The Effect of Labor Migration on Native Wages

An Empirical Analysis of the Norwegian Construction Sector

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Preface

This thesis marks the end of the five-year master's program in Economic Theory and Econometrics at the Department of Economics, University of Oslo.

The thesis is written as a part of a research project on «Labor migration to Norway » at the Frisch Centre, financed by the Ministry of Labor. Statistics Norway has provided the necessary micro data for the period 1998 to 2011, which has made it possible to implement the empirical analysis.

I would like to express my gratitude to my supervisor Bernt Bratsberg at the Frisch Centre for his helpful advice, guidance and comments throughout the writing process. This thesis would not have been possible without his assistance.

I am grateful for the outstanding effort and constructive feedback provided by André Kallåk Anundsen. Together with my dear fellow students, the happy memories throughout these challenging studies are unforgettable. The love and continuous moral support devoted by my parents and brother has helped me to stay motivated for the completion of the five-year master's program.

Any inaccuracies or errors in this thesis are my responsibility alone.

Dunja Kazaz

January 2013

Abstract

Immigration and the effects thereof, is an important economic and political issue. It constitutes an important part of the complex phenomenon widely referred to as globalization. Immigration results in stronger competition in the labor market, and may affect the development of wages. As more and more immigrants choose to move from one country to another, the lives of the residents in the destination countries often undertake unanticipated changes. The scope, composition and impacts of immigration on “receiving” countries, their labor markets and how it affects native workers may differ on the basis of the degree of substitutability. Labor migration increases the supply of workers, and in selected industries, immigration can be an advantage for native workers who work in the same sector, through the complementarities of labor as a production input. This thesis examines the recent development in the Norwegian construction sector, with a particular focus on the evolution of wages of native workers following an unprecedented large influx of immigrant workers.

There are many reasons why Norway has become attractive and is considered as one of the top destinations for migrant workers. In recent years most immigrant workers entering the Norwegian labor market originate from Central and Eastern Europe. This can in large parts be seen as consequences of the eastward enlargement of the European Union, which occurred in 2004 and 2007. An important determination for the labor market responses and adjustments will depend on the skill composition and background of the migrants. In this thesis, I investigate the Norwegian construction sector with registry data from 1998 to 2011. The thesis builds on and is inspired by the theoretical and empirical framework established in Bratsberg and Raaum (2012). My focus in the empirical analysis is on the wages of native workers employed in construction-sector firms during this period.

I divide the construction sector into 15 main activity groups, and examine the development in the immigrant employment share within these activities as well as for the sector as a whole. The empirical analysis is based on registry data, where I use the variation in immigrant inflows over time and within groups defined at the national level. An important finding in my study is that there is a negative correlation between increases in the immigrant share in the construction sector and the growth in native wages – a result that corroborates the main findings of Bratsberg and Raaum (2012). When controlling for individual fixed effects, I correct for the bias created by systematic native attrition. This causes the estimated effects of

an increase in the immigrant employment share on wages to become more negative. In particular, it indicates that systematic attrition of low-wage native workers from activities with growth in immigrant employment creates a positive correlation which biases estimates that overlook native attrition towards zero. In addition, I find that citizens of the new EU countries dominate the recent immigrant inflow and account for most of the downward pressure on the wage growth of native workers in the construction sector.

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1 Introduction

Many analyses of migration decisions take the following hypothesis formulated by Nobel Laureate John Hicks as a point of departure: "Differences in net economic advantages, chiefly differences in wages, are the main causes of migration"(Hicks, 1932, p.72). Such analyses often view the migration of workers as a form of human capital investment, where workers calculate the value of the different employment opportunities before choosing the option that maximizes the net present value of their lifetime earnings (Borjas, 2008, p.322).

The EEA (European Economic Area) Agreement[1] is the main foundation of the Norwegian association with the EU. One of the main goals with the common European labor market was to increase the mobility of labor in order to create more efficient labor markets. As a consequence of the membership, labor was free to move across country borders. Due to Norway's membership in the EEA, it is plausible to believe that Norway, and particularly her labor market, has been affected by the closer integration of European labor markets.

During the last couple of years, Norway has experienced a great influx of migrant workers from the new EU member countries, especially from Poland (Meld. St. 18 (2007-2008), Arbeidsinnvandring (In Norwegian, "Labor Migration")). Besides seasonal work within agriculture, the labor migrants after the EU-expansions in 2004 and 2007 have mainly been recruited to male-dominated sectors, such as the construction sector. There is also an increasing trend in the hiring of migrant workers to parts of the service sector (restaurant, hotel, cleaning and private household) and industry. Norwegian businesses will need special expertise in order to meet the competition from international companies. In particular, Norwegian companies need to attract people with relevant skills and knowledge from abroad that can provide value and strengthen innovation in the future. The increased immigration raises questions on whether such labor supply shocks cause adjustments in employment and wages among native Norwegians, a question that will be at the core of this thesis.

In the case of Norway, the construction sector is the sector that has been most affected by the expansion of the EU. If immigration leads to a downward pressure on wages in this sector, it will also lower the costs of production. Furthermore, it may influence the prices consumers

[1] The EEA Agreement is an agreement between the EFTA (European Free Trade Association) countries; Norway, Lichtenstein, Iceland and EU's 27 member countries. Combined, they form the EEA.

are facing, and due to the increased immigration they may enjoy more services at lower prices.

The data provided by Statistics Norway through the project «Labor Migration to Norway» at the Frisch Centre shows that over the period 1998 to 2011, and in particular after the EU expansion in 2004 and 2007, there has been a sharp increase in the influx of labor migrants. This thesis examines the variation in the immigrant share in the construction sector, and its effect on the wage growth of native workers. A main question that I aim to answer in this thesis is: *What are the effects of labor migration on wages of native workers?*

Some of the main findings of the empirical analysis in this thesis are the following: There is evidence that native workers in the Norwegian construction sector are negatively affected by labor migration, in terms of the development in wages over the period 1998-2011. In particular, there seems to be a clear tendency that it is the least educated workers who are most affected by the increased immigration.

The rest of the thesis is organized in the following way: In the next section, I provide some background which motivates the analysis in this thesis. In Section 3, I discuss various theoretical models that are relevant to analyze the effects on wages of a positive supply shock induced by an increased inflow of immigrant workers. Section 4 outlines some empirical approaches commonly considered in the literature. A literature review is provided in Section 5. The data used for the empirical analysis is discussed in Section 6. In Section 7, I report the results from the empirical analysis. The final section concludes the thesis.

2 Background

In general, immigrants are attracted to large metropolitan centers of commercial activity. There are several reasons for this. First, immigrants are logically attracted to growing cities that are relatively successful. Second, they tend to move to cities with a historical presence of immigrants, most likely cities where their families have settled down. The weight of "push" factors (famine, discrimination, social immobility, low wages and unemployment) versus "pull" factors (high wages, high demand for labor, peace, law and order) will determine if an individual decides to migrate or not. Factors discouraging migration are so-called "stay" factors, such as family ties, familiarity, friendships etc. "Stay away" factors are language barriers, cultural barriers, war and crime (Bodvarsson and Van den Berg, 2009, pp. 6-13). In the case of the US, a third of the immigrant population lived in Los Angeles, Miami and New York in 1990. This suggests clustering among immigrants in some selected geographical areas (Borjas, 2003, pp. 1336-1337). Prior to 1980, most immigrants who migrated to Norway came from countries that are geographically and culturally close. Today's situation is somewhat different, and most immigrants are originally from countries further away in both respects (Bratsberg et al., 2012).

Through the establishment of the common European labor market in 1994, most Western Europeans gained access to the Norwegian labor market. The EU has expanded substantially throughout the past decades, and the greatest expansion occurred in 2004, where the number of countries was increased by 10. Furthermore, in 2007 Romania and Bulgaria gained EU accession. The majority of the new countries are so-called former East Bloc countries. State policies shape international migration flows, and after the EU enlargement the number of border controls has been reduced (Friberg and Tronstad, 2012).

Migration patterns and its consequences for labor market conditions can be described as a result of the interaction between supply (motivation factors, job- and income factors and costs of mobility) and demand (economic growth and globalization of economic activity which has induced people to move more frequently between countries than before) factors. These factors are influenced by the economic cycle, as well as changes in institutional factors, laws and regulations. The analysis of migration flows will for example be affected by the expansion of the EU in 2004, and also wage regulations. In addition, one has to distinguish between types of migration depending on the origin of the immigrants. The migrants from EU15[2]and other Western countries have a distribution of workers that is more similar to the domestic labor force than other immigrants. Studies of the immigration to Norway in the 1990's suggest that labor migrants who typically arrive from nearby countries tend to stay in the destination country for a shorter period than other migrants. In addition, they are more inclined to move out of the country than other groups of immigrants. (Bratsberg et al., 2005; 2007). Like the immigration pattern in other European countries until the mid-2000s, immigration in Norway has mainly been driven by an increased inflow of individuals from developing countries that are less substitutable with the native workforce, and therefore have small impacts on native wages.

A central feature is to differentiate between labor migration and workers posted by foreign employers. Statistics Norway (SSB) divides labor migrants into two groups:

«Employed immigrants who are registered as residents and employees at short term (...). Employees on short term include people who are expected to stay for less than six months in Norway, and are therefore not registered resident according to the population register » (SSB 2010)

In a study from 2006, Friberg and Tyldum (2007) established results indicating that leased personnel within the construction sector often have worse and more insecure wage and work conditions than migrants employed in Norwegian companies. This is mainly due to workers from the EU often being perceived as cheaper and more flexible labor for companies. This is because they are subject to different rules for working conditions, taxation, social security, detection and wages than ordinary labor migrants. Many countries in Europe are still struggling with the current debt crisis and they experience higher unemployment rates, especially among youth, and/or lower income groups, than the average level in Northern Europe. This gives potential for the flow of migrant workers to Norway to continue.

The terms for the leased work force are strongly influenced by the interaction between labor market regulations as well as other factors influencing supply and demand. The relative difference between the economic climate in the country of origin and the destination country will also affect how much labor is supplied and the quantity demanded. While there is good

[2] The EU15 was the number of member countries in the European Union prior to the accession of ten candidate countries on May 2004. The EU15 comprised Austria, Belgium, Denmark, Finland, Portugal, Spain, United Kingdom, Sweden, France, Greece, Ireland, Luxembourg, Netherlands, Italy and Germany.

data on individuals that receive a work permit in Norway, the situation is different for leased construction workers. This is due to lack of necessary information for creating the data. Based on a simple supply and demand framework, one could expect that migrants would get incentivized to accept a lower wage as a result of increased supply and reduced demand. What characterizes the latest years of labor migration is that it has mainly been concentrated to sectors with production fluctuations and specific recruitment needs.

2.1 Recent development in construction prices

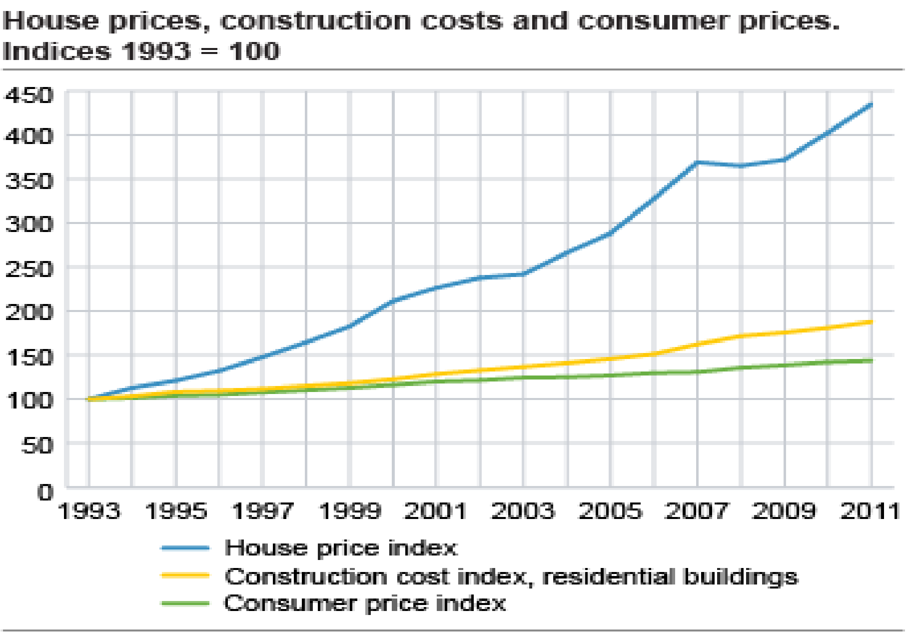

Figure 1: *The aggregate development in consumer and construction sector price indices*
Source: Statistics Norway. http://www.ssb.no/bygg/fig01-bpi.gif

The graphs in Figure 1 indicate that the overall construction cost index has been held relatively steady, and slightly increasing after 2000, whereas housing prices have grown exceptionally. However, the consumer price index (CPI) has followed the same trend as the construction cost index, but the construction costs have also risen in real terms (deflated by the CPI).

Decomposing the construction cost index into indices for carpentry, plumbing and electrical installation shows that the costs for electrical installation and plumbing have increased the most in the period from 1978 to 2005. This is illustrated in Figure 2.

Figure 4.2. **Construction cost index for multi-dwelling houses. Indices for carpentry, plumbing and electrical installation. 1978=100**

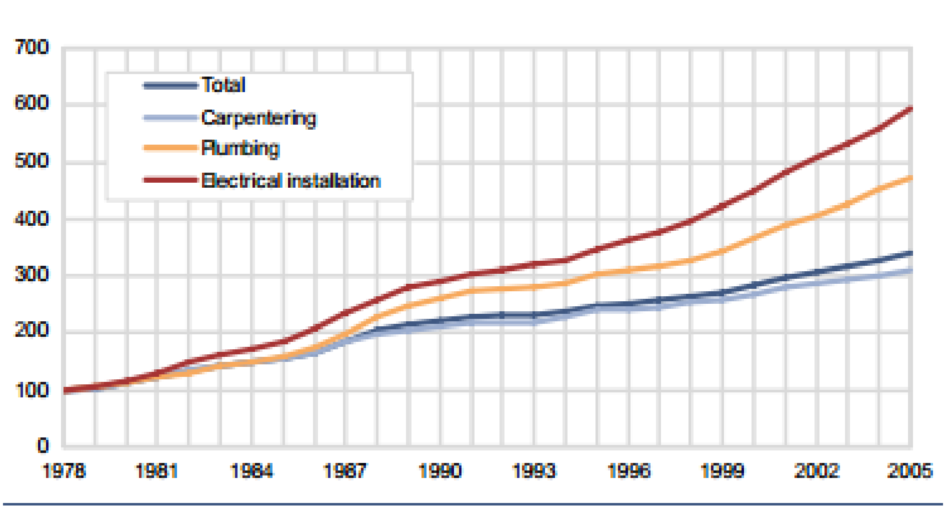

Figure 2: *Decomposed construction cost index*

Source: Statistics Norway.

http://www.ssb.no/english/subjects/08/02/30/nos_d372_en/nos_d372_en.pdf

In the labor market, it is expected that immigrants can compete with Norwegian native workers with similar education and skills, and one can therefore examine the impact on wages of the expansion of the EU-cooperation. Against this background, it is not surprising that political debates on immigration policy have mostly been concerned with the economic aspects, and especially the potential adverse effects on labor market outcomes of native-born workers. The competition between immigrants and natives may have caused a downward pressure on wages (or at least slowed the wage growth) in sectors that have experienced a large inflow of immigrants. This may be seen as an important force in explaining the occurrence and existence of fear of immigration displacing native workers in the labor market, or in bidding down wages. However, one can not only consider immigrants as substitutes for native workers in production. It must also be taken into account that workers in some respects are complementary factors in the production process. In some industries, immigration can be an advantage for native workers who work in the same sector, through the complementarities of labor as a production input. This is because greater shares of immigrants can lead to an overall increase in the society's welfare through a higher valuation of the native workers' services and products, which in turn can be reflected in higher overall wages in the sector considered.

2.2 Why expected free market wage adjustments do not happen in practice

Standard economic theory suggests that an increase in the supply of labor will result in a reduction in the wage in order for the firms to be willing to employ more workers. This may explain why competition among immigrants and natives may have caused a downward pressure on wages (or at least the wage growth) in sectors that have experienced a large inflow of immigrant workers. It can in part be seen as an important force in explaining the occurrence and existence of a fear of immigrant workers displacing native workers in the labor market, or bidding down wages.

Meanwhile, there may be numerous reasons why the wage effect is dampened. One example is the characterization of the newly supplied labor. Complementarities will in practice imply that one type of labor becomes more productive when the use of some other types of labor increase, which would have the effect of dampening the wage reduction following an inflow of immigrant workers. There may also exist a fear of attrition of workers from activities with growing immigrant employment. Selective attrition could bias the estimates of the impact of labor migration in an empirical analysis.

Other factors that could dampen the initial negative wage effect are institutions and collective wage bargaining. The Norwegian labor markets are institutionally regulated through complex multi-level processes of collective bargaining, with various actors in the market. Salary requirements in the construction sector are the same for foreign workers and posted workers employed by foreign firms. Wage differences can therefore be seen in the context of how the laws are enforced. The average wage in the construction sector was 174 kr./hour in 2005, but almost all the Polish workers centered in the Oslo-region earned less than this. An important finding of the *Polonia in Oslo* study (Friberg and Tyldum, 2007) is that the majority of Polish workers are hired through temporary staffing agencies or foreign-owned subcontracting firms, while less than one fifth are permanently employed by Norwegian companies. It is worthwhile to notice the limitation of this study; the generalization of the 2006 Polonia Survey can only be attributed to the population of Polish migrants in the Oslo area.

In 1993, the Norwegian authorities passed a law, namely the Law on the general agreement (In English, “Lov om allmenngjøring av tariffavtaler”)[3], in order to ensure equal wages and work conditions for foreign and Norwegian workers. The background for imposing this law was the fear that the EEA Agreement would lead to social dumping. In a piecewise manner, the Tariff Tribunal (In English, “Tariffnemnda”) has implemented decisions regarding tariff agreements in parts of the construction sector since 2004. From January 1st , 2007, regulations on the general application (In English, “allmenngjøring”) of collective agreement were introduced for all construction sites in Norway. The stated purpose of the new agreement was to protect foreign workers from having worse wage and working conditions than Norwegian workers in the same sector.

This agreement includes everyone who works in the industry, regardless of whether the worker is covered by the collective agreement. That is, the agreement is applicable to all persons performing work within the specific area, and it also covers non-union foreign companies and workers. In the autumn of 2006, the minimum wage in the construction sector was 132 kr./hour for skilled workers and 123 kr./hour for unskilled workers with one year of experience. For unskilled workers without experience, the minimum wage was 118 kr./hour. From April 1st 2012, the minimum wage of skilled workers had increased to 169 kr./hour, while the wage for unskilled workers was adjusted to 152 kr./hour.[4] In the empirical analysis, I will examine whether the introduction of the minimum wages has had any impact on the wage development in the construction sector.

Labor migration to Norway will in general be determined by a comparison of the opportunities created relative to the home country or other potential destination countries. Relevant aspects in this respect are the general attractiveness and scope of jobs and services. For instance, factors like language barriers and climate make it less attractive for migrants to come to Norway. For most people considering leaving their home country, the costs associated with migration such as moving away from the social environment they are used to, may discourage them from doing so. This is especially so if the costs of moving are larger

[3] http://www.fafo.no/Oestforum/Kunnskapsbase/Temasider/allmenngj.htm
[4] http://www.arbeidstilsynet.no/fakta.html?tid=90849

than the potential benefits. Exchange rates, the cost of living, tax issues and the rights to claim social benefits are other types of costs that may affect each migrant's decision making. One could argue that if a group of people from the same country already has migrated, then a social network may already have been established. This could reduce uncertainty and improve the choice opportunities in such a way that more migrants decide to apply for jobs in Norway, which again can create a dynamic mechanism such that initial migrants reinforce future labor migration. Expansions of social migrant networks provide access to information and social support for new migrants, which reduce the costs associated with migration and risks. These networks seem to increase the expected returns of migration.

In a study from 2006 of Norwegian enterprises in various industries including the construction sector, Dølvik et al (2006) revealed that the lack of domestic labor was the most important motive for hiring workers from the new EU member states. In addition, it emerged that reduced costs and labor flexibility are important for the decision making in many companies. In fear of "welfare tourism" and social dumping, a number of countries introduced transitional arrangements.

The Norwegian transitional arrangements for the new Eastern European EU countries entailed 6 months of free movement for job seekers. However, for job seekers to do so entails a requirement of full-time employment and national salary. The transitional arrangements function as a minimum wage regulation, and apply to labor migrants from the new member countries of the EU employed in Norwegian companies. Thus, the free float of services is not included in these arrangements. The transitional regulations did not, however, create insurmountable hurdles for citizens of the new member states. For example, the job requirement is a mild constraint facing a labor migrant from these countries. For employment beyond twelve months, the Norwegian labor legislation applies, when the employment is related to the employer registered in Norway. If permission has been granted for twelve months, the next renewal application can be granted a permit for the ordinary EU regulations, given that the terms upon expiry of the permit have been met. As a consequence of the many renewals, transitional provisions on wages and work conditions do not apply anymore, and more and more people come under the provisions in the ordinary EU regulations[5].

