented autoregressive (FAVAR) model as one of the solutions to this problem. Bernanke et al (2005) defined FAVAR as a combination of standard VAR and factor analysis for large data sets. Bernanke et al (2005) indicated three advantages of using FAVAR. First, FAVAR allows us to use multiple indicators of economic concepts, so we do not need to assume that the concepts are observed. Second, we can determine whether or not the additional information connected to the unobserved factors is relevant. Third, FAVAR can be used to measure the dynamic responses of not only the main variables but many related variables.

In this paper I use FAVAR to investigate the relative contribution of each type of factor in explaining the movement in unemployment in the U.S. I will use many cyclical and structural variables that have been indicated in the literature to have an important relationship with unemployment. My methodology should reduce the bias in accessing to relative importance of cyclical versus structural factors in explaining U.S. unemployment.

The rest of this paper will have several sections. One section discusses the literature review. Another section discusses the empirical work including data, variables, the model, and the results. The last section will be the conclusion.

1.2 Literature Review

The main purpose of this section is to identify the available cyclical and structural variables that have been indicated in the literature to have an important relationship with unemployment. More specifically, I review what previous researchers have done in this area and select the variables that have an impact on unemployment. More focus will be on selecting the structural variables because the cyclical variables like GDP and vacancy are commonly used in almost all the past studies.

The common way to analyze and identify the cyclical portion of unemployment is with both Okun's law and the Beveridge Curve.

Okun's law is an empirical negative relationship between the changes in unemployment rate and the changes in real output. The idea of Okun's law is that more workers are required to produce more goods and services within an economy. Therefore, higher real output means higher employment and lower unemployment, (Edward, 2007). Based on Okun's law, Sala (2012), Chen (2011) and others identify the real output (GDP) as the key cyclical factor that affects unemployment. They found that real GDP has high power to explain the movement in unemployment.

The Beveridge curve is the other common way to identify the cyclical variables that affect unemployment. Diamond and Sahin (2015) defined the Beveridge curve as "the negative relationship between the unemployment rate and the vacancy rate over the course of a business cycle". Vacancy rate is the number of unfilled jobs expressed as a proportion of the labor force. Diamond and Sahin (2015) stated that The Beveridge curve is one of the most established stylized facts of macroeconomics.

Based on the idea of the Beveridge curve, Sala (2012), Diamond (2013), Supan (1991) and others identify vacancy rate as the other key cyclical variable when analyze the sources of unemployment. In this paper, I will use both real GDP and vacancy rate as the cyclical variables that affect unemployment in the U.S.

The structural unemployment is the part of unemployment that is caused by structural changes including the changes in institutional framework, technological changes, changes in legislations and political changes. To identify the structural variables, I have to look for the variables that measure these changes within an economy.

The wage rate is a common structural variable in the literature. Wage rate is strongly related to labor supply and labor demand. It is also related to the bargaining power of workers and employers and the power of unions in the economy. many studies used wage rate as a structural variable. For example, Anosova (2013), Maidorn (2003), Lindbeck (1999) and others used wage rate as one of the structural variables. They found that wage rate has a significant impact on unemployment.

The minimum wage rate is one of the structural variables that is related to the changes in laws and regulations within an economy. Magruder (2013) tested the effect of the minimum wage rate in Indonesia on employment. Magruder (2013) found that formal minimum wage rate can increase formal employment and decreases informal employment.

Magruder (2013) tested the effect of the shock to the productivity as one of the structural shocks on unemployment in Austria. The results indicated that productivity shocks can explain part of the structural unemployment in Austria. Chen (2008) tested the effect of productivity on unemployment in the U.S. The results showed that productivity has positive effect on unemployment in the short-run and a negative effect on unemployment in the long run.

Unemployment insurance or benefits is one of the structural variables that are related to legislation within an economy. Arrans et al (2009) tested the relationship between the changes in unemployment insurance and unemployment rate in Spain. The results suggested that the decrease in unemployment insurance benefit levels decreased unemployment.

Technological progress within an economy is believed to have an impact on labor market outcomes since it could reduce the number of workers needed for a specific operation. Based on

Solow theory, total factor productivity (TFP) is one measure of technological change. Moreno (2012) tested the effect of TFP on unemployment using OECD data. The results showed that the technological progress reduces unemployment for individuals receiving training. In addition, it increases the unemployment of unskilled workers without training.

Investment is one of the variables that has a strong relation with unemployment based on Keynes' general theory. Keynes' general theory stated that Investments determines effective demand, and then affect unemployment. Investment is a structural variable since it is related to the institution framework, financial structure, and saving behavior within an economy. Smith and Zoega (2009) provided evidence that investment is important for analyzing unemployment in OECD countries.

Foreign direct investment (FDI) is another structural variable that is related to the openness of an economy. Mucuk and Demirsel (2013) tested the relation between FDI and unemployment for seven developing countries. The results showed that FDI has a significant impact on unemployment.

Based on the above discussion, I will use eight structural variables in my empirical work. These variables are: wage rate, minimum wage rate, labor productivity, TFP, private sector investments, government investments, and FDI.

1.3 The Empirical Analysis

The goal of this section is to discuss the data and variables used in this paper, the methodology, the model, and the results. Table (1.1) shows the cyclical and structural variables that used in this paper. As mentioned before, I select the cyclical and structural variables based on the economic theory and the past literature.

Table 1. 1 Cyclical and Structural Variables Used to Explain Unemployment

Variable	**Type**
Real GDP Growth	Cyclical
Vacancy Rate	cyclical
Wage Rate	structural
Federal Minimum Wage Rate	structural
Productivity	structural
Unemployment benefits	structural
Private sector investments	structural
Government investments	structural
FDI	structural
TFP	structural

Real GDP Growth represents the output growth of the U.S economy which has a negative relationship with unemployment based on Okun's Law. Vacancy represent the total unfilled jobs which has a negative relationship with unemployment based on the Beveridge Curve. Both Real GDP Growth and Vacancy Rate are used to represent the cyclical factors that affect unemployment rate.

The other eight variables shown in Table (1.1) represent the structural factors that affect unemployment. Wage rate represents structural framework of setting wages in the U.S. labor market. Federal Minimum Wage represents the changing in the legislation regards minimum wage rate. Productivity (real output per hour) represents the changing in the productivity or skills in the U.S. economy. Unemployment Benefits represents the changing in the legislation regards unemployment insurance and other benefits. Private sector Investments, Government Investment, and Forging Direct Investment (FDI) represent legislation, the saving rate, and the financial institution structure. Total Factor Productivity (output growth less than the contribution of capital and labor) represents changes in technological progress.

The data used in this paper are quarterly data with a sample period from 1971: Q1 – 2014: Q4. Most of the data are taken from the federal reserve bank of St. Louis (FRED). For data on the vacancy variable, I used the composite Help-Wanted Index constructed by Barnichon (2010). That is because vacancy data constructed based on Job Opening and Labor Turnover Survey (JOLTS) started in 2001. Diamond and Sahin (2015) used the composite Help-Wanted Index to represent vacancy rate. For total factor productivity, I used data constructed by Fernald (2014).

1.3.1 The Methodology

In this paper I use a factor augmented vector autoregression (FAVAR) model Introduced by Bernanke et al (2005). I use FAVAR to identify the relative contribution of cyclical and structural factors in explaining the movement in U.S. unemployment. Following Bernanke et al (2005) I do two steps to run the FAVAR. First, I construct the factors using the principal components analysis introduced by Stock and Watson (2002). Second, I run a standard VAR model including real GDP growth, Vacancy Rate, Unemployment, and the constructed factors from the eight structural variables. I use impulse responses and variance decomposition to provide the results.

In the first step, I follow the principal components analysis introduced by Stock and Watson (2002) to construct the factors from the eight structural variables. Stock and Watson (2002) show that when we have large number of indicators, we can forecast relatively one or two of unobserved latent factors. They use principal components analysis to estimate the factors. Their results showed that the constructed factors were efficient and consistent indicators.

The results of using p principal component analysis to construct the factors from the eight structural variables is shown in Figure (1.1). Figure (1.1) shows that one factor (F) can be used to characterizes the eight structural factors.

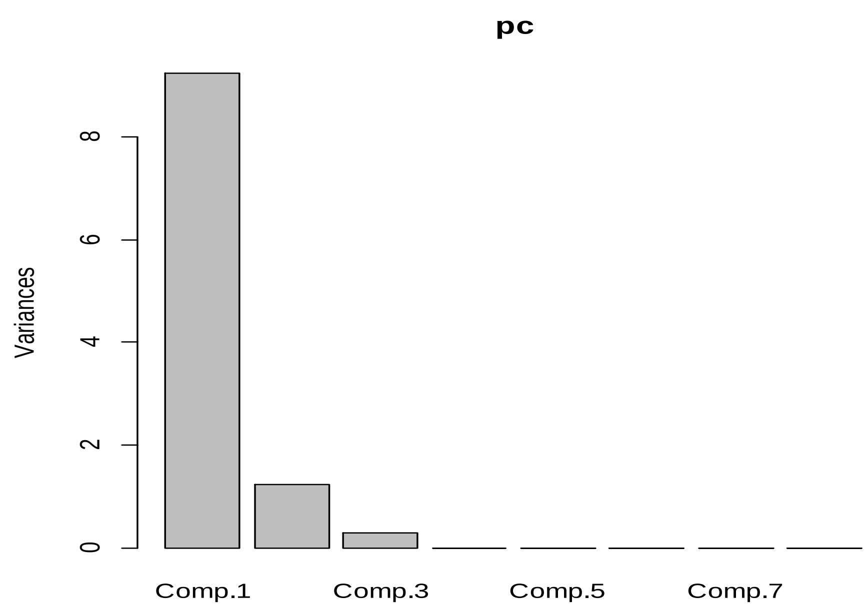

Figure 1. 1 Scree Plot for Selecting the Number of Factors

In the second step, I run a four variable VAR model. The model has three variables (Real GDP Growth, Vacancy Rate, Unemployment) and one factor (F).

The Model is:

$$Z_t = C + A_1 Z_{t-1} + A_2 Z_{t-2} + A_3 Z_{t-3} \ldots \ldots .. + A_p Z_{t-p} + \epsilon_t \qquad (1.1)$$

Where:

$$Z_t = \begin{bmatrix} Y_t \\ F_t \end{bmatrix}, \qquad Y_t = \begin{bmatrix} GDP_t \\ Vacancy_t \\ Unemployment_t \end{bmatrix}, \qquad t = 1,2,3, \ldots \ldots \ldots .176$$

Augmented Dickey–Fuller test was used to test the data series for stationary and AIC criteria for determining the lag length. The unit root test showed that GDP and F are differenced stationary while unemployment rate and vacancy rate are level stationary. AIC criteria indicated three lags to be used as the lag length.

I estimate the VAR with all stationary data series, three lags, and cholesky decomposition with order (F Vacancy GDP Unemployment). The cholesky ordering indicate that the structural changes happen first which affect the vacancy rate. That is because the structural changes can affect the matching process and the skills requirements. Then, the changes in vacancy rate contemptuously effects the GDP and unemployment rate.

1.3.2 The Results

The results are shown in Figure (1.2). Figure (1.2) shows that the unemployment rate decreases significantly as a response to the increase in real GDP growth. This result confirms Okun's law (the negative relationship between unemployment rate and GDP growth). Figure (1.2) shows that the unemployment rate decreases significantly as a response to the increase in vacancy rate. This result confirms the Beveridge Curve (the negative relationship between unemployment rate and vacancy rate). Therefore, the results show that GDP and Vacancy rate as cyclical factors has significant impact on unemployment rate in the U.S. economy.

Figure (1.2) shows that the unemployment rate increases significantly as a response to the shocks to the structural variables. This result confirms that the structural factors play a role in the slow decline in unemployment rate.

The results confirm that the movement in the U.S. unemployment can be explained by both cyclical and structural factors.

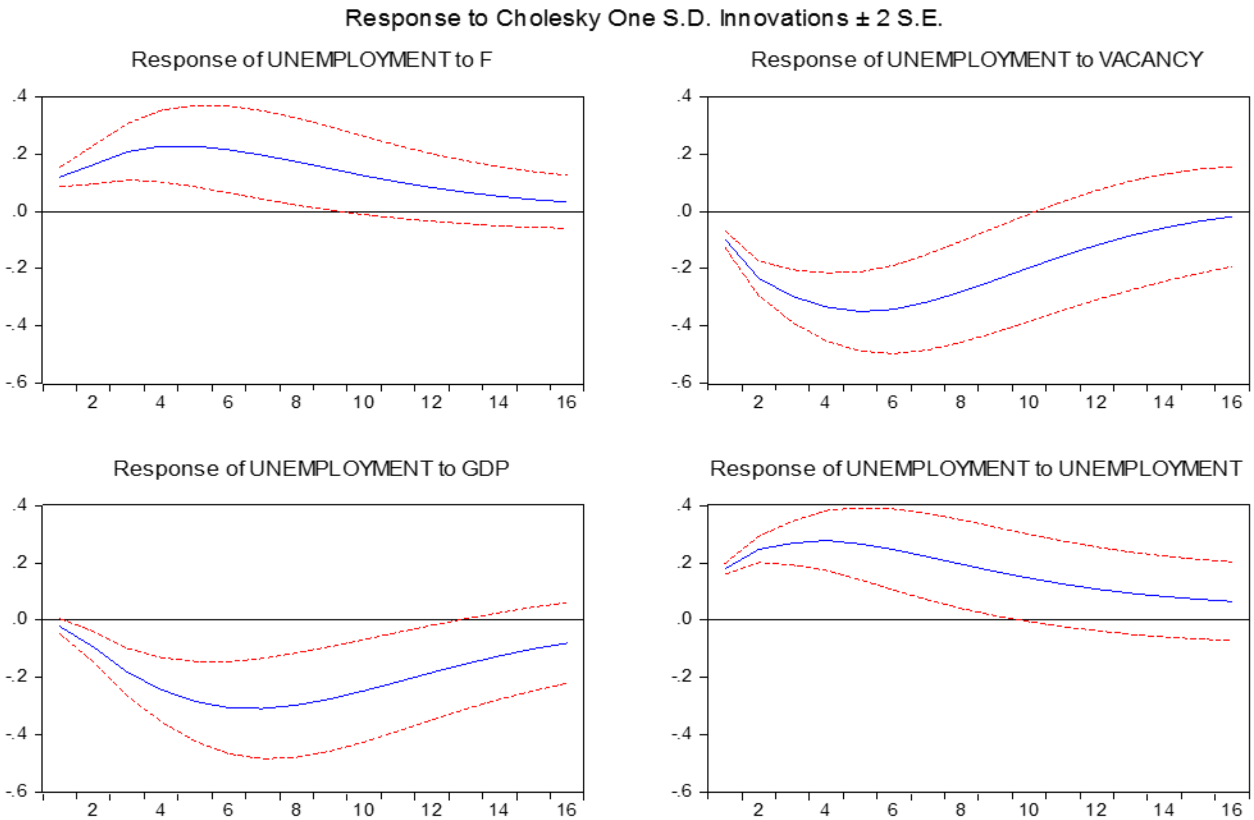

Figure 1. 2 The Impulse Responses from FAVAR

These results are in line with the past literature which agreed that unemployment can be explained by both cyclical and structural factors. The important issue here is to identify the relative contribution of cyclical and structural variables in the U.S. unemployment.

Table (1.2) provides the forecast error variance decomposition for Unemployment rate. Table (1.2) indicates that the shocks to structural variables but not to cyclical variables has a big impact on unemployment in the short run.

Table (1.2) shows that in the long run, the contribution of cyclical factors (GDP growth and vacancy) in the forecast error variance of unemployment is about 60%. The contribution of structural factors in the forecast error variance of unemployment is about 16%. These results, in general, indicate that cyclical factors contribute more than structural factors in the forecast error variance of unemployment which is in line with the literature.

Table 1. 2 Forecast Error Variance Decomposition of Unemployment

Period	S. E	F	Vacancy	GDP	Unemployment
1	0.00012	25.65	16.54	0.81	56.99
6	0.00022	16.93	36.20	19.79	27.08
12	0.00024	15.04	34.11	28.19	22.66
18	0.00024	14.78	32.99	29.32	22.90
24	0.00024	14.73	32.73	29.27	23.27
∞	0.00024	14.72	32.33	29.22	23.74

However, the results in Table (1.2) indicate that the contribution of cyclical and structural factors in the movement of the U.S. unemployment were overestimated in the past literature. For example, Chen et al (2001) found that in the U.S economy about 75% of the forecast error variance of unemployment is due to cyclical factors and 25% is due to Structural factors. Farooq et al (2015) Found that only real GDP as a cyclical factor can explain 63% of the movement in U.S. unemployment and the rest is due to other factors.

