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The Impact of Government Policy on the Matching Efficiency of Minnesota's Labor Market

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by

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Abstract

Matching efficiency is one of the most important labor market indicators. It demonstrates how effectively the labor market matches unemployed workers to job vacancies. Various factors, including government policy, might have an impact on matching efficiency. The main objective of this thesis is to explore the influence of government policy on the matching efficiency of Minnesota in 1995-2017. The paper describes the process of calculating the monthly values of matching efficiency based on a Cobb-Douglas matching function with constant returns to scale. This empirically obtained variable is used for examining the relationship between the calculated matching efficiency of the labor market of Minnesota and elements of government policy. This research studies the impact of a minimum wage, government spending, refugee arrivals, and Medicaid enrollment on the state's matching efficiency. Empirical analysis shows that only one investigated potential predictor of matching efficiency has a positive correlation with the response variable.

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Chapter I: Introduction

Matching efficiency is the ability of the labor market to match unemployed workers to vacant jobs. Besides the fact that it is an important labor market indicator in itself, matching efficiency is a substantial determinant of an unemployment rate, which is one of the major indicators of economic activity. The decline of the labor market's matching efficiency means that fewer job matches are formed in the current time period, and it has a negative impact on the economy through increased unemployment and reduced welfare.

This thesis explores the matching efficiency of the labor market of Minnesota in 1995-2017 and several factors related to government policy which might have an influence on matching efficiency fluctuations. The research is based on the Diamond-Mortensen-Pissarides labor search-matching model. According to Barnichon and Figura (2015), this model has become "the canonical framework to introduce equilibrium unemployment in macroeconomic models" (p.222). In the framework of this model, the number of new hires is modeled with a Cobb-Douglas matching function with constant returns to scale. The number of new hires at a given time period is the product of multiplying three factors: number of unemployed, number of vacancies, and matching efficiency.

Matching efficiency measures the productivity of the process of matching job seekers to available jobs. It is examined from two different perspectives, which makes this study more relevant. The first perspective shows the ability of unemployed workers to find a new job. It is important for job seekers to keep in mind that demand for labor force is satisfied by the most suitable job candidates. In other words, for being successful in the labor market, job seekers should have skills and abilities in demand. A government can impact the matching efficiency of the labor market by stimulating people to obtain more demanded occupations, skills, and abilities. For example, several years ago, a report by Manyika et al. (2011) warned of huge talent shortages for data and analytics. This report predicted that “by 2018, the United States alone could face a shortage of 140,000 to 190,000 people with deep analytical skills as well as 1.5 million managers and analysts with the know-how to use the analysis of big data to make effective decisions”. Realizing the demand, many public universities launched new degree and certificate programs in Data Analytics. These actions positively impact the matching efficiency of the labor market and employment.

On the other hand, matching efficiency demonstrates the effectiveness of companies and nonprofit institutions in the labor market. Matching efficiency is the measure of how efficiently HR departments fill the job vacancies of their companies. According to a KPMG-sponsored study (2012), business leaders across the globe reckon their HR teams are “ineffective” and “consistently fail to demonstrate any form of value to their organization”. An improvement in labor market performance of firms and organizations might be another way to increase the matching efficiency of the labor market.

Two parts of the aggregate matching function – the monthly numbers of new hires and unemployed people in Minnesota – are available from the Current Population Surveys. The third variable, the number of job vacancies, is not available; but a reliable proxy variable for numbers of vacancies is computed in Chapter III of this paper. After this estimation, it is possible to calculate the fourth, and the main part of the matching efficiency function - monthly values of the matching efficiency of Minnesota.

It is well-known that government policy might have the microeconomic effects which can change the incentives for individual economic decisions of the labor market’s participants. Consequently, the implementation of government policy might intentionally or unintentionally have an impact on the main indicators of the labor market, including its matching efficiency. The aim of this thesis is to study how the matching efficiency dynamics in Minnesota, found during this research, are affected by the state's government policy. The paper studies the impact of such elements of government policy as a minimum wage, government spending, refugee arrivals, and Medicaid enrollment. The influence of these factors on the matching efficiency of Minnesota's labor market and the levels of significance of this effect are estimated by creating the linear regression model.

The rest of the thesis is organized as follows: Chapter II reviews the literature related to the matching efficiency of the labor market and to the impact of government policy on the labor market. The first section of Chapter III describes the procedure of constructing the composite vacancy posting variable, which combines the print and online help-wanted advertisements in Minnesota; the second section demonstrates the process of calculation of the monthly values of matching efficiency. Chapter IV estimates the influence of elements of government policy on the matching efficiency of Minnesota's labor market. Finally, Chapter V concludes.

Chapter II: Literature Review

Matching Efficiency of Labor Market

The review of the literature related to the matching efficiency of the labor market shows that the most prevalent study in this field is a search and matching theory. The main concepts of this study and alternative theories are explored in this section.

Search and matching theory. In one of the fundamental papers of the search and matching theory, Blanchard and Diamond (1989) explore the relationship between unemployment and vacancies, or the Beveridge curve. In their opinion, this relation is understudied despite of the fact that it contains important information about the labor market. The authors affirm that about 7 million workers move into or out of employment every month, and they investigate these gross flows using data for the postwar USA. Besides this, the main objectives of this paper are to examine a matching process and interpret the Beveridge relation.

The researchers introduce a simple aggregate matching function, which presents the complex process of matching unemployed workers to available jobs. The reviewed paper describes new matches as a function of both unemployment and vacancies. This interpretation of the matching function is used as a main foundation of our thesis.

Blanchard and Diamond find the strong and stable relation between new hires and both unemployment and vacancies. Empirical data of this paper shows that “short- and medium-term fluctuations in unemployment have been due mainly to aggregate activity shocks, shocks that lead to both more (less) job creation and less (more) job destruction, rather than to changes in the degree in reallocation intensity, which lead to parallel movements in job creation and job destruction” (p.50).

Another basic conceptual paper of the search and matching theory models a job-specific shock process in the matching model of unemployment with non-cooperative wage behavior (Mortensen and Pissarides, 1994). The authors establish a model of endogenous job creation and job destruction and incorporate it into the matching approach to equilibrium unemployment and wage determination.

Mortensen and Pissarides assume that each job in the labor market can be either “filled and producing” or “vacant and searching”. Job creation occurs when a company with an unfilled job and a worker meet and start producing; and job destruction takes place when a filled job separates and leaves the market. According to the researchers, opening a new job vacancy is not job creation, it is only creating a job vacancy. Workers can be “employed and producing” or “unemployed and searching”. To simplify the model, the authors do not consider search on the job. The rate at which available jobs and unemployed workers meet is defined in this paper by the homogeneous-of-degree-one matching function of vacancies and unemployed workers. Our thesis is based on this definition and the assumptions of the reviewed paper.

The results of this research show that an aggregate shock causes a negative correlation between job creation and job destruction. Oppositely, a dispersion shock induces a positive correlation. In addition, Mortensen and Pissarides conclude that the job destruction process has more unstable dynamics comparing with the job creation process.

The paper of Petrongolo and Pissarides (2001) surveys recent work on the existence and stability of the aggregate matching function. According to the authors, “the matching function summarizes a trading technology between agents who place advertisements, read newspapers and magazines, go to employment agencies, and mobilize local networks that eventually bring them together into productive matches” (p.391). The main idea of this paper is that the complex exchange process is summarized by a well-behaved function that defines the number of jobs created at any moment in time in terms of the number of workers looking for jobs, the number of firms looking for workers, and a small number of other variables. In this survey the researchers concentrate on the microfoundations underlying the matching function and on its empirical effectiveness.

Investigating the microfoundations behind the aggregate matching function, Petrongolo and Pissarides explore other variables that influence the matching rate. The other variables in this research can be divided into two groups. The first group consists of everything that individuals do during their search. The variables from the second group are unrelated to individual search decisions. According to the researchers, the shifts in the matching function that are unrelated to the search decisions of individuals are by cause of technological advances in matching and aggregation issues.

The authors admit the complexity of studied concept: “the matching function is a black box: we have good intuition about its existence and properties but only some tentative ideas about its microfoundations” (p.424). They draw a conclusion that aggregation problems induce some of the shifts in the aggregate matching function, however, these shifts are not significant enough to make the aggregate function unstable.

Barnichon and Figura (2015) intend to better understand fluctuations in matching efficiency. To this purpose, they create an aggregate matching function that integrates heterogeneity across workers and labor market segmentation. The authors incorporate worker heterogeneity by admitting different levels of search effectiveness across workers. The labor market segmentation is incorporated by assuming that the labor market is segmented in submarkets, where each submarket is characterized by a matching technology. Under these assumptions, workers can only match with the available vacancies in their submarkets because of geographic distance, skill mismatch, or degree requirements. Our thesis examines the matching efficiency of the labor market of Minnesota, which is the segment of the U.S. labor market.

Considering worker heterogeneity and market segmentation, Barnichon and Figura show that matching efficiency has cyclical fluctuations due to variations in the degree of heterogeneity in the labor market. Estimating the aggregate matching function, the authors find that “the regression residual, which captures movements in matching efficiency, displays procyclical fluctuations and a dramatic decline after 2007” (p.222). The reasons of this decline are the essential deterioration of the average characteristics of unemployed workers and notable growth of dispersion in labor market conditions.

This thesis determines monthly values of matching efficiency using calculated monthly values of help-wanted advertisements as a proxy variable for job vacancies. The process of computing monthly values of help-wanted advertisements follows the report of Barnichon (2010). This paper builds a vacancy posting index by combining the print Help-Wanted Index (HWI) with the online HWI.

The Conference Board help-wanted online data series is observable only since May 2005, therefore the author recovers the online HWI for the time period from January 1995 until May 2005 (assuming that there are no online help-wanted advertisements until the introduction of the World Wide Web in 1995) by estimating the share of print advertising.

The same approach is used in this thesis for recovering the monthly values of online help-wanted advertisements in Minnesota. The difference between two papers lies in the polynomial function which is used for estimating the share of printed advertising. Barnichon uses a quartic polynomial function, whereas this thesis works with a septic polynomial.

Alternative theories. The view of unemployment and vacancies of Shimer (2007) is conceptually diverse from the point of view of the search and matching theory. The author makes a perceptive distinction between search and mismatch. According to this paper, the search theory states that unemployed workers actively search for a new employer after leaving their old jobs. Oppositely, the mismatch model of Shimer claims that unemployed workers are attached to their geographic locations and occupations. The researcher describes that “mismatch is a theory of former steel workers remaining near a closed plant in the hope that it reopens. Search is a theory of former steel workers moving to a new city to look for positions as nurses.” (p.1074).

This paper creates a dynamic stochastic model of mismatch and promotes the hypothesis that at any point in time, the skills and geographical location of unemployed workers are poorly matched with the skill requirements and location of job openings. According to the author, the rate at which unemployed workers find jobs is contingent on three factors: the rate at which unemployed workers obtain more demanded occupations or move to locations with available jobs, the rate at which jobs are created in locations with available workers, and the rate at which employed workers leave jobs in locations with suited unemployed workers.

Shimer states that the mismatch model explains much of the variability in vacancies and unemployment and clarifies why these variables have similar perseverance. In addition, this model predicts that the job finding rate will decline with unemployment duration even if workers are homogeneous. The author claims that these findings are problematic in the matching model.

In his other paper, Shimer (2005) argues that the search and matching theory cannot explain the cyclical behavior of two of its central elements, unemployment and vacancies, which are both highly volatile and strongly negatively correlated in U.S. data. In addition, according to the author, the search and matching model cannot interpret the strong procyclicality of the job finding rate of an unemployed worker.

The researcher concentrates on two causes of shocks: changes in labor productivity and changes in the separation rate of employed workers from their jobs. Shimer claims that “a search and matching model in which wages are determined by Nash bargaining cannot generate substantial movements along a downward-sloping Beveridge curve in response to shocks of a plausible magnitude. A labor productivity shock results primarily in higher wages, with little effect on the V/U ratio. A separation shock generates an increase in both unemployment and vacancies” (p.45). However, the author emphasizes that his research is not an attack on the search and matching theory, but rather a critique of the Nash bargaining assumption which is generally used for wage determination.

Brown, Merkl, and Snower (2009) introduce an incentive theory of labor market matching. This theory explains the labor market matching process using microeconomic incentives. The authors have doubts that the matching function is constant with respect to labor market policies that are implemented to improve the effectiveness of the matching process. In addition, various labor and macroeconomic shocks might also impact the matching function. The researchers argue that in analyzing the effects of many macroeconomic shocks, including labor policies, the matching function may be replaced by a choice-theoretic framework that deals with the basic microeconomic decisions determining the matching process.

The authors calibrate their incentive model for the economy of the United States and demonstrate that it can describe some important empirical regularities which the traditional matching model does not explain. According to the researchers, this model creates labor market variabilities that are close to the empirical data for the unemployment rate, job finding rate, and separation rate. Also, it generates a strong negative correlation between the job finding rate and unemployment rate. In addition, the incentive model clarifies a strong negative correlation between job creation and job destruction.

Brown, Merkl, and Snower conclude that the matching function depicts matches as the output of a matching technology that mechanically connects unemployed workers and available jobs. Contrastingly, their incentive theory “explains the matching probability in terms of the firm’s job offer incentive and the worker’s job acceptance incentive. Similarly, the separation probability is explained in terms of the firm’s firing incentive and the worker’s quit incentive. These incentives depend on all the parameters of the model, including policy and macro parameters” (p.23).

Kohlbrecher, Merkl, and Nordmeier (2016) focus on the potential role of idiosyncratic productivity for job creation. The authors use German administrative wage data to calibrate their model and to demonstrate how idiosyncratic productivity shocks influence the elasticity of the job finding rate with respect to market tightness.

The researchers assume that every worker meet a firm with a constant probability. This would be a special case of a Cobb-Douglas contact function in which the overall number of contacts does not respond to vacancies. The paper denotes this case as a degenerate contact function. As a result of different idiosyncratic productivity, firms select workers with larger realizations.

Kohlbrecher, Merkl, and Nordmeier show “analytically and numerically that the degenerate contact function with idiosyncratic productivity shocks generates an equilibrium comovement between matches, unemployment, and vacancies that is observationally equivalent to a Cobb-Douglas constant returns contact function” (p.3).

According to the authors, one of their contributions is to demonstrate that dynamic labor market models with vacancy free entry and idiosyncratic productivity create a time-series behavior that is consistent with matching function estimations. The researchers make a conclusion that the combined model with traditional contact function and idiosyncratic productivity shocks has important implications.

According to Chugh and Merkl (2016), selection as an important margin of adjustment in hiring decisions of firms is a long-standing realistic idea, but macro-labor analysis has not emphasized it much. This research is mostly concentrated on the cross-sectional distribution of idiosyncratic productivity for new workers. To explore this dispersion, the researchers use the 1982 U.S. Employer Opportunity Pilot Project (EOPP) data. The focus of the authors in this paper, unlike many others who use the EOPP data, is on the cross-sectional dispersion of training costs of new hires.

The results of the selection model are determined by a distributional assumption about heterogeneous training characteristics, and, consecutively, these results depend on "how large the mass of individuals is that moves across the endogenously time-varying selection threshold conditional on aggregate productivity shocks" (p.1372).

Using microeconomic data on heterogeneity in training costs allows Chugh and Merkl to demonstrate that the labor selection model displays large fluctuations in aggregate labor markets. Based on this paper's microcalibration, an efficient labor selection mechanism, conditional on productivity shocks, can explain approximately 40% of empirically relevant fluctuations in the U.S. job finding rate. The researchers consider that the efficient selection model's results, which are several times larger than in an efficient search and matching model, are valid for both partial and general equilibrium fluctuations.

Elements of Government Policy and Labor Market

The impact of specific elements of government policy (a minimum wage, government spending, refugee arrivals, and Medicaid enrollment) on matching efficiency is not addressed in the literature. Therefore, this section of the second chapter explores the relationship between the mentioned elements of government policy and the labor market, not its matching efficiency. Based on the review of the literature, this section highlights important conclusions (some of them contradictory to each other) from studies of the labor market effects of government policy.

Minimum Wage. Stonecipher and Wilcox (2015) focus on the relationship between an increase in the minimum wage and the loss of jobs. Besides analyzing existing research, this report undertakes more extensive research into states which raised the minimum wage in recent years.

The authors compare job growth in states where the minimum wage was raised since January 1, 2014 with states where the minimum wage increase did not happen. In addition, this paper compares the current numbers of jobs in cities and counties where the minimum wage increased at least one year ago with the number of jobs before this rise.

The researchers claim that their analysis of existing research did not find clear evidence to approve the statement that the increase in the minimum wage causes employers to reduce jobs. Additionally, this study's investigation of employment statistics did not find the confirmation of employment loss in states which have increased the minimum wage. Moreover, this examination found more evidence that the increase in the minimum wage has resulted in the faster increase of employment in these states. As a result, Stonecipher and Wilcox conclude that employment statistics in cities and counties where the minimum wage has increased do not show the decline in the levels of employment.