[5] http://www.lo.no/s/lonntariff1/Tidligere-tariffoppgjor/Tariff-2006/Seriositet-i-arbeidslivet-/?c=444&t=681

For citizens of Estonia, Latvia, Poland, the Czech Republic, Slovakia, Slovenia, Lithuania and Hungary, the Norwegian transitional arrangements were phased out May 1st 2009. The implication of this is that there is no longer a requirement that immigrants from these countries have a Norwegian salary in order to get a residence permit. Furthermore, it is also possible to stay based on part-time work. Transitional arrangements for workers from Bulgaria and Romania were abolished in May 2012.

Thus, labor migration will affect and be affected by both the development in wage and work conditions in the sending and receiving countries. Immigration, particularly from EEA-countries, has in recent years contributed to meet the need for labor and eliminate bottlenecks in production. This has been a major contributor to the development of a more flexible economy characterized by a lower pressure on costs. At the same time, unemployment has been low and Norway has had stable economic growth (Meld. St. 18 (2007-2008), Arbeidsinnvandring, (In Norwegian, “Labor Migration”)). However, for new migrant labor, wage and work conditions will typically be worse than for natives. Do these differences equalize over time? In the aftermath of increased labor supply, problems like social dumping, illegal immigration and undeclared work can occur. Clearly, one can question whether this trend may pose a challenge to the Norwegian social model and its stability in the long run, which is characterized by a compressed wage structure and a generous welfare state (Friberg and Tronstad, 2012).

3 Classical Labor Market Theory

The following section is primarily based on Bodvarsson and Van den Berg (pp. 107-130, 2009). The theoretical model is also inspired by Borjas (1994), Johnson (1980), Altonji and Card (1991) and Ottaviano and Peri (2006 and 2008).

3.1 Model alternatives

Whether one considers a traditional one-sector labor market model with two inputs or a model with multiple sectors and inputs, the predicted effects of immigration on native labor market outcomes will differ. In the framework of a one-sector model, the economy can change the wage structure as a response to an immigrant shock. Single-sector models with a closed economy have traditionally been the workhorse model of labor economists. The focus of these models are on short-term effects, while the multiple sector models that pay attention to longer term effects have been the tradition for most research provided by trade economists. When the economy produces multiple goods, its responses to the immigrant shock are to adjust the mix of products it produces. Long run features of immigration are the main focus among trade economists. Labor economists focus on how short run distributional effects are influenced by production, labor demand and labor supply functions (Bodvarsson and Van den Berg, 2009, pp.121-122 and pp.129-130).

3.1.1 Distributional effects of immigration

According to Johnson's model (Johnson, 1980), immigration will affect the various native-born groups in the destination country differently. Johnson considers a domestic economy, and focuses on continued illegal immigration to the US. The paper suggests that the most important effects when the economy is not in recession are on the wages of low-skilled workers. High-skill workers, on the other hand, may gain from immigration since they are likely to be complementary to low-skill immigration. A higher wage-gap between low and high skill workers and the relative increase in returns to high-skill occupations may induce more people to acquire more education and training. Further, Johnson argues that the skill distribution is endogenous to immigration.

Altonji and Card (1991) measure the effects of immigration on the less-skilled natives by using variation in the fraction of immigrants across different cities. Their contribution to the literature was an extension of Johnson's model from 1991, but rather than looking at a national economy, Altonji and Card based their analysis on a city economy. Immigrants are assumed to be perfect substitutes within each skill group, and there are only two skill categories: High and low-skilled workers. Including additional features of the labor market such as the heterogeneity of skill composition within the immigrant pool and the endogeneity of local demand to immigration, the model hypothesizes that the outcomes of unskilled natives depend on these features. An implication of the model is that wages of unskilled natives remain unchanged if skill distributions are identical and all local output is consumed locally. In order for immigration to affect wages, there must be trade of goods beyond the local market and skill distributions must differ. One limitation of the model is that it does not allow for internal native migration, while it allows for a reduction in per capita labor supply when the wage falls. It is likely that unskilled natives will leave when their wage is reduced, and therefore dampen -- or even neutralize -- the adverse effect of immigration. Another limitation is the assumption of labor market clearing. Unionization and minimum wages are examples of factors that may prevent the market from clearing.

In the Ottaviano and Peri model (2006, 2008), the predicted distributional effects are mainly influenced by the form of the production function. They follow the skill cell approach introduced by Borjas (2003), where the national labor market is divided into various skill cells. There are 32 different skill cells in total. Within each cell, immigrants are imperfectly substitutable with natives and natives are substitutable with other natives. Given that workers have the same level of education, they will be substitutes across skill cells and complements otherwise. Immigrants and natives are not perfect substitutes within the same occupation or for the same levels of experience or education due to different capital endowments. This presumption is based on an argument that there are differences in education, culture, etc. Another aspect of the model is that an influx of immigrants into a country increases the labor supply of different occupations, and newcomers will flow into different skill cells over time. The substitutability across educational categories will determine the strength of this effect.

3.2 Stylized closed economy case

The following model is taken from Borjas, (1994, p. 1696).

3.2.1 Assumptions

Let us assume a linear, homogeneous production function, where Q units of a single good is produced in a competitive economy. Furthermore, we assume that the economy is closed, and that the labor force is divided into two groups, where N_s denotes the number of skilled workers, whereas N_u is the number of unskilled workers. The total number of workers in this economy is therefore given by $N = N_s + N_u$. The two groups are assumed to be complementary in the production process, but skilled immigrants are assumed to be substitutes with skilled natives. This is the case for unskilled workers as well.

The cost function is given by $Qc(w_s, w_u)$, where $c(w_s, w_u)$ is the unit cost function. The price of the output equals the unit cost of production. This implies that $\vartheta = c(w_s, w_u)$, where ϑ denotes the output price. D_i is the demand for labor for the two groups $i = s, u$, of workers, depending on the product price and the wage the employer has to pay each group. The output demand function is given by $D_i(w_i, \vartheta)$. The share of unskilled workers in the population is given as $b \in (0,1)$. This ensures that there will always be some skilled and some unskilled workers. We also assume perfect competition in the product and labor market, so that equilibrium prices are equal to the marginal cost of the product and labor respectively.

3.2.2 The model

When the economy is closed, the following conditions must be satisfied in equilibrium. Labor market equilibrium requires

- $N_s L_s(w_s, \vartheta) = \ Q \frac{\partial c\ (w_s, w_u)}{\partial w_s} = Qc_s(w_s, w_u)$
- $N_u L_u(w_u, \vartheta) = \ Q \frac{\partial c\ (w_s, w_u)}{\partial w_u} = Qc_u(w_s, w_u)$

where $c_i = \frac{\partial c}{\partial w_i}$ for $i = s, u$. $L_i(wi, \vartheta)$ is the labor supply function of type-i worker, which depends on the product price ϑ, and the wage the workers receive. Product market equilibrium requires

- $Q = N_s D_s(w_s, \vartheta) + N_u D_u(w_u, \vartheta)$

3.2.3 Effects of a positive supply shock

Suppose that the economy experiences an exogenous immigration inflow of ΔN workers, where a fraction $\beta \epsilon (0,1)$ is unskilled workers. In the new equilibrium, the effect on wages for unskilled and skilled workers will depend on the fraction of unskilled workers among the new immigrants, $\beta \epsilon (0,1)$, compared to the fraction of unskilled workers originally in the economy, $b \epsilon (0,1)$. When $\beta = b$, i.e the distribution of workers remains the same, the wages for both unskilled and skilled workers will be unchanged as well. On the other hand, if $\beta > b$, there will be a larger share of unskilled labor among the immigrants than originally in the country. The implication of this relative increase in the supply of unskilled labor is that the wage of unskilled workers will decrease and the wage of skilled workers will increase. In general, the model gives clear predictions about how immigration affects the wages. More specifically, the earnings of domestic workers will change as long as the fraction of unskilled workers is not the same among immigrants and the domestic labor market ($b \neq \beta$). In the case of $\beta > b$, if one assumes that wages are higher for skilled than for unskilled workers, the shock induced by the immigration inflow will contribute to widen income inequalities among the workers in the economy, since the wage of unskilled workers will fall while the wage of skilled workers will increase.

3.2.4 Graphical illustration

An increase in immigration of low-skilled workers in a closed economy could be examined as in Figure 3. A positive immigration shock will cause the supply curve for low-skilled labor to shift to the right (From Supply to Supply' in the right panel of Figure 3). The shift in the supply curve results in a new equilibrium wage for low-skilled workers, that is lower than the initial wage (wu'<wu). As a consequence, the equilibrium employment level increases (LU' > LU) since low-skilled labor has become relatively cheaper than skilled labor. Since skilled labor is a complement to low-skilled labor, the increase in supply of low-skilled labor, will increase the demand for skilled labor as well (the shift from Demand to Demand' in the left panel of Figure 3). Thus, the equilibrium wage for skilled workers will increase (ws' > ws). This is also the case for the equilibrium employment level (LS' > LS). The magnitude of the changes in wages will depend on the elasticity of the demand curves. The more inelastic the demand curve is, the greater is the effect on wages of a positive -- immigrant-induced -- shift in the supply of low skilled workers. At the same time, a more inelastic demand curve implies that the quantity change will be smaller.

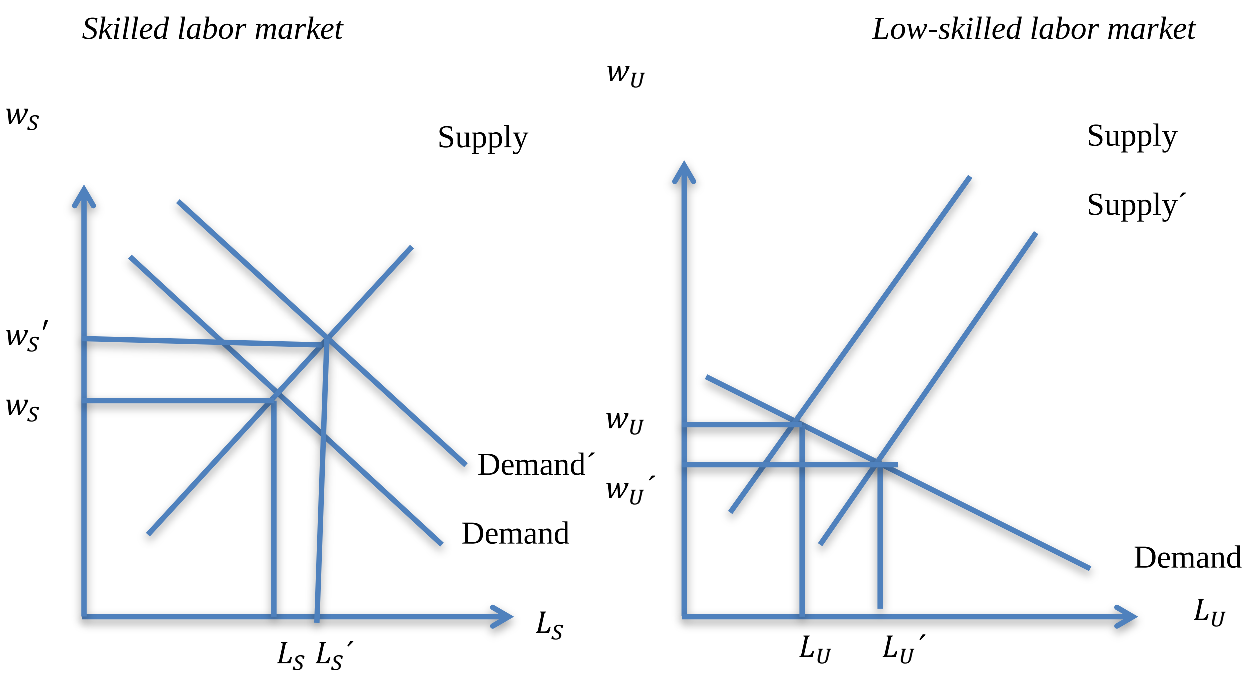

Figure 3: *Graphical illustration of the effect of a positive immigrant supply shock on the economy* L represents employment, and w represents wages, in each skill group. We see that in the labor market for skilled workers, the wage increases from w_S to $w_S´$, while in the market for low-skilled workers, the wage decreases from w_U to $w_U´$.

3.3 Theoretical framework for a small open economy

If we consider a small economy that produces two goods, we can for instance divide the labor force in two groups; skilled and unskilled labor. Prices are assumed to be determined at the world market. Based on a standard supply and demand framework, the theory predicts that an inflow of immigrant labor into a certain skill group will cause the relative wage of natives who belong to this group to decline. The size of the wage reduction will depend on the degree of substitutability between native workers and immigrants with similar skills as well as the degree of substitutability between skill groups. If natives and immigrants are perfect substitutes, wages of natives and immigrants should be equally affected by a positive labor supply shock induced by an influx of immigrants.

Using a nested CES production function[6], the direct partial effect is negative when the inflow of immigration consists of workers who are perfect substitutes to the native workers. Graphically, this can be illustrated as a downward movement along the demand curve for native labor of similar skill composition as the newly arrived immigrants. When substitution is imperfect, there will be a smaller partial negative impact on native wages. If they are imperfect substitutes within a given skill cell, the impact of immigration on native wages should be smaller on native than immigrant wages. Newly arrived immigrants will cause earlier immigrants to experience a larger wage adjustment if they are exposed to labor market competition (Bratsberg et al., 2012).

Borjas (2003) argues that workers who have different levels of experience are imperfect substitutes even though they have the same level of schooling. For this reason, he suggests that both schooling and experience should be the basis for constructing skill groups.

Using a nested CES production function (Bowles, 1970; Card and Lemieux, 2001), we can estimate the elasticities of substitution for different levels of schooling among labor. Consider an economy with an aggregate production function of the following type

$$Y_t = h(K_t, L_{1t}, L_{2t}, \dots, L_{nt})$$

where Y_t is output in period t, K_t is the flow of capital services and $L_j = L_1, L_2, \dots, L_n$ are the input levels of schooling. To simplify matters, I will assume that K_t is exogenous. The reason is that my primary interest is in the dynamics and substitution of (and between) different labor inputs. Including the efficiency of the input, μ_{jt} we can rewrite the CES production function as

$$Y_t = \left[\sum_{i=1}^{J} \mu_{jt}\, L_{jt}^{\rho}\right]^{1/\rho}$$

[6] The nested CES function is a CES function which is divided into sub-functions, and has the restriction that the income elasticity is set to 1. The arguments in the function are therefore split into pairs. Different levels (nests) allow for the introduction of the appropriate elasticity of substitution. This flexibility allows different elasticities of substitution to exist between the aggregates, represented by the sub-functions.

where ρ reflects the degree of substitution *between* the labor types. In the following, let σ_J denote the elasticity of substitution between the labor types, such that $\rho = 1 - \sigma_J^{-1}$. Further, as in Bratsberg and Raaum (2012), L_j is a CES-type aggregate of the quantities of native labor, N_{jt} and immigrant labor,M_{jt} in group or occupation $j = 1, \dots, J$:

$$L_{jt} = \left[N_{jt}^{\pi} + \varphi_{jt} M_{jt}^{\pi}\right]^{1/\pi}$$

By defining σ_M as the elasticity of substitution *within* the two labor inputs, we have that $\pi = 1 - \sigma_M^{-1}$. In order to allow for imperfect substitution between natives and immigrants within labor type, we have the condition that $-\infty < \pi \leq 1.$ The parameter φ_{jt} measures the relative productivity of the immigrant labor which lies in the range

$$\varphi_{jt} \in [0,1]$$

According to classical labor market theory, in a competitive labor market, the marginal product of labor equals the wage. Thus, we can derive the following expression for the native wage based on the CES production function

$$W_{jt}^{N} = Y_t^{1-\rho} \mu_{jt} L_{jt}^{-(\pi-\rho)} N_{jt}^{-(1-\pi)} \tag{1}$$

With reference to the econometric analysis of the paper, the authors take the logarithm of (1) in order to get an expression for the percentage change in the wages following a one percent change in one of the explanatory variables. Equation (1) in log form is denoted as

$$\ln W_{jt}^{N} = (1-\rho) lnY_t + ln\mu_{jt} - \left(1 - \frac{\rho}{\pi}\right) ln\left(1 + \frac{M_{jt}}{N_{jt}}\right) + \left(\frac{\pi^2 - 2\pi + \rho}{\pi}\right) lnN_{jt} - \left(1 - \frac{\rho}{\pi}\right)\varepsilon_{jt} \tag{2}$$

Where $\varepsilon_{jt} = ln\left(\frac{N_{jt}^{\pi} + \varphi_{jt} M_{jt}^{\pi}}{N_{jt} + M_{jt}}\right)$

ε_{jt} will equal zero if immigrant and native labor are perfectly substitutable. Bratsberg and Raaum (2012) consider

$$ln\left(1 + \frac{M_{jt}}{N_{jt}}\right) = -ln(1-m)$$

as the key exogenous variable, where m denotes the immigrant employment share.

The empirical counterpart to (2) that Bratsberg and Raaum (2012) consider is

$$lnW_{ijt}^{N} = \theta_{BR}\ln(1 + \frac{M_{jt}}{N_{jt}}) + \beta' X_{it} + \gamma_j + \tau_t + u_i + \omega_{ijt} \qquad (3)$$

With reference to the econometric analysis of this thesis, the econometric counterpart to (2) is given by the following relationship for the (log) wage of a native worker i belonging to group j in year t

$$lnW_{ijt}^{N} = \theta p_{jt} + \beta' X_{it} + \gamma_j + \tau_t + u_i + \omega_{ijt} \qquad (4)$$

The immigrant share, p_{jt} is defined as

$$p_{jt} = \frac{M_{jt}}{M_{jt}+N_{jt}} \qquad (5)$$

I will focus specifically on the variable p_{jt} in the empirical analysis of this thesis. In the expression for the immigrant share variable, M_{jt} is the number of immigrants, and N_{jt} is the number of natives in year t, in activity j. θ is the direct partial wage effect of immigration holding native employment and output constant. τ_t picks up time fixed effects while γ_j includes group fixed effects. Further, ω_{ijt} includes remaining factors such as transitory wage components. u_i is a fixed individual error component. X_{it} is a vector containing a measure of age, gender, educational attainment and other individual wage determinants.

Like Bratsberg and Raaum do in (3), I also ignore the impact via changes in ε_{jt} in (4). In the case where immigrants and natives are perfect substitutes as well as equally productive, ε_{jt} will be zero. The authors argue that in the rest of the cases, if we ignore ε_{jt}, we will create an omitted-variable bias towards zero in the coefficient estimate of $\left(1 + \frac{M_{jt}}{N_{jt}}\right)$, since the derivative of ε_{jt} is negative. If the values of φ_{jt} and π are close to one, the bias will be so small that it can be considered negligible. By decomposing the direct partial wage effect, θ_{BR} into an expression of the substitution elastisities σ_M and σ_J, one can look at their magnitudes' impact.

$$\theta_{BR} = -\left(1 - \frac{\rho}{\pi}\right) = -\frac{1 - \left(\sigma_J/\sigma_M\right)}{\sigma_J(1 - 1/\sigma_M)}$$

The direct effect of a positive immigrant supply shock on the wage of native workers of labor type j is negative if $\sigma_J < \sigma_M$. I assume that $\sigma_M > 1$. If natives and immigrants are perfect substitutes, $\sigma_M = \infty$, the expression for θ_{BR} reduces to

$$\theta_{BR} = -\frac{1}{\sigma_J}$$

which means that the substitutability of labor across types is the only parameter that affects the native wage adjustment. In the case where natives and immigrants are imperfect substitutes the direct partial wage effect of immigration will be less responsive.

I will return to the differences between my operationalization of equation (4) and the operationalization chosen by Bratsberg and Raaum (2012) in Section *6 Data and Descriptive Statistics*. In that section, I will also demonstrate how the results from the two operationalizations may be compared.

3.4 Long run adjustment processes

The wage and employment adjustments that are induced by the arrival and settlement of immigrants trigger native workers to react and potentially out-migrate from affected regions (Bodvarsson and Van den Berg, 2009, pp.120-121). In a model presented by Borjas (2006), the wage impacts caused by immigration are spread from the local to the national level. An underlying assumption is that there will be labor market imbalances through excess supply or demand that encourages native mobility across regional labor markets regardless of immigration. It is also assumed that no internal migration occurs. This model is a significant contribution to the literature of the economics of immigration, since Borjas incorporates natives' relocation decisions not only based on immigrant-induced wage disparities but also migration as a response to regional wage differences. He concludes that internal migration neutralizes the effects of the supply shock caused by immigration on the regional wage structure.

3.5 The labor demand effect

There are weaknesses of the labor market model because it utilizes the convenient *ceteris paribus* assumption in order to draw the attention towards wage and/ or employment effects of immigration shocks. Meanwhile, it lacks thorough elaboration on the demand effect of immigration by assuming either a closed economy with fixed prices or a “small” open economy where prices are assumed to be determined at the world market. Despite the convenience this infers, it gives a somewhat misleading picture of the overall effects. That is because immigrants who arrive become consumers as well as workers (Bodvarsson and Van den Berg, 2009, pp.122-123). Before immigrants find jobs, they purchase goods and services and thus demand is raised before supply. It is reasonable to believe that immigrants will spend at least part of their earnings on food, housing and services in the local market, and therefore the derived demand for labor will be affected by the immigrants’ consumption patterns. Even though this aspect is important, I choose not to focus on it in the empirical analysis in order to maintain the narrow scope I have chosen for the thesis. The rationale behind this choice also has to do with the time constraint I am subject to.

