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Essays in Labor Economics and International Economics

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FLORIDA INTERNATIONAL UNIVERSITY

Miami, Florida

ESSAYS IN LABOR ECONOMICS AND INTERNATIONAL ECONOMICS

A dissertation submitted in partial fulfillment of the

requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

Seyed Javad Nosratabadi

2019

To: Dean John F. Stack, Jr.

Steven J. Green School of International and Public Affairs

This dissertation, written by Seyed Javad Nosratabadi, and entitled Essays in Labor Economics and International Economics, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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Florida International University, 2019

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DEDICATION

I dedicate this thesis to my inspiring and beloved parents, wife, and brother for their endless love, support, and encouragement, and for being the architect of my life.

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I would like to thank Tobias Pfutze, Cem Karayalcin, Mihaela Pinteä and Stav Fainshmidt for their guidance and support. I also benefited from discussions with Hassan Afrouzi, Hassan Nosratabadi, and many seminar participants.

ABSTRACT OF THE THESIS
ESSAYS IN LABOR ECONOMICS AND INTERNATIONAL ECONOMICS

by

Seyed Javad Nosratabadi

Florida International University, 2019

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This dissertation includes three essays in labor economics and international economics. The first essay studies the relationship between the amount of a loan demanded by firms and their labor demand. Governments have developed small loan programs with a reduced interest rate to decrease unemployment in Iran. Using longitudinal, firm-level data from the years 2005 to 2010 in Iran, this study examines the effect of one Iranian province's loan program on employment based on two different methods of evaluating causal effects. The first method applies a difference-in-difference fixed effects matching estimator to estimate the employment effect of the program. The second method applies the generalized propensity score to estimate the impact of the amount of a loan on employment. The results from the first method suggest that the loan program has a positive and significant effect on the employment of treated firms. The results from the second method suggest that the estimated employment effects increase with the amount of the loan, whereas there is a decrease in the marginal effects of an additional amount of loan.

The second essay investigates how the difference between firms' inflation expectations, measured by the loan amounts they demand, and actual inflation affects their labor demand. In addition, I examine the relationship between firms' inflation expectations and wages in an individualistic bargaining model in which individual workers bargain over wages with their employers. Theoretically, the model shows

that a firm's actual labor demand meets its expected labor demand if the firm has a rational expectation regarding inflation. On the other hand, the firm's actual labor demand does not meet its expected labor demand if the firm cannot forecast inflation correctly. Empirically, I use firm-level data from a province in Iran between 2004 and 2011 to test the model's predictions. The empirical results confirm that there is a specific loan amount for which firms' expected labor demands meet their actual ones. In contrast, there is a gap between firms' expected labor demands and their actual ones for any other loan amount. Furthermore, the result indicates that there is a positive and significant relationship between the loan amounts demanded by firms and wages. These results can be explained by firms' inflation expectations and show that they are not consistent with full-information rational expectations models, though they are not far away from them.

The third essay examines the effects of the trade sanctions imposed on Iran in 2010 on employment, demand for skilled labor, and wages. I use industrial manufacturing data that cover 10 years before and 5 years after the sanction, 28 provinces, and more than 200 different industries. The results regarding the employment impact of the trade sanctions show that there was remarkable job destruction, most notably in domestically active industries, during the sanction period. The decomposition of the increase in the aggregate demand for skilled labor sheds light on the fact that it comes from labor reallocation within industries, not from across industries. The trade sanctions adversely affected both exporters' and non-exporters' total-factor productivity; however, non-exporters endured a larger negative impact. This induced biased technological change between exporters and non-exporters, which resulted in a market share reallocation towards exporters. As a result, the demand for skilled production workers and their per-capita real average wage increased, whereas the demand for non-production workers and their per-capita real average wage decreased during the sanction years. This opposite effect is explained by the elasticity of substitution.

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CHAPTER 1

INTRODUCTION

Undoubtedly, the labor market is one of the most important markets in any economy. At the micro level, individual firms interact with employees, hiring them, firing them, and raising or cutting wages. Firms need capital to be able to expand their businesses, create new jobs, and hire new workers. Moreover, firms' inflation expectations matter and those expectations influence firms' labor demand, capital demand, and wages.

In addition, the labor market and international trade interact with each other in an open economy. In labor and international economics, understanding the relationship of trade, labor, and wages have received considerable attention from both international and labor economists. Thus, investigating the impact of the trade shocks on the labor market is crucial for policymakers as well.

The main promise of small and medium enterprises (SMEs) is the reduction of unemployment and boosting of economic growth. SMEs account for a significant share of employment and GDP around the world, but when SMEs do not have easy access to finance, the economy faces some negative consequences like economic growth and job creation restraint, enterprise collapse, and vulnerability. Clearly, loans provided by banks are one of the primary sources of financing for SMEs to encourage them to invest, expand their businesses, and finally hire new workers.

In Iran, governments have developed small loan programs to support small enterprises and encourage them to invest and hire new workers. Chapter two studies the employment impact of a small loan program allocated between 2005 and 2010 to Hamedan micro and small enterprises (MSEs) in Iran. There have been very few studies to assess this policy using appropriate data and econometric methods. Most of the studies of loan effects have relied on simple comparisons

before and after the policy interventions, with little use of comparison groups of non-recipients and have not applied recent developments in econometrics, either. On the other hand, my research aims to contribute to estimating the employment impact of the intervention and the amount of the loan by using much better data and by applying recent econometric methods developed for estimating causal effects with such data.

In empirical research and for policy purposes, the measurement of inflation expectations has taken three forms: 1. empirical constructs based on observed inflation trends, 2. estimates derived from inflation-protected security yields, and 3. survey data of economists and households. For example, Coibion, Gorodnichenko, and Kumar (2017) implemented a new survey of firms' macroeconomic beliefs in New Zealand and document a number of novel stylized facts from this survey. The main result of their paper is that managers' average forecasts of inflation have been systematically higher than actual inflation. This emphasizes that there are pervasive departures from full-information rational expectations for the case of firms. In addition, other studies show the same result in the consumer survey as well.

Then the question is how firms' inflation expectations, measured by the size of the loan demanded by them, affect their labor demand and wages. To answer this question, in chapter three, I consider a model to investigate the deviation of the firms' expected labor demand from the actual one due to their inflation expectations. In addition, I examine the relationship between firms' inflation expectations and wages in an individualistic bargaining model where individual workers bargain over wages with their employer.

Finally, chapter four studies the impact of economic sanctions against Iran on its labor market. Particularly, it investigates the effect of the trade sanctions against Iran on the relative demand for skilled labor and the wage premium. Indeed, exporters pay higher wages and have more skilled workers than their domestic

counterparts. Moreover, we observe that exporters and importers, which are likely the ones that suffered more from the sanctions, must reallocate their labor in terms of their wages and skill. I use the industrial firm survey (IFS) data and develop a methodology to estimate the effect of the trade sanctions on the relative demand for skilled labor and the wage premium.

CHAPTER 2

THE IMPACT OF SMALL LOAN PROGRAMS ON EMPLOYMENT FOR MICRO AND SMALL ENTERPRISES: EVIDENCE FROM A PROVINCE IN IRAN

2.1 Introduction

The main purpose of small and medium enterprises (SMEs) is to reduce unemployment and boost economic growth. SMEs play a key role in job creation and GDP growth around the world. When SMEs do not have easy access to credit, the economy faces adverse consequences such as disruptions to economic growth, job creation restraint, enterprise collapse, and vulnerability. D. Birch (1979); D. L. Birch (1981) argued that supporting small businesses, the main engine of job creation, is crucial for job growth. Moreover, many studies have confirmed that easy access to credit is a critical factor for new firms (Patzelt and Shepherd (2009); Hartarska and Gonzalez-Vega (2006)).

In general, public policy in support of SMEs includes both financial and non-financial supports. On the one hand, access to finance in supporting SMEs consists of grants and awards, reduced interest rate loans, loan guarantees and R&D support etc. On the other hand, non-financial supports, commonly offered for free or at minimum cost, provide services such as business advice, guided preparation, labor training etc. In Iran, governments have developed small loan programs with reduced interest rates to support small enterprises financially. Clearly, reduced interest rate loans are one of the primary sources of financing for SMEs to encourage them to invest, expand their businesses, and hire new workers.

But the question is, do reduced interest rate loans to SMEs increase employment? The answer to this question is not straightforward because these kinds of loans can

produce opposite effects on employment. First, reduced interest rate loans, which provide the capital with a lower cost to firms, may incentivize firms to expand their businesses (scale effect), which would increase employment. Second, loans influence the relative price of capital and labor and may cause some firms to substitute capital for labor, if capital and labor are gross substitutes (substitution effect), which would reduce employment. As a result, the employment effect of the loans is ambiguous in general (J. Brown and Earle (2013)).

This study focuses on analyzing the employment impact of a particular small loan program with a reduced interest rate allocated between 2005 and 2010 to Hamedan ¹ micro and small enterprises (MSEs). Based on the available data, this study uses two different methods to evaluate the employment effect of the intervention and loans. In the first method, a DID fixed effects matching estimator (Heckman, Ichimura, and Todd (1998)) makes it possible to initially match some firms' characteristics to control the differences between treated and non-treated firms, and then, to measure the employment impact of the policy before and after the intervention. In the second method, arguing that it is important to apply an estimation to infer causal effects based on the continuous treatment variable, estimates are made using the dose-response function (DRF) and the treatment effect function (TEF) (or marginal effect function). One of the advantages of using this method is to consider heterogeneities along different loan amounts and to determine the optimal amount of loans.

The results from the first method suggest positive average effects on employment of treated firms of about 2.66 jobs at the mean for the full sample and about 1.15 jobs at the mean for micro-sized firms. In addition, it is estimated that each billion Iranain Rial (IRR)² of loans creates about 4.02 and 3.33 jobs for the full sample and micro-sized firms, respectively. The results from the second method

¹A province in Iran.

²The exchange rate with the U.S. dollar was around \$1 = 10000 IRR during program years.

suggest that the estimated employment effects increase with the amount of the loan significantly for both full sample and micro-sized firms. In contrast, the marginal effects decrease with the amount of the loan for both full sample and micro-sized firms using parametric partial means (PPM) method. It emphasizes that marginal effects are smaller for a larger amount of the loan. Moreover, the results illustrate that there is an optimal level of loan that maximizes employment; the marginal effects decrease with the amount of the loan and reach negative value for micro-sized firms using semi-parametric inverse weighting (SPIW) method.

Few studies exist about the employment impact of reduced interest rate loans on SMEs in developing countries, while many studies examined loan guarantee programs or focused on developed countries. For example, Maggioni, Sorrentino, and Williams (1999) examined the effect of the direct government loan with a reduced interest rate on sales, sales growth, and change in employees of firms in Italy. They found that there is no significant difference with regard to growth between treated and non-treated new ventures, however, government aid improved the technology of firms.

Craig, Jackson, Thomson, et al. (2006) investigated the effect of the SBA-guaranteed loans on economic performance in low-income markets in the U.S. They found that there is a positive and significant relationship between the level of employment and the amount of the loan; the magnitude of this correlation is relatively larger in low-income markets. J. Brown and Earle (2013) estimated the employment impacts of the SBA loan guarantees from 1976 to 2010 in the U.S. The results implied average positive effects on employment of about 3 jobs at the mean. In addition, each million dollars could increase the employment by about 5.4 jobs. Bia and Mattei (2012) assessed the effect of financial aid on the employment of different firm-size in a region in northern Italy. They found that there is an increasing relationship between the financial aid amount and employment of firms. However, the marginal effects reduce with the amount of financial aid and have a

maximum point for small and medium or large firms, respectively. There are many other studies that assessed the effect of access to finance on firms (e.g. Cowling and Mitchell (2003); Garcia-Tabuenca and Crespo-Espert (2010); Lenihan and Hart (2006); Taymaz and Üçdoğruk (2009); Patzelt and Shepherd (2009); Morris and Stevens (2010); Cortes (2010); Kahn, Rahman, and Wright (2016); Al Mamun, Abdul Wahab, and Malarvizhi (2010); Castillo, Maffioli, Rojo, and Stucchi (2014); Honjo and Harada (2006); Kang and Heshmati (2008); Pergelova and Angulo-Ruiz (2014); Lerner (2000); Cowling (2010)).

Moreover, most studies have not used control groups and simply relied on comparing the treated groups before and after the interventions without even applying recent developments in econometrics. For instance, Oh, Lee, Heshmati, and Choi (2009) examined the loan guarantees program in Korea; Mole, Hart, Roper, and Saal (2009) assessed the effect of the Business Link program in the UK on sales and employee growth; Mole, Hart, Roper, and Saal (2011) investigated the Growth Services Range support program in New Zealand; while Rotger, Gørtz, and Storey (2012) evaluated the North Jutland Entrepreneurial Network program in Denmark. On the other hand, this study aims to contribute to estimating the employment impact of the intervention and the amount of the loan by using firm-level data and applying new econometric methods introduced to infer causal effects based on comparing two treated and non-treated firms before and after the intervention.

Finally, the study joins different methods developed by different authors who inference causal effects based on binary or continuous treatments (e.g., Bia and Mattei (2012); Bia, Mattei, et al. (2008); Bia, Flores, Flores-Lagunes, Mattei, et al. (2014); Flores-Lagunes, Gonzalez, and Neumann (2012); Hirano and Imbens (2004); Heckman, Ichimura, and Todd (1997, 1998); Heckman, LaLonde, and Smith (1999); Kluve, Schneider, Uhlenborff, and Zhao (2012); J. Brown and Earle (2013)).

The study continues as follows. Section two presents the small loan program in Iran, data, and summary statistics. Section three explains two different methods employed to estimate the impact of the program on employment. Section four provides the results. Finally, section five concludes.

2.2 The MSEs loan program in Iran and data

Unemployment in Iran has been a persistent problem throughout the last two decades, with the unemployment rate holding, on average, at about 12% during that time. Governments have developed small loan programs with reduced interest rates to encourage investment and employment throughout the country to combat high unemployment. This research focuses on one small loan program legislated through Law 101 that started in the province of Hamedan during the last two months of 2005 and continued through 2011. On average, the amount of loans paid to firms was 1.5% of the GDP for each year during the program's existence.

The program included all Iranian provinces in the service, manufacturing, and agriculture sectors. Only micro-sized firms (those with fewer than 10 workers) and small-sized firms (with fewer than 50 and more than or equal to 10 workers) were eligible to apply for the loans. Most loans had a maximum amount of 10 billion IRR, except for the food industry in which the maximum was 30 billion IRR. The firms fell into the categories of new business, expansion, renovation, new construction, buildings, equipment, and so on. Usually loans had 5 to 7 maturity years. Generally, the regular interest rate of borrowing a loan from public banks was between 12 to 14% through the duration of the program ³. On the other hand, the program awarded loans with interest rate from 4 up to 6% which has been subsidized by the government during program years. This reduced interest rate depended on the type of business, time, region, amount of the loan, and maturity years. Finally, firms were allowed to receive a loan only once from this program.

³The interest rate of borrowing a loan from private banks was much higher than this range.

To qualify, a business had to be a micro- or small-sized firm, an eligible type of business, able to hire new workers, for-profit, of good character, and possess a feasible business plan. Borrowers were to deposit at least 10% of the total loan amount into the bank account where they received it. The Labor Administration of Hamedan made approval decisions for applications and the banks made final decisions for loan amounts. Banks were to consider the applications and respond to the applicants during a 15-day period after submission and, if needed, provide a reason for rejecting an application.

Table 2.1 presents the total amount of loans paid and the total number of firms that received loans in Iran and Hamedan during the program years, showing that both amounts are low in 2005 because the program began during last two months of that year ⁴. On the other hand, the amount of loans paid steadily increased in 2006 to 2007, declining thereafter. The maximum amount of loans paid is estimated to be about 98 trillion IRR (lent to 324,538 firms) and 3.4 trillion IRR (lent to 14,255 firms), respectively, in Iran and Hamedan in 2007. The minimum amount of loans paid is estimated to be about 1.9 trillion IRR (lent to 10,637 firms) and 5.6 billion IRR (lent to 22 firms), respectively, in Iran and Hamedan in 2005.

This study focuses on Hamedan loan program because of data availability. In particular, the study implements firm-level data collected by the Labor Administration of Hamedan province. The main part of the data comprises the results of a survey that used a primitively designed questionnaire during the program years. In the survey, a sample of MSEs that participated (did not participate) in the loan program were randomly selected and fell into treated (non-treated) firm categories. In total, the data is annual, covers the years 2004 through 2011, and contains information about firms and firm owners. The total number of surveyed firms is

⁴I do not have access to the years 2010 and 2011 information. Nevertheless, this information is not used for estimating in this study and the main data set will be subsequently discussed.

342, which includes 133 treated firms ⁵ and 209 non-treated firms ⁶. Unfortunately, comparing the population sample (Table 2.1) and surveyed sample indicates that the number of surveyed firms is very small, then it cannot be taken for granted that it has the same observable characteristics of the population of interest. As a result, this issue implies somehow a source of possible limitations in the external validity of results.

Table 2.2 presents information on the amount of loans paid and the number of sampled treated firms that received loans for the full sample and micro-sized firms during the program years. Table 2.3 presents the descriptive statistics of the variables for both sampled treated and non-treated firms. Employment is defined as the employment level during 2004 to 2011. First difference employment is defined as the difference between the employment level one year after receiving the loan and the employment level before receiving the loan for treated firms. The latter outcome is the outcome of interest variable when using the second method⁷.

2.3 Estimation strategies

For this study, I use two methods to estimate the impact of the loan program and the amount of loans on firms' employment. In the first method, let's $Treated_{it} \in \{0, 1\}$ indicates that firm i receives a loan in year t , and let N_{it+s}^1 be number of workers at time $t+s$, $s \geq 0$, coming years. N_{it+s}^0 is the number of workers if firm i had not received a loan. Then, $N_{it+s}^1 - N_{it+s}^0$ is the loan's causal effects for firm i at time $t+s$ and the average treatment effect (ATE) on the treated firms is $E\{N_{it+s}^1 - N_{it+s}^0 | Treated_{it} = 1\} = E\{N_{it+s}^1 | Treated_{it} = 1\} - E\{N_{it+s}^0 | Treated_{it} = 1\}$. The problem with this method is that N_{it+s}^0 , the average employment outcome

⁵ All of these firms received a loan with the same interest rate (4%) and did not take up loans from other sources outside the program during the program years.

⁶ These firms might apply to a loan from the program and were rejected and they did not take up loans from other sources outside the program during the program years as well.

⁷This interest is subsequently explained.

of firm i that receives the loan if it had not received the loan, is unobserved and we have to estimate it. Basically, we replace the average employment of non-treated firms, $E\{N_{it+s}^0 | Treated_{it} = 0 \ \forall \ t\}$ with $E\{N_{it+s}^0 | Treated_{it} = 1\}$ to solve this problem.

However, if treated and non-treated firms are different in major characteristics, we should use matching techniques to eliminate such differences. Usually, we apply the propensity score matching (PSM) method for estimating causal effects under the unconfoundedness assumption in a binary treatment variable case (Rosenbaum and Rubin (1983a)). As a result, within the first step of analysis, I estimate the probability of becoming eligible for loans (PS) using a probit regression and check the balancing property that shows distributions of the treatment status $Treated_i$ and the observable variables X_i are independent of each other, once conditioned on the PS ⁸.

There are two issues that arose in the course of the research. First, as indicated above, the program started during the last two months of 2005 and only a couple of firms received loans in 2005 in the sample. Obviously, the outcome impact of the loan for firms that received the loan in 2005 is too negligible in the same year. Therefore, I place the firms who received the loans in 2005 in 2006. Second, as shown in Table 2.3, there are some start-up firms in both the treated and non-treated samples. On the one hand, if I exclude start-ups due to lack of employment history, this exclusion implies a negative bias since start-ups may have a stronger employment response to loans than existent firms. On the other hand, lack of employment history for start-ups prevents matching. To deal with this problem, I impute 0s in place of employment history for start-ups and include a dummy for such cases. However, this implies somehow overestimating the program's effect, which presents a source of potential bias for this study.

⁸See Appendix A for more details about estimating PSM and its balancing property test.

Since my data is longitudinal and includes at least two years of information prior to the intervention, I use a DID fixed effects specification to control both time-variant and time-invariant unobserved factors correlated to the outcome which may cause bias in my estimations (e.g., Abadie (2005); Heckman, Ichimura, and Todd (1998)). Therefore, in the second step of estimation method, as Heckman et al. (1997); Heckman, Ichimura, and Todd (1998); Heckman et al. (1999) recommended, I combine Kernel matching on the PS with the DID fixed effects method to estimate the effect of the intervention on employment and also to adjust the treated and non-treated firms' differences.

The employment regression takes the form:

$$N_{it} = \alpha_i + \tau_t + SU_i + \beta X_{it} + \epsilon_{it} \quad (2.1)$$

where N is number of workers. X_{it} is a set of treatment variables, and β are the coefficients of interest that show the effect of the loan program or the amount of loans. The first simple treatment variable is a post-loan dummy, which takes a value of one for treated firms in the year and all subsequent years of receiving the loan and is equal to 0 for non-treated firms in all years. Other specifications include the real amount of loan (the amount of the loan converted to real 2004 prices using the consumer price index (CPI) of the selected province) in the year and all subsequent years of receiving the loan (equal to 0 for non-treated firms in all years), expressed in billions IRR. I include the real loan amount and the real loan amount squared as well. i indexes firms and t indexes the years, $t = \dots -3, -2, -1, 0, 1, 2, 3, \dots$, such that $t < 0$ in the pre-loan (pre-program) years, $t = 0$ in the year of the loan was received (program began), and $t > 0$ in the post-loan (post-program) years for treated (non-treated) firms. α_i and τ_t are firms and years fixed effects dummies, respectively. SU_i is a dummy variable that takes a value of one if firm i is a start-up firm. Finally, ϵ is an idiosyncratic error.

The fixed effects methods rely on the validity of the parallel trends assumption. This assumption states that treated and non-treated outcome trends should be parallel in the absence of treatment. It is, unfortunately, untestable and may be difficult to accept when non-treated firms are too different from treated firms. Because of this reason, I estimate the above employment regression on both the unmatched sample and matched sample in which I select those non-treated firms which are the most analogous to treated firms in terms of their characteristics and pretreatment employment history. I do this to make sure that I am selecting only those non-treated firms that have parallel pretreatment employment trends to the treated firms.

Furthermore, the reliability of the DID fixed effects matching estimator depends on the unconfoundedness assumption which states that the potential outcome is uncorrelated to the intervention conditional on a set of observable variables (e.g., Imbens and Wooldridge (2009)). I can not test this unconfoundedness assumption directly, but I assess it partially in three ways and mention it in Appendix A.

A drawback of the aforementioned approach is that it does not consider the possible differences among treated firms and it simply categorizes all of them as the treatment group without taking into account that they receive different level of loans. In fact, we expect that firms, who demand different amounts of loans, will be different in their labor market outcomes because the amount of the loan is related to their performances and characteristics (Bia and Mattei (2012)). For this reason, in the second method, I apply an estimation method in which I estimate the DRF and the TEF to infer causal effects based on the continuous treatment variable. One of the advantages of using this method is to consider heterogeneities along different loan amounts and to determine the optimal amount of loans.

As I have mentioned above, the amount of the loan depends on firms' characteristics which means that firms who receive different loan amounts can systematically differ in important characteristics. Hirano and Imbens (2004) developed the gener-

alized propensity score (GPS) method as an extension of binary treatment variables, which is introduced by Rosenbaum and Rubin (1983b), to adjust these differences in the case of continuous treatment variables.

Suppose $i = 1, \dots, N$ is indicating the sample size and $Y_i(t)$, for $t \in \tau$ indicates a potential outcome of unit i for the continuous treatment variable t and I allow τ belongs to the interval $[t_0, t_1]$. I am interested in estimating the average DRF, $\mu(t) = E[Y_i(t)]$.

Similar to the PS approach, the GPS method relies on the weak unconfoundedness assumption that after controlling for the pretreatment observable variables, it is no problem to draw the causal inference. Hirano and Imbens (2004) introduced weak unconfoundedness assumption, which requires that the selection into the treatment is conditionally independent of each potential outcome given the pretreatment variables: $Y_i(t) \perp T_i | X_i \forall t \in \tau$. This assumption is not testable directly and does not need to be generally applicable; the weak pretreatment covariates can cast serious doubt on this assumption. Nevertheless, I assess this assumption indirectly and mention it in Appendix A.

Given weak unconfoundedness assumption, Hirano and Imbens (2004) define the GPS. Let $r(t, x)$ be the density of the treatment conditional on the covariates. Then the GPS is $R_i = r(T_i, X_i)$ ⁹. The GPS has a balancing property similar to that of the standard PS and, as a result, I can eliminate important differences in the covariates, which may cause bias in my estimations, by applying the GPS. Basically, given pretreatment variables X_i and under the weak unconfoundedness assumption, then

$$\beta(t, r) = E[Y_i(t) | r(t, X_i) = r] = E[Y_i | T_i = t, R_i = r] \quad (2.2)$$

⁹See Appendix A for more details.

$$\mu(t) = E[\beta(t, r(t, X_i))] \quad (2.3)$$

where $\mu(t)$ is the DRF and I can estimate it at t by taking average of $\mu(t, r(t, X_i))$ over X_i and holding treatment level t constant (PPM method) (Newey (1994)). Moreover, by averaging the DRF over the covariates X_i for each level t , I also compute the derivatives of $\mu(t, r(t, X_i))$, that we can define as the marginal causal effect or treatment effect function, $\mu(t + \Delta t) - \mu(t)$, of a variation of the treatment level, Δt , on the outcome variable.

Now, I consider how to apply the above method in my application. Basically, I can estimate the DRF using the GPS in two steps. First, I estimate the GPS parametrically under various alternative distributional assumptions to find a distribution that is a better fit with my data given the covariates. Specifically, I assume that:

$$g(T_i|X_i) \sim \psi(h(\gamma, X_i), \sigma^2) \quad (2.4)$$

where $g()$ is a suitable transformation of the treatment variable, ψ is a flexible distribution, $h(\gamma, X_i)$ is a flexible function of the covariates depending on an unknown parameter vector γ , and σ^2 is a scale parameter.

The log transformation and applying normal distribution of the treatment variable is the common specification for a non-negative continuous treatment variable (Kluve et al. (2012); Hirano and Imbens (2004)). However, treatment cannot be assumed to be normally distributed; assuming a normal distribution of the treatment given the covariates has several drawbacks. To make the GPS estimation more reasonable, I estimate the GPS under flexible distributions such as gaussian, inverse-gaussian, and gamma and select the model that best fits my data. To estimate the GPS in these cases, a possible solution is to replace the linear regression with the generalized linear model (GLM) developed by McCullagh (1984).

Let $\hat{R}_i$ be the estimated GPS. After estimating $\hat{R}_i$, in the second step, I need to estimate the conditional expectation of Y_i on T_i and $\hat{R}_i$ using a quadratic approximation including the interaction:

$$\beta(t, r) = E[Y_i|T_i, \hat{R}_i] = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 \hat{R}_i + \alpha_4 \hat{R}_i^2 + \alpha_5 T_i \cdot \hat{R}_i \quad (2.5)$$

Next I estimate the DRF, while holding the treatment level constant at a specific level, through averaging $E[Y_i|T_i, \hat{R}_i]$ over the GPS at that particular treatment level:

$$\mu(\hat{t})_{PPM} = \frac{1}{N} \sum_{i=1}^N [\hat{\alpha}_0 + \hat{\alpha}_1 t + \hat{\alpha}_2 t^2 + \hat{\alpha}_3 \hat{R}_i + \hat{\alpha}_4 \hat{R}_i^2 + \hat{\alpha}_5 t \cdot \hat{R}_i] \quad (2.6)$$

I refer to this as the PPM estimator.