Meer and West (2016) explore whether the minimum wage effects employment through a discrete change in its level or if it is reflected over time. The researchers use a long-time (1975-2012) panel of aggregate employment metrics for the population of employers in the USA.

The researchers state that the prior literature has mostly assumed that an increase in the minimum wage has minimal effects on employment. However, they argue that if the true effects are dynamic, conclusions in the previous related literature would misjudge this relationship. The authors show that job growth is systematically negatively affected by the minimum wage. The findings of the reviewed paper illustrate that employment essentially declines due to increases in the minimum wage.

Meer and West find that "their results are robust to a number of specifications and that the minimum wage reduces employment over a longer period of time than the literature has focused on in recent years" (p.518).

Government Spending. According to Abrams (1999), empirical research in the literature found a negative relationship between government size and economic growth.

The researcher provides several reasons to suppose that there is a connection between government size and unemployment. Big governments mean large income tax rates. In their turn, large tax rates might affect work-leisure decisions of individuals and could extend search time between bouts of unemployment. Also, big governments would presumably finance public health insurance. Consequently, the cost of unemployment to the individual might be reduced by profitable unemployment insurance schemes. In addition, assuming all other factors equal, big governments reduce the size of the private sector. The author considers that unemployment arising from a reduction in one specific part of the private sector cannot be quickly reabsorbed into other parts of the private sector.

This report shows that a one percent increase in government spending as a percent of GDP would enhance the unemployment rate by approximately 0.36 of one percent. The researcher draws a conclusion that his findings in this paper "support the hypothesis that increases in government size, ceteris paribus, generally provide expenditure and tax effects that raise reported unemployment (p.400)".

Ramey (2012) examines whether increases in government spending stimulate private activity. Particularly, the author explores the effects of government spending on labor markets.

The researcher begins her investigation of the effects of government spending on unemployment by developing a case study of labor markets during the World War II (WWII) period. Using the Variance-Covariance (VAR) methods on various samples she uncovers that an increase in government spending reduces unemployment. However, Ramey finds that "in the great majority of time periods and specifications, all of the increase in employment after a positive shock to government spending is due to an increase in government employment, not private employment" (p.2). According to these results, the employment effects of government spending appear by the direct hiring of workers, but not through stimulating the private sector to hire more workers. The author makes a conclusion that government spending does not stimulate private activity.

In her other paper, Ramey (2011) reviews the state of knowledge about the government spending multiplier and estimates the multiplier value for a temporary, deficit-financed increase in government purchases. The author concludes that "the aggregate multiplier for a temporary rise in government purchases not accompanied by an increase in current distortionary taxes is probably between 0.8 and 1.5" (p.683). Also, she reports that each $35,000 of government spending produces one extra job.

Refugee Arrivals. The purpose of the paper of Ruiz and Vargas-Silva (2013) is to review the economics literature on the impacts of forced migration. According to the authors, most studies have concentrated in a few forced migration situations, specifically: internal displacement in Northern Uganda, internal displacement in Colombia, the refugee inflow from Burundi and Rwanda to Tanzania and the forced migration due to events related to WWII.

The researchers draw a conclusion that "the impact of the refugee arrivals on the receiving communities seems to be mixed, with the literature clearly identifying winners and losers" (p.783). According to this paper, agricultural producers can take advantage of the cheaper labor force represented by forced migrants. In addition, food aid funds for refugees lead to the increase in demand for products of agricultural producers, therefore they might be an example of winners. The potential losers might contain the unemployed local workers who were displaced by forced migrants in the labor market.

Card (1990) examines the consequences of the Mariel Boatlift, when Cuban immigrants arrived in Miami on boats from May to September 1980 and increased the labor force of the Miami metropolitan area by 7%. This paper summarizes the effects of the Boatlift on the Miami labor market, concentrating on wages and unemployment rates of less-skilled workers. The research uses individual micro-data for 1979-1985.

The researcher concludes that the arrival of about 125,000 Cuban refugees did not have a substantial impact on the Miami labor market. The wages rate and unemployment of less-skilled non-Cuban workers in Miami were unaffected. Nevertheless, the author distinguishes Miami from other American cities because of large waves of immigrants before the Mariel Boatlift, which helped this city to be better prepared to accept new immigrants. For this reason, the Miami labor market was able to absorb the Mariel immigrants promptly and without economic damages.

Mayda, Parsons, Peri, and Wagner (2017) explore the long-term influence of refugees on the U.S. labor market over the period 1980-2010. In this report the authors provide new empirical evidence by investigating the economic impact of refugee resettlement in the USA on local labor markets.

The empirical analysis of this paper uses exogenous variation in refugee cases "without U.S. ties", or refugees who did not choose the initial specific location of resettlement within the country because they did not have friends or family members in the USA. The researchers make a conclusion that "their results provide robust causal evidence that there is no adverse long-term impact of refugees on the U.S. labor market" (p.16).

Medicaid Enrollment. According to Garthwaite, Gross, and Notowidigdo (2014), health insurance in the United States is tightly connected to employment. Many Americans can access affordable health insurance only through their employer. Therefore, extensions of public health insurance might have essential effects on the labor market.

In 2005, approximately 170,000 adults in Tennessee lost public health insurance coverage as a result of a discontinuation of the expansion of TennCare, the state's Medicaid system. This paper uses this cessation to estimate the effect of public health insurance eligibility on the labor supply of childless adults.

The authors find that a large increase in labor supply among individuals working more than 20 hours a week and having private, employer-provided health insurance was caused by the TennCare disenrollment. The researchers also examine the dynamic effects of this disenrollment and discover that it almost immediately resulted in the increase in job search behavior, employment, and health insurance coverage.

The results of this paper show that public health insurance eligibility can have substantial effects on labor supply. Garthwaite, Gross, and Notowidigdo conclude that “the labor supply changes appear to be a means of securing access to private health insurance, and they demonstrate a large amount of employment lock” (p.690). The authors assume that if the main reason for staying on the job for some workers is to afford health insurance, the Medicaid expansion under the Affordable Care Act (ACA) may reduce labor supply.

Duggan, Goda, and Jackson (2017) consider that provisions of the ACA weaken the tie between employment and health insurance. To identify the effect of the ACA on insurance coverage and labor market outcomes in the first year after its implementation, the authors use proxies for expected treatment “intensity” of the ACA.

The researchers admit that it is difficult to distinguish the effects of the law from other changes that would have happened without it. The authors consider that health insurance coverage might rise essentially because of growth in economic activity. Therefore, it is basically an empirical question what portion of the increase in health insurance coverage was caused by the ACA and what part was induced by other factors.

According to the researchers, their results indicate that the ACA had a significant impact on overall health insurance coverage. They find that Medicaid coverage is increasing in both expansion and non-expansion states, however, the increase in expansion states is approximately three times larger. Duggan, Goda, and Jackson find “little evidence of changes in labor force participation, employment, self-employment, part-time status, wages, or hours that occurred differentially in places where ACA-induced coverage gains were the highest” (p.6). Therefore, the results of this paper suggest that the implementation of the ACA mostly did not affect labor market outcomes in 2014.

Chapter III: Matching Efficiency of Minnesota

Introduction

The third chapter of this paper presents the process of calculating monthly values of the matching efficiency of Minnesota in 1995-2017.

According to Blanchard and Diamond (1989), the matching function relates the flow of new hires to the stocks of vacancies and unemployment. The matching function is assumed increasing in both its arguments, concave and homogeneous of degree 1. Barnichon and Figura (2015) consider that in a continuous time framework, the flow of hires is typically modeled with a Cobb-Douglas matching function with constant returns to scale.

The equation of the matching function is

$$\boldsymbol{H_t = m_t\, U_t^{\sigma}\, V_t^{1-\sigma}} \quad \textbf{(1)}$$

where H_t is the number of new hires at a given time t,

U_t is the number of unemployed at a given time t,

V_t is the number of vacancies at a given time t,

m_t is the value of matching efficiency at a given time t.

Matching efficiency has the range between 0 and 1 (or 100%). This indicator might be equal to 1 (100%) only if the number of unemployed at a given time is equal to the numbers of vacancies and new hires. If matching efficiency is equal to 0, there are no any new hires.

Petrongolo and Pissarides (2001) state that on average, an unemployed worker finds a job during a given time t with probability H_t / U_t. If we imagine the hypothetical situation in the labor market where matching efficiency is equal to 1, this probability would also be equal to 1 (100%). The inverse of this probability is the duration of unemployment for an average unemployed worker. Similarly, a vacant job is filled with probability H_t / V_t. According to the authors, “the aggregate matching function is a useful device for introducing heterogeneities across workers, by making the probability H_t / U_t depend on individual characteristics” (p.392).

Integrated Public Use Microdata Series (IPUMS) by Flood, King, Ruggles, and Warren (2017) provide the numbers of new hires in Minnesota from 1995. The numbers of unemployed in Minnesota are also available on the IPUMS website. A composite help-wanted data that monitors the number of help-wanted advertisements in major sources will be used as a proxy variable for vacancy posting. The total number of help-wanted advertisements will be computed in the next section. Finally, the monthly values of the matching efficiency of the state’s labor market will be calculated in the last section of this chapter.

Calculating Total Number of Help-Wanted Advertisements

This section describes the construction of the composite help-wanted data of Minnesota that combines print help-wanted advertisements available over 1970-2009 with online help-wanted advertisements available since May 2005.

The print help-wanted advertisements data is the seasonally adjusted time series with cyclical fluctuations (Figure 3.1).

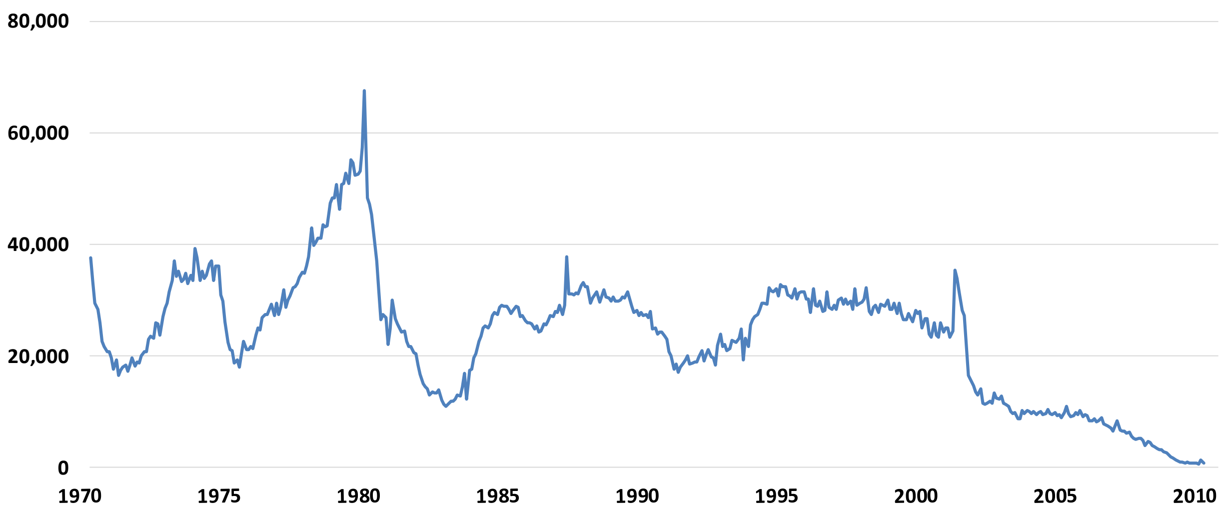

Figure 3.1. *Print Help-Wanted Advertisements in Minnesota, 1970-2009*

The online help-wanted advertisements data is also the seasonally adjusted data series. In Figure 3.2 below we can see that online advertisements have cyclical fluctuations (e.g. a trough in 2009 during the last recession).

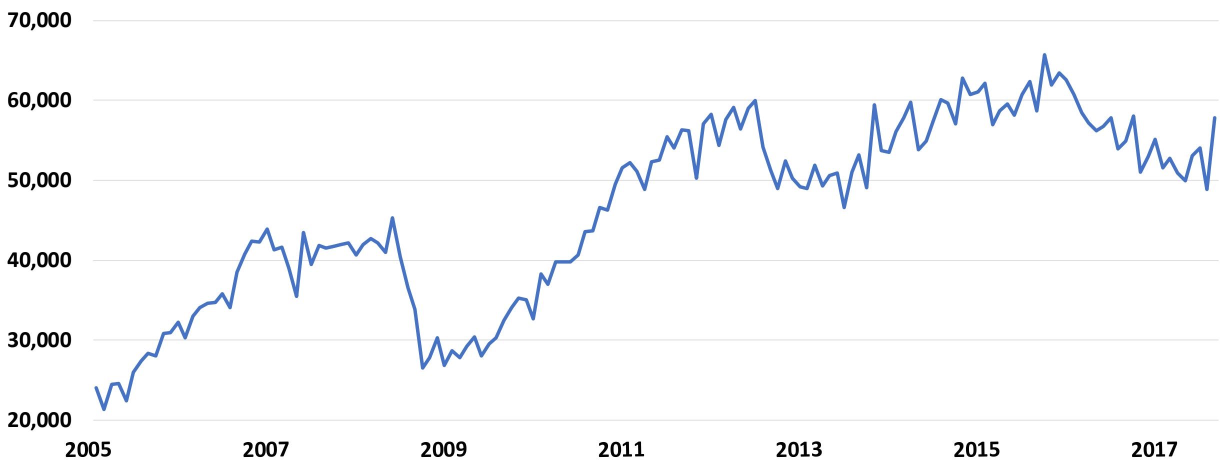

Figure 3.2. *Online Help-Wanted Advertisements in Minnesota, May 2005-2017*

Let's denote PA_t and OA_t the number of print help-wanted advertisements and online help-wanted advertisements respectively. The total number of advertisements (the combination of print and online advertisements) is TA_t, where $TA_t = PA_t + OA_t$, and $S^{PA}{}_t$ is the share of print help-wanted advertisements in total advertisements.

There are four separate periods:

1) January 1970 - December 1994. Let's assume that the first online advertisements appeared after the introduction of the World Wide Web in 1995, therefore $\boldsymbol{TA_t = PA_t}$. This period will not be used for this research, but it will be necessary for estimating $S^{PA}{}_t$.

2) January 1995 - April 2005. PA_t is available for this period, but OA_t is not. We need to estimate the share of print advertising to recover OA_t: $\boldsymbol{OA_t = PA_t \times (1 - S^{PA}{}_t) / S^{PA}{}_t}$. After that we can calculate TA_t: $\boldsymbol{TA_t = PA_t + OA_t}$.

3) May 2005 - December 2009. Both parts of the total number of advertisements, PA_t and OA_t, are observable, thus $\boldsymbol{TA_t = PA_t + OA_t}$.

4) January 2010 - December 2017. Let's assume that there is no printed job posting during this period (even if there were some printed advertisements, let's suppose they duplicated existed online job postings), therefore $\boldsymbol{TA_t = OA_t}$.

To obtain an estimate of S^{PA}_t, let's follow Barnichon (2010), and interpret the downward trend in print help-wanted advertisements over 1995-2009 as "a secular decline in print advertising due to the emergence of online advertising and the world wide web" (p.176). The author fitted a quartic polynomial in his paper, however a septic polynomial is fitted to print help-wanted advertisements over 1970-2009 for this research. Figure 3.3 shows the actual values of print help-wanted advertisements and the values of the septic polynomial function for the 1995-2009 period.