4 Approaches to the Empirical Analysis

4.1 Area analysis approach

When searching for empirical evidence of the impact of immigration, one can look at a cross-section of cities or regions and use variation in immigrant density to identify its effect on labor market outcomes of natives. One looks at the local level and submarkets are defined by geographical region. A potential threat to this approach is that factor price equalization may be obtained due to free trade. This means that an uneven distribution of immigrants within a country may not create wage differences in the long run, since wages can be equalized through the trade of factors and goods. If there are large differences in marginal productivities and high costs of moving and trading between countries, the wage convergence across countries is unlikely to be materialized.

Immigrants tend to self-select into the most attractive local labor markets where good economic conditions give increased hope and higher perceived chances of getting a job. Regions with high wage rates will therefore receive a lot of immigration. If native workers choose to move out of (or at least not into) a specific area as a response to high immigrant inflows, the wage effect will leak from the local to the national labor market (Bratsberg et al., 2012).

It is therefore a crucial challenge to identification within this approach that immigrants endogenously choose to move to areas where the opportunities and economic prospects are most favorable. Instruments such as the lagged immigrant stock, network effects or exogenous shocks in labor supply are therefore often used in order to avoid this bias. Friedberg and Hunt (1995) argue that one can find instruments for the changes in immigrant density in order to reduce the bias caused by immigrants choosing regions with improving outcomes. However, it is difficult to find a suitable instrument. Following the presented arguments, it is a challenge to identify local labor market effects since regional boundaries are easier to cross than national borders.

4.1.1 Evidence from the US labor market

A significant part of the empirical literature is based on US data, and the studies utilizing the area analysis approach often find small and insignificant wage effects of immigration. In a paper by Friedberg and Hunt (1995), it is argued that there is no empirical evidence of economically significant reductions in native employment. More specifically, they claim that the United States has only experienced a 1% reduction in native wages as a result of a 10% increase in the fraction of immigrants in the population.

Borjas et al. (1996) argue that one can derive the effect of immigration on native wages by comparing wages between immigrant-intensive and non-immigrant intensive areas. For the estimates to be valid, they assume that a given exogenous flow of immigrants is uncorrelated with the levels or changes in labor supply or labor demand between different areas, and given time for wages of native workers to adjust after various potential supply shocks. The paper presents estimates of a cross-sectional regression that examines the effect of immigration on log weekly earnings of natives using a random sample of immigrant workers and another sample of native workers. The Public Use samples of the 1980 and 1990 Census of Population are used in the empirical analysis. The authors find that women's wages are positively related to immigrant/native ratios. However, the sign of the male estimates is negative in 1980 and positive for 1990. This might be due to an omitted variable bias. To address this problem, the authors choose to examine changes in native wages in an area over time. Education variables are added to the specification to control for national changes in demand for workers by education group. In addition, they include area specific dummy variables to control for local changes in labor demand. Regressions for metropolitan statistical areas and states both with and without area dummy variables and education variables included are used in order to determine whether the extent of geographic coverage has an impact on the results. By including educational groups in the regression, the estimates show that education groups that experienced particularly large increases in labor supply, induced by immigration, had large decreases in pay relative to other educational groups in the same area.

4.1.2 Natural Experiments

One particular example of exogenous supply shocks is the so-called Mariel boatlift, which occurred in 1980. Fidel Castro allowed Cubans to migrate to Miami during a period of a couple of months. An advantage of natural experiments is that it measures an event where immigrants are not able to self-select into the most attractive labor markets. Natural experiments can eliminate the estimation problem of immigrants choosing locations based on labor market conditions (the selection bias), since the immigrant inflow is exogenous. Analysis of the Mariel boatlift shows no strong effect on wages or employment opportunities of any group of natives in Florida, as the refugees were absorbed quickly into the labor market (Card, 1990). A drawback of these types of experiments is that there are limited numbers of independent observations. In addition, critics claim that natives will out-migrate in response to influx of immigrants and this may cause the net effect of immigration on factor supplies to equal zero. Borjas is one of these critics, and therefore tried to focus on another approach; factor proportions analysis. The problem of endogeneity of location choices has led researchers to focus on variation in immigrant inflows over time within different skill or industry groups defined at the national level.

4.2 Factor proportions approach

The factor proportions approach examines the impact of immigration through its effect on the aggregate supply of labor with different skills within a country. It assumes that the effects of immigration and trade are sufficiently diffused between areas because of native migration or capital responses. Borjas (1999, p. 1753) summarizes the different steps in this approach in the following way: "the factor proportions approach compares a nation's actual supplies of workers in particular skill groups to those it would have had in the absence of immigration and then uses outside information on the elasticity of substitution among skill groups to compute the relative wage consequences of the supply shock". These studies are based on treating immigration as a source of increased national supply of workers of the relevant skill and trade as a source of changes in the supply of skill, and then estimate the elasticity of substitution of changes in labor supply on wages. Therefore, national skill groups which are defined by education, experience and individual attachment will largely be determined by educational choice.

If group specific factors such as technological change that affect the wage trend are correlated with changes in the immigrant share over time, these estimates will be biased (Bratsberg and Raaum, 2012). Although this approach by design reduces the influence of endogenous native responses, it remains susceptible to bias if immigrant supply shocks and native labor market participation are related. For instance, native attrition may be non-random (Bratsberg et al., 2012). That is, if native labor force participation decisions change as a response to immigrant supply shocks, the estimates are subject to a bias.

4.2.1 Evidence from the US labor market

Okkerse (2008) provides a literature review, where the different empirical approaches are discussed in terms of methodology and results. One of the examples which Okkerse points to is the study by Borjas et al. (1997) who consider the U.S. labor market in the period from 1980 to 1995. The paper presents results on the contribution of immigrants to the increasing wage gap in the considered period. The influx of immigrants had increased the relative supply of high school dropouts by 14.9%. In those 15 years, the wage differential between skilled and unskilled workers increased from 30.1% to 41%. The associated drop in the relative wage of high school dropouts was 4.8 percentage points, so immigration is assumed to be responsible for 44% of the widening wage gap.

In a paper from 2003, Borjas increases the number of labor aggregates by using a CES technology which contains three levels. The estimates he obtains from the empirical analysis are calculations of the wage impact of the immigrant influx that the US experienced between 1980 and 2000. Borjas (2003) concludes that workers at the lowest part and those at the top of the education distribution are most affected. For workers with the lowest educational attainment, the wage decreased by 8.9%, and for workers at the top of this distribution the wage decreased by 4.9%.

5 Literature Review

Reviews of international empirical studies show both positive and negative wage and employment effects of immigration, and researchers often conclude that there are no or small effects. The empirical literature shows no consensus on the impacts of immigration, and in particular the magnitude of the substitution elasticities (Bratsberg and Raaum, 2012).

5.1 Effects on the Norwegian labor market

In the paper “Wage Impacts of Immigration in Norway” (Bratsberg et al., 2012), immigration induced wage impacts are studied by applying the national skill cell approach. The following section gives a detailed description of the approach and findings of the paper, since this thesis is closely related to the analysis in that paper.

Immigrants and natives are divided into market groups determined by education, work experience and year of observation. How wage adjustments following immigrant supply shocks are distributed across groups of workers will be determined by the elasticity of substitution between immigrants and natives. The empirical analysis starts by replicating Borjas (2003), using the same model specification and variable definitions as in the original study, though data for Norway rather than the US is considered.

Wage effects are estimated using a population-based data set with individual panel information. An advantage of the data structure is that it allows for examining selective native employment where unobserved worker characteristics are correlated with the immigrant share within cells. The authors control for education and work experience in the empirical model. In addition, they control for year fixed effects and within-cell variation in native labor supply. One of the main contributions from this method is that it controls for the following interactions; educ*exper, educ*year, and exper*year, where educ and exper denotes education and experience, respectively. This way the authors delineate the market when applying the national skill cell approach, which allows for the study of the effect of immigration. They use market clusters by education, year and experience, and immigration such that immigrant induced supply shocks are captured by changes in the immigrant employment share in each cluster. This implies that the method requires good data. By including skill-group specific indicators for the business cycle, the authors allow for within-cell variation in labor demand.

This variation is based on detailed individual unemployment records. A positive bias may occur if immigrant inflows are responsive to skill-group specific labor demand shocks.

5.1.1 Heterogeneity in native-immigrant substitution

One specific challenge to this approach is to allocate immigrants to the appropriate education-experience cell. Effective experience is calculated and immigrants coming to Norway from developing countries are allocated into experience cells on the basis of years of actual employment. Immigrants from different countries are expected to have unequal substitutability with native workers. The heterogeneity in native-immigrant substitution stems from the fact that neighboring countries exhibit culture and language similarities as well as common educational attainment within the same institutional structure. However, immigrants who originate from far away do not share the same cultural and linguistic factors. Thus, it is important to differentiate between origin region in order to explain substitutability and labor force participation. Due to similarities in educational systems, language and labor markets the human capital of Nordic residents is highly transferable. Nordic workers are therefore close substitutes to native workers in Norway. The wage effects are likely to vary across immigrant types, because immigrants from high-income countries are actively searching for jobs while refugee status and family reunification are common reasons why immigrants from developing countries come to Norway.

Migration costs are often higher for immigrants coming from developing countries than from the nearby Nordic countries, but the latter might be more sensitive to variations in demand conditions than the former. The immigrant labor force is split by origin into 3 regions: 1) the Nordic countries, 2) other European countries plus North America, Australia and New Zealand (where former Yugoslavia and Turkey are excluded) and 3) The rest of the world.

A common labor region for the Nordic countries has existed since 1954. Nordic citizens' temporary cross-border mobility is often not recorded in administrative population records because they do not need a permit to take up work or residence within the Nordic region. One objective with the factor proportions analysis is that relative wages may be affected by immigration that is confounded with other skill-group specific labor supply or demand shocks. For instance a skill-biased technological change that increases the demand for relatively young and high skilled workers could be an example of a confounding factor.

Data that cover all residents of Norway during 1993-2006 are extracted from several administrative registers. Over the sample period, the immigrant labor force share has increased from 5 to 10 % with primarily immigrants from developing countries. The empirical analysis is restricted to male wage earners, and focuses on the direct partial wage effect. This is the effect of an immigrant-induced increase in supply, holding capital, aggregate supplies and native supplies constant, on the wage paid to the same native skill group. To estimate this effect, educational attainment and work experience is used to classify individuals into 32 skill groups (4 levels of education*8 experience groups = 32). Residency, wage earnings, labor force participation, educational attainment, work experience and country of origin are the main variables.

If wage effects are the same for natives and immigrants, the two groups are perfect substitutes. By using individual panel data, the problem of selective native attrition is addressed. In the empirical analysis, there might be sources of imprecise measurement of the true immigrant labor force share. More specifically, information about the exact measures of pre-migration work experience, the age of the worker when entering the labor market or if the worker has been out of the labor force is usually not available. School systems are typically different from one country to another, and therefore difficult to classify consistently. Another measurement issue is that the data does not include the share of immigrant workers that are not registered as residents in Norway. Undercounting may result in a so-called scaling bias, where estimates of the effect of immigration are inflated.

Potential experience from abroad is assumed to be comparable to experience obtained in Norway in the baseline case. For newly arrived immigrants, educational attainment is often missing. Their schooling distribution is assumed to be approximately the same as to the observed immigrants with the same characteristics of age, gender and origin. Immigrants from the Nordic countries have similar earnings profiles to those of natives. However, the picture is different for immigrants from developing countries. They earn substantially less at arrival, but during the 10-15 years of residence and work experience in Norway the gap is reduced. Estimates for the sample period show that skill groups with low education and short experience have a high concentration of immigrants. There seems to be a pattern where Nordic immigration affects wages more than immigration from developing countries, which is consistent with the theory that says that immigrants from countries nearby have a higher substitutability than immigrants from distant origins.

5.2 The Norwegian construction sector

Bratsberg and Raaum (2012) argue that there are two main countries that immigrant construction employment draws heavily on in Norway; Sweden and Poland. The Swedish workers came as a consequence of the downturn in the Swedish construction sector following the Swedish banking crisis in the 1990s. In the subsequent years, the Swedish construction sector recovered, and the Swedish workers employed in Norway returned to their home country. Since the construction sector is characterized by demand conditions that move together across segments, the authors use licensing requirements in the Norwegian construction sector as a source of exogenous variation in immigrant employment across trades, in order to identify the wage impacts of immigration. In order to be allowed to work as an electrician, it is required that the worker hold a certificate issued by the Directorate for Civil Protection and Emergency Planning. The authors found that looking at different segments of the construction sector, changes in immigrant employment turned out to be uneven. Electrical installation and plumbing companies are subject to licensing requirements concerning certification and authorization of skills according to national standards. This has made it difficult for migrant workers to enter these segments. Over the sample period there was a substantial growth in immigrant employment in carpenter and painting firms while there was almost no change in immigrant employment in activities with licensing requirements.

With the use of panel data, Bratsberg and Raaum derive and estimate micro-level wage equations, accounting for individual fixed effects. They find that immigration is associated with low-wage workers who leave the sector. This attrition creates a spurious positive correlation between immigration and native wages which masks the underlying negative effect of immigration on individual wages. The authors concentrate their focus on wages of workers employed in construction-sector firms during the period of 1998-2005. In order to identify each worker and the firm, administrative payroll records submitted to tax authorities are used. The firm identifier is used to give the worker an industry affiliation, and the immigrant status is then drawn from the central population register and the register of work permits to the pay record.

The payroll data for the construction sector indicated that 57 % of the immigrant workers were registered as residents outside Norway. Workers had a D-number[7] attached to the payroll, and were employed with a temporary work permit. Among the 174,000 workers employed in the construction sector only between 15,000 and 22,000 of them were immigrant workers in the payroll data. There is clear evidence that immigrant construction employment follows the fluctuations in the building cycles, and the immigrant share has increased from 8% in 1999 to 11% in 2005. Since the data only relies on registered employment contracts, those who work unregistered will not be captured, and thus there is a fear of measurement error in the paper's immigrant employment share variable. This may potentially mean that the true immigrant employment share in the construction sector is understated, in which case the true wage effect of immigration may be understated as well. For that reason, any measured effect on wages draw on immigrant employment that is registered, where unregistered and workers employed by temporary employment agencies are excluded.

In order to analyze the relationship between immigrant employment and wages of native-born workers, the authors use a sample that consists of 918,082 wage observations of 217,151 native-born construction workers. The daily wage is constructed by dividing total pay on the number of days of the employment contract. Both instrumental variables estimation with certification requirements used as an instrument and a difference- in-difference approach is used. They conclude that selective native attrition as well as selective immigrant entry causes bias in the conventional estimator of the immigration wage impact. The major findings in the paper indicate that a 10 % increase in immigration is associated with a 0.6 % reduction in wages. For low and semi-skilled workers within the construction sector, the empirical results suggest that immigrant and native labor are close to perfect substitutes. This group of workers had the largest effect on wages of increased immigrant employment. Estimates also suggest that a 10% increase in immigrant employment reduces prices of construction services by 0.4-1.1%.

[7] A D-number is a registration number that is given to people intending to stay in Norway for a short period only. D-numbers are used for identification purposes in the same way as personal identification numbers. They are temporary assigned to persons residing in Norway 6 months or less.

5.3 Beyond Norwegian borders

A lot of empirical analyses focused on the United States find that a 10 percent increase in the fraction of immigrants in the population in the working age is associated with a reduction in native wages of at most 1 percent. Friedberg and Hunt (1995) conclude that there is no evidence of economically significant reductions in native employment. Not even natives who should be the closest substitutes with immigrant labor have been found to be significantly “harmed”. The theoretical literature on immigration suggests that the impact of immigrants on native’s income growth depends on the immigrants’ human capital level. The effect of immigration on labor market outcomes is small. Manacorda et al. (2012) study the UK labor market and find that more recent immigrants seem to be less substitutable with natives than longer-term immigrants. Their results indicate that immigrants and natives appear to be imperfect substitutes in production.

A majority of previous research on the U.S. labor market has concluded that migration hurts natives, and especially the low-skilled. Ottaviano and Peri (2006) follow a similar argumentation and utilize an empirical approach where they incorporate an estimate of the substitutability of immigrants and natives with similar experience and education levels. Estimates show evidence of small but significant degree of imperfect substitutability. A one percentage point increase in immigration was associated with a 0.6-1.7% increase in average native wages. Following the same framework of Ottaviano and Peri (2006), Ottaviano and Peri (2008) go further. In that paper, emphasis is put on a production function that examines the competition and combination of workers with different skills and the cross-skill complementarity effects of immigration on wages. Like the findings in the paper from 2006, they find that there is a significantly large negative substitution effect of 6% of new immigrants on previous immigrants.

The results of the US labor market found by Ottaviano and Peri (2012) resemble those of Manacorda et al. (2012). They find that there is a small degree of imperfect substitutability between natives and immigrants in their sample period from 1990 to 2006. Immigration had a small positive effect (0.6%) on average native wages in the long run. Also for low skilled native workers with no high school degree, the associated effect of immigration was small (0.6-1.7%). Meanwhile, immigration had a large negative effect on wages (-6.7%) for previous immigrants. The paper concludes that immigration to the United States had at most a modest negative long-run effect on the real wages of the least educated natives.

6 Data and Descriptive Statistics

As mentioned, this thesis builds on the paper "*Immigration and Wages: Evidence from Construction*" (Bratsberg and Raaum, 2012). In this section, I will use the theoretical model described in Section 3.3 of this thesis, as a basis for the empirical analysis. Since endogenous location choices of people have led more researchers the last decade to focus on the factor proportions analysis approach, I choose to apply this method as well. I use the variation in immigrant inflows over time and within groups defined at the national level. My contribution through this thesis is based on an extension of the sample period employed in Bratsberg and Raaum (2012). Through the project "Labor migration to Norway" at the Frisch Centre, Statistics Norway has made micro data available for the period 1998 to 2011. For this reason, registry based analysis of labor migration will largely build on micro data obtained from the worker registry, pay and tax deducted from the national registry and tax authorities. I will concentrate the focus in the empirical analysis on wages of native workers employed in construction-sector firms during this period.

6.1 Advantages and disadvantages

By aggregation of individual data, it has become possible to create key variables such as the number of Eastern European workers and examine the development in foreign labor employment in the construction sector. Registry data will provide information on the mobility of labor migrants across, into and out of the Norwegian labor market, but it will not draw a complete picture of their working conditions. These data do not give specific information on what contracts, pension rights etc. workers have. An advantage of sector specific studies is that one can connect data and analysis on different levels of aggregation. Aggregate register data can describe the development in mobility, employment volume, labor and work terms among labor migrants, as well as how other workers within the same industry are affected. Since the data only relies on registered employment contracts, those who work unregistered will not be captured, and thus there is a fear of measurement error in the immigrant employment share variable, p_{jt}employed by Bratsberg and Raaum (2012). This may potentially cause the true immigrant employment share in the construction sector to be understated, which will also affect the estimated wage effect of immigration. Therefore any measured effect on wages will draw on immigrant employment that is registered, where unregistered workers and those employed by temporary employment agencies are excluded. Native attitudes towards immigration will be influenced by how immigrants affect their labor market opportunities, and immigration laws are usually perceived as controversial. Variation in immigrant flows across units of the labor market is used as a basis for the empirical identification. Due to labor mobility across geographical areas and between sectors, this may in turn cause comparisons of labor market with high and low immigrant shares to be misleading.

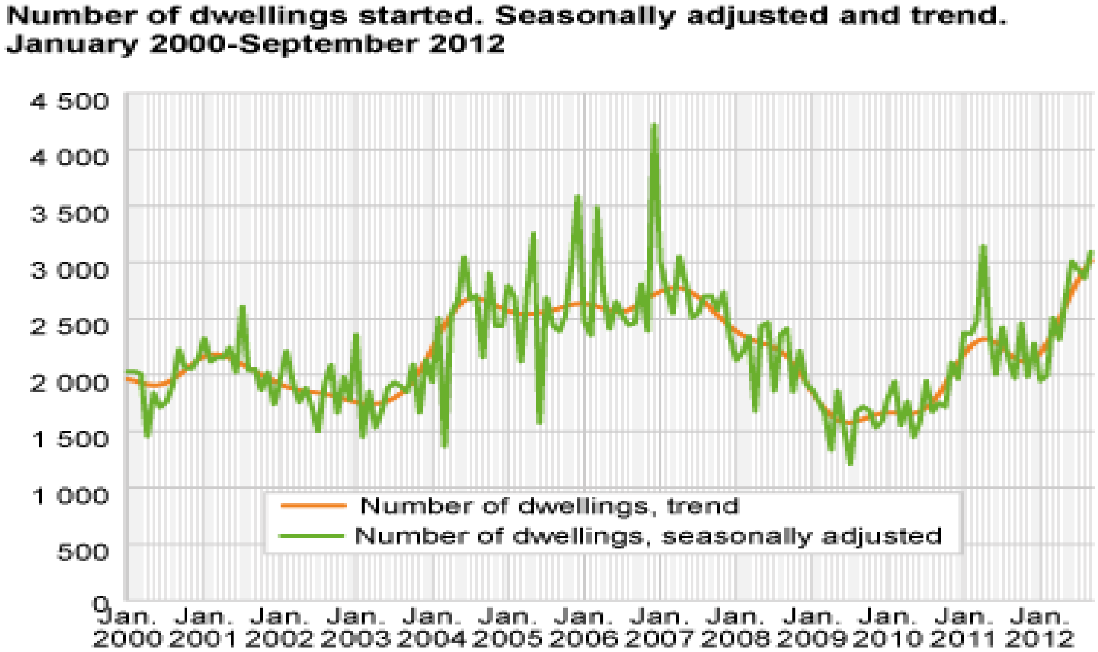

Figure 4: *Housing starts*

Source: Statistics Norway. http://www.ssb.no/byggeareal_en

Figure 4 illustrates the cycles of the construction sector represented by monthly housing starts. In accordance with the argumentation in Bratsberg and Raaum (2012), the construction sector is characterized by demand conditions that move together across segments. As seen from Figure 4, the Norwegian construction sector experienced an increase in housing starts in the period from January 2003 until January 2007, right before the start of the financial crisis in 2007-2008. From then on, the sector suffered stagnation in the number of started dwellings. The figure indicates that the demand conditions stabilized in the subsequent one-year period, and the sector seemed to have recovered from the economic downturn. The number of started dwellings began to increase again in 2010, indicating a construction boom.