The above analysis provides evidence that the FAVAR method used in this paper can help reducing the potential biased results in such studies. However, the results of this paper showed that there still a big part (about 20%) of unemployment is not explained. One possible explanation is that the unexplained part of unemployment is due to the increase in the frictional unemployment, Daly et al (2011).

1.4 Conclusion

Many studies indicated that the rate of unemployment in the U.S. is still high in the U.S. or declines slowly after the last recessions. Since stimulative polices were not fully successful in decreasing unemployment rate, researcher think that structural factors could play a role in the slow movement of the U.S. unemployment. Therefore, researchers have been trying to measure the relative contribution of cyclical and structural factors in the U.S. unemployment. In this paper, I used FAVAR approach to investigate the relative contribution of cyclical and structural factors in the U.S. unemployment.

The results showed that the cyclical factors (GDP and Vacancy) reduced the U.S. unemployment which is consistent with the idea of Okun's low and Beveridge curve. The results showed that structural factors increase the rate of unemployment which affect the unemployment decline.

The results showed that the cyclical factors (GDP growth and vacancy) can explain about 60% of the forecast error variance of unemployment while the structural factors can explain about 16%. However, about 20% of unemployment was not explained. One possible explanation is that it is due to the increase in the frictional unemployment.

These results, in general, indicated that cyclical factors have more contribution than structural factors in the movement of the U.S. unemployment. However, the results indicated that the contribution of cyclical and structural factors in U.S. unemployment were overestimated in the past literature.

CHAPTER II

EDUCATION-OCCUPATION MISMATCH IN THE U.S. LABOR MARKET

2.1 Introduction

Education-Occupation relationship is an important aspect of the economic development. That is because the labor market outcomes are strongly related to workers' education and experiences. In other words, achieving the best labor market outcomes requires utilizing efficiently almost all workers' investments in education (Gavrel & Rebière, 2016). Therefore, theoretically, it is expected that an efficient labor market can fully utilize workers' investments in education and training. However, in reality, sometimes for specific reasons that could not be the case. (Quinan & Rubb,2005)

Most of the labor markets in developed and developing countries suffer in some degree from what is called Education-Occupation mismatch. The Education-Occupation mismatch has two forms, one is called "Overqualification" and the other is called "Underqualification".

Overqualification means that individuals hold education levels that are higher than their occupations' requirements of education. Underqualification means that individuals hold education levels that are lower than their occupations' requirements of education.

Education-Occupation mismatch is one of the problems that negatively affect the labor market outcomes. For example, workers are expected to utilize their investments in education when they take jobs, but sometimes they don't. In addition, employers are expected to hire workers who hold education levels that fit their vacancies' requirements of education, but sometimes they don’t. As a result, the workers’ performance on the jobs will not be good enough to achieve the best outcomes. (Sloane, 2003).

Many studies in the literature investigated the existence of Education-Occupation mismatch in different labor markets. Some studies in the literature investigate the factors that cause the Education-Occupation mismatch. In this paper, I examine the existence of Education-Occupation mismatch in the US labor market. In addition, I investigate the impact of business cycle on the Education-Occupation relationship in the US labor market.

What motivate me to do this study is that the Education-Occupation relationship can be affected by the business cycles. More specifically, it is speculated that the recessions impact negatively the Education-Occupation relationship. In other words, recession period can increase the Education-Occupation mismatch. On the other hand, it is expected that when the economy is doing well the Education-Occupation mismatch reduces (Brynin & Longhi, 2009).

The paper tests the existence and the magnitude of Education-Occupation mismatch in the US labor market over the years 2006 to 2012 (year by year). This period covers the time of the Great Recession which is from 2007 to 2009. The Great Recession represents the bad time in the US economy, and it is expected to intensify the Education-Occupation mismatch problem. In contrast, the period from 2010 to 2012 can represent relatively better time in the US economy and it is expected to decrease the Education-Occupation mismatch problem.

The importance of this paper is to explore and understand the channels that can transfer the effect of business cycles to the Education-Occupation relationship. In addition, this paper tests whether business cycles affect the Education-Occupation relationship in the US labor market.

The channels that transfer the effect of business cycles to the Education-Occupation relationship are the factors that make individuals determine to take jobs that don’t fit their level of education. Therefore, when the business cycles impact these factors, the individuals' decisions to take specific jobs could be affected. As a result, the business cycles could have an impact on the Education-Occupation relationship.

For example, the recession could lead to limited job opening, and it could also lead to long-run unemployment. That can create high job competition which makes it hard to get a job. As a result, individuals may be forced to take jobs that don't fit their level of education. Therefore, prolonged recession could increase the Education – Occupation mismatch.

This paper hypothesizes that business cycles in the US economy can significantly affect the Education – Occupation relationship. The paper tests this hypothesis by estimating the changes in the probabilities that individuals work for jobs that don't fit their levels of education (Education-Occupation mismatch). Then, the paper tests whether or not the estimated changes in the probabilities of Education-Occupation mismatch are different over different time points in the business cycle.

The rest of this paper is organized as follows: One section discusses the literature review. Another section discusses the empirical work including data, variables, the model, and the results. The last section is the conclusion.

2.2 Literature Review

The first part of this section reviews the factors that could make individuals determine to take jobs that don't fit their levels of education. These factors are the channels that transfer the effects of business cycles to the Education-Occupation relationship. The second part of this section reviews studies that investigated the existence of the Education - Occupation mismatch.

There are many theories or explanations that provide reasons why individuals take jobs that don't fit their levels of education. One of these theories is called Job-search failure. The basic idea of this theory is that initial Education–Occupation mismatch can be due to job-search failure and can be corrected over time. That is, new graduates or new participants in the labor market do not have enough experiences to apply for the appropriate jobs. However, when they know more about the job market, they will make right decisions and apply for appropriate jobs. (Buchel, 2001; and Nicaise,2000).

In addition to the lack of experiences, asymmetric information about the jobs requirements could be another source of "Job-search failure". Individuals don't have enough information about the jobs requirements. Therefore, their levels of education are more likely to be mismatched with their occupations. (Quinn & Rubb, 2005)

In the good time, when more workers are needed, employers post their vacancies through job matching agencies. These agencies can better help new graduates applying for jobs that fit their levels of education and thus reducing the Education-Occupation mismatch.

The career mobility theory is another theory stating that individuals could take jobs where their education is not fully utilized at the first time. The idea is that individuals think that they may first take jobs that don't quite fit their levels of education, but after they get more training and experiences, they can then move to better positions. (Sicherman, 1991)

In the recession time (bad time), workers would try first to at least keep their current jobs. Therefore, workers are more likely to stay and don't move from job to job. The lack of labor mobility can increase the Education-Occupation mismatch.

Another theory is related to individuals 's social benefits. Some individuals invest in more education because of their interest in social benefits. For example, some individuals want to be known as smart or intelligent. In addition, some Individuals may look for specific life style. At the end those kinds of individuals are usually not as concerned about matching their education with their occupations. (Collins, 1979; Heath & Cheung, 1998).

In the recession time, investing in education could be very costly. Therefore, it is more likely that in recession time workers don't invest in education which can affect the Education-Occupation relationship.

The next theory is the Job competition theory. This theory has two sides of view: First, because of high competition or limited job openings, individuals with higher levels of education may settle with jobs for which they are overeducated. Second, employers can hire candidates who hold education levels that are higher than the job requirements, allowing them to save training costs. That is because employer know that the more education individuals have, the less need and cost of training those highly educated workers. (Muysken & Weel, 1999). Thus, in the recession time, as job competition heightens, Overqualification increases.

Individuals preferences and constraints are other theories that explain the Education – Occupation mismatch. The basic idea of these theories is that some individuals prefer to work in specific jobs. For example, some individuals prefer to work in specific location. Some individuals may prefer not to work out of their community and be uprooted.

In addition, there may be some constraints that make individuals take jobs that don't fit their levels of education. For example, individuals may not be able to travel to another location or they may not be allowed to work in a specific area. (Nordina & Rootha, 2010). It is possible that cyclical fluctuation in the economy affect the individuals decisions related to their jobs, and that can affect the Education-Occupation relationship.

On-the-job training is another theory that explains a source of Education-Occupation mismatch. In this theory, workers first take jobs that don't fit their levels of education in order to receive on-the-job training. After they get the training, they are (theoretically) supposed to search and get better jobs (Hersch, 1991; Sicherman, 1991).

In the recession time, even if workers receive on job training, they would not quit their current jobs and search for new jobs because they know it is hard to get a new job. Therefore, workers may keep their current jobs that don't fit their education levels for a while. As a result, the Education-Occupation relationship will be affected.

Finally, the theory of long-run unemployment which is strongly related to prolonged recession in the economy. The idea of this theory is that workers take jobs that don't fit their levels of education because they have been or otherwise expect to remain unemployed for a long time. In other words, they try to find any available job (which is better than remaining unemployed) with the expectation of getting better jobs when those jobs are available (Brynin & Longhi, 2009).

The second part of the literature review section reviews some empirical studies about Education - Occupation mismatch. Reviewing what researchers have done testing the existence of the Education-Occupation mismatch can help setting the model of this paper. In addition, it can help selecting the variables and data to do the test.

Robst (2007) considers the relationship between college majors and occupations. This paper used probit model to test the Education – Occupation mismatch. This paper used years of schooling to test the match between schooling and occupations. The paper used data from the US National Survey of College Graduates. The data provides information about the relation between the work activities and the college majors. This paper tested whether the study fields (like history, economics …. etc.) can affect the Education – Occupation relationship. The results showed that 45% of workers report that their job is only partially related or not related to their fields of study.

Quinna and Rubb (2006) tested the Education – Occupation mismatch in Mexico. They also used probit model to test the Education – Occupation mismatch. The paper constructed a new method of measuring the education requirements of occupations. The results showed that the Education – Occupation mismatch exists in Mexico.

Dolton & Silles (2008) tested the existence of Education – Occupation mismatch. They used data from a survey that has information about the graduates from one of the UK universities. The results showed that Education – Occupation mismatch exists, and it affects the earnings.

2.3 The Empirical Analysis

The goal of this section is to examine the effect of business cycles on the Education – Occupation relationship in the US labor market. First, the paper tests the existence of Education-Occupation mismatch in the US labor market for the years 2006 to 2012. This period has bad time (recession) in the US economy which is from 2007 to 2009. The period also has relatively good time in the US economy which is from 2010 to 2012.

I estimate the changes in the probabilities that individuals who hold specific level of education work for jobs that don't fit that level of education (the changes in the probability of Education-Occupation mismatch). If the changes in the probabilities of Education-Occupation mismatch were significant, the Education-Occupation mismatch exists in the US labor market.

Second, the paper tests the behavior of the estimated changes in the probabilities of Education-Occupation mismatch over different points of time during the business cycle. It is expected that the probabilities of Education-Occupation mismatch change over different points of time during the business cycle. If that is the case, we can say that the business cycle has an impact on the Education – Occupation relationship in the US labor market.

2.3.1 The Data

The data used in this paper is taken from ACS (American Community Survey) for the years 2006 – 2012. The data is cross sectional data and has different samples for each year (i.e, sample from 2006, sample from 2007 …, and sample from 2012). The data has the necessary information that can be used in this paper. The data has information about individuals' levels of education and individuals' types of occupations. Therefore, I can use this information to identify whether or not individuals work for jobs that don't fit their levels of education (Education-Occupation mismatch).

The data has information about employment status which can help identify the individuals who have jobs. The data has information about sex, age, and race, which can be used as control variables. These demographic variables are important since they can affect the individuals' decisions to take specific jobs.

The limitation of the data is that it doesn't have information about the education levels required for the jobs. Therefore, I use two sources to get the missing information. The first source is the Occupational Outlook Handbook from the Bureau of Labor Statistics website. The second source is the OnNET OnLine website. I use these two sources to get information about the required education for each job title listed in the samples.

2.3.2 Sample Statistics

Table (2.1) shows the samples statistics for each year (2006 – 2012). The samples include individuals who are US citizens and non-US citizens. Table (2.1) shows the number of unemployed individuals that are dropped from each sample. I dropped the unemployed individuals because they don't have jobs. Therefore, they are not included in the Education – Occupation relationship.

Table 2. 1 Sample Statistics

Items	2006	2007	2008	2009	2010	2011	2012
No. Unemployed	150,977	154,470	155,611	163,202	171,701	193,598	193,084
Self-employed	138,416	137,524	130,317	127,954	124,388	121,129	118,958
Final No. of Observations	1,173,445	1,175,049	1,176,446	1,172,70	1,169,844	1,154,391	1,147,895

Table (2.1) shows the number of self-employed individuals. Self-employed individuals run their own jobs and decide their Education-Occupation themselves. However. It is still possible for the Education – Occupation mismatch to exist for this group. Therefore, I treat them as separate group when testing the effect of business cycles on Education – Occupation relationship. Table (2.1) shows the final number of observations for each year after cleaning the data from the missing observations.

The occupations statistics for each year are shown in Table (2.2). Table (2.2) shows the number of jobs titles that require specific levels of education and the number of individuals who are working in these jobs. The statistics shown in Table (2.2) were identified by using two sources of information. First, I use the ACS 2010 basic codes that identify and sort each job title for each year's sample. Second, I use the Occupational Outlook HandbooK from the Bureau of Labor Statistics website and the OnNET Online Website that describe the required education level for each job title.

For example, for the 2006 sample, there are 216 job titles that require high school level of education, and there are 475,507 individuals working in these jobs. However, some of those individuals may not have high school diploma. They may have different levels of education and take these jobs causing the Education-occupation mismatch.

Table 2. 2 Occupations Statistics

Items	2006	2007	2008	2009	2010	2011	2012
Jobs require high school	216	216	216	216	216	216	216
Individuals work in these jobs	475,705	470,836	467,953	465,509	465,508	463,112	456,936
Jobs require Associate degree	80	80	80	80	80	80	80
Individuals work in these jobs	196,650	194,415	191,720	192,276	188,866	185,889	183,396
Jobs require BA	106	106	106	106	106	106	106
Individuals work in these jobs	349,178	356,595	360,800	357,442	356,084	342,971	345,270
Jobs require MA	19	19	19	19	19	19	19
Individuals work in these jobs	42,285	43,479	43,799	43,278	42,046	40,545	41,257
Jobs require PhD	16	16	16	16	16	16	16
Individuals work in these jobs	35,237	36,144	37,033	36,927	36,983	36,102	36,172

Table (2.3) shows the education levels statistics for each year's sample. It shows the number of individuals who hold High School, Associate Degree, Bachelor's Degree, Master's Degree, and PhD Degree. For example, in the 2006 sample, the number of individuals who hold high school level is 264,657.

Table 2. 3 Education Statistics

Items	2006	2007	2008	2009	2010	2011	2012
Individuals who hold HS	264,657	263,367	599,140	594,819	589,512	587,215	575,270
Individuals who hold Associate degree	108,452	110,059	111,380	111,453	126,095	112,899	114,412
Individuals who hold BA	238,357	243,685	245,665	246,443	276,393	236,818	242,503
Individuals who hold MA	99,229	103,233	102,619	104,545	112,168	102,227	105,146
Individuals who hold PhD	39,558	39,863	41,062	41,185	39,304	40,154	40,170

Table (2.4) shows the demographic statistics for each year's sample. Table (2.4) shows the number of males and females, the number of individuals who are White, Black, American Indian, Asian, and other races.

Table 2. 4 Demographic Statistics

Items	2006	2007	2008	2009	2010	2011	2012
Male	591,987	592,194	592,269	590,715	589,858	584,523	581,345
Female	581,468	582,855	584,177	581,989	579,986	569,868	566,550
White	1,001,908	1,003,238	1,006,509	1,000,763	994,11 1	971,131	966,219
Black	110,057	109,736	112,624 1	112,793	116,020	120,783	118,048
American Indian	9,850	10,134	10,018	10,029	10,514	12,593	12,873
Asian	2,323	2,211	2,460	2,588	2,817	2,763	2,949
Other Races	2,602	2,561	1,959	2,433	2,471	2,426	2,302

Table (2.5) shows the Education-Occupation statistics for each year's sample. It shows the number of individuals whose education levels match their occupations' requirements of education. In addition, it shows the number of individuals whose education levels do not match their occupations' requirements of education.