I also estimate the DRF using a SPIW estimator based on Kernel methods proposed by Flores-Lagunes et al. (2012) to avoid any misspecification. Such misspecification can result in a bias regarding my estimation, and basically, it is not reasonable to insist ex ante to any certain specification for $\beta(t, r)$. In this method, I use the estimated GPS to assign a weight for each observation to adjust the covariate differences. If $K(u)$ is a Kernel function and h is the bandwidth satisfying $h \rightarrow 0$ and $Nh \rightarrow \infty$ as $N \rightarrow \infty$, then the SPIW approach is accomplished using a local linear regression of Y_i on T_i with weighted Kernel function $\tilde{K}_{h,X}(T_i - t) = K_h(T_i - t)/\hat{R}_i$, where $K_h(z) = h^{-1}K(z/h)$. Formally, the SPIW Kernel Estimator of the average DRF is defined as follows:

$$\mu(\hat{t})_{SPIW} = \frac{D_0(t)S_2(t) - D_1(t)S_1(t)}{S_0(t)S_2(t) - S_1^2(t)} \quad (2.7)$$

where $S_j(t) = \sum_{i=1}^N \tilde{K}_{h,X}(T_i - t)(T_i - t)^j$ and $D_j(t) = \sum_{i=1}^N \tilde{K}_{h,X}(T_i - t)(T_i - t)^j Y_i$, $j = 0, 1, 2$.

I refer to this as the SPIW estimator.

Similar to the PS method, it is important to choose firms that are in the common support of the GPS. Here, I follow the approach proposed by Flores-Lagunes et al. (2012) to restrict the analysis to those firms within common support condition. I impose the common support condition when I want to estimate the DRF under the SPIW method because it makes more sense to do so with a Kernel estimator ¹⁰.

After estimating the GPS for each sample specification, it is necessary to check that the balancing property is satisfied in every sample specification. Indeed, the GPS should eliminate any significant differences in the covariates. I apply the likelihood ratio (LR) test proposed by Flores-Lagunes et al. (2012) to assess the balancing property ¹¹.

Taking everything into consideration, I implement the PPM method under flexible distributions of the treatment variable to find the better fit with data. I also implement the SPIW approach imposing the common support, using a kernel, and selecting a global bandwidth based on the approach proposed by Fan and Gijbels (1996).

2.4 Results

2.4.1 Estimates from the DID fixed effects matching estimator

The results of estimated PSs based on the probit regressions are in Appendix A (Table A.1) and for both samples, the balancing property has been satisfied and the common support has been selected (Appendix A: Figures A.1 and A.2, Tables A.2 and A.3). Tables 2.4 and 2.5 represent the results of the employment regression estimation for the unmatched and matched samples for the full sample and micro-sized firms, respectively. I focus on the matched sample since it is the approach of interest in this study. Column (1) includes only post-loan dummy.

¹⁰For more details about common support condition and Kernel estimator read Bia et al. (2014).

¹¹Read Appendix A for more details.

Column (2) includes both the post-loan dummy and the real amount of loan. Column (3) includes the post-loan dummy, the real amount of loan, and the real amount of loan squared.

Table 2.4 shows that the estimates of the post-loan dummy for the matched sample are somewhat smaller than the unmatched sample for the full sample. The estimate suggests an average treatment effect of 2.66 additional jobs on the treated firms. The coefficients in columns (2) and (3) are rather similar to columns (5) and (6) after including the real loan amount. When I include the real amount of loan, the estimate suggests that each million IRR could create 4.02 jobs (column (2)). Results based on the quadratic specification in columns (3) and (6) show the relationship is slightly concave.

Table 2.5 shows that the estimates of the post-loan dummy for the matched sample are somewhat smaller than the unmatched sample in micro-sized firms as well. The estimate suggests an average treatment effect of 1.15 additional jobs on the treated firms. The coefficients in columns (2) and (3) are rather similar to columns (5) and (6) after including the real loan amount. When the real loan amount is included, the estimates imply an increase of 3.33 jobs per billion IRR of loans (column (2)). Results based on the quadratic specification in columns (3) and (6), shows the relationship is largely concave.

Figures 2.1 (a, b), respectively, show the corresponding evolution of unmatched and matched mean employment for each year before and after receipt of the loan (program began) for treated (non-treated) firms for the full sample. The plot for matched sample (Figure 2.1 b) shows that the employment of treated firms is sort of constant at 2-3 number of workers for years before receiving the loan, but beyond the year received the loan starts to increase and continues to increase until 4 years after the treatment; at the last year it declines a little bit.

Similarly, Figures 2.2 (a, b), respectively, show the corresponding evolution of unmatched and matched mean employment for each year before and after receipt

of loan (program began) for treated (non-treated) firms for micro-sized firms. The plot for the matched sample (Figure 2.2 b) demonstrates that the employment of treated micro-sized firms is sort of constant at 2 number of workers for years before receiving the loan, but beyond the year received the loan starts to increase and continues to increase all years after receiving the loan.

2.4.2 Estimates from the DRFs and the TEFs

The first step to estimate the DRFs is to estimate the GPS by modeling the continuous treatment T_i (the real amount of the loan) given the observable characteristics. A commonly used specification for a non-negative continuous treatment variable to estimate the GPS is a log-normal distribution (Kluve et al. (2012); Hirano and Imbens (2004)). My treatment variable and its log transformation are also non-negative and continuous (Figures 2.3 and 2.4), however, I hesitate to commit ex ante to any one specification and instead estimate a number of flexible generalized linear models (McCullagh (1984)) and choose the model that best fits my data.

I estimate several plausible specifications by GLMs and choose the model that best fits the data according to the Deviance measure of McCullagh and Nelder (1989), the Akaike information criteria (AIC), and also the value of the log-likelihood (LL) function. Across all alternative specifications, a gamma model with a log transformation attains the best model to fit the data for both full sample and micro-sized firms and is, thus, employed to model the GPS in a better way (Appendix A: Table A.4). After estimating the GPS for each sample specification, I apply the LR test proposed by Flores-Lagunes et al. (2012) to check the balancing property. The tests have been satisfied for both samples under imposing and without imposing the common support condition (Appendix A: Tables A.5 and A.6).

In order to estimate the DRFs, I choose the first difference employment as my interested outcome variable. I do this because, first, this variable corresponds to the DID specification, which is a better specification to control unobserved, time-invariant factors affecting all firms at the same time; second, firms received the loans in different years and I have access to their employment just one year after receiving the loan for a few of them ¹². Therefore, to be consistent among all different firms I choose first difference employment, measured in employment difference one year after receiving the loan and before receiving the loan. The range of the treatment level for which I want to consider the employment impact of the amount of the loan is between 20 million IRR to 800 million IRR because more than 90% of the firms received a real amount in this range.

In the first method, I estimate the DRFs under the log-gamma distribution assumption of the treatment based on the PPM approach, and then I estimate the TEFs for a 200 million IRR differences ($\Delta\mu = 200000000$) for the full sample, and 100 million IRR differences ($\Delta\mu = 100000000$) for micro-sized firms. The reason for this is that it is arguable that 200 million IRR is irrelevant for micro-sized firms, which on average received loans of about 200 million IRR. In Figures 2.5 and 2.6, I plot the DRFs and TFTs and the 95% confidence interval based on 1000 bootstrap replications for the full sample and micro-sized firms, respectively.

The DRFs (Figures 2.5 and 2.6) suggest that the first difference employment is an increasing function of the loan levels for both the full sample and micro-sized firms. The average first difference employment appears to be positive and statistically significant for any loan levels (they are significant even for large amounts of the loan).

Moreover, the TEF (Figure 2.5) is always decreasing as the loan level increases and the estimated marginal effects are statistically significantly different from zero for any loan levels in the full sample. It emphasizes that marginal effects are

¹²For example, in my data, 5 firms received the loan in 2010 and I only have access to their employment for the next year (2011).

smaller for a larger amount of the loan. For example, increasing the loan amount from 40 million IRR to 240 million IRR leads to hiring 1.56 (S.E.=0.56) extra workers, but only 1.15 (S.E.=0.39) extra workers are hired when increasing the amount of the loan from 100 million IRR to 300 million IRR. Figure 2.6 suggests that the TEF is always decreasing for all loan levels for micro-sized firms. The estimated marginal effects are statistically significantly different from zero for all loan levels up to 600 million IRR. For instance, increasing the loan amount from 200 million IRR to 300 million IRR leads to hiring 0.50 (S.E.=0.19) additional workers. This amount is 0.31 (S.E.=0.15) when increasing the amount of the loan from 600 million IRR to 700 million IRR.

In the second method, I estimate the DRFs under the log-gamma distribution of the treatment, imposing common support condition, and based on the SPIW approach. I also estimate the TEFs for same marginal difference levels for the full sample and micro-sized firms and plot the results (Figures 2.7 and 2.8).

The story differs based on the SPIW approach for both full sample and micro-sized firms. For the full sample, the DRF (Figure 2.7) shows that the first employment difference increases with the amount of loan up to 300 million IRR and is almost constant up to loan level 500 million IRR, then it continues to rise gradually. However, the DRF (Figure 2.7) is significant for all loan levels except for the range between 300 to 500 million IRR where it is constant. On the contrary, the DRF (Figure 2.8) suggests that the first employment difference always increases with the amount of the loan in micro-sized firms. Similarly, the DRF (Figure 2.8) is significant for all loan levels except for the range between 300 and 500 million IRR.

In addition, Figures 2.7 and 2.8 suggest that an additional amount of loan does not have any significant effect on employment. Precisely, the TEFs (Figures 2.7 and 2.8) are not even significant at the 10% level. Figure 2.7 suggests that the TEF decreases as the amount of the loan increases and also reaches negative

value for the loan level 300 million IRR, then increases gradually. In contrast, Figure 2.8 suggests that the TEF is always decreasing as the amount of the loan increases and also reaching negative value for the loan level greater than 700 million IRR. Therefore, evidence exists that increasing the amount of the loan may force micro-sized firms to hire new employees for the loan amount smaller than 700 million IRR, although not all of them are even significant at the 10% level.

2.5 Conclusion

My estimates of the effect of a small loan program in Iran on employment during the years 2005 to 2010 in this paper are based on two different methods of evaluating causal effects. In the first method, I used a DID fixed effects matching estimator to estimate the employment effect of the policy based on comparing two treated and non-treated firms before and after the intervention for the full sample and micro-sized firms. I estimated the PS and used the Kernel matching on the PS to eliminate the major differences between treated and non-treated firms. In the second method, I applied generalized propensity score, which is based on a continuous treatment variable to estimate the DRF and TEF to realize the employment effect of the loan level for the full sample and micro-sized firms. I used the longitudinal data including 342 firms during 2004 to 2011 for a province in Iran.

The results from the first method can be summarized as follows. I found positive and significant average effects on the employment level of treated firms of about 2.66 jobs at the mean for the full sample and 1.15 jobs at the mean for the micro-sized firms. Moreover, I found an increase of about 4.02 and 3.33 jobs for each billion IRR of loans for the full sample and micro-sized firms, respectively.

The results from the second method suggest that the estimated employment effects increase with the amount of loan between 20 to 800 million IRR significantly for both full sample and micro-sized firms based on the PPM approach. In contrast,

the marginal effects reduce with the amount of loans for both full sample and micro-sized firms based on the same approach. Precisely, the estimated marginal effects based on the PPM method are significant for any loan levels in the full sample and less than 600 million IRR for micro-sized firms. In contrast, the results based on the SPIW method suggest that there are no significant marginal effects for both full sample and micro-sized firms.

The estimated DRFs and TEFs are crucial for policy makers. They provide useful insights to determine the optimal amount of loans, that is, the loan level which maximizes the DRF. The treatment level at which the DRF is maximized is named “location of the optimal dose,” and the maximum amount attained by the DRF is named “size of the optimal dose” following Flores et al. (2007). In my study, for the full sample, the estimated DRFs suggest an increasing relation between first difference employment and level of loans, makes it difficult to determine the optimal amount of loans.

Although the estimated DRF based on the PPM method is increasing in the amount of loan in micro-sized firms, it seems that its curvature is weakened for loan levels greater than 600 million IRR based on the SPIW method. Thus, I could determine the loan level 600 million IRR as the location of the optimal dose (see Figure 2.8). The estimated first difference employment at 600 million IRR is 2.89 (size of the optimal dose), with a standard error of 1.68 (statistically different from 0 under 90% confidence). This result suggests that medium-high loan levels are more effective than extremely low or high loan levels, documented by (Bia & Mattei, 2012) as well.

In Iran, several organizations raised controversial issues about the cost of creating a job during the program years. The ministry of cooperatives, labor, and social welfare of Iran documented that the average cost of creating a job was about 190 million IRR in small-sized firms in 2007 which matches the result of this study.

Table 2.1: Loans paid and number of firms that received a loan during 2005 to 2011 in Iran and Hamedan

Iran								
Year	2005	2006	2007	2008	2009	2010	2011	Sum
Number of firms	10637	281091	324538	41816	13450	N.A.	N.A.	N.A.
Loans paid (trillion IRR)	1.9	68.5	98	32	17.5	15.7	2.6	236.4
Hamedan								
Year	2005	2006	2007	2008	2009	2010	2011	Sum
Number of firms	22	13448	14255	1173	223	N.A.	N.A.	N.A.
Loans paid (billion IRR)	5.6	2287.8	3393.3	1222.7	985.6	767.8	190.5	8853.6

Table 2.2: Loans paid and number of firms that received a loan for different sample specifications

Full sample							
Year	2005	2006	2007	2008	2009	2010	Sum
Number of firms	8	39	57	15	9	5	133
Loans paid (million IRR)	1090	12970	35802	29695	5930	1150	86637
Micro-sized firms							
Year	2005	2006	2007	2008	2009	2010	Sum
Number of firms	8	34	49	11	7	5	114
Loans paid (million IRR)	1090	11910	13772	5970	3310	1150	37202

Table 2.3: Descriptive Statistics: Means (Standard Errors in parentheses)

Variables	Full sample		Micro-sized firms	
	Treated	Non-treated	Treated	Non-treated
Employment	5.76 (7.77)	5.84 (5.98)	3.68 (2.27)	4.05 (2.29)
First difference employment	3.12 (4.72)	- -	2.02 (2.12)	- -
Loan amount (million IRR)	651 (1680)	- -	326 (509)	- -
Loan amount-10th percent	50	-	45	
Loan amount-25th percent	100	-	80	-
Loan amount-Median	200	-	180	-
Loan amount-75th percent	350	-	300	-
Loan amount-90th percent	1170	-	950	-
Firm owner characteristics				
Sex (Male)	0.91	0.94	0.93	0.95
Age	44	41	44	42
Education (High School diploma or lower)	0.73	0.71	0.75	0.73
Firm characteristics				
Sector of activity				
Service	0.40	0.60	0.40	0.58
Manufacturing	0.24	0.17	0.20	0.17
Agriculture	0.36	0.23	0.40	0.25
City				
Asadabad	0.29	0.08	0.32	0.08
Bahar	0.03	0.06	0.03	0.07
Hamedan	0.24	0.42	0.20	0.41
Kabodarahang	0.08	0.03	0.09	0.03
Malaer	0.19	0.20	0.19	0.21
Nahavand	0.07	0.11	0.06	0.10
Razan	0.10	0.10	0.11	0.10
Start-ups	0.41	0.24	0.40	0.24
Sample size	133	209	114	183

Table 2.4: The impact on employment for the full sample (Standard Errors in parentheses)

Dependent variable: employment level (number of workers)						
Independent variables	Matched			Unmatched		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-loan dummy	2.66*** (0.25)	0.90*** (0.25)	0.78*** (0.27)	2.74*** (0.20)	1.02*** (0.18)	0.91*** (0.20)
Real amount of loan (billion IRR)		4.02*** (0.19)	4.54*** (0.53)		4.00*** (0.14)	4.50*** (0.40)
Real amount of loan squared			-0.08 (0.08)			-0.08 (0.06)
Pre-loan dummy		-0.21 (1.46)			-0.83 (0.60)	
Firms fixed effects ^(a)	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies ^(a)	Yes	Yes	Yes	Yes	Yes	Yes
Start-ups dummy	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations ^(b)	2640	2640	2640	2736	2736	2736
Number of firms ^(b)	330	330	330	342	342	342
R^2 ^(b)	0.007	0.04	0.04	0.01	0.15	0.15

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

^aI did not include the fixed effects when estimating the pre-loan dummy specification, because of the problem of collinearity resulting in an unbalanced panel data in this case as well.

^bNumber of observations, number of firms, and R^2 are for post-loan dummy specification results.

Table 2.5: The impact on employment of micro-sized firms (Standard Errors in parentheses)

Dependent variable: employment level (number of workers)						
Independent variables	Matched			Unmatched		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-loan dummy	1.15*** (0.15)	0.44*** (0.17)	0.07 (0.20)	1.35*** (0.11)	0.64*** (0.12)	0.28** (0.15)
Real amount of loan (billion IRR)		3.33*** (0.40)	6.53*** (1.03)		3.28*** (0.29)	6.39*** (0.73)
Real amount of loan squared			-2.08*** (0.62)			-2.07*** (0.45)
Pre-loan dummy		0.35 (0.28)			-0.56*** (0.23)	
Firm level fixed effects ^(a)	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies ^(a)	Yes	Yes	Yes	Yes	Yes	Yes
Start-ups dummy	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations ^(b)	2264	2264	2264	2376	2376	2376
Number of firms ^(b)	283	283	283	297	297	297
R^2 ^(b)	0.06	0.06	0.07	0.05	0.07	0.07

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

^aI did not include the fixed effects when estimating the pre-loan dummy specification, because of the problem of collinearity resulting in an unbalanced panel data in this case as well.

^bNumber of observations, number of firms, and R^2 are for post-loan dummy specification results.

Figure 2.1: The evolution of mean employment for the full sample

“0” is the loan received (program began) year for treated (non-treated) firms in above figures. “-6” refers to 6 years before treatment and “5” is the 5 years after treatment. We have the non-treated firm’s employment history for only two years before the program began.

Figure 2.2: The evolution of mean employment for micro-sized firms

“0” is the loan received (program began) year for treated (non-treated) firms in above figures. “-6” refers to 6 years before treatment and “5” is the 5 years after treatment. We have the non-treated firm’s employment history for only two years before the program began.

Figure 2.3: Histogram of the real amount of loan in billion IRR and its log transformation for the full sample

Figure 2.4: Histogram of the real amount of loan in billion IRR and its log transformation for micro-sized firms

Figure 2.5: The DRF and the TEF for the full sample using PPM approach (Treatment level = the real amount of the loan in million IRR)

Figure 2.6: The DRF and the TEF for micro-sized firms using PPM approach (Treatment level = the real amount of the loan in million IRR)

Figure 2.7: The DRF and the TEF for the full sample using SPIW approach (Treatment level = the real amount of the loan in million IRR)

Figure 2.8: The DRF and the TEF for micro-sized firms using SPIW approach (Treatment level = the real amount of the loan in million IRR)

CHAPTER 3

DO FIRMS' INFLATION EXPECTATIONS MATTER IN THEIR LABOR DEMAND AND WAGES?

3.1 Introduction

Firms' uncertainty about future inflation makes their decision-making more difficult. Indeed, firms' inflation expectations not only affect their own businesses but also influence current inflation. In the new Keynesian Phillips curve model (see Clarida, Gali, and Gertler (1999) or Woodford (2011)), inflation expectations are a key determinant of current inflation. Hence, central banks must monitor firms' inflation expectations because they are crucial in determining the desired inflation and unemployment rates.

When firms seek to invest in their businesses or simply to finance their ongoing operations, they may take out loans. Obviously, firms' demand for loans depends on their expectations about future economic activity and inflation, which may affect firms' investment process (Sealey (1979); Pazarbasioglu et al. (1996)). In addition, wages may change in response to an increase in firms' inflation expectations under an imperfect labor market condition. Therefore, considering firms' inflation expectations and their effects on their loan demands, demand for factors of production, and wages is critical to study to understand the effectiveness of monetary policy on the labor market.

This chapter studies how firms behave differently toward their demand for factors of production and wages when inflation expectations, measured by the loan amounts they demand, vary across firms. Since the process of acquiring information about inflation is costly and firms do not have perfect information regarding it, their inflation expectations will be set at different levels (Coibion, Gorodnichenko, Kumar, and Pedemonte (2018)). As a result of these dispersed inflation expectations

and the existence of an imperfect labor market, wages and the demand for factors of production should be different across firms. Precisely, this study aims to show the difference between a firm that has a greater-than-actual inflation expectation and another firm that has a lower-than-actual inflation expectation in regard to their demand for factors of production and wages when a bargaining mechanism sets wages.

To answer this question, theoretically, I consider a two-period model in which I allow firms to take out a loan and invest it during the first period and then use the new level of capital and hire workers in the second period. In fact, this model allows me to compare the expected labor demand with the actual labor demand under a dispersed inflation expectation across firms in the second period. Therefore, in the first part of this chapter, I consider how firms' demand for labor and capital and wages will be affected by firms' inflation expectations under a two-period bargaining model in which individual workers can bargain over wages with their employers.

Empirically, I test the main predictions of the theoretical model by using longitudinal firm-level data from Hamedan province in Iran from 2004 to 2011. During this period, Iran dealt with high, volatile inflation that ranged from 10% to 25% and a high unemployment rate that ranged from 10% to 14%. To combat the high unemployment, the Iranian government developed a small loan program to support small enterprises and encourage them to invest and hire new workers. Obviously, this highly volatile inflation situation made firms' formation of inflation expectations more difficult and dispersed, which may have influenced their loan demand, demand for factors of production, and wages. In the model, I measure firms' inflation expectations by the amounts of the loans they demanded from the small loan program. My argument is that firms with high inflation expectations would demand larger loans.

The first prediction of the model is that firms that expect a rise in their products' prices will accept higher wages demanded by workers. This is basically because of the bargaining mechanism in the labor market, whereby employers and employees bargain over wages individually. The expectation of an increase in price will convince firms to accept the higher wages demanded by workers because of an increase in the marginal revenue product of labor. Second, the model shows that firms that forecast inflation correctly not only invest exactly as much as they expected but also hire exactly the number of workers they expected. On the contrary, firms with inaccurate inflation expectations not only are not able to invest as much as they expected but also are not able to hire exactly the number of workers they expected. Precisely, firms that overestimate inflation will demand less labor than they expected, and in contrast, firms that underestimate inflation will demand more labor than they expected.

The empirical analysis confirms the predictions of the theoretical model. It includes estimating four separate equations—one for the wage, one for the actual labor demand, one for the expected labor demand, and one for the difference between the actual labor demand and the expected labor demand—as dependent variables on the loan amount as the independent variable. It is found that there is a positive and strongly significant relationship between wages and loan amount. This relationship indicates that firms that demand larger loans precisely because of higher inflation expectations agree to pay higher wages to their workers.

Furthermore, the results suggest that both actual and expected labor demands are equal to the loan amount of about 200 million Iranian Rial (IRR) ¹ but there is a gap between them for any other loan amount. In detail, the expected labor demand is overestimated for any loan amount greater than about 200 million IRR, and in reverse, the expected labor demand is underestimated for any loan amount less than about 200 million IRR. However, the difference between actual and

¹The exchange rate with the U.S. dollar was around \$1 = 10000 IRR.

expected labor demands is not statistically significantly different from 0, indicating that firms' actual labor demand is not that far from their expected labor demand.

This gap between expected and actual labor demand among different loan amounts can be explained by firms' inflation expectations. In fact, the model argues that firms that demand a larger loan precisely because of higher inflation expectations and realize that actual inflation is less than their expectations are not able to hire exactly the number of workers they expect for two reasons: First, they do not invest as much as they expected to, and second, the actual real wage would be greater than their expected real wage. By contrast, firms that demand a smaller loan precisely because of lower inflation expectations and realize that actual inflation is greater than their expectations are able to hire even more workers than expected for the same two reasons: First, they invest even more than they expected to, and second, the actual real wage would be less than their expected real wage. Finally, firms that forecast inflation correctly and have rational expectations demand the rational loan amount and are able to invest as much as they expect to, and their expected real wage would be equal to the actual one, as a consequence of which, they hire exactly the number of workers they expected to.

One important aspect of the empirical result of this study is to confirm that firms have dispersed inflation expectations, as documented by other studies as well. For example, Kumar, Afrouzi, Coibion, and Gorodnichenko (2015) found that in spite of 25 years of inflation targeting and a long history of low and stable inflation in New Zealand, firms are unaware of the central bank's objectives, and they do not have adequate information about inflation dynamics. They report that the dispersion of firms' inflation expectations is between 2 and 3 percentage points. Similar Bryan, Meyer, and Parker (2015) showed that firm managers in the U.S. also have much higher as well as more dispersed expectations of inflation. Coibion and Gorodnichenko (2015) studied data of inflation expectations in Ukraine, where inflation has been high and volatile. They show that, like households, firms

strongly disagree in their predictions about inflation, with a standard deviation of about 10.9%. In contrast, Afrouzi (2017) conducted a survey of firms' inflation expectations in Iran, a country that has experienced highly volatile inflation over the last four decades. The result shows that firms' inflation expectations are relatively precise, and their average expectation is only 2 percentage points away from the actual inflation, and despite the high volatility of inflation, the dispersion of their expectations is only 3.5 percentage points.

On average, I find that about 60% of firms underestimated inflation, 30% overestimated inflation, and finally, just 10% had a rational expectation regarding inflation and could forecast it correctly. Although it seems that firms' inflation expectations are not consistent with full-information rational expectations models, they are relatively accurate, and firms' inflation expectations are not that far away from actual inflation, as confirmed by Afrouzi (2017).

Another important aspect of this study relates to the loan program's efficiency in terms of creating jobs. First, the results show that marginal effects are larger for smaller loans, which means that firms that receive smaller loans have more incentive to hire new workers than firms that receive larger loans. Second, the main result of this study explains that firms that receive larger loans hire fewer workers than expected, and in contrast, firms that receive smaller loans hire more workers more than expected. In fact, this gap between the actual labor demand and the expected labor demand originates from firms' inflation expectations, which cause uncertainty in firms' labor demand decisions. Therefore, I argue that firms that demand smaller loans are able to invest and utilize them more efficiently than firms that demand larger loans precisely because of their higher inflation expectations.

The main contribution of this study is to show that firms act differently in the labor market when they have different levels of inflation expectations. Thus, firms' inflation expectations affect their economic decisions, particularly, their wages and labor demands. Generally, we can divide studies that are related to this

study into two areas: First, papers that explore the formation of firms' inflation expectations, which I already mentioned above; second, papers that investigate the effects of inflation expectations on employment and wage setting. For example, Kaihatsu, Shiraki, et al. (2016) investigated the relationship between Japanese firms' inflation expectations and wages using data from 2004 to 2016. Their empirical results show that there is a positive and significant correlation between wages and firms' medium- to long-term inflation expectations; however, an increase in firms' short-term inflation expectations will decrease wages. Ratti (1985) presented a partial equilibrium model of the labor market that allows the real wage, the expected real wage, and the level of employment to be expressed as functions of unexpected inflation, inflation uncertainty, and supply shocks. His regression equation estimation using U.S. data from 1948 to 1980 suggests that inflationary surprises and uncertainty cause countercyclical movement in real wages. He finds that a rise in unexpected inflation depresses real wages and raises expected wages and the level of employment.

The theoretical approach of this study is somewhat related to McDonald and Solow (1981), Diamond (1982), and especially, Pissarides (1987) and Rotemberg (1999), with an extension to a dynamic model. In Pissarides (1987), workers can bargain individually or collectively in a union. Rotemberg (1999) considered a model in which workers bargain with their employer individually and shows that, since workers' real wages depend on their marginal products, the rise in real wages induced by an increase in labor demand will be dampened. The empirical approach of this study has been developed by different authors who estimate the causal effects of a continuous treatment (e.g., Hirano and Imbens (2004); Kluve et al. (2012); Bia and Mattei (2012); Bia et al. (2008); Flores-Lagunes et al. (2012)).

The study proceeds as follows: Section 2 illustrates the dynamic model of firms' investment plan in an individualistic bargaining model in which individual workers bargain over wages with their employer and derives testable predictions. Section

3 explains the empirical part of the study, including the labor market and small loan program in Iran, data, estimation strategy, and results. Finally, section 4 concludes.