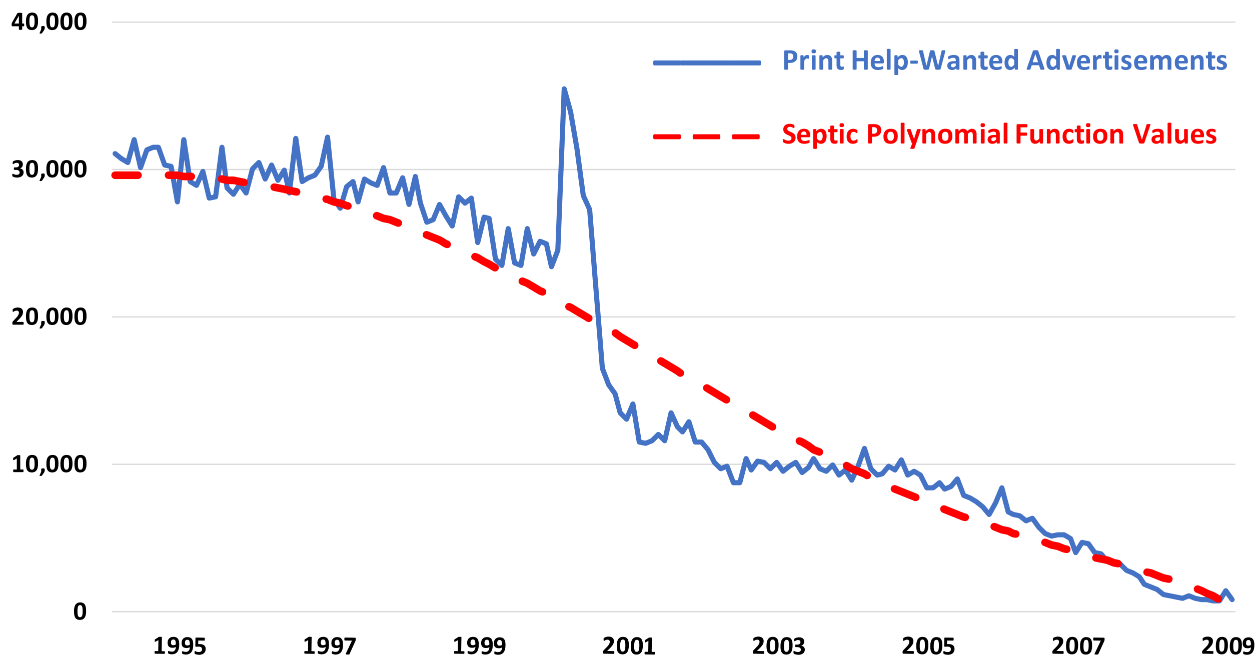

Figure 3.3. *Print Help-Wanted Advertisements and Septic Polynomial Values, 1995-2009*

As a result, we can estimate the print share at time t as the ratio of the septic polynomial's value at time t to the septic polynomial's value in January 1995 (Figure 3.4).

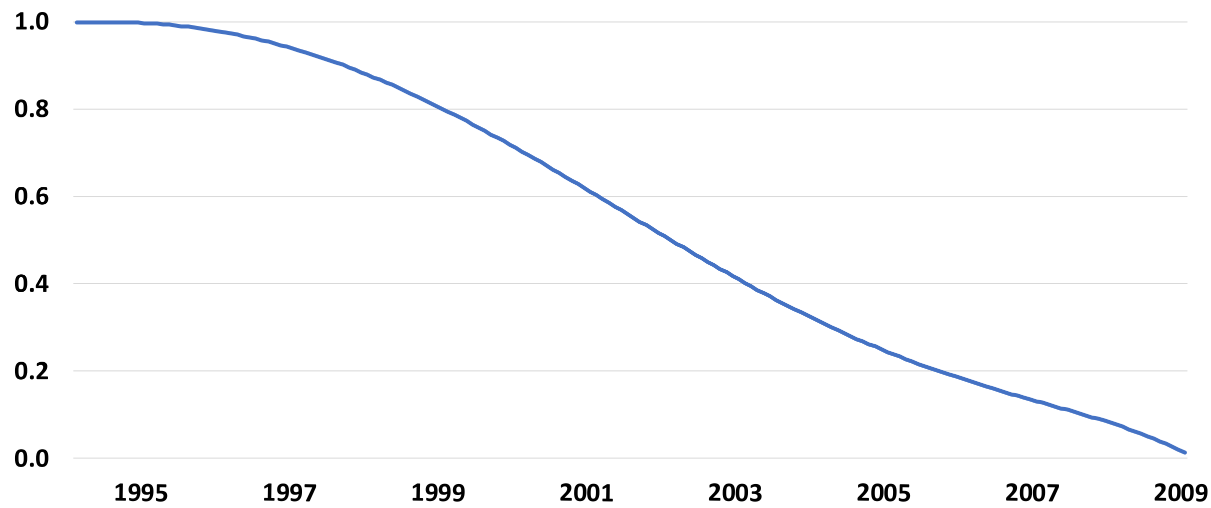

Figure 3.4. *Estimated Share of Print Advertising in Minnesota, 1995-2009*

The values of printed advertisements and online advertisements are available from May 2005. Therefore, it is possible to compare the estimated share of print advertising with its real share over May 2005 - December 2009. (Figure 3.5).

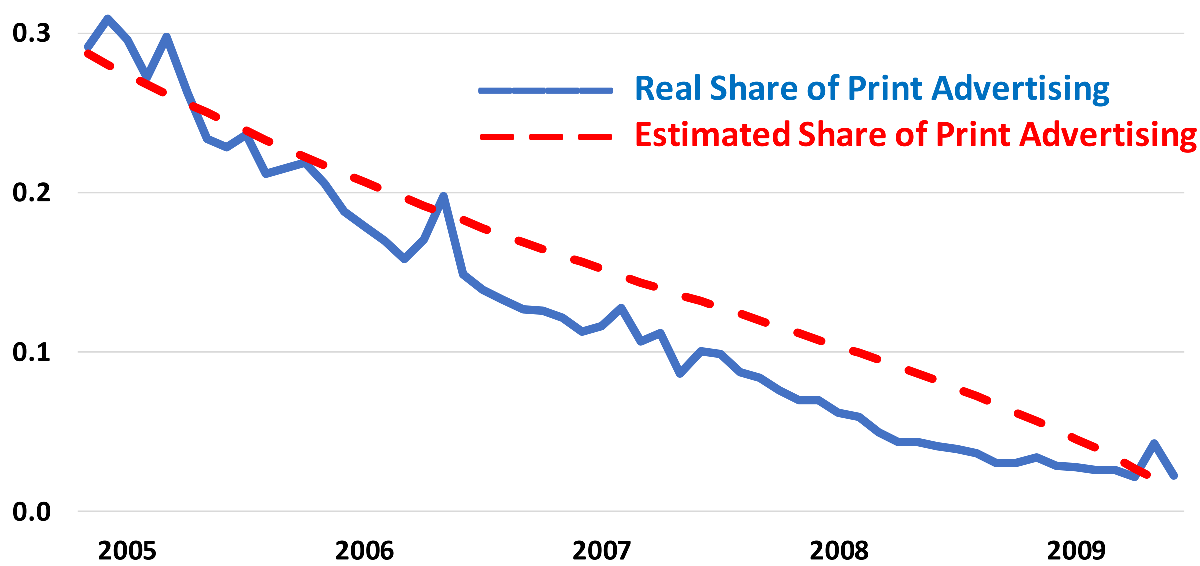

Figure 3.5. *Real and Estimated Shares of Print Advertising in Minnesota, May 2005-2009*

As we can see in Figure 3.5, these two time series are close to each other. Consequently, we can make a conclusion that the estimated share of print advertising calculated using the septic polynomial function is justified, and it might be used for calculating the total number of advertisements.

Now it is possible to compute the total number of help-wanted advertisements in Minnesota in 1995-2017 using the following steps of the simple algorithm:

First, let's calculate the total numbers for the period of January 1995 - May 2005 using the share of print advertising.

Second, we can calculate the total numbers for the period from June 2005 until December 2009 adding up printed advertisements and online advertisements.

Finally, the total numbers of advertisements for the period of January 2010 - December 2017 are the same as the numbers of online advertisements.

Figure 3.6 represents the result of this calculation – the total number of help-wanted advertisements.

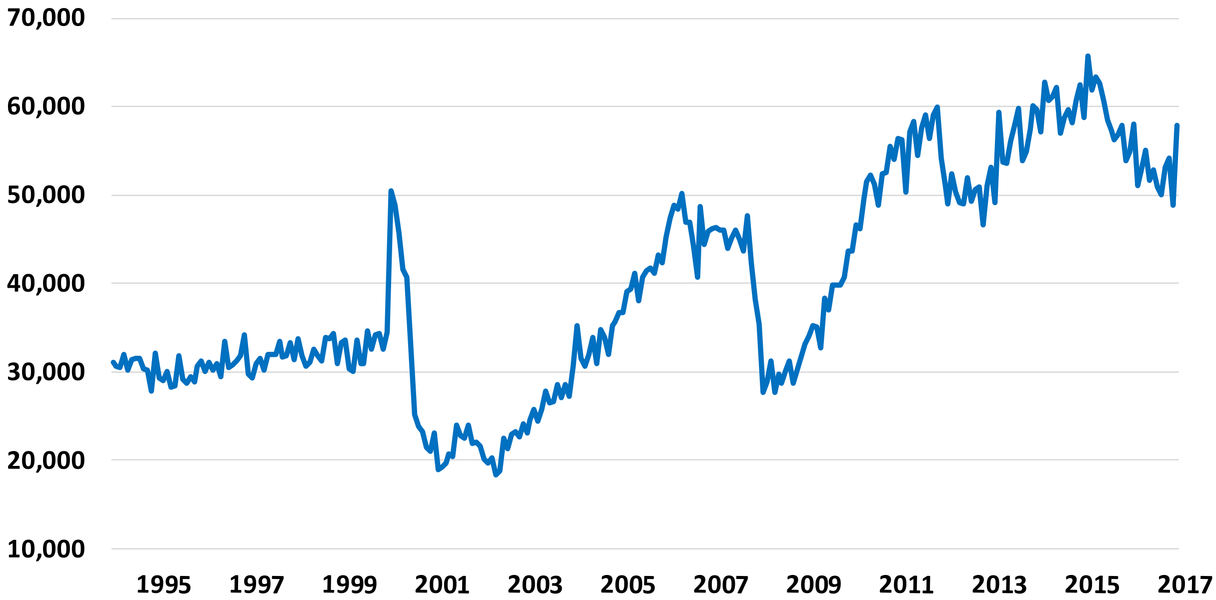

Figure 3.6. *Total Help-Wanted Advertisements in Minnesota, 1995-2017*

Calculating Matching Efficiency

This section of the third chapter calculates monthly values of matching efficiency.

The job finding rate (JFR) at a time t, f_t is the ratio of new hires to the stock of unemployed, $f_t = \frac{H_t}{U_t}$ and

$$\boldsymbol{f_t = m_t U_t^{\sigma-1} V_t^{1-\sigma}}$$

Denoting $\theta_t = \frac{V_t}{U_t}$, we have

$$\boldsymbol{f_t = m_t \theta_t^{1-\sigma}} \quad \textbf{(2)}$$

where $\theta_t = \frac{V_t}{U_t}$ is the average labor market tightness (LMT) at a time t.

Let's take natural logarithms of both sides of the equation (2):

$$\boldsymbol{\ln f_t = \ln m_t + (1-\sigma) \ln \theta_t}$$

We can represent the natural logarithm of matching efficiency at any given time t as the sum of its mean and the residual at time t:

$$\boldsymbol{\ln m_t = \ln \overline{m} + \varepsilon_t}$$

where $\ln \overline{m}$ is the mean of a sample $\ln m_1, \ln m_2, \ldots, \ln m_t$.

Using the fact that $\ln \overline{m}$ is constant and equal to the value of the intercept, we can estimate the matching function in this log-linear form:

$$\boldsymbol{\ln f_t = \ln \overline{m} + (1-\sigma) \ln \theta_t + \varepsilon_t} \quad \textbf{(3)}$$

This equation allows us to calculate the matching efficiency of the labor market of Minnesota in 1995-2017.

Firstly, let's calculate the values of the job finding rate dividing the numbers of new hires by the numbers of unemployed: $f_t = \frac{H_t}{U_t}$. The results are presented in Figure 3.7.

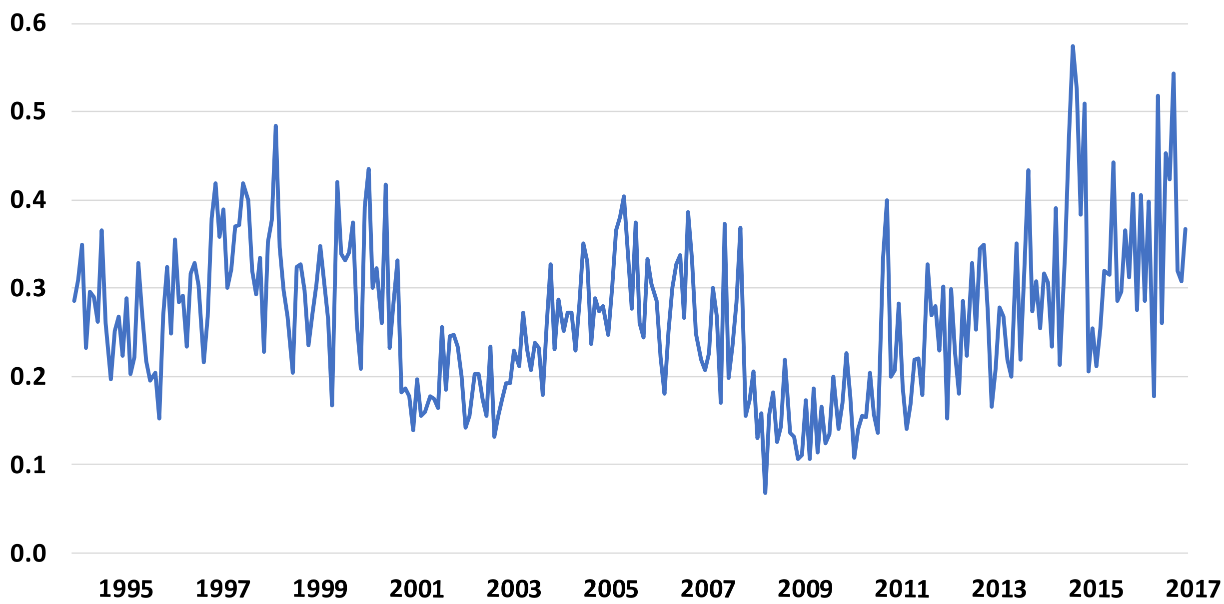

Figure 3.7. *Job Finding Rate in Minnesota, 1995-2017*

Secondly, we calculate the average labor market tightness dividing the numbers of vacancies by the numbers of unemployed: $\theta_t = \frac{V_t}{U_t}$ (Figure 3.8).

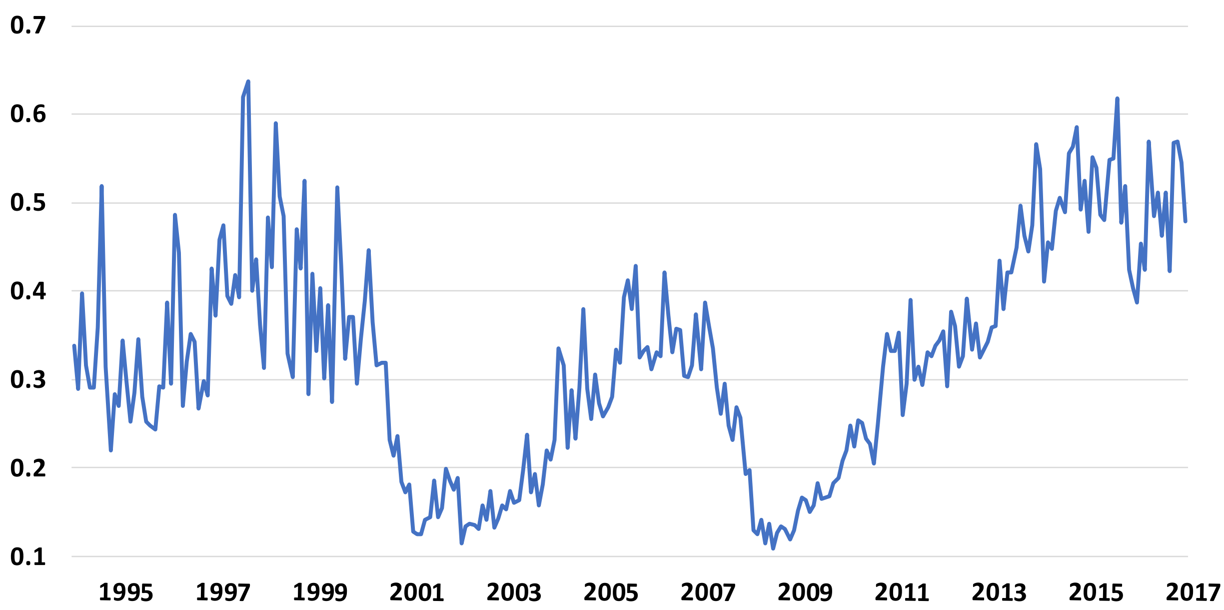

Figure 3.8. *Average Labor Market Tightness in Minnesota, 1995-2017*

Next, let's estimate equation (3), $\boldsymbol{\ln f_t = \ln \bar{\bar{m}} + (1\text{-}\sigma) \ln \theta_t + \varepsilon_t}$, over 1995-2017 creating the simple linear regression model. The natural logarithm of the job finding rate is the predicted variable, and the natural logarithm of the average labor market tightness is the predictor variable of this model. Table 3.1 presents the results of this model.