Table 2. 5 Education - Occupations Matches Statistics

Items	2006	2007	2008	2009	2010	2011	2012
Matched individuals who hold HS	123,064	122,294	306,550	305,497	304,447	304,031	297,859
Matched individuals who hold Associate degree	25,945	26,269	26,568	26,657	26,742	26,923	26,939
Matched individuals who hold BA	129,746	132,434	146,221	133,775	148,895	126,721	129,186
Matched individuals who hold MA	13,910	13,918	14,254	14,508	14,302	13,717	14,024
Matched individuals who hold PhD	24,413	24,868	24,933	25,559	21,790	24,621	24,803
Total number of matched individuals	317,534	320,517	505,575	506,923	604,213	497,106	493,790
Total number of mismatched individuals	855,921	854,532	670,871	665,781	687,000	657,285	654,105

2.3.3 The Model and Variables

Following Robst (2007), I use a probit model to examine the effect of business cycles on the Education – Occupation relationship in the US labor market. More specifically, I estimate the changes in the probabilities of Education-Occupation mismatch over different points of time in the business cycle.

That is, I run the model for each year (2006 to 2012 year by year). Then I examine the differences in the estimated changes in the probability of Education-Occupation mismatch for each year and for each level of education. For example, I examine the differences between the estimated changes in the probability of Education-Occupation mismatch for master's degree holders and for the years 2007, 2008, …2012. That can help indicating the impact of business cycles on the Education – Occupation relationship in the US labor market.

The estimation model:

$$P_r(Y_i = 1/X_i) = \varphi[C + X_i\beta + D_i\alpha] \tag{2.1}$$

Where Y_i is the dependent variable which represents the Education-Occupation match or mismatch for the individual (i) given X_i. Y_i takes the values of (0,1). The value one represents that the individual (i) works in occupation that does not fit his/her level of education. The value zero represents that the individual i works in occupation that fits his/her level of education. φ is the cumulative normal distribution function, where 0 < φ (Z) < 1. The $[C + X_i\beta + D_i\alpha]$ in this model represents the Z -Value or Z index.

X_i is the set of control variables. The control variables used here are age, age^2, sex (male), and race for individual (i). These control variables are important since they can affect an individual's decision to take a specific occupation.

D_i represents a set of dummy variables that identify each level of education. The dummy variables represent the individuals who hold Associate degree, Bachelor's degree, master's degree, and PhD degree. Individuals who hold high school degree will be treated as the reference group since almost all occupations require at least high school level. In addition, I use one dummy variable in the model to represent the self-employed individuals

The data has information about the education levels and the occupations of self-employed individuals. Therefore, I can examine the Education-Occupation mismatch of this group.

2.3.4 The Baseline Results and Discussion

In this section, I discuss the estimated results to determine whether the business cycle in the US economy has an impact on the Education-Occupation relationship. First, I discuss the existence of Education-Occupation mismatch in the US labor market. More specifically, I discuss the magnitudes and significance of the changes in the probability of Education-Occupation mismatch for each level of education. Second, I discuss the changes in the probability of Education-Occupation mismatch over different points of time in the business cycles.

The estimated results for all years' samples are shown in Table (2.6). Table (2.6) shows the estimated changes in the probability of Education-Occupation mismatch including both "overqualification" and "underqualification" cases.

Table (2.6) shows that holding an Associate degree significantly decreases the probability of Education-Occupation mismatch by 6% in the 2006 and 2007 samples. However, holding an Associate degree significantly increases the probability of Education-Occupation mismatch to around 33% in the 2008 to 2012 samples.

Table 2. 6 Changes in the Probability of Education-Occupation Mismatch (Overqualification and Underqualification)[1]

The Variables	2006	2007	2008	2009	2010	2011	2012
Associate degree	-0.065***	-0.064***	0.232***	0.233***	0.238***	0.236***	0.242***
BA	-0.327***	-0.327***	-0.083***	-0.083***	-0.078***	-0.073***	-0.069***
MA	0.052***	0.057***	0.384***	0.381***	0.397***	0.392***	0.395***
PhD	-0.391***	-0.397***	-0.151***	-0.162***	-0.152***	-0.152***	-0.155***
Age	0.015***	0.011***	-0.022***	-0.023***	-0.030***	-0.026***	-0.022***
Age2	-0.005	-0.002	0.033***	0.034***	0.039***	0.034***	0.023***
Male	-0.007***	-0.005***	-0.044***	-0.047***	-0.046***	-0.047***	-0.045***
Black	0.011***	0.012***	0.010***	0.005***	0.005***	0.013***	-0.012***
American Indian	0.023***	0.022***	0.040***	0.034***	0.045***	0.039***	0.042***
Asian	-0.052***	-0.047***	-0.024**	-0.045***	-0.041**	-0.029***	-0.028***
Other races	-0.053***	-0.035***	-0.008	-0.031***	-0.020**	-0.015	-0.017*
Self-employed	0.010***	0.013***	0.029***	0.032***	0.033***	0.036***	0.037***

Crosby (2002) shows that to get an Associate degree, it is required to complete about 60 college credits. In addition, Associate degrees are more occupationally focused degrees. Therefore, Associate degrees holders can be considered as skilled workers and they are more likely to get jobs that fit their level of education which reduces the Education-Occupation mismatch.

However, in the recession when the jobs competition is high, employers may prefer bachelor's degree holders more than Associate degrees holders. That is, Associate degrees holders may not be able to get jobs that fit their level of education which increases the Education-Occupation mismatch. The interaction between labor supply and labor demand is not the only source of Education-Occupation mismatch. There are many other personal reasons that could be affected by the business cycle and thus affect the Education-Occupation relationship for Associate degree holders.

[1] *** significant at 1%, ** significant at 5%, * significant at 10%

Table (2.6) shows that holding a bachelor's degree significantly decreases the probability of Education-Occupation mismatch in all years' samples. However, the changes in the probabilities of Education-Occupation mismatch in the 2008 to 2012 are lower than those in the 2006 and 2007 samples.

That is, the change in the probability of Education-Occupation mismatch decreases by 32% in the 2006 and 2007, and it decreases to around 8% in the 2008 to 2012.

Fischer (2013) shows that bachelor's degree holders are preferred by employers more than high school diploma and Associate degree holders. That is because employers think that bachelor's degree holders can generally make better employees than those who have only high school diploma or Associate degree. As a result, holding a bachelor's degree significantly decreases the probability of Education-Occupation mismatch.

However, in the recession when the jobs competition is high, Bachelor's degrees holders may take jobs that don't fit their level of education which increases the Education-Occupation mismatch. Beside the interaction between labor supply and labor demand, the personal reasons could be affected by the business cycle and thus affect the Education-Occupation relationship of bachelor's degree holders.

Table (2.6) shows that holding a master's degree significantly increases the probability of Education-Occupation mismatch in all years' samples. However, the changes in the probabilities of Education-Occupation mismatch in the 2008 to 2012 are higher than those in the 2006 and 2007 samples. That is, the change in the probability of Education-Occupation mismatch increases by 5% in the 2006 and 2007, and it increases by around 38% in the 2008 to 2012.

According to Occupational Outlook Handbook of the Bureau of Labor Statistics, there are two reasons that may explain these results. One reason is that there are high number of master's degree holders and limited number of jobs that required master's degree level.

The other reason is that some employers post jobs that require bachelor's degree, but they prefer candidates who hold master's degree, which encourage master's degree holders to take these jobs, (Pappano, 2011).

Therefore, master's degree holders are more likely to take jobs that don't fit their education levels. In addition, in recession, less jobs that required master's degree may be opened, and that can affect the Education-Occupation relationship of master's degree holders.

Table (2.6) shows that holding a PhD degree significantly decreases the probability of Education-Occupation mismatch in all years' samples. However, the changes in the probabilities of Education-Occupation mismatch in the 2008 to 2012 are lower than these in the 2006 and 2007 samples.

That is, the change in the probability of Education-Occupation mismatch decreases by 39% in the 2006 and 2007, and it decreases by around 16% in the 2008 -2012. From one side, the PhD degree is the highest professional degree, and there are limited number of individuals who can attain it. From other side, occupations that require a PhD level of education can't normally be filled by individuals who hold other education levels.

Therefore, Education-Occupation mismatch is not as likely to happen for PhD holders unless there are personal reasons that could cause the mismatch. it is possible for recession to affect the Education-Occupation relationship of PhD degree holders by affecting the number of jobs opening and the personal decisions to take a job.

The results in Table (2.6) indicate that the Education-Occupation mismatch exists in the US labor market for all levels of education. The Education-Occupation mismatch can exist for many reasons that are related to labor supply and labor demand interaction or related to personal decisions.

Figure (2.1) shows that the US economy had a recession period from 2007-2009 when the unemployment rate was high.

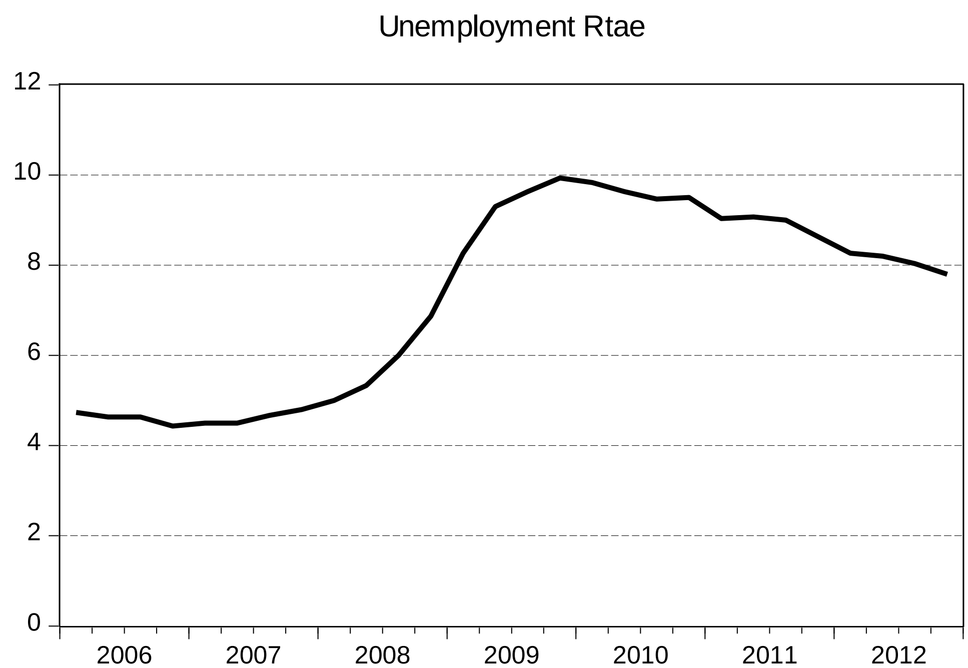

Figure 2. 1 The Unemployment Rate of the US Economy from 2006 to 2012[2]

Figure (2.2) shows the changes in the probability of Education-Occupation mismatch for each level of education over the years 2006-2012. Figure (2.2) shows that the probability of Education-Occupation mismatches increases after 2007 for all levels of education. That reflects the impact of the recession (the Great Recession) on the factors that lead to the Education-

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[2] This graph was taken from FRED (Federal Reserve Bank of St. Louis) website.

Occupation mismatch taken as a whole. Figure (2.2) indicates that business cycles can impact the Education-Occupation relationship in the US labor market.

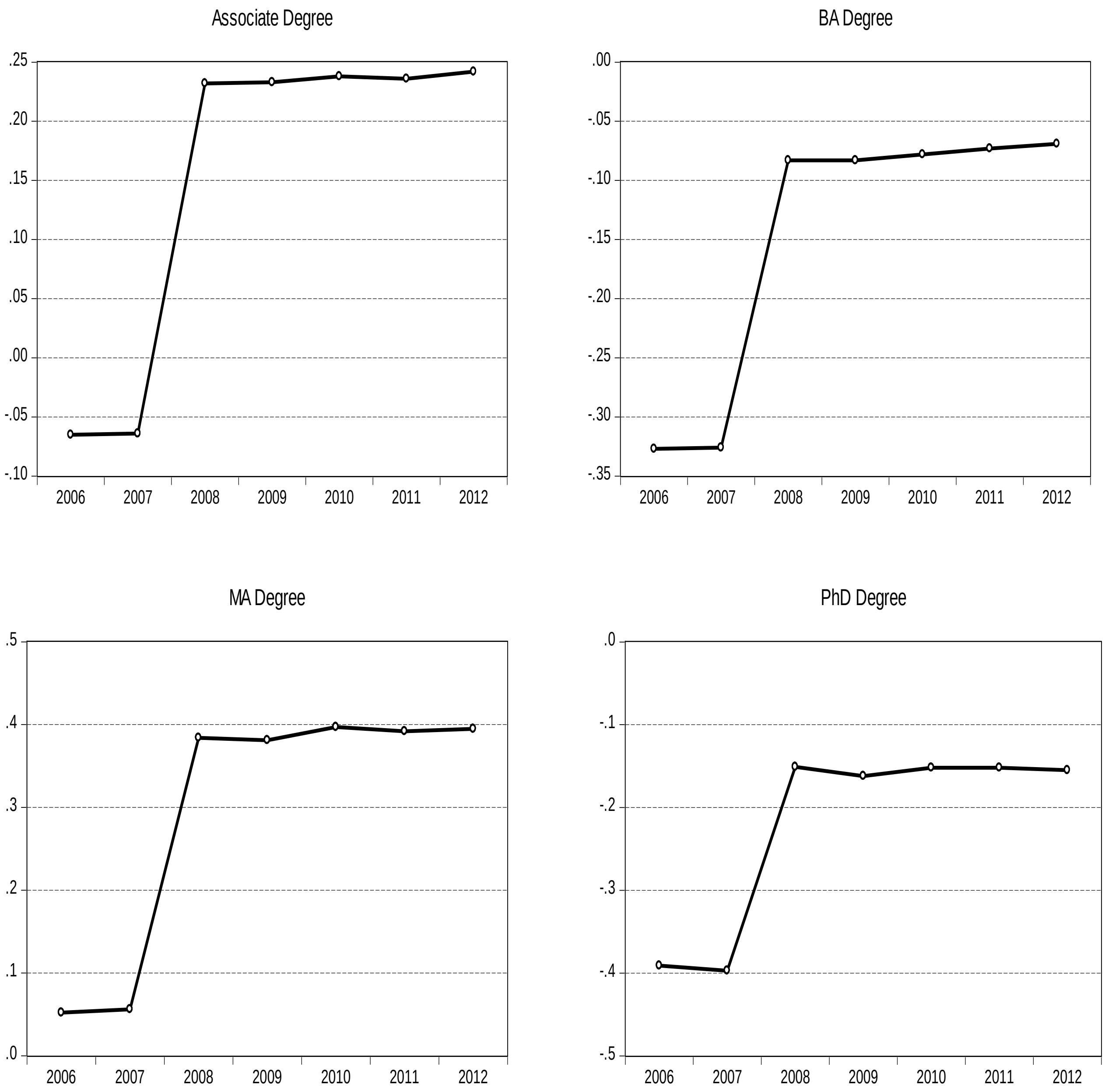


Figure 2. 2 Changes in the Probability of Education-Occupation Mismatch Over Time (Overqualification and Underqualification)

The demographic characteristic in Table (2.6) show that being a male significantly decreases the probability of Education-Occupation mismatch for all years' samples. This might suggest a possibility of sex discrimination in the US labor market. In addition, the results show that when an individual gets older, the probability of Education-Occupation mismatch significantly increases in most of the years' samples. This might suggest a possibility of age discrimination in the US labor market.

Table (2.6) shows that being Black or American Indian, the probability of Education-Occupation mismatch significantly increases for all years' samples. However, being Asian or from other races, the probability of Education-Occupation mismatch significantly decreases for all years' samples. That indicate a possibility of race discrimination in the US labor market towards Black and American Indian individuals.

Table (2.6) shows that if an individual is self-employed, the probability of Education-Occupation mismatch significantly increases for all years' samples. In other words, self-employed individuals are more likely to take jobs that don't fit their level of education. That is because they own and manage their business and choose their occupations themselves (it's one side decision).

However, the changes in the probabilities of Education-Occupation mismatch in the 2008 to 2012 are higher than these in the 2006 and 2007 samples. That is, the business cycles can also affect Education-Occupation relationship of self-employed individuals.

2.4 Overqualification And Underqualification

The baseline results in Table (2.6) show the effect of business cycles on the Education – Occupation relationship in the US labor market. The baseline results were estimated by pooling both cases of Education-Occupation mismatch (overqualification and underqualification). In other words, overqualification and underqualification cases were set to be as one case "Education – Occupation mismatch".