3.2 The Model

Since investors do not have sufficient information to assess the riskiness of investing in small firms, equity financing is difficult for small firms to secure. Thus, firms prefer debt financing over equity financing, and I assume that small firms do not finance their businesses by issuing equity. Clearly, loans provided by banks are one of the primary sources of debt financing for small firms. As the literature has emphasized, a firm i 's loan demand depends on its expected investment, the loan's interest rate, its expected inflation rate, and its expected production in period t : The employment regression takes the form

$$L_{it}^d = L(I_{it}^e, i_{L_{it}}, \pi_{it}^e, y_{it}^e) \quad (3.1)$$

where $L_{I_{it}^e}, L_{\pi_{it}^e}, L_{y_{it}^e} > 0$, and $L_{i_{L_{it}}} < 0$. I_{it}^e is the expected investment; $i_{L_{it}}$ is the loan interest rate; π_{it}^e is the expected inflation rate; and y_{it}^e is the expected production.

It is important that firms' loan demands depend on their forward-looking expectations (Laffont and Garcia (1977); Sealey (1979)). As a matter of fact, these forward-looking expectations are the source of the firms' uncertainty and cause firms' actual decisions to deviate from their expectations. Firms' expected investment is expected to have a positive effect on their demand for loans. The demand for loans also depends negatively on their interest rates. Higher loan interest rates cause ongoing operations and investment to be delayed for a given expected rate of inflation (Blundell-Wignall, Gizycki, et al. (1992)). Moreover, the demand for loans depends positively on inflation expectations. Firms prefer to borrow more if they expect higher inflation in the future because a higher level

of inflation would erode the value of a nominal loan (Pazarbasioglu et al. (1996)). Finally, expectations of higher production can lead to a higher demand for loans.

Firms make a dynamic decision towards investing a loan in their production process, and since this process takes time, I use a dynamic profit function. Extending the model presented by Rotemberg (1999) into a two-period profit function, I aim to find the conditions that characterize small firms' profit-maximizing choices about labor and capital. Firms' profit-maximizing decisions occur at the beginning of period 1, when they receive their loans.

A small firm i takes prices as given in a competitive market of both final goods and capital. However, wages are determined based on individualistic bargaining between employers and workers. I suppose that we have $\bar{N}$ workers who are willing to work at a reservation wage w_r . So, if wages are greater than w_r while employment is less than $\bar{N}$, we will face involuntarily unemployed workers who are willing to work but cannot find jobs. The wage rate agreement depends on the bargaining power δ between employers and workers. δ is a parameter between 0 and 1 where workers have all the bargaining power when it equals 1 and employers have all the bargaining power when it equals 0. After the bargaining is finalized, firms have to make a long-term contract run for two periods, and that contract specifies nominal wages for the next two periods. So, employers cannot adjust the wage rate² after making the contract during two periods. However, firms can fire workers at any time. Moreover, firms incur an additional setup cost φ per worker each period.³

I will now establish some basic assumptions about the model. Firm i uses labor and capital factors in order to produce a final output good in each period. Firm i 's production function is $y_{it} = f(k_{it}, n_{it})$, where $t = 1, 2$ and f is assumed to be a concave function in each k and n . Basically, the concavity assumption of the

²So, wages are sticky.

³For more details, see Rotemberg (1999).

production function corresponds to a strictly positive marginal product in each k and n ($f_n, f_k > 0$) and a strictly diminishing marginal product in each of them ($f_{nn}, f_{kk} < 0$)⁴. Figure 1 shows the timing of the events for firm i .

As we can see in Figure 3.1, firm i uses existing capital (k_{i1}) and hires labor (n_{i1}) to produce $y_{i1} = f(k_{i1}, n_{i1})$ in the first period. Firm i receives the loan (L_{i1}^d) at the beginning of period 1 and it starts to invest the loan in its business and will end up with k_{i2} level of the capital at the end of period 1. So, $I_{i1} = k_{i2} - k_{i1}$ is the firm's investment in period 1. Then, firm i uses k_{i2} and hires labor n_{i2} to produce $y_{i2} = f(k_{i2}, n_{i2})$ in the second period and does not invest in this period.

Since firms exist in competitive markets for both output goods and capital, the price of firm i 's output (p_t) and the price of its capital good (p_t^k)⁵ are given to the firm during both periods. Thus, $\pi_t = (p_t/p_{t-1}) - 1$ is the consumer price inflation rate between t and $t - 1$. However, firm i has an expectation about $p_2 = p_1^e$ ⁶ at the beginning of the first period, when it is making a decision to maximize its profit for both entire periods. As a result, firm i also has an expectation about k_{i2} (k_{i1}^e) and n_{i2} (n_{i1}^e).

The wage results from a game between workers and firms based on a bargaining mechanism. The general Nash equilibrium of the game between workers and firms over wages (w) is⁷

$$w = w_r + \delta \max [0, pf_n(n, k) - w_r] \quad (3.2)$$

⁴ f_n, f_{nn} , and f_{nnn} represent the first, second, and third derivatives with respect to labor, respectively. Moreover, based on the two above concepts, I can state that $f_{nnn}, f_{kkk} > 0$, $f_{nk}, f_{kn} > 0$, and $f_{nkn}, f_{knk} < 0$.

⁵Throughout, I set $p_t^k = 1$.

⁶Then, $\pi_1^e = (p_1^e/p_1) - 1$.

⁷For more details about how to determine this wage, see Rotemberg (1999).

As a result, wages w_{i1} and w_{i2} (w_{i1}^e) are

$$w_{i1} = w_{r1} + \delta \max [0, p_1 f_n(n_{i1}, k_{i1}) - w_{r1}] \quad (3.3)$$

$$w_{i1}^e = w_{r2} + \delta \max [0, p_1^e f_n(n_{i2}^e, k_{i2}^e) - w_{r2}] \quad (3.4)$$

where w_{i1}^e is firm i 's expectation about the wage in the second period. As we can see, when δ equals 1, we have the outcome that represents when employees have all the bargaining power and they can obtain their full marginal product if $p f_n(n, k) > w_r$. On the other hand, employers have all the bargaining power when δ is equal to 0, and the employees obtain w_r . If $0 < \delta < 1$, then the bargaining power is more equally divided between employees and employers. I suppose that δ will not change over the two periods, which means that the bargaining power will remain unchanged between employees and employers. In addition, I suppose that workers' reservation wages do not change over the two periods as well ($w_{r1} = w_{r2} = w_r$). The latter is reasonable, based on the standard job search models, when we do not face significant changes in the offered wage distribution, the arrival rate of job offers, and the job search cost (Jones (1988); Kiefer and Neumann (1979)). From the macroeconomic point of view, there is no significant change in the labor demand that could impact both the overall wage distribution and the unemployment duration and therefore affect reservation wages (Prasad (2003)).

Equation 3.2 suggests that, *ceteris paribus*, firm i may accept the higher wages demanded by workers when it expects an increase in its prices. This is mainly because of an increase in the marginal revenue product of labor. Thus, if there is a bargaining mechanism, we may expect to observe a correlation between firms' inflation expectations and wages that they accept to pay.

Based on all the above basics, the small firm i 's expected present value of profit (Π_i^e) from the perspective of period 1 and using the nominal interest rate r is

$$\Pi_i^e = \underbrace{p_1 f(k_{i1}, n_{i1}) - w_{i1} n_{i1} - \varphi n_{i1} - \overbrace{(k_{i1}^e - k_{i1})}^I}_{\text{period-1 profit}} + \underbrace{\frac{p_1^e f(k_{i1}^e, n_{i1}^e) - w_{i1}^e n_{i1}^e - \varphi n_{i1}^e + k_{i1}^e}{1+r}}_{\text{present value of period-2 profit}} \quad (3.5)$$

Firm i 's choice variables are the quantities of labor in periods 1 and 2 ((n_{i1}) and (n_{i1}^e)), and the quantity of capital at the end of period 1 (k_{i1}^e), which is invested in the first period and will be used in the second period. k_{i1} is a pre-determined factor, so it is already determined at the beginning of period 1.

The results from first-order conditions with respect to n_{i1} , n_{i1}^e , and k_{i1}^e , after plugging w_{i1} and w_{i1}^e into the profit function and assuming $pf_n(n, k) > w_r$, are, respectively,⁸

$$(1 - \delta)f_{1n} - \delta f_{1nn}n_{i1} = \frac{(1 - \delta)w_r + \varphi}{p_1} \quad (3.6)$$

$$(1 - \delta)f_{2n} - \delta f_{2nn}n_{i1}^e = \frac{(1 - \delta)w_r + \varphi}{p_1^e} \quad (3.7)$$

$$f_{2k} - \delta f_{2nk}n_{i1}^e = \frac{r}{p_1^e} \quad (3.8)$$

There are unique and optimal solutions for equations 3.6, 3.7, and 3.8 if Π_i^e is concave everywhere, so, for all n and k ,

$$(1 - \delta)f_{1nn} - \delta\{f_{1nn} + n_{i1}f_{1nnn}\} < 0 \quad (3.9)$$

⁸ f_{1n} represents the first derivative of the production function with respect to labor in period 1. f_{1nn} represents the second derivative of the production function with respect to labor in period 1.

$$(1 - \delta)f_{2nn} - \delta\{f_{2nn} + n_{i1}^e f_{2nnn}\} < 0 \quad (3.10)$$

$$f_{2kk} - \delta f_{2nkk} n_{i1}^e < 0 \quad (3.11)$$

In addition, we need to check that the boundary conditions for n and k are satisfied:

$$\lim_{n \rightarrow 0} \frac{\partial \Pi}{\partial n} > 0 \quad \text{and} \quad \lim_{n \rightarrow \infty} \frac{\partial \Pi}{\partial n} < 0 \quad (3.12)$$

$$\lim_{k \rightarrow 0} \frac{\partial \Pi}{\partial k} > 0 \quad \text{and} \quad \lim_{k \rightarrow \infty} \frac{\partial \Pi}{\partial k} < 0 \quad (3.13)$$

If f exhibits diminishing returns and equations 3.9, 3.10, 3.11, 3.12, and 3.13 are satisfied while δ is sufficiently small (more bargaining power for employers, which is the standard case in the literature), there exist optimal solutions. I consider a Cobb-Douglas production function to show the existence of solutions explicitly:

$$y_{it} = n_{it}^\alpha k_{it}^{1-\alpha}, \quad 0 < \alpha < 1 \quad (3.14)$$

This production function exhibits a strictly positive marginal product in each k and n and a strictly diminishing marginal product in each of them as well. The first-order condition 3.6 is given by

$$n_{i1} = \frac{\alpha(1 - \alpha\delta)p_1 y_{i1}}{(1 - \delta)w_r + \varphi} \quad (3.15)$$

Similarly, the first-order conditions 3.7 and 3.8 give us the expected labor and capital demands for the second period:

$$n_{i1}^e = \frac{\alpha(1 - \alpha\delta)p_1^e y_{i1}^e}{(1 - \delta)w_r + \varphi} \quad (3.16)$$

$$k_{i1}^e = (1 - \alpha)(1 - \alpha\delta) \frac{p_1^e y_{i1}^e}{r} \quad (3.17)$$

Therefore, my solutions for capital and labor demands represent a global optimum with strictly positive employment. To prove this, I need to show that conditions 3.9, 3.10, 3.11, 3.12, and 3.13 will be satisfied. The second-order conditions 3.9, 3.10, and 3.11 are given by

$$\alpha(\alpha - 1)(1 - \alpha\delta)n_{i1}^{\alpha-2}k_{i1}^{1-\alpha} < 0 \quad (3.18)$$

$$\alpha(\alpha - 1)(1 - \alpha\delta)(n_{i1}^e)^{\alpha-2}(k_{i1}^e)^{1-\alpha} < 0 \quad (3.19)$$

$$-\alpha(1 - \alpha)(1 - \alpha\delta)(n_{i1}^e)^{\alpha-1}(k_{i1}^e)^{-\alpha-1} < 0 \quad (3.20)$$

As we can see, all three equations 3.18, 3.19, and 3.20 will be satisfied. Moreover, the boundary conditions of the profit function are given by

$$\frac{\partial \Pi_i}{\partial n_{i1}} = \alpha(1 - \alpha\delta)n_{i1}^{\alpha-1}k_{i1}^{1-\alpha} - \frac{(1 - \delta)w_r + \varphi}{p_1^e} \quad (3.21)$$

$$\frac{\partial \Pi_i}{\partial n_{i1}^e} = \alpha(1 - \alpha\delta)(n_{i1}^e)^{\alpha-1}(k_{i1}^e)^{1-\alpha} - \frac{(1 - \delta)w_r + \varphi}{p_1^e} \quad (3.22)$$

$$\frac{\partial \Pi_i}{\partial k_{i1}^e} = (1 - \alpha)(1 - \alpha\delta)(n_{i1}^e)^\alpha(k_{i1}^e)^{-\alpha} - \frac{r}{p_1^e} \quad (3.23)$$

One can easily evaluate that $\lim_{n_{i1} \rightarrow 0} \frac{\partial \Pi_i}{\partial n_{i1}} > 0$ for a lower reservation wage, $\lim_{n_{i1} \rightarrow \infty} \frac{\partial \Pi_i}{\partial n_{i1}} < 0$, $\lim_{n_{i1}^e \rightarrow 0} \frac{\partial \Pi_i}{\partial n_{i1}^e} > 0$ for a lower reservation wage, $\lim_{n_{i1}^e \rightarrow \infty} \frac{\partial \Pi_i}{\partial n_{i1}^e} < 0$, $\lim_{k_{i1}^e \rightarrow 0} \frac{\partial \Pi_i}{\partial k_{i1}^e} > 0$, and $\lim_{k_{i1}^e \rightarrow \infty} \frac{\partial \Pi_i}{\partial k_{i1}^e} < 0$.

Finally, using 3.3 and 3.4 and assuming $pf_n(n, k) > w_r$, the resulting wages are

$$w_{i1} = w_{i1}^e = \frac{(1 - \delta)(1 - \alpha\delta + \delta)w_r + \delta\varphi}{1 - \alpha\delta} \quad (3.24)$$

which demonstrates that both w_{i1} and w_{i1}^e just depend positively on the reservation wage and φ must exceed $\delta(1 - \alpha)w_r$ to ensure that the wage is above the reservation wage.

So, I could show that there are solutions based on some properties related to the production function. As we can see in equations 3.15, 3.16, and 3.17, firm i 's first-period labor demand just depends on workers' reservation wage (p_1 and k_{i1} are given to firm i), but firm i 's second-period expected labor and capital demands depend on its expected price and expected production. In fact, firm i 's second-period expected labor demand depends on the expected real reservation wage $\left(\frac{w_r}{p_1^e}\right)$ and the expected production (y_{i1}^e). Similarly, firm i 's second-period expected capital demand depends on the expected real interest rate $\left(\frac{r}{p_1^e}\right)$ and the expected production y_{i1}^e . Grasso and Ropele (2016) investigated the relationship between firms' inflation expectations and their expected investment. They find that a 1% increase in expected inflation raises firm' expected investment expenditure by about 2.5%. Since the variable of interest is the expected labor demand in this study, I will focus on that henceforth.

To show how firm i 's inflation expectation can cause its expected labor demand to deviate from its actual one, let's first focus on the first period. If firm i realizes $\pi_1^e < \pi_2^a$ ($\pi_1^e > \pi_2^a$), then $p_1^e < p_2^a$ ($p_1^e > p_2^a$) and $\frac{r}{p_1^e} > \frac{r}{p_2^a}$ ($\frac{r}{p_1^e} < \frac{r}{p_2^a}$), and this results in $k_{i1}^e < k_{i2}^a$ ($k_{i1}^e > k_{i2}^a$). It seems that, given expected production, if firm i 's expected inflation does not meet the actual inflation, it is not able to invest as much as it expected. In contrast, if firm i realizes $\pi_1^e = \pi_2^a$, then $p_1^e = p_2^a$ and $\frac{r}{p_1^e} = \frac{r}{p_2^a}$, and this results in $k_{i1}^e = k_{i2}^a$. It seems that if firm i has a rational expectation

⁹ a stands for actual.

regarding inflation, it is able to invest exactly as much as it expected by the end of the first period.

Regarding comparing the expected labor demand and the actual labor demand in the second period, if firm i realizes $\pi_1^e < \pi_2^a$ ($\pi_1^e > \pi_2^a$), then $p_1^e < p_2^a$ ($p_1^e > p_2^a$) and $\frac{w_{ri}}{p_1^e} > \frac{w_r}{p_2^a}$ ($\frac{w_r}{p_1^e} < \frac{w_r}{p_2^a}$), then this results in $n_{i1}^e < n_{i2}^a$ ($n_{i1}^e > n_{i2}^a$). In fact, for a given expected production, if firms realize that the actual inflation rate is greater (less) than their expectations, their actual real reservation wage would be less (greater) than expected, and in consequence, their actual labor demand would be greater (less) than expected. In contrast, if firm i realizes $\pi_1^e = \pi_2^a$, then $p_1^e = p_2^a$ and $\frac{w_r}{p_1^e} = \frac{w_r}{p_2^a}$, and this results in $n_{i2}^e = n_{i2}^a$ for a given expected production. When firms realize that the actual inflation rate is equal to their expectations, their actual real reservation wage is equal to their expected one, and in consequence, their actual labor demand is equal to their expected one. As a result of putting the two periods together, if firm i realizes $\pi_1^e < \pi_2^a$ ($\pi_1^e > \pi_2^a$), its production expectation turns out wrong ($y_{i1}^e < y_{i2}^a$ and $y_{i1}^e > y_{i2}^a$, respectively), and if it realizes that $\pi_1^e = \pi_2^a$, its production expectation turns out right ($y_{i1}^e = y_{i2}^a$).

Now, I am able to consider how the loan amount demanded by firm i impacts its labor demand and how its expected labor demand deviates from its actual one under dispersed inflation expectations across firms. If firm i receives the loan and invests it in its business, it will end up with k_{i2} level of capital by end of the first period. As a result of a higher level of capital, firm i will demand more labor in the second period, so there should be a positive relationship between labor demand and loan amount (Bia and Mattei (2012); Nosratabadi (2018); J. Brown and Earle (2013); Craig et al. (2006); Morris and Stevens (2010); Pergelova and Angulo-Ruiz (2014)). However, there are three different channels that cause the expected labor demand to deviate from its actual value: firm i 's investment, production, and inflation expectations. I have already argued that both investment and production expectations depend on inflation expectation.

Undoubtedly, measuring firms' inflation expectations is a difficult task; basically, surveys are conducted to extract firms' inflation and price expectations by asking some questions related to general inflation, cost, or the price of firms' products in the future. However, I am able to indirectly measure firms' inflation expectations through the loan amount they demanded in this study. As shown in equation 3.1, firm i 's loan demand depends on its expected future investment ($I_{i1}^e = k_{i1}^e - k_{i1}$), the interest rate ($i_{L_{it}}$), its inflation expectation (π_{it}^e), and expected production (y_{it}^e). So, given expected investment, expected production, and interest rate, equation 3.1 shows that the higher the inflation expectation, the larger the loan demanded by firm i .

Suppose L_{i1}^{d*} is the rational loan amount demanded by firm i and represents $\pi_1^e = \pi_2^a$, given all other variables affecting the loan demand. Based on the same above argument, if firm i demands a loan of amount L_{i1}^{d*} , it ends up with $k_{i1}^e = k_{i2}^a$ because its expected real interest rate will be equal to the actual one. In fact, L_{i1}^{d*} represents that firm i has a rational expectation regarding inflation and can correctly forecast it, and as a result, it invests as much as it expected by the end of period 1. Consequently, I can state that $n_{i1}^e = n_{i2}^a$ because, first, firm i invests as much as it expected, and second, its actual real reservation wage equals its expectation. Thus, I can argue that the firm has a correct expectation regarding its expected production ($y_{i1}^e = y_{i2}^a$) as well.

On the contrary, if $L_{i1}^d > L_{i1}^{d*}$, which represents $\pi_1^e > \pi_2^a$ for given expected investment, expected production, and interest rate, then $k_{i1}^e > k_{i2}^a$, because firm i 's expected real interest rate is underestimated, and as a result, it invests less than it expected. Consequently, $n_{i1}^e > n_{i2}^a$ because firm i not only invests less than expected but also, its actual real reservation wage is greater than its expectation. Similarly, if $L_{i1}^d < L_{i1}^{d*}$, which represents $\pi_1^e < \pi_2^a$ for given expected investment, expected production, and interest rate, then $k_{i1}^e < k_{i2}^a$ because firm i 's expected real interest rate is overestimated, and as a result, it invests more than it expected to.

Consequently, $n_{i1}^e < n_{i2}^a$ because firm i not only invests more than expected but also, its actual real reservation wage is less than its expectation. Taking everything into consideration, it seems that firm i 's production expectation is inaccurate in these cases as well ($y_{i1}^e > y_{i2}^a$ and $y_{i1}^e < y_{i2}^a$, respectively). As a matter of fact, there should be a specific loan amount (a rational amount) for which $n_{i1}^e = n_{i2}^a$, and for a lesser amount, $n_{i1}^e > n_{i2}^a$, and for a greater amount, $n_{i1}^e < n_{i2}^a$, as depicted in Figure 3.2.

3.3 Empirical results

3.3.1 The labor market and small loan programs in Iran and Hamedan

Unemployment in Iran has been a persistent problem throughout the last two decades, with the unemployment rate holding, on average, at about 12% during that time. Governments have developed small loan programs with reduced interest rates to encourage investment and employment throughout the country to combat high unemployment. This research focuses on one small loan program legislated through Law 101 that started in the province of Hamedan during the last 2 months of 2005 and continued through 2011. On average, the amount of loans paid to firms was 1.5% of GDP for each year during the program's existence.

The unemployment rate fluctuated and stayed high during the program's years in both Hamedan and Iran as a whole, as depicted in Figure 3.3. As we observe in Figure 3.3, the unemployment rate gradually increased from 10% to 18% in Hamedan and then declined to 10%. On the other hand, the unemployment rate was more stable but still high for the entire country during the program's years.

Figure 3.4 (a, b) shows employment in Iran as a whole and Hamedan during the program's years. Figure 3.4a shows that employment gradually increased from 2004 to 2007 and then began to fluctuate in Iran. On the other hand, Figure 3.4b suggests that employment experienced a sharp decline from 2004 to 2010 for Hamedan and then started to increase. As a result, the employment growth rate

should demonstrate high fluctuation during the program's years for both Iran as a whole and Hamedan, as depicted in Figure 3.5.

Figures 3.4 (a, b) and 3.5 illustrate that, especially in Hamedan, many people lost their jobs during the program's years. In fact, job losses had been going on since 2004, accelerated drastically starting in 2005, and ended in 2010. Figure 3.6 depicts the labor force participation rate for Iran as a whole and Hamedan. As we observe in this figure, the labor force participation rate gradually declined during the program's years, which indicates that many job-seekers and people who lost their jobs just gave up their job searches, perhaps because they were discouraged.

Taking everything into consideration, we could argue that unemployed workers' reservation wages would decline in this labor market, where unemployed people faced long unemployment and there was no significant change in the aggregate labor demand. S. Brown and Taylor (2013) and Schmieder, Von Wachter, and Bender (2013) show that there is a negative relationship between unemployment duration and reservation wages. For example, S. Brown and Taylor (2013) suggest that the sensitivity of reservation wages with respect to unemployment duration is about -0.84 .

Figure 3.7 displays the inflation rate for Iran as a whole and for Hamedan during the program's years. As we can observe, the inflation rate was very high and volatile during the program's years for both Iran as a whole and Hamedan in particular. This instability created a situation in which firms formed their inflation expectations under uncertainty, which made their expected labor demand deviate from their actual labor demand. Technically, this is mainly because of the dependence of the labor market's reaction to unexpected inflation on the flexibility of nominal wages. Usually, wages are not perfectly flexible because of contractual arrangements between workers and employers. For example, in a contract between a firm and a worker, which is an enforced law in Iran, the nominal wage is fixed for a specified period of time. If nominal wages are sticky in the short run, the actual

real wage differs from the expected real wage when there is a difference between expected and actual inflation (Holland (1984)).

Regarding the loan program in Iran as a whole and in Hamedan, Table 3.1 presents the total amount of loans paid and the total number of firms that received loans in Iran as a whole and Hamedan during the program's years, showing that both amounts were low in 2005 because the program began during last 2 months of that year ¹⁰. On the other hand, the amount of loans paid steadily increased in 2006 to 2007, declining thereafter. The maximum amount of loans paid is estimated to be about 98 trillion IRR (lent to 324,538 firms) and 3.4 trillion IRR (lent to 14,255 firms), respectively, in Iran as a whole and in Hamedan in 2007. The minimum amount of loans paid is estimated to be about 1.9 trillion IRR (lent to 10,637 firms) and 5.6 billion IRR (lent to 22 firms), respectively, in Iran as a whole and Hamedan in 2005.

The program included all Iranian provinces in the service, manufacturing, and agriculture sectors. Only micro-sized firms (those with fewer than 10 workers) and small-sized firms (with fewer than 50 and at least 10 workers) were eligible to apply for the loans. Most loans had a maximum amount of 10 billion IRR, except for the food industry, in which the maximum was 30 billion IRR. The firms fell into the categories of new business, expansion, renovation, new construction, land, buildings, equipment, and so on. Usually, loans had 5 to 7 maturity years. Generally, the regular interest rate of a loan from public banks was between 12 and 14% through the duration of the program ¹¹. On the other hand, the program awarded loans with interest rates from 4 to 6%, which were subsidized by the government during the program's years. This reduced interest rate depended on the type of business, time, region, amount of the loan, and maturity years. Finally, firms were allowed to receive a loan only once from this program.

¹⁰I do not have access to the information for 2010 and 2011. As such, this information is not used for estimating in this study, and the main dataset will be subsequently discussed.

¹¹The interest rate of a loan from private banks was much higher than this range.

To qualify, a business had to be a micro- or small-sized firm, an eligible type of business, able to hire new workers, for-profit, of good character, and possess a feasible business plan. Borrowers were to deposit at least 10% of the total loan amount into the bank account where they received it. The Labor Administration of Hamedan made approval decisions for applications, and the banks made final decisions for loan amounts. Banks were to consider the applications and respond to the applicants during a 15-day period after submission and, if needed, provide a reason for rejecting an application.

After the loans were received, the labor administration would monitor the firms that received the loans for the next year to observe how they were investing the loans in their businesses and collect the necessary information like the number of workers they hired. Firms needed to follow the worker's law of labor administration, and they had to make a year-long contract with workers. Based on the contract, firms were not able to change the wage during that year, but they could fire the workers by letting them know just 1 month before that.

3.3.2 Data and Descriptive Analyses

The loan program was active in all provinces in Iran, but this study focuses on one province because of data availability. In particular, the study implements firm-level data collected by the Labor Administration of Hamedan province. The main part of the data comprises the results of a survey that used a primitively designed questionnaire during the program's years in Hamedan. In the survey, a sample of micro and small enterprises (MSEs) that participated in the loan program (treated firms) were randomly selected. In total, the data are annual, cover the years 2004 through 2011, and contain information about firms and firm owners. The total number of surveyed firms is 133 ¹². Unfortunately, comparing the population sample (Table 1) and the surveyed sample indicates that the number

¹²All of these firms received loans with the same interest rate (4%) and did not take out loans from other sources outside the program during the program's years.

of surveyed firms is very small, so it cannot be taken for granted that it has the same observable characteristics as the population of interest.

Generally, the questionnaire contains two main parts. The first part collects information on the characteristics of the MSEs and their owners' demographics, such as sex, age, education, industry, the city where the firm is located, the size (number of workers) of the firm, etc. The second part collects information including participation in the loan program, the loan amount, the year and month received, etc.

Table 3.2 presents information on the amount of loans paid and the number of treated firms that received loans for the full sample and micro-sized firms during the program's years. Table 3.3 presents the summary statistics of the variables. n_1 is defined as the employment level in the year the loan was received. n_2 is defined as the employment level 1 year after receiving the loan. The actual first difference employment (AFDE) is defined as the difference between the employment level 1 year after receiving the loan and the employment level before receiving the loan. Another variable is the expected first difference employment (EFDE), which was collected when firms were receiving the loan. In fact, firms were asked the question, "How many workers do you expect to hire by 1 year after receiving the loan and investing it in your business?" w_1 and w_2 are the average production worker wages in the year the loan was received and 1 year after receiving the loan, respectively. In addition, first difference wage (FDW) is defined as the difference between w_2 and w_1 .