Table 3.1. *Results and Estimates of the Model with ln (JFR) as the Response Variable and ln (LMT) as the Control Variable*

Linear Regression Equation:	
ln (JFR) = -0.658473 + 0.593867 * ln (LMT)	
Summary of Fit:	
Observations	276
RSquare	0.522468
RSquare Adj.	0.520726
Root Mean Square Error	0.241143
Durbin-Watson Statistic	1.517417
Parameter Estimates:	
Intercept:	
Estimate	-0.658473
Standard Error	0.044107
t Ratio	-14.93
Prob > | t |	< 0.0001*
ln (LMT):	
Estimate	0.593867
Standard Error	0.034299
t Ratio	17.31
Prob > | t |	< 0.0001*
F Ratio	299.7840
Prob > F	< 0.0001*

Note: * Significant at the 1 percent level.

As we can see in the table above, RSquare is 0.5225, which means that more than half of the total variation is explained by the model. The correlation between two variables is very strong (0.7228) and positive. The estimated coefficient of the regressor and the F ratio of the model are statistically significant at the 1% level. Figure 3.9 plots the empirical job finding rate, its predicted value, and the residuals of the model.

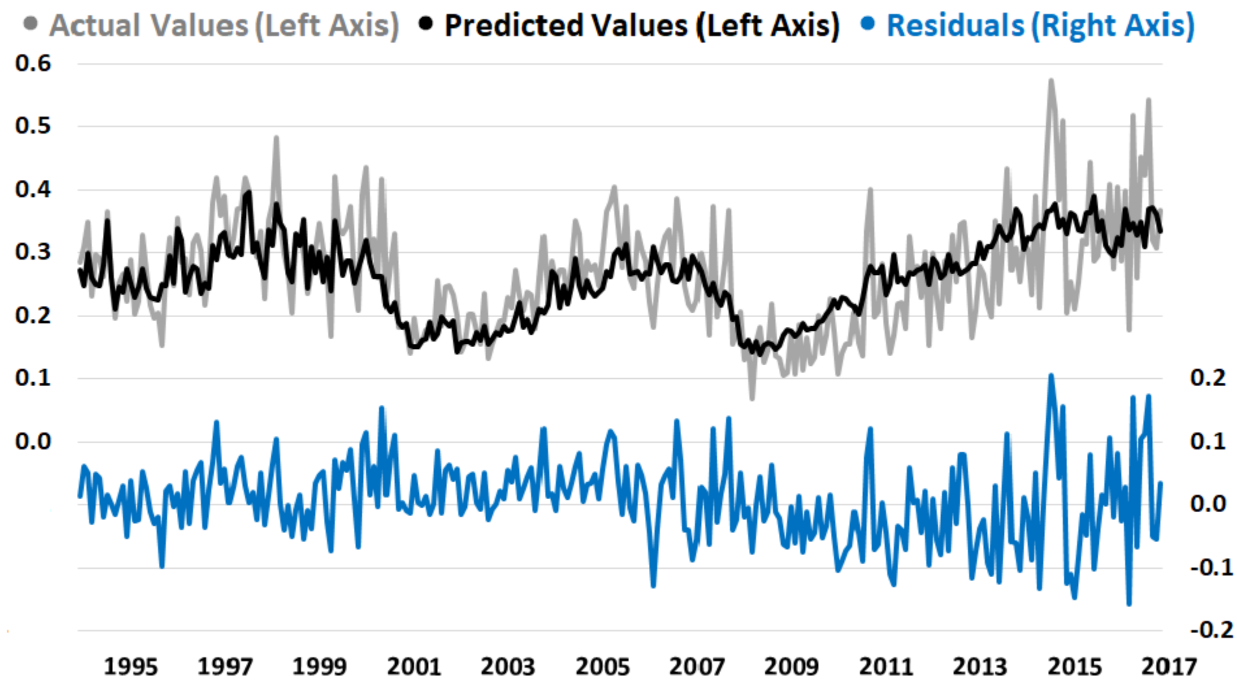

Figure 3.9. *Residuals, Actual and Predicted Values of the Model with ln (JFR) as the Response Variable and ln (LMT) as the Control Variable*

This linear regression estimates the coefficient of the independent variable of this model. Equation (3) defines the value of this coefficient as the value of *1-σ*. According to the regression equation of this model, *1-σ* is 0.594. Consequently, *σ* is 1 - 0.594 = 0.406. All other necessary parts for the last computation – the numbers of new hires, numbers of unemployed, and numbers of new vacancies – were already available. Therefore, let's make the last step of the process of calculating the monthly values of matching efficiency using the following formula:

$$\boldsymbol{m_t = \frac{H_t}{U_t^{\sigma} V_t^{1-\sigma}}} \quad \textit{(4)}$$

The results of this calculation - the values of the matching efficiency of Minnesota's labor market in 1995-2017 - are shown in Figure 3.10.

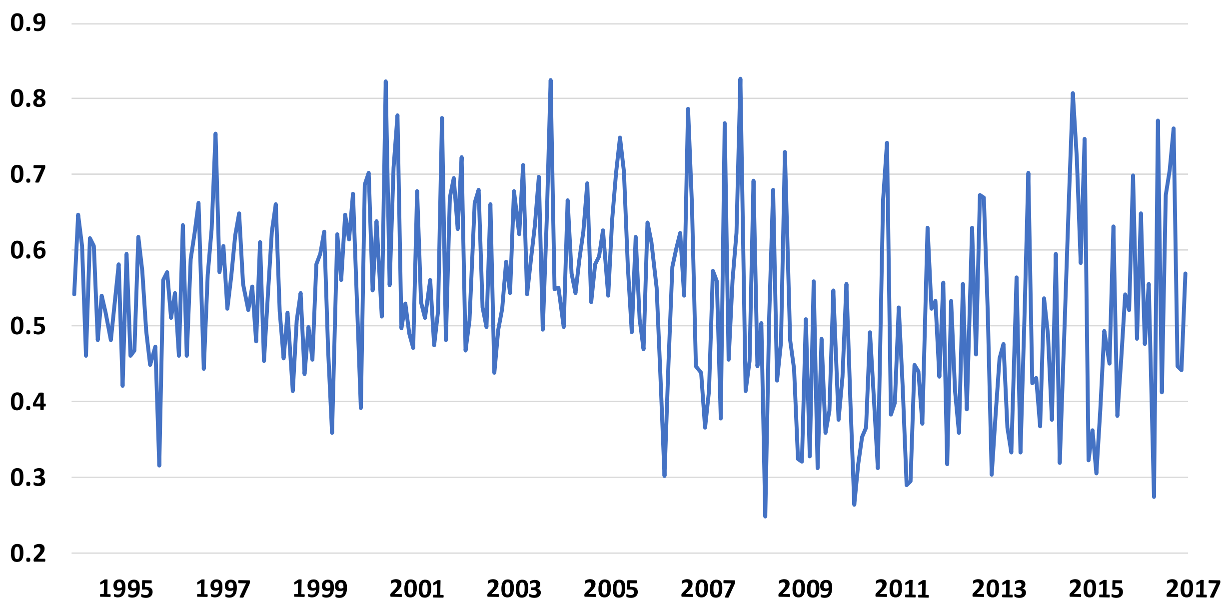

Figure 3.10. *Matching Efficiency of Minnesota's Labor Market, 1995-2017*

We can compare two indicators of the labor market – the calculated matching efficiency and an unemployment rate. Figure 3.11 presents the matching efficiency of the labor market of Minnesota and the state's unemployment rate at the same graph.

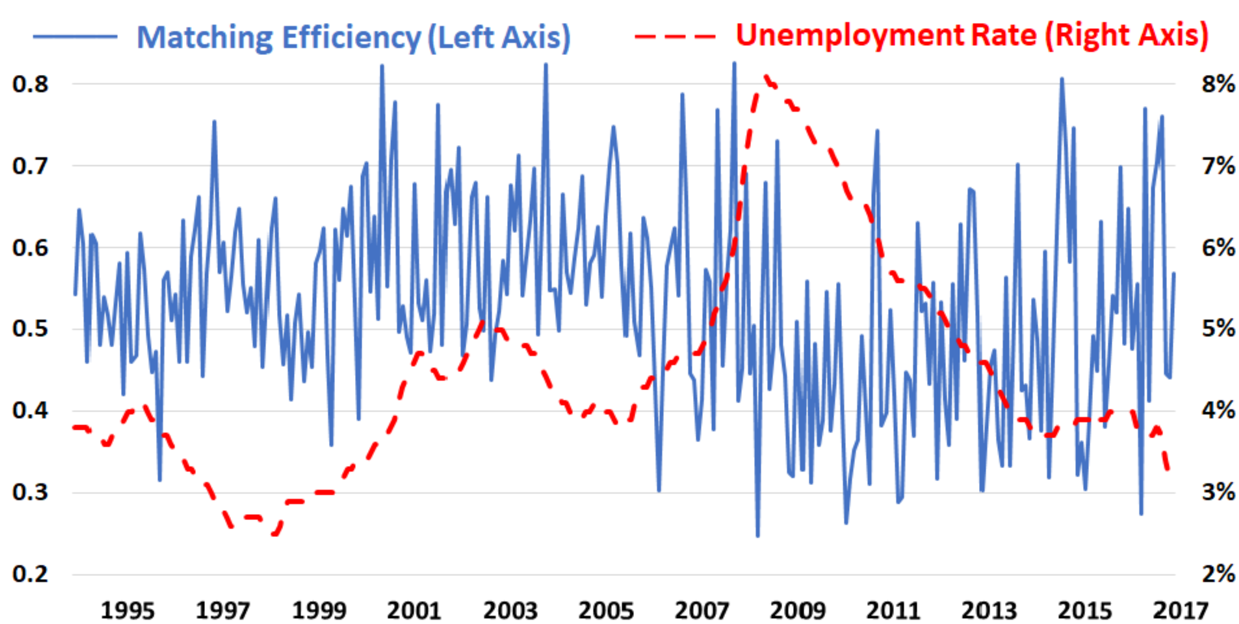

Figure 3.11. *Matching Efficiency and Unemployment Rate in Minnesota, 1995-2017*

The value of the correlation coefficient between two variables is -0.2581, which means that there is a weak negative correlation between two variables. This empirical conclusion confirms the theoretical assumption that the increase in matching efficiency positively effects on the labor market reducing the unemployment rate.

The actual values of the unemployment rate, its predicted values by the regression model, which has the equation *Unemployment Rate = 0.0596 - 0.0279*Matching Efficiency*, and the residuals of this model, are presented in Figure 3.12. We can see that the residuals display a systematic pattern, it is a clear sign that there is a positive serial correlation and that this model fits the data poorly.

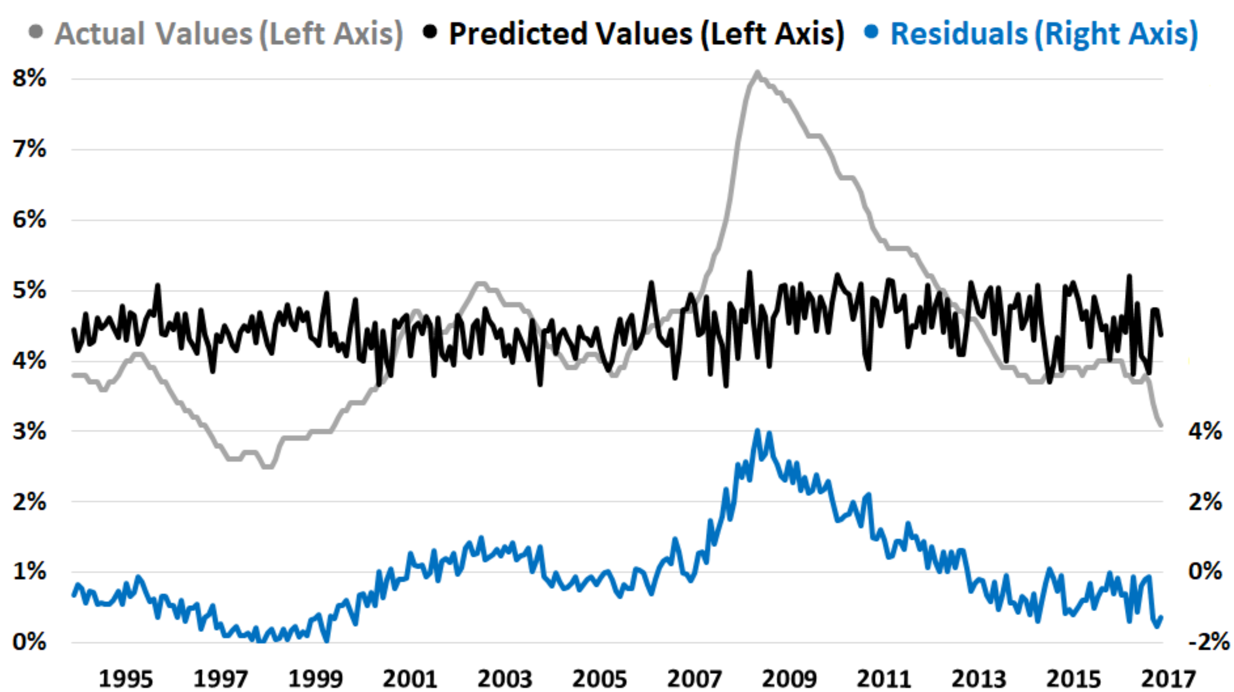

Figure 3.12. *Residuals, Actual and Predicted Values of the Model with the Unemployment Rate as the Response Variable and Matching Efficiency as the Control Variable*

Chapter IV: Matching Efficiency and Government Policy

This chapter examines a correlation between the matching efficiency of the labor market of Minnesota and the elements of government policy. Particularly, this research studies a minimum wage, government spending, refugee arrivals, and Medicaid enrollment.

Matching Efficiency and Minimum Wage

The minimum wage in the United States is set by U.S. labor law and a range of state and local laws. Employers generally have to pay workers the highest minimum wage prescribed by federal, state, and local law. Since July 24, 2009, the federal government has mandated a nationwide minimum wage of $7.25 per hour. Since January 1, 2018, small employers in Minnesota, whose annual receipts are less than $500,000 and who do not engage in interstate commerce, can pay their employees $7.87 per hour. For large employers, the minimum wage is $9.65 per hour. This research uses the minimum wage for the large employers in Minnesota.

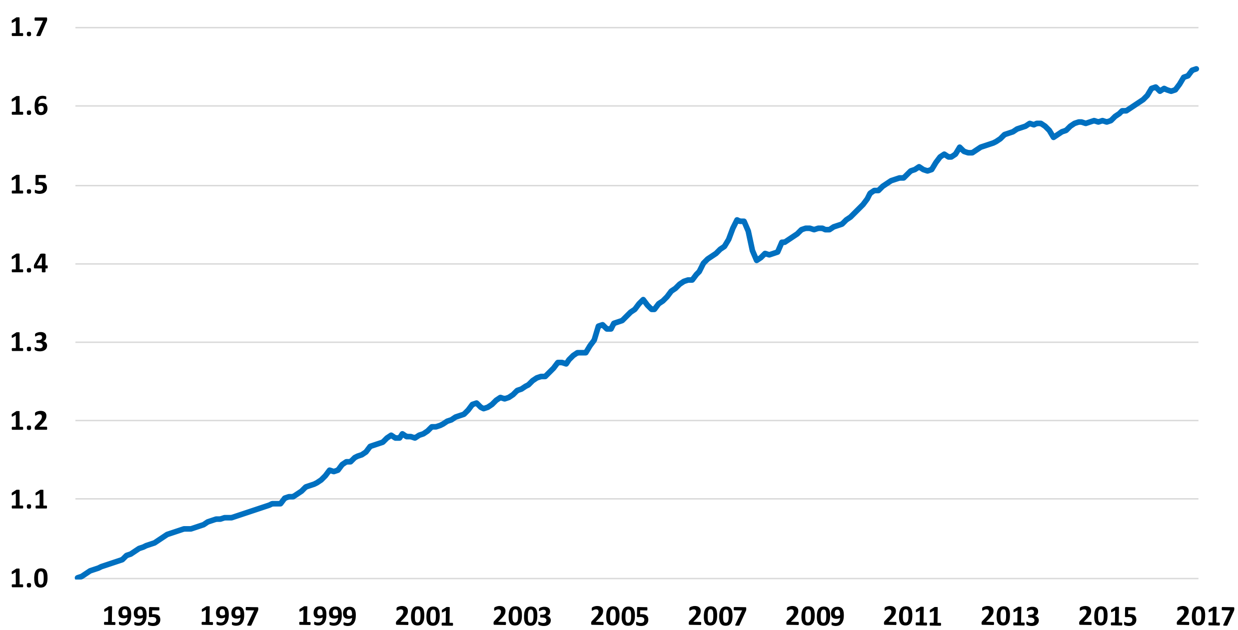

Figure 4.1. *National Consumer Price Index, 1995-2017.* (Jan 1995 = 1)
Source: https://fred.stlouisfed.org

Let's assume that the correlation between matching efficiency and the minimum wage depends on the U.S. inflation rate. For this reason, we can use the Consumer Price Index (CPI) as a measure that examines the weighted average of prices of a basket of consumer goods and services. The CPI is used to adjust the minimum wage for inflation.