However, it is important to investigating the effect of business cycles on overqualification and underqualification cases separately. This analysis can provide more details about the effect of business cycles on Education – Occupation relationship. The results of this analysis can be used better by policy makers to reduces the Education – Occupation mismatch problem and achieve the best labor market outcomes.

2.4.1 Overqualification Case

In this part, I focus only on the overqualified individuals as mismatched individuals. Using same probit model and same variable, I estimate the changes in the probability of Overqualification mismatch for each years' sample.

The results of overqualification case are shown in Table (2.7). Table (2.7) shows that holding an Associate degree significantly decreases the probability of Overqualification mismatch by 22% in the 2006 and 2007 samples. However, holding an Associate degree significantly increases the probability of Overqualification mismatch by about 23% in the 2008 to 2012 samples.

Table (2.7) shows that holding a bachelor's degree significantly decreases the probability of Overqualification mismatch in the 2006 and 2007 samples. However, holding a bachelor's degree significantly increases the probability of Overqualification mismatch by around 22% in the 2008 to 2012 samples.

Table (2.7) shows that holding a master's degree significantly increases the probability of Overqualification mismatch in all years' samples. However, the change in the probability of Overqualification mismatch become higher in the 2008 to 2012 samples relative to the 2006 and 2007 samples.

Table 2. 7 Changes in the Probability of Education-Occupation Mismatch (Overqualification)[3]

The Variables	2006	2007	2008	2009	2010	2011	2012
Associate Degree	-0.229***	-0.232***	0.227***	0.233***	0.237***	0.232***	0.239***
BA	-0.247***	-0.244***	0.218***	0.217***	0.220***	0.216***	0.223***
MA	0.202***	0.207***	0.623***	0.617***	0.629***	0.619***	0.627***
PhD	-0.257***	-0.261***	0.218***	0.207***	0.212***	0.206***	0.205***
Age	-0.012***	-0.012***	-0.109***	-0.099***	-0.104***	-0.087***	-0.092***
Age^2	0.022***	0.020***	0.115***	0.101***	0.104***	0.083***	0.088***
Male	0.055***	0.056***	0.049***	0.045***	0.049***	0.050***	0.047***
Black	0.051***	0.051***	0.082***	0.077***	0.076***	0.085***	0.081***
American Indian	0.058***	0.055***	0.106***	0.092***	0.101***	0.096***	0.107***
Asian	-0.094***	-0.075***	-0.035***	-0.056***	-0.049***	-0.039***	-0.038***
Other Races	-0.091***	-0.062***	-0.020*	-0.037***	-0.029***	-0.012	-0.023**
Self-Employed	0.033***	0.035***	0.058***	0.060***	0.062***	0.063***	0.068***

Table (2.7) shows that holding a PhD degree significantly decreases the probability of Overqualification mismatch in the 2006 and 2007 samples. However, holding a PhD degree significantly increases the probability of Overqualification mismatch in the 2008 to 2012 samples. The reason that lead to the results in Table (2.7) is that recession can increase the overqualification case for all levels of education which is in line with the baseline results.

Figure (3) shows the changes in the probability of Overqualification mismatch for each level of education over the years 2006-2012. Figure (2.3) shows that the changes in the probability of Overqualification mismatch increases after 2007 for all levels of education. Figure (2.3) indicates that the business cycles can impact the Overqualification case in the US labor market. More specifically, recession increases the probability of Overqualification mismatch in the US

[3] *** significant at 1%, ** significant at 5%, * significant at 10%

labor market. That is because of high job competition and high unemployment rates which lead individuals to settle on jobs that keep them overqualified.

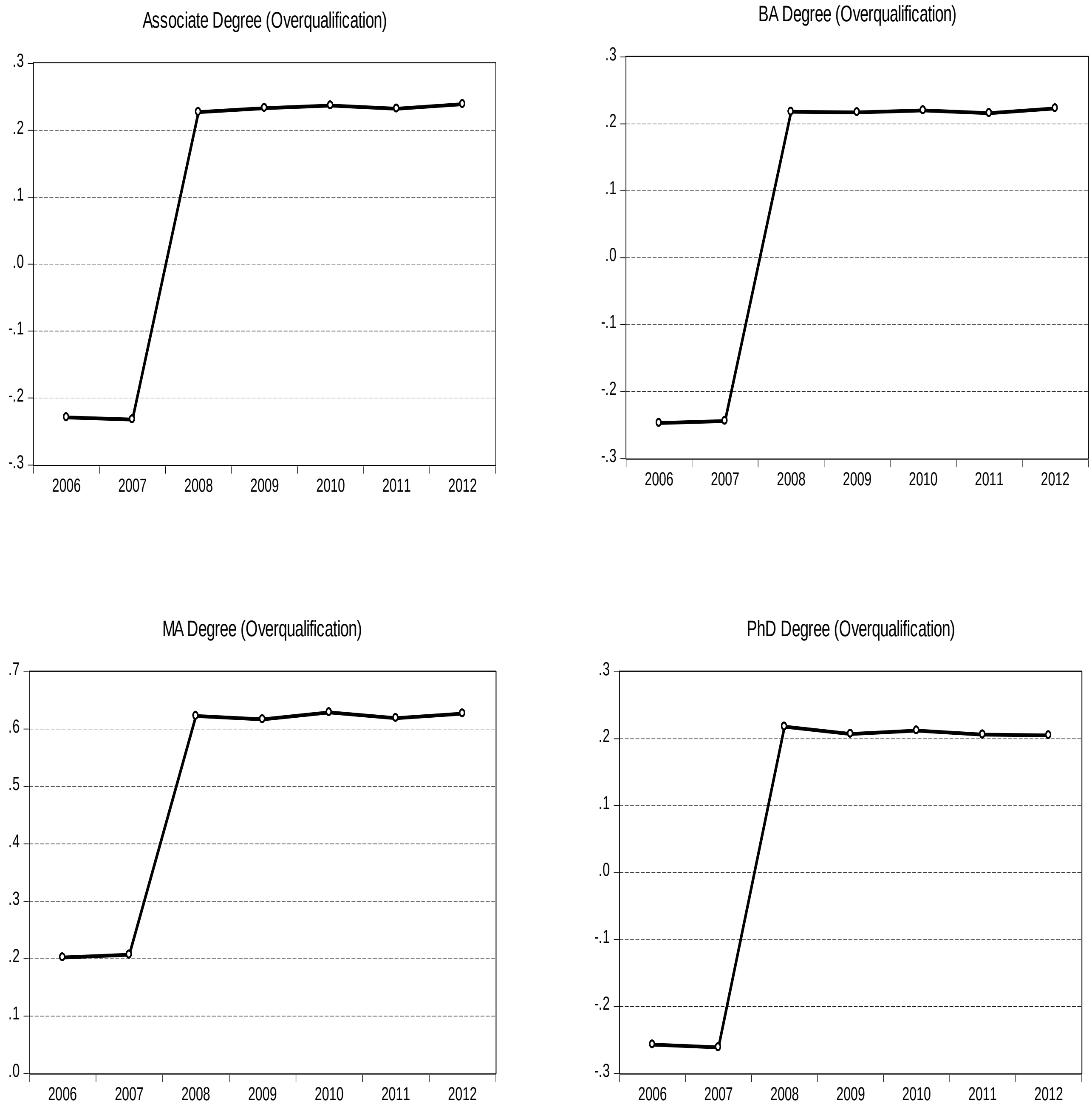


Figure 2. 3 Changes in the Probability of Education-Occupation Mismatch Over Time (Overqualification)

2.4.2 Underqualification Case

In this part, I focus on the underqualified case of Education-Occupation. Using same probit model and same variable, I estimate the changes in the probability of Underqualification mismatch.

The results of Underqualification case are shown in Table (2.8). Table (2.8) shows that holding an Associate degree significantly increases the probability of Underqualification mismatch for all years' samples. However, the change in the probability of Underqualification mismatch become lower in the 2008 to 2012 samples relative to the 2006 and 2007 samples.

Table 2. 8 Changes in the Probability of Education-Occupation Mismatch (Underqualification)[4]

The Variables	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Associate Degree	0.129***	0.132***	0.013***	0.009***	0.010***	0.012***	0.012***
BA	-0.125***	-0.124***	-0.322***	-0.322***	-0.318***	-0.312***	-0.308***
MA	-0.150***	-0.149***	-0.371***	-0.359***	-0.351***	-0.341***	-0.341***
Age	0.021***	0.017***	0.081***	0.072***	0.069***	0.060***	0.068***
Age^2	-0.022***	-0.018***	-0.078***	-0.067***	-0.064***	-0.052***	-0.060***
Male	-0.058***	-0.057***	-0.089***	-0.090***	-0.089***	-0.090***	-0.084***
Black	-0.033***	-0.032***	-0.053***	-0.054***	-0.052***	-0.053***	-0.050***
American Indian	-0.029***	-0.026***	-0.042***	-0.035***	-0.033***	-0.034***	-0.040**
Asian	0.013*	-0.002	-0.044***	-0.041***	-0.041***	-0.042***	-0.048***
Other Races	0.027**	0.018**	-0.004	-0.014	-0.013	-0.025***	-0.013
Self-Employed	-0.029***	-0.028***	-0.039***	-0.038***	-0.039***	-0.036***	-0.039***

Table (2.8) shows that holding a bachelor's degree significantly decreases the probability of Underqualification mismatch for all years' samples. However, the change in the probability of

[4] *** significant at 1%, ** significant at 5%, * significant at 10%

Underqualification mismatch become lower in the 2008 to 2012 samples relative to the 2006 and 2007 samples.

Table (2.8) shows that holding a master's degree significantly decreases the changes in the probability of Underqualification mismatch in all years' samples. However, the change in the probability of Underqualification mismatch become lower in the 2008 to 2012 samples relative to the 2006 and 2007 samples.

Figure (2.4) shows the changes in the probability of Underqualification mismatch for each level of education over the years 2006-2012. Figure (2.4) shows that the changes in the probability of Underqualification mismatch decreases after 2007 for all levels of education. Figure (2.4) indicates that the business cycles can impact the Underqualification case in the US labor market. More specifically, the recession decreases the probability of Underqualification mismatch in the US labor market.

These results are expected since jobs opening is very limited and unemployment rate is high in the recession. Therefore, employer would not be forced to hire individuals who hold low level of education to fill vacancies that require high level of education.

Figure (2.5) shows the comparison between the baseline results and the Overqualification case's results. Figure (2.6) shows the comparison between baseline results and the underqualification case's results. Figure (2.5) and Figure (2.6) indicate that business cycles especially recessions can impact the factors the determine the labor supply in a way that increases the Overqualification mismatch. In addition, it can impact the factors the determine the labor demand in a way that decreases the Underqualification mismatch. Figure (2.5) and Figure (2.6) indicate that the Overqualification mismatch is the case that derives the baseline results.

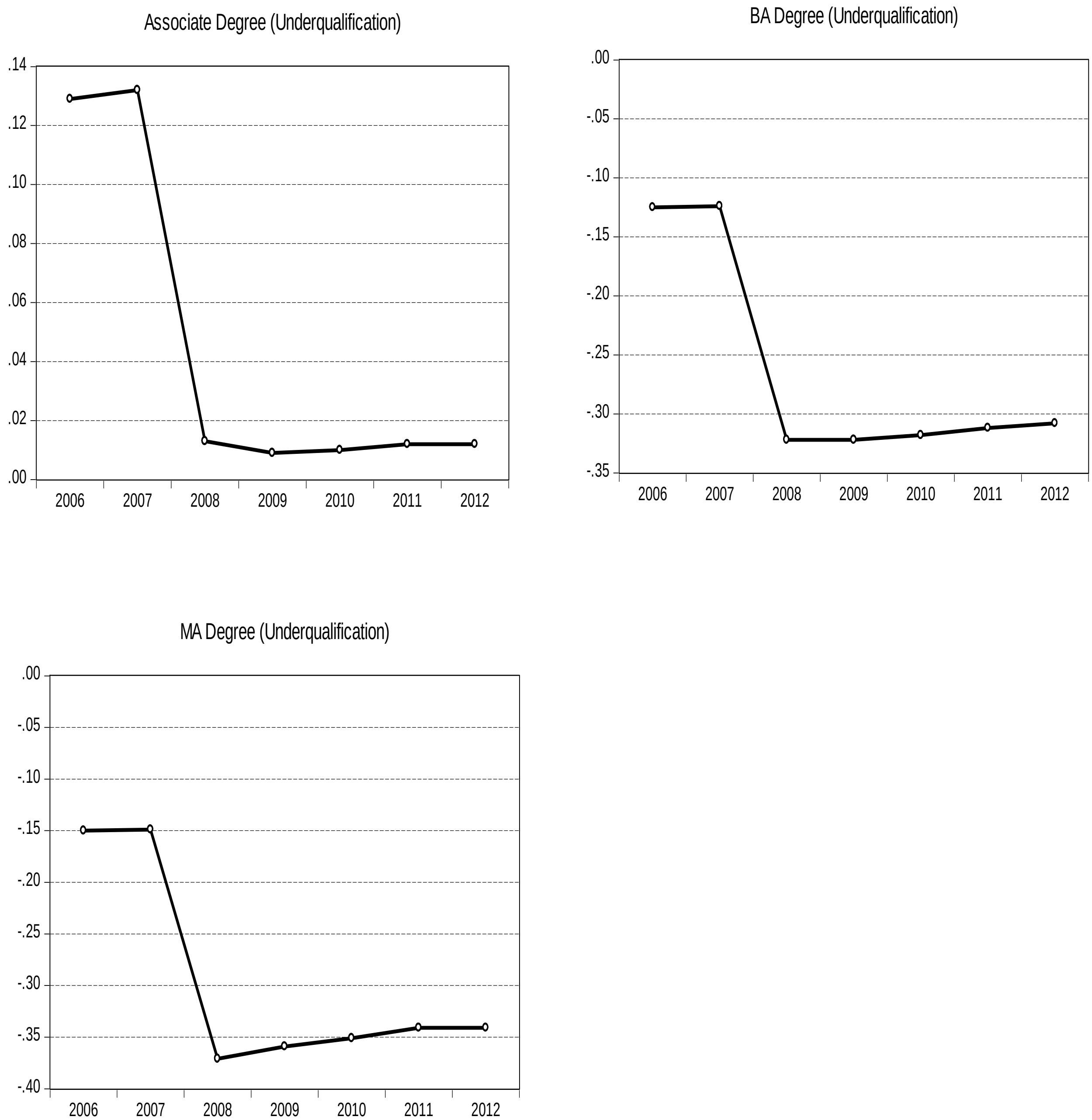


Figure 2. 4 Changes in the Probability of Education-Occupation Mismatch Over Time (Underqualification)