Tables 3.2 and 3.3 show that the amount of an awarded loan depends intensively on firm size. On average, micro-sized firms received a much lower loan amount than the other firms. For instance, 114 micro-sized firms received 43% of the total amount of loans, but only 19 small-sized firms received the remaining share. In this study, analyses of the full sample and micro-sized firms are made disjointedly because, first, many observations are available for these two samples and, second,

they seem to be extremely heterogeneous with respect to both the loan amount received and the firm's characteristics.

Figure 3.8 (a, b) plots the distribution of employment errors (the difference between AFDE and EFDE (DFDE hereafter)) for the full sample and for micro-sized firms. There is significant heterogeneity in beliefs across firms about employment, although the dispersion of beliefs is symmetric around actual values in both samples. About 75% of firms made relatively small errors, within one worker of the actual employment in the full sample. Approximately 20% of firms made errors of between one and four workers, and a few firms (5%) made errors of more than four workers in the full sample. It seems that micro-sized firms were more accurate, and the dispersion of beliefs is largely symmetric around actual values. About 85% of firms made relatively small errors, within one worker of the actual employment, approximately 10% of firms made errors of between one and four workers, and a few firms (5%) made errors of more than four workers. Coibion et al. (2017) finds a similar distribution of unemployment rate errors among New Zealand firms.

3.3.3 Estimation Strategy

Fortunately, I can draw causal effects based on the available data in this study. We expect that firms that demand different loan amounts, will have different labor market outcomes because the amount of the loan is related to their performances and characteristics (Bia and Mattei (2012)). For this reason, I apply an estimation method in which I estimate the DRF and the TEF to infer causal effects based on the continuous treatment variable. One of the advantages of using this method is to consider heterogeneities among different loan amounts and to determine the optimal loan amount.

Since the main purpose of this study is to compare the expected labor demand with the actual labor demand among different sizes of loans, I will estimate the effect of the loan amount on AFDE and EFDE. Moreover, I will estimate the effect

of the loan amount on FDW to see how firms' paid wages differ by loan size. These variables correspond to the difference-in-difference specification, which is a better specification to eliminate unobserved factors that might simultaneously affect the outcome variables. Thus, AFDE, EFDE, and FDW are interested outcome variables in this study.

The problem is that the loan amount depends on firms' characteristics, which means that firms that receive different loan amounts can systematically differ in important characteristics. In order to adjust these differences in the case of continuous treatment variables, Hirano and Imbens (2004) developed the generalized propensity score (GPS) as an extension of binary treatment variables introduced by Rosenbaum and Rubin (1983b).

Suppose $i = 1, \dots, N$ indicates the sample size and $Y_i(t)$, for $t \in \tau$, indicates a potential outcome of unit i for the continuous treatment variable t , and I allow that τ belongs to the interval $[t_0, t_1]$. I am interested in estimating the average DRF, $\mu(t) = E[Y_i(t)]$.

Similar to the binary setting propensity score approach, the GPS method relies on the weak unconfoundedness assumption that after controlling for the pretreatment observable variables, it is no problem to draw the causal inference. Hirano and Imbens (2004) introduced the weak unconfoundedness assumption, which requires that the selection of the treatment be conditionally independent of each potential outcome given the pretreatment variables: $Y_i(t) \perp T_i | X_i \forall t \in \tau$.

This assumption is not directly testable and does not need to be generally applicable; the weak pretreatment covariates can cast serious doubt on this assumption. I assess this assumption indirectly by assuming that unconfoundedness holds conditional on all the pre-treatment variables such as sex dummy, age, age squared, education dummies, city dummies, firm's employment 1 year prior to receiving the loan, the square of the firm's employment 1 year prior to receiving the loan, and the firm's employment 1 year prior minus its employment 2 years before receiving

the loan. By using the employment level, trend, and observable characteristics, I am trying to match all firms in terms of their pretreatment covariates.

In addition, I include the industry, whether the firm is a start-up, and the year of receiving the loan dummies for the following reasons: First, the loan amount depends on the type of industry; second, I include a start-up dummy mainly because start-up firms may have received a different size of loan; and finally, I include the year dummies, since firms received their loans in different years, which can affect the probability of receiving them. For example, if there was a change in the program's characteristics through the years, that would have affected the probability of firms' receiving different-sized loans.

There are two issues that arose in the course of the research. First, as indicated above, the program started during the last 2 months of 2005, and only a couple of firms received loans in 2005 in the sample. Obviously, the outcome impacts of the loans for firms that received their loans in 2005 are negligible in the same year. Therefore, I place the firms that received their loans in 2005 in 2006. Second, as shown in Table 3, there are some start-up firms in both the treated and the non-treated samples. On the one hand, if I exclude start-ups due to their lack of employment history, this exclusion implies a negative bias, since start-ups may have a stronger employment response to loans than existent firms. On the other hand, start-ups' lack of employment history prevents matching. To deal with this problem, I impute 0s in place of employment history for start-ups and include a dummy while estimating GPSs.

Given the weak unconfoundedness assumption, Hirano and Imbens (2004) define the GPS. Let $r(t, x)$ be the density of the treatment conditional on the covariates. Then, the GPS is $R_i = r(T_i, X_i)$. The GPS has a balancing property similar to that of the standard propensity score (PS), and as a result, I can eliminate important differences in the covariates that may cause bias in my estimations by applying the GPS. Basically, given pretreatment variables X_i and under the weak

unconfoundedness assumption, then

$$\beta(t, r) = E[Y_i(t)|r(t, X_i) = r] = E[Y_i|T_i = t, R_i = r] \quad (3.25)$$

$$\mu(t) = E[\beta(t, r(t, X_i))] \quad (3.26)$$

where $\mu(t)$ is the DRF, and I can estimate it at t by taking average of $\mu(t, r(t, X_i))$ over X_i and holding treatment level t constant (Newey (1994)). Moreover, by averaging the DRF over the covariates X_i for each level t , I also compute the derivatives of $\mu(t, r(t, X_i))$, which we can define as the marginal causal effect or treatment effect function, $\mu(t + \Delta t) - \mu(t)$, of the variation of the treatment level, Δt , on the outcome variable.

Now, I consider how to apply the above method. Basically, I can estimate the DRF using the GPS in two steps. First, I estimate the GPS parametrically under various alternative distributional assumptions to find a distribution that is a better fit with my data given the covariates. Specifically, I assume that

$$g(T_i|X_i) \sim \psi(h(\gamma, X_i), \sigma^2) \quad (3.27)$$

where $g()$ is a suitable transformation of the treatment variable, ψ is a flexible distribution, $h(\gamma, X_i)$ is a flexible function of the covariates depending on an unknown parameter vector γ , and σ^2 is a scale parameter.

The log transformation and applying the normal distribution of the treatment variable are common specifications for a non-negative and continuous treatment variable (Hirano and Imbens (2004); Kluve et al. (2012)). However, treatment cannot be assumed to be normally distributed; assuming a normal distribution of the treatment given the covariates has several drawbacks. To make the GPS estimation more reasonable, I estimate the GPS under flexible distributions such

as gaussian, inverse-gaussian, and gamma and select the model that best fits my data. To estimate the GPS in these cases, a possible solution is to replace the linear regression with the generalized linear model (GLM) developed by McCullagh (1984).

Let $\hat{R}_i$ be the estimated GPS. After estimating $\hat{R}_i$, in the second step, I need to estimate the conditional expectation of Y_i on T_i and $\hat{R}_i$ using a quadratic approximation including the interaction

$$\beta(t, r) = E[Y_i|T_i, \hat{R}_i] = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 \hat{R}_i + \alpha_4 \hat{R}_i^2 + \alpha_5 T_i \cdot \hat{R}_i \quad (3.28)$$

Next I estimate the DRF while holding the treatment level constant at a specific level by averaging $E[Y_i|T_i, \hat{R}_i]$ over the GPS at that particular treatment level:

$$\mu(\hat{t}) = \frac{1}{N} \sum_{i=1}^N [\hat{\alpha}_0 + \hat{\alpha}_1 t + \hat{\alpha}_2 t^2 + \hat{\alpha}_3 \hat{R}_i + \hat{\alpha}_4 \hat{R}_i^2 + \hat{\alpha}_5 t \cdot \hat{R}_i] \quad (3.29)$$

After estimating the GPS for each sample specification, it is necessary to check that the balancing property is satisfied in every sample specification. Indeed, the GPS should eliminate any significant differences in the covariates. I apply the likelihood ratio (LR) test proposed by Flores-Lagunes et al. (2012) to assess the balancing property.

3.3.4 Results

The first step to estimate the DRFs is to estimate the GPS by modeling the continuous treatment T_i (the real amount of the loan) given the observable characteristics. A commonly used specification for estimating the GPS with a non-negative continuous treatment variable is a log-normal distribution (Kluve et al. (2012); Hirano and Imbens (2004)). My treatment variable and its log transformation are also non-negative and continuous (Figures 3.9 and 3.10); however, I hesitate to commit ex ante to any one specification and instead estimate a number of flexible gener-

alized linear models (McCullagh (1984)) and choose the model that best fits my data.

I estimate several plausible specifications with GLMs and choose the model that best fits the data according to the deviance measure of McCullagh and Nelder (1989), the Akaike information criteria (AIC), and the value of the log-likelihood (LL) function. Across all alternative specifications, a gamma model with a log transformation attains the best model to fit the data for both the full sample and micro-sized firms and is thus employed to model the GPS better (Table 3.4). In particular, I apply the Akaike information criteria to select among the alternative distributions and the deviance measure and the value of the log-likelihood function to select among the link functions (Hardin, Hilbe, and Hilbe (2007)).

After estimating the GPS for each sample specification, I need to check the balancing property. The method that I use to test the balancing property is equivalent to the approach proposed by Flores-Lagunes et al. (2012). In this approach, I estimate the unrestricted model in which a log-gamma transformation of T is estimated on all covariates and the GPS up to a cubic term. Then, I compare the unrestricted and restricted (the model in which all coefficients of covariates or the GPS are equal to 0) models using the LR test. We expect that, conditional on the GPS, covariates' explanatory power should be weakened if the GPS adjusts the covariates' differences. Based on the LR tests in Table 3.5, the restricted models, where all covariates' coefficients are equal to 0 (top panels), are preferred to the models where all the GPS coefficients are equal to 0 (bottom panels). This shows that the GPS plays a key role. Therefore, I argue that the balancing property of the GPSs is satisfied.

In the second step, I estimate the DRFs based on the approach mentioned above, and then I estimate the TEFs for 200 million IRR differences ($\Delta\mu = 200000000$) for the full sample and 100 million IRR differences ($\Delta\mu = 100000000$) for micro-sized firms. The reason to do this is that it could be argued that 200 million IRR is

irrelevant for micro-sized firms, which on average received loans about 200 million IRR. The range of the treatment level for which I want to consider the employment impact of the loan amount is between 20 million IRR and 800 million IRR because more than 90% of the firms received a real amount in this range.

The first interested outcome variable is FDW. I generate Figures 3.11 and 3.12, in which I plot the DRFs and TEFs and the 95% confidence interval based on 1,000 bootstrap replications for the full sample and micro-sized firms, respectively.

DRFs (Figures 3.11 and 3.12) suggest that the FDW is an increasing function of the loan amount. It appears to be positive and statistically significant for any loan amount. Moreover, Figure 3.11 shows that the TEF always decreases as the loan amount increases and the estimated marginal effects are significant at the 10% level or less for a loan amount less than 200 million IRR in the full sample. It emphasizes that the marginal effects are smaller for a larger loan. For example, increasing the loan amount from 40 million IRR to 240 million IRR led to paying workers a higher wage by about 30,000 IRR (S.E.=2592), but only a 14,000 IRR (S.E.=2169) higher wage was paid due to increasing the loan amount from 100 million IRR to 300 million IRR. Figure 3.12 suggests that the estimated marginal effects are significant under 95% confidence for all loan levels up to 600 million IRR in micro-sized firms. For instance, increasing the loan amount from 40 million IRR to 140 million IRR led to paying workers a higher wage by about 26,000 IRR (S.E.=1676), but this amount was 12,500 IRR (S.E.=1633) due to increasing the loan amount from 100 million IRR to 200 million IRR.

As a result of the FDW estimation on the loan amount, I can argue that firms that demanded and received a larger loan paid higher wages to their workers in the second period. Using equation 3.2, this could be interpreted as being because firms that demanded larger loans precisely because of higher inflation expectations contracted to pay workers higher wages because they expected that the marginal revenue product of labor would increase.

The second set of outcome variables of interest are AFDE and EFDE. As in Figures 3.11 and 3.12, I generate Figures 3.13 and 3.14 by plotting the DRFs and TFTs and the 95% confidence interval based on 1,000 bootstrap replications for the full sample and micro-sized firms, respectively. I plot both the AFDE and the EFDE estimations in just one graph to be able to compare them to each other.

The DRFs (Figures 3.13 and 3.14) suggest that both the AFDE and the EFDE are increasing functions of the loan levels for both the full sample and micro-sized firms. Both appear to be positive and statistically significant for any loan size, even for large loans.

Moreover, Figure 3.13 shows that the TEFs of both the AFDE and the EFDE always decrease as the loan size increases and the estimated marginal effects are statistically significantly different from 0 for any loan size in the full sample. Figure 3.14 suggests that the TEFs of both AFDE and EFDE always decrease for all loan levels for micro-sized firms. The estimated marginal effects are statistically significantly different from 0 for all loan sizes up to 600 million IRR. Generally, these figures emphasize that marginal effects are smaller for a larger loan.

Comparing the DRFs of the AFDE and the EFDE in Figure 3.13 for the full sample, we observe that there is a gap between the two for any loan amount larger and smaller than about 150 million IRR. In fact, we observe that the AFDE equals the EFDE for a loan of about 150 million IRR, the EFDE is greater than the AFDE for any loan larger than 150 million IRR, and in reverse, the EFDE is less than the AFDE for any loan smaller than 150 million IRR. On average, the difference between the AFDE and the EFDE is about -0.40 at a loan amount of 800 million IRR, which shows that firms that received loans of 800 million IRR expected to hire about 5.57 workers but only could hire about 5.17 workers by end of the next year. In contrast, the difference between the AFDE and the EFDE is about 0.44 at the loan amount of 20 million IRR, which shows that firms that

received a 20 million IRR loan expected to hire about 0.81 workers, but they could hire about 1.25 workers by end of the next year on average.

Comparing the DRFs of the AFDE and the EFDE in Figure 3.14 for micro-sized firms, we observe that there is a gap between the two for any loan amount larger and smaller than about 200 million IRR. In fact, we observe that the AFDE equals the EFDE for a loan of about 200 million IRR, the EFDE is larger than the AFDE for any loan larger than 200 million IRR, and in reverse, the EFDE is smaller than the AFDE for any loan smaller than 200 million IRR. On average, the difference between the AFDE and the EFDE is about -0.47 at the loan amount of 800 million IRR, which shows that firms that received 800 million IRR loans expected to hire about 4.97 workers, but they only could hire about 4.50 workers by end of the next year. In contrast, the difference between the AFDE and the EFDE is about 0.36 at the loan amount of 20 million IRR which shows that firms that received 20 million IRR loans expected to hire about 0.82 workers, but they could hire about 1.18 workers by end of the next year on average.

To determine whether the difference between AFDE and EFDE is significant or not, I estimate the effect of the loan amount on the difference between AFDE and EFDE (DFDE). In fact, I choose the DFDE as my outcome variable of interest and the real loan amount as the continuous treatment in this case. Similarly, I estimate the DRFs and TEFs of the DFDE for both the full sample and micro-sized firms.

As expected, the DRFs (Figures 3.15 and 3.16) suggest that both DFDEs are decreasing functions of the loan amount for both the full sample and micro-sized firms. In addition, TEFs (Figures 3.15 and 3.16) are always negative for both the full sample and micro-sized firms. The DRF (Figure 3.15) always decreases as the loan amount increases and reaches 0 at 150 million IRR and then becomes negative for the full sample. Similarly, the DRF (Figure 3.16) always decreases as the loan amount increases and reaches 0 at 200 million IRR and then becomes negative for micro-sized firms. None of the DRFs and TEFs are statistically different from 0,

suggesting that along with different-sized loans, there is no significant difference between the AFDE and the EFDE. As a result, although there is a gap between the AFDE and the EFDE among different loan amounts, the difference is not significant, and firms were predicting their labor demand correctly.

3.3.5 Assessing Unconfoundedness Assumption

I construct an indirect way to test the unconfoundedness assumption in the continuous treatment variable case. I perform placebo tests recommended by Heckman and Hotz (1989), which are based on estimating the treatment variable on a “placebo outcome.” A placebo outcome is a variable that is not affected by the treatment. Thus, there should be no effect; otherwise, there is evidence against the unconfoundedness assumption. Usually, we apply lagged outcomes as placebo outcomes. Therefore, if estimation results suggest that there is a positive and significant relationship between the treatment and the lagged outcome variables conditional on covariates, it casts doubt the validity of the unconfoundedness assumption (Flores-Lagunes et al. (2012)).

I consider the employment level of the year prior to receiving the loan and the wage level of the year the loan was received as placebo outcomes. Thus, there should not be any significant correlation between the employment level of the year prior to receiving the loan and the loan amount because firms had not received the loan yet. In addition, there should not be any significant correlation between the wage level of the year the loan was received and the loan amount. Figures 3.17–3.20 present plots similar to those of Figures 3.13–3.16 and use the employment level of the year prior to receiving the loan and the wage level in the year the loan was received as outcomes.¹³ None of the estimated treatment effects are statistically different from 0 except in a small range of loan amounts

¹³To estimate the DRF and the TEF of the placebo outcome, I exclude the variables that are strongly correlated to the employment level of the year prior to receiving the loan (placebo outcome).

(300–700 million IRR) in micro-sized firms, where the employment placebo outcome estimates are statistically less than 0.

In summary, my exercise to assess the unconfoundedness assumption shows that there is no significant correlation between the treatment variable and the placebo outcomes conditional on covariates. Therefore, my exercise provides evidence of the reliability of my estimates.

3.4 Conclusion

Inflation expectations matter and, according to the new Keynesian Phillips curve, the inflation expectations of firms are especially important. In this study, I investigate the effects of firms' inflation expectations, measured by the loan amounts they demanded, on wages and their actual and expected labor demands. Theoretically, I construct a model in which I show that the difference between a firm's inflation expectation and the actual inflation creates a gap between its expected and actual labor demand. Moreover, by employing an individualistic bargaining model in which workers and employers can bargain over wages and make a long-term contract after bargaining is complete, I show that firms that expect higher future inflation will agree to pay higher wages requested by workers. Furthermore, it seems that rigid nominal wages, which prevent wages from adjusting to changes in unanticipated prices, cause actual labor demand to deviate from its expected value.

Empirically, using longitudinal firm-level data from Hamedan province in Iran over the years 2004 to 2011, I test the two main theoretical results of this study. First, I estimate the change of nominal wages over 2 consecutive years on the loan amount as a proxy of firms' inflation expectations. The result suggests that there is a positive and significant relationship between wages and the loan amount. The argument to explain this relationship is that firms that demand larger loans

precisely because of their higher inflation expectations may pay higher wages because they expect a higher level of the marginal revenue product of labor.

Moreover, I investigate how firms that demanded different loan amounts may differ in terms of their actual and expected labor demand. Separately, I estimate the relationship between both the actual and the expected labor demand and the loan amount. My estimates show that firms' actual and expected labor demands are equal for the loan amount of about 200 million IRR but there is a gap between them for any other loan amount. Precisely, the expected labor demand is overestimated for any loan amount larger than about 200 million IRR, while the expected labor demand is underestimated for any loan amount smaller than about 200 million IRR.

The gap between the expected and the actual labor demand can be explained by firms' inflation expectations. In fact, firms that demanded larger (smaller) loans precisely because of their higher (lower) inflation expectations and whose inflation expectations were not equal to the actual inflation not only were unable to invest as much as they expected but also were unable to hire as many workers as they expected. In contrast, firms that forecast inflation correctly not only could invest exactly as much as they expected but also could hire exactly the number of workers they expected.

However, the difference between the actual labor demand and the expected labor demand is not significantly different from 0 among the different loan amounts, showing that firms predicted their labor demand correctly. This shows that there is dispersion in firms' inflation expectations, but they are not that far from the actual inflation. The results show that about 30% of firms overestimated inflation. In contrast, 60% of firms underestimated inflation. Finally, just about 10% of firms forecast inflation correctly, and they had full-information rational expectations. As a matter of fact, it seems that there is a pervasive and systematic deviation from full-information rational expectations among firms, as documented by Coibion

et al. (2017); however, these deviations are relatively small, and firms' inflation expectations are close to the actual inflation, as documented by Afrouzi (2017) as well.

In addition, comparing firms' actual and expected labor demands among the different loan amounts, I can consider the loan program's efficiency in terms of its ability to create new jobs. The results show that, although firms that demanded larger loans created more jobs, they could not hire as many workers as they expected to. On the other hand, firms that demanded smaller loans were able to even more hire workers than expected. Since the marginal effects were smaller for a larger loan amount, the smaller loans were more effective than the larger ones. Therefore, it seems that firms that demanded smaller loans invested their loans more efficiently in their businesses and were able to utilize them better than firms that demanded larger loans precisely because of higher inflation expectations.

Table 3.1: Loans paid and number of firms that received a loan during 2005 to 2011 in Iran and Hamedan

Iran								
Year	2005	2006	2007	2008	2009	2010	2011	Sum
Number of firms	10637	281091	324538	41816	13450	N.A.	N.A.	N.A.
Loans paid (trillion IRR)	1.9	68.5	98	32	17.5	15.7	2.6	236.4
Hamedan								
Year	2005	2006	2007	2008	2009	2010	2011	Sum
Number of firms	22	13448	14255	1173	223	N.A.	N.A.	N.A.
Loans paid (billion IRR)	5.6	2287.8	3393.3	1222.7	985.6	767.8	190.5	8853.6

Table 3.2: Loans paid and number of firms that received a loan for different sample specifications

Full sample							
Year	2005	2006	2007	2008	2009	2010	Sum
Number of firms	8	39	57	15	9	5	133
Loans paid (million IRR)	1090	12970	35802	29695	5930	1150	86637
Micro-sized firms							
Year	2005	2006	2007	2008	2009	2010	Sum
Number of firms	8	34	49	11	7	5	114
Loans paid (million IRR)	1090	11910	13772	5970	3310	1150	37202

Table 3.3: Descriptive Statistics: Means (Standard Errors in parentheses)

Variables	Full Sample	Micro-sized firms
Employment in period 1 (n_1)	5.73 (7.65)	3.62 (2.20)
Employment in period 2 (n_2)	6.00 (8.27)	3.87 (2.14)
Actual First Difference Employment (AFDE)	3.12 (4.72)	2.02 (2.12)
Expected First Difference Employment (EFDE)	3.26 (5.18)	1.99 (2.18)
Wage in period 1 (w_1) (million IRR)	2.78 (1.02)	2.73 (1.04)
Wage in period 2 (w_2) (million IRR)	3.56 (1.09)	3.48 (1.10)
First Difference Wage (FDW) (million IRR)	0.78 (0.22)	0.75 (0.23)
Loan amount (million IRR)	651 (1680)	326 (509)
Loan amount-10th percentile	50	45
Loan amount-25th percentile	100	80
Loan amount-median	200	180
Loan amount-75th percentile	350	300
Loan amount-90th percentile	1170	950
Firm owner characteristics		
Sex (Male)	0.91	0.93
Age	44	44
Education (High School diploma or lower)	0.73	0.75
Firm characteristics		
Sector of activity		
Service	0.40	0.40
Manufacturing	0.24	0.20
Agriculture	0.36	0.40
City		
Asadabad	0.29	0.32
Bahar	0.03	0.03
Hamedan	0.24	0.20
Kabodarahang	0.08	0.09
Malaer	0.19	0.19
Nahavand	0.07	0.06
Razan	0.10	0.11
Start-ups	0.41	0.40
Sample size	133	114

Table 3.4: GLM specification

	Distribution	Gaussian		Inverse Gaussian		Gamma	
	Link	T*	Ln(T)	T	Ln(T)	T	Ln(T)
Full sample	AIC	44.01	42.41	58.47	58.47	151.74	40.92
	Deviance	7.42e+19	1.56e+19	1.00e-06	1.02e-06	14921.18	141.49
	LL	-2906.15	-2802.56	-3867.38	-3867.38	-10090.36	-2700.51
Micro-sized firms	AIC	42.07	41.60	57.84	57.87	40.40	40.36
	Deviance	8.61e+18	5.42e+18	8.62e-07	8.92e-07	104.87	100.20
	LL	-2377.00	-2350.68	-3278.05	-3278.05	-2281.96	-2279.63

*Treatment variable (the real amount of loan).

Table 3.5: Balancing test

	Full sample	Micro-sized firms
Unrestricted model: T^* on GPS , GPS^2 , GPS^3 , and X 's*		
Test restriction that all covariates coefficients are equal to 0		
Restricted log likelihood	-2684.85	-2249.83
Unrestricted log likelihood	-2665.58	-2247.26
Test statistic	38.53	5.12
p-value	0.70	0.99
Number of restrictions	20	20
Test restriction that all the GPS coefficients are equal to 0		
Restricted log likelihood	-2700.51	-2279.63
Unrestricted log likelihood	-2665.58	-2247.26
Test statistic	69.87	64.73
p-value	0.00	0.00
Number of restrictions	1	1
Number of observations	133	114

T^* is Treatment variable (the real loan amount) and X 's* are covariates.

Figure 3.1: Timing of events for firm i in the two-period framework

Figure 3.2: The relationship between the second-period labor demand and the loan amount

Figure 3.3: The unemployment rate for Iran and Hamedan

Figure 3.4: Employment for Iran and Hamedan

(a) Iran (in millions)

(b) Hamedan (in thousands)

Figure 3.5: The employment growth rate for Iran and Hamedan

Figure 3.7: The inflation rate for Iran and Hamedan

Figure 3.6: The labor force participation rate for Iran and Hamedan

Figure 3.8: Distributions of employment errors (DFDE)

- Kernel density estimates of distributions of errors.

Figure 3.9: Histogram of the real loan amount in billion IRR and its log transformation for the full sample

Figure 3.10: Histogram of the real loan amount in billion IRR and its log transformation for micro-sized firms

Figure 3.11: The DRF and the TFE of FDW for the full sample (FDW in thousand IRR and the real loan amount in million IRR)

Figure 3.12: The DRF and the TFE of FDW for micro-sized firms (FDW in thousand IRR and the real loan amount in million IRR)

Figure 3.13: The DRF and the TFE of AFDE and EFDE for the full sample (the real loan amount in million IRR)

Figure 3.14: The DRF and the TFE of AFDE and EFDE for micro-sized firms (the real loan amount in million IRR)

Figure 3.15: The DRF and the TFE of DFDE for the full sample (the real loan amount in million IRR)

Figure 3.16: The DRF and the TFE of DFDE for micro-sized firms (the real loan amount in million IRR)

Figure 3.17: The DRF and the TFE of a wage placebo outcome for the full sample (wage in thousand IRR and the real loan amount in million IRR)

Figure 3.18: The DRF and the TFE of a wage placebo outcome for micro-sized firms (wage in thousand IRR and the real loan amount in million IRR)

Figure 3.19: The DRF and the TFE of an employment placebo outcome for the full sample (the real loan amount in million IRR)

Figure 3.20: The DRF and the TFE of an employment placebo outcome for micro-sized firms (the real loan amount in million IRR)

CHAPTER 4

EMPLOYMENT, SKILL UPGRADING, AND INTERNATIONAL TRADE: THE CASE OF SANCTIONS AGAINST IRAN

4.1 Introduction

Economic sanctions are used by countries to put pressure on and restrict economic relations with the target country, aiming to change its behavior (Galtung (1967)). There are different types of sanctions, such as embargoes, blockades, export controls, tariffs, travel bans, import bans, and asset freezes (Morgan, Bapat, and Krustev (2009)). Specifically, trade sanctions are imposed to limit the target country's import and export capabilities, which may cause a reduction in its welfare. During 2010 to 2013, a series of sanctions, the Iran Sanctions Act, adversely affected Iran's economy and ended with Iran's decision to accept the Joint Comprehensive Plan of Action, or JCPOA, finalized on July 14, 2015 (Katzman (2010)).