6.2 Immigrant employment shares

Immigrant construction workers are persons who are not born in Norway. Bratsberg and Raaum (2012) use licensing requirements in the Norwegian construction sector as a source of exogenous variation in immigrant employment across trades. This allows them to identify the wage impacts of immigration. In order to get permission to work as an electrician in Norway, it is required to hold a certificate issued by the Directorate for Civil Protection and Emergency Planning. Electrical installation and plumbing companies are subject to licensing requirements concerning certification and authorization of skills according to national standards. This makes it more difficult for migrant workers to enter these segments. In the empirical analysis, I will expect to find that the effect of labor migration on native wages will be smaller in activities with licensing requirements than activities where licensing is not required. However, there exists a concern that the barriers to entry in activities such as plumbing and electrical installation not only apply to immigrants, but also natives. If this is the case, we will falsely attribute low wage growth in certain activities during a construction boom to inflows of immigrants. In reality, the low wage growth in these activities may be caused by native flows across industries. However, I do not discuss this aspect any further in this thesis due to the scope of this thesis as well as the time constraint I am subject to.

In the two following figures (Figure 5 and 6) I include those with construction employment on the continental shelf. Bratsberg and Raaum (2012) exclude these workers, and the numbers will therefore differ somewhat from their study. Figure 5 describes the development in the employment of natives and immigrants in the construction sector during the considered sample period from 1998 to 2011. Notice that the number of natives is measured in per 10,000, while the number of immigrants is measured in per 1000, in order to reduce the difference in the employment levels and therefore allow us to more easily compare the qualitative developments over time. As the figure illustrates, there has been a substantial increase in the absorption of immigrant workers in the Norwegian construction sector throughout the sample period. Not surprisingly, the figure provides support to the arguments related to the impact of the EU enlargement in 2004 and 2007, discussed in Section 1 and Section 2 of this thesis. In 2008, the aggregate percentage share of immigrants in the sector had reached its peak at almost 20%.

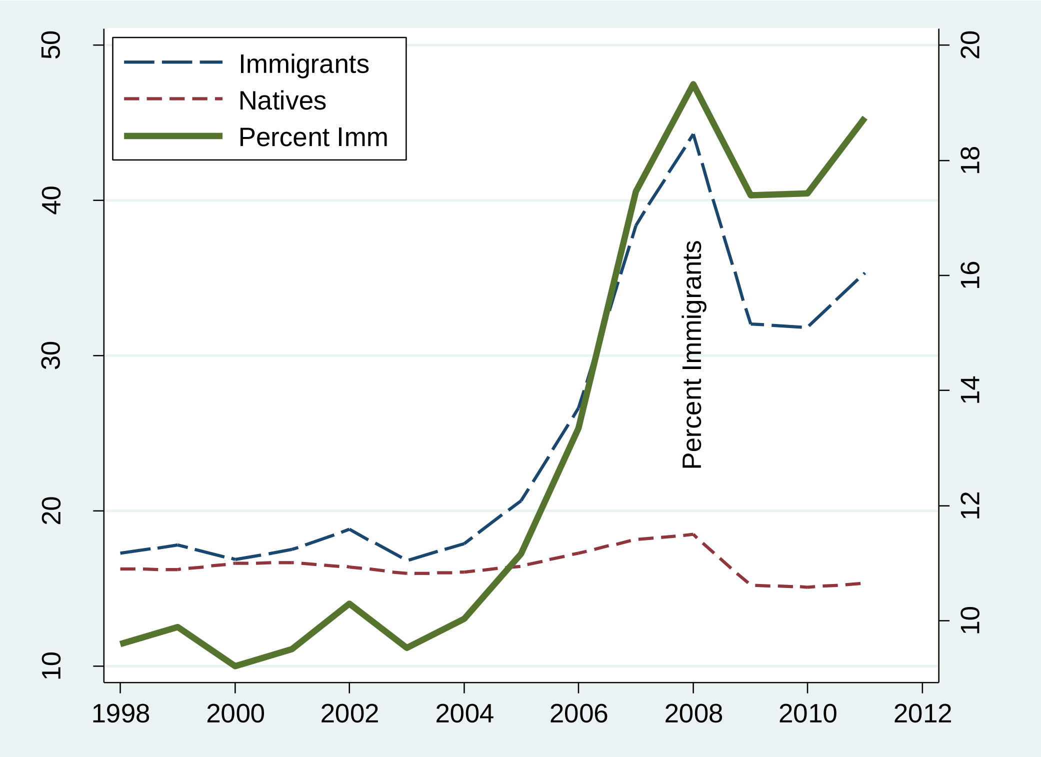

Figure 5: *Native and Immigrant Construction Employment*

Source: My own tabulations from the register data for the entire sample period.

Figure 5 draws a clear picture of the major impact immigration has had on the Norwegian labor market, and especially on the construction sector. Since Norway was largely unaffected by the international economic downturn during and after the financial crisis, the country emerged as a very attractive destination for European migrant workers. This may have reinforced the initially large influx of labor immigrants. Thus, Figure 5 provides evidence of record levels of immigration after the first enlargement of the EU took place in 2004.

6.2.1 Key variables

In the econometric analysis, I control for years of schooling, gender, activity, age and year at which the observation was collected. As presented in Section 3.3 of this thesis, the fraction of immigrant workers in each activity, j in year t, is defined as

$$p_{jt} = \frac{M_{jt}}{M_{jt}+N_{jt}} \tag{5}$$

where M_{jt} and N_{jt} is the number of immigrants and natives in group j and year t, respectively. Of particular interest is the expansion of the European Union in 2004 where the Baltic States, Cyprus, Malta, Slovenia, Slovakia, Hungary, Czech Republic and Poland gained EU accession. In addition, the inclusion of Romania and Bulgaria in 2007 is important. I will come back to the impact these changes have had in the empirical analysis.

The EU expansions are treated as positive exogenous shifts in the aggregate labor supply of immigrants to the Norwegian construction sector I divide the construction sector into 15 activities based on the employer's five-digit SIC[8] code. In the period 1998 through 2008, the SIC2002 code of 45 is used. This means that all groups within the construction sector are classified with a four-digit code where the two first numbers are 45, which indicates the industry classification. For the rest of the sample period (2009 through 2011), I use the code of 43. The reason for the change has to do with Statistics Norway's choice of classification of the activities. Moreover, I rearrange and group the activities in a somewhat different way than Bratsberg and Raaum. For the same reason, I construct 15 separate activities rather than 16. This is to get continuity throughout the whole sample period. Out of the 16 main activities in the construction sector the authors created, the 16th activity, "Rental of equipment with operator" (SIC2002 code 45500) is not included as a separate activity in my data set. From 2009, this activity is counted within the 7th activity, "Other special building construction". After the publication of Bratsberg and Raaum's paper, Statistics Norway has developed a new subgroup within the first activity, "Site preparation" where test drilling (SIC2002 code 45120) is included.[9] The last change compared to the initial paper is that I move "isolation work" (SIC2002 code 45320) from "Other building completion" to "Other installation".

To examine how the share of immigrant construction workers, p_{jt} is distributed across the 15 activities and over the sample period, I have plotted the average annual change in the immigrant employment share in Figure 6. Throughout the empirical analysis I cluster the 15 activities with the 14 years of observation. This means that I have 14*15=210 observations of the immigrant share variable in total. It can be seen that most of the activities have

[8] The Standard Industrial Classification (abbreviated SIC) is a system for classifying industries by a four-digit code. Statistics Norway's definition of SIC: "SIC is primarily a statistical standard. The standard will be the basis for coding units according to principal activity in Statistics Norway's Business register and units in the Central Coordinating Register of Legal Units. The SIC is one of the most important standards of economic statistics, and it will make it possible to compare and analyze statistical data both at the national/international level and over time. (http://www4.ssb.no/stabas/ClassificationFrames.asp?ID=342101&Language=en)

experienced an increase in the immigrant share from 2004 and onwards. This illustrates the absorption of Eastern European workers into the construction sector, as a consequence of the increased labor migration after the EU expansion. In Figure 5, it can be seen that the immigrant employment share in the construction sector has increased over time and in particular in the years after 2004. When I decompose this aggregate measure of the immigrant employment share over the sample period, it is interesting to see how unevenly distributed p_{jt} is across different activities. It is important to have this in mind so that the immigrant employment fluctuations do not get overstated, when I consider the development in the

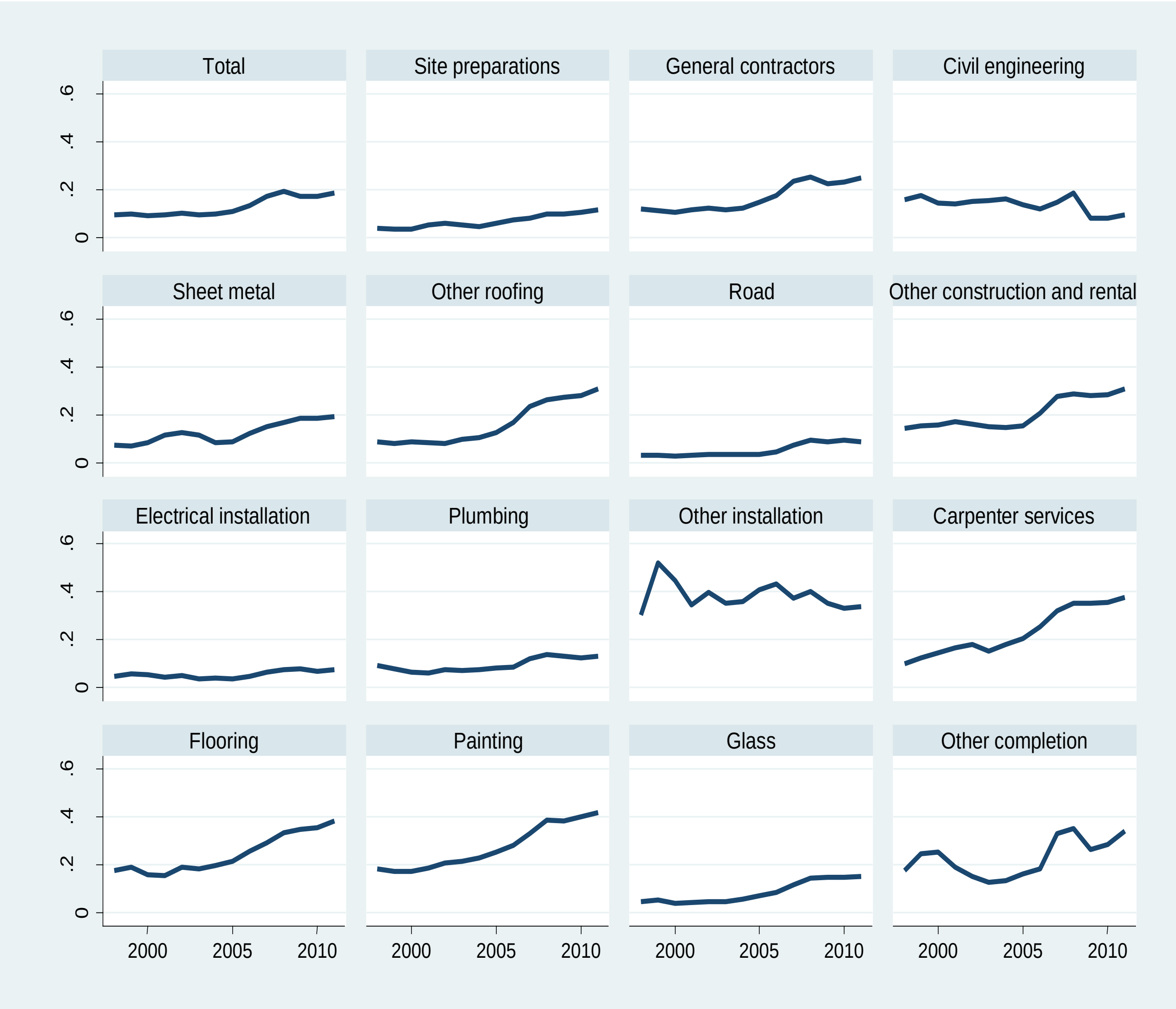

Figure 6: *Development in the immigrant share variable,* p_{jt} *within the 15 activities*

Source: My own calculations on the change in the immigrant share over the period from 1998 to 2011.

immigrant share variable, p_{jt}over time, which is presented in Figure 6. For comparison purposes, the first graph, “Total”, redisplays one component from Figure 5 and describes the overall change in the immigrant employment, in the period from 1998 to 2011. It illustrates a stable path for p_{jt}at around 10%, from 1998 to 2004-2005. Thereafter, the immigrant share among construction workers increases sharply from 2005 to 2007, and stabilizes at approximately 20%. For instance, in activity 11 (Carpenter services) even though it has been a large increase in the immigrant share, from 10% in 1998 to 40% in 2011, this activity constitutes few workers. I find a similar development in activity 12 (Flooring) and 14 (Painting). Meanwhile, there seems to be almost no change in the immigrant employment in electrical installation. This is in line with what I expected, when I discussed potential consequences of professions subject to licensing requirements within the construction sector in Section 6.1. However, in the other activities, where certification is common, and the overall share of construction workers are greater than 2%, there seems to be a positive development in the relative employment of immigrants captured by the immigrant share variable, p_{jt}. In activities “Site preparations”, “Civil engineering”, “Electrical Installation”, “Road”, “Plumbing”, “Other installation”, and “Glass” such requirements are common.

6.3 Wage sample

My wage data contains 79 variables and a total of 1,769,859 observations of 301,435 individuals. The study of interest is individuals in the age 16-64 who are employed in the construction sector. My wage data set is slightly different from the one used in Bratsberg and Raaum (2012). One of the main differences is that they included people aged 18-60. In addition, they exclude workers that were employed in activities connected to petroleum in the North Sea. Meanwhile, I include these workers in my wage data in the following regression analysis. For that reason, I am not able to perfectly replicate their numerical results, but the signs of the estimates are in accordance with economic theory and estimates are very close to the results obtained in Bratsberg and Raaum (2012).

The payroll data are constructed such that each worker is only counted once if they have multiple pay records. Missing values and observations indicating no pay records are omitted from the sample. In order to examine the fluctuations and development in work and wage terms for the construction sector in more detail, I chose to build on the framework established in Bratsberg and Raaum (2012). Administrative payroll records submitted to the tax registry by employers, and registry based income files are used to draw on the income information. I extract every pay record that is collected from registers of establishments. This allows me to construct the wage data and classify the self-employed. Since the data includes business numbers, it also permits further classification of the workplace and therefore also the industry, as well as employees. More specifically, each payroll record includes a firm identifier and a personal identifier for the worker. The firm identifier is used to give the worker an industry affiliation (i.e. a Standard Industrial Classification, SIC). These affiliations are collected from registers of establishments where each unit is classified by Statistics Norway according to what the main activity of the firm is. Further, firm records with construction-sector affiliation are extracted (i.e. two-digit SIC2002 and SIC2007codes). Table 1 provides a summary of the distribution of workers within the 15 categories over my sample.

Activity	Frequency	Percent	Cumulative	Certification common
1.Site Preparation	138,809	7.88	7.88	Yes
2.General contractors projects (incl. bridges, tunnels)	511,160	28.03	36.92	No
3.Civil engineering	73,097	4.15	41.07	Yes
4.Sheet metal	24,931	1.42	42.49	No
5.Other roofing	14,213	0.81	43.29	No
6.Road	211,506	12.01	55.31	Yes
7.Renting of equipment with operator and other special building construction	139,599	7.93	63.24	No
8.Electrical installation	348,601	19.80	83.04	Yes
9.Plumbing	181,361	10.30	93.34	Yes
10.Other installation	8,875	0.50	93.84	Yes
11.Carpenter services, plastering	31,061	1.76	95.61	No
12.Flooring	11,069	0.63	96.24	No
13.Painting	48,481	2.75	98.99	No
14.Glass	11,126	0.63	99.62	Yes
15.Other building completion	6,667	0.38	100.00	No
Total	1,760,556	100.00	100.00	

Table 1: *The distribution of native construction workers across activities*[10]

Source: My own tabulations of the main activity for the workers in the sample

Most individuals in my sample - 28% of the total observations - were registered as general contractors (activity 2). Electrical installation is the second largest activity, accounting for 19.80% of the observations. In the period 1998 to 2011 very few workers were employed in activity 4, 5, 10, 11, 12, 13, 14 and 15 (confer Table 1 for the activity type corresponding to the activity number). More specifically, each of these groups account for only 0-3% of the overall employment. It is therefore more interesting to see how the employment of immigrants in the largest activities has changed in the period from 1998 to 2011. This is shown in Figure 6.

[10] An overview of the characterization of the 15 groups in terms of SIC2002 and SIC2007 codes is presented in Appendix 1

Statistics Norway has established the Norwegian Standard Classification of Education (NUS2000),[11] where education is divided into three main levels; compulsory education (level 1-2), secondary education (level 3-5) and tertiary education (level 6-8). Table 2 gives a summary of how the individuals in my sample are spread out in the different groups. Out of the 1,760,556 observations in the sample, most workers in the construction sector have completed upper secondary school (47.88%). I find that only 2% of the workers in my data set hold a PhD. Therefore, it is reasonable to consider persons working in the construction sector in general as low-skilled rather than high-skilled (confer theory presented in Section 3 for a more thorough discussion on workers skills).

Education	Frequency	Percent	Cumulative
2. Lower secondary education	482,063	27.38	27.38
3. Upper secondary education, basic education	195,733	11.12	38.50
4. Upper secondary education, final year	842,881	47.88	86.37
5. Post-secondary non-tertiary education	95,546	5.43	91.80
6. First stage of tertiary education, undergraduate level	118,128	6.71	98.51
7. First stage of tertiary education, graduate level	25,922	1.47	98.98
8. Second stage of tertiary education, (postgraduate education)	283	0.02	100.00
Total observations	1,760,556	100.00	100.00

Table 2: *The distribution of the construction workers' completed education*
Source: My own tabulations of the educational attainment of the workers in the sample

I am particularly interested in determining whether an increase in the immigrant share causes changes in the daily wage of construction workers. As argued earlier, salary information is available from the administrative payroll records and the personal income for each worker is obtained from the tax authorities. Payment in cash is defined by Statistics Norway as

[11] http://www4.ssb.no/stabas/ItemsFrames.asp?ID=430502&Language=nb&VersionLevel=ClassVersion

“the sum of all cash benefits that are paid to the employee during a calendar year. It includes salary, overtime pay and fees, vacation pay and option benefits.”[12]

Since wages are distributed across different time periods, the registry data contains a mixture of payments per month or year, depending on each individual. For this reason, I keep the “pay” record for the main job for each individual and year. That is, I only extract wages for one observation per individual per year. It is the highest wage for the individual under consideration that is extracted. In order to capture the percentage change in the daily wage, I construct the log of the daily wage of natives. I start by dividing total pay/salary for each individual on the duration (in days) of the employment contract, which I denote as $daily_{ijt}$. Next, I take the log of this variable and denote it as $lndaily_{ijt}$. In the empirical analysis, the log wage for a native worker i, belonging to group j and year t is specified as

$$lnW_{ijt}^{N} = lndaily_{ijt}$$

lnW_{ijt}^{N} is used as the main dependent variable in the empirical analysis.

[12] http://www.ssb.no/emner/09/01/begreper/begreper.html

7 Empirical Analysis and Results

In this chapter, the econometric modeling and the empirical results are presented. All estimations are performed using Stata, version 12.0. I use OLS as the estimation method, although Bratsberg and Raaum also apply an alternative strategy based on instrumental variable estimation (IV) with licensing requirements as an IV. Their IV estimates are very close to the OLS estimates in their Table 1 (Bratsberg and Raaum, 2012, p. 1189). Because of this, the authors decide to proceed with the OLS method, since it is more efficient than the IV estimator, though the estimates will still be biased asymptotically if the regressor is not exogenous. One of the main differences between the use of panel data sets compared to pure time series data and pure cross sectional data is that the panel data set allows analysis based on the same individuals across time (Wooldridge, 2009, p.444). It makes it possible to examine the turnover of workers in the construction sector. The panel data exploits information on the dynamic reactions of the individuals who are subject to the analysis (Kennedy, 2008, p.282).

All regressions control for fixed effects for the 15 main activities in the construction sector, denoted by γ_j. This means that I add 15-1=14 dummy variables for these activities in my estimated models. Activity 1, "Site preparation" is the omitted activity in the outputs of the regression analyses, and is therefore considered as the reference activity. I also include individual fixed effects[13] for each of the workers in the data set, denoted as u_i, and year fixed effects, τ_t . There are 13 year dummies in total. 1998 is the reference year throughout the analysis. Time fixed effects control for unobserved variables that change over time but are constant across entities. The error term ω_{ijt} is often called an idiosyncratic error, or time-varying error in the literature, because it represents other unobserved factors that change over time and affect the dependent variable (Wooldridge, 2009, p.456).