Figure 4.1 above presents the monthly values of the national CPI for the time period of 1995-2017 with the base period of January 1995 (for simplicity let's assume that January 1995 is the base month).

The dynamics of the state minimum wage in Minnesota and the federal minimum wage in 1995-2017 are presented in Table 4.1.

Table 4.1. *Dynamics of Minimum Wage in Minnesota, 1995-2017*

Time Period	State Minimum Wage	Federal Minimum Wage
01/01/1995 – 09/30/1996	**$4.25**	**$4.25**
10/01/1996 – 08/31/1997	$4.25	**$4.75**
09/01/1997 – 07/31/2005	**$5.15**	**$5.15**
08/01/2005 – 07/23/2007	**$6.15**	$5.15
07/24/2007 – 07/23/2008	**$6.15**	$5.85
07/24/2008 – 07/23/2009	$6.15	**$6.55**
07/24/2009 – 07/31/2014	$6.15	**$7.25**
08/01/2014 – 07/31/2015	**$8.00**	$7.25
08/01/2015 – 07/31/2016	**$9.00**	$7.25
08/01/2016 – 12/31/2017	**$9.50**	$7.25

Source: http://www.dli.mn.gov
Note: **the actual minimum wage (bold)** is the highest of two wages.

As we can see in the table above, in 2017 the minimum wage in Minnesota increased more than twice since 1995. But this increase is nominal. For obtaining the real increase in the state's minimum wage, we can calculate the real minimum wage using the national Consumer Price Index. Figure 4.2 presents the dynamics of both nominal and real minimum wage in Minnesota at the same graph.

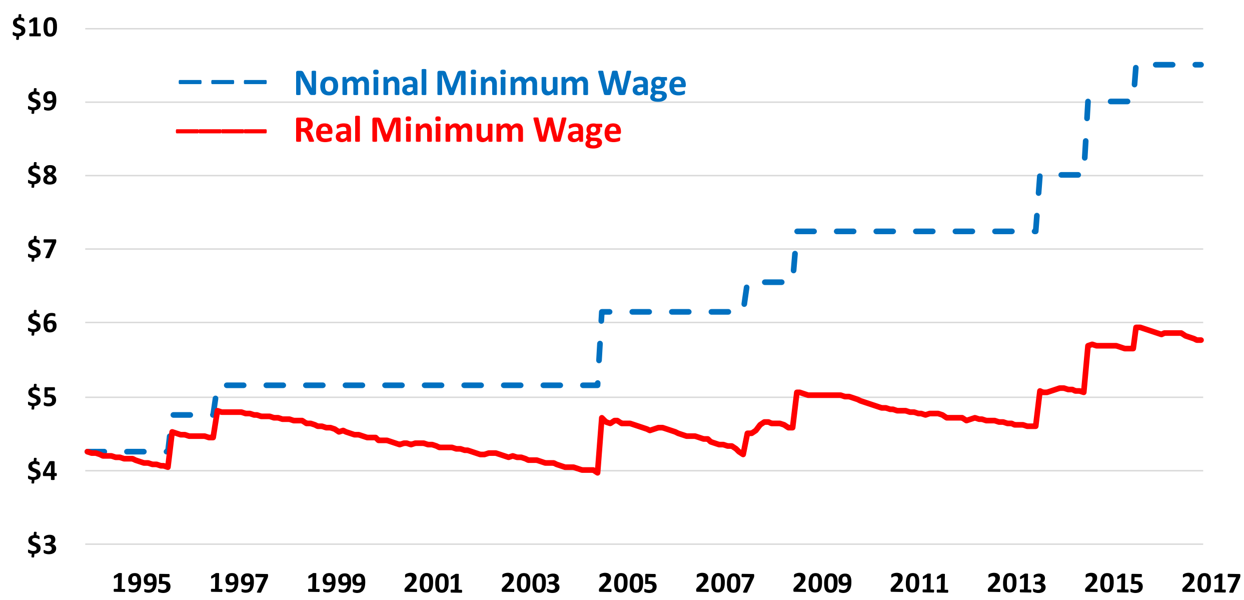

Figure 4.2. *Nominal and Real Minimum Wage in Minnesota, 1995-2017*

According to Figure 4.2, the real minimum wage in Minnesota in December of 2017 increased by almost 1.4 times since January of 1995.

Theoretically, there is a positive correlation between the minimum wage hikes and increased unemployment, especially for young and unskilled workers. This research explores the correlation between the real minimum wage and the matching efficiency of the whole labor market of Minnesota. This correlation is equal to -0.1468. We can conclude that the correlation between two variables is negative and negligible.

Figure 4.3 compares the actual values of matching efficiency with the predicted values by the linear regression model (the equation is *Matching Efficiency = 0.7083 - 0.0377*Real Minimum Wage)* and shows the residuals of this model.

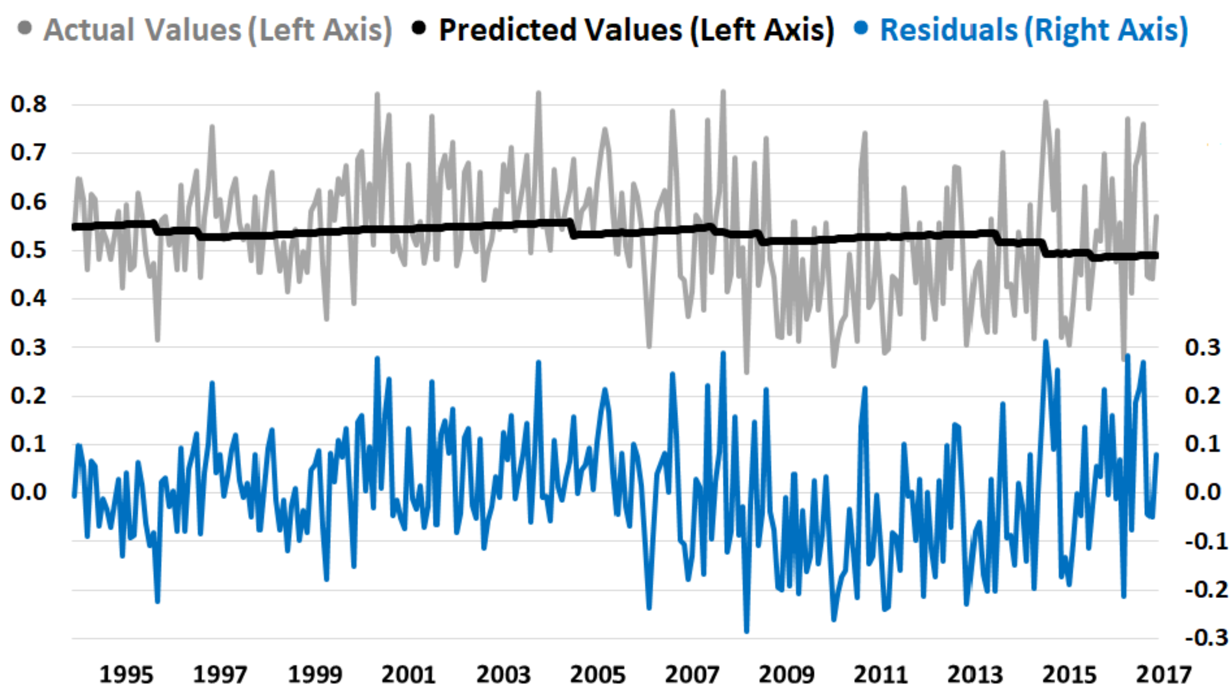

Figure 4.3. *Residuals, Actual and Predicted Values of the Model with Matching Efficiency as the Response Variable and the Real Minimum Wage as the Control Variable*

Matching Efficiency and Government Spending

The second variable, which might be correlated with the matching efficiency of the labor market of Minnesota, is government spending. This part of research uses the values of Minnesota's total government spending, which includes state and local government spending. The values of federal government spending also might have an influence on the labor market of Minnesota. However, the purpose of this thesis is to find the correlation between matching efficiency and government policy in Minnesota, and the government of Minnesota does not relate to federal government spending.

Table 4.2 presents the annual values (in billions of dollars) of government spending in Minnesota in 1995-2017 and the values of government spending as a percentage of gross domestic product (GDP) of Minnesota.

Table 4.2. *State and Local Government Spending in Minnesota, 1995-2017*

Year	**State ($ bln)**	**Local ($ bln)**	**Total**	
			($ bln)	**% of GDP**
1995	10.7	16.3	27.0	20.0
1996	11.3	16.6	27.9	19.1
1997	11.5	16.7	28.2	17.9
1998	12.4	18.1	30.5	18.2
1999	13.4	18.5	31.9	18.1
2000	15.7	19.7	35.4	18.5
2001	16.4	20.9	37.3	19.1
2002	18.4	22.1	40.5	19.9
2003	19.3	22.5	41.8	19.3
2004	18.5	23.0	41.5	18.0
2005	19.4	23.5	42.9	17.6
2006	19.8	24.7	44.5	17.8
2007	21.2	26.0	47.2	18.2
2008	23.1	27.8	50.9	19.3
2009	25.1	29.3	54.4	21.1
2010	27.5	28.5	56.0	20.7
2011	27.4	28.3	55.7	19.7
2012	27.8	28.8	56.6	19.3
2013	27.0	28.9	55.9	18.4
2014	29.6	30.0	59.6	18.8
2015	30.4	30.8	61.2	18.7
2016	31.4	31.7	63.1	18.8
2017	32.3	32.7	65.0	18.8

Source: https://www.usgovernmentspending.com

In 2017, total state and local government spending was $65 bln, which is 2.4 times more than $27 bln in 1995. Nevertheless, this research uses the values of government spending as a percentage of GDP of Minnesota, which is the more informative indicator. Both time series – government spending in billions of dollars and government spending as a percentage of Minnesota's GDP – are presented in Figure 4.4.

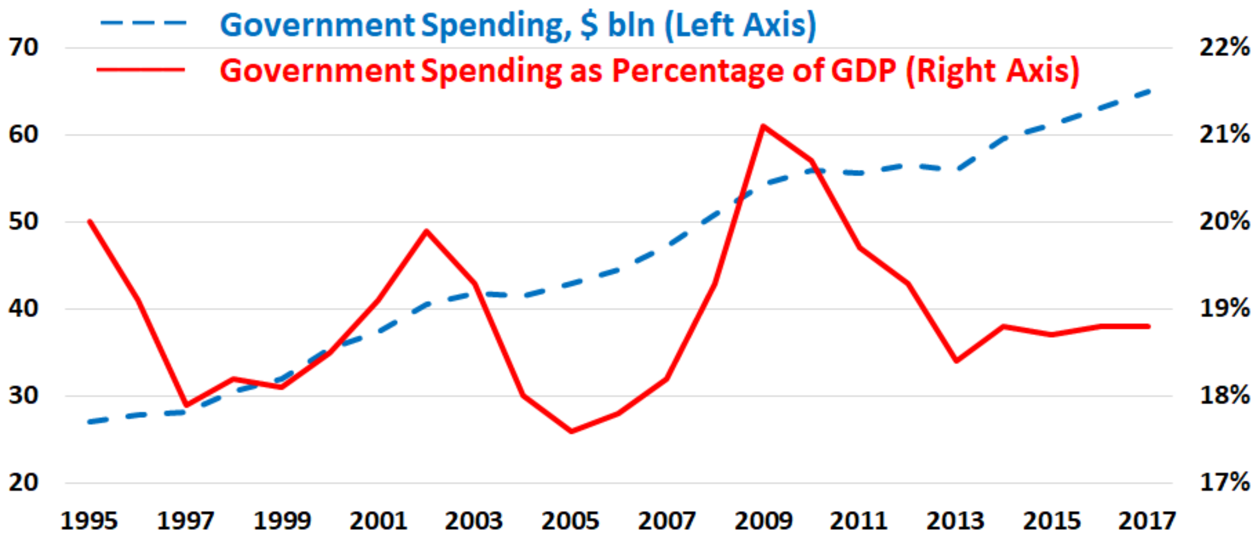

Figure 4.4. *Government Spending in Minnesota: Values and Percentage of GDP, 1995-2017*

As we can see in this figure, government spending as a percentage of GDP had cyclical fluctuations during 1995-2017.

In theory, government spending can create jobs to reduce unemployment. However, the impact of increased (or decreased) government spending (in any level – federal, state, or local) on the labor market's matching efficiency of the specific state (or an economy as a whole) is mostly unknown.

The correlation coefficient between the matching efficiency of the labor market of Minnesota and total (state and local) government spending in Minnesota as a percentage of state's GDP is equal to -0.2188. This means that there is a weak negative correlation between two variables.

The actual values of matching efficiency, its predicted values by the regression equation *Matching Efficiency = 1.0944 - 2.9709*Government Spending (% of GDP),* and the residuals are presented in Figure 4.5.

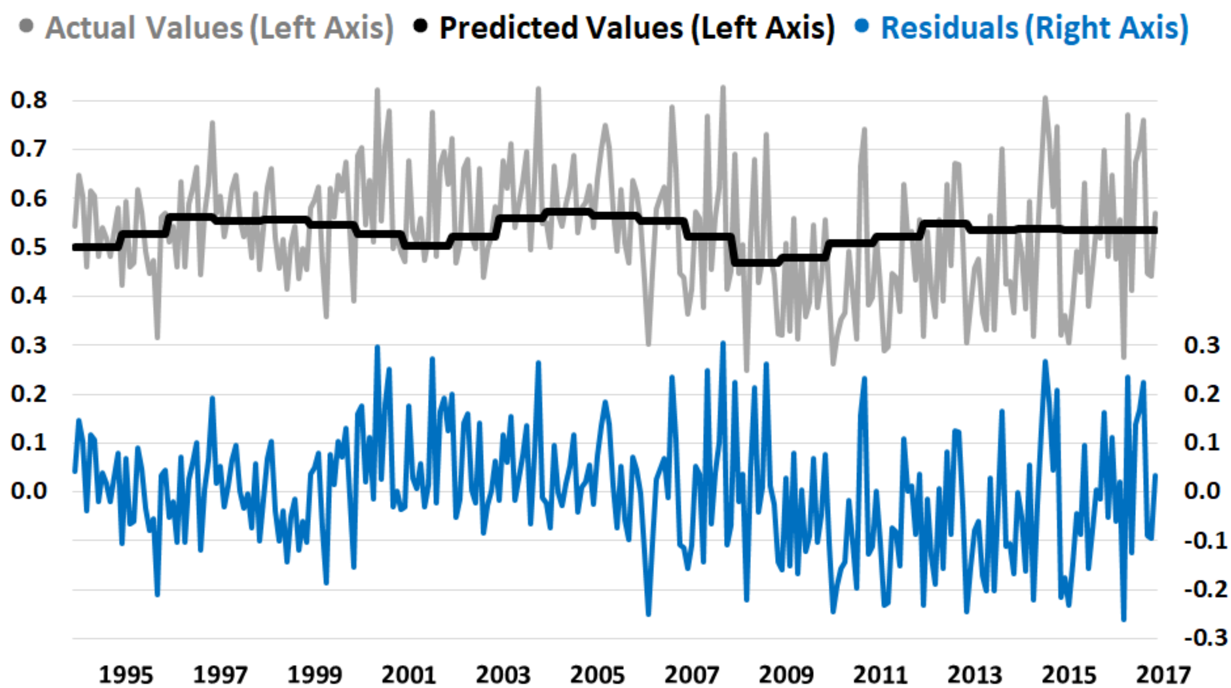

Figure 4.5. *Residuals, Actual and Predicted Values of the Model with Matching Efficiency as the Response Variable and Government Spending (% of GDP) as the Control Variable*

Matching Efficiency and Refugee Arrivals

The next factor, which might have an impact on the matching efficiency of the labor market of Minnesota, is refugee arrivals. It is widely known that several last decades Minnesota is among top states for refugee resettlement. The immigration policy in Minnesota is the important part of the policy of the state's government which effects different socioeconomic aspects of the state, including its labor market. There are a lot of different opinions (sometimes very controversial opinions) about the level of effectiveness of the immigration policy in Minnesota.

This section of the paper uses the primary refugee arrivals to Minnesota as the variable of research. Annual numbers of the primary refugee arrivals in 1995-2016 are presented in Table 4.3. At the time of writing this paper, the number of primary refugee arrivals for the last year (2017) is not available, therefore 2017 year is not used for this chapter's objectives.