This chapter studies the impact of the economic sanctions imposed on Iran in 2010 on its labor market. Particularly, I investigate the effect of the economic sanctions on employment, the relative demand for skilled labor, and the wage premium in manufacturing industries. Indeed, trade sanctions change internationally active firms' behavior regarding exporting and importing by increasing trade costs. Haidar (2017) showed how non-oil exporters deflected their exports towards non-sanctioning countries after the sanctions imposed on Iran between 2008 and 2011. His results suggest that the amount of exports even increased after the sanctions. This result shows that firms can figure out ways to solve their export problems when trade sanctions are imposed on them; however, they may face other issues that they are not able to overcome. For example, if firms are restricted from importing new technology due to trade sanctions, such as embargoes on importing new equipment, their production technology will be influenced negatively. There is

still a lack of empirical evidence about the impact of trade sanctions on firms' or industries' behavior, particularly regarding their labor demand.

One of the most important questions is, what is the effect of the trade sanctions on manufacturing industries' employment? Moreover, is there any difference between internationally active industries and domestically active ones? What sector has been most affected by the trade sanctions? This type of questions will be answered in the first part of this study. Since trade sanctions are supposed to decrease the openness in the target state, it is expected that exporters' foreign market share is reduced, which may result in a reduction of their employment. In other words, if exporters lose the demand for their products abroad because of the sanctions, we expect to observe job destruction. However, industries, including non-exporters, may behave differently if trade sanctions affect their production technology. As literature emphasizes (for example, Melitz (2003); Bernard and Jensen (2004); Halpern, Koren, and Szeidl (2005); Olly and Pakes (1996); Pavcnik (2002)), there is a correlation between trade and productivity. This suggests that industries' labor demand differs between those involving international trade and those that just sell their products domestically. Therefore, we expect that trade sanctions differently affect the employment of internationally active and domestically active industries.

Another aspect of the effect of trade sanctions on the labor market is related to their structural impact. In fact, the question is how trade sanctions influence the composition of labor demand in terms of skill. As literature suggests (for example, Bound and Johnson (1992); Berman, Bound, and Griliches (1994); Bustos (2011)), there are two explanations for a change in the demand for skilled labor: international trade and biased technological change. Any increase in either one increases the demand for skilled labor. In addition, Acemoglu (2003) showed how these two may be related and how international trade induces skill-biased technical change. Thus, by arguing that trade sanctions cause a change in the bias of

technology between exporters and non-exporters, first, I examine the effect of trade sanctions on the total factor productivity (TFP) of exporters and non-exporters, and second, I investigate any change in the relative demand for skilled labor and, as a result, the wage premium in the second part of this study.

I use manufacturing industry-level data collected by the Statistical Center of Iran (SCI) to analyze the effect of the trade sanctions on the Iranian labor market. These data are unique because they cover periods before and after the sanctions were imposed in 2010, all the provinces of Iran, and more than 200 different industries. Precisely, the data cover 10 years before and 5 years after the sanctions, which enables me to compare the post-sanction period with the previous period. In addition, they include manufacturing industries with up to four digits of International Standard Industrial Classification (ISIC).

The results of my attempt to assess the effect of the sanctions on employment show that internationally active industries' derived labor demand decreased significantly by about 10% during the sanction period. Across different internationally and domestically active groups, first, all of them experienced a decline in the employment growth rate. Second, non-exporters experienced a larger decline in their employment growth rate than exporters. In addition, within the non-exporter group, industries that neither exported nor imported endured the largest decrease in their employment growth rate. By contrast, within the exporter group, industries that both exported and imported endured the smallest decrease in their employment growth rate. For example, during the sanction years, 17,347 jobs were created in industries that both exported and imported, while 30,342 jobs were lost by all other industries, which leaves us with 12,995 jobs lost overall. Thus, the results suggest that those industries that just sold their products domestically were adversely affected by the sanctions more than those industries that were involved in trade and sold their products abroad.

To consider how the trade sanctions influenced the relative demand for skilled labor, I start by decomposing my two measures of skilled workers (share of non-production workers out of total employment and share of skilled production workers out of total production workers) in changes within and between industries. This decomposition matters, since the H-O model predicts that an increase in the relative demand for skilled labor could result from a reallocation of labor towards skill-intensive industries (Bustos (2011)). However, the results from this study suggest that the within component mostly dominates the between component, which means that the increase in the relative demand for skilled labor comes from labor reallocation within industries. This result confirms that the trade sanctions may have changed the demand for skilled labor by changing the bias of technology. Comparing industries' skill intensity before and after the sanctions reveals interesting changes. On the one hand, industries upgraded their non-production workers more slowly during the sanction years than before the sanctions. On the other hand, industries upgraded their skilled production workers faster during the sanction years than before the sanctions. In addition, industries upgraded their skilled production workers faster than their non-production workers. Finally, exporters are more skill-intensive than non-exporters, and there is a considerable difference between their skill upgrading process.

I present a simple model based on the work by Acemoglu (2003) to show the effect of the trade sanctions on the relative demand for skilled labor through biased technological change. In the model, the economy consists of two exported and non-exported goods, which are produced by the export and non-export sectors, respectively. Exporters and non-exporters hire both skilled and unskilled labor to produce; however, exporters are more skill-intensive. There is an elasticity of substitution between skilled and unskilled workers, which plays a crucial role in my model. I argue that the trade sanctions induced biased technological change by affecting the relative productivity of the two sectors. The model's prediction is

that there is a positive relationship between the productivity of exporters relative to non-exporters and the relative demand for skilled labor if the elasticity of substitution between skilled and unskilled workers is greater than unity; otherwise, there is a negative relationship. The mechanism is that, under the assumption that the elasticity of substitution between skilled and unskilled workers is greater than unity, if the trade sanctions induce technological change biased towards exporters, then the price of exporters relative to non-exporters will rise, which results in a reallocation of market share towards exporters, an increase in the relative demand for skilled labor, and a wage premium.

The first step to test the prediction of the model is to estimate exporters' and non-exporters' TFP to understand how the trade sanctions induced biased technological change. First, I find that exporters had a higher level of TFP than non-exporters, which is consistent with many other studies. Second, the main result is that both exporters' and non-exporters' TFP dropped significantly during the sanction years; however, the drop in non-exporters' TFP is larger than the drop in exporters' TFP. Therefore, I conclude that the TFP of exporters increased relative to that of non-exporters after the sanctions, which means a change in the bias of technology towards exporters. This may be explained by the degree of exporters' and non-exporters' flexibility when faced with the imposed sanctions. Since exporters have easier access to hard currency and have better connections and resources abroad, they could find a way to overcome issues related to the sanctions, but non-exporters do not have as much flexibility to make the situation better. As mentioned earlier, Haidar (2017) found that exporters could export their products to other countries rather than those that imposed the sanctions, which resulted in an increase in aggregate exports; however, non-exporters still have to sell their products domestically.

After realizing that there was an increase in the relative TFP of exporters and non-exporters, I estimate the impact of the trade sanctions on the relative

demand for my two measures of skill. The results show that there was a decrease in the demand for non-production workers, and in contrast, there was an increase in the demand for skilled production workers. The former caused a reduction in the real average wage per worker, and the latter caused an increase in the real average wage per worker. This opposite effect can be explained by the elasticity of substitution between skilled and unskilled workers. Many studies find that the elasticity of substitution between non-production and production workers is less than unity, so based on my model, an increase in the productivity of exporters relative to non-exporters reduces the relative demand for non-production workers and the real average wage per worker after the sanctions were imposed. On the contrary, many studies show that the elasticity of substitution between more or less educated workers is greater than unity, and based on my model, an increase in the productivity of exporters relative to non-exporters increases the relative demand for skilled production workers and the real average wage per worker after the sanctions were imposed.

The rest of the chapter proceeds as follows: Section 2 reviews the studies that are the most relevant to this study. Section 3 states the sanctions imposed on Iran. Section 4 introduces the dataset. Section 5 assesses the effect of the trade sanctions on employment. Section 6 examines the effect of the trade sanctions on the relative demand for skilled labor and wages. Finally, section 7 concludes. The appendix includes some proofs.

4.2 A review of previous work

There is no study that specifically investigates the effect of economic sanctions on the labor market; however, there are other studies that analyze the consequences of international trade on the labor market. Regarding the effect of trade on employment across sectors, the Heckscher–Ohlin–Samuelson (H-O-S) model makes some useful predictions. The H-O-S model predicts that as an economy moves from

autarky to more openness, the import sector shrinks as the export sector expands. Thus, we expect that employment in the export sector increases while employment in the import sector decreases. Therefore, the main result of the H-O-S model is a redistribution of employment away from the import sector and towards the export sector.

Greenaway, Hine, and Wright (1999) examined the effect of an increase in trade volumes on employment in the UK by using a panel of 167 manufacturing industries. They develop a model to estimate a dynamic labor demand function while attempting to connect the effect of trade on employment through productivity. Their results suggest that both imports and exports reduce the level of derived labor demand, and the effects are even stronger in trade with the EU and US compared to trade with East Asia when taking the origin of imports into account. In contrast, Gregory and Greenhalgh (1997) found that the UK's employment grew due to increasing trade. Similarly, Messerlin (1995) estimated a positive employment impact of trade in France between 1980 and 1992, although there was a negative impact during 1988 and 1992 because of the economic expansion.

Levinsohn (1999) investigated the effect of substantial trade liberalization in Chile on employment. In particular, he examines the pattern of job creation and job destruction caused by the trade liberalization policy. He finds that the combination of macroeconomic shocks and trade liberalization reduced net employment in manufacturing industries by about 8%. Revenga (1992) showed how changes in import prices affected employment and wages in manufacturing industries of the US over the period 1977–1987. She finds that the dramatic appreciation of the dollar reduced wages and employment by about 2% and 4.5–7.5%, respectively. Biscourp and Kramarz (2007) analyzed the relationship between trade and employment using the French Customs files. They show that there is a strong correlation between imports and the destruction of production jobs. In addition, their results show that this correlation even is stronger for larger firms.

One of the most important channels through which international trade affects the labor market, and in particular, the demand for skilled labor, is productivity. There are many studies that evaluate the effect of trade on industries' and firms' productivity. Melitz (2003) developed a model in which he shows how the exposure to trade induces inter-firm reallocations towards more productive firms, and as a result, this leads to growth in the aggregate industry productivity. Bernard and Jensen (2004) explore the relationship between exporting and productivity growth in the US manufacturing industry. First, they show that exporters grow faster than non-exporters in terms of both shipments and employment. Second, they suggest that exporting generates a reallocation of resources from less efficient plants to more efficient plants, and as a consequence, total-factor productivity grows by up to 40% in the manufacturing industry as a whole.

Halpern et al. (2005) investigated the effect of imports on productivity using a panel of Hungarian manufacturing firms from 1992 to 2001. They extend the method introduced by Olly and Pakes (1996) to estimate the role of imports in total-factor productivity. Their results show that imports were responsible for 30% of the growth in aggregate total-factor productivity in Hungary during the 1990s. In another study, using an extended dataset, Halpern, Koren, and Szeidl (2015) suggested that importing of inputs increased a firm's revenue productivity by 22%, and these imports accounted for 25% of Hungarian productivity growth between 1993 and 2002.

Thangavelu and Rajaguru (2004) examined the relationship between trade and productivity using a dataset comprising nine developing Asian countries. In detail, they estimate the short-run and long-run effects of exports and imports on productivity and labor productivity. They find that trade has a positive and significant effect on productivity and output growth, although imports are mostly responsible for this effect. In addition, imports' long-run effect on productivity growth is greater than their short-run effect. Pavcnik (2002) aimed to show the effect

of trade liberalization on plant productivity using panel data on manufacturing in Chile. She allows that productivity varies over time and across traded and non-traded goods. Her findings show that trade liberalization improves within-plant productivity in the import-competing sector.

Bernard, Jensen, and Schott (2006) investigated the relationship between trade costs and productivity among US manufacturing industries and plants. Their results show that there is a negative relationship between industries' productivity growth and trade costs. Moreover, they find that a decrease in industry-level trade costs increases productivity growth within firms. Amiti and Konings (2007) studied the effect of cutting tariffs on productivity using Indonesian plant-level manufacturing census data from 1991 to 2001. The main result of this study is that a 10% decrease in input and output tariffs increases the productivity of firms that import their inputs by 12% and 6%, respectively.

The literature has focused on two possible explanations for the increase in the demand for skilled labor: the increase in international trade and biased technological change. Although these two possible explanations, trade and technology, may be related (Acemoglu (2003)), Berman et al. (1994) suggested a method to decompose the increase in the demand for skilled labor into the *between* and *within* components. In fact, it is argued that international trade causes the increase in demand for skilled labor between industries, holding industries' technology constant, and that biased technological change causes the increase in demand for skilled labor within industries. Therefore, if the within-industry component dominates the between one, we would argue that international trade influences the demand for skilled labor through biased technological change (Bustos (2011)).

There are some studies that investigate the effects of international trade and biased technological change on the demand for skilled labor, and as a result, the wage premium. For example, Bound and Johnson (1992) studied the reasons for the dramatic increase in the relative wages of educated workers in the United States

during the 1980s. They conclude that the main reason was the change in bias of technology, which led to an increase in the demand for skilled labor. Berman et al. (1994) also examined the same phenomenon in US manufacturing over the same period. Their results confirm that biased technological change was mostly responsible for the increase in demand for skilled workers, not international trade.

Along the same lines as the above studies, Bernard and Jensen (1997) suggested that the increase in the relative demand for skilled labor is associated with the increase in employment of exporters. In fact, exporting plants were mostly responsible for that increase in the wage gap between skilled and unskilled workers. Machin and Van Reenen (1998) examined the relationship between technical change, which is measured by R&D intensity, and the relative demand for skilled labor in the US and other OECD countries. Their results show that skill-biased technical change significantly increases the relative demand for skilled labor.

Galiani and Sanguinetti (2003) studied the effect of Argentina's trade liberalization on wage inequality during the 1990s. They find that although there is a correlation between deepening import penetration and the increase in wage inequality, deepening trade was relatively responsible for that increase. Pavcnik (2003) examined whether the within-industry skill upgrading is associated with adoption of skilled-biased technology. She finds that capital deepening can explain the increase in the relative demand for skilled workers; however, other technology adoption measures do not have significant effects on skill upgrading.

Michaels (2008) investigated how the US Interstate Highway System (IHS), which has reduced transportation cost and, as a result, increased the trade-related activities among cities, has influenced the relative demand for skilled labor. He shows that IHS has increased the relative demand for skilled workers in skill-abundant counties and decreased it elsewhere. Verhoogen (2008) developed a model in which he shows that quality upgrading causes trade increases and wage inequality. He uses a panel data of Mexican manufacturing plants to investigate the

relationship between the exchange rate shock and within-industry wage inequality. His results show that the exchange rate devaluation increased exports by more productive plants, which led them to upgrade quality and, as a result, raise wage inequality.

Bustos (2011) examined the effect of regional free trade on the demand for skilled labor using a panel of Argentinean manufacturing firms during 1992–1996, which covers the trade liberalization period. The main results show that, first, skill upgrading happens within firms instead of between industries; second, exporters are faster than non-exporters in terms of upgrading skills; and third, those firms that upgrade skills also upgrade their technology. Moreover, the trade liberalization between Argentina and Brazil increased the relative demand for skilled labor among Argentinean firms. Fieler, Eslava, and Xu (2014) studied the impact of trade liberalization on quality and the skill premium in Colombia. They find that trade liberalization increased both the skill premium and skill intensity in manufacturing firms. In addition, both exporters and importers upgraded quality, which led to an increase in the relative demand for skilled labor. Cravino and Sotelo (2017) investigated the influence of international trade on employment and the relative wages of unskilled workers in the manufacturing sector. Their results suggest that international trade reduces both employment and the relative wage of unskilled workers, and the effect is even greater in developing countries.

4.3 The sanctions against Iran

Iran has experienced strict sanctions imposed by the United Nations Security Council (UNSC) during the last 20 years. The main aim of these sanctions has been to prevent Iran from producing nuclear weapons; however, they could also affect the Iranian economy, mostly through disconnecting Iran from world trade. On 31 July 2006, following the report by the International Atomic Energy Agency (IAEA), the UNSC demanded that Iran suspend all enrichment-related and

reprocessing activities, including research and development. On December 2006, the UNSC passed Resolution 1737 to impose tougher sanctions on Iran in response to its failure to meet the IAEA's requirements. This resolution banned Iran from importing materials and technology related to its nuclear program and froze the assets of companies and individuals who were involved in nuclear activities.

In March 2007, the UNSC voted to strengthen sanctions on Iran by banning individuals who had engaged in the nuclear program from traveling and by freezing their assets. In the same year, the US imposed a unilateral sanction against Iran in which 20 organizations related to Iran's Islamic Revolutionary Guard Corps were blocked from accessing the US financial system. This act by the US was its second and toughest sanction since imposing its first sanction on Iran on November 1979 due to its seizing the American Embassy in Tehran and taking hostage the people inside.¹

The UNSC passed Resolution 1803 in March 2008 "to exercise vigilance in entering into new commitments for public provided financial support for trade with Iran, including the granting of export credits, guarantees or insurance, to their nationals or entities involved in such trade, in order to avoid such financial support contributing to the proliferation-sensitive nuclear activities, or to the development of nuclear weapon delivery system."² Based on this resolution, countries around the world, such as the US, EU, Australia, and Canada, started to impose sanctions on non-oil export and import sectors in Iran.

President Obama offered to begin new negotiations with Iran over ending its nuclear activities in March 2009; however, the toughest sanctions were imposed on Iran during 2010 to 2015. In 2010, both the UNSC and the US Congress passed sanctions on Iran; several banks and financial institutions were blacklisted, Iran

¹The sanction in 1979 included freezing about \$12 billion in Iranian assets, including bank deposits, gold, and other properties, and a trade embargo; however, these sanctions were later lifted. The US and Iran discontinued their diplomatic relationship in 1979, but they continued to trade with each other.

²UNSC Resolution 1803.

was banned from buying heavy weapons such as missiles and helicopters, sanctions were placed on Iran's energy sectors and trade, the arms embargo was tightened, etc. Moreover, all Iranian banks were disconnected from SWIFT (the Society for Worldwide Interbank Financial Telecommunications)³ in March 2012, which prevented them from making international transactions.

Although the dataset used in this study covers a long period, between 2001 and 2015, I consider only the sanctions imposed on Iran in 2010 for two main reasons. First, these sanctions were the toughest that Iran has ever experienced. The whole economy was influenced by these sanctions, and this was the period in which Iran's economy faced the biggest challenge. For example, Iran's Rial currency depreciated substantially, and people experienced a very high inflation rate during this period. Second, as I mentioned earlier, the dataset used covers 10 years before and 5 years after the sanctions, which gives us a very good range of years to compare before and after imposing it.

On 20 July 2015, after 5 years of negotiation between Iran and the P5+1,⁴ the UNSC passed Resolution 2231, the Joint Comprehensive Plan of Action (JCPA), known commonly as the Iran deal, which is an agreement on the Iranian nuclear program between Iran and the P5+1 to ensure that Iran's nuclear activities will be exclusively peaceful. Based on this agreement, the UNSC made a schedule to suspend and eventually lift UNSC sanctions. Nevertheless, President Trump pulled the US out of the Iran deal in a break with European allies on 5 November 2018.

Obviously, trade sanctions imposed on Iran will raise the trade cost for exporters and importers. In particular, disconnection of SWIFT will make international transactions impossible for exporters and importers, which again increases their trade cost. In addition, non-exporters will be adversely affected by trade sanctions that intend to prevent them from utilizing and importing the new technological

³The global provider of secure financial messaging services.

⁴The P5+1 refers to the UNSC's five permanent members (the P5), namely China, France, Russia, the United Kingdom, and the United States, plus Germany.

achievements of other countries around the world. Therefore, trade sanctions likely influence the productivity of the entire economy as well. However, as Milton Friedman stated on 21 January 1980, “All in all, economic sanctions are not an effective weapon of political warfare.”

On the one hand, most economists believe that sanctions have had negative effects on Iran’s economy, specifically the depreciation of Iranian Rial. On the other hand, the public and private sectors do not agree that sanctions have had a negative impact on Iran’s economy. Frequently, Iranian governments have stated that sanctions have had no effect on Iran’s economy. For instance, President Mahmoud Ahmadinejad⁵ said that foreign leaders who “still think sanctions are an effective means are politically retarded.”⁶ Speaker of Parliament Ali Larijani said that “the impact of the US sanctions on Iranian people’s lives are negligible”⁷; however, the Minister of Foreign Affairs of Iran’s Mohammad Javad Zarif added that “the situation will be very difficult, as the role of the US dollar in the international financial system is widespread and inclusive.”⁸

4.4 Data

The data that I use in this study are from the Industrial Firms Survey (IFS) collected by the Statistical Center of Iran (SCI). Although the survey collects data at the firm level, the SCI reports them with the four-digit ISIC classification each year. The data cover firms with more than 10 employees, operating in more than 200 manufacturing industries, located in 28 provinces,⁹ and over the period

⁵The former president of Iran.

⁶ADNKronos International, 24 December 2010.

⁷BBC News Agency, 27 January 2017.

⁸BBC interview, 3 October 2018.

⁹Iran has 31 provinces now. Khorasan province was divided into three provinces (North Khorasan, South Khorasan, and Central Khorasan) in 2004, and Tehran province was divided into two provinces (Tehran and Alborz) in 2010. I combined these new provinces into the ones they were part of before the division.

2001–2015. So, the dataset has three dimensions: the four-digit ISIC classification, province, and year.

The IFS collects information on many different variables, such as production, sales, exports, imports, investment, output and input, energy, materials, non-production and production employment by sex, skill structure of production employment by sex, wages, capital, etc. The wage is the total wage-bill paid to all employees, and the data do not collect wages by skill level. In detail, the data cover four different types of production workers, in order of skill level: unskilled workers, skilled workers, technician workers, and engineering workers; however, we only observe the total wage paid to total workers, including non-production and production workers.

Since industry- and province-level deflators are not available, all nominal values presented in Iranian Rial are converted in real terms using the Consumer Price Index (CPI) or Producer Price Index (PPI) collected from Central Bank of Iran, with 2011 serving as the base year. I define an exporter as an industry that exports at least a portion of its products to foreign countries and a non-exporter as an industry that sells its production only domestically at any point in time. Similarly, I define an importer as an industry that imports either raw materials or capital from foreign countries and a non-importer as an industry that does not import anything as an input factor of its production process at any point in time.

Table 4.1 presents the structure of industries that are active in international markets. Industries are categorized according to their export and import status into four groups: only export, only import,¹⁰ export and import, and neither export nor import. Table 4.1 displays for the different internationalization categories the fraction of unweighted data in the first column and the fraction of data weighted by sales in the second column. The results suggest that 39% of industries that were active in foreign markets, which both exported and imported, represent the

¹⁰Sum of imported raw materials and capital.

largest part of Iranian sales—about 86%. The share of sales for those industries that only import, which involves 43% of total industries, is just 9%.

4.5 Employment and trade sanctions

I examine the effect of trade sanctions on employment using two different methods. In the first method, I compute the employment growth rate using the approach recommended by Davis and Haltiwanger (1999) to compare it over time and among four internationally active groups. In fact, I divide the whole period into three different sample periods: 2001–2005, 2006–2010, and 2011–2015, the last of which covers the toughest sanctions period. I compute the employment growth rate in industry i and province j in each sample period as follows:

$$L_{ij}^B = \frac{L_{ij}^{2001} + L_{ij}^{2002}}{2}, L_{ij}^E = \frac{L_{ij}^{2004} + L_{ij}^{2005}}{2} \quad (4.1)$$

$$L_{ij}^B = \frac{L_{ij}^{2006} + L_{ij}^{2007}}{2}, L_{ij}^E = \frac{L_{ij}^{2009} + L_{ij}^{2010}}{2} \quad (4.2)$$

$$L_{ij}^B = \frac{L_{ij}^{2011} + L_{ij}^{2012}}{2}, L_{ij}^E = \frac{L_{ij}^{2014} + L_{ij}^{2015}}{2} \quad (4.3)$$

where L_{ij}^B and L_{ij}^E are the average number of employees at the beginning and at the end of each sample period, respectively.

Then, I calculate the average employment over the sample period as $\bar{L}_{ij} = \frac{L_{ij}^B + L_{ij}^E}{2}$ and use it to compute the employment growth rate in industry i and province j over the sample period: $\Delta L_{ij} = \frac{L_{ij}^E - L_{ij}^B}{\bar{L}_{ij}}$. Finally, I take an average of ΔL_{ij} to find the average employment growth rate for the whole economy and across four internationally active groups. Moreover, I define the average change of the number of employees as $ACNE_{ij} = \Delta L_{ij} \cdot L_{ij}^B$ and then take a sum of $ACNE_{ij}$

to find the average change in the number of employees for the whole economy and across four internationally active groups.

Table 4.2 presents the employment growth rates and *ACNE* for all industries and four internationally active groups across the three different sample periods. It shows that the employment growth rate decreased within each group and all industries across the three different periods.¹¹ For example, total employment among all industries increased by 17.29%, representing 21,263 jobs on average, between 2001 and 2005. This rate was 9.97%, which represents 71,004 jobs on average, between 2006 and 2010. In contrast, the total employment among all industries declined by 0.22%, representing 12,995 jobs lost on average, between 2011 and 2015. Therefore, the most jobs were created between 2006 and 2010 by manufacturing industries, for which the group “exports and imports” alone accounts for 70,414 jobs out of 71,004. Also, that is the only group that never experienced a negative employment growth rate; however, its employment growth rate decreased over time.

In addition, it seems that the drop in the employment growth rate was less for exporters than for non-exporters in the sanctions period (from 2011 to 2015). In fact, the average employment growth rates were about -10.44% and 2.20% for non-exporters and exporters, respectively. This result suggests that non-exporters have been negatively influenced by sanctions more than exporters. Moreover, within non-exporter industries, industries that neither exported nor imported experienced the largest decreased in employment growth rate; however, industries that only imported lost the largest number of workers: on average, about 22,416 jobs during the sanction years.

During the sanctions period, on average, 12,995 jobs were lost. Although 17,347 jobs were created by the group “exports and imports,” 30,342 jobs were lost by the other three remaining groups. As a result of my exploration of the effect of

¹¹It only increased for the group “exports only” between 2006 and 2010; after that, it declined.

sanctions on the employment of manufacturing industries, it seems that sanctions could impact manufacturing industry jobs negatively. All industries, including internationally active industries, have been adversely affected by sanctions and lost jobs; however, the magnitude of the effect is different among groups. In fact, the results suggest that industries that just sold their products domestically experienced a larger negative impact than industries that got involved in trade and sold their products abroad.

In the second method, arguing that there are important limitations associated with the aforementioned method to examine the effect of trade sanctions on employment, I employ a regression analysis, as recommended by Greenaway et al. (1999), to overcome those limitations. In fact, I estimate the labor demand based on a dynamic panel data model in which I assume the representative firm in industry i , in province j , and in period t has a Cobb-Douglass production function:

$$Q_{ijt} = A_{ijt} L_{ijt}^{\beta} K_{ijt}^{\alpha} \quad (4.4)$$

where Q is real output, K is capital, L is labor, and A is the total factor productivity (TFP).

After maximizing the profit function and deriving labor and capital demands and substituting the capital demand into the production function, we have

$$Q_{ijt} = A_{ijt} \left(\frac{\alpha}{\beta} \frac{L_{ijt} w_{ijt}}{r} \right)^{\alpha} L_{ijt}^{\beta} \quad (4.5)$$

where w is the wage and r is the price of capital.¹² Taking the logarithm and rearranging equation 4.5, we can derive the derived demand for labor as

$$\ln(L_{ijt}) = \phi_0 + \phi_1 \ln\left(\frac{w_{ijt}}{r}\right) + \phi_2 \ln(Q_{ijt}) \quad (4.6)$$

¹²I assume the capital market is a perfect competition market, so the price of capital will only change over time. Therefore, adding time dummies in estimation will capture the change in the price of capital over time.

where $\phi_0 = -(\ln A_{ijt} + \alpha \ln \alpha - \alpha \ln \beta)/(\alpha + \beta)$; $\phi_1 = -\alpha/(\alpha + \beta)$; $\phi_2 = 1/(\alpha + \beta)$.