[13] The fixed effects estimator is actually the OLS estimator applied when using the fixed effects model. The transformation used to produce the fixed effects estimator takes an individual's observation on an explanatory variable and subtracts from it the average of all of that individual's observations on that explanatory variable. (Kennedy, 2008, p.289). This transformation removes the individual intercepts.

7.1 The Effect of Immigration on the Native Wage

The dependent variable of interest, lnW_{ijt}^{N} measures the logarithm of the daily wage of worker i, in activity j, in period t. Since I start by re-estimating some of the regressions of Bratsberg and Raaum (2012), I will initially restrict the years of observations to only include the period 1998-2005. For this reason, the years of observation will vary in the following regressions, depending on time period of interest. Following the theory presented in Section 3.3, Bratsberg and Raaum derive an equation for the determination of the log wage of a native worker in the construction sector. For a native worker i, in group j and year t, the empirical counterpart to equation (2) is

$$lnW_{ijt}^{N} = \theta_{BR}\ln(1 + \frac{M_{jt}}{N_{jt}}) + +\beta' X_{it} + \gamma_j + \tau_t + u_i + \omega_{ijt} \qquad (3)$$

where θ_{BR} is the direct partial wage effect of immigration. τ_t is a time dummy, while $\gamma_j$includes group fixed effects. Further, ω_{ijt} includes remaining factors such as transitory wage components. u_i is a fixed individual error component. X_{it} consists of the age, the age variable squared, gender, educational attainment and other factors representing individual wage determinants.

In this thesis, the immigrant employment share is at the core of the empirical analysis. I focus on estimations of the following baseline regression:

$$lnW_{ijt}^{N} = \theta p_{jt} + \beta' X_{it} + \gamma_j + \tau_t + u_i + \omega_{ijt} \qquad (4)$$

The corresponding coefficient estimate $\hat{\theta}$, which is estimated in the regressions links the two empirical functional forms in the following way[14]:

$$\hat{\theta} \approx \frac{\hat{\theta}_{BR}}{1-\bar{p}} \qquad (6)$$

[14] The derivative of the logarithm of the native wage with respect to the immigrant share is $\frac{lnW_{ijt}^{N}}{\partial p_{jt}} = \theta$. According to the specification in Bratsberg and Raaum (2012), where the main explanatory variable of interest is $\left(1 + \frac{M}{N}\right)$, the derivative of the native wage with respect to the immigrant share is $\frac{lnW_{ijt}^{N}}{\partial p_{jt}} = \theta_{BR} \frac{\partial\left[1+\frac{M_{jt}}{N_{jt}}\right]}{\partial p_{jt}} = \theta_{BR} \frac{1}{1-p} = \frac{\hat{\theta}_{BR}}{1-p}$

Here, $\bar{p}$ represents the mean of the immigrant share over the period 1998-2005. The authors calculate the average immigrant share to be 0.084 (Bratsberg and Raaum, 2012, p.1203). This implies that the denominator equals 1- 0.084 = 0.916. A rough approximation suggests that $\hat{\theta}$ should be 10 % higher than $\hat{\theta}_{BR}$ in absolute value. In Section 6.2, I discussed the differences between the data set employed in this paper and in Bratsberg and Raaum (2012). Due to this difference, the transformation I perform in (6) gives similar but not the exact same estimates. That is why $\hat{\theta}$ is almost equal to ($\approx$) $\frac{\hat{\theta}_{BR}}{1-\bar{p}}$.

7.1.1 Results

Results from estimating a modified version of (4), without including individual fixed effects (u_i), are presented in Table 3, Column (1). Ignoring individual fixed effects, causes the OLS estimate of θ to be close to zero. My estimated value of θ is $\hat{\theta}$ = -0.138, and its corresponding t-value is -0.90 and the immigration share variable is therefore found to be statistically insignificant at any conventional significance level. With 918,082 observations, Bratsberg and Raaum estimate θ to be $\hat{\theta}_{BR}$ = -0.103 (Bratsberg and Raaum, 2012, p.1189), when applying this conventional approach, which is a little more than 10% smaller (in absolute value) than my estimate. This can be ascribed to the different data and sample definitions applied in this thesis. In accordance with the authors' argument, the failure of considering any correlation between within-group change in the immigrant share and unobserved individual wage determinants creates a bias. This is because corr(p_{jt}, u_i) > 0. The result therefore suggests that there is no effect of immigration on Norwegian construction workers in the period from 1998 to 2005.

Table 3: *The impact of immigration on the log native wage*

Dependent variable	lnW_{ijt}^N	lnW_{ijt}^N
	(1)	(2)
Immigrant share	-0.138 (0.154)	-0.671*** (0.237)
Control variables: - age - age^2 - gender - years of schooling - activity	 Yes Yes Yes Yes Yes	 No Yes No Yes Yes
Period	1998-2005	1998-2005
Fixed effects: - group - year - individual	 Yes Yes No	 Yes Yes Yes
Observations	952,833	952,833
Individual fixed effects	0	223,068
Cluster	Yes	Yes
R^2	0.174	0.612

Notes: Standard errors are reported in parentheses and are clustered within 210 activity-by-year cells. *significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level. The stars illustrate the two-sided p-value where the hypothesis is that every coefficient is different from zero, is tested. In order to reject the null-hypothesis, then the p-value must be lower than 0.01 for 99% certainty, 0.05 for 95% certainty and 0.10 for 90% certainty. If the hypothesis is rejected then the explanatory variable has a significant impact on the dependent variable. This form of hypothesis testing is conducted for all estimates in every table in the empirical analysis.

In Column (2), I present the main results from the estimation of (4). I include the individual fixed effects, u_i which means that I consider correlation between unobserved individual wage determinants and within-group change in the immigrants share. u_i is considered to be constant over time and is often referred to as unobserved heterogeneity or individual heterogeneity in econometric theory (Wooldridge, 2009, p. 456). For this reason, there is no time subscript on this variable. It can be seen that when controlling for individual fixed effects, I find a greater negative impact of the immigrant share on the wage growth of natives in the construction sector, compared to the findings in Column (1). The coefficient estimate is now $\hat{\theta}$ = -0.671, and it is statistically significant at the 1% level. I correct for the bias created by native attrition out of the construction sector, and this is reflected by the stronger negative impact of the immigrant share on the percentage change in native daily wages. The finding that the estimate in Column (1) is more positive, and closer to zero, than the estimate in Column (2), shows that there is a positive correlation between the individual error component (i.e the individual fixed effect) and the immigrant employment share in the data. The indication is that this positive correlation is caused by systematic attrition of low-wage native workers from activities with growth in immigrant employment. According to the coefficient transformation in (6), the implied estimate of $\hat{\theta}$ from the estimation in Column (2) in Table 3 should be $\frac{-0.724}{0.916} = -0.790$ to give the exact same results as Bratsberg and Raaum (2012, p.1189). Thus, I do not find the exact same point estimate, and I suspect that this has to do with the different data definitions and operationalization used in this thesis. The results presented in Table 3 indicate that it is important to control for individual fixed effects. I will therefore continue to run regressions both with and without individual fixed effects in the other specifications I consider, in order to see how it affects the estimates.

Next, I examine the effect on the log native wage of a change in the immigrant share, $p_{jt}$by running (4) on the entire sample, which contains data from 1998 to 2011. The result of the estimation is presented in Column (2), in Table 4.

Table 4: *The impact of immigration on the log native wage*

Dependent variable	lnW_{ijt}^{N}	lnW_{ijt}^{N}
	(1)	(2)
Immigrant share	-0.288*** (0.072)	-0.622*** (0.108)
Control variables: - age - age^2 - gender - years of schooling - activity	 Yes Yes Yes Yes Yes	 No Yes No Yes Yes
Period	1998-2011	1998-2011
Fixed effects: - group - year - individual	 Yes Yes No	 Yes Yes Yes
Observations	1,760,556	1,760,556
Individual fixed effects	0	301,435
Cluster	Yes	Yes
R^2	0.229	0.588

Notes: Standard errors are reported in parentheses and are clustered within 210 activity-by-year cells. *significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

When controlling for individual fixed effects, the coefficient of the log native wage is $\hat{\theta} = -0.662$. This estimate is significant at the 1% level. The variables that are included in the regression explain 59% of the variation in the dependent variable, lnW_{ijt}^{N} (R^2 =0.588). Unlike the results of the OLS estimation presented in Column (1) in Table 3, the coefficient of the immigrant share in Column (1) in Table 4 is highly significant. Even though the estimation of equation (4) when u_i is excluded, yields a coefficient of the immigrant share that is statistically significant at all conventional significance levels, R^2 is quite low (R^2 = 0.229). Thus, I find evidence that immigration has had an overall negative impact on the wage growth of native workers in the construction sector.

7.1.2 The effect on native wages after the EU expansion, restricting the sample period to the time interval 2006-2011

Thus far, I have examined the impact of the immigrant share for the entire sample period, and done a re-estimation of some of the results in Bratsberg and Raaum (2012). In Figure 5, we saw that the Norwegian construction sector had experienced a boom in the employment of immigrant construction workers after the expansion of the EU in 2004 and 2007. Of particular interest is to investigate whether this boom has had a stronger downward pressure on native wages for the period from 2006 to 2011 than for the whole sample (Table 4). The OLS estimation of equation (4), within this time period, is presented in Table 5.

Table 5: *The impact of immigration on the log native wage*

Dependent variable	lnW_{ijt}^N	lnW_{ijt}^N
	(1)	(2)
Immigrant share	-0.079 (0.105)	-0.736*** (0.214)
Control variables: - age - age^2 - gender - years of schooling - activity	 Yes Yes Yes Yes Yes	 No Yes No Yes Yes
Period	2006-2011	2006-2011
Fixed effects: - group - year - individual	 Yes Yes No	 Yes Yes Yes
Observations	807,723	807,723
Individual fixed effects	0	207,050
Cluster	Yes	Yes
R^2	0.189	0.678

Notes: Standard errors are reported in parentheses and are clustered within 210 activity-by-year cells. *significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

In Column (1) we see that the OLS estimate of $\hat{\theta}$ = -0.079, and it is statistically insignificant. The estimate of the coefficient of the immigrant share, p_{jt} in Column (2) is negative, and so far the one with the strongest downward pressure on native log wages, lnW_{ijt}^N. Since the estimate $\hat{\theta}$ = -0.736 is highly significant, I can conclude that the impact of immigration on the log of native wages has been greater after 2005 than in the period from 1998 to 2005 (Table 3). In addition, this estimate is even higher than the aggregate estimate for the entire sample period (Table 4).

7.1.3 Measuring the effect of the EU expansion by a separate immigrant share variable

Next, I want to check whether the share of the new EU immigrants, denoted by $pnyeu_{jt}$, has a larger (absolute) impact on the native wages than the average immigrant share variable, p_{jt}. Countries included in this new variable are Bulgaria (B), Poland (P), Estonia (E), Czech Republic (CR), Romania (R), Hungary (H), Slovenia (Sl), Slovakia (S), Lithuania (Li) and Latvia (La). I define the variable $pnyeu_{jt}$ as

$$pnyeu_{jt} = \frac{N(B, E, CR, H, SI, S, Li, La, P, R)_{jt}}{N_{jt} + M_{jt}}$$

The denominator includes all native and immigrant construction workers, while the numerator captures the number of immigrants from the given countries. I choose to modify equation (4) in order to include the new variable, $pnyeu_{jt}$. Thus, the new baseline model reads

$$lnW_{ijt}^{N} = \theta p_{jt} + \delta pnyeu_{jt} + \beta' X_{it} + \gamma_j + \tau_t + u_i + \omega_{ijt} \tag{8}$$

Table 6 contains results of four estimations of equation (8), where different variables are controlled for. In Column (1) and (3), the variable representing the immigrant share, p_{jt} is excluded from the estimated equation. Further, Column (3) and (4) includes results for the estimation of equation (8), where individual fixed effects are excluded.

Table 6: *The impact of general immigration and new EU immigration on the log native wage*

Dependent variable	lnW_{ijt}^{N}	lnW_{ijt}^{N}	lnW_{ijt}^{N}	lnW_{ijt}^{N}
	(1)	(2)	(3)	(4)
Immigrant share	X	-0.062 (0.136)	X	0.183 (0.118)
New EU immigrant share	-0.667*** (0.106)	-0.619*** (0.152)	-0.378*** (0.065)	-0.518*** (0.119)
Control variables: - age - age^2 - gender - years of schooling - activity	 No Yes No Yes Yes	 No Yes No Yes Yes	 Yes Yes Yes Yes Yes	 Yes Yes Yes Yes Yes
Period	1998-2011 Full sample	1998-2011 Full sample	1998-2011 Full sample	1998-2011 Full sample
Fixed effects: - group - year - individual	 Yes Yes Yes	 Yes Yes Yes	 Yes Yes No	 Yes Yes No
Observations	1,760,032	1,760,032	1,760,032	1,760,032
Individual fixed effects	301,297	301,297	0	0
Cluster	Yes	Yes	Yes	Yes
R^2	0.588	0.588	0.566	0.229

Notes: Standard errors are reported in parentheses and are clustered within 210 activity-by-year cells.
*significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.
X indicates that the variable was not included in the regression.

Comparing the estimates of $pnyeu_{jt}$ that are presented in Table 6 indicates that the immigrants from the new EU countries account for most of the downward pressure on the wage growth of native workers in the construction sector. The regressions that include both the total immigrant share and the EU immigrant share show that the estimated coefficient on the former is not statistically significant. Meanwhile, I find a negative and highly significant effect of the coefficient of the share of new EU countries in the entire analysis. When I include individual fixed effects and the immigrant share variable as shown in Column (2), the isolated effect of EU immigrant share is estimated to be $\hat{\delta} = -0.619$. That means that, all other things equal, a one percentage point increase in the employment share of new EU member citizens leads to a 0.619 percent reduction in native wages.

7.1.4 The effect of the immigrant share on native wages, given various restrictions on the educational attainment

When I examine how differences in the education level change the effect of the immigrant share, p_{jt}on (the log of) daily wages in the construction sector, I find that the higher level of education, the smaller is the negative impact on native wages. Table 7 presents results of the estimation of equation (4), at different education levels for the period from 1998 to 2011. All estimations are performed including individual fixed effects since I noticed its importance for the precision of the estimates, when I analyzed the results that are reported in Table 3-6.

More specifically, when I ran the regression with individual fixed effects for the entire sample period 1998-2011, I obtained an estimate of the coefficient of p_{jt}equal to $\hat{\theta}$ = -0.622 (Column (2) in Table (4)). This estimate is almost the same as the ones shown in Column (1) and (4) in Table 7. In Column (4) I have 1,616,223 observations of construction workers who have completed schooling up to, and including high school level (6.Post-secondary non-tertiary education). The corresponding coefficient of the variable for the immigrant share is $\hat{\theta}$ = -0.665 in Column (4).

All estimates of θ in Table 7 except for the highly educated native workers (Column (2)), are statistically significant at the 1% significance level. In the high-education sample, the effect of the immigrant share is estimated to be $\hat{\theta}$ = -0.004 (in Column (2)) and is found to be statistically insignificant. This may indicate that immigrants with higher education do not contribute to a decrease in the wage growth of native workers with higher education, such as various university degrees. Meanwhile, when I restrict the sample such that I only account for construction workers who have completed schooling up to upper secondary education (excluding the final year), I find an estimate of θ equal to $\hat{\theta}$ = -0.756 (Column (5)). This estimate is the most negative one among all estimates in the empirical analysis that is presented in Table 7. A similar estimate is presented in Column (3), which includes workers who have obtained up to, and including the final year in the upper secondary education. In Table 2, I found that 38.42% of the individuals in my sample have completed schooling up to upper secondary school (excluding the final year). Thus, there seems to be a clear tendency that it is the least educated workers, which we can characterize as low-skilled, who have the strongest negative influence on native wages.

Table 7: *The impact of immigration on the log native wage, controlled for educational attainment*

Dependent variable	lnW_{ijt}^{N}	lnW_{ijt}^{N}	lnW_{ijt}^{N}	lnW_{ijt}^{N}	lnW_{ijt}^{N}
	(1)	(2)	(3)	(4)	(5)
Immigrant share	-0.634*** (0.109)	-0.004 (0.131)	-0.702*** (0.119)	-0.665*** (0.113)	-0.756*** (0.153)
Educational attainment: 2. Lower secondary education	X		X	X	X
3. Upper secondary education,	X		X	X	X
4. Upper secondary education, final year	X		X	X	
5. Post-secondary non-tertiary education	X			X	
6. First stage of tertiary education, undergraduate level	X	X			
7. First stage of tertiary education, graduate level		X			
8. Second stage of tertiary education		X			
Control variables: - age - age^2 - gender - activity	 No Yes No Yes	 No Yes No Yes	 No Yes No Yes	 No Yes No Yes	 No Yes No Yes
Period	1998-2011	1998-2011	1998-2011	1998-2011	1998-2011
Fixed effects: - group - year - individual	 Yes Yes Yes	 Yes Yes Yes	 Yes Yes Yes	 Yes Yes Yes	 Yes Yes Yes
Observations	1,734,351	144,333	1,520,677	1,616,223	677,796
Individual fixed effects	296,558	29,935	261,666	274,146	158,659
Cluster	Yes	Yes	Yes	Yes	Yes
R^2	0.582	0.728	0.568	0.570	0.619

Notes: Standard errors are reported in parentheses and are clustered within 210 activity-by-year cells.*significant at the 10% level, ** significant at the 5% level,***significant at the 1% level. X reflects included education level

7.1.5 Including the general application of tariff agreements

As argued in Section 2 and as illustrated in Figure 5, Norway attracted a considerable amount of labor migrants from the new EU countries after the enlargement of the union in 2004 and 2007. The step-wise implementation of the general application of tariff agreements in the Norwegian construction sector was fully accomplished January 1st, 2007. Since the majority of the sector was included in the arrangements by 2006, I want to examine whether this introduction has had any effect on the wage growth of native workers in excess of the other variables which I control for. For this reason, I construct an interaction variable that captures any additional effect of the general application of tariff agreements. First, I create a variable which captures this from 2006 and onwards, in the following way:

$$allmenn = year > 2005$$

which means that $allmenn = 1$ if year > 2005 and $allmenn = 0$ otherwise. The new variable of interest is the tariff immigrant share variable, which I denote $allmenn_p$.

$$allmenn_p = allmenn * p_{jt}$$

where $allmenn$ is multiplied by the immigrant share variable, p_{jt}. My baseline equation for the empirical analysis, equation (4), changes to

$$lnW_{ijt}^{N} = \theta p_{jt} + \varphi allmenn_p + \beta' X_{it} + \gamma_j + \tau_t + u_i + \omega_{ijt} \quad (9)$$

(9) is estimated on the full sample, from 1998 to 2011. Results are presented in Table 8.

Table 8: *The impact of immigration on the log native wage when controlling for minimum wages*

Dependent variable	lnW_{ijt}^{N}	lnW_{ijt}^{N}
	(1)	(2)
Immigrant share	0.125 (0.105)	-0.151 (0.126)
Tariff immigrant share	-0.306*** (0.065)	-0.348*** (0.066)
Control variables: - age - age^2 - gender - years of schooling - activity	 Yes Yes Yes Yes Yes	 No Yes No Yes Yes
Period	1998-2011	1998-2011
Fixed effects: - group - year - individual	 Yes Yes No	 Yes Yes Yes
Observations	1,760,556	1,760,556
Individual fixed effects	0	301,435
Cluster	Yes	Yes
R^2	0.565	0.588

Notes: Standard errors are reported in parentheses and are clustered within 210 activity-by-year cells. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

In Column (1) I have excluded the individual dummy variable, while it is included in the estimation of the results in Column (2). The OLS estimation of equation (9) yields insignificant estimates of the coefficient of the immigrant share variable, p_{jt}. Meanwhile, the impact of the new interaction variable is negative and significant at a 1% level, in both estimations. The results indicate that the general application of tariff agreements, captured by the tariff immigrant share variable, have a negative effect on the log native wage. This may imply that the agreements for the construction sector which were intended to prevent social dumping may not have had this effect. However, I do not find these results that convincing as the findings in Column (2) in Table 3 and 5, where the estimated impact of the immigrant share is $\hat{\theta} = -0.671$ and $\hat{\theta} = -0.736$, respectively. The comparison of the results from 1998-2005 provided in Table 3 and the results from 2006-2011 in Table 5 is a stronger test because the specification is more flexible. This is because everything is allowed to change, while the regressions in Table 8 which include interactions between p_{jt} and $allmenn$ are very restrictive since they require that only $p_{jt}$is allowed to change, while everything else is held unchanged over time.

7.1.6 Effects on income

So far, the dependent variable has been the log daily wage of natives. An alternative measure is the log income. The log of income for a native worker, i working in activity j in year t is constructed by taking the logarithm of the total pay/salary for each individual in the construction sector. The new dependent variable of interest is therefore the log income, lnI_{ijt}^{N} and it is given by

$$lnI_{ijt}^{N} = \ln(total\ pay_{ijt})$$

Table 9 provides the results of regressions controlling for most of the same variables as in the specifications in the previous tables of this thesis.