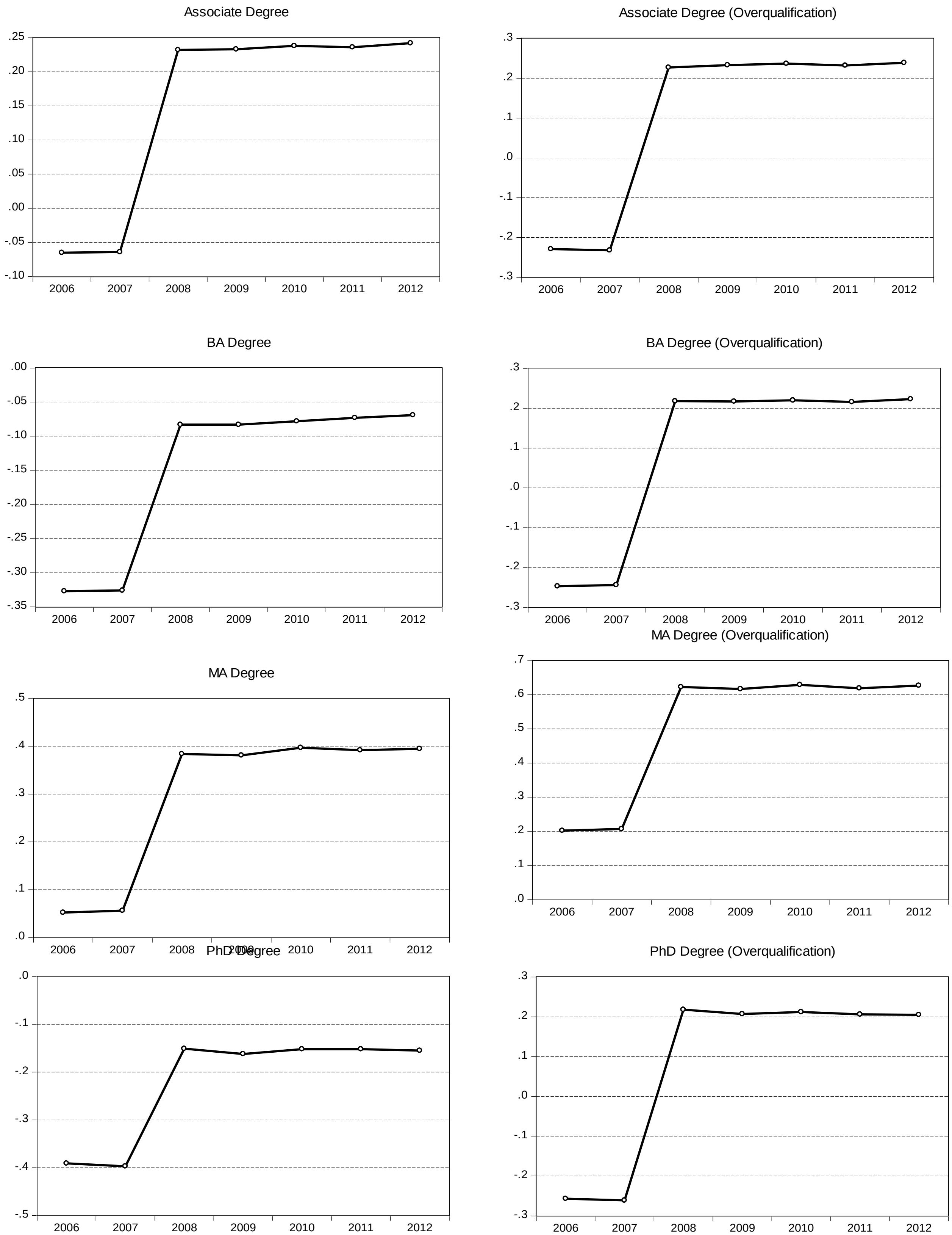


Figure 2. 5 Changes in the Probability of Education-Occupation Mismatch Over Time (Comparison with Overqualification Case)

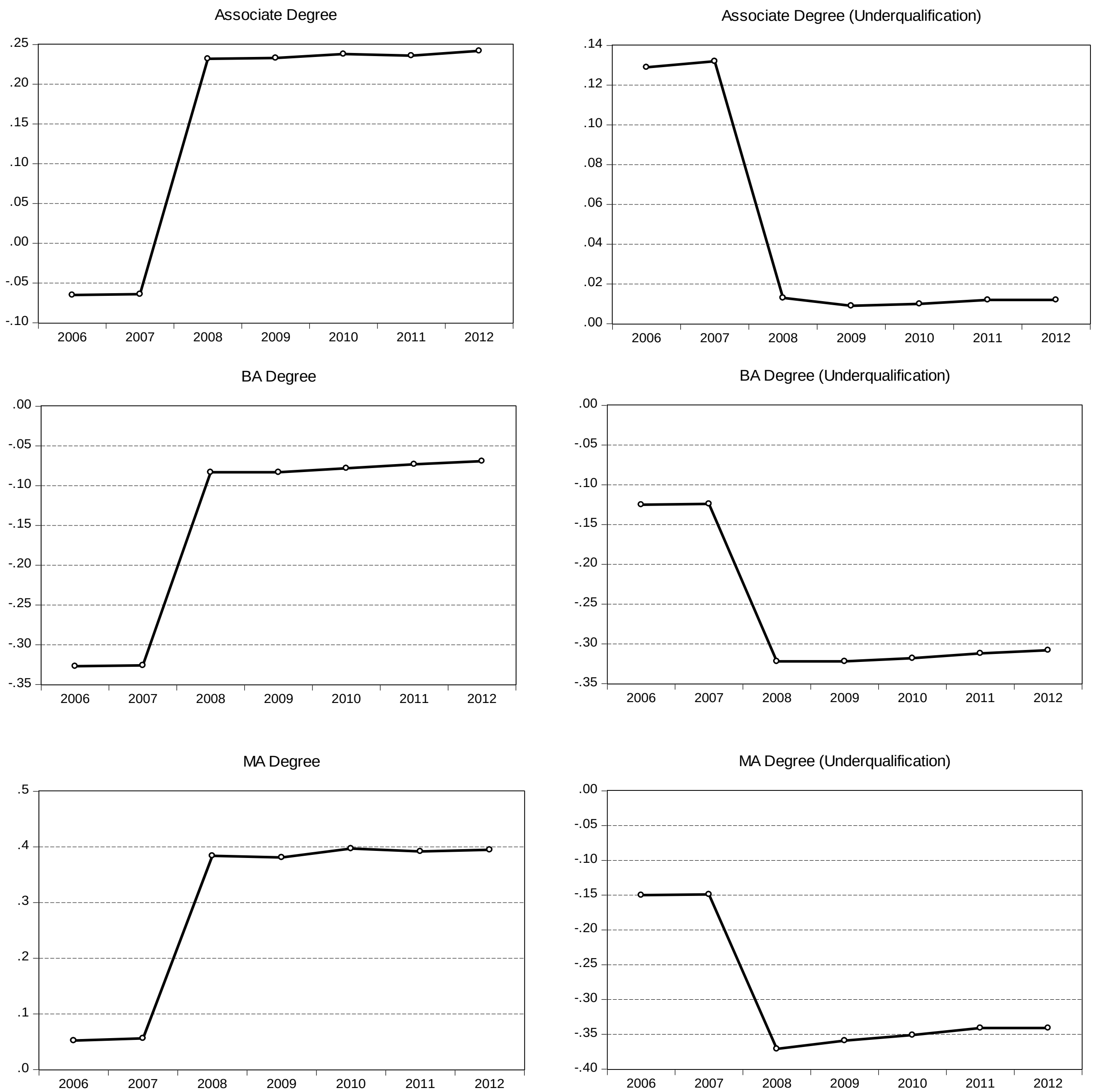


Figure 2. 6 Changes in the Probability of Education-Occupation Mismatch Over Time
(Comparison with Underqualification Case)

2.5 Robustness Check

Since we have three types of Education-occupation relationships (match, overqualified, and underqualified), we can run a multinomial logit model as robustness check. In this model the dependent variable (Y) has three categories of outcomes (Match, Overqualification, and Underqualification). Y takes a value of (0) representing the match case which is the reference or base case. Y takes the value (1) representing overqualification case, and Y takes the value (2) representing underqualification case.

The Model:

$$Logit\ (P_i) = Log\ \left[\frac{P_i}{1-P_i}\right] = \beta_0 + \beta_1 X_i \tag{2.2}$$

Where, $P_r(Y_i = 1\ or\ 2\ /X_i) = P_i$ is the distribution function.

The results of using multinomial logit model are shown in Table (2.9) and Table (2.10). These results are the marginal effects (the changes in the probability of Education -Occupation mismatch relative to the match case). Table (2.9) shows the marginal effects of overqualification case relative to the match case. Table (2.10) shows the marginal effects of Underqualification case relative to match case.

Table (2.9) shows that overqualification increases after 2007 for all levels of education. Therefore, the results in Table (2.9) confirm that recession can impact the factors the determine the labor supply in a way that increases the Overqualification mismatch.

Table (2.10) shows that Underqualification decreases after 2007 for all levels of education. Therefore, the results in Table (2.10) confirm that recession can impact the factors the determine the labor demand in a way that decreases the Underqualification mismatch.

Table 2. 9 Change in the Probability of Being Overqualified Relative to the Probability of Being Matched[5]

The Variables	2006	2007	2008	2009	2010	2011	2012
Associate Degree	-0.188	-0.188	0.298	0.305	0.31	0.302	0.312
BA	-0.259	-0.258	0.218	0.215	0.218	0.215	0.22
MA	0.161	0.167	0.652**	0.645	0.660*	0.649*	0.657*
PhD	0.818	0.807	1.126	1.105	1.094	1.103	1.096
Age	-0.005	-0.006	-0.114	-0.103	-0.109	-0.092	-0.096
Age^2	0.016	0.016	0.122***	0.108**	0.113***	0.091***	0.094
Male	0.036	0.037	0.04	0.037	0.038	0.039	0.037
Black	0.04	0.039	0.083	0.077	0.076	0.086	0.082
American Indian	0.049	0.047	0.113*	0.097*	0.109	0.103*	0.114**
Asian	-0.094	-0.074	-0.039***	-0.063	-0.055	-0.044	-0.043
Other Races	-0.087	-0.06	-0.02	-0.038	-0.029	-0.011	-0.024
Self-Employed	0.028	0.03	0.064	0.066	0.069	0.069	0.074

Table 2. 10 Change in the Probability of Being Underqualified Relative to the Probability of Being Matched[6]

The Variables	2006	2007	2008	2009	2010	2011	2012
Associate Degree	0.065	0.066	0.005	0.003	0.003	0.004	0.004
BA	-0.07	-0.07	-0.229	-0.223	-0.222	-0.219	-0.214
MA	-0.095	-0.093	-0.203	-0.191	-0.185	-0.182	-0.181
Age	0.013	0.011	0.054	0.047	0.045	0.039	0.044
Age^2	-0.013	-0.011	-0.052	-0.043	-0.041	-0.033	-0.038
Male	-0.034	-0.033	-0.057	-0.056	-0.056	-0.057	-0.054
Black	-0.021	-0.021	-0.04	-0.04	-0.038	-0.04	-0.038
American Indian	-0.018	-0.017	-0.034	-0.029	-0.027	-0.028	-0.033
Asian	0.029	0.02	0.015	0.015	0.013	0.011	0.01
Other Races	0.024	0.018	0.01	0.006	0.008	-0.001	0.006
Self-Employed	-0.013	-0.012	-0.018	-0.018	-0.018	-0.016	-0.018

[5] *** significant at 1%, ** significant at 5%, * significant at 10%

[6] *** significant at 1%, ** significant at 5%, * significant at 10%

Figure (2.7) and Figure (2.8) indicate that the business cycle can impact the Education-Occupation relationship. Figure (2.7) and Figure (2.8) show the same pattern as baseline results which indicate that the baseline results are robust.

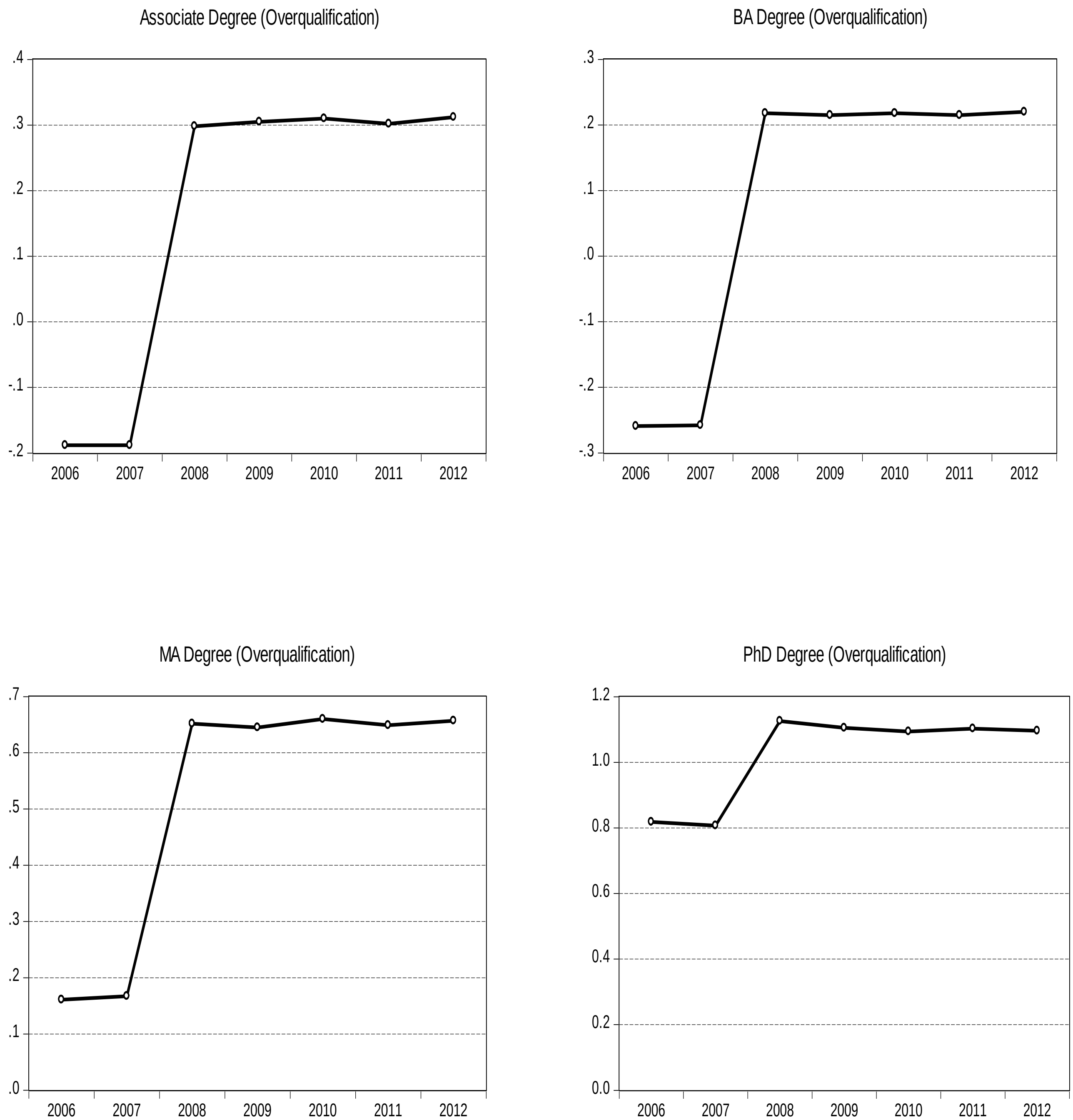


Figure 2. 7 Change in the Probability of Being Overqualified Relative to the Probability of Being Matched

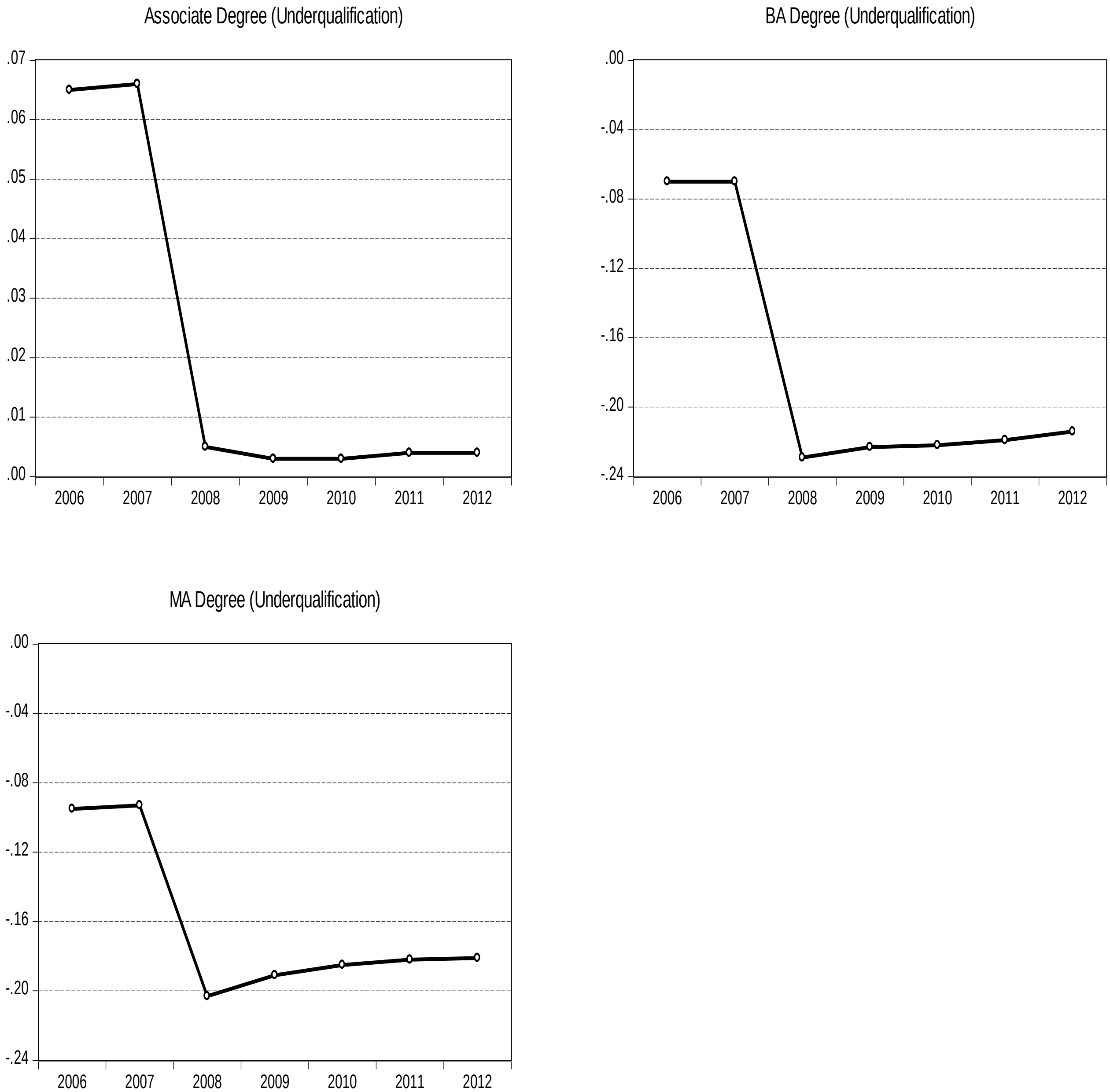


Figure 2. 8 Change in the Probability of Being Underqualified Relative to the Probability of Being Matched

2.6 Conclusion

The labor market outcomes are strongly related to worker's education. Therefore, we should utilize worker's investment in education to achieve the best outcomes. However, sometimes for specific reasons that could not happen, resulting in Education-Occupation mismatch.