As we can see, TFP in the production function depends on time, which indicates that the productivity factor may change over time. In addition, some studies demonstrate that international trade influences productivity. For example, Bernard, Eaton, Jensen, and Kortum (2003) suggested that aggregate productivity increases as trade costs decrease. Thus, arguing that trade sanctions, which increases trade costs, may affect firms' productivity, and therefore industry productivity, I assume that TFP in the production function varies with time and depends on international trade in the following procedure:

$$A_{ijt} = e^{\delta_0 T} e^{\delta_1 S_t} M_{ijt}^{\delta_2} X_{ijt}^{\delta_3} \quad (4.7)$$

where T is the time trend and S is a sanctions dummy, which takes a value of 1 in the year that sanctions are imposed and all subsequent years but otherwise is 0. M is imports and X is exports. Then, after taking the logarithm and substituting equation 4.7 into equation 4.6,

$$\ln(L_{ijt}) = \phi_0^* - \mu_0 T - \mu_1 S_t - \mu_2 \ln(M_{ijt}) - \mu_3 \ln(X_{ijt}) + \phi_1 \ln\left(\frac{w_{ijt}}{r}\right) + \phi_2 \ln(Q_{ijt}) \quad (4.8)$$

where $\phi_0^* = -(\alpha \ln \alpha - \alpha \ln \beta)/(\alpha + \beta)$; $\mu_0 = \mu \delta_0$; $\mu_1 = \mu \delta_1$; $\mu_2 = \mu \delta_2$; $\mu_3 = \mu \delta_3$; $\mu = 1/(\alpha + \beta)$.

The existence of employment adjustment costs and the bargaining procedure cause the employment level to deviate from a steady state. This suggests adding the lag of employment into the employment function (King and Thomas (2006)). In addition, if employment is the aggregated employment of some firms within an industry in which firms are observing different adjustment costs, then heterogeneity effects suggest using additional lags. Moreover, the existence of serially correlated

technology shocks forces us to use an even longer lag structure (Greenaway et al. (1999)).

Therefore, I suggest estimating a dynamic labor demand function equation in which I did not add lags of variables T and S :

$$\begin{aligned} \ln(L_{ijt}) = & \lambda_i + \gamma_j + \eta_t - \mu_0 T - \mu_1 S_t - \sum_k \mu_{2k} \ln(M_{ij,t-k}) - \sum_k \mu_{3k} \ln(X_{ij,t-k}) \\ & + \sum_k \phi_{0k} \ln(L_{ij,t-k}) + \sum_k \phi_{1k} \ln(w_{ij,t-k}) + \sum_k \phi_{2k} \ln(Q_{ij,t-k}) + \epsilon_{ijt} \end{aligned} \quad (4.9)$$

where λ_i , γ_j , and η_t are industry, province, and year fixed effects, respectively. L is total employment, w is real wage per worker, Q is real output, M is imports' share of output, X is exports' share of output.

In order to estimate equation 4.9, I take the first difference of all variables to ensure that the time series are stationary. So, the industry and province fixed effects, which allow for constant unobserved differences among industries and provinces over time, are transformed. I use the two-step generalized method of moments (GMM) approach developed by Arellano and Bond (1991) to estimate equation 4.9 in first difference. In this method, the lags of endogenous variables at $t - 2$ and earlier are used as instruments. There are two tests that we need to check to make sure that the estimates are unbiased and consistent. First, the equation should be free of second- and higher-order serial correlation. Therefore, test statistics, which are distributed normally, along with p-values are reported in Table 4.4 under the null hypothesis of no second- or higher-order serial correlation. Second, the validity of instruments needs to be checked. I test it using the Hansen test with the null hypothesis that instruments are valid for the model under the asymptotic distribution of chi-squared. The results are reported in Table 4.4.

Before we consider the results of the estimation, Table 4.3 shows changes in the variables included in the estimation equation over the three different aforementioned

sample periods and across two-digit ISIC. It shows that the employment growth rate for all industries decreased over the three sample periods; however, it is substantially different across two-digit ISIC. In detail, the employment growth rates are 14.87%, 16.95%, and 1.73% in 2001–2005, 2006–2010, and 2011–2015, respectively. During the sanction years, manufacture of apparel, manufacture of paper, and manufacture of radio, television, and communication equipment recorded the largest increases in their employment; in contrast, publishing, printing, and reproduction of recorded media and manufacture of coke, refined petroleum products, and nuclear fuel recorded the largest decreases in their employment.

Real output was severely influenced by sanctions. The real output growth rate reduced from 56.19% in sample period 2006–2010 to –22.81% in sample period 2010–2015. Many industries’ output was adversely affected during the sanction years. For instance, publishing, printing, and reproduction of recorded media; manufacture of coke, refined petroleum products, and nuclear fuel; and manufacture of motor vehicles, trailers, and semi-trailers recorded the largest decreases in their real output. However, manufacture of paper and manufacture of radio, television, and communication equipment recorded the largest increases in their real output. Such a sharp and sudden decline in both real output and employment in the sanction years reflects that a period of significant shocks occurred in these industries.

Average real wages decreased in 2011 and could not return to their 2010 level even 5 years after sanctions were imposed. This may be because, as a result of diminishing labor demand in this period, nominal wages declined for the given labor supply. Comparing exports’ and imports’ share of output reflects that exports’ share reduced dramatically in the sanctions period; however, industries were able to increase their import share remarkably. This may be another channel for explaining the sharp declines in employment and output. In fact, increases in industries’ imports will reduce their derived labor demand and as a result will diminish their output as well (Greenaway et al. (1999)). In a nutshell, the results in Table 4.3

confirm the results reported in Table 4.2 regarding the negative impact of sanctions on employment. In addition, it seems that sanctions had a negative impact on manufacturing industries' output and export share as well.

Table 4.4 presents the results of the model estimations. Column (1) reports the estimates without including trade. Columns (2) and (3) report the estimates including trade, where column (2) includes only exports and column (3) includes both exports and imports. All specifications include the sanction dummy variable (S_t). Hansen tests and second-order serial correlation tests are reported at the bottom of Table 4.4.

As we can see in Table 4.4, both wages and output have the expected effects on all specifications. Increases in output have a positive effect on the level of derived labor demand in both the short run and the long run, whereas increases in wages significantly reduce the labor demand in the short run but do not have any significant effect in the long run. Since the coefficient of the lagged dependent variable is positive, both output's and wages' impacts on employment level are persistent. Finally, all specifications passed both Hansen and second-order serial correlation tests. In other words, the Hansen test indicates that the instruments are valid for the model, and the second-order serial correlation test suggests that there is no second- or higher-order serial correlation.

Adding exports' and imports' shares to the base specification did not change the magnitudes or signs of coefficients, which indicates the robustness of the specifications. Surprisingly, as far as the effect of the trade on the labor demand is concerned, columns (2) and (3) suggest that there is no relationship between trade volumes and the level of derived labor demand. Indeed, none of the export or import shares has a significant effect on the level of employment, neither in the short run nor in the long run.

Turning to the sanctions dummy variable, we see that all estimates are negative and statistically significantly different from 0 for all specifications. This suggests

that the average level of derived labor demand decreased in the sanction years compared to the prior periods. For example, columns (1) and (3) show that the employment growth rate declined by about 10% during the sanctions period. This rate is 6% based on the column (2). As we can observe, here again, the estimation results confirm the results that I have found based on the previous methods. Therefore, I claim that sanctions could remarkably decrease the labor demand among manufacturing industries in Iran.

4.6 Demand for Skills and trade sanctions

In this section, I investigate the relationship between trade sanctions and the demand for skills. I define two variables to measure the share of skilled labor: first, the share of non-production workers out of total employment, as many other studies, such as Berman et al. (1994), use this measure; second, the share of skilled production workers out of total production workers. IFS classifies production workers into four different categories: (1) unskilled workers (those whose job requires no specific training), (2) skilled workers (those whose job requires little specific training), (3) technician workers (those who have at least an associate's degree and whose job requires specific training), and (4) engineer workers (those who have at least a bachelor's degree and work on the production line). For the purpose of this study, I combine the first two categories and define them as unskilled production workers and combine the last two categories and define them as skilled production workers. The share of skilled production workers out of total production workers should be a better measurement than the first one because it is more likely to be influenced by trade sanctions.

As I mentioned earlier, in order to identify whether international trade or biased technological change led to a change in the demand for skilled labor, we need to decompose the whole change into the *between* and *within* components. As Berman et al. (1994) and Bernard and Jensen (1997) recommended, I perform the following

industry-sector decomposition of the change in the skilled labor share using the method developed by Davis and Haltiwanger (1999):

$$\Delta P = \sum_i \Delta S_i \bar{P}_i + \sum_i \Delta P_i \bar{S}_i \quad (4.10)$$

where:

$$P_i = \frac{Y_i}{L_i}, \quad S_i = \frac{L_i}{L} \quad (4.11)$$

$$\Delta P_i = P_i^E - P_i^B, \quad \Delta S_i = S_i^E - S_i^B \quad (4.12)$$

$$\bar{P}_i = \frac{P_i^E + P_i^B}{2}, \quad \bar{S}_i = \frac{S_i^E + S_i^B}{2} \quad (4.13)$$

with Y indicating non-production (skilled production) workers, L the total (total production) workers, i the industry, and B and E the beginning and the end of the sample period, as defined in the previous section. Thus, S_i is the share of the total (total production) workers of industry i out of all (total production) workers. The first term on the right reports the change in aggregate demand for skills attributable to shifts in employment shares between industries, whereas the second term reports the change in aggregate demand for skills attributable to shifts in employment shares within industries.

Table 4.5 reports the between and within components of both the share of non-production workers out of total employment and the share of skilled production workers out of total production workers for export and non-export sectors. As before, I perform the decomposition separately for three different sample periods. Comparing the rates of the share of non-production workers out of total employment over the three different periods shows that the demand for non-production workers decreased by 1.66 percentage points per year from 2001 to 2005, then increased

by 1.11 percentage points per year from 2006 to 2010 before finally increasing by 0.74 percentage points per year from 2011 to 2015. Thus, it seems that the rate decelerated over the sanctions period compared with 2006–2010. In contrast, comparing the rates of the share of skilled production workers out of total production workers over the three different periods shows that the demand for skilled production workers accelerated over time. The demand for skilled production workers increased at a rate of 1.09 percentage points per year from 2001 to 2005, then increased to 1.57 points per year in 2006–2010 and then to 1.65 points per year in 2011–2015, which indicates that it accelerated even during the sanction years.

In addition, the within-industry component dominates the between-industry one in most cases. For example, the within component accounts for 0.94 of the 1.09 percentage point per year increase in the share of skilled production workers out of total production workers in the 2001–2005 period. There are just two out of the six cases in which the between-industry component weakly dominates the within-industry one. For instance, the between component accounts for 0.49 of the 0.74 percentage point per year increase in the share of non-production workers out of total employment in the 2011–2015 period. Thus, these findings suggest that the increase in the demand for skilled labor is mostly explained by upgrading skills within each industry, which is consistent with the findings of Berman et al. (1994) and Bernard and Jensen (1997). As a result, it seems that the main cause of the increase in the demand for skilled labor is biased technological change rather than international trade. In other words, international trade affects the demand for skilled labor through the adoption of production technology. Therefore, in the next section, I will develop a theoretical model to investigate the effects of trade sanctions on demand for skilled labor through affecting industries' technology. By this, I mean that I assume trade sanctions will adversely affect industries' technology which will cause industries to increase their demand for skilled labor.

4.6.1 Theory

In this section, I develop a simple model to illustrate the effect of international trade on the demand for skilled labor and the wage premium (the wages of skilled labor divided by the wages of unskilled labor) based on the model presented by Acemoglu (2003), which is based on the standard Heckscher-Ohlin trade model. I consider a small open economy that participates in international trade and consists of two export (x) and non-export (nx) sectors. Each sector consists of many different manufacturing industries. Exporters use advanced technology, which is more skill-intensive, to produce and sell their products both domestically and internationally with a fixed price given by all other trading partners. In contrast, non-exporters use a low level of technology, which is less skill-intensive, to produce and sell their products just domestically with a competitive price given by the equilibrium in the country's market.

We expect that trade sanctions adversely affect both sectors' technology, which is consistent with Bernard et al. (2003) model and has also been tested by Bernard et al. (2006). These studies find that as trade costs fall, the aggregate industry productivity will rise. As a result, one might expect trade sanctions to reduce industry productivity because they increase trade costs; however, the magnitude of the effect in each sector is not known within my model. In fact, I assume that there is an exogenous shock that adversely affects both sectors' production technologies with different magnitudes.

I present the discussion from the point of view of the small open economy. The small open economy is endowed with $\bar{s}$ units of skilled labor and $\bar{u}$ units of unskilled labor. So, $\bar{l} = \bar{s} + \bar{u}$ represents the total labor force.

4.6.1.1 Preferences

All consumers have identical preferences for two exported and non-exported goods. Consumption is aggregated and defined by a constant elasticity of substitution

(CES) utility:

$$\begin{aligned} \text{Max } U(c_{nx}, c_x) &= \left[\theta(c_{nx})^{\frac{\sigma-1}{\sigma}} + (1-\theta)(c_x)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \quad 0 < \theta < 1 \text{ and } 0 \leq \sigma < \infty \\ \text{s.t. } p_{nx}c_{nx} + p_xc_x &= I \end{aligned} \quad (4.14)$$

where c_x and c_{nx} are the total consumption of exported and non-exported goods, respectively. σ is the elasticity of substitution between the two goods. p_x and p_{nx} are the price of exported and non-exported goods, respectively. I is the total expenditure of the small open economy. Since the market for these two goods is competitive, the relative price of exported goods from the market clearing condition is

$$\frac{1-\theta}{\theta} \left(\frac{c_x}{c_{nx}} \right)^{-\frac{1}{\sigma}} = \frac{p_x}{p_{nx}} = p \quad (4.15)$$

Then, using the expenditure equation,

$$c_{nx} = \frac{I}{p_{nx} \left(1 + \left(\frac{1-\theta}{\theta} \right)^{\sigma} p^{1-\sigma} \right)} \quad \text{and} \quad c_x = \frac{I}{p_x \left(1 + \left(\frac{1-\theta}{\theta} \right)^{-\sigma} p^{\sigma-1} \right)} \quad (4.16)$$

4.6.1.2 Productions

I assume that both sectors use skilled and unskilled labor to produce; however, the relative share of skilled labor is larger in the export sector. In particular, let the production of these two sectors be a Cobb-Douglas CRS:

$$q_{nx} = A_{nx} u_{nx}^{\beta_1} s_{nx}^{\beta_2}, \quad 0 < \beta_i < 1 \quad \text{and} \quad \beta_1 + \beta_2 = 1 \quad (4.17)$$

$$q_x = A_x u_x^{\gamma_1} s_x^{\gamma_2}, \quad 0 < \gamma_i < 1 \quad \text{and} \quad \gamma_1 + \gamma_2 = 1 \quad (4.18)$$

where A_{nx} and A_x are the production technologies of the non-export and export sectors, respectively. I assume that $A_x > A_{nx}$ and $\beta_1 > \gamma_1$, which ensures that exporters are a more productive and skill-intensive sector.

The industries in each sector act competitively, and hence, the relative demand for skilled labor in each sector is given by

$$\phi_{nx}^d = \frac{s_{nx}}{u_{nx}} = \left(\frac{\beta_2}{\beta_1}\right) \frac{w^u}{w^s} < \phi_x^d = \frac{s_x}{u_x} = \left(\frac{\gamma_2}{\gamma_1}\right) \frac{w^u}{w^s}, \quad \text{since} \quad \left(\frac{\beta_2}{\beta_1}\right) < \left(\frac{\gamma_2}{\gamma_1}\right) \quad (4.19)$$

where w^s and w^u are the wages of skilled and unskilled labor, respectively. ϕ_{nx}^d and ϕ_x^d are the relative demand for skilled labor in the non-export and export sectors, respectively. However, the aggregate relative demand for skilled labor can be written as

$$\phi^d = \frac{s^d}{u^d} = \frac{s_x + s_{nx}}{u_x + u_{nx}} = \frac{w^u}{w^s} \frac{\beta_2 p_{nx} q_{nx} + \gamma_2 p_x q_x}{\beta_1 p_{nx} q_{nx} + \gamma_1 p_x q_x} = \frac{w^u}{w^s} \frac{\beta_2 + \gamma_2 \left(\frac{r_x}{r_{nx}}\right)}{\beta_1 + \gamma_1 \left(\frac{r_x}{r_{nx}}\right)} = \frac{w^u}{w^s} \frac{\beta_2 + \gamma_2 r}{\beta_1 + \gamma_1 r} \quad (4.20)$$

where ϕ^d is the aggregate relative demand for skilled labor. $r_x = p_x q_x$ and $r_{nx} = p_{nx} q_{nx}$ are exporters' and non-exporters' revenue, respectively, and $r = \frac{r_x}{r_{nx}}$ is the relative revenue of the export sector.

As we can see in equation 4.20, given the wage premium $\omega = \frac{w^s}{w^u}$, the only factor that can shift the aggregate relative demand for skilled labor is the relative revenue of the export sector (r). In particular, an increase in r will increase the demand for skilled labor ($\frac{\partial \phi^d}{\partial r} > 0$).

Since the labor market is perfectly competitive, the value of the marginal product of labor has to be equal to the wage rate, and from the labor market

equilibrium condition, we have

$$\begin{aligned} u^d = u_x + u_{nx} &= \frac{\beta_1 p_{nx} q_{nx}}{w^u} + \frac{\gamma_1 p_x q_x}{w^u} = \frac{\beta_1 p_{nx} q_{nx} + \gamma_1 p_x q_x}{w^u} = \bar{u} \\ \Rightarrow w^u \bar{u} &= \beta_1 p_{nx} q_{nx} + \gamma_1 p_x q_x \end{aligned} \quad (4.21)$$

$$\begin{aligned} s^d = s_x + s_{nx} &= \frac{\beta_2 p_{nx} q_{nx}}{w^s} + \frac{\gamma_2 p_x q_x}{w^s} = \frac{\beta_2 p_{nx} q_{nx} + \gamma_2 p_x q_x}{w^s} = \bar{s} \\ \Rightarrow w^s \bar{s} &= \beta_2 p_{nx} q_{nx} + \gamma_2 p_x q_x \end{aligned} \quad (4.22)$$

If we add equations 14 and 15:

$$I = w^u \bar{u} + w^s \bar{s} = (\beta_1 + \beta_2) p_{nx} q_{nx} + (\gamma_1 + \gamma_2) p_x q_x = p_{nx} q_{nx} + p_x q_x = r_{nx} + r_x \quad (4.23)$$

Equation 4.23 shows that the total revenue of both sectors equals the total income of the labor force, which has to be equal to the total expenditure of the small open economy.

Then, from equation 4.16 and equilibrium in the non-exported goods market ($c_{nx} = q_{nx}$),

$$r = \frac{r_x}{r_{nx}} = \frac{I}{r_{nx}} - 1 = \left(\frac{1-\theta}{\theta} \right)^\sigma p^{1-\sigma} \quad (4.24)$$

Thus, the relative revenue of exporters depends on the relative price of exported goods. The effect of a change in p is complex because it depends on the elasticity of substitution. If σ is greater than 1, then $\frac{\partial r}{\partial p} < 0$, and an increase in the relative price of exported goods will decrease the relative revenue of exporters. In contrast, if σ is less than 1, then $\frac{\partial r}{\partial p} > 0$, and an increase in the relative price of exported goods will increase the relative revenue of exporters.

Skilled labor demand in the export sector and unskilled labor demand in the non-export sector are given by

$$\gamma_2 p_x A_x u_x^{\gamma_1} s_x^{\gamma_2-1} = w^s \quad (4.25)$$

$$\beta_1 p_{nx} A_{nx} u_{nx}^{\beta_1-1} s_{nx}^{\beta_2} = w^u \quad (4.26)$$

If we divide equation 4.25 by 4.26 and rearrange it using equation 4.19:

$$p = \frac{p_x}{p_{nx}} = \frac{\beta_1^{\beta_1} \beta_2^{\beta_2}}{\gamma_1^{\gamma_1} \gamma_2^{\gamma_2}} \frac{A_{nx}}{A_x} \left(\frac{w^s}{w^u} \right)^{\beta_1-\gamma_1} = \frac{\beta_1^{\beta_1} \beta_2^{\beta_2}}{\gamma_1^{\gamma_1} \gamma_2^{\gamma_2}} \frac{\omega^{\beta_1-\gamma_1}}{\alpha} \quad (4.27)$$

where $\alpha = \frac{A_x}{A_{nx}}$ is the relative production technology of the export sector (bias of technology). As we can see in equation 4.27, given the wage premium (ω), the only factor that can change the relative price of exported goods (p) is the relative production technology of the export sector (α). The Balassa-Samuelson Model confirms the same result: that the greater the relative production technology of the export sector, the smaller the relative price of exported goods (Asea and Corden (1994)).

4.6.1.3 Equilibrium

By entering equation 4.27 into equation 4.24, we can derive

$$r = \frac{r_x}{r_{nx}} = \frac{I}{r_{nx}} - 1 = \left(\frac{1-\theta}{\theta} \right)^\sigma p^{1-\sigma} = \left(\frac{1-\theta}{\theta} \right)^\sigma \left(\frac{\beta_1^{\beta_1} \beta_2^{\beta_2}}{\gamma_1^{\gamma_1} \gamma_2^{\gamma_2}} \right)^{1-\sigma} \alpha^{\sigma-1} \omega^{(\beta_1-\gamma_1)(1-\sigma)} \quad (4.28)$$

and then the equilibrium wage premium is determined when the relative supply of skilled labor (ϕ^s) equals the aggregate relative demand for skilled labor (ϕ^d):

$$\phi^d = \frac{s^d}{u^d} = \omega^{-1} \frac{\beta_2 + \gamma_2 \left[\left(\frac{1-\theta}{\theta} \right)^\sigma \left(\frac{\beta_1^{\beta_1} \beta_2^{\beta_2}}{\gamma_1^{\gamma_1} \gamma_2^{\gamma_2}} \right)^{1-\sigma} \alpha^{\sigma-1} \omega^{(\beta_1-\gamma_1)(1-\sigma)} \right]}{\beta_1 + \gamma_1 \left[\left(\frac{1-\theta}{\theta} \right)^\sigma \left(\frac{\beta_1^{\beta_1} \beta_2^{\beta_2}}{\gamma_1^{\gamma_1} \gamma_2^{\gamma_2}} \right)^{1-\sigma} \alpha^{\sigma-1} \omega^{(\beta_1-\gamma_1)(1-\sigma)} \right]} = \frac{\bar{s}}{\bar{u}} = \phi^s \quad (4.29)$$

Equation 4.29 demonstrates the main factors affecting the wage premium and shows that the aggregate relative demand for skilled labor is only a function of parameters and the wage premium. For a given bias of technology, as captured by α , ϕ^d is a downward sloping curve ($\frac{\partial \phi^d}{\partial \omega} < 0$),¹³ as shown in Figure 4.1. As ϕ^s is vertical, there is one and only one equilibrium wage premium, ω^* . In addition, Figure 4.1 represents the relative demand for skilled labor in each sector based on equation 4.19 (ϕ_x^d and ϕ_{nx}^d). ϕ^d is placed between ϕ_{nx}^d and ϕ_x^d .¹⁴

4.6.1.4 International trade

In this section, I consider the effect of a change in α on the labor market equilibrium condition. If international trade induces biased technological change (any change in α), then for a given wage premium, it affects the aggregate relative demand for skilled labor; however, the effect depends on σ . If σ is greater than 1, then $\frac{\partial \phi^d}{\partial \alpha} > 0$, and an improvement in the bias of technology increases the relative demand for skilled labor. In contrast, if $0 < \sigma < 1$, then an improvement in the bias of technology reduces the relative demand for skilled labor.

Figure 4.2 illustrates the effect of an increase in α on the labor market equilibrium condition when $\sigma > 1$.¹⁵ An increase in α reallocates market share (r) from

¹³Proof in Appendix B.

¹⁴Proof in Appendix B.

¹⁵ In Figure 4.2, “b” stands for before the increase and “a” stands for after the increase.

non-exporters to exporters $\left(\frac{\partial r}{\partial \alpha} > 0\right)$,¹⁶ which shifts the relative demand for skilled labor, as shown in Figure 4.2. This results in an increase in the wage premium, which reallocates equilibrium, as it induces both exporters and non-exporters to use relatively less skilled labor. All effects would be opposite if $0 < \sigma < 1$, and there is no effect if $\sigma = 1$ exactly.

4.6.2 Empirical evidence

4.6.2.1 Trade sanctions and bias of technology

The first step to show the effect of trade sanctions on the demand for skilled labor is to consider how trade sanctions affect the bias of technology, which is the relative level of production technology of two sectors. Thus, we first need to estimate the level of production technology and, second, to investigate the effect of trade sanctions on each sector's productivity.

In the first stage, to determine TFP, I consider an industry with a Cobb-Douglas production function,

$$Q_{ijt} = A_{ijt} K_{ijt}^{\beta_1} L_{ijt}^{\beta_2} M_{ijt}^{\beta_3} \quad (4.30)$$

where production in industry i , province j , and year t , Q_{ijt} , is a function of labor, L_{ijt} ; capital, K_{ijt} ; and materials, M_{ijt} . As I mentioned earlier, I am assuming that TFP, A_{ijt} , will be affected by international trade policy. Taking the natural logs of equation 4.30, which I denote by small letters, I estimate

$$q_{ijt} = \beta_0 + \beta_1 k_{ijt} + \beta_2 l_{ijt} + \beta_3 m_{ijt} + \epsilon_{ijt} \quad (4.31)$$

The dependent variable is the value of output, deflated by CPI. Materials include both domestic and imported inputs and are adjusted by CPI as well. I estimate

¹⁶Proof in Appendix B.

equation 4.31 using a fixed effects estimator including industry, province, and year dummies for industries in each two-digit ISIC separately. The estimated inputs' coefficients are reported in Table 4.6. As we can observe, material's share is much bigger than those of labor and capital in the production process of all industries, as expected and found by other studies such as Amiti and Konings (2007).

Using estimated input coefficients, we can calculate the log of TFP (*tfp*) as follows:

$$tfp_{ijt} = \ln(A_{ijt}) = q_{ijt} - \hat{\beta}_1 k_{ijt} + \hat{\beta}_2 l_{ijt} - \hat{\beta}_3 m_{ijt} \quad (4.32)$$

Figure 4.3 shows the average estimated *tfp* trends for all industries and separately for export and non-export sectors between 2001 to 2015. As we can observe, *tfp* had a slightly upward trend from 2001 to 2010, and then it started to decline from 1.97 to 1.90 during the sanction period. Exporters have a higher productivity level than non-exporters, on average, which is consistent with many other studies, such as Bernard, Jensen, and Lawrence (1995), Wagner (2007), and Bernard and Jensen (2004). In addition, both exporters and non-exporters have almost the same *tfp* trend pattern and fluctuations before and after the sanction year. Although both sectors' *tfp* reduced after the sanction year, it seems that non-exporters' *tfp* dropped more than exporters'. As a result, trade sanctions adversely affected both sectors' productivity levels, and it seems that non-exporters suffered more than exporters, which means the relative productivity of exporters should increase.

To see exactly what happened to the relative productivity of the two sectors, in the second stage, I specify the possible links between trade sanctions and the bias of technology by specifying the differential changes, which allows me to compare the effect of the trade sanctions on the relative *tfp* before and after the sanction year as follows:

$$tfp_{ijt} = \delta_0 + \delta_1 S_t + \delta_2 EX_{ijt} + \delta_3 (S_t \cdot EX_{ijt}) + \epsilon_{ijt} \quad (4.33)$$

where S is a sanctions dummy variable, as before. EX is an export dummy variable that takes the value of 1 for an industry i in province j at year t that exports and otherwise is 0. I estimate equation 4.33 using a fixed effects estimator including industry, province, year dummies, and the estimated coefficients are reported in Table 4.7.