Table 9: *The impact of immigration on the log income*

Dependent variable	lnI_{ijt}^{N}	lnI_{ijt}^{N}
	(1)	(2)
Immigrant share	-0.147** (0.070)	-0.554*** (0.178)
Control variables: - age - age^2 - gender - years of schooling - activity	 Yes Yes Yes Yes Yes	 No Yes No Yes Yes
Period	1998-2011	1998-2011
Fixed effects: - group - year - individual	 Yes Yes No	 Yes Yes Yes
Observations	1,760,556	1,760,556
Individual fixed effects	0	301,435
Cluster	Yes	Yes
R^2	0.253	0.652

Notes: Standard errors are reported in parentheses and are clustered within 210 activity-by-year cells. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

The regression results presented in Column (1) in Table 9 show similar qualitative results as the tables 3-5, but the estimates are slightly less negative. Both estimates of θ in Table 9 are statistically significant at the 5 % level, while the estimate in Column (2) is also significant 1% significance level. When I ran the regression with 301,435 individual fixed effects for the entire sample period 1998-2011, I obtained an estimate of the coefficient of p_{jt}equal to $\hat{\theta}$ = -0.554 (Column (2)). Thus, when comparing these results with the previous analyses, using the log income as the dependent variable, does not provide any additional insight.

8 Conclusion

Labor migration to Norway has the last decades contributed to an incredible increase in the country's aggregate labor supply. Since Norway was largely unaffected by the international economic downturn during and after the financial crisis, the country emerged as a very attractive destination for European migrant workers. The country experienced record levels of immigration after the first enlargement of the EU took place in 2004. It is reasonable to expect that this has had impacts on the evolution of wages and employment among native workers. Such effects are not always easy to trace out in the available data, and identification of causal effects requires good data as well as correct empirical approaches.

According to standard economic theory, an influx of immigrants will cause a positive shift in the labor supply curve which creates a downward pressure on wages. The aggregate effect on the labor market will depend on the elasticity of the demand curve. For this reason, wages will decrease more when the demand curve is inelastic than when it is more elastic.

In this thesis, I study the effects of labor migration on wages within the Norwegian construction sector, by utilizing the theoretical and empirical strategies developed in Bratsberg and Raaum (2012). I apply the national skill cell approach in the empirical analysis, and my results corroborate with their main findings. The wage sample is based on registry data, and specifies the distribution of workers according to different levels of educational attainment. It indicates that persons working in the construction sector in general can be considered as low-skilled rather than high-skilled. The two activities, general contractors projects (including bridges and tunnels) and electrical installation are by far the largest in terms of employment in the overall sector. The immigrant employment share follows a stable path around 10% from 1998 to 2004-2005. Thereafter, it increases sharply from 2005 to 2007 and stabilizes at approximately 20%. I find that for professions subject to licensing requirements within this sector, there seems to be very small or no change in the immigrant employment share. This is evident for the main activities electrical installation and plumbing. Meanwhile, I find that the largest increase in the relative employment of immigrants in the activity comprising carpenter services, where the immigrant employment share had increased from 10% in 1998 to almost 40% in 2011.

In the empirical analysis I detect the importance of the inclusion of individual fixed effects in the regressions. This implies that I correct for bias created by native attrition by considering correlation between unobserved individual wage determinants and within-group change in the immigrant share. The operationalization results in negative and highly statistically significant estimates on the effect on native daily wages throughout most of the analysis. The indication is that the positive correlation between the individual error component (i.e. the individual fixed effects) and the immigrant share is caused by systematic attrition of low-wage native workers from activities with growth in immigrant employment.

I find that the higher level of education, the smaller is the negative impact on native wages. By extracting the newly attached Eastern European member countries into a separate immigrant employment share variable, the econometric results indicate that workers from these countries account for most of the downward pressure on the wage growth of native workers in the construction sector. I conclude that the impact of immigration on the log of native wages has been greater after 2005 than in the period from 1998 to 2005.

Further research on the long-term consequences of labor migration where other aspects than the impact of immigrant induced labor supply shocks on native wages are examined, may shed a more positive light than the findings of this thesis.

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Appendix 1

This table presents an overview of the classification of the 15 main groups in the construction sector which I use in the empirical analysis in this thesis.

Activity	SIC2002 codes (1998-2008)	SIC2007 codes (2009-2011)	Certification common
1. Site Preparation	45100,45120	43110,43120	Yes
2. General contractors projects (incl. bridges, tunnels)	45211	41200	No
3. Civil engineering	45212	42130, 42220, 42210,42910	Yes
4. Sheet metal	45221	43911	No
5. Other roofing	45229	43919	No
6. Road	45230,45240	42120,42990,42 110	Yes
7. Renting of equipment with operator and other special building construction	45250,45500	43990	No
8. Electrical installation	45310	43210	Yes
9. Plumbing	45330	43220	Yes
10. Other installation	45340,45320	43290	Yes
11. Carpenter services, plastering	45420,45410	43320,43310	No
12. Flooring	45430	43330	No
13. Painting	45441	43341	No
14. Glass	45442	43342	Yes
15. Other building completion	45450	43390	No

Appendix 2

In this appendix I provide the complete results obtained from the estimations in Stata.

Re-estimating a part of the analysis in Bratsberg and Raaum (2012) for the period from 1998 to 2005

```
reg lnwage p age age2 i.educ sex i.act i.year if year<2006, cl(act_yr)

Linear regression                                      Number of obs =  952833
                                                       F( 31,    119) = 1018.27
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1737
                                                       Root MSE      =  .56047

                              (Std. Err. adjusted for 120 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.1381713   .1542586    -0.90   0.372    -.4436187    .1672761
         age |   .0729654   .0016577    44.02   0.000     .0696831    .0762478
        age2 |  -.0008016   .0000197   -40.60   0.000    -.0008407   -.0007625
             |
        educ |
          3  |   .1098048    .007921    13.86   0.000     .0941204    .1254891
          4  |    .195492   .0078999    24.75   0.000     .1798494    .2111347
          5  |   .2305067   .0091672    25.14   0.000     .2123546    .2486587
          6  |   .3514782   .0134113    26.21   0.000     .3249224     .378034
          7  |   .5660474   .0275875    20.52   0.000     .5114214    .6206734
          8  |   .6974194   .0302485    23.06   0.000     .6375243    .7573145
             |
         sex |  -.2264092   .0061411   -36.87   0.000    -.2385691   -.2142493
             |
         act |
          2  |   -.018767   .0123499    -1.52   0.131    -.0432211     .005687
          3  |   .1849488   .0231581     7.99   0.000     .1390935    .2308042
          4  |  -.0825418   .0107587    -7.67   0.000    -.1038452   -.0612384
          5  |  -.0059683   .0127363    -0.47   0.640    -.0311875    .0192509
          6  |   .0740207   .0089543     8.27   0.000     .0562904    .0917511
          7  |   .0300353   .0182604     1.64   0.103    -.0061221    .0661926
          8  |   .0061907   .0075945     0.82   0.417    -.0088472    .0212286
          9  |   .0261353   .0076373     3.42   0.001     .0110127    .0412579
         10  |   .0489473   .0531449     0.92   0.359    -.0562849    .1541794
         11  |  -.1538256   .0183209    -8.40   0.000    -.1901028   -.1175484
         12  |  -.0297268   .0259894    -1.14   0.255    -.0811884    .0217347
         13  |  -.0911574   .0235051    -3.88   0.000    -.1376999   -.0446149
         14  |  -.0283785   .0109981    -2.58   0.011    -.0501559    -.006601
         15  |  -.0330432   .0229122    -1.44   0.152    -.0784117    .0123253
             |
        year |
       1999  |   .0385722    .009478     4.07   0.000     .0198048    .0573396
       2000  |    .045221     .00952     4.75   0.000     .0263705    .0640715
       2001  |   .1094185   .0067815    16.13   0.000     .0959905    .1228464
       2002  |    .149087   .0058031    25.69   0.000     .1375964    .1605777
       2003  |    .178962   .0058198    30.75   0.000     .1674383    .1904857
       2004  |   .2204228   .0067489    32.66   0.000     .2070593    .2337863
       2005  |   .2683716   .0075272    35.65   0.000     .2534671    .2832761
             |
       _cons |   4.818591   .0377907   127.51   0.000     4.743762     4.89342
------------------------------------------------------------------------------
```

```
areg lnwage p age2 i.act i.year if year<2006, absorb(id) cl(act_yr)

Linear regression, absorbing indicators          Number of obs   =     952833
                                                 F(  23,    119) =      93.70
                                                 Prob > F        =     0.0000
                                                 R-squared       =     0.6124
                                                 Adj R-squared   =     0.4939
                                                 Root MSE        =     0.4386

                               (Std. Err. adjusted for 120 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |   -.671014     .23715    -2.83   0.005    -1.140595   -.2014333
        age2 |  -.0013968   .0001002   -13.94   0.000    -.0015952   -.0011983
             |
         act |
          2  |   .0581343    .026529     2.19   0.030     .0056041    .1106644
          3  |   .1713604   .0508767     3.37   0.001     .0706194    .2721015
          4  |  -.0182011   .0275973    -0.66   0.511    -.0728465    .0364444
          5  |   .0466429   .0344039     1.36   0.178    -.0214803     .114766
          6  |   .0457092   .0217436     2.10   0.038     .0026547    .0887637
          7  |   .0710883   .0337041     2.11   0.037     .0043507    .1378258
          8  |  -.0379023   .0233372    -1.62   0.107    -.0841123    .0083078
          9  |  -.0150785   .0244971    -0.62   0.539    -.0635853    .0334283
         10  |   .1868212   .0880093     2.12   0.036     .0125539    .3610884
         11  |   .0344599   .0328194     1.05   0.296    -.0305259    .0994457
         12  |   .1142689   .0438055     2.61   0.010     .0275296    .2010082
         13  |   .0732042   .0456633     1.60   0.112    -.0172137    .1636221
         14  |   .0312161     .05675     0.55   0.583    -.0811545    .1435868
         15  |   .1198751   .0478771     2.50   0.014     .0250738    .2146765
             |
        year |
        1999 |   .1550744   .0157704     9.83   0.000     .1238474    .1863015
        2000 |   .2768765   .0191832    14.43   0.000     .2388917    .3148612
        2001 |   .4600581   .0258441    17.80   0.000     .4088841     .511232
        2002 |   .6222452   .0322212    19.31   0.000     .5584441    .6860464
        2003 |   .7665868   .0394562    19.43   0.000     .6884596     .844714
        2004 |   .9365496   .0474059    19.76   0.000     .8426811    1.030418
        2005 |   1.122427   .0546793    20.53   0.000     1.014157    1.230698
             |
       _cons |   8.240859   .1341396    61.43   0.000     7.975249    8.506468
-------------+----------------------------------------------------------------
          id |   absorbed                                    (223068 categories)
```

The entire period (1998-2011):

```
reg lnwage p age age2 i.educ sex i.act i.year, cl(act_yr)

Linear regression                                      Number of obs = 1760556
                                                       F( 37,   209) = 1670.94
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2289
                                                       Root MSE      =  .56519

                               (Std. Err. adjusted for 210 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.2882285   .0722037    -3.99   0.000    -.4305694   -.1458875
         age |   .0717104   .0010796    66.43   0.000     .0695822    .0738386
        age2 |  -.0007804   .0000126   -61.87   0.000    -.0008053   -.0007555
             |
        educ |
          3  |   .1110879     .00648    17.14   0.000     .0983133    .1238624
          4  |    .202249   .0070056    28.87   0.000     .1884382    .2160598
          5  |   .2477924   .0080353    30.84   0.000     .2319517    .2636331
          6  |   .3701797   .0112241    32.98   0.000     .3480529    .3923066
          7  |   .6106525   .0239885    25.46   0.000     .5633622    .6579429
          8  |   .6698275   .0279801    23.94   0.000     .6146681    .7249868
             |
         sex |  -.2161283   .0050437   -42.85   0.000    -.2260714   -.2061852
             |
         act |
          2  |  -.0160214    .008652    -1.85   0.065    -.0330778     .001035
          3  |   .1748948   .0128075    13.66   0.000     .1496464    .2001432
          4  |   -.077092    .007856    -9.81   0.000    -.0925791   -.0616049
          5  |   .0235508   .0134774     1.75   0.082    -.0030183    .0501199
          6  |   .0886592    .011542     7.68   0.000     .0659054    .1114129
          7  |   .0421037   .0118006     3.57   0.000     .0188403    .0653671
          8  |  -.0010226   .0060773    -0.17   0.867    -.0130032     .010958
          9  |   .0114979   .0068878     1.67   0.097    -.0020806    .0250764
         10  |   .0938011   .0243699     3.85   0.000     .0457589    .1418434
         11  |  -.1544884   .0153615   -10.06   0.000    -.1847718    -.124205
         12  |  -.0213505   .0167602    -1.27   0.204    -.0543912    .0116902
         13  |  -.0877465   .0167039    -5.25   0.000    -.1206761   -.0548168
         14  |  -.0529399   .0095856    -5.52   0.000    -.0718369    -.034043
         15  |  -.0005482   .0163209    -0.03   0.973    -.0327228    .0316265
             |
        year |
       1999  |   .0387158   .0137718     2.81   0.005     .0115664    .0658652
       2000  |   .0441633   .0125507     3.52   0.001      .019421    .0689055
       2001  |   .1087847   .0117649     9.25   0.000     .0855916    .1319778
       2002  |   .1501411   .0090651    16.56   0.000     .1322703    .1680118
       2003  |   .1790831    .009599    18.66   0.000     .1601599    .1980064
       2004  |   .2210295   .0088886    24.87   0.000     .2035067    .2385524
       2005  |   .2704792   .0093102    29.05   0.000     .2521253    .2888332
       2006  |    .334748   .0090099    37.15   0.000      .316986    .3525101
       2007  |   .4123501   .0119437    34.52   0.000     .3888046    .4358956
       2008  |    .477077   .0144918    32.92   0.000     .4485083    .5056458
       2009  |   .4800675   .0131523    36.50   0.000     .4541394    .5059956
       2010  |   .5225202   .0136705    38.22   0.000     .4955704      .54947
       2011  |   .5696101   .0156782    36.33   0.000     .5387023    .6005178
             |
       _cons |   4.838573   .0255192   189.61   0.000     4.788265    4.888881
```

```
areg lnwage p age2 i.act i.year, absorb(id) cl(act_yr)

Linear regression, absorbing indicators          Number of obs   =    1760556
                                                 F(  29,    209) =     192.23
                                                 Prob > F        =     0.0000
                                                 R-squared       =     0.5878
                                                 Adj R-squared   =     0.5026
                                                 Root MSE        =     0.4539

                                (Std. Err. adjusted for 210 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.622136   .1079562    -5.76   0.000    -.8349587   -.4093133
        age2 | -.0011044   .0000502   -21.99   0.000    -.0012034   -.0010054
             |
         act |
          2  |   .0566785   .0137551     4.12   0.000     .0295621     .083795
          3  |    .131948   .0238382     5.54   0.000     .0849538    .1789422
          4  |  -.0059363   .0173597    -0.34   0.733    -.0401589    .0282862
          5  |   .1047141   .0221753     4.72   0.000     .0609981    .1484301
          6  |   .0727576   .0099211     7.33   0.000     .0531994    .0923158
          7  |   .0993839   .0171705     5.79   0.000     .0655343    .1332335
          8  |  -.0278291   .0128943    -2.16   0.032    -.0532486   -.0024096
          9  |  -.0143992   .0142165    -1.01   0.312    -.0424253     .013627
         10  |   .1701861   .0386927     4.40   0.000     .0939082    .2464641
         11  |   .0293984   .0218186     1.35   0.179    -.0136144    .0724112
         12  |   .0973475   .0301366     3.23   0.001     .0379369    .1567581
         13  |   .0853226   .0272024     3.14   0.002     .0316963    .1389488
         14  |  -.0025531   .0266527    -0.10   0.924    -.0550957    .0499895
         15  |   .1245544   .0247828     5.03   0.000     .0756981    .1734108
             |
        year |
        1999 |   .1316908   .0151888     8.67   0.000     .1017478    .1616338
        2000 |   .2295761   .0156303    14.69   0.000     .1987629    .2603894
        2001 |   .3877732   .0174074    22.28   0.000     .3534565    .4220899
        2002 |   .5234607   .0186602    28.05   0.000     .4866744     .560247
        2003 |   .6397539   .0216583    29.54   0.000     .5970571    .6824506
        2004 |   .7788005   .0256133    30.41   0.000     .7283071     .829294
        2005 |   .9306221   .0301204    30.90   0.000     .8712433    .9900009
        2006 |   1.099975   .0340817    32.27   0.000     1.032787    1.167163
        2007 |   1.295645   .0390456    33.18   0.000     1.218671    1.372619
        2008 |   1.474946   .0438271    33.65   0.000     1.388546    1.561346
        2009 |   1.575375   .0480381    32.79   0.000     1.480674    1.670076
        2010 |   1.712805   .0519262    32.99   0.000     1.610438    1.815171
        2011 |   1.867716   .0575137    32.47   0.000     1.754335    1.981097
             |
       _cons |   7.571202   .0552862   136.95   0.000     7.462212    7.680192
-------------+----------------------------------------------------------------
          id |   absorbed                                (301435 categories)
```

Period 2006-2011

```
reg lnwage p age age2 i.educ sex i.act i.year if year>2005, cl(act_yr)

Linear regression                                      Number of obs =  807723
                                                       F( 29,    89) = 1589.03
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1891
                                                       Root MSE      =  .57013

                                 (Std. Err. adjusted for 90 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.0794595   .1045623    -0.76   0.449    -.2872226    .1283036
         age |    .070251    .001386    50.69   0.000     .0674971    .0730049
        age2 |  -.0007569   .0000154   -49.03   0.000    -.0007876   -.0007263
             |
        educ |
          3  |   .1095193   .0111449     9.83   0.000     .0873746     .131664
          4  |   .2091867   .0115951    18.04   0.000     .1861474    .2322259
          5  |   .2652025   .0122039    21.73   0.000     .2409536    .2894515
          6  |   .3901888    .017001    22.95   0.000     .3564082    .4239694
          7  |   .6627036   .0330403    20.06   0.000     .5970532    .7283541
          8  |    .632287   .0514837    12.28   0.000       .52999     .734584
             |
         sex |  -.2020798   .0074623   -27.08   0.000    -.2169071   -.1872524
             |
         act |
          2  |  -.0523034   .0149578    -3.50   0.001    -.0820242   -.0225825
          3  |   .1387561   .0094636    14.66   0.000     .1199521    .1575602
          4  |  -.0925445   .0123929    -7.47   0.000     -.117169   -.0679201
          5  |   .0202852   .0200939     1.01   0.315     -.019641    .0602114
          6  |   .1246303   .0106019    11.76   0.000     .1035645    .1456962
          7  |   .0014087   .0189153     0.07   0.941    -.0361756     .038993
          8  |  -.0010745   .0091242    -0.12   0.907     -.019204    .0170551
          9  |  -.0125386   .0085597    -1.46   0.146    -.0295466    .0044694
         10  |    .029572   .0294313     1.00   0.318    -.0289073    .0880513
         11  |  -.2267628   .0250708    -9.04   0.000     -.276578   -.1769475
         12  |  -.0836511   .0277871    -3.01   0.003    -.1388635   -.0284386
         13  |   -.169993    .029327    -5.80   0.000    -.2282651   -.1117208
         14  |  -.0896366    .009894    -9.06   0.000    -.1092958   -.0699774
         15  |  -.0167609   .0248372    -0.67   0.502    -.0661118      .03259
             |
        year |
       2007  |   .0686826   .0075711     9.07   0.000      .053639    .0837263
       2008  |   .1296258   .0112334    11.54   0.000     .1073052    .1519463
       2009  |   .1353738   .0072413    18.69   0.000     .1209854    .1497621
       2010  |   .1776266   .0081857    21.70   0.000     .1613618    .1938914
       2011  |    .222422   .0109478    20.32   0.000      .200669     .244175
             |
       _cons |   5.177594   .0363992   142.24   0.000      5.10527    5.249919
------------------------------------------------------------------------------
```

```
areg lnwage p age2 i.act i.year if year>2005, absorb(id) cl(act_yr)

Linear regression, absorbing indicators          Number of obs   =     807723
                                                 F(  21,     89) =      44.22
                                                 Prob > F        =     0.0000
                                                 R-squared       =     0.6778
                                                 Adj R-squared   =     0.5668
                                                 Root MSE        =     0.4167

                                (Std. Err. adjusted for 90 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.7357866   .2140751    -3.44   0.001    -1.161149   -.3104239
        age2 |  -.0015252   .0001165   -13.09   0.000    -.0017567   -.0012938
             |
         act |
          2  |   .0619158   .0328067     1.89   0.062    -.0032704    .1271021
          3  |   .0812147   .0235168     3.45   0.001     .0344873    .1279422
          4  |  -.0340421   .0334641    -1.02   0.312    -.1005346    .0324505
          5  |   .1975064   .0499656     3.95   0.000     .0982257     .296787
          6  |   .0686785   .0150299     4.57   0.000     .0388144    .0985425
          7  |   .1341146   .0424499     3.16   0.002     .0497675    .2184618
          8  |  -.0559465   .0189663    -2.95   0.004    -.0936322   -.0182608
          9  |  -.0422927   .0191079    -2.21   0.029    -.0802597   -.0043257
         10  |   .2305187   .0652322     3.53   0.001     .1009037    .3601338
         11  |   .0836808   .0562946     1.49   0.141    -.0281753    .1955369
         12  |   .0955935   .0570809     1.67   0.098     -.017825    .2090119
         13  |   .1321828   .0647539     2.04   0.044     .0035181    .2608475
         14  |   .0049873   .0440304     0.11   0.910    -.0825001    .0924747
         15  |    .181308    .056495     3.21   0.002     .0690536    .2935625
             |
        year |
       2007  |   .2242212   .0187894    11.93   0.000     .1868871    .2615552
       2008  |   .4330828   .0270038    16.04   0.000     .3794269    .4867387
       2009  |   .5632137   .0329657    17.08   0.000     .4977117    .6287158
       2010  |   .7312222    .041487    17.63   0.000     .6487884     .813656
       2011  |   .9184375   .0540103    17.00   0.000     .8111203    1.025755
             |
       _cons |   8.953906    .166395    53.81   0.000     8.623283     9.28453
-------------+----------------------------------------------------------------
          id |   absorbed                                   (207050 categories)
```