Table 4.3. *Primary Refugee Arrivals to Minnesota, 1995-2016*

Year	**Refugee Arrivals**	
	Numbers	**% of Population**
1995	2,566	0.056
1996	2,189	0.047
1997	1,424	0.030
1998	1,863	0.039
1999	3,917	0.082
2000	4,011	0.081
2001	2,793	0.056
2002	1,032	0.021
2003	2,403	0.048
2004	7,351	0.144
2005	5,326	0.104
2006	5,355	0.104
2007	2,868	0.055
2008	1,203	0.023
2009	1,265	0.024
2010	2,321	0.044
2011	1,891	0.035
2012	2,264	0.042
2013	2,160	0.040
2014	2,505	0.046
2015	2,244	0.041
2016	3,186	0.058

Source: http://www.health.state.mn.us

We can see in the table above that the largest values of this variable (more than 5,000 arrivals) are located in the middle of the studied time period (in 2004-2006). It should be noted that every year from 1995 until 2016, the numbers of primary refugee arrivals to Minnesota were larger than one thousand people.

Figure 4.6 presents both the numbers of refugee arrivals and the numbers of refugee arrivals as a percentage of the population of Minnesota.

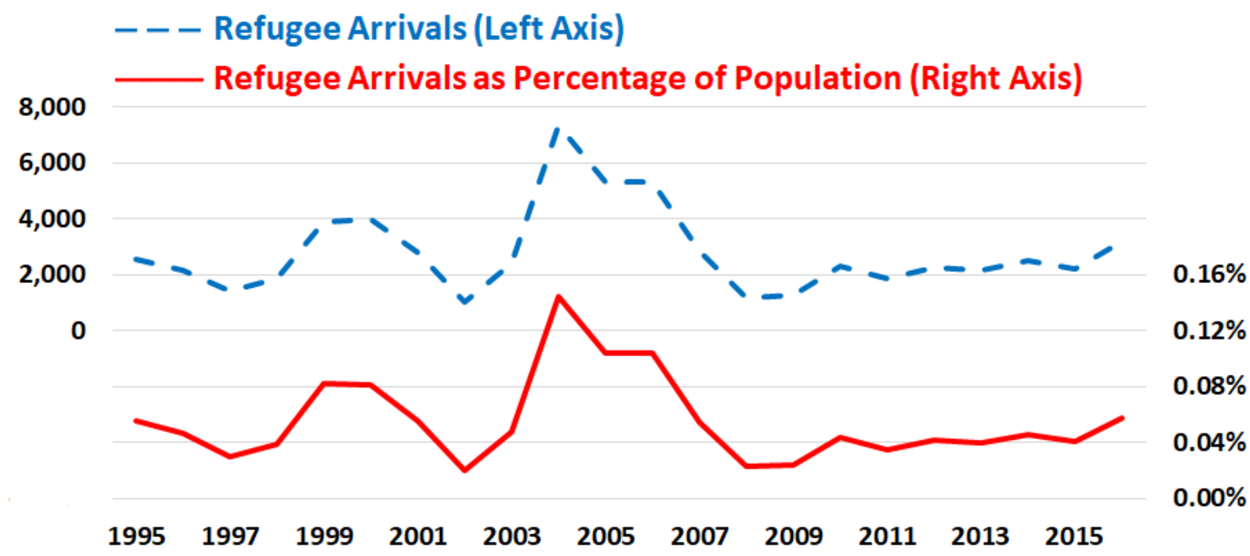

Figure 4.6. *Primary Refugee Arrivals to Minnesota, 1995-2016*

The figure above shows that two time series have almost identical dynamics. Therefore, we can draw a conclusion that there is no essential difference between them as the predictors of the matching efficiency of the labor market of Minnesota. However, this research uses the numbers of the primary refugee arrivals to Minnesota as the potential predictor of the state's matching efficiency.

There is no clear position about the impact of the refugee arrivals on the labor market. Even authors, who consider that refugees might increase public expenditure, public debt, and unemployment, admit that these assumptions are highly vague, and depend on the numbers of refugees, the duration of the procedures for processing and deciding asylum applications, and how soon refugees find jobs in the labor markets of receiving communities. The empirical relationship between the numbers of refugee arrivals and the matching efficiency of the national and local labor markets is unknown.

The correlation between the numbers of the primary refugee arrivals to Minnesota (in thousands) and matching efficiency is equal to 0.2163. Therefore, we can make a conclusion that there is a weak and positive empirical correlation between the primary refugee arrivals to Minnesota and the matching efficiency of the state's labor market.

Figure 4.7 presents the actual values of matching efficiency, the predicted values, and the residuals of the model which has the equation *Matching Efficiency = 0.4824 + 0.0171*Refugee Arrivals*.

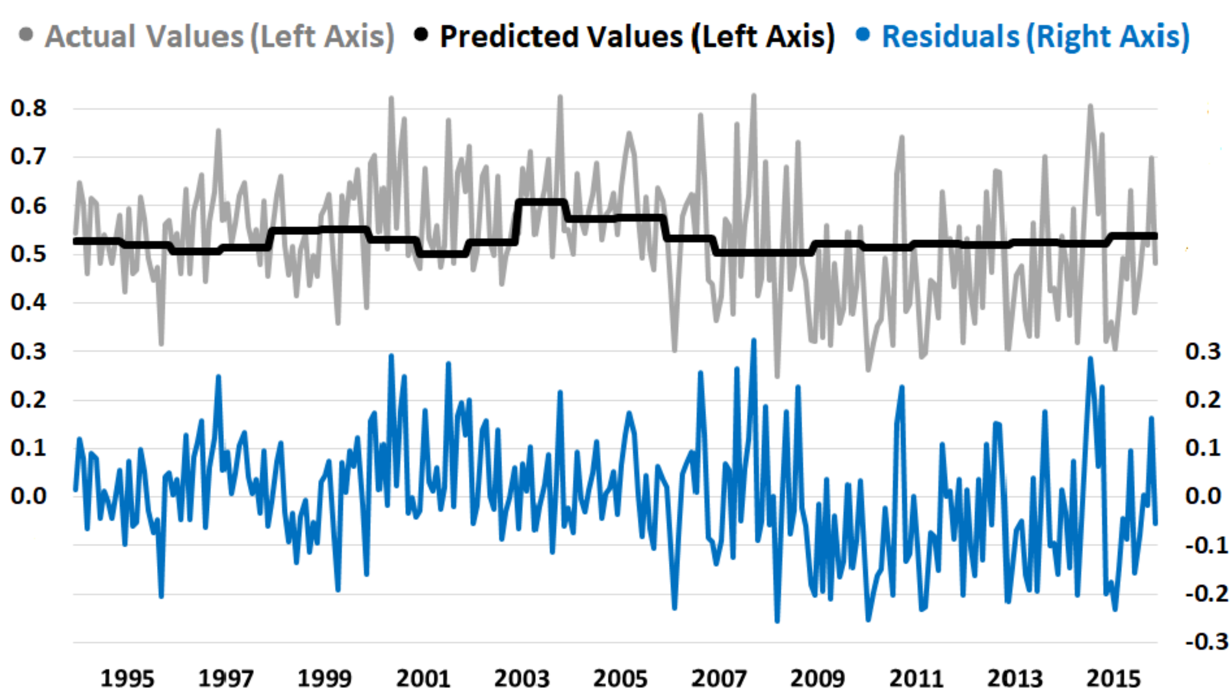

Figure 4.7. *Residuals, Actual and Predicted Values of the Model with Matching Efficiency as the Response Variable and Primary Refugee Arrivals as the Control Variable*

Matching Efficiency and Medicaid Enrollment

The last variable in this research, which might have an influence on the matching efficiency of the labor market of Minnesota, is Medicaid enrollment. The Patient Protection and Affordable Care Act (the ACA, or Obamacare), passed in 2010, revised and expanded Medicaid eligibility starting in 2014.

Table 4.4. *Health Insurance Coverage Status in Minnesota, 1995-2016*

Year	All Insured People		Medicaid Coverage	
	Numbers in thousands	%	Numbers in thousands	%
1995	4,260	92.0	542	11.7
1996	4,229	89.8	550	11.7
1997	4,329	90.8	631	13.2
1998	4,385	90.7	424	8.8
1999	4,556	93.4	388	8.0
2000	4,502	92.0	331	6.8
2001	4,582	93.1	388	7.9
2002	4,657	92.1	477	9.4
2003	4,634	91.3	488	9.6
2004	4,702	91.7	433	8.4
2005	4,740	92.4	486	9.5
2006	4,692	91.1	608	11.8
2007	4,775	92.0	573	11.0
2008	4,717	91.6	628	12.2
2009	4,724	90.9	697	13.4
2010	4,776	90.9	745	14.2
2011	4,819	91.2	773	14.6
2012	4,895	92.0	773	14.5
2013	4,923	91.8	779	14.5
2014	5,081	94.1	895	16.6
2015	5,187	95.5	988	18.2
2016	5,237	95.9	990	18.1

Source: https://www.census.gov

According to the National Conference of State Legislatures, Medicaid – a federal/state partnership with shared authority and financing – is a health insurance program for low-income individuals, children, their parents, the elderly and people with disabilities. Medicaid pays for health care for more than 74.5 million people nationally. Although participation is optional, all 50 states participate in the Medicaid program. However, eligibility for Medicaid benefits varies widely among the states – all states must meet federal minimum requirements, but they have options for expanding Medicaid beyond the minimum federal guidelines.

Minnesota is among 32 states in which Medicaid expansion under the ACA was adopted. The annual numbers of all insured people in Minnesota and the numbers of Minnesotans covered by Medicaid are presented in Table 4.4 above. The numbers for the last year, 2017, are not available yet, therefore this section uses the 1995-2016 period. Table 4.4 shows that in 2016 only about four percent of Minnesotans were still uninsured. The number of state's residents enrolled in Medicaid in 2016 is almost 1 million, which is approximately twice larger than it was in 1995 and about three times larger than it was in 2000.

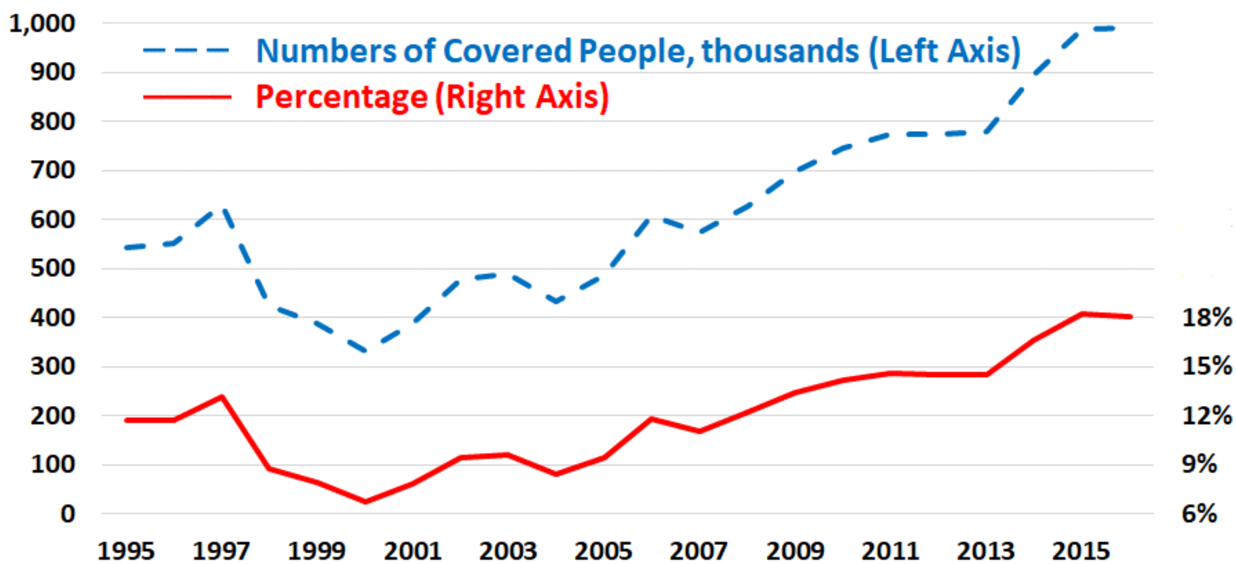

Figure 4.8. *People Covered by Medicaid and Percentage of Covered People, 1995-2016*

The number of people covered by the Medicaid program as a percentage of the state's total population might be a more informative indicator. Figure 4.8 above presents the numbers of Minnesotans enrolled in Medicaid and the percentage of enrolled people at the same graph, and we can see that there is almost no difference between dynamics of these two variables.

The correlation coefficient between the matching efficiency of labor market of Minnesota and the percentage of people covered by Medicaid program is equal to -0.3188. It means that there is a moderate negative correlation between two variables. This empirical conclusion confirms the assumptions in the related literature that Medicaid expansion may have a negative effect on the labor market.

The actual values of matching efficiency, its predicted values by the regression equation *Matching Efficiency = 0.6733 - 0.0118 * % of Medicaid Enrollment,* and the residuals are presented in Figure 4.9.

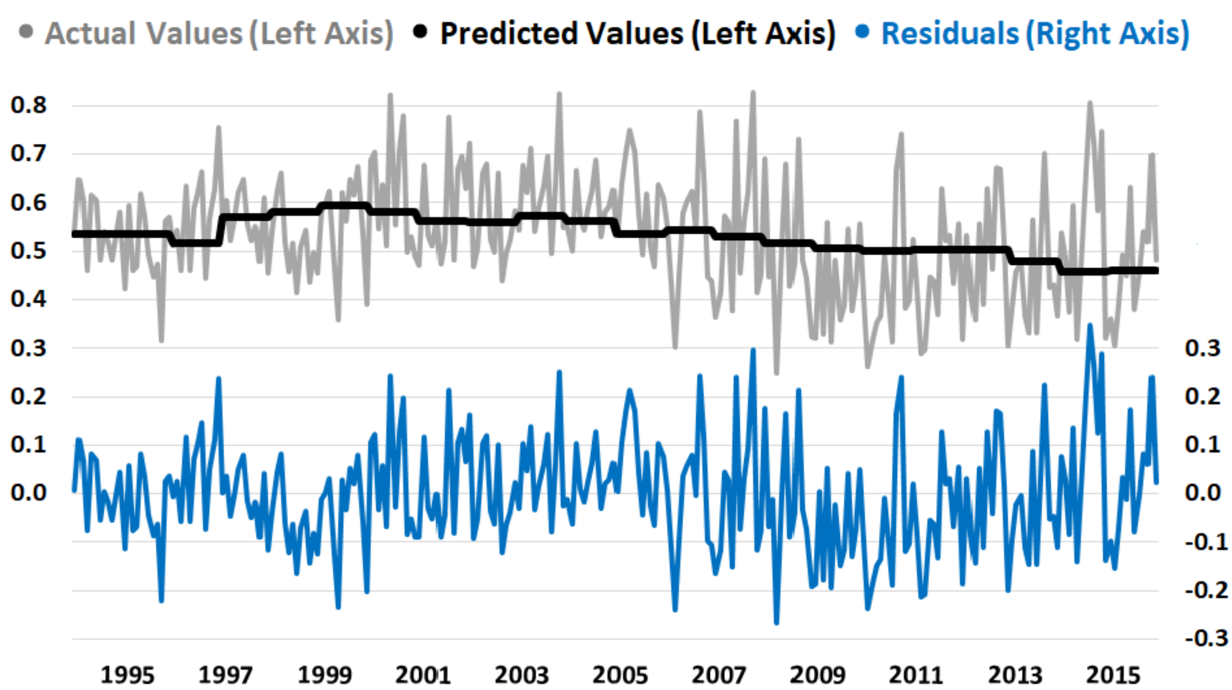

Figure 4.9. *Residuals, Actual and Predicted Values of the Model with Matching Efficiency as the Response Variable and Percentage of Medicaid Enrollment as the Control Variable*

Matching Efficiency and Combination of Studied Factors

The model with all available predictors of the matching efficiency of Minnesota's labor market is explored at the end of this chapter.

According to Wooldridge (2013), multiple regression analysis is more adaptable to ceteris paribus analysis because it allows us to explicitly control for many other factors that simultaneously affect the dependent variable. The author considers that "this is important both for testing economic theories and for evaluating policy effects when we must rely on nonexperimental data. Because multiple regression models can accommodate many explanatory variables that may be correlated, we can hope to infer causality in cases where simple regression analysis would be misleading" (p.68).

The multiple linear regression model is built for these purposes. Matching efficiency is a regressand of this model. The real minimum wage, government spending as a percentage of GDP, the primary refugee arrivals, and people covered by Medicaid program as a percentage of the total population are regressors of this model.

There are no any theoretical assumptions in the economic and econometric literature about joint significance of these four independent variables in the regression model where the matching efficiency of the labor market is the response variable.

The results of this model are presented in Table 4.5. According to the statistical summary of this model, 12.08% of the total variation is explained by the regression model and the value of adjusted RSquare is 10.72%. Only one predictor – the percentage of people covered by Medicaid – is statistically significant at the 1 percent level. Three other predictors are not statistically significant.