The reported results in Table 4.7 make two very important facts clear to us. First, both exporters and non-exporters experienced a drop in their tfp during the sanction year. Second, the drop in non-exporters' tfp is larger than the drop in exporters' tfp , which means the relative tfp of exporters increases after sanctions. Precisely, the tfp of non-exporters dropped significantly from 2.182 (δ_0) to 2.148 ($\delta_0 + \delta_1$)(about 3.4% decrease), but exporters' tfp dropped from 2.196 ($\delta_0 + \delta_2$) to 2.175 ($\delta_0 + \delta_1 + \delta_2 + \delta_3$)(about 2.1% decrease). Thus, trade sanctions significantly increased the bias of technology toward exporters by $\delta_3 = 0.013$ (about 1.3%) (an increase in α in my model).

To understand why trade sanctions have a greater adverse effect on non-exporters than on exporters, it is worth looking at the amount of exports and imports traded by the two sectors before and after the sanction year.

Table 4.8 presents the real amount of imported raw materials and capital and the real amount of exports separately for the two sectors before and after the sanction year. In addition, those variables are reported as a share of output as well. Although exporters reduced their imports of both materials and capital during the sanction years, surprisingly, their exports almost doubled during the same period. In contrast, non-exporters increased their imports, particularly of raw materials, during the sanction years. Haidar (2017) show how Iranian non-oil exporters increased their aggregate exports to new non-sanctioning countries after sanctions were imposed in 2008. Therefore, exporting to new destinations would be a solution for exporters to stay away from sanctions and even improve their situation; however, they may need to adjust their prices.

Another explanation would be related to exporters' and non-exporters' access to a hard currency like the dollar. Since the Central Bank of Iran provides dollars to its market and there was a lack of dollars during the sanction years because of a huge reduction in Iran's oil sales, the exchange rate for the dollar to the IRR increased by about 15 times in the black market and about four times according to the Central Bank of Iran. This may have caused a big problem for non-exporters to overcome while importing materials. In fact, exporters, which are selling their product abroad, have access to hard currency, which gives them more flexibility to overcome the dollar shortage than non-exporters have. Although it seems that exporters are more flexible than non-exporters when exposed to sanctions, we do not have a clear explanation of why non-exporters endure greater adverse effect than exporters. Thus, this question remains ambiguous and needs to be studied further, which is outside the scope of this study.

4.6.2.2 Trade sanctions, demand for skilled labor, and wage premium

The main finding of the previous section was that trade sanctions induce technological change that is biased toward exporters. This effect suggests that the demand for skilled labor should increase and, as a result, the wage premium should rise through the mechanism highlighted in the model, assuming the elasticity of substitution between skilled and unskilled labor is greater than 1 ($\sigma > 1$). Therefore, in this section, I focus on identifying the effects of the trade sanctions on the wage premium, regardless of how the mechanism works. There is one issue that arose over the course of the research. Since the data just include the total wages of all workers, it is not possible to estimate the effect of sanctions on the wage premium. Thus, I will choose the average wage per worker as my dependent variable. My argument is that if trade sanctions increase, then the wage premium in an industry, which means the relative wage of skilled labor, increases, so the average wage per worker should increase in that industry as well.

Using the model introduced by Katz and Murphy (1992), which explains the changes in the relative wages of skilled and unskilled labor, I estimate the effects of trade sanctions on the average wage per worker through the following specification:

$$\begin{aligned} \ln(w_{ijt}) = & \theta_0 + \theta_1 S_t + \theta_2 \ln\left(\frac{S_{ijt}}{L_{ijt}}\right) + \theta_3 \left(S_t \cdot \ln\left(\frac{S_{ijt}}{L_{ijt}}\right)\right) \\ & + \theta_4 \ln(\text{MinWage}_t) + \theta_5 \text{Unemp}_{jt} + \epsilon_{ijt} \end{aligned} \quad (4.34)$$

where w is the real average wage per worker, deflated by CPI. $\frac{S}{L}$ is the relative demand for skilled labor out of that for total labor based on my two different definitions: first, the share of non-production workers out of total employment, and second, the share of skilled production workers out of total production workers. Following Autor, Katz, and Kearney (2008), I add the unemployment rate as a measure of labor market cyclical conditions to control the unobserved demand shifts and the real minimum wage, deflated by CPI, as a control variable. Finally, i , j , and t index industry, province, and year, respectively. This specification has two main differences from the one developed by Autor et al. (2008). First, since w is not the relative wage and we have the relative demand instead of the relative supply of skilled labor on the right-hand side of the equation, we cannot interpret coefficient θ_2 as the inverse elasticity of substitution between skilled and unskilled labor $\left(\frac{1}{\sigma}\right)$. Second, since $\frac{S}{L}$ is the relative demand for skilled labor, we expect to find a positive value for θ_2 instead of a negative one where we have the relative supply of skilled labor on the right-hand side of the equation. In fact, we expect that when the relative demand for skilled labor increases, the average wage per worker increases.

The coefficient of interest is θ_3 , which represents the relationship between the real average wage per worker and the relative demand for skilled labor after the sanction year. Our expectation is that θ_3 will be greater than 0 and significant if the elasticity of substitution between skilled and unskilled labor is greater than 1

($\sigma > 1$); otherwise, we expect θ_3 to be less than 0 and significant, which indicates that there is a decrease in the relative demand for skilled labor, and as a result, the average wage per worker will decline after the sanctions were imposed. I estimate equation 4.34 using a fixed effects estimator including industry, province, and year dummies, and the estimated coefficients are reported in Table 4.9.

The sanction dummy coefficients in columns (3) and (6) show that after controlling the real minimum wage and the unemployment rate, the real average wage declines after the sanctions by about 15% and 10%, respectively. This probably suggests that as the overall labor demand declines after the sanction, which is the main result of estimating the dynamic labor demand function in the previous section, the real average wage per worker decreases. Moreover, the results illustrate that a 1% increase in the real minimum wage raises the real average wage per worker by about 1%, which captures the most explanatory power in the real average wage per worker change. In addition, the unemployment rate has a modest positive explanatory power in explaining the real average wage trend. Although the inclusion of the real minimum wage changes the sign of the sanction dummy, which speaks to the critical role of the demand growth trend in explaining the evolution of the real average wage per worker, adding both the minimum wage and the unemployment rate does not much alter the model's other coefficients.

A closer look at the data provides us with a clear pattern of the real average wage per worker trend between 2001 and 2015. As shown in Figure 4.4, first, exporters pay higher wages than non-exporters. This is mainly because export industries are more skilled labor-intensive industries than non-exporters, as shown in Figure 4.5 and confirmed by other studies, such as Bernard et al. (1995), Wagner (2007), and Bernard and Jensen (2004). Second, the real average wage per worker gradually rose by about 30% from 2001 to 2010; however, we observe a sharp decline in the real average wage per worker after 2010, which continues to decrease till 2013 and then starts to increase. This pattern suggests that the real average

wage dramatically declines after the sanction year, which is consistent with the above results.

All specifications suggest that the relative demand for skilled labor coefficients are positive and statistically significantly different from 0. These coefficients confirm that as the relative demand for skilled labor increases, the real average wage per worker increases at equilibrium. The coefficients of the share of non-production workers out of total employment (columns (1), (2), and (3)) are slightly greater than the coefficients of the share of skilled production workers out of total production workers (columns (4), (5), and (6)). In particular, the model in column (3) indicates a significant positive impact of the relative demand for non-production workers with an estimated coefficient of about 0.09; however, the estimated coefficient of the relative demand for skilled production workers based on the model in column (6) is about 0.07.

Finally, the variable of interest in my study is the interaction of the sanction dummy and the relative demand for skilled labor. Looking at columns (1) to (3), we observe that the coefficients for the interaction of the sanction dummy and the share of non-production workers out of total employment are negative and statistically significantly different from 0. Based on my theoretical model, this could happen when the elasticity of substitution between non-production workers (skilled workers) and production workers (unskilled workers) is less than 1 ($\sigma < 1$). In fact, the theoretical model predicts that if $\sigma < 1$, then trade sanctions that induce biased technological change decrease the relative demand for skilled labor, and as a result, the wage premium decreases. Gujarati and Dars (1972) and Freeman and Medoff (1982) showed that the elasticity of substitution between non-production and production workers is less than unity for most US manufacturing industries. For example, Gujarati and Dars (1972) found that the elasticity of substitution is statistically significantly less than unity in industries 22, 23, 24, 25, 26, 27, 30, 31, and 32, and in the remaining industries (20, 28, 29, 33, 34, 35, 36, 37, 38) it was

statistically 0. Industry 21 is the only one with an elasticity greater than 0. These results show that since there is less-than-unity statistically significant evidence of substitution between non-production and production workers in most industries, these two labor inputs are not necessarily complementary factors of production. Given that $\sigma < 1$, now I can argue based on my regression model that the negative value of coefficient θ_3 makes sense, and it suggests that trade sanctions decrease the share of non-production workers out of total employment and, in consequence, significantly reduce the real average wage per worker.

In contrast, looking at columns (4) to (6), we can observe that the coefficients for the interaction of the sanction dummy and the share of skilled production workers out of total production workers are positive and statistically significantly different from 0. Based on my theoretical model, this could happen when the elasticity of substitution between skilled production workers and unskilled production workers is greater than 1 ($\sigma > 1$). In fact, the theoretical model predicts that if $\sigma > 1$, then trade sanctions that induce biased technological change increase the relative demand for skilled labor, and as a result, the wage premium increases. Many studies find that elasticity of substitution between more and less educated workers is greater than 1. As I have mentioned earlier, skilled production workers are more educated than unskilled production workers in my study. One of the widely cited studies is Katz and Murphy (1992), whose estimate of the elasticity of substitution is about 1.4, and Autor et al. (2008) extended the period and find that it is about 1.6. Heckman, Lochner, and Taber (1998) and Ciccone and Peri (2005) estimated that it is about 1.5. As a matter of fact, given that $\sigma > 1$ and based on my theory, the positive value of coefficient θ_3 suggests that trade sanctions increase the share of skilled production workers out of total production workers, and in consequence, they significantly raise the real average wage per worker.

Figures 4.5 and 4.6 show the trends of non-production workers' share of total employment and skilled production workers' share of total production workers,

respectively and separately for exporters and non-exporters between 2001 and 2015. These figures have some notable features. First, as we expect, exporters are more skilled labor-intensive industries than non-exporters. Second Berman et al. (1994) mentioned, “production employment is more cyclically sensitive than non-production employment,” but we can observe the opposite case in these figures. In fact, non-production employment seems to fluctuate more than that of production workers. Furthermore, we can observe that the share of non-production workers out of total employment does not change that much after the sanction year and even starts to decline in 2013 for all industries (Figure 4.5). Third, skilled production workers’ share shows a clear upward trend from 0.12 to 0.19 between 2001 and 2015 in Figure 4.6. Finally, although skilled production workers’ share shows an increase with a constant rate during the sanctions period, non-production workers’ share experiences a diminishing acceleration during the same period compared to the prior period. Put both the regression’s and the trends’ results together, and it seems that industries decreased their relative demand for non-production workers and increased their relative demand for skilled production workers after the sanction year.

4.7 Conclusion

Trade sanctions are imposed to change the behavior of other governments; however, they influence the economy of the country that is targeted. Iran has experienced economic sanctions imposed by the UNSC, the US Congress, and other countries around the world during the past 40 years. In 2010, both the UNSC and the US Congress passed sanctions on Iran, which included blacklisting several banks and financial institutions; this was the toughest sanction imposed on Iran. This chapter studies how the particular trade sanction imposed in 2010 affected employment and the skill premium in manufacturing industries in Iran. To assess the employment impact of the trade sanction, I estimate a dynamic labor demand function by

incorporating imports and exports in the model and implying that the trade sanctions influence industries' derived labor demand through their productivity. Then, arguing that trade sanctions influence exporters' and non-exporters' production technology in different ways, I develop a model to show how this causes a biased technological change that leads to a change in the relative demand for skilled labor and, as a consequence, the wage premium.

Using manufacturing industry-level data collected by the SCI that cover 10 years before and 5 years after the sanctions, all of Iran's provinces, and more than 200 different industries, the results are summarized as follows:

First, although there is no significant relationship between industries' labor demand and any of their imports or exports, the trade sanctions had a negative effect on industries' labor demand. The result shows that the trade sanctions decreased labor demand growth by about 10% in internationally active industries. Moreover, the results show that the trade sanctions affected manufacturing industry jobs negatively. All industries, including internationally active industries, have been adversely affected by the sanctions and lost jobs; however, the magnitude of the effect is different between exporters and non-exporters. In fact, the results suggest that non-exporters experienced a larger negative impact than exporters.

Regarding the effect of the sanctions on the relative demand for skilled labor, first, we need to investigate how the sanctions induced biased technological change between exporters and non-exporters. The results suggest that both exporters and non-exporters were adversely affected by the sanctions; however, non-exporters experienced a larger decline in their total-factor productivity than exporters. This means that the sanctions induced biased technological change, and as a result, an increase in the relative demand for skilled labor raised the wage premium. The results show that there was a decrease in the relative share of non-production workers out of total employment after the sanctions, which led to a decrease in the real average wage per worker. On the contrary, there was an increase in the

relative share of skilled production workers out of total production workers after the sanctions, which led to an increase in the real average wage per worker. This difference is explained by the amount of the elasticity of substitution between skilled and unskilled workers. In fact, the theoretical model explains that there is an increase in the relative demand for skilled labor under the assumption of elasticity of substitution between skilled and unskilled workers larger than unity, and otherwise, there is a decrease in the relative demand for skilled workers. Thus, the sanctions changed the structure of the labor demand from non-production workers toward skilled production workers, of which the former may cause a reduction in the real average wage per worker and the latter a rise in the real average wage per worker.

Table 4.1: Exporting and non-exporting industries

Groups	Non-weighted (%)	Weighted by sales (%)
Exports only	3	3
Exports and imports	39	86
Imports only	43	9
Neither exports nor imports	15	2

Table 4.2: Employment growth rate and export-import status

Groups	Period	Employment growth rate (%)	<i>ACNE</i>
All	2001-2005	17.29	21263
All	2006-2010	9.97	71004
All	2011-2015	-0.22	-12995
Exports only	2001-2005	9.23	-152
Exports only	2006-2010	18.58	411
Exports only	2011-2015	-3.29	-1757
Exports and imports	2001-2005	19.19	9849
Exports and imports	2006-2010	11.75	70414
Exports and imports	2011-2015	7.70	17347
Imports only	2001-2005	15.02	9720
Imports only	2006-2010	8.50	268
Imports only	2011-2015	-10.13	-22416
Neither exports nor imports	2001-2005	19.24	1846
Neither exports nor imports	2006-2010	3.49	-89
Neither exports nor imports	2011-2015	-10.76	-6169

Table 4.3: Employment, production, wages, exports and imports

ISIC	Employment (thousands)									Real output (trillion IRR)								
	2001	2005	% change	2006	2010	% change	2011	2015	% change	2001	2005	% change	2006	2010	% change	2011	2015	% change
All	913	1049	14.87	1060	1240	16.95	1232	1253	1.73	887	1460	64.19	1670	2620	56.19	2550	1970	-22.81
15	121	156	29.53	160	187	16.84	183	214	16.82	104	161	54.38	169	226	34.04	212	261	22.92
17	129	100	-22.36	93	78	-15.92	75	70	-6.44	46.5	52.9	13.72	57.1	49.7	-12.85	42.2	36.2	-14.07
18	3.1	3.2	2.10	3.6	0.8	-77.51	0.5	3.3	476.23	0.9	1.7	86.36	1.3	0.5	-61.76	1.2	1.3	8.73
19	10	6.0	-41.57	7.2	5.7	-21.47	4.8	5.3	8.47	4.3	3.4	-20.36	5	3.3	-32.42	2.9	2.5	-14.74
20	5.9	3.8	-35.89	5.4	1.9	-65.20	4.7	4.8	3.12	2.4	1.7	-29.04	4.1	1.6	-60.13	5.1	7.3	41.30
21	6.5	11	79.14	12	13	6.36	10	16	56.47	5.4	12	117.97	12.6	10.1	-19.22	6.9	14.2	105.11
22	—	10	—	10	8	-24.36	8	0.5	-92.58	—	5.1	—	4.4	3.9	-10.08	4.3	0.7	-83.09
23	6.6	7.7	16.06	8.5	24.4	184.74	22.5	18.6	-17.05	33	63	91.40	84	760	800.85	815	364	-55.38
24	63	71	13.14	73	110	49.85	113	131	16.26	105	159	51.18	227	371	63.06	379	378	-0.02
25	31	45	45.19	48	52	7.76	52	54	0.99	22.8	451	97.83	46.9	46.2	-1.52	46.3	43	-7.06
26	119	136	14.22	143	166	16.29	163	149	-8.21	61.5	89.8	46.00	94	116	26.56	112	86.2	-22.69
27	67	71	5.32	70	111	54.61	113	127	12.54	115	207	80.35	276	305	10.43	262	233	-11.33
28	40	65	60.55	65	67	2.45	68	65	-4.77	26.6	51.7	94.87	56	52.7	-5.81	48	49.5	3.20
29	69	77	11.39	75	76	0.99	75	72	-4.14	41.8	63.7	52.49	69.4	67.9	-2.10	55.7	55.1	-1.15
30	—	2.6	—	2.2	4.7	111.60	4.4	5.4	22.11	—	1.8	—	1.2	4.9	307.48	3.7	3.6	-3.94
31	33	41	21.40	40	47	17.89	47	40	-14.35	27.9	45	61.15	51.9	60.1	15.96	49	36.6	-25.32
32	9.2	8.0	-13.00	4.5	4	-11.88	3.5	6.1	70.88	12.1	9.5	-21.14	5.4	3.5	-34.54	2.7	10.3	273.86
33	7.2	9.3	28.80	9.1	9.6	4.57	10.4	9.7	-6.58	3.2	4.8	50.48	5	8.5	69.64	8.2	9.4	15.27
34	62	100	60.74	109	138	26.45	125	127	1.83	157	342	117.19	361	383	6.09	302	176	-41.55
35	9.3	8.2	-11.49	9.4	5	-46.77	5.3	67	27.54	6.6	11.8	77.80	12.7	5	-60.43	5.1	6.5	26.59
36	6.8	12	79.60	12	4.8	-62.05	11	10	-8.93	3	6.5	114.83	6.9	2.4	-64.91	5.9	5	-14.67

Table 4.3: Continued

ISIC	Real wage per worker (million IRR)									Export share in output								
	2001	2005	% change	2006	2010	% change	2011	2015	% change	2001	2005	% change	2006	2010	% change	2011	2015	% change
All	98	110	12.83	123	128	4.39	115	123	7.01	0.075	0.084	12.23	0.100	0.109	9.78	0.126	0.127	0.76
15	84	88	4.64	95	95	0.35	88	89	1.21	0.050	0.054	6.66	0.069	0.052	-24.75	0.069	0.079	13.44
17	74	79	6.55	85	87	2.03	75	73	-1.79	0.035	0.062	78.84	0.068	0.040	-41.24	0.043	0.065	48.83
18	54	63	16.16	77	63	-18.33	66	84	27.33	0.042	0.016	-61.65	0.023	0.058	150.70	0.316	0.159	-49.46
19	64	62	-3.20	68	80	16.10	66	67	1.69	0.228	0.438	91.56	0.327	0.399	22.05	0.396	0.455	14.88
20	86	110	27.95	123	127	2.96	91	107	17.76	0.015	0.013	-14.32	0.008	0.005	-40.22	0.004	0.011	170.94
21	95	115	20.84	117	116	-0.77	101	89	-11.51	0.004	0.14	208.67	0.018	0.015	-20.32	0.010	0.021	116.23
22	–	107	–	120	134	11.26	96	76	-20.59	–	0.000	–	0.001	0.004	233.19	0.002	0.104	3756.42
23	171	184	7.49	263	218	-17.04	222	254	14.70	0.019	0.025	29.42	0.100	0.098	-2.04	0.124	0.053	-56.83
24	123	130	6.12	159	176	10.51	167	169	1.15	0.282	0.289	2.71	0.314	0.387	23.16	0.403	0.395	-2.03
25	89	94	5.68	101	104	2.58	83	91	9.20	0.044	0.027	-37.75	0.034	0.033	-0.86	0.037	0.071	90.22
26	84	100	18.25	104	109	5.53	92	99	7.00	0.054	0.056	3.20	0.049	0.079	61.29	0.075	0.119	58.65
27	148	170	14.87	212	179	-15.57	150	182	20.92	0.136	0.212	55.51	0.178	0.080	-55.17	0.062	0.139	122.67
28	91	91	-0.04	103	118	14.54	101	99	-2.30	0.073	0.026	-64.70	0.038	0.023	-37.46	0.027	0.032	19.38
29	93	107	14.94	112	109	-2.61	94	101	7.77	0.014	0.045	219.26	0.039	0.048	21.34	0.060	0.043	-27.14
30	–	105	–	93	140	49.55	126	209	64.91	–	0.000	–	0.002	0.000	-85.76	0.000	0.002	582.90
31	94	104	10.53	113	123	8.08	101	107	5.85	0.022	0.030	38.33	0.032	0.033	1.22	0.036	0.046	26.12
32	100	125	24.87	126	117	-7.01	81	102	25.58	0.004	0.003	-16.89	0.013	0.002	-80.08	0.003	0.000	-83.36
33	74	77	4.60	95	115	20.63	84	99	18.28	0.013	0.015	12.86	0.025	0.007	-71.96	.0.006	0.018	174.85
34	141	159	13.00	170	174	2.34	166	176	5.82	0.012	.011	-4.80	0.016	0.016	4.67	0.009	0.013	34.45
35	98	112	14.67	122	117	-4.07	78	204	160.67	0.022	0.043	87.16	0.045	0.020	-54.95	0.044	0.005	-88.44
36	78	92	17.44	85	89	3.96	83	98	17.82	0.014	0.000	-63.84	0.005	0.011	115.56	0.062	0.007	-87.32

Table 4.3: Continued

ISIC	Import share in output									ISIC description
	2001	2005	% change	2006	2010	% change	2011	2015	% change	
All	0.100	0.121	20.39	0.094	0.052	-43.97	0.049	0.069	42.08	
15	0.067	0.072	7.62	0.089	0.065	-26.30	0.072	0.101	40.68	Manufacture of food products and beverages
17	0.107	0.108	1.41	0.133	0.085	-35.97	0.109	0.138	26.80	Manufacture of textiles
18	0.073	0.058	-21.12	0.033	0.008	-74.61	0.007	0.156	1911.01	Manufacture of wearing apparel; dressing and dyeing of fur
19	0.036	0.035	-2.21	0.062	0.065	5.97	0.048	0.088	81.99	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear
20	0.031	0.017	-44.92	0.045	0.041	-12.58	0.116	0.097	-16.75	Manufacture of wood and of products of wood and cork, except furniture
21	0.079	0.115	46.60	0.144	0.105	-27.33	0.112	0.304	171.47	Manufacture of paper and paper products
22	–	0.155	–	0.032	0.035	10.87	0.118	0.028	-75.90	Publishing, printing and reproduction of recorded media
23	0.019	0.034	76.40	0.039	0.002	-93.66	0.003	0.007	118.35	Manufacture of coke, refined petroleum products and nuclear fuel
24	0.058	0.072	23.84	0.095	0.051	-46.41	0.033	0.045	36.65	Manufacture of chemicals and chemical products
25	0.276	0.172	-37.56	0.160	0.106	-33.26	0.119	0.140	17.20	Manufacture of rubber and plastics products
26	0.041	0.036	-12.08	0.032	0.033	3.78	0.020	0.056	173.67	Manufacture of other non-metallic mineral products
27	0.077	0.096	23.87	0.111	0.105	-6.08	0.054	0.043	-20.45	Manufacture of basic metals
28	0.046	0.108	131.57	0.092	0.069	-24.57	0.069	0.132	92.65	Manufacture of fabricated metal products, except machinery and equipment
29	0.141	0.092	-35.02	0.096	0.066	-30.37	0.128	0.098	-23.90	Manufacture of machinery and equipment not elsewhere classified (n.e.c.)
30	–	0.076	–	0.150	0.082	-44.96	0.155	0.454	193.03	Manufacture of office, accounting and computing machinery
31	0.150	0.084	-43.86	0.094	0.147	55.32	0.068	0.099	45.96	Manufacture of electrical machinery and apparatus n.e.c.
32	0.382	0.189	-50.52	0.293	0.243	-17.24	0.060	0.572	845.44	Manufacture of radio, television and communication equipment and apparatus
33	0.114	0.077	-32.51	0.087	0.023	-73.64	0.058	0.059	1.40	Manufacture of medical, precision and optical instruments, watches and clocks
34	0.141	0.242	71.11	0.096	0.068	-28.65	0.105	0.082	-21.70	Manufacture of motor vehicles, trailers and semi-trailers
35	0.198	0.158	-19.95	0.150	0.186	23.92	0.178	0.181	1.91	Manufacture of other transport equipment
36	0.056	0.036	-34.26	0.085	0.050	-40.46	0.087	0.079	-10.05	Manufacture of furniture; manufacturing n.e.c.

Table 4.4: Dynamic labor demand equations: estimation results

Dependent variable: $\ln(L_t)$	All variables in first differences		
	(1)	(2)	(3)
$\ln(L_{t-1})$	0.851*** (28.40)	0.853*** (28.34)	0.855*** (28.29)
$\ln(L_{t-2})$	0.116*** (6.01)	0.115*** (5.96)	0.115*** (5.90)
$\ln(w_t)$	-0.0543*** (-2.76)	-0.0537*** (-2.72)	-0.0541*** (-2.75)
$\ln(w_{t-1})$	0.0322 (1.20)	0.0330 (1.23)	0.0322 (1.19)
$\ln(w_{t-2})$	0.0255 (1.26)	0.0261 (1.28)	0.0273 (1.32)
$\ln(Q_t)$	0.310*** (18.00)	0.310*** (17.89)	0.310*** (17.94)
$\ln(Q_{t-1})$	-0.228*** (-11.91)	-0.229*** (-12.10)	-0.230*** (-12.13)
$\ln(Q_{t-2})$	-0.0579*** (-3.83)	-0.0583*** (-3.85)	-0.0592*** (-3.85)
S_t	-0.103*** (-6.35)	-0.0601*** (-3.96)	-0.0954* (-1.66)
$\ln(X_t)$		0.00435 (1.34)	0.00430 (1.33)
$\ln(X_{t-1})$		-0.00526 (-1.57)	-0.00510 (-1.51)
$\ln(X_{t-2})$		-0.00201 (-0.71)	-0.00217 (-0.77)
$\ln(M_t)$			0.000124 (0.06)
$\ln(M_{t-1})$			-0.00319 (-1.62)
$\ln(M_{t-2})$			0.00118 (0.62)
Constant	-0.0242 (-0.42)	-0.0332 (-0.56)	-0.0351 (-0.61)
Observations	3318	3318	3318
Hansen test (df)(p-value)	100.52 (97)(0.38)	101.46 (97)(0.35)	102.43 (97)(0.33)
Second order serial correlation test (p-value)	-0.90 (0.36)	-0.85 (0.39)	-0.85 (0.39)

1. t statistics in parentheses.

2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3. Time dummies' coefficients are not reported.