Education-Occupation mismatch is one of the problems that negatively affect the labor market outcomes. Analyzing the factors that lead to change the Education-Occupation relationship can help improve the labor market outcomes. Many factors can affect the Education-Occupation relationship. Some of these factors are personal (related to the labor supply) and some are related to the market condition (related to the labor demand) at a specific time.

This paper reviews the factors that lead to Education-Occupation mismatch. This paper also examines the existence of Education-Occupation mismatch in the US labor market. In addition, this paper investigates the effect of business cycle on the Education-Occupation relationship in the US labor market.

This paper uses probit model and samples for the years 2006 to 2012 (year by year) to do the analysis. The results of this paper indicate that Education-Occupation mismatch exists in the US labor market. The results also indicate that the business cycles can affect the Education Occupation relationship in the US labor market. The robustness check indicates that the baseline results are robust.

CHAPTER III

A STUDY OF IMMIGRANTS PARTICIPATION IN THE US LABOR MARKET

3.1 Introduction

Studies show that the labor markets in the United States and most of other developed countries have growing number of immigrants workers, (LaLonde& Topel, 1991). Some analysts consider that immigrants participation is good for these labor markets since skilled immigrants can fill the vacancies and provide important services.

However, others consider that immigrants participation is costly for these labor markets. That is because it increases the competition for jobs between natives and immigrant workers especially for less skilled or low paid jobs (Card, 2001). It also may reduce the motivations for native individuals to get more skills because they know that employer can easily fill their needs by hiring skilled immigrants (Altonji & Card, 1991).

With the contracting views on the effect of immigrants' participation, it is necessary to effectively manage and balance the benefits and costs of immigrants participation in the labor market. The starting point to do that is by having information about two things. First, we need to have information about why immigrants are willing to leave their countries and work in other countries. In other words, we should know the motivations that lead immigrants to move and work outside their countries in general. In addition, we should know the motivations that lead immigrants to decide to work in a specific country like the US.

Second, we need to have information about the differences between immigrant groups' participation in a specific labor market. More specifically, we need to know which groups of immigrants are more likely to participate in a specific labor market than others.

The important questions are "why having this information is important?", and "How can this information help effectively manage and balance the benefits and costs of immigrants participation in the labor market?".

Having information about the motivations that lead immigrants to work in specific labor market is important to formulate economic policies. That is because we may use these motivations to affect individuals' decisions to work in that labor market. These motivations could be related to individuals' "personal motivations" or could be related to a specific labor market, (Mundell, 1968).

To effectively achieve the policy goals, we need to have information about the differences between immigrant groups' participation in a specific labor market (Czaika & De Haas, 2013). In other words, we should identify the policy's targets which is the main goal of this paper.

The targets in our case are the groups of immigrants that are more likely to participate in the US labor market than other groups of immigrants. Identifying the targets is important since it helps policy makers focus more on specific groups than others. That may help adopting effective policies that manage and balance the benefits and costs of immigrants participation in the labor market.

For example, assume immigrants from China have higher probability of participation in the US labor force (PPLF) than immigrants from Iraq. In this case we should place more focus on immigrants from China than immigrants from Iraq. That is because immigrants from China have already had willingness to work in the US labor market, so we may start looking for skilled immigrants from China first. In addition, Immigrants from China may have enough skilled workers who can compensate the needs of skilled works in the US labor market.

Therefore, we may not need to look for skilled workers from other groups of immigrants which saves time and cost. However, if skilled immigrants from China can't compensate the needs of skilled works, we can second look for immigrants from other groups who can compensate the needs of skilled works in the US labor market.

Same idea can be applied on unskilled immigrants assuming that unskilled immigrants may create problems in the labor market. That is, some restrictions may be applied on unskilled immigrants from China first since they have already had higher willingness to work in the US labor market relative to other immigrant groups. That can help reduces the costs of unskilled immigrants participation in the labor market.

The main goal of this paper is to identify the policy targets. That can be the starting point to effectively manage and balance the benefits and cost of immigrants participation in the US labor market. More specifically, this paper identifies the targets or the groups of immigrants that are more likely to participate in the US labor force. That can be done through estimating the changes in the probability of participation in the US labor force (PPLF) (will be discussed in the empirical section).

The rest of this paper has several sections. One section discusses the literature review. Another section discusses the empirical work which includes the sample, data, the model, and the results. The last section will be the conclusion.

3.2 Literature Review

This section provides information about the motivations that can lead individuals to work outside their countries. First, this section reviews some studies that identify the personal motivations that lead immigrants to work outside their countries. Second, it reviews some studies that identify the motivations that lead immigrants to work especially in the US labor market. Having this information is important to formulate economic policies. That is because these motivations can be used to affect individuals' decisions to work in the US labor market.

Brunow et al (2015) and Morshed (2017) show that individuals are always seeking for high real income. Therefore, the differences in the real income per capita especially between developing and developed countries may encourage individuals to search jobs outside their countries. Affecting the expected earned income affect immigrants decisions to work outside their countries. For example, applying additional taxes on income can change the expected earned income and then affect the immigrants decisions to work outside their countries.

Remittances is another factor that lead individuals to work outside their countries. Individuals can send money (remittances) to support their families in their home countries (Hanson, 2007). Applying maximum limits on remittances may affect the immigrants decisions to work outside their countries.

Another factor that makes individuals decide to work outside their countries is the travel restrictions (Agiomirgianakis & Zervoyianni, 2001). Applying some travel restrictions like high entry fees or residency limitations can affect immigrants' decisions to work outside their countries.

King & Ruiz (2003) show that Globalization phenomenon has been encouraging individuals to work outside their countries. For example, establishing multinational companies have been increasing the movement of workers between different countries. It is possible to apply some limitations on the multinational companies that let their workers move and work for their branches outside their countries. It is possible also to encourage the multinational companies to let their skilled workers move and work for their branches outside their countries.

Liu-Farrer (2009) and Rodgers & Rodgers (2000) show that studying aboard is one of the important factors that lead immigrant to worker outside their countries. Most universities in the developed countries have been giving scholarships for students around the world. some of those students stay and work outside their home countries after graduation. Increasing scholarships for international students and giving them the permission to work may attract more skilled worker and benefit the labor market.

Toossi (2002) provides information about the massive demographic changes in some of the developed countries. The paper indicates that these countries suffered from the shortage of young workers. That encourages young immigrants to move and work in these countries. Applying some age restrictions can change the young immigrants' decision to work outside their countries. It is also possible to apply some motivations to attract young immigrants if needed.

Caliendo et al (2017) show that the high unemployment rate motivates individuals to work outside their countries where there are jobs available. That is, individuals from high unemployment rate countries try to find jobs outside their countries especially when the high unemployment rate stays for a long time. We can apply some incentives to attract skilled immigrants whose countries have high unemployment rate. We can also apply some restrictions on unskilled immigrants whose countries have high unemployment rate assuming that they may create problems.

The next few studies identify the advantages of working in the US labor market. They identify the motivations that lead immigrants to work especially in the US labor market.

Brancaccio et al (2017) and Rodgers & Rodgers (2000) show that the structure of each labor market can be another motivation for individuals to work outside their countries. They show that the US labor market is more flexible than other labor markets of most developed countries. The flexibility of the US labor market makes it more attractive for immigrants. That is because it allows the workers to easily move from job to job which gives them more options to get better jobs. The flexibility of the US labor market can help attracting skilled immigrants. However, we can apply some restrictions to limit the flexible movement of immigrant workers and make the US labor market less attractive.

Gustman & Steinmeier (1998) and Borjas (2011) show that immigrant workers in the US labor market have received good benefits under the social security system. That can make the US labor market more attractive for immigrant workers. Social security benefits may be a good motivation to attract skilled immigrants to work in the US labor market especially if their countries don't have similar system.

Farber & Valletta (2015), Lalive (2007), and Atkinson & Micklewright (1991) show that unemployment benefits or compensations can attract immigrant workers. That is because they still have income in the time of recessions or when they are unemployed until they get new job. Affecting the unemployment compensations that go to immigrant workers may affect immigrant's decision to work in the US labor market.

Overall, the motivations listed above are the common motivations that lead immigrant workers to participate in the US labor market. The key point here is that we can affect these motivations to effectively manage and balance the benefits and costs of immigrants' participation in the US labor force.

3.3 The Empirical Analysis

The goal of this section is to identify the policies' targets. As mentioned before, the targets are the groups of immigrants that are more likely to participate in the US labor force than other immigrant groups. This section identifies the policies' targets in two steps.

In the first step, it presents statistics about the groups of immigrants (from different foreign countries) and about their participation in the US labor force. That can identify all groups of immigrants that are participating in the US labor force in the sample. In the second step, it empirically estimates the changes in the probability of participation of all immigrant groups in the US labor force (PPLF). Then, we can identify the targets, which are the immigrant groups that have higher positive values of the changes in PPLF.

This section also discusses the data, sample statistics, the model used in this paper, and the results.

3.3.1 The Data

The data used in this paper is taken from ACS (American Community Survey) and the Bureau of Labor Statistics. The data are cross sectional for the year of 2010, and they were taken from IPUMS website. This sample is a weighted sample that represent 1% of the US census data.

The limitation of the ACS data is that it doesn't have information about labor market conditions. Therefore, data about unemployment rate and wages were taken from the Bureau of Labor Statistics website.

I selected this data because it has information about participation status in the US labor force, education, marital status, family size, age, race, and sex. In addition, the data has information about citizenship status which is important to identify the immigrants (non-citizen) groups. Therefore, the data can provide information about the variables that can affect the decision to participate in the labor force.

3.3.2 Sample Statistics

The descriptive statistics of the sample is shown in Table (3.1). Table (3.1) shows the number of individuals who are included in the sample. The individuals who are below 17 years or over 66 years are excluded from the sample. I exclude individuals under 17 years old because they still minor, and they are more likely not to participate in the US labor force. In addition, I exclude individuals over 66 years old because they are mostly in the retirement age. Table (3.1) shows the final total number of sample observations after cleaning the data from missing observations.

Table 3. 1 Sample Statistics

Item	Number
Number of observation (basic data)	15,057,480
Number of individuals with age under 17 who are dropped from the sample	208,076
Number of individuals with age over 66 who are dropped from the sample	1,965,078
Final number of observations after cleaning the missing data	9,429,107

Table (3.2) provides statistics about labor force participation for US citizens, US naturalized citizens, and non-citizens in the sample. Table (3.2) shows that the sample has 6,005,530 US citizens, 468,723 US naturalized citizen, and 515,216 non-citizens participating in the US labor force. Even naturalized US citizens are originally immigrants, I treat them as US citizen. That is because they have already become US citizens. In addition, the goal of this paper is to help policy maker managing and balancing the participation of new immigrants in the US labor market. Table (3.2) shows that non-citizens in the sample represent about 8% of the total participants in the US labor force.

Table 3. 2 Labor Force Participation Statistics (Based on Citizenship Status)

Citizenship Status	Total	Participants	Non-Participants
US citizens	8,105,519	6,005,530	2,099,989
Naturalized Citizen	602,981	468,723	134,258
Non- US Citizen	720,607	515,216	205,391

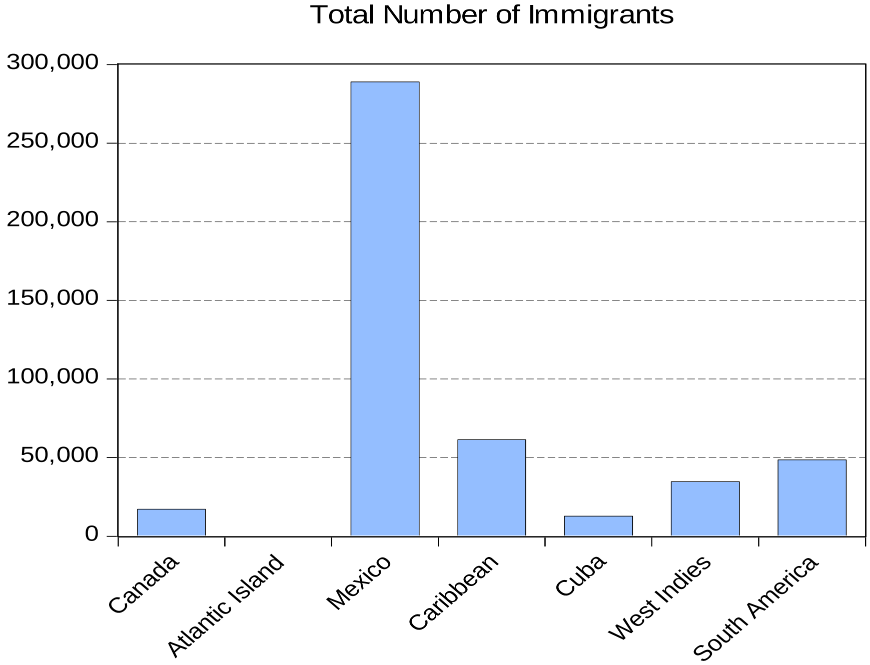
The next few tables provide statistics about the groups of immigrants (based on countries of origin) and their participation in the US Labor Force. I use Figureures also to compare between total number of immigrants and percentage of participation in the US labor force. That can be the first step to identify the targets.

Table (3.3) shows statistics about immigrants from North and South America countries. Table (3.3) shows that the sample has seven groups of immigrants from North and South America.

Table 3. 3 Labor Force Participation Statistics (North and South America Countries)

Country	Total	Participants	Non-Participants
Canada	17,136	12,230	4,906
Atlantic Island	553	397	156
Mexico	288,980	204,529	84,451
Caribbean	61,512	48,143	13,369
Cuba	12,847	9,251	3,596
West Indies	34,689	25,563	9,126
South America	48,646	36,770	11,876

Figure (3.1) shows that Mexico has the highest number of immigrants among North and South America countries. However, immigrants from Mexico have the lowest group's percentage of participation in the US labor force among these countries. The group's percentage of participation is the number of participants from a foreign country or area (Mexico as an example) in the US labor force divided by the total number of immigrants from that country or area.