Measuring the effect of the EU expansion by a separate immigrant share variable

```
areg lnwage p pnyeu age2 i.act i.year, absorb(id) cl(act_yr)


Linear regression, absorbing indicators          Number of obs   =    1760032
                                                 F(  30,    208) =     213.92
                                                 Prob > F        =     0.0000
                                                 R-squared       =     0.5879
                                                 Adj R-squared   =     0.5028
                                                 Root MSE        =     0.4539

                              (Std. Err. adjusted for 209 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.0622561   .1358154    -0.46   0.647    -.3300072    .2054951
       pnyeu |  -.6191394    .151724    -4.08   0.000    -.9182533   -.3200255
        age2 |  -.0011107    .000049   -22.69   0.000    -.0012072   -.0010142
             |
         act |
          2  |   .0267845   .0144578     1.85   0.065     -.001718    .0552871
          3  |   .0876517    .022981     3.81   0.000     .0423462    .1329572
          4  |  -.0277124   .0183884    -1.51   0.133    -.0639639     .008539
          5  |   .0682311   .0225718     3.02   0.003     .0237323    .1127299
          6  |    .070365   .0110157     6.39   0.000     .0486483    .0920817
          7  |   .0461128   .0180968     2.55   0.012     .0104362    .0817894
          8  |  -.0324266   .0135063    -2.40   0.017    -.0590533   -.0057999
          9  |  -.0359857   .0155449    -2.31   0.022    -.0666314     -.00534
         10  |   .0422554   .0393894     1.07   0.285    -.0353983    .1199091
         11  |  -.0179047   .0203918    -0.88   0.381    -.0581058    .0222963
         12  |   .0274487   .0310237     0.88   0.377    -.0337125    .0886099
         13  |   .0065412   .0281183     0.23   0.816    -.0488921    .0619745
         14  |  -.0152246   .0276184    -0.55   0.582    -.0696725    .0392233
         15  |   .0551502   .0247754     2.23   0.027     .0063071    .1039933
             |
        year |
        1999 |   .1320291   .0145385     9.08   0.000     .1033675    .1606907
        2000 |    .233516   .0156848    14.89   0.000     .2025944    .2644376
        2001 |   .3908134   .0172724    22.63   0.000      .356762    .4248649
        2002 |   .5238048   .0185711    28.21   0.000     .4871931    .5604164
        2003 |   .6451687    .021186    30.45   0.000     .6034019    .6869355
        2004 |    .786018   .0249079    31.56   0.000     .7369138    .8351223
        2005 |   .9394498   .0289144    32.49   0.000      .882447    .9964526
        2006 |    1.10881   .0330201    33.58   0.000     1.043713    1.173907
        2007 |   1.303446   .0380818    34.23   0.000     1.228371    1.378522
        2008 |   1.480811   .0427486    34.64   0.000     1.396535    1.565087
        2009 |   1.585032   .0463686    34.18   0.000     1.493619    1.676444
        2010 |   1.725332   .0501787    34.38   0.000     1.626408    1.824257
        2011 |   1.882461   .0556237    33.84   0.000     1.772802     1.99212
             |
       _cons |   7.551294   .0554418   136.20   0.000     7.441994    7.660594
-------------+----------------------------------------------------------------
          id |   absorbed                                  (301297 categories)
```

```
areg lnwage pnyeu age2 i.act i.year, absorb(id) cl(act_yr)


Linear regression, absorbing indicators          Number of obs   =    1760032
                                                 F(  29,    208) =     224.24
                                                 Prob > F        =     0.0000
                                                 R-squared       =     0.5879
                                                 Adj R-squared   =     0.5028
                                                 Root MSE        =     0.4539

                               (Std. Err. adjusted for 209 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       pnyeu |  -.6665531   .1058062    -6.30   0.000    -.8751431   -.4579631
        age2 |  -.0011109    .000049   -22.68   0.000    -.0012075   -.0010143
             |
         act |
          2  |   .0225608   .0109344     2.06   0.040     .0010044    .0441172
          3  |   .0828263   .0201431     4.11   0.000     .0431155    .1225371
          4  |  -.0305395   .0172966    -1.77   0.079    -.0646387    .0035597
          5  |   .0635954   .0198197     3.21   0.002      .024522    .1026687
          6  |   .0705087   .0111901     6.30   0.000      .048448    .0925693
          7  |   .0392698   .0112042     3.50   0.001     .0171815     .061358
          8  |   -.032618   .0135692    -2.40   0.017    -.0593687   -.0058673
          9  |  -.0382219   .0148756    -2.57   0.011    -.0675481   -.0088957
         10  |    .026517   .0236157     1.12   0.263    -.0200397    .0730738
         11  |  -.0243618   .0151726    -1.61   0.110    -.0542735    .0055499
         12  |   .0187326   .0240867     0.78   0.438    -.0287527     .066218
         13  |  -.0034071    .018206    -0.19   0.852    -.0392991    .0324848
         14  |  -.0164751   .0275088    -0.60   0.550    -.0707069    .0377567
         15  |   .0472806    .018121     2.61   0.010     .0115562     .083005
             |
        year |
       1999  |   .1319776   .0144821     9.11   0.000      .103427    .1605281
       2000  |   .2338313   .0156436    14.95   0.000     .2029909    .2646717
       2001  |    .390958   .0173461    22.54   0.000     .3567614    .4251546
       2002  |   .5235896   .0185839    28.17   0.000     .4869526    .5602266
       2003  |   .6454554   .0212878    30.32   0.000     .6034879    .6874228
       2004  |   .7863368    .025012    31.44   0.000     .7370274    .8356463
       2005  |   .9396954   .0289909    32.41   0.000     .8825417    .9968492
       2006  |   1.108655   .0330072    33.59   0.000     1.043583    1.173726
       2007  |   1.302419   .0377816    34.47   0.000     1.227935    1.376903
       2008  |   1.479255   .0420748    35.16   0.000     1.396308    1.562203
       2009  |   1.584023   .0461442    34.33   0.000     1.493053    1.674993
       2010  |   1.724512   .0500458    34.46   0.000      1.62585    1.823174
       2011  |    1.88157   .0555249    33.89   0.000     1.772106    1.991033
             |
       _cons |   7.548845   .0543554   138.88   0.000     7.441687    7.656003
-------------+----------------------------------------------------------------
          id |   absorbed                                   (301297 categories)
```

```
reg lnwage pnyeu age age2 i.educ sex i.act i.year, cl(act_yr)

Linear regression                                      Number of obs = 1760032
                                                       F( 37,   208) = 1491.81
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2291
                                                       Root MSE      =  .56513

                               (Std. Err. adjusted for 209 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       pnyeu |  -.3779078   .0653288    -5.78   0.000    -.5066992   -.2491164
         age |   .0717353    .001078    66.54   0.000       .06961    .0738606
        age2 |  -.0007807   .0000126   -61.90   0.000    -.0008055   -.0007558
             |
        educ |
          3  |   .1112635    .006484    17.16   0.000     .0984806    .1240464
          4  |   .2024696   .0070035    28.91   0.000     .1886626    .2162766
          5  |   .2479573   .0080448    30.82   0.000     .2320976     .263817
          6  |   .3704582   .0112181    33.02   0.000     .3483425    .3925739
          7  |   .6110662   .0239195    25.55   0.000     .5639104     .658222
          8  |   .6705166   .0279921    23.95   0.000      .615332    .7257011
             |
         sex |  -.2157402   .0050456   -42.76   0.000    -.2256871   -.2057932
             |
         act |
          2  |  -.0292582   .0050507    -5.79   0.000    -.0392152   -.0193011
          3  |   .1506336   .0102711    14.67   0.000     .1303848    .1708825
          4  |  -.0878791   .0067783   -12.96   0.000    -.1012421   -.0745161
          5  |   .0055033   .0099215     0.55   0.580    -.0140562    .0250629
          6  |    .087946   .0096883     9.08   0.000     .0688461    .1070459
          7  |   .0174944   .0060241     2.90   0.004     .0056182    .0293707
          8  |  -.0039028   .0061227    -0.64   0.525    -.0159733    .0081678
          9  |  -.0001117   .0073922    -0.02   0.988    -.0146849    .0144615
         10  |   .0310033   .0142939     2.17   0.031     .0028238    .0591827
         11  |   -.174349   .0094878   -18.38   0.000    -.1930535   -.1556444
         12  |   -.054492   .0107632    -5.06   0.000    -.0757108   -.0332731
         13  |  -.1256043   .0083855   -14.98   0.000    -.1421357   -.1090729
         14  |  -.0585638    .010765    -5.44   0.000    -.0797863   -.0373414
         15  |  -.0343811    .012207    -2.82   0.005    -.0584464   -.0103159
             |
        year |
        1999 |   .0386046   .0135426     2.85   0.005     .0119063     .065303
        2000 |   .0457398   .0119159     3.84   0.000     .0222485    .0692312
        2001 |   .1097954    .011491     9.55   0.000     .0871416    .1324491
        2002 |   .1494556   .0087599    17.06   0.000      .132186    .1667252
        2003 |   .1807384    .008742    20.67   0.000     .1635042    .1979726
        2004 |   .2237001   .0084108    26.60   0.000     .2071187    .2402815
        2005 |   .2743072   .0087578    31.32   0.000     .2570417    .2915727
        2006 |   .3393322   .0088589    38.30   0.000     .3218676    .3567969
        2007 |   .4181407   .0120181    34.79   0.000     .3944478    .4418336
        2008 |   .4823904   .0143133    33.70   0.000     .4541728    .5106081
        2009 |   .4866256   .0119791    40.62   0.000     .4630095    .5102417
        2010 |    .530525   .0123403    42.99   0.000     .5061968    .5548532
        2011 |   .5792786   .0150371    38.52   0.000     .5496341    .6089232
             |
       _cons |   4.823405   .0245981   196.09   0.000     4.774911    4.871898
------------------------------------------------------------------------------
```

```
reg lnwage p pnyeu age age2 i.educ sex i.act i.year, cl(act_yr)

Linear regression                                      Number of obs = 1760032
                                                       F( 38,   208) = 1470.82
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2291
                                                       Root MSE      =  .56513

                                 (Std. Err. adjusted for 209 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |   .1825671   .1183876     1.54   0.125    -.0508263    .4159604
       pnyeu |  -.5178185    .118626    -4.37   0.000    -.7516818   -.2839552
         age |   .0717256   .0010788    66.49   0.000     .0695989    .0738523
        age2 |  -.0007805   .0000126   -61.84   0.000    -.0008054   -.0007556
             |
        educ |
          3  |   .1112624   .0064848    17.16   0.000     .0984781    .1240466
          4  |   .2024947   .0070023    28.92   0.000     .1886901    .2162992
          5  |   .2479621   .0080463    30.82   0.000     .2320994    .2638249
          6  |   .3704499   .0112192    33.02   0.000      .348332    .3925678
          7  |   .6110698   .0239088    25.56   0.000     .5639352    .6582045
          8  |   .6705044   .0280012    23.95   0.000     .6153019     .725707
             |
         sex |  -.2156905   .0050455   -42.75   0.000    -.2256373   -.2057436
             |
         act |
          2  |  -.0420775   .0090396    -4.65   0.000    -.0598984   -.0242566
          3  |   .1360827   .0118888    11.45   0.000     .1126447    .1595207
          4  |  -.0964672    .008819   -10.94   0.000    -.1138533   -.0790812
          5  |   -.008687   .0125484    -0.69   0.490    -.0334254    .0160513
          6  |   .0885637   .0093696     9.45   0.000     .0700922    .1070352
          7  |  -.0022865   .0135688    -0.17   0.866    -.0290365    .0244634
          8  |   -.004086   .0061723    -0.66   0.509    -.0162542    .0080822
          9  |  -.0065642   .0086029    -0.76   0.446    -.0235242    .0103959
         10  |  -.0162289   .0319716    -0.51   0.612    -.0792588    .0468011
         11  |   -.194248   .0150672   -12.89   0.000    -.2239519   -.1645441
         12  |  -.0803222   .0199144    -4.03   0.000    -.1195822   -.0410622
         13  |  -.1551946    .020613    -7.53   0.000    -.1958317   -.1145575
         14  |  -.0621437   .0116679    -5.33   0.000    -.0851462   -.0391413
         15  |  -.0566928    .018456    -3.07   0.002    -.0930777   -.0203079
             |
        year |
       1999  |   .0383326   .0130699     2.93   0.004     .0125662    .0640989
       2000  |   .0465501   .0121799     3.82   0.000     .0225383     .070562
       2001  |   .1100771   .0113874     9.67   0.000     .0876276    .1325266
       2002  |   .1485913   .0086645    17.15   0.000     .1315098    .1656728
       2003  |   .1812874   .0085416    21.22   0.000     .1644481    .1981266
       2004  |   .2243133   .0082349    27.24   0.000     .2080787    .2405478
       2005  |   .2746618   .0085059    32.29   0.000     .2578929    .2914307
       2006  |   .3384657   .0086299    39.22   0.000     .3214525     .355479
       2007  |   .4147302   .0117656    35.25   0.000     .3915351    .4379252
       2008  |   .4774012   .0141818    33.66   0.000     .4494427    .5053598
       2009  |   .4831892   .0111609    43.29   0.000     .4611862    .5051922
       2010  |   .5275891    .011418    46.21   0.000     .5050792     .550099
       2011  |   .5760983   .0143668    40.10   0.000     .5477752    .6044215
             |
       _cons |   4.815833   .0248616   193.71   0.000      4.76682    4.864846
------------------------------------------------------------------------------
```