Table 4.5. *Results and Estimates of the Model with Matching Efficiency as the Response Variable and Four Studied Variables as the Control Variables*

Linear Regression Equation:	
ME = 0.986592 - 0.002749*RMW - 1.797846*%GS + 0.003582*RA - 0.009400*%MdE	
Summary of Fit:	
Observations	264
RSquare	0.120776
RSquare Adj.	0.107197
Root Mean Square Error	0.113110
Durbin-Watson Statistic	1.699611
Parameter Estimates:	
Intercept:	
Estimate	0.986592
Standard Error	0.211160
t Ratio	4.67
Prob > | t |	< 0.0001*
Real Minimum Wage:	
Estimate	-0.002749
Standard Error	0.024020
t Ratio	-0.11
Prob > | t |	0.9090
Government Spending (% of GDP):	
Estimate	-1.797846
Standard Error	0.935352
t Ratio	-1.92
Prob > | t |	0.0557
Refugee Arrivals:	
Estimate	0.003582
Standard Error	0.005859
t Ratio	0.61
Prob > | t |	0.5415
% of Medicaid Enrollment:	
Estimate	-0.009400
Standard Error	0.003211
t Ratio	-2.93
Prob > | t |	0.0037*
F Ratio	8.8945
Prob > F	< 0.0001*

Note: * Significant at the 1 percent level.

However, according to the value of the F ratio, the overall regression model is statistically significant at the 1 percent level. Therefore, we can conclude that four control variables of this model are jointly statistically significant at this level.

Figure 4.10 presents the actual values of matching efficiency, its predicted values, and the residuals of this model.

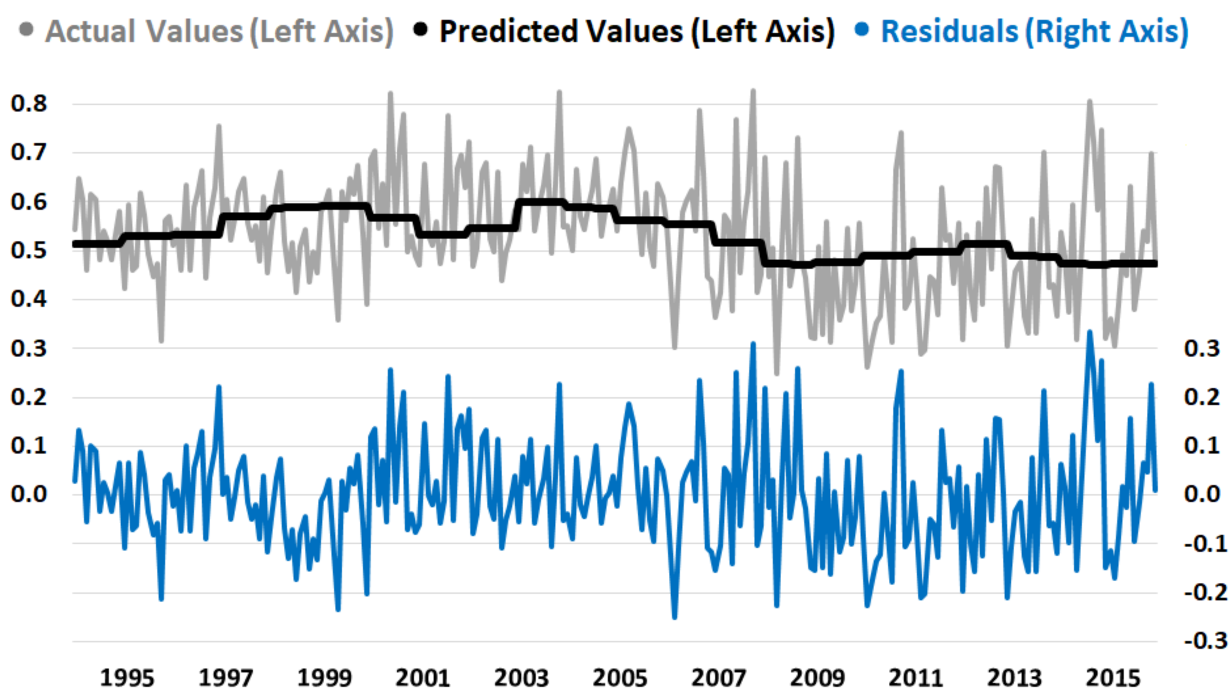

Figure 4.10. *Residuals, Actual and Predicted Values of the Model with Matching Efficiency as the Response Variable and Four Studied Variables as the Control Variables*

For better understanding the results of this regression model, it is useful to look at the correlation coefficients between studied variables. Table 4.6 shows that the response variable, matching efficiency, does not have strong association with independent variables. The highest value of the correlation coefficients is about -0.32 between matching efficiency and Medicaid enrollment. The absolute values of the correlation coefficients between the regressand and other regressors are close to 0.2.

Table 4.6. *Correlation Coefficients between Studied Variables*

	ME	RMW	GS%GDP	RA	%MdE
Matching Efficiency	**1**	**-0.2114**	**-0.2252**	**0.2163**	**-0.3188**
Real Minimum Wage	**-0.2114**	**1**	**0.1048**	**-0.2093**	**0.7042**
Gov. Spend. as % of GDP	**-0.2252**	**0.1048**	**1**	**-0.5726**	**0.2420**
Refugee Arrivals	**0.2163**	**-0.2093**	**-0.5726**	**1**	**-0.3577**
% of Medicaid Enrollment	**-0.3188**	**0.7042**	**0.2420**	**-0.3577**	**1**

In addition, we can see that multicollinearity is present in the data. Some independent variables are strongly correlated with each other. For example, the correlation coefficient between the real minimum wage and Medicaid enrollment is about 0.7.

According to Larose and Larose (2015), “multicollinearity leads to instability in the solution space, leading to possible incoherent results” (p.259). The authors claim that in a data set with severe multicollinearity, it is possible that the F-test for the overall regression is significant, while all t-tests for the individual predictors are not significant. In our case, the situation is almost the same, the F ratio of the overall regression is significant at the 1 percent level, whereas the t ratios of three predictors are not statistically significant at the 5 percent level.

Chapter V: Conclusion

This thesis computes the matching efficiency of the labor market of Minnesota in 1995-2017 and investigates the impact of government policy on the calculated matching efficiency.

In the time framework analyzed in this paper, matching efficiency has a weak and negative linear correlation with the unemployment rate in Minnesota. This empirical finding confirms the theoretical assumption that these two important indicators of the labor market have a negative correlation.

The real minimum wage has a negative correlation with matching efficiency, which confirms the assumptions in the literature that the increase in the minimum wage reduces employment. However, the linear correlation between two variables is weak.

The correlation between matching efficiency and government spending as a percentage of Minnesota's GDP is slightly stronger that the previous correlation. The correlation coefficient is negative and this empirical result of research supports the theoretical assumptions in the related literature that government spending for the most part has a negative economic impact on the labor market.

There is only one element of government policy explored in this research which has a positive correlation with matching efficiency. This predictor is the number of primary refugee arrivals to Minnesota. According to the equation of the simple linear regression model, the increase in the refugee arrivals by one thousand people leads to the increase in matching efficiency by 0.017 (or 1.7%). Despite of the weak correlation between two variables, this empirical conclusion might be used as an evidence-based argument in a polemic about the economic impact of refugee arrivals to Minnesota. However, it should be noted that government policy directly does not affect the specific numbers of refugee arrivals. The state's government can stop the process of refugee resettlement in Minnesota (in this case the number of refugee arrivals would be zero), but the government cannot directly increase or reduce these numbers after opening the doors to refugees from different countries. The particular annual numbers of the refugee arrivals depend on other social or economic factors, but do not depend on government policy.

The impact of Medicaid enrollment on the matching efficiency of Minnesota is negative and stronger than the effect of other three predictors. The linear correlation between two variables is equal to -0.32. The theoretical assumptions in the related literature that the Medicaid expansion reduces employment and, consequently, has a negative effect on the labor market, are confirmed by the empirical results of this research.

Nevertheless, it should be emphasized that all conclusions above might be false if the initial data is not trustworthy. Concretely, one of the main variables, which is used in this paper, is the number of new hires. In the framework analyzed in this thesis, the number of new hires means the number of unemployed people who have found a job. Unfortunately, the variable, which is available from the Current Population Surveys, does not distinguish workers who have found their jobs being unemployed and people who have simply changed their jobs without being unemployed. If workers from the second group represent the majority of the new hires, for that time period the calculated value of the job finding rate is not reliable for this research. Hypothetically, it might be possible that the job finding rate might have the value greater than 1, which makes the values of matching efficiency for those periods inaccurate in the framework of the Cobb-Douglas matching function with constant returns to scale.

The other problem with this variable is that people from other states might use online advertisements of Minnesota's companies to find new jobs and move to Minnesota. In this case, the number of new hires can also rise without any participation of unemployed residents of Minnesota. For this reason, the initial data might not be credible in the framework of the Cobb-Douglas matching function.

Further empirical research in this field is clearly warranted to study the impact of the other elements of government policy on the matching efficiency of the labor market. The implications of this study might be very useful for additional explorations of the labor market.

One direction for further research is comparing the levels of the matching efficiency of different states or industries and examining the causes of these differences. The study of differences might be useful for an insight into reasons of the state-to-state migration and an investigation of factors making specific states and industries more attractive than others.

Another direction is to study how effectively government policy impacts on the labor market's matching efficiency. The further research in this field might help to find more effectual tools to reduce the unemployment rate and to achieve the higher rates of consistent economic growth.

This thesis is only a small step in these directions. Nevertheless, it is hoped that this paper would serve as a local illustration of important processes of a whole economy.

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Appendix 1

Job Finding Rate in Minnesota (1995-2017)

Jan 1995	0.2851	Jan 1998	0.3586	Jan 2001	0.3915	Jan 2004	0.1923
Feb 1995	0.3094	Feb 1998	0.3897	Feb 2001	0.4357	Feb 2004	0.2287
Mar 1995	0.3496	Mar 1998	0.3000	Mar 2001	0.3000	Mar 2004	0.2120
Apr 1995	0.2321	Apr 1998	0.3211	Apr 2001	0.3223	Apr 2004	0.2719
May 1995	0.2963	May 1998	0.3693	May 2001	0.2601	May 2004	0.2306
Jun 1995	0.2905	Jun 1998	0.3720	Jun 2001	0.4170	Jun 2004	0.2075
Jul 1995	0.2617	Jul 1998	0.4184	Jul 2001	0.2320	Jul 2004	0.2381
Aug 1995	0.3659	Aug 1998	0.3992	Aug 2001	0.2837	Aug 2004	0.2325
Sep 1995	0.2604	Sep 1998	0.3200	Sep 2001	0.3308	Sep 2004	0.1791
Oct 1995	0.1960	Oct 1998	0.2929	Oct 2001	0.1820	Oct 2004	0.2591
Nov 1995	0.2516	Nov 1998	0.3337	Nov 2001	0.1867	Nov 2004	0.3266
Dec 1995	0.2670	Dec 1998	0.2279	Dec 2001	0.1780	Dec 2004	0.2302
Jan 1996	0.2237	Jan 1999	0.3514	Jan 2002	0.1394	Jan 2005	0.2877
Feb 1996	0.2890	Feb 1999	0.3768	Feb 2002	0.1966	Feb 2005	0.2521
Mar 1996	0.2028	Mar 1999	0.4832	Mar 2002	0.1545	Mar 2005	0.2725
Apr 1996	0.2221	Apr 1999	0.3465	Apr 2002	0.1595	Apr 2005	0.2721
May 1996	0.3279	May 1999	0.2973	May 2002	0.1777	May 2005	0.2293
Jun 1996	0.2694	Jun 1999	0.2674	Jun 2002	0.1742	Jun 2005	0.2825
Jul 1996	0.2175	Jul 1999	0.2034	Jul 2002	0.1640	Jul 2005	0.3512
Aug 1996	0.1958	Aug 1999	0.3242	Aug 2002	0.2565	Aug 2005	0.3299
Sep 1996	0.2047	Sep 1999	0.3265	Sep 2002	0.1843	Sep 2005	0.2360
Oct 1996	0.1521	Oct 1999	0.2980	Oct 2002	0.2455	Oct 2005	0.2877
Nov 1996	0.2691	Nov 1999	0.2351	Nov 2002	0.2473	Nov 2005	0.2734
Dec 1996	0.3245	Dec 1999	0.2710	Dec 2002	0.2337	Dec 2005	0.2802
Jan 1997	0.2478	Jan 2000	0.3026	Jan 2003	0.2000	Jan 2006	0.2474
Feb 1997	0.3544	Feb 2000	0.3474	Feb 2003	0.1415	Feb 2006	0.3008
Mar 1997	0.2840	Mar 2000	0.3064	Mar 2003	0.1559	Mar 2006	0.3656
Apr 1997	0.2907	Apr 2000	0.2652	Apr 2003	0.2024	Apr 2006	0.3797
May 1997	0.2340	May 2000	0.1667	May 2003	0.2032	May 2006	0.4044
Jun 1997	0.3167	Jun 2000	0.4206	Jun 2003	0.1751	Jun 2006	0.3409
Jul 1997	0.3290	Jul 2000	0.3392	Jul 2003	0.1553	Jul 2006	0.2765
Aug 1997	0.3027	Aug 2000	0.3309	Aug 2003	0.2344	Aug 2006	0.3738
Sep 1997	0.2163	Sep 2000	0.3409	Sep 2003	0.1317	Sep 2006	0.2610
Oct 1997	0.2676	Oct 2000	0.3738	Oct 2003	0.1554	Oct 2006	0.2436
Nov 1997	0.3788	Nov 2000	0.2589	Nov 2003	0.1741	Nov 2006	0.3332
Dec 1997	0.4194	Dec 2000	0.2079	Dec 2003	0.1916	Dec 2006	0.3054

Jan 2007	0.2860	Jan 2010	0.1102	Jan 2013	0.1529	Jan 2016	0.2541
Feb 2007	0.2213	Feb 2010	0.1733	Feb 2013	0.2988	Feb 2016	0.2114
Mar 2007	0.1809	Mar 2010	0.1065	Mar 2013	0.2261	Mar 2016	0.2545
Apr 2007	0.2496	Apr 2010	0.1863	Apr 2013	0.1801	Apr 2016	0.3190
May 2007	0.3002	May 2010	0.1140	May 2013	0.2860	May 2016	0.3147
Jun 2007	0.3263	Jun 2010	0.1653	Jun 2013	0.2238	Jun 2016	0.4428
Jul 2007	0.3373	Jul 2010	0.1238	Jul 2013	0.3278	Jul 2016	0.2860
Aug 2007	0.2663	Aug 2010	0.1346	Aug 2013	0.2532	Aug 2016	0.2953
Sep 2007	0.3866	Sep 2010	0.1996	Sep 2013	0.3446	Sep 2016	0.3660
Oct 2007	0.3328	Oct 2010	0.1398	Oct 2013	0.3487	Oct 2016	0.3126
Nov 2007	0.2486	Nov 2010	0.1700	Nov 2013	0.2738	Nov 2016	0.4076
Dec 2007	0.2195	Dec 2010	0.2263	Dec 2013	0.1654	Dec 2016	0.2747
Jan 2008	0.2075	Jan 2011	0.1755	Jan 2014	0.2086	Jan 2017	0.4052
Feb 2008	0.2257	Feb 2011	0.1084	Feb 2014	0.2779	Feb 2017	0.2860
Mar 2008	0.2995	Mar 2011	0.1401	Mar 2014	0.2671	Mar 2017	0.3973
Apr 2008	0.2681	Apr 2011	0.1550	Apr 2014	0.2188	Apr 2017	0.1781
May 2008	0.1700	May 2011	0.1540	May 2014	0.1991	May 2017	0.5173
Jun 2008	0.3725	Jun 2011	0.2038	Jun 2014	0.3510	Jun 2017	0.2610
Jul 2008	0.1988	Jul 2011	0.1572	Jul 2014	0.2194	Jul 2017	0.4526
Aug 2008	0.2351	Aug 2011	0.1364	Aug 2014	0.3224	Aug 2017	0.4225
Sep 2008	0.2847	Sep 2011	0.3347	Sep 2014	0.4331	Sep 2017	0.5431
Oct 2008	0.3683	Oct 2011	0.3993	Oct 2014	0.2731	Oct 2017	0.3192
Nov 2008	0.1555	Nov 2011	0.1989	Nov 2014	0.3079	Nov 2017	0.3075
Dec 2008	0.1726	Dec 2011	0.2071	Dec 2014	0.2541	Dec 2017	0.3676
Jan 2009	0.2055	Jan 2012	0.2822	Jan 2015	0.3161		
Feb 2009	0.1295	Feb 2012	0.1880	Feb 2015	0.3061		
Mar 2009	0.1575	Mar 2012	0.1402	Mar 2015	0.2333		
Apr 2009	0.0685	Apr 2012	0.1691	Apr 2015	0.3899		
May 2009	0.1571	May 2012	0.2190	May 2015	0.2125		
Jun 2009	0.1819	Jun 2012	0.2207	Jun 2015	0.3367		
Jul 2009	0.1254	Jul 2012	0.1788	Jul 2015	0.4709		
Aug 2009	0.1441	Aug 2012	0.3270	Aug 2015	0.5739		
Sep 2009	0.2186	Sep 2012	0.2689	Sep 2015	0.5259		
Oct 2009	0.1356	Oct 2012	0.2793	Oct 2015	0.3829		
Nov 2009	0.1313	Nov 2012	0.2299	Nov 2015	0.5089		
Dec 2009	0.1058	Dec 2012	0.3013	Dec 2015	0.2050		