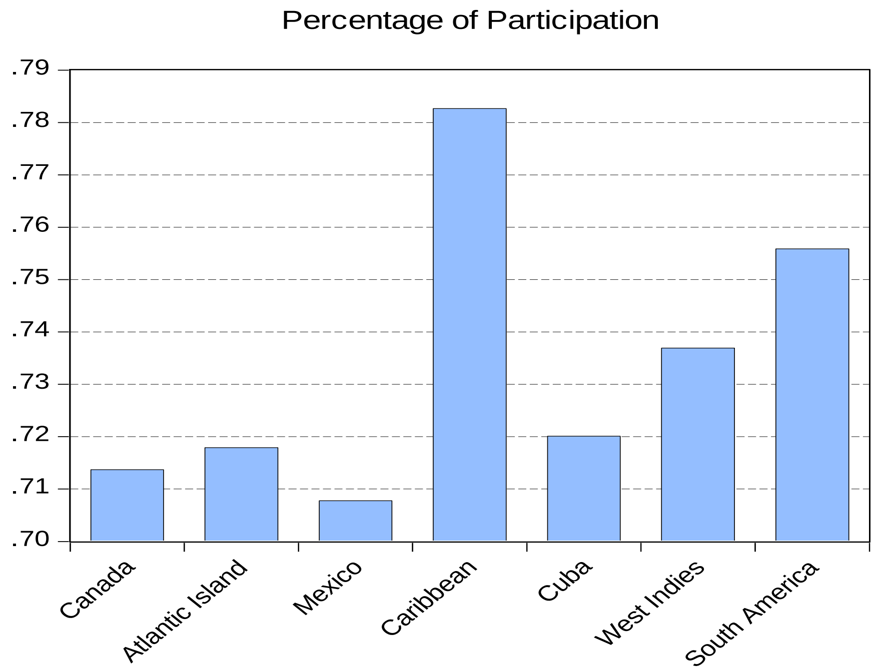


Figure 3. 1 Total Number of Immigrants and Percentage of Participation (North and South America Countries)

Figure (3.1) shows that the Caribbean group has the highest group's percentage of participation in the US labor force even though its total number of immigrants is lower than Mexico.

Figure (3.1) shows that having high number of immigrants does not always mean having high group's percentage of participation in the labor force. Thus, we still need to estimate the changes in the probability of participation in the US labor force to identify the targets. Then, we can combine all this information to carefully identify the groups of immigrants that are more likely to participate in the labor force.

Table (3.4) shows statistics about Immigrants from European countries and their labor force participation in the US labor force. Table (3.4) shows that the sample has twenty-eight groups of immigrants from European countries.

Figure (3.2) shows that Germany has the highest number of immigrants among European countries. Figure (3.2) shows that immigrants from Bulgaria have the highest group's percentage of participation in the US labor force than others. Figure (3.2) indicates again that having high number of immigrants (the case of Germany) does not mean having the highest group's percentage of participation in the labor force.

Table (3.5) shows statistics about Immigrants from Asian countries and their labor force participation in the US labor force. Table (3.5) shows that the sample has twenty-four groups of immigrants from Asia.

Figure (3.3) shows that India has the highest number of immigrants among Asian countries. Figure (3.3) shows that immigrants from Philippines have the highest group's percentage of participation in the US labor force. Again, Figure (3.3) confirms that having high number of immigrants does not always mean having the highest group's percentage of participation in the US labor force.

Table 3. 4 Labor Force Participation Statistics (European Countries)

Country	Total	Participants	Non-Participants
Denmark	698	520	178
Finland	416	299	117
Iceland	118	81	37
Norway	593	387	206
Sweden	1,130	764	366
England	6,738	5,079	1,659
Scotland	1,093	788	305
Ireland	2,090	1,610	480
Belgium	629	442	187
France	3,022	2,246	776
Netherlands	1,647	1,249	425
Switzerland	803	561	242
Albania	820	586	234
Greece	1,323	961	362
Italy	3,296	2,356	940
Portugal	2,457	1,831	626
Spain	1,607	1,133	474
Austria	643	471	172
Bulgaria	1,188	930	258
Czechoslovakia	1,082	786	296
Germany	8,925	6,236	2,689
Hungary	738	509	229
Poland	6,065	4,538	1,527
Romania	1,859	1,402	457
Yugoslavia	3,275	2,543	732
Estonia	147	110	37
Latvia	209	159	50
Lithuania	504	384	120

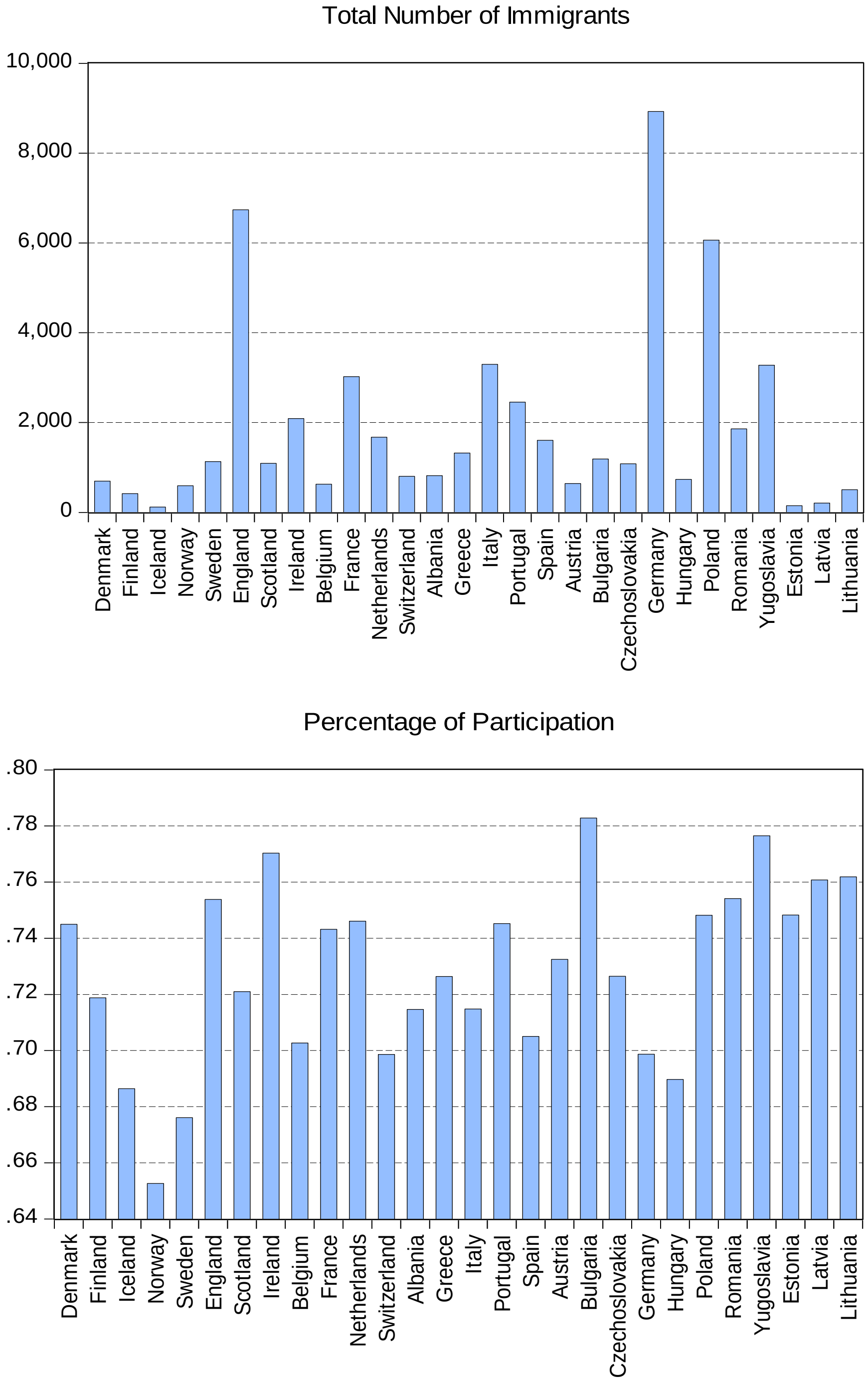
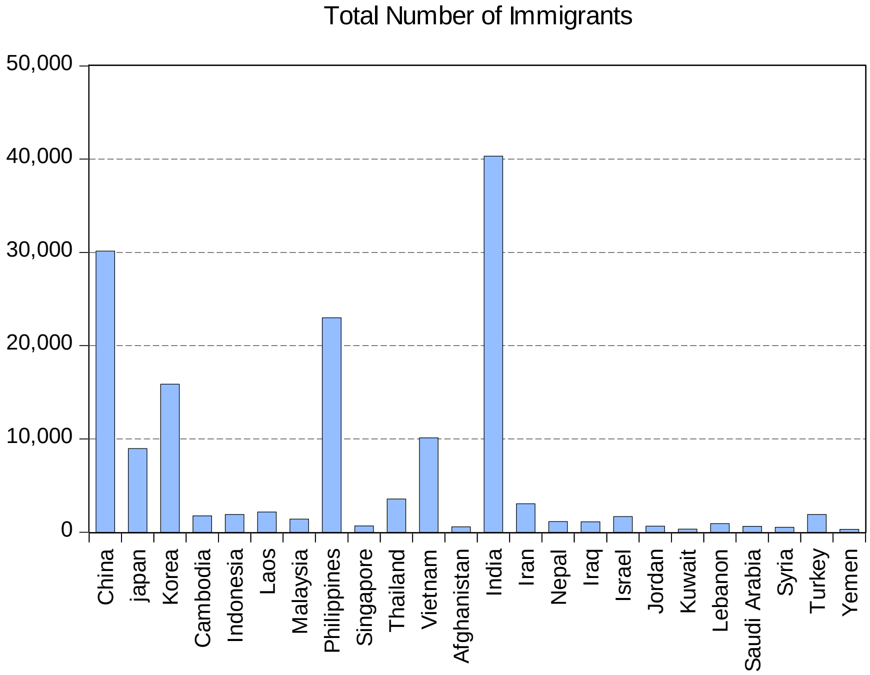


Figure 3. 2 Total Number of Immigrants, and Percentage of Participation (Europe Countries)

Table 3. 5 Labor Force Participation Statistics (Asia Countries)

Country	Total	Participants	Non-Participants
China	30,145	20,465	9,680
japan	8,973	5,410	3,563
Korea	15,860	8,860	7,000
Cambodia	1,755	1,100	655
Indonesia	1,901	1,284	617
Laos	2,157	1,368	789
Malaysia	1,410	1,014	396
Philippines	22,986	17,273	5,714
Singapore	664	432	232
Thailand	3,564	2,235	1,329
Vietnam	10,118	6,552	3,566
Afghanistan	572	330	242
India	40,317	28,490	11,827
Iran	3,055	2,059	996
Nepal	1,135	804	331
Iraq	1,108	659	449
Israel	1,679	1,175	504
Jordan	652	379	273
Kuwait	340	194	146
Lebanon	927	587	340
Saudi Arabia	635	210	425
Syria	520	313	207
Turkey	1,907	1,306	601
Yemen	299	156	143

Table (3.6) shows statistics about Immigrants from Africa, Australia and New Zealand, and Pacific Islands, and about their participation in the US labor force. Figure (3.4) shows that immigrants from Africa have the highest number of immigrants. However, Immigrants from Australia and New Zealand have the highest groups' percentage of participation in the US labor force.



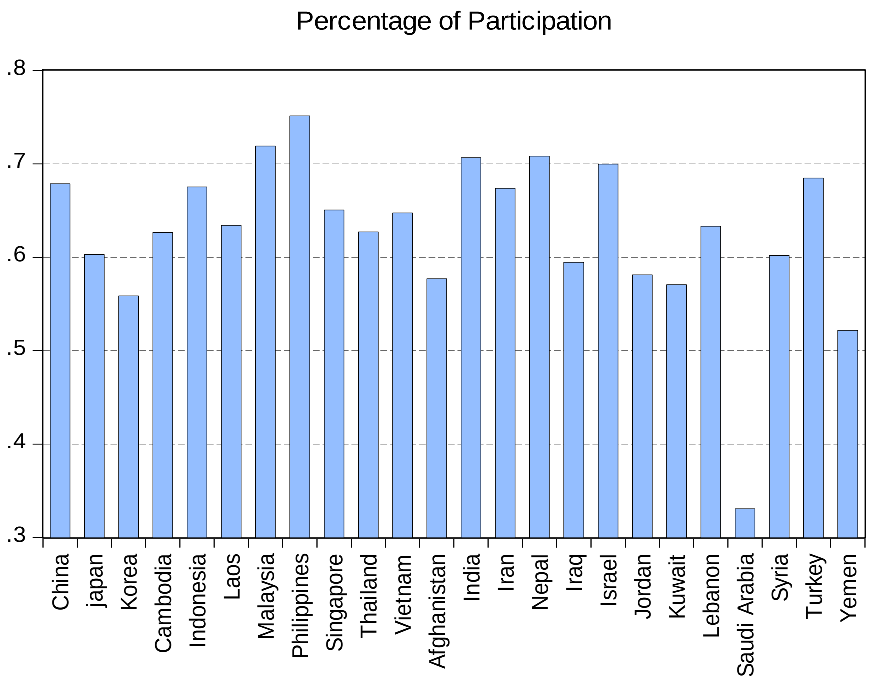


Figure 3. 3 Total Number of Immigrants, and Percentage of participation (Asia Countries)

Table 3. 6 Labor Force Participation Statistics (Other Countries)

Country	**Total**	**Participants**	**Non-Participants**
Africa	24,394	18,528	5,866
Australia and New Zealand	3,003	2,331	672
Pacific Islands	1,354	987	367

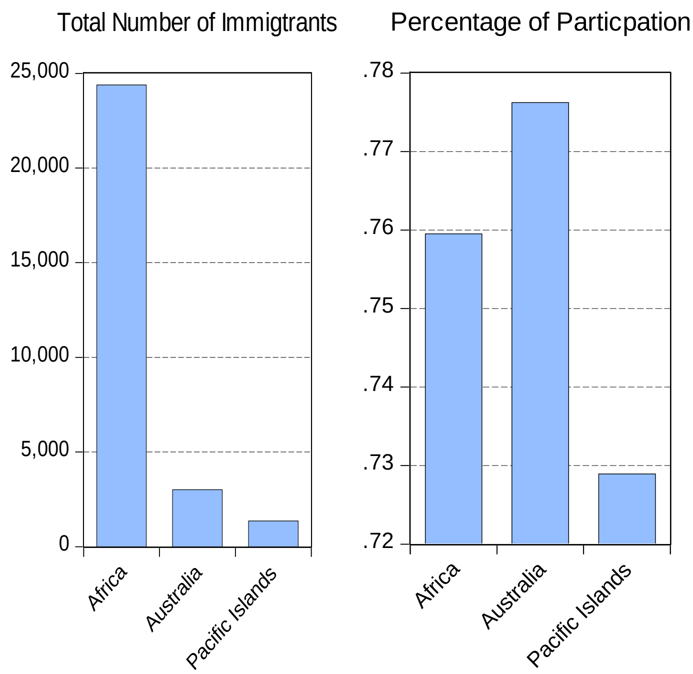


Figure 3. 4 Total Number of Immigrants, and Percentage of Participation (Other Countries)

3.3.3 Identifying the Targets

The goal of this part is to identify the targets. In other words, identify the groups of immigrants that are more likely to participate in the labor market than others. That can be done by estimating the changes in the probability of participation in the US labor force as being from a foreign country relative to US citizens.

The signs (positive or negative) and the magnitude of the change in the probability of participation can help identify the policy's targets. For example, let assume that the changes in probability of participation in the US labor force was 0.02 for immigrants from China and 0.04 for immigrants from Iraq. That means, the PPLF increases by 2% if immigrants were from China and 4% if immigrants were from Iraq relative to US citizens. These numbers indicate that immigrants from Iraq are more likely to participate in the US labor force relative to US citizen than immigrants from China.

The groups that have the highest positive magnitudes of the changes in probability of participation will be the policy's targets, and more focus in policy making should be first on these targets than others. In our example, we should pay more attention on immigrants from Iraq than immigrants from China.

In addition, it is also important to focus second on the groups of immigrants that have high number of immigrants in the US like Mexico, China, and India. Even their probability of participation in the US labor force are not the highest, they may benefit the US labor market. In addition, they may create problems in the US labor market. Placing more focus on these groups can help effectively balance and manage the benefits and cost of immigrants participation in the US labor force.

3.3.4 The Model and Variables

The model:

$$P_r(Y_i = 1/X) = \emptyset[C + X_i\beta + D_i\alpha] \qquad (3.1)$$

Following Hafeez & Ahmad (2002) I use a probit model to estimate the changes in PPLF based on being from a specific foreign country relative to the US citizens. Y_i in this model represents the dependent variable, and it takes the values of (0,1). The value one represents that the person (i) participates in the US labor force. The value zero represents that the person (i) does not participate in the US labor force.

$\emptyset$ in this model is the cumulative normal distribution function, where $0 < \emptyset\ (Z_i) < 1$. The $[C + X_i\beta + D_i\alpha]$ in this model represents the Z-Value or Z index. X_i is the set of control variables. D_i in this model represents a set of dummy variables that identify each foreign country in the sample.