Decomposing the educational attainment and examining how this changes the estimate of the coefficient of the immigrant employment share variable.

```
areg lnwage p age2 i.act i.year if educ<7, absorb(id) cl(act_yr)

Linear regression, absorbing indicators          Number of obs   =    1734351
                                                 F(  29,    209) =     195.72
                                                 Prob > F        =     0.0000
                                                 R-squared       =     0.5822
                                                 Adj R-squared   =     0.4960
                                                 Root MSE        =     0.4553

                              (Std. Err. adjusted for 210 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.6344224   .1087654    -5.83   0.000    -.8488402   -.4200045
        age2 |  -.0011048   .0000509   -21.71   0.000    -.0012051   -.0010045
             |
         act |
          2  |   .0549687   .0136912     4.01   0.000     .0279781    .0819594
          3  |   .1340508   .0242187     5.54   0.000     .0863066     .181795
          4  |   -.006603    .017234    -0.38   0.702    -.0405778    .0273718
          5  |   .1027836   .0223284     4.60   0.000     .0587659    .1468013
          6  |   .0745283   .0095589     7.80   0.000     .0556841    .0933724
          7  |   .1009199   .0171007     5.90   0.000     .0672078    .1346319
          8  |  -.0282547   .0129127    -2.19   0.030    -.0537105   -.0027988
          9  |  -.0139239   .0140485    -0.99   0.323    -.0416187    .0137709
         10  |   .1733043   .0389197     4.45   0.000     .0965787    .2500299
         11  |   .0281919   .0218592     1.29   0.199    -.0149008    .0712847
         12  |   .0979083   .0298972     3.27   0.001     .0389695    .1568471
         13  |   .0854998   .0271572     3.15   0.002     .0319626     .139037
         14  |  -.0037121   .0265762    -0.14   0.889    -.0561038    .0486796
         15  |   .1225707   .0250671     4.89   0.000      .073154    .1719875
             |
        year |
       1999  |   .1310709   .0149622     8.76   0.000     .1015748    .1605671
       2000  |   .2283529   .0157513    14.50   0.000     .1973012    .2594046
       2001  |   .3862554   .0175439    22.02   0.000     .3516699     .420841
       2002  |   .5217406   .0188895    27.62   0.000     .4845023    .5589789
       2003  |    .637554   .0219465    29.05   0.000      .594289    .6808189
       2004  |    .776246   .0259983    29.86   0.000     .7249935    .8274986
       2005  |   .9285035   .0305482    30.39   0.000     .8682814    .9887257
       2006  |   1.097444   .0345999    31.72   0.000     1.029235    1.165654
       2007  |   1.293443   .0396787    32.60   0.000     1.215221    1.371665
       2008  |   1.472429   .0445342    33.06   0.000     1.384635    1.560223
       2009  |    1.57192   .0489092    32.14   0.000     1.475501    1.668338
       2010  |   1.709072   .0529026    32.31   0.000     1.604781    1.813363
       2011  |   1.864288   .0585689    31.83   0.000     1.748826     1.97975
             |
       _cons |   7.564247   .0555637   136.14   0.000      7.45471    7.673784
-------------+----------------------------------------------------------------
          id |   absorbed                                 (296558 categories)
```

```
areg lnwage p age2 i.act i.year if educ>5, absorb(id) cl(act_yr)

Linear regression, absorbing indicators          Number of obs   =     144333
                                                 F(  29,    209) =     258.81
                                                 Prob > F        =     0.0000
                                                 R-squared       =     0.7281
                                                 Adj R-squared   =     0.6569
                                                 Root MSE        =     0.3690

                              (Std. Err. adjusted for 210 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.0038701   .1314651    -0.03   0.977    -.2630376    .2552974
        age2 |  -.0008037   .0000242   -33.27   0.000    -.0008513   -.0007561
             |
         act |
          2  |   .0451389   .0227709     1.98   0.049     .0002489    .0900289
          3  |   .0453421   .0256567     1.77   0.079     -.005237    .0959211
          4  |  -.0299758   .0572185    -0.52   0.601    -.1427752    .0828236
          5  |   .1547548   .0568115     2.72   0.007     .0427578    .2667519
          6  |   .0604384   .0196875     3.07   0.002     .0216269    .0992499
          7  |   .0042011   .0329228     0.13   0.899    -.0607023    .0691044
          8  |   .0381992   .0298051     1.28   0.201    -.0205579    .0969564
          9  |   .0215534   .0309614     0.70   0.487    -.0394832      .08259
         10  |  -.0234103   .0580663    -0.40   0.687     -.137881    .0910603
         11  |   .0113635   .0497196     0.23   0.819    -.0866526    .1093797
         12  |    .098495   .0767999     1.28   0.201    -.0529067    .2498966
         13  |   .1289702   .0736544     1.75   0.081    -.0162305    .2741709
         14  |    .140394    .075637     1.86   0.065    -.0087152    .2895031
         15  |   .0102553   .0593524     0.17   0.863    -.1067507    .1272613
             |
        year |
        1999 |   .1316208   .0191469     6.87   0.000     .0938751    .1693665
        2000 |   .2249221   .0148844    15.11   0.000     .1955794    .2542649
        2001 |   .3681044   .0180021    20.45   0.000     .3326155    .4035933
        2002 |   .4846568   .0173882    27.87   0.000     .4503781    .5189356
        2003 |   .5986007   .0184515    32.44   0.000     .5622258    .6349755
        2004 |   .7232134   .0214313    33.75   0.000     .6809643    .7654626
        2005 |   .8467814   .0205554    41.20   0.000     .8062588    .8873039
        2006 |   .9959744   .0213532    46.64   0.000     .9538793     1.03807
        2007 |   1.144706   .0233025    49.12   0.000     1.098768    1.190644
        2008 |     1.3084   .0280268    46.68   0.000     1.253148    1.363651
        2009 |   1.434693    .027414    52.33   0.000     1.380649    1.488736
        2010 |   1.545712   .0281272    54.95   0.000     1.490263    1.601161
        2011 |   1.670622   .0319093    52.36   0.000     1.607716    1.733527
             |
       _cons |   7.640008   .0394149   193.84   0.000     7.562306     7.71771
-------------+----------------------------------------------------------------
          id |   absorbed                                  (29935 categories)
```

```
areg lnwage p age2 i.act i.year if educ<5, absorb(id) cl(act_yr)

Linear regression, absorbing indicators          Number of obs   =    1520677
                                                 F(  29,    209) =     179.17
                                                 Prob > F        =     0.0000
                                                 R-squared       =     0.5683
                                                 Adj R-squared   =     0.4785
                                                 Root MSE        =     0.4610

                               (Std. Err. adjusted for 210 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.7019116   .1189705    -5.90   0.000    -.9364476   -.4673755
        age2 |  -.0011454   .0000559   -20.49   0.000    -.0012556   -.0010352
             |
         act |
          2  |   .0560327   .0152707     3.67   0.000     .0259284    .0861369
          3  |   .1419042   .0264259     5.37   0.000     .0898088    .1939996
          4  |  -.0082462   .0183654    -0.45   0.654    -.0444514    .0279589
          5  |   .1020602   .0239335     4.26   0.000     .0548782    .1492423
          6  |   .0717928   .0102587     7.00   0.000     .0515689    .0920167
          7  |   .1086164   .0186925     5.81   0.000     .0717665    .1454664
          8  |  -.0356202    .013995    -2.55   0.012    -.0632097   -.0080308
          9  |  -.0138215   .0151991    -0.91   0.364    -.0437846    .0161417
         10  |   .1808656   .0426242     4.24   0.000     .0968371    .2648941
         11  |   .0345223   .0240943     1.43   0.153    -.0129767    .0820213
         12  |   .1057858   .0300939     3.52   0.001     .0464592    .1651123
         13  |    .088151   .0291661     3.02   0.003     .0306534    .1456485
         14  |  -.0171335   .0264877    -0.65   0.518    -.0693509    .0350839
         15  |   .1238455   .0276584     4.48   0.000     .0693203    .1783706
             |
        year |
       1999  |   .1305639   .0154051     8.48   0.000     .1001946    .1609332
       2000  |   .2293214   .0178178    12.87   0.000     .1941957    .2644471
       2001  |   .3890703    .019269    20.19   0.000     .3510838    .4270568
       2002  |   .5268894   .0211742    24.88   0.000     .4851471    .5686317
       2003  |   .6442716   .0245147    26.28   0.000     .5959439    .6925993
       2004  |   .7848776    .029065    27.00   0.000     .7275794    .8421759
       2005  |   .9409715   .0340619    27.63   0.000     .8738226     1.00812
       2006  |   1.113169   .0389044    28.61   0.000     1.036474    1.189864
       2007  |   1.313919   .0448851    29.27   0.000     1.225433    1.402404
       2008  |   1.494926    .050118    29.83   0.000     1.396124    1.593727
       2009  |   1.592426    .055253    28.82   0.000     1.483501     1.70135
       2010  |   1.734164   .0595663    29.11   0.000     1.616736    1.851592
       2011  |   1.893024   .0656758    28.82   0.000     1.763552    2.022496
             |
       _cons |   7.563393   .0592159   127.73   0.000     7.446656     7.68013
-------------+----------------------------------------------------------------
          id |   absorbed                                  (261666 categories)
```

```
areg lnwage p age2 i.act i.year if educ<6, absorb(id) cl(act_yr)

Linear regression, absorbing indicators          Number of obs   =    1616223
                                                 F(  29,    209) =     191.55
                                                 Prob > F        =     0.0000
                                                 R-squared       =     0.5695
                                                 Adj R-squared   =     0.4815
                                                 Root MSE        =     0.4588

                               (Std. Err. adjusted for 210 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.6652177   .1125472    -5.91   0.000    -.8870908   -.4433445
        age2 |  -.0011338    .000053   -21.38   0.000    -.0012383   -.0010292
             |
         act |
          2  |   .0540853   .0142752     3.79   0.000     .0259434    .0822272
          3  |   .1388222   .0253775     5.47   0.000     .0887935    .1888508
          4  |  -.0082181   .0176083    -0.47   0.641    -.0429307    .0264945
          5  |    .102024   .0230301     4.43   0.000      .056623     .147425
          6  |   .0739544   .0097366     7.60   0.000     .0547598    .0931491
          7  |   .1039383   .0175462     5.92   0.000     .0693481    .1385285
          8  |    -.03498   .0131988    -2.65   0.009    -.0609999   -.0089601
          9  |  -.0182735    .014657    -1.25   0.214    -.0471681    .0106211
         10  |   .1813394   .0405181     4.48   0.000      .101463    .2612159
         11  |     .02932   .0224784     1.30   0.194    -.0149934    .0736333
         12  |   .0974112   .0300176     3.25   0.001     .0382351    .1565872
         13  |   .0847984   .0280086     3.03   0.003     .0295828    .1400139
         14  |  -.0110557   .0265478    -0.42   0.678    -.0633915    .0412801
         15  |   .1251018   .0257784     4.85   0.000     .0742827    .1759209
             |
        year |
       1999  |   .1313229   .0151069     8.69   0.000     .1015414    .1611043
       2000  |   .2296083   .0166239    13.81   0.000     .1968362    .2623804
       2001  |   .3887001   .0183286    21.21   0.000     .3525675    .4248328
       2002  |   .5259837   .0198845    26.45   0.000     .4867838    .5651837
       2003  |   .6427363   .0230445    27.89   0.000     .5973068    .6881659
       2004  |    .782829   .0272849    28.69   0.000     .7290402    .8366179
       2005  |   .9372063   .0319863    29.30   0.000     .8741492    1.000263
       2006  |    1.10807   .0363519    30.48   0.000     1.036407    1.179733
       2007  |   1.307227   .0418125    31.26   0.000     1.224799    1.389656
       2008  |    1.48761    .046806    31.78   0.000     1.395338    1.579883
       2009  |   1.586185   .0515108    30.79   0.000     1.484638    1.687732
       2010  |    1.72564   .0555867    31.04   0.000     1.616058    1.835223
       2011  |   1.882982   .0615508    30.59   0.000     1.761642    2.004322
             |
       _cons |   7.563016   .0567121   133.36   0.000     7.451216    7.674817
-------------+----------------------------------------------------------------
          id |   absorbed                                 (274146 categories)
```

```
areg lnwage p age2 i.act i.year if educ<4, absorb(id) cl(act_yr)

Linear regression, absorbing indicators          Number of obs   =     677796
                                                 F(  29,    209) =      95.12
                                                 Prob > F        =     0.0000
                                                 R-squared       =     0.6193
                                                 Adj R-squared   =     0.5029
                                                 Root MSE        =     0.4886

                                (Std. Err. adjusted for 210 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.7562541   .1534986    -4.93   0.000    -1.058858   -.4536502
        age2 |  -.0010782   .0000746   -14.45   0.000    -.0012253    -.000931
             |
         act |
          2  |   .0507075   .0212274     2.39   0.018     .0088602    .0925547
          3  |   .1523165   .0358326     4.25   0.000     .0816769    .2229561
          4  |  -.0248177   .0251571    -0.99   0.325    -.0744119    .0247765
          5  |   .1329082   .0322352     4.12   0.000     .0693604     .196456
          6  |   .0741517   .0147675     5.02   0.000     .0450393    .1032641
          7  |   .1195227   .0244582     4.89   0.000     .0713062    .1677391
          8  |  -.0287732   .0195684    -1.47   0.143    -.0673499    .0098036
          9  |  -.0114852   .0206738    -0.56   0.579    -.0522412    .0292707
         10  |    .158019    .057285     2.76   0.006     .0450885    .2709495
         11  |   .0494271   .0311676     1.59   0.114     -.012016    .1108703
         12  |   .0924288   .0391845     2.36   0.019     .0151813    .1696764
         13  |      .0837   .0366389     2.28   0.023     .0114708    .1559292
         14  |  -.0024344   .0414977    -0.06   0.953     -.084242    .0793732
         15  |   .1308902    .039234     3.34   0.001     .0535451    .2082353
             |
        year |
       1999  |   .1267765   .0195176     6.50   0.000     .0882998    .1652532
       2000  |   .2271426   .0218282    10.41   0.000     .1841109    .2701743
       2001  |   .3696309   .0262247    14.09   0.000     .3179322    .4213297
       2002  |   .5036262   .0306899    16.41   0.000     .4431247    .5641276
       2003  |   .6116106   .0351595    17.40   0.000      .542298    .6809233
       2004  |   .7485173   .0411082    18.21   0.000     .6674775    .8295571
       2005  |   .9001447   .0478217    18.82   0.000       .80587    .9944194
       2006  |   1.066056   .0541992    19.67   0.000     .9592086    1.172903
       2007  |   1.258878   .0626662    20.09   0.000     1.135339    1.382417
       2008  |   1.425139   .0704529    20.23   0.000      1.28625    1.564029
       2009  |   1.504853   .0791552    19.01   0.000     1.348808    1.660897
       2010  |   1.678262   .0893966    18.77   0.000     1.502027    1.854497
       2011  |   1.865763   .1033239    18.06   0.000     1.662072    2.069453
             |
       _cons |   7.557105   .0891509    84.77   0.000     7.381354    7.732855
-------------+----------------------------------------------------------------
          id |   absorbed                                   (158659 categories)
```

```
reg lnwage p allmenn_p age age2 i.educ sex i.act i.year, cl(act_yr)

Linear regression                                      Number of obs = 1760556
                                                       F( 38,   209) = 1535.54
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2291
                                                       Root MSE      =  .56513

                               (Std. Err. adjusted for 210 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |   .1254586   .1045373     1.20   0.231     -.080624    .3315413
   allmenn_p |  -.3062668   .0647428    -4.73   0.000    -.4338995   -.1786342
         age |   .0717276   .0010793    66.46   0.000        .0696    .0738552
        age2 |  -.0007805   .0000126   -61.84   0.000    -.0008054   -.0007557
             |
        educ |
          3  |   .1111154   .0064826    17.14   0.000     .0983357    .1238951
          4  |   .2023643   .0070036    28.89   0.000     .1885575    .2161711
          5  |   .2478551   .0080422    30.82   0.000     .2320008    .2637093
          6  |   .3701789   .0112284    32.97   0.000     .3480435    .3923143
          7  |   .6107439   .0239386    25.51   0.000     .5635519    .6579359
          8  |   .6698543   .0280072    23.92   0.000     .6146415    .7250671
             |
         sex |  -.2157347   .0050454   -42.76   0.000    -.2256812   -.2057882
             |
         act |
          2  |  -.0377319    .008728    -4.32   0.000    -.0549382   -.0205257
          3  |   .1505708   .0104675    14.38   0.000     .1299355    .1712062
          4  |  -.0896499   .0080503   -11.14   0.000    -.1055202   -.0737797
          5  |    .007029   .0127653     0.55   0.582    -.0181362    .0321943
          6  |   .0952557    .010307     9.24   0.000     .0749367    .1155746
          7  |    .010169   .0123045     0.83   0.409    -.0140878    .0344257
          8  |   .0022447   .0064818     0.35   0.729    -.0105333    .0150227
          9  |   .0055164   .0071948     0.77   0.444    -.0086673       .0197
         10  |   .0027827   .0296729     0.09   0.925    -.0557137    .0612792
         11  |   -.189447   .0151398   -12.51   0.000    -.2192933   -.1596007
         12  |  -.0618573    .017903    -3.46   0.001    -.0971509   -.0265638
         13  |  -.1350521   .0171828    -7.86   0.000     -.168926   -.1011783
         14  |  -.0536363   .0111401    -4.81   0.000    -.0755976    -.031675
         15  |  -.0389545   .0173961    -2.24   0.026    -.0732487   -.0046603
             |
        year |
       1999  |   .0380565   .0123507     3.08   0.002     .0137087    .0624044
       2000  |   .0458501   .0120009     3.82   0.000     .0221917    .0695086
       2001  |   .1092427   .0109964     9.93   0.000     .0875646    .1309208
       2002  |   .1476304    .008214    17.97   0.000     .1314374    .1638234
       2003  |   .1795838   .0084394    21.28   0.000     .1629466     .196221
       2004  |   .2196914   .0080271    27.37   0.000     .2038669     .235516
       2005  |    .265291   .0083493    31.77   0.000     .2488314    .2817506
       2006  |   .3595121   .0104171    34.51   0.000     .3389761    .3800482
       2007  |   .4324325   .0126305    34.24   0.000      .407533    .4573319
       2008  |   .4951267   .0151521    32.68   0.000     .4652563    .5249972
       2009  |    .499598   .0127739    39.11   0.000     .4744159    .5247801
       2010  |    .541907   .0130498    41.53   0.000     .5161809    .5676331
       2011  |   .5877731   .0150704    39.00   0.000     .5580636    .6174826
             |
       _cons |   4.812614   .0244928   196.49   0.000     4.764329    4.860899
------------------------------------------------------------------------------
```

```
areg lnwage p allmenn_p age2 i.act i.year, absorb(id) cl(act_yr)

Linear regression, absorbing indicators          Number of obs   =    1760556
                                                 F(  30,    209) =     218.61
                                                 Prob > F        =     0.0000
                                                 R-squared       =     0.5879
                                                 Adj R-squared   =     0.5027
                                                 Root MSE        =     0.4539

                               (Std. Err. adjusted for 210 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |   -.151444   .1257555    -1.20   0.230    -.3993559    .0964679
   allmenn_p |  -.3476793   .0657396    -5.29   0.000    -.4772771   -.2180816
        age2 |  -.0011071   .0000494   -22.42   0.000    -.0012045   -.0010098
             |
         act |
          2  |   .0325901    .014201     2.29   0.023     .0045946    .0605856
          3  |   .1050582   .0225754     4.65   0.000     .0605534    .1495629
          4  |  -.0197194   .0180855    -1.09   0.277    -.0553728     .015934
          5  |   .0858886   .0221226     3.88   0.000     .0422766    .1295005
          6  |   .0783296    .010105     7.75   0.000     .0584089    .0982504
          7  |   .0618425   .0179163     3.45   0.001     .0265227    .0971622
          8  |   -.025355   .0133971    -1.89   0.060    -.0517658    .0010558
          9  |  -.0218534   .0147428    -1.48   0.140     -.050917    .0072102
         10  |   .0703727   .0392277     1.79   0.074    -.0069599    .1477053
         11  |  -.0100361   .0208574    -0.48   0.631    -.0511539    .0310818
         12  |   .0502758   .0295394     1.70   0.090    -.0079576    .1085091
         13  |   .0315473   .0275433     1.15   0.253    -.0227509    .0858456
         14  |  -.0047726   .0273781    -0.17   0.862    -.0587451       .0492
         15  |   .0755901   .0240726     3.14   0.002     .0281339    .1230463
             |
        year |
       1999  |   .1313108   .0143423     9.16   0.000     .1030366    .1595849
       2000  |   .2319239   .0157023    14.77   0.000     .2009688     .262879
       2001  |   .3888574   .0171632    22.66   0.000     .3550223    .4226925
       2002  |   .5215439   .0185236    28.16   0.000     .4850269    .5580609
       2003  |   .6415379   .0213786    30.01   0.000     .5993925    .6836833
       2004  |   .7787389    .025409    30.65   0.000     .7286481    .8288298
       2005  |   .9263972   .0296729    31.22   0.000     .8679007    .9848937
       2006  |   1.129852   .0330539    34.18   0.000      1.06469    1.195013
       2007  |   1.320268   .0378232    34.91   0.000     1.245704    1.394832
       2008  |   1.497485   .0426637    35.10   0.000     1.413378    1.581591
       2009  |   1.599831   .0465409    34.37   0.000     1.508081    1.691581
       2010  |   1.737359   .0502608    34.57   0.000     1.638275    1.836442
       2011  |   1.891095   .0557067    33.95   0.000     1.781275    2.000914
             |
       _cons |   7.545554   .0558698   135.06   0.000     7.435413    7.655694
-------------+----------------------------------------------------------------
          id |   absorbed                                   (301435 categories)
```

An alternative measure: income

```
reg lninc p age age2 i.educ sex i.act i.year, cl(act_yr);

Linear regression                                      Number of obs = 1760556
                                                       F( 37,   209) =  846.73
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2528
                                                       Root MSE      =  .71106

                              (Std. Err. adjusted for 210 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
       lninc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.1474959   .0704492    -2.09   0.037    -.2863781   -.0086138
         age |    .110578   .0019116    57.85   0.000     .1068095    .1143464
        age2 |  -.0011662   .0000211   -55.29   0.000    -.0012077   -.0011246
             |
        educ |
          3  |   .1457343   .0062529    23.31   0.000     .1334074    .1580611
          4  |   .2719233   .0075159    36.18   0.000     .2571066    .2867399
          5  |   .2700268   .0086219    31.32   0.000     .2530298    .2870238
          6  |   .3428621   .0128101    26.77   0.000     .3176087    .3681156
          7  |   .6460431   .0211447    30.55   0.000     .6043589    .6877272
          8  |    .645042   .0543378    11.87   0.000     .5379216    .7521624
             |
         sex |  -.3178844   .0080326   -39.57   0.000    -.3337196   -.3020491
             |
         act |
          2  |   .0140074   .0098687     1.42   0.157    -.0054475    .0334624
          3  |    .141229   .0116598    12.11   0.000     .1182432    .1642149
          4  |  -.0290373   .0091447    -3.18   0.002    -.0470649   -.0110097
          5  |  -.0095941   .0164827    -0.58   0.561    -.0420877    .0228995
          6  |   .0455975   .0124611     3.66   0.000      .021032    .0701629
          7  |   .0064171   .0118414     0.54   0.588    -.0169269    .0297611
          8  |   .0974237   .0083515    11.67   0.000     .0809596    .1138877
          9  |   .0965743   .0077436    12.47   0.000     .0813087    .1118398
         10  |   .0296795   .0246214     1.21   0.229    -.0188585    .0782176
         11  |  -.1418936   .0156614    -9.06   0.000    -.1727682    -.111019
         12  |  -.0239539   .0168974    -1.42   0.158    -.0572652    .0093573
         13  |  -.0870812   .0164247    -5.30   0.000    -.1194605   -.0547019
         14  |   .0010989   .0118562     0.09   0.926    -.0222741    .0244719
         15  |  -.1023376   .0189249    -5.41   0.000    -.1396458   -.0650293
             |
        year |
       1999  |    .051245   .0129581     3.95   0.000     .0256996    .0767903
       2000  |    .079362   .0135794     5.84   0.000     .0525919    .1061321
       2001  |    .126567    .017675     7.16   0.000     .0917229    .1614111
       2002  |   .1949951   .0090104    21.64   0.000     .1772322    .2127579
       2003  |   .2241975   .0092277    24.30   0.000     .2060061    .2423889
       2004  |   .2696856   .0097095    27.78   0.000     .2505445    .2888267
       2005  |   .3220595   .0098636    32.65   0.000     .3026146    .3415043
       2006  |   .3743697   .0112199    33.37   0.000     .3522511    .3964884
       2007  |    .453394   .0135638    33.43   0.000     .4266547    .4801334
       2008  |    .533472   .0142824    37.35   0.000     .5053159    .5616281
       2009  |   .5460797   .0125448    43.53   0.000      .521349    .5708103
       2010  |   .5736442   .0123282    46.53   0.000     .5493407    .5979478
       2011  |   .6184342   .0128147    48.26   0.000     .5931716    .6436968
             |
       _cons |   9.563699   .0418747   228.39   0.000     9.481148     9.64625
```

```
------------------------------------------------------------------------------
```

```
areg lninc p age2 i.act i.year, absorb(id) cl(act_yr);

Linear regression, absorbing indicators           Number of obs   =    1760556
                                                  F(  29,    209) =      80.72
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.6517
                                                  Adj R-squared   =     0.5798
                                                  Root MSE        =     0.5332

                               (Std. Err. adjusted for 210 clusters in act_yr)
------------------------------------------------------------------------------
             |               Robust
       lninc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           p |  -.5541144   .1775433    -3.12   0.002    -.9041197   -.2041091
        age2 |  -.0015837   .0000621   -25.48   0.000    -.0017062   -.0014612
             |
         act |
          2  |   .0440151   .0271687     1.62   0.107    -.0095447     .097575
          3  |   .1209051   .0241347     5.01   0.000     .0733264    .1684838
          4  |   .0205436   .0232129     0.89   0.377    -.0252178     .066305
          5  |   .0982306    .034207     2.87   0.005     .0307955    .1656656
          6  |   .0585365   .0220264     2.66   0.008     .0151141    .1019588
          7  |   .0848564   .0302791     2.80   0.006     .0251648    .1445479
          8  |   .0405495   .0224647     1.81   0.073     -.003737     .084836
          9  |   .0407353   .0213452     1.91   0.058    -.0013443    .0828148
         10  |   .1844793    .059442     3.10   0.002     .0672966     .301662
         11  |   .0232837   .0373911     0.62   0.534    -.0504284    .0969958
         12  |   .0849588   .0452583     1.88   0.062    -.0042624    .1741799
         13  |   .0766462   .0456364     1.68   0.095    -.0133205    .1666129
         14  |  -.0052905   .0360596    -0.15   0.883    -.0763777    .0657966
         15  |   .0930995   .0388982     2.39   0.018     .0164164    .1697827
             |
        year |
       1999  |   .1469026   .0176926     8.30   0.000     .1120237    .1817814
       2000  |    .298917   .0218386    13.69   0.000     .2558648    .3419691
       2001  |   .4725118   .0284778    16.59   0.000     .4163712    .5286524
       2002  |    .668244   .0256204    26.08   0.000     .6177364    .7187516
       2003  |   .8139109   .0292562    27.82   0.000     .7562357     .871586
       2004  |   .9959091   .0331816    30.01   0.000     .9304956    1.061323
       2005  |   1.195049   .0382608    31.23   0.000     1.119622    1.270476
       2006  |   1.404035   .0434896    32.28   0.000     1.318301     1.48977
       2007  |   1.650988   .0502332    32.87   0.000     1.551959    1.750016
       2008  |   1.887318   .0569936    33.11   0.000     1.774962    1.999674
       2009  |   2.039561   .0636869    32.02   0.000      1.91401    2.165112
       2010  |   2.202596   .0688285    32.00   0.000     2.066909    2.338283
       2011  |   2.426598   .0728544    33.31   0.000     2.282974    2.570221
             |
       _cons |   13.75016   .0692053   198.69   0.000     13.61373    13.88659
-------------+----------------------------------------------------------------
          id |   absorbed                                    (301435 categories)
```