The impact of welfare-to-work programs on the number of welfare benefit recipients in Dutch municipalities.

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Abstract:

In this thesis a cross-municipality analyses is conducted on the effect of active labour market policies (ALMP) on the number of welfare benefit recipients. For the variables, ALMP-spending and ALMP-programs the results show a significant relationship with the number of welfare benefit recipients in a fixed effects and a first difference model. In trying to reduce the endogeneity problem, the effect of the variables ratios, and numbers of the different ALMP-categories on the number of welfare benefit recipients was also analysed. However, no relationship could be found for these variables.

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1: Introduction

In this thesis the effect of active labour market policies (ALMP) on the reduction of unemployment will be examined. ALMP is a popular method in trying to reduce unemployment. In 2008 the Dutch municipalities have spent approximately 2 billion euros on welfare-to-work programs (Tempelman, Berden & Kok, 2010: 8). With these amounts spent on ALMP, it is important to know the effectiveness of these efforts in reducing unemployment.

Since 2004 the Dutch municipalities are financially responsible for the reintegration of welfare benefit recipients[1] and the non-insured unemployed, this was arranged in the Act on Work and Income Assistance (WWB) (Berkel & Aa, 2005: 335). The central Dutch government provides municipalities with a fixed budget for social welfare. When municipalities exceed their budget, they have to fund the exceeding amount in other ways. When they have budget left over, they are free to spend it on other public services, or lower local tax rates. This gives municipalities an incentive to improve efficiency and effectiveness of their reintegration responsibilities (Berkel & Aa, 2005: 335).

A cross-municipality comparison can be conducted for the Netherlands. Past research has generally focused on cross-country comparisons and micro studies to specific ALMP-programs. Within the Netherlands the municipalities are solely responsible for the reintegration of welfare benefit recipients. Therefore, a municipality comparison can be conducted for ALMP on the number of welfare benefit recipients. The institutional settings related to unemployment are necessary to correct for in cross-country comparisons, but they are very similar for the different Dutch municipalities. It is not necessary to check for these different institutional settings in a municipality comparison. With the advantage of having more similar external factors between municipalities in comparison to countries, this thesis tries to give a better insight in the effect of ALMP on welfare benefit recipiency.

ALMP can be divided into four main categories. The OECD and Statistics Netherlands (CBS) have different categories for this. In this thesis the distribution of the CBS will be used, because these data are available for the Dutch municipalities. The categories are: wage subsidies, WIW/ID-jobs (subsidized work for a company or government, inflow is no longer

[1] In this thesis welfare benefit recipients are considered people who cannot provide for themselves and do not have an income insurance, in Dutch they get a “bijstanduitkering” .

possible since 2004), participation places (gain work experience while maintaining benefits) and other. Most ALMP-programs are registered in the category other.

ALMP and unemployment have an endogenous relationship because ALMP spending responds to changing labour market conditions (Martin, 2015: 6). Therefore the number of welfare benefit recipients is also expected to have an endogenous relationship with ALMP. It is unlikely that the spending ratios on the four categories of ALMP have an endogenous relationship with unemployment (Boone & Ours, 2009). For the Netherlands the spending ratios for the different ALMP programs are not known, but the numbers of reintegration programs in the different categories are registered by the CBS. These can be used to look at the effectiveness of ALMP to reduce unemployment.

The research question in this thesis will be: *What is the effect of welfare-to-work programs (ALMP) on the number of* welfare benefit recipients *in the Dutch municipalities?* The focus will be on the effect of ALMP-spending and the number of ALMP-programs on the number of welfare benefit recipients, to find out whether the public funds and efforts are effectively spent. A regression analysis will be conducted with publicly available data retrieved from StatLine by CBS.

In the second section of this thesis the theoretical framework will be introduced. First a short literature review will present the important related literature on ALMP. Hereafter the hypotheses and conceptual model will be formulated. In the third section of this thesis, the data and empirical model will be described. The fourth section will show the results and the analysis of these results, and in the final section conclusions will be drawn.

2: Theoretical framework

First the background of structural unemployment will be explained. Structural unemployment is unemployment not resulting from supply and demand fluctuations. A closer look at this type of unemployment is important because most ALMP measures try to influence the structural unemployment. Secondly other factors that affect unemployment are discussed. Thirdly the ways ALMP can influence unemployment will be illustrated. Hereafter the relevant studies on ALMP including studies on ALMP within Dutch municipalities are examined and finally the hypotheses and conceptual model are formulated.

2.1: Structural unemployment

The neoclassical model of unemployment is useful for explaining the effects that different ALMP measures have on unemployment. The OECD defines structural unemployment as "The level of unemployment compatible with stable inflation in a medium-term perspective." (Gersing, 1997: 4). In the neoclassical model workers and firms negotiate wages. Firms decide the level of employment, output and prices after an agreement on the level of wages has been reached (Alogoskoufis & Manning, 1988: 432). Therefore the labour demand of companies depends on the level of wages, prices and other factors. When (real) wages increase, unemployment will rise because of the rising costs for companies (Alogoskoufis & Manning, 1988: 432). As illustrated in Figures 1 and 2 with the labour demand curve, employment decreases when (real) wages increase. The wage