Following Bowen & Finegan (2015) the control variables I use are age, sex (male), marital status (married), family size, race, and education for individual (i). In addition, I use some control variables that represent the market conditions, which are unemployment rate, average wage and farm and non-farm area. These control variables are important since they are the factors that can affect an individual's decision to participate in the US labor force.

3.3.5 The Results and Discussion

The results in Table (3.7) show the changes in the probability of participation in the US labor force (PPLF). The results show that age and age2 have significant negative relationship with PPLF. The increase in age decreases the PPLF by about 0.6%.

The increase in age2 decreases the PPLF by about 0.01%. That is not expected since young workers have low level of education and lack of experience and training. Therefore, young workers are more likely not to participate in the labor force (Hafeez & Ahmad, 2002). However, Hipple (2016) presumably shows that this negative relationship could be due to some cyclical factors, such as longer-term age structural changes.

Table 3. 7 The Marginal Effects (The Changes in the Probability of Participating in the US Labor Force)[7]

Variable	Marginal Effects	Variable	Marginal Effects
Age	-0.006***	Bulgaria	-0.005
Age2	-0.0001***	Czechoslovakia	-0.060***
Male	0.098***	Germany	-0.050***
Married	0.061***	Hungary	-0.082***
Family size	0.003***	Poland	-0.045***
White	0.048***	Romania	-0.048***
Non-farm	-0.023***	Yugoslavia	-0.012
Undergraduate	-0.173***	Estonia	-0.026
Graduate	0.007***	Latvia	-0.026
Unemployment	-0.005***	Lithuania	-0.019
Wage	0.005***	China	-0.065***
Canada	-0.046***	Japan	-0.110***
Atlantic Islands	-0.004	Korea	-0.149***
Mexico	-0.087***	Indonesia	-0.064***
Caribbean	-0.002	Laos	-0.099***
Cuba	-0.025***	Malaysia	-0.026**
West Indies	0.012***	Philippines	0.020***
South America	-0.010***	Singapore	-0.090***
Denmark	-0.031*	Thailand	-0.093***
Finland	-0.040*	Vietnam	-0.061***
Iceland	-0.78*	India	-0.078***
Norway	-0.097***	Iran	-0.091***
Sweden	-0.094***	Nepal	-0.059***
England	-0.006	Iraq	-0.175***
Scotland	-0.037***	Israel	-0.122***
Ireland	-0.022**	Jordan	-0.219***
Belgium	-0.081***	Kuwait	-0.225***
France	-0.047***	Lebanon	-0.166***
Netherlands	-0.024**	Saudi Arabia	-0.402***
Switzerland	-0.075***	Syria	-0.188***
Albania	-0.077***	Turkey	-0.139***
Greece	-0.067***	Yemen	-0.282***
Italy	-0.062***	Africa	0.013***
Portugal	-0.043***	Pacific Islands	-0.021*
Spain	-0.075***	Australia	-0.013
Austria	-0.031*		

[7] *** significant at 1%, ** significant at 5%, * significant at 10%

The results indicate that being a male significantly increases the PPFL by 10%. That is expected since female participation can be negatively affected by childbearing and child-raising activities (Smith-Lovin& Tickamyer, 1978).

The results show that being married significantly increases the PPFL by 0.6%. That is expected because married individuals have more life responsibilities. Having children or expecting to have children can motivate the couples to participate in the labor market (Mincer, 1962).

The results show that family size has significant positive relationship with PPLF. The increase in family size increases the PPLF by about 0.3%. That is expected because a large family size will exert high pressure on the financial resources of the households. That can motivate the parents to participate in the labor market (Hafeez & Ahmad, 2002).

The results show that education significantly increases the PPFL by 0.7%. As educational attainment increases, the PPLF will increase. It is expected because education can improve skills and make the individuals more marketable for job opportunities (Young, 1983).

The results show that unemployment has significant negative relationship with PPLF. Parkinson (2018) shows that the negative relationship between unemployment and the labor force participation is due some to factors. These factors are less demand for labor and fewer availability of jobs.

The results show that wage has significant positive relationship with PPLF. That is expected since wage is a key part of individuals earning. The higher the wage rate the higher the incentive to participate in the labor force. however, some can think that high wages can be costly for employers and lead to reduce job opportunities. Wessels, (2001) shows that the high level of wage not always lead to reduce jobs opportunitie. Wessels, (2001) shows that employer may cut non-wage cost like health benefits and on-the-job training to offset the high wage costs.

The next few paragraphs present results about the changes in PPLF based on being from a specific foreign country. This exercise can help identify the policy targets which is the goal of this paper.

By looking at the countries from North and South America in Table (3.7), we can see that the only positive change in PPFL is when the immigrants are from West Indies. Being from West Indies significantly increases the PPLF by about 1%. Therefore, we may need to pay more attention to immigrants from West Indies than immigrants from other countries of North and South America. Figure (3.5) shows the comparison between the changes in PPLF based on being from North and South America countries.

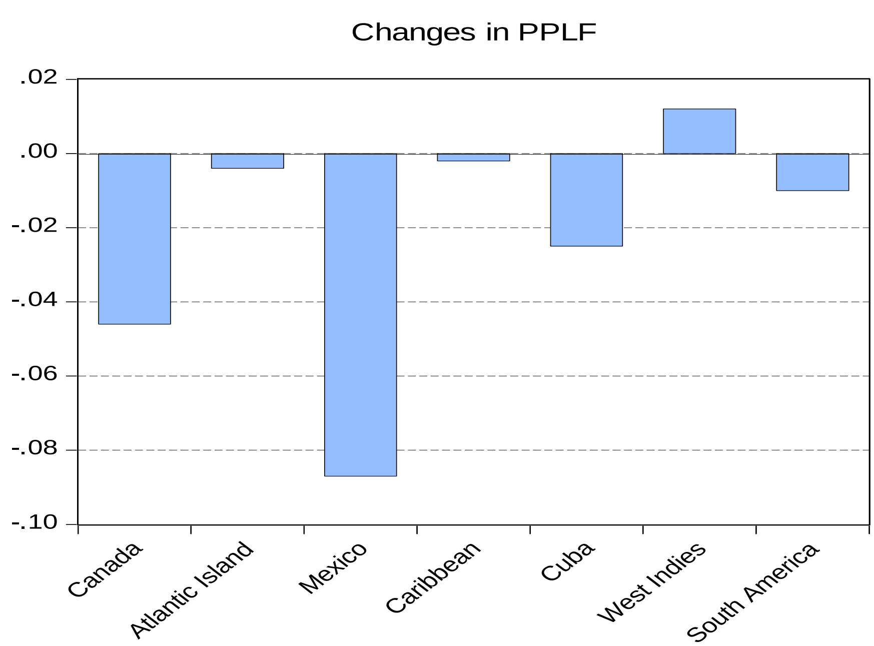


Figure 3. 5 Changes in the Probability of Participation in the US Labor Force (North and South America)

Table (3.7) shows that being from any of the European countries significantly decreases the PPLF. Therefore, immigrants from European countries may not be of much policy concern in the first place even they are skilled workers. However, if skilled immigrants from polices' targets were not enough to fill the vacancies, we can then motivate immigrants from European countries who are skilled workers to fill the vacancies in the US labor market. Figure (3.6) shows the comparison between the changes in PPLF based on being from European countries.

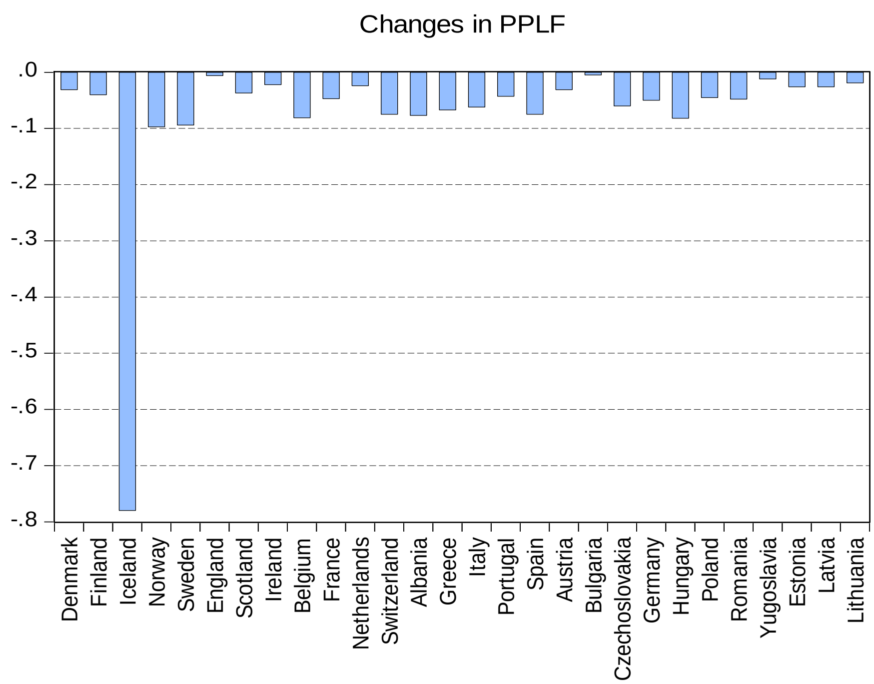


Figure 3. 6 Changes in the Probability of Participation in the US Labor Force (Europe)

Table (3.7) shows that being from Philippines significantly increases the PPLF by about 2%. This is the only positive change in PPLF among immigrant groups of Asian countries. Thus, policy concern should be directed to immigrants from Philippines among immigrants from Asian countries. Figure (3.7) shows the comparison between the changes in PPLF based on being from Asian countries.

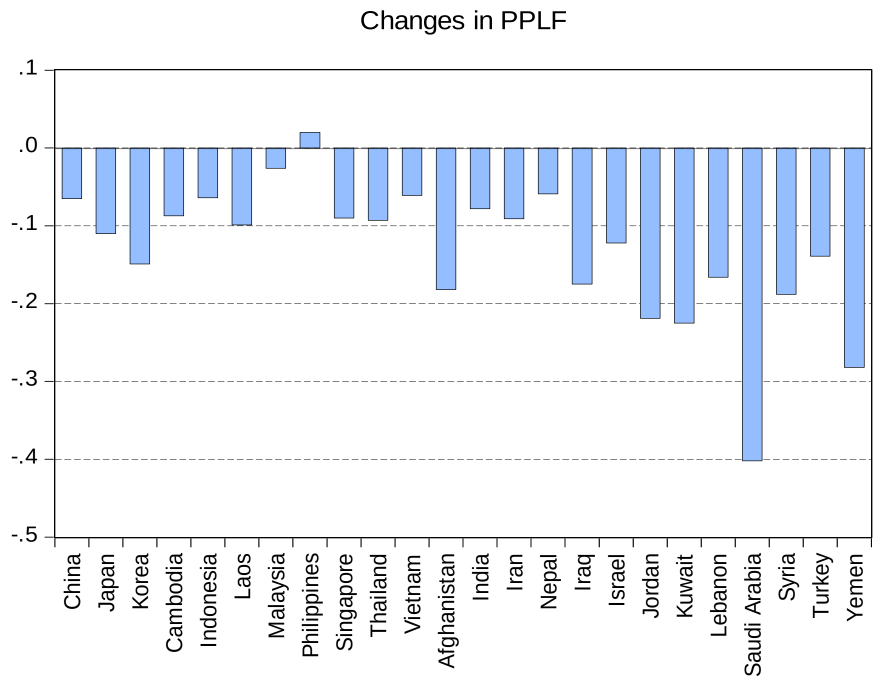


Figure 3. 7 Changes in the Probability of Participation in the US Labor Force (Asia)

The results show that being from Africa significantly increases the PPLF by about 1.5%. The results show the being from Australia or Pacific Islands significantly decreases the PPLF. Therefore, policy concern may need to be directed to immigrants from Africa in the first place. Figure (3.8) shows the comparison between the changes in PPLF based on being from Africa, Australia, and Pacific Islands.

Figure (3.9) shows the countries or areas that have the highest positive changes in PPLF among all countries in the sample, which represent the potential policies targets. It appears that immigrants from Philippines have the highest PPLF. Therefore, more attention may need to be paid on immigrants from Philippines in the first place. If the policy priority is to increase skilled immigrants, policy makers may investigate skill composition of the target groups in the first place.

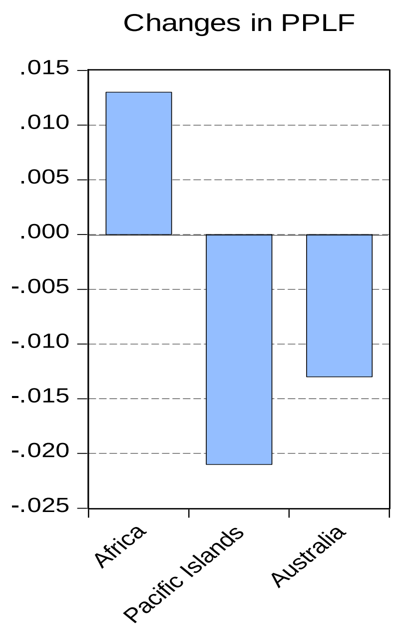


Figure 3. 8 Changes in the Probability of Participation in the US Labor Force (Other Countries)

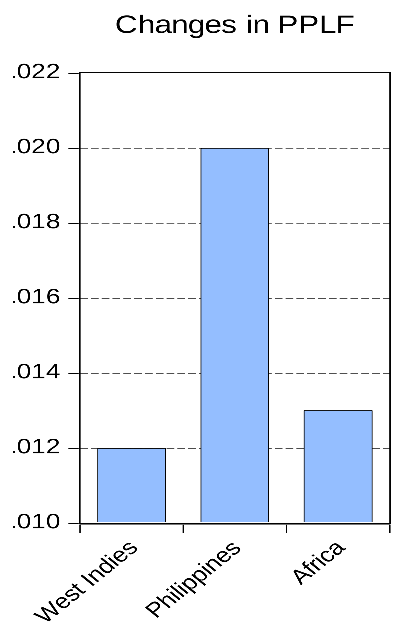


Figure 3. 9 Countries that have Higher Changes in the Probability of Participation in the US Labor Force (the targets)

However, if more skilled workers are needed, we can motivate immigrants from other countries that are not identified as targets. This sequential policy strategy can take advantage of immigrants from targets since they already want to work in the US labor market, and thus reduce the cost of motivating other groups. At the end, this strategy will increase the benefits and reduce the cost of immigrants participation in the US labor market.

This study is to only Identifies some focus groups (targets). That is just the starting point since there are many other factors needed to be considered to adopt effective policies. For example, the skills of immigrants, the sectors they work in, the number of skilled workers needed in the US labor market that cannot be filled by natives, and others. Collecting and ascertaining all these factors can provide a more complete picture and help adopt the effective policies.

3.4 Conclusion

The increased immigrants participation in the US labor markets has been the interest of labor economists. From one side, skilled immigrant workers have been providing crucial services and that benefits the US labor market. From the other side, other type of immigrant workers can create some problems (or costs) for the US labor market. Therefore, it is necessary to effectively manage and balance the benefits and costs of immigrants participation in the US labor market.

This paper provides the information needed as starting point to adopt the effective labor market policies. More specifically, this paper helps identifying the motivations that lead immigrants to decide to work in the US labor market that can used for policy making. In addition, this paper helps identifying the policies targets (immigrant groups that are more likely to participate in the US labor force)

The paper shows that there are 62 group of immigrants in the sample from different foreign countries or areas. Seven groups of immigrants from North and South America, twenty-eight groups of immigrants from Europe, twenty-four groups of immigrants from Asia, Africa, Australia, and Pacific islands.

The results of this paper show that immigrants from West Indies, Philippines, and Africa are identified as potential policy targets. That is because they have the highest positive changes in PPLF among all foreign countries in the sample. Therefore, we may need to pay more attention on immigrants from these countries or areas.

In addition, we may also need to pay attention on the groups of immigrants that have high number of immigrants in the US like Mexico, China, and India. Even their probability of participation in the US labor force are not the highest, they may benefit or create cost to the US labor market. Placing more focus on these groups can help effectively balance and manage the benefits and cost of immigrants participation in the US labor force.

The information provided by this paper is important but not enough to adopt comprehensive labor market policies. We need also to know the skill composition of immigrants, the sectors they work in, and other information. Collecting all this information can help adopt the effective labor market policies that can increase the benefits and reduce the costs of immigrants participation in the US labor market.

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