4. All models are estimated using robust two-step orthogonal deviations GMM.

Table 4.5: Industry-sector decompositions of the share of employment

	Share of non-production workers of total employment		Share of skilled production workers of total production workers	
	Between	Within	Between	Within
2001-2005				
Export	-0.41	-1.12	0.03	0.86
Non-export	0.03	-0.16	0.12	0.08
	-0.38	-1.28	0.15	0.94
Total		-1.66		1.09
2006-2010				
Export	0.84	0.48	0.97	0.53
Non-export	-0.31	0.10	-0.08	0.15
	0.53	0.58	0.89	0.68
Total		1.11		1.57
2011-2015				
Export	0.90	0.26	0.52	1.07
Non-export	-0.41	-0.01	-0.17	0.23
	0.49	0.25	0.35	1.30
Total		0.74		1.65

Table 4.6: Estimation of production function coefficients

ISIC	Capital	Labor	Material
15	0.016	0.292	0.695
17	0.011	0.277	0.729
18	0.007	0.203	0.756
19	0.017	0.127	0.848
20	0.008	0.303	0.709
21	0.002	0.177	0.834
22	0.001	0.388	0.627
23	0.009	0.037	0.830
24	0.009	0.328	0.744
25	0.002	0.210	0.803
26	0.021	0.255	0.749
27	0.012	0.241	0.810
28	0.022	0.303	0.711
29	0.013	0.251	0.749
31	0.018	0.348	0.680
32	0.007	0.383	0.696
33	0.019	0.255	0.677
34	0.013	0.222	0.747
35	-0.005	0.227	0.765
36	-0.002	0.472	0.619

1. Industry 30 is eliminated because of a lack of observation.
2. Industry, province, and year dummies' coefficients are not reported.
3. Negative capital coefficients are not statistically significant different from zero.

Table 4.7: Trade sanctions and TFP for export and non-export sectors

Dependent variable: tfp				
Coefficients	S.E.	t	F(1,14397)	p-value
$\delta_0=2.182$	0.023	93.14	-	0.000
$\delta_1=-0.034$	0.011	-3.09	-	0.000
$\delta_2=0.014$	0.005	2.75	-	0.006
$\delta_3=0.013$	0.007	1.73	-	0.084
$\delta_0 + \delta_1=2.148$	-	-	8494.23	0.000
$\delta_0 + \delta_2=2.196$	-	-	8775.60	0.000
$\delta_0 + \delta_1 + \delta_2 + \delta_3=2.175$	-	-	8851.35	0.000
Observations			14538	
R^2			0.70	

Industry, province, and year dummies' coefficients are not reported.

Table 4.8: Import and export by exporters and non-exporters after and before the sanction year (mean values)

Sector	Period	Import				Export	
		Raw materials		Capital			
		Real (million IRR)	Share of output (%)	Real (million IRR)	Share of output (%)	Real (million IRR)	Share of output (%)
Export	Before	254591	7.0	29432	1.4	281681	9.0
Export	After	188100	7.0	24592	0.8	575834	11.1
Non-export	Before	20418	3.9	3595	1.4	0	0
Non-export	After	37744	5.5	2854	1.6	0	0

Industry, province, and year dummies' coefficients are not reported.

Table 4.9: Trade sanctions, the relative demand for skilled labor, and the real average wage

Dependent variable: Log of real average wage per worker						
	The share of non-production workers in total employment			The share of skilled production workers in total production workers		
	(1)	(2)	(3)	(4)	(5)	(6))
Sanction	0.181 (0.016)	-0.152 (0.026)	-0.146 (0.026)	0.213 (0.014)	-0.108 (0.025)	-0.102 (0.025)
Log relative demand of skilled labor	0.093 (0.005)	0.093 (0.005)	0.093 (0.005)	0.073 (0.003)	0.073 (0.003)	0.073 (0.003)
Sanction*Log relative demand of skilled labor	-0.024 (0.007)	-0.024 (0.007)	-0.024 (0.007)	0.014 (0.004)	0.014 (0.004)	0.014 (0.004)
Log real minimum wage		1.127 (0.088)	1.122 (0.088)		1.086 (0.088)	1.082 (0.088)
Unemployment rate			0.002 (0.000)			0.002 (0.000)
Constant	3.915 (0.024)	5.492 (0.126)	5.459 (0.126)	3.943 (0.024)	5.462 (0.125)	5.431 (0.126)
Observations	15068	15068	15068	14645	14645	14645
R^2	0.40	0.40	0.40	0.41	0.41	0.41

Industry, province, and year dummies' coefficients are not reported.

Figure 4.1: Labor market equilibrium

Figure 4.2: The effect of an increase in the bias of technology (α) on the labor market equilibrium.

Figure 4.3: TFP trends and trade sanctions

Figure 4.4: Real average wage per worker trends

Figure 4.5: Share of non-production workers out of total employment trends

Figure 4.6: Share of skilled production workers out of total production workers trends

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Appendices

Appendix A

PS and GPS

A.1 Propensity Score Matching (PSM)

The probit regresses a dummy for treated and non-treated firms on the following covariates: sex dummy, age, age squared, education dummies, city dummies, the employment of treated firm in the previous year of receiving the loan (program began for the non-treated firm), the square of employment of treated firm in the previous year of receiving the loan (program began for the non-treated firm), the employment of treated firm in the previous year of receiving the loan minus its employment two years before receiving the loan (program began for the non-treated firm). By adding the employment level, trend, and observable characteristics, I am trying to match both treated and non-treated firms in terms of not only their employment trends but also their observed characteristics. To make sure that my matching method is working properly, I test it by comparing the equality of number of workers between treated and non-treated firms in the pretreatment period.

I only select those treated and non-treated firms within the common support of the PS. I carry out the analysis with 0.1 bandwidth, which means that the PS ratio of the treated to non-treated firms is between the range of 0.9 and 1.1. Finally, I assign the Kernel weights to the non-treated firms. In details, I give the treated firms a weight of one and the non-treated firms their kernel weights.

Figures A.1 and A.2 compare the PS distributions before and after matching for the full sample and micro-sized firms. In both samples, the PS distributions of treated and non-treated firms are similar after matching. Therefore, the matching method was successful in finding firms with similar PS.

A.2 Assessing unconfoundedness assumption under the DID fixed effects matching estimator

The first step to examine the effectiveness of my matching approach is to check the balance property. In fact, matching techniques should eliminate or reduce significant differences of pretreatment variables between treated and non-treated firms. I test this by comparing the mean differences of pretreatment variables before and after matching (Tables A.2 and A.3).

Second, I compare the employment level of treated versus non-treated firms over years prior receiving loans (program began for non-treated firms). The “pre-program test” of Heckman and Hotz (1989) compares the outcome variable of treated and non-treated groups in the pretreatment period. In fact, there should be no pretreatment significant difference between treated and non-treated firms since they have not yet received the loan (program began for non-treated firms), and if there is such a difference, it would provide evidence of selection bias (J. Brown and Earle (2013)). For this purpose, I use the same employment regression, but, first, replace the post-loan dummy with a pre-loan dummy, which takes a value of 1 and 0 for treated and non-treated firms, respectively. Second, I estimate the equation just prior to the loan period. If I find significant differences between the employment level of treated and non-treated firms prior to the loan period, it means there is a systematic selection bias and my matching method cannot eliminate those differences.

Finally, I implement a “placebo test” that separates the impact of the loan amount and the program itself. In fact, the test considers the effect of receiving the loan and the loan amount, separately. If loans increase employment because they provide easy access to capital, then the program itself should not have any significant effect on the employment while controlling the amount of the loan and it is logical that the employment impact should rise with the amount of the loan. As a result, if it is a likely estimation that program participation will affect employment

regardless of the amount of the loan, there is a selection bias in the program. I can implement this test by adding both the post-loan dummy and the amount of the loan in the same employment regression specification. I also add a quadratic form for the amount of the loan to consider the nonlinear effect (J. Brown and Earle (2013)).

As shown in Tables 2.4 and 2.5, there are no significant differences in the employment level between matched treated and non-treated firms in the pretreatment period (pre-loan dummy) for both full sample and micro-sized firms; this implies that the “pre-program” test has been satisfied. For example, there was a significant difference in the employment level between unmatched treated and non-treated firms in the pretreatment period for micro-sized firms that could be eliminated after matching, which means that the matching technique could eliminate that difference.

However, the estimated coefficients on the post-loan dummy in columns (2) and (3) in Table 2.4 are still statistically significantly different from 0, their magnitudes and significance declined compared with columns (5) and (6). As a result, although the matching technique could not completely eliminate the selection into the treatment group, it partially reduces selection bias in the estimates. It also suggests that the employment increase from a loan received is related only to the loan amount, not to the selection into the treatment group. Thus, I argue that the “placebo test” has been partially passed by using the combined DID matching estimator in the full sample.

However, the estimated coefficient on the post-loan dummy in column (2) in Table 2.5 is statistically significantly different from 0, it is statistically insignificantly different from 0 in column (3) when applying a quadratic specification (the value decreases to 0.07). This suggests that the employment impact of the loan program is related only to the amount of the loan, not to the loan program itself and also indicates that the matching technique reduces selection bias in the estimates.

Thus, I argue that the “placebo test” has been passed by using the combined DID matching estimator in micro-sized sample.

Taking everything into consideration, the results passed the balancing property, “pre-program”, and “placebo” tests, which emphasize that my matching procedure was successful in reducing the selection bias in the estimates.

As shown in the unmatched column of Table A.2, treated and non-treated firms are significantly different in some characteristics prior matching (we can reject the null hypothesis for 9 variables). This suggests that treated firms self-selected into the loan program. However, after using the matching method, I can not reject the null hypothesis for any variable including the trend in employment before the beginning of the program in the matched column of Table A.2.

As shown in the unmatched column of Table A.3, treated and non-treated firms are significantly different in some characteristics prior matching (we can reject the null hypothesis for 10 variables). This suggests that treated firms self-selected into the loan program. However, after using the matching method, I can not reject the null hypothesis for any variable (the only variable that I can reject the null hypothesis is the employment one year prior to the treated firm receiving the loan (program began for the non-treated firm)). However, the difference between treated and non-treated firms is not significant under 95% and is quantitatively small as well. This slight difference is clearly not a threat to my identification strategy.

A.3 Estimation of the GPS

In my application, I assume that unconfoundedness holds conditional on all the pretreatment variables used for estimating PS based on the probit regression and also include the industry, start-ups, and year of receiving the loan dummies in this case. This is because the amount of the loan depends on the type of industry. I include a start-up dummy mainly because start-up firms may have received a loan of a different size, and I also include the year dummies since firms received

the loans in different years, which can affect the probability of receiving it. For example, if there was a change in the characteristics of the program along program years, it would have affected the probability of receiving different sized loans for treated firms.

The method that I use to test the balancing property is equivalent to the approach proposed by Flores-Lagunes et al. (2012). In this approach, I estimate the unrestricted model in which a log-gamma transformation of T is estimated on all covariates and the GPS up to a cubic term. Then, I compare the unrestricted and restricted (the model that all coefficients of covariates or the GPS are equal to 0) models using the LR test. We expect that conditional on the GPS, covariates explanatory power should have been weakened, if the GPS adjusts the covariates differences. Based on the LR tests in Table A.6, the restricted models, where all covariates coefficients are equal to 0 (top panels), are preferred to the models where all the GPS coefficients are equal to 0 (bottom panels). This shows that the GPS plays a key role. Therefore, I argue that the balancing property of the GPSs is satisfied.

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A.4 Assessing unconfoundedness assumption under the DRFs and the TEFs

I construct an indirect way to test the unconfoundedness assumption in the continuous treatment variable case. I perform placebo tests recommended by Heckman and Hotz (1989), similar to the “pre-program” test that I used in the previous approach. The test is based on estimating the treatment variable on a “placebo outcome” which is a variable that is not affected by the treatment. Thus, there should be no effect, otherwise there is an evidence against the unconfoundedness assumption. Usually, we apply lagged outcomes as placebo outcomes. Therefore, if estimation results suggest that there is a positive and significant relationship between the treatment and the lagged outcome variables conditional on covariates, it casts doubt the validity of the unconfoundedness assumption (Flores-Lagunes et al. (2012)).

I consider the employment level of the year prior to receiving the loan as a placebo outcome. Thus, there should not be any significant correlation between the employment level prior to receiving the loan and the amount of the loan because firms had not yet received the loan. Figures A.3 to A.6 present plots similar to those of Figures 2.5 to 2.8 and employ the employment level of the year prior to receiving the loan as an outcome ¹. None of the estimated treatment effects based on both methods are statistically different from 0 except in a small range of loan levels (300-500 million IRR) in micro-sized firms, where the estimates are statistically less than 0.

In summary, my exercise to assess the unconfoundedness assumption shows that there is no significant correlation between the treatment variable and the

¹For estimating the DRF and the TEF of the placebo outcome, I exclude the variables that are strongly correlated to the employment level of the year prior to receiving the loan (placebo outcome).

placebo outcome conditional on covariates. Therefore, my exercise provides an evidence on the reliability of my estimates.

Table A.1: The probability of participating in the program (Standard Error (SE))

	Full sample		Micro-sized firms	
Variables	Coef.	SE	Coef.	SE
Sex	-0.20	0.03	-0.18	0.04
Age	0.03	0.006	0.04	0.006
Age squared	-0.0003	0.00006	-0.0004	0.00007
Education: High school diploma or lower	-0.04	0.04	0.09	0.03
Education: Undergraduate	-0.04	0.04	0.04	0.03
Education: Graduate	-	-	0.15	0.05
Asadabad	0.04	0.05	0.58	0.03
Bahar	-0.33	0.02	-	-
Hamedan	-0.32	0.03	0.19	0.05
Kabodarahang	-	-	0.53	0.04
Malaer	-0.24	0.03	0.31	0.05
Nahavand	-0.28	0.03	0.22	0.06
Razan	-0.21	0.03	0.33	0.05
n_{t-1} ^a	-0.03	0.003	-0.1	0.009
n_{t-1} squared	0.0009	0.0001	0.007	0.0009
$n_{t-1} - n_{t-2}$ ^b	0.01	0.008	-0.008	0.02
Number of observations	342		297	
LR χ^2 (df) (p value)	467.32 (14) (0.00)		505.80 (15) (0.00)	
Log likelihood R^2	-1594.66		-1329.30	
Pseudo R^2	0.12		0.16	

- Dropped because of collinearity.

^a The treated firm's employment in the previous year of receiving the loan (program began for the non-treated firm).

^b The treated firm's employment in the previous year of receiving the loan minus its employment two years before receiving the loan (program began for the non-treated firm).

Table A.2: Balancing test for the full sample (t-statistics in parentheses)

Variables	Unmatched		Diff.	Matched		Diff.
	Treated	Non-treated		Treated	Non-treated	
Sex	0.90	0.94	-0.04** (-2.00)	0.90	0.90	0.00 (0.02)
Age	43.68	41.52	2.16*** (2.85)	43.51	43.44	0.07 (0.10)
Age squared	2013.4	1849.8	163.6*** (2.36)	2001.2	2001.9	-0.7 (-0.01)
Education: High school diploma or lower	0.72	0.71	0.01 (0.45)	0.71	0.69	0.02 (0.47)
Education: Undergraduate	0.23	0.24	-0.01 (-0.40)	0.24	0.25	-0.01 (-0.37)
Education: Graduate	0.04	0.04	0.00 (-0.16)	0.04	0.04	0.00 (-0.26)
Asadabad	0.31	0.08	0.23*** (8.66)	0.28	0.25	0.03 (0.79)
Bahar	0.03	0.06	-0.03** (-2.13)	0.03	0.03	0.00 (-0.12)
Hamedan	0.23	0.42	-0.19*** (-5.97)	0.24	0.28	-0.04 (-1.46)
Kabodarahang	0.06	0.02	0.04*** (2.68)	0.07	0.07	0.00 (-0.05)
Malaer	0.18	0.19	-0.01 (-0.55)	0.18	0.16	0.02 (0.82)
Nahavand	0.07	0.11	-0.04** (-1.91)	0.07	0.07	0.00 (0.03)
Razan	0.10	0.09	0.01 (0.42)	0.10	0.10	0.00 (0.02)
n_{t-1} ^a	2.95	4.35	-1.4*** (-3.22)	3.09	3.76	-0.67 (-1.35)
n_{t-1} squared	50.54	53.81	-3.27 (-0.21)	52.83	62.91	-10.08 (-0.48)
$n_{t-1} - n_{t-2}$ ^b	0.17	0.09	0.08 (0.77)	0.17	0.11	0.06 (0.84)
Number of firms	133	209		127	203	
LR χ^2	157.02			11.35		
$p > \chi^2$	0.00			0.65		
Pseudo R^2	0.14			0.01		

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$ ^a The employment of treated firm in the previous year of receiving the loan (program began for the non-treated firm).^b The employment of treated firm in the previous year of receiving the loan minus its employment two years before receiving the loan (program began for the non-treated firm).

Table A.3: Balancing test for micro-sized firms (t-statistics in parentheses)

Variables	Unmatched		Diff.	Matched		Diff.
	Treated	Non-treated		Treated	Non-treated	
Sex	0.93	0.94	-0.01 (-0.80)	0.92	0.91	0.01 (0.27)
Age	43.79	41.57	2.22*** (2.67)	43.35	43.34	0.01 (0.01)
Age squared	2029	1857.5	171.5** (2.24)	1998.5	1990.6	7.9 (0.09)
Education: High school diploma or lower	0.50	0.42	0.08** (2.19)	0.47	0.44	0.03 (0.09)
Education: Undergraduate	0.24	0.30	-0.06* (-1.83)	0.26	0.28	-0.02 (-0.33)
Education: Graduate	0.08	0.06	0.02 (1.38)	0.08	0.08	0.00 (0.04)
Asadabad	0.34	0.08	0.26*** (8.91)	0.29	0.25	0.04 (1.06)
Bahar	0.02	0.07	-0.05*** (-2.67)	0.03	0.03	0.00 (-0.30)
Hamedan	0.19	0.40	-0.21*** (-6.38)	0.21	0.26	-0.05 (-1.24)
Kabodarahang	0.07	0.02	0.05*** (2.77)	0.05	0.07	-0.02 (-0.67)
Malaer	0.18	0.20	-0.02 (-0.79)	0.20	0.17	0.03 (1.11)
Nahavand	0.06	0.09	-0.03 (-1.53)	0.07	0.08	-0.01 (-0.41)
Razan	0.10	0.09	0.01 (0.44)	0.12	0.12	0.00 (-0.15)
n_{t-1}^a	1.81	2.94	-1.13*** (-6.15)	2.04	2.40	-0.36* (-1.89)
n_{t-1} squared	8.40	15.25	-6.85*** (-3.83)	9.46	11.63	-2.17 (-1.14)
$n_{t-1} - n_{t-2}^b$	0.04	0.10	-0.06 (-1.50)	0.05	0.04	0.01 (0.15)
Number of firms	114	183		102	181	
LR χ^2		164.77			9.94	
$p > \chi^2$		0.00			0.82	
Pseudo R^2		0.17			0.01	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$ *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

^a The employment treated firm in the previous year of receiving the loan (program began for the non-treated firm).

^b The employment treated firm in the previous year of receiving the loan minus its employment two years before receiving the loan (program began for the non-treated firm).

Table A.4: GLM specification

	Distribution	Gaussian		Inverse Gaussian		Gamma	
	Link	T*	Ln(T)	T	Ln(T)	T	Ln(T)
Full sample	AIC	44.01	42.41	58.47	58.47	151.74	40.92
	Deviance	7.42e+19	1.56e+19	1.00e-06	1.02e-06	14921.18	141.49
	LL	-2906.15	-2802.56	-3867.38	-3867.38	-10090.36	-2700.51
Micro-sized firms	AIC	42.07	41.60	57.84	57.87	40.40	40.36
	Deviance	8.61e+18	5.42e+18	8.62e-07	8.92e-07	104.87	100.20
	LL	-2377.00	-2350.68	-3278.05	-3278.05	-2281.96	-2279.63

*Treatment variable (the real amount of the loan).

I apply the Akaike information criteria to select among the alternative distributions and deviance measure and the value of the log-likelihood function to select across link functions (Hardin et al. (2007)).

Table A.5: Balancing test without imposing common support condition

	Full sample	Micro-sized firms
Unrestricted model: T^* on GPS , GPS^2 , GPS^3 , and X 's*		
Test restriction that all covariates coefficients are equal to 0		
Restricted log likelihood	-2684.85	-2249.83
Unrestricted log likelihood	-2665.58	-2247.26
Test statistic	38.53	5.12
p-value	0.70	0.99
Number of restrictions	20	20
Test restriction that all the GPS coefficients are equal to 0		
Restricted log likelihood	-2700.51	-2279.63
Unrestricted log likelihood	-2665.58	-2247.26
Test statistic	69.87	64.73
p-value	0.00	0.00
Number of restrictions	1	1
Number of observations	133	114

T^* is Treatment variable (the real amount of the loan) and X 's* are covariates.

Table A.6: Balancing test under imposing common support condition

	Full sample	Micro-sized firms
Unrestricted model: T^* on GPS , GPS^2 , GPS^3 , and X 's*		
Test restriction that all covariates coefficients are equal to 0		
Restricted log likelihood	-2434.20	-2089.92
Unrestricted log likelihood	-2429.19	-2087.08
Test statistic	10.03	5.69
p-value	0.96	0.99
Number of restrictions	20	20
Test restriction that all the GPS coefficients are equal to 0		
Restricted log likelihood	-2457.33	-2117.69
Unrestricted log likelihood	-2429.19	-2087.08
Test statistic	56.29	61.22
p-value	0.00	0.00
Number of restrictions	1	1
Number of observations	122	106

T^* is Treatment variable (the real amount of the loan) and X 's* are covariates.

Figure A.1: Propensity score distributions for the full sample

Figure A.2: Propensity score distributions for micro-sized firms

Figure A.3: The DRF and the TEF of a placebo outcome for the full sample using PPM approach (Treatment level = the real amount of the loan in million IRR)

Figure A.4: The DRF and the TEF of a placebo outcome for micro-sized firms using PPM approach (Treatment level = the real amount of the loan in million IRR)

Figure A.5: The DRF and the TEF of a placebo outcome for the full sample using SPIW approach (Treatment level = the real amount of the loan in million IRR)

Figure A.6: The DRF and the TEF of a placebo outcome for micro-sized firms using SPIW approach (Treatment level = the real amount of the loan in million IRR)

Appendix B

Derivatives

Proof that $\frac{\partial \phi^d}{\partial \omega} < 0$

Let's assume that $\delta = (\beta_1 - \gamma_1)(1 - \sigma)$ and $C = \left(\frac{1-\theta}{\theta}\right)^\sigma \left(\frac{\beta_1^{\beta_1} \beta_2^{\beta_2}}{\gamma_1^{\gamma_1} \gamma_2^{\gamma_2}}\right)^{1-\sigma} \alpha^{\sigma-1} > 0$.

Then from equation 4.29:

$$\phi^d = \omega^{-1} \frac{\beta_2 + \gamma_2 C \omega^\delta}{\beta_1 + \gamma_1 C \omega^\delta} = \frac{\beta_2 + \gamma_2 C \omega^\delta}{\beta_1 \omega + \gamma_1 C \omega^{\delta+1}} \quad (\text{B.1})$$

Taking the derivative of equation (B.1) respect to ω :

$$\begin{aligned} \frac{\partial \phi^d}{\partial \omega} &= \frac{(\gamma_2 C \delta \omega^{\delta-1})(\beta_1 \omega + \gamma_1 C \omega^{\delta+1}) - (\beta_1 + \gamma_1 C(\delta+1)\omega^\delta)(\beta_2 + \gamma_2 C \omega^\delta)}{(\beta_1 \omega + \gamma_1 C \omega^{\delta+1})^2} \\ &= \frac{\beta_1 \gamma_2 C \delta \omega^\delta + \gamma_1 \gamma_2 C^2 \delta \omega^{2\delta} - \beta_1 \beta_2 - \beta_1 \gamma_2 C \omega^\delta - \beta_2 \gamma_1 C \delta \omega^\delta - \gamma_1 \gamma_2 C^2 \delta \omega^{2\delta} - \beta_2 \gamma_1 C \omega^\delta - \gamma_1 \gamma_2 C^2 \omega^{2\delta}}{(\beta_1 \omega + \gamma_1 C \omega^{\delta+1})^2} \\ &= \frac{\delta C \omega^\delta (\beta_1 \gamma_2 - \beta_2 \gamma_1) - C \omega^\delta (\beta_1 \gamma_2 + \beta_2 \gamma_1) - \beta_1 \beta_2 - \gamma_1 \gamma_2 C^2 \omega^{2\delta}}{(\beta_1 \omega + \gamma_1 C \omega^{\delta+1})^2} \end{aligned}$$

If $\sigma \geq 1$, which means $\delta \leq 0$, then $\frac{\partial \phi^d}{\partial \omega} < 0$.

If $0 \leq \sigma < 1$, which means $0 < \delta < 1$, then $\frac{\partial \phi^d}{\partial \omega}$ is less than 0 when,

$$\delta C \omega^\delta (\beta_1 \gamma_2 - \beta_2 \gamma_1) < C \omega^\delta (\beta_1 \gamma_2 + \beta_2 \gamma_1) + \beta_1 \beta_2 + \gamma_1 \gamma_2 C^2 \omega^{2\delta},$$

which is always true because $\delta C \omega^\delta (\beta_1 \gamma_2 - \beta_2 \gamma_1)$ is always less than

$$C \omega^\delta (\beta_1 \gamma_2 + \beta_2 \gamma_1).$$

Proof: $\phi_{nx}^d < \phi^d < \phi_x^d$

Let's first prove that $\phi^d < \phi_x^d$:

$$\begin{aligned}
\frac{w^u}{w^s} \frac{\beta_2 + \gamma_2 r}{\beta_1 + \gamma_1 r} < \frac{\gamma_2 w^u}{\gamma_1 w^s} &\Rightarrow \frac{\beta_2 + \gamma_2 r}{\beta_1 + \gamma_1 r} < \frac{\gamma_2}{\gamma_1} \Rightarrow \beta_2 \gamma_1 + \gamma_1 \gamma_2 r < \beta_1 \gamma_2 + \gamma_1 \gamma_2 r \\
&\Rightarrow \beta_2 \gamma_1 < \beta_1 \gamma_2 \Rightarrow \frac{\beta_2}{\beta_1} < \frac{\gamma_2}{\gamma_1}
\end{aligned} \tag{B.2}$$

Now, prove that $\phi_{nx}^d < \phi^d$:

$$\begin{aligned}
\frac{\beta_2 w^u}{\beta_1 w^s} < \frac{w^u}{w^s} \frac{\beta_2 + \gamma_2 r}{\beta_1 + \gamma_1 r} &\Rightarrow \frac{\beta_2}{\beta_1} < \frac{\beta_2 + \gamma_2 r}{\beta_1 + \gamma_1 r} \Rightarrow \beta_2 \beta_1 + \beta_2 \gamma_1 r < \beta_2 \beta_1 + \beta_1 \gamma_2 r \\
&\Rightarrow \beta_2 \gamma_1 r < \beta_1 \gamma_2 r \Rightarrow \frac{\beta_2}{\beta_1} < \frac{\gamma_2}{\gamma_1}
\end{aligned} \tag{B.3}$$

Proof: $\frac{\partial r}{\partial \alpha} > 0$

First, given the wage premium,

$$\frac{\partial r(\omega)}{\partial \alpha} = \begin{cases} < 0 & \text{if } 0 < \sigma < 1 \\ = 0 & \text{if } \sigma = 1 \\ > 0 & \text{if } \sigma > 1 \end{cases} \tag{B.4}$$

Second, to find $\frac{\partial r}{\partial \alpha}$, we need to take a total derivative from the labor market equilibrium condition $\phi^d = \phi^s$ with respect to α :

$$\frac{\partial \phi^d(\omega, r)}{\partial \alpha} = \frac{\partial \phi^d(\omega, r)}{\partial \omega} \frac{\partial \omega}{\partial \alpha} + \frac{\partial \phi^d(\omega, r)}{\partial r} \frac{\partial r}{\partial \alpha} = \frac{\partial \phi^s}{\partial \alpha} = 0 \tag{B.5}$$

Note that $\frac{\partial \phi^d(\omega, r)}{\partial \omega} < 0$ and $\frac{\partial \phi^d(\omega, r)}{\partial r} > 0$.

Then:

If $0 < \sigma < 1$, since $\frac{\partial \omega}{\partial \alpha} < 0$, then the second term of the R.H.S. has to be negative, which results in $\frac{\partial r}{\partial \alpha} < 0$.

If $\sigma = 1$, since $\frac{\partial \omega}{\partial \alpha} = 0$, then the second term of the R.H.S. has to be 0, which results in $\frac{\partial r}{\partial \alpha} = 0$.

If $\sigma > 1$, since $\frac{\partial \omega}{\partial \alpha} > 0$, then the second term of the R.H.S. has to be positive, which results in $\frac{\partial r}{\partial \alpha} > 0$.

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