Appendix 2

Average Labor Market Tightness in Minnesota (1995-2017)

Jan 1995	0.3386	Jan 1998	0.4573	Jan 2001	0.3878	Jan 2004	0.1743
Feb 1995	0.2887	Feb 1998	0.4750	Feb 2001	0.4467	Feb 2004	0.1606
Mar 1995	0.3972	Mar 1998	0.3936	Mar 2001	0.3643	Mar 2004	0.1639
Apr 1995	0.3152	Apr 1998	0.3854	Apr 2001	0.3164	Apr 2004	0.1974
May 1995	0.2912	May 1998	0.4181	May 2001	0.3193	May 2004	0.2375
Jun 1995	0.2905	Jun 1998	0.3923	Jun 2001	0.3185	Jun 2004	0.1726
Jul 1995	0.3585	Jul 1998	0.6191	Jul 2001	0.2316	Jul 2004	0.1926
Aug 1995	0.5193	Aug 1998	0.6375	Aug 2001	0.2140	Aug 2004	0.1576
Sep 1995	0.3142	Sep 1998	0.4003	Sep 2001	0.2364	Sep 2004	0.1809
Oct 1995	0.2201	Oct 1998	0.4351	Oct 2001	0.1846	Oct 2004	0.2192
Nov 1995	0.2834	Nov 1998	0.3616	Nov 2001	0.1728	Nov 2004	0.2100
Dec 1995	0.2702	Dec 1998	0.3130	Dec 2001	0.1816	Dec 2004	0.2322
Jan 1996	0.3443	Jan 1999	0.4826	Jan 2002	0.1286	Jan 2005	0.3355
Feb 1996	0.2967	Feb 1999	0.4276	Feb 2002	0.1242	Feb 2005	0.3166
Mar 1996	0.2516	Mar 1999	0.5895	Mar 2002	0.1247	Mar 2005	0.2221
Apr 1996	0.2852	Apr 1999	0.5075	Apr 2002	0.1406	Apr 2005	0.2878
May 1996	0.3448	May 1999	0.4843	May 2002	0.1444	May 2005	0.2334
Jun 1996	0.2806	Jun 1999	0.3288	Jun 2002	0.1854	Jun 2005	0.2908
Jul 1996	0.2523	Jul 1999	0.3021	Jul 2002	0.1436	Jul 2005	0.3792
Aug 1996	0.2483	Aug 1999	0.4696	Aug 2002	0.1552	Aug 2005	0.2899
Sep 1996	0.2439	Sep 1999	0.4250	Sep 2002	0.1986	Sep 2005	0.2553
Oct 1996	0.2927	Oct 1999	0.5249	Oct 2002	0.1850	Oct 2005	0.3058
Nov 1996	0.2903	Nov 1999	0.2828	Nov 2002	0.1753	Nov 2005	0.2727
Dec 1996	0.3865	Dec 1999	0.4188	Dec 2002	0.1890	Dec 2005	0.2585
Jan 1997	0.2959	Jan 2000	0.3326	Jan 2003	0.1150	Jan 2006	0.2691
Feb 1997	0.4867	Feb 2000	0.4034	Feb 2003	0.1336	Feb 2006	0.2809
Mar 1997	0.4429	Mar 2000	0.3016	Mar 2003	0.1373	Mar 2006	0.3338
Apr 1997	0.2695	Apr 2000	0.3846	Apr 2003	0.1358	Apr 2006	0.3188
May 1997	0.3199	May 2000	0.2748	May 2003	0.1307	May 2006	0.3933
Jun 1997	0.3517	Jun 2000	0.5177	Jun 2003	0.1575	Jun 2006	0.4118
Jul 1997	0.3420	Jul 2000	0.4286	Jul 2003	0.1406	Jul 2006	0.3795
Aug 1997	0.2669	Aug 2000	0.3230	Aug 2003	0.1742	Aug 2006	0.4284
Sep 1997	0.2984	Sep 2000	0.3704	Sep 2003	0.1323	Sep 2006	0.3247
Oct 1997	0.2816	Oct 2000	0.3704	Oct 2003	0.1425	Oct 2006	0.3325
Nov 1997	0.4259	Nov 2000	0.2958	Nov 2003	0.1570	Nov 2006	0.3361
Dec 1997	0.3723	Dec 2000	0.3457	Dec 2003	0.1530	Dec 2006	0.3110

Jan 2007	0.3314	Jan 2010	0.1659	Jan 2013	0.2924	Jan 2016	0.5514
Feb 2007	0.3269	Feb 2010	0.1630	Feb 2013	0.3770	Feb 2016	0.5394
Mar 2007	0.4209	Mar 2010	0.1503	Mar 2013	0.3603	Mar 2016	0.4863
Apr 2007	0.3718	Apr 2010	0.1571	Apr 2013	0.3141	Apr 2016	0.4808
May 2007	0.3313	May 2010	0.1827	May 2013	0.3267	May 2016	0.5489
Jun 2007	0.3571	Jun 2010	0.1644	Jun 2013	0.3919	Jun 2016	0.5492
Jul 2007	0.3554	Jul 2010	0.1670	Jul 2013	0.3336	Jul 2016	0.6181
Aug 2007	0.3034	Aug 2010	0.1677	Aug 2013	0.3633	Aug 2016	0.4779
Sep 2007	0.3019	Sep 2010	0.1831	Sep 2013	0.3246	Sep 2016	0.5182
Oct 2007	0.3163	Oct 2010	0.1890	Oct 2013	0.3338	Oct 2016	0.4238
Nov 2007	0.3735	Nov 2010	0.2072	Nov 2013	0.3424	Nov 2016	0.4028
Dec 2007	0.3113	Dec 2010	0.2202	Dec 2013	0.3595	Dec 2016	0.3866
Jan 2008	0.3869	Jan 2011	0.2475	Jan 2014	0.3602	Jan 2017	0.4528
Feb 2008	0.3602	Feb 2011	0.2247	Feb 2014	0.4337	Feb 2017	0.4244
Mar 2008	0.3356	Mar 2011	0.2530	Mar 2014	0.3790	Mar 2017	0.5686
Apr 2008	0.2907	Apr 2011	0.2502	Apr 2014	0.4207	Apr 2017	0.4840
May 2008	0.2605	May 2011	0.2331	May 2014	0.4212	May 2017	0.5108
Jun 2008	0.2953	Jun 2011	0.2269	Jun 2014	0.4495	Jun 2017	0.4631
Jul 2008	0.2480	Jul 2011	0.2042	Jul 2014	0.4964	Jul 2017	0.5119
Aug 2008	0.2312	Aug 2011	0.2490	Aug 2014	0.4624	Aug 2017	0.4223
Sep 2008	0.2681	Sep 2011	0.3139	Sep 2014	0.4440	Sep 2017	0.5675
Oct 2008	0.2562	Oct 2011	0.3516	Oct 2014	0.4746	Oct 2017	0.5696
Nov 2008	0.1928	Nov 2011	0.3324	Nov 2014	0.5667	Nov 2017	0.5454
Dec 2008	0.1968	Dec 2011	0.3323	Dec 2014	0.5380	Dec 2017	0.4789
Jan 2009	0.1297	Jan 2012	0.3531	Jan 2015	0.4101		
Feb 2009	0.1242	Feb 2012	0.2596	Feb 2015	0.4558		
Mar 2009	0.1408	Mar 2012	0.2949	Mar 2015	0.4483		
Apr 2009	0.1147	Apr 2012	0.3905	Apr 2015	0.4903		
May 2009	0.1369	May 2012	0.2996	May 2015	0.5048		
Jun 2009	0.1084	Jun 2012	0.3142	Jun 2015	0.4890		
Jul 2009	0.1270	Jul 2012	0.2936	Jul 2015	0.5560		
Aug 2009	0.1331	Aug 2012	0.3312	Aug 2015	0.5631		
Sep 2009	0.1313	Sep 2012	0.3261	Sep 2015	0.5860		
Oct 2009	0.1186	Oct 2012	0.3375	Oct 2015	0.4920		
Nov 2009	0.1290	Nov 2012	0.3439	Nov 2015	0.5243		
Dec 2009	0.1514	Dec 2012	0.3547	Dec 2015	0.4675		

Appendix 3

Matching Efficiency in Minnesota (1995-2017)

Jan 1995	0.5423	Jan 1998	0.5706	Jan 2001	0.6871	Jan 2004	0.5426
Feb 1995	0.6470	Feb 1998	0.6063	Feb 2001	0.7031	Feb 2004	0.6774
Mar 1995	0.6050	Mar 1998	0.5219	Mar 2001	0.5464	Mar 2004	0.6206
Apr 1995	0.4606	Apr 1998	0.5656	Apr 2001	0.6382	Apr 2004	0.7129
May 1995	0.6165	May 1998	0.6199	May 2001	0.5123	May 2004	0.5415
Jun 1995	0.6053	Jun 1998	0.6484	Jun 2001	0.8226	Jun 2004	0.5890
Jul 1995	0.4812	Jul 1998	0.5562	Jul 2001	0.5530	Jul 2004	0.6332
Aug 1995	0.5400	Aug 1998	0.5215	Aug 2001	0.7086	Aug 2004	0.6967
Sep 1995	0.5179	Sep 1998	0.5512	Sep 2001	0.7790	Sep 2004	0.4944
Oct 1995	0.4816	Oct 1998	0.4801	Oct 2001	0.4964	Oct 2004	0.6383
Nov 1995	0.5321	Nov 1998	0.6104	Nov 2001	0.5294	Nov 2004	0.8253
Dec 1995	0.5808	Dec 1998	0.4542	Dec 2001	0.4903	Dec 2004	0.5478
Jan 1996	0.4214	Jan 1999	0.5416	Jan 2002	0.4714	Jan 2005	0.5503
Feb 1996	0.5946	Feb 1999	0.6241	Feb 2002	0.6785	Feb 2005	0.4991
Mar 1996	0.4603	Mar 1999	0.6613	Mar 2002	0.5318	Mar 2005	0.6657
Apr 1996	0.4679	Apr 1999	0.5184	Apr 2002	0.5113	Apr 2005	0.5701
May 1996	0.6171	May 1999	0.4572	May 2002	0.5607	May 2005	0.5441
Jun 1996	0.5730	Jun 1999	0.5176	Jun 2002	0.4738	Jun 2005	0.5882
Jul 1996	0.4928	Jul 1999	0.4141	Jul 2002	0.5192	Jul 2005	0.6246
Aug 1996	0.4477	Aug 1999	0.5078	Aug 2002	0.7756	Aug 2005	0.6883
Sep 1996	0.4733	Sep 1999	0.5428	Sep 2002	0.4813	Sep 2005	0.5310
Oct 1996	0.3155	Oct 1999	0.4370	Oct 2002	0.6689	Oct 2005	0.5816
Nov 1996	0.5610	Nov 1999	0.4977	Nov 2002	0.6955	Nov 2005	0.5914
Dec 1996	0.5708	Dec 1999	0.4545	Dec 2002	0.6285	Dec 2005	0.6257
Jan 1997	0.5108	Jan 2000	0.5818	Jan 2003	0.7224	Jan 2006	0.5394
Feb 1997	0.5435	Feb 2000	0.5957	Feb 2003	0.4678	Feb 2006	0.6393
Mar 1997	0.4606	Mar 2000	0.6243	Mar 2003	0.5069	Mar 2006	0.7014
Apr 1997	0.6334	Apr 2000	0.4678	Apr 2003	0.6625	Apr 2006	0.7488
May 1997	0.4604	May 2000	0.3590	May 2003	0.6805	May 2006	0.7038
Jun 1997	0.5890	Jun 2000	0.6218	Jun 2003	0.5249	Jun 2006	0.5773
Jul 1997	0.6223	Jul 2000	0.5610	Jul 2003	0.4980	Jul 2006	0.4915
Aug 1997	0.6632	Aug 2000	0.6473	Aug 2003	0.6616	Aug 2006	0.6184
Sep 1997	0.4436	Sep 2000	0.6149	Sep 2003	0.4380	Sep 2006	0.5091
Oct 1997	0.5680	Oct 2000	0.6743	Oct 2003	0.4942	Oct 2006	0.4684
Nov 1997	0.6289	Nov 2000	0.5338	Nov 2003	0.5227	Nov 2006	0.6367
Dec 1997	0.7541	Dec 2000	0.3906	Dec 2003	0.5844	Dec 2006	0.6110

Jan 2007	0.5511	Jan 2010	0.3203	Jan 2013	0.3173	Jan 2016	0.3619
Feb 2007	0.4300	Feb 2010	0.5090	Feb 2013	0.5333	Feb 2016	0.3050
Mar 2007	0.3024	Mar 2010	0.3282	Mar 2013	0.4146	Mar 2016	0.3905
Apr 2007	0.4492	Apr 2010	0.5592	Apr 2013	0.3583	Apr 2016	0.4928
May 2007	0.5786	May 2010	0.3128	May 2013	0.5557	May 2016	0.4493
Jun 2007	0.6015	Jun 2010	0.4829	Jun 2013	0.3903	Jun 2016	0.6321
Jul 2007	0.6235	Jul 2010	0.3584	Jul 2013	0.6292	Jul 2016	0.3806
Aug 2007	0.5407	Aug 2010	0.3888	Aug 2013	0.4620	Aug 2016	0.4578
Sep 2007	0.7874	Sep 2010	0.5469	Sep 2013	0.6723	Sep 2016	0.5408
Oct 2007	0.6593	Oct 2010	0.3760	Oct 2013	0.6689	Oct 2016	0.5205
Nov 2007	0.4461	Nov 2010	0.4329	Nov 2013	0.5174	Nov 2016	0.6994
Dec 2007	0.4389	Dec 2010	0.5560	Dec 2013	0.3037	Dec 2016	0.4830
Jan 2008	0.3647	Jan 2011	0.4023	Jan 2014	0.3825	Jan 2017	0.6486
Feb 2008	0.4139	Feb 2011	0.2630	Feb 2014	0.4563	Feb 2017	0.4759
Mar 2008	0.5728	Mar 2011	0.3168	Mar 2014	0.4753	Mar 2017	0.5555
Apr 2008	0.5583	Apr 2011	0.3528	Apr 2014	0.3658	Apr 2017	0.2740
May 2008	0.3778	May 2011	0.3658	May 2014	0.3328	May 2017	0.7709
Jun 2008	0.7687	Jun 2011	0.4916	Jun 2014	0.5644	Jun 2017	0.4123
Jul 2008	0.4550	Jul 2011	0.4037	Jul 2014	0.3326	Jul 2017	0.6737
Aug 2008	0.5609	Aug 2011	0.3114	Aug 2014	0.5097	Aug 2017	0.7049
Sep 2008	0.6220	Sep 2011	0.6661	Sep 2014	0.7015	Sep 2017	0.7603
Oct 2008	0.8269	Oct 2011	0.7427	Oct 2014	0.4251	Oct 2017	0.4459
Nov 2008	0.4134	Nov 2011	0.3825	Nov 2014	0.4314	Nov 2017	0.4408
Dec 2008	0.4532	Dec 2011	0.3984	Dec 2014	0.3673	Dec 2017	0.5692
Jan 2009	0.6911	Jan 2012	0.5237	Jan 2015	0.5367		
Feb 2009	0.4468	Feb 2012	0.4187	Feb 2015	0.4881		
Mar 2009	0.5045	Mar 2012	0.2895	Mar 2015	0.3757		
Apr 2009	0.2478	Apr 2012	0.2955	Apr 2015	0.5953		
May 2009	0.5115	May 2012	0.4480	May 2015	0.3189		
Jun 2009	0.6805	Jun 2012	0.4389	Jun 2015	0.5149		
Jul 2009	0.4269	Jul 2012	0.3701	Jul 2015	0.6674		
Aug 2009	0.4772	Aug 2012	0.6303	Aug 2015	0.8072		
Sep 2009	0.7300	Sep 2012	0.5231	Sep 2015	0.7224		
Oct 2009	0.4810	Oct 2012	0.5324	Oct 2015	0.5834		
Nov 2009	0.4430	Nov 2012	0.4334	Nov 2015	0.7467		
Dec 2009	0.3247	Dec 2012	0.5576	Dec 2015	0.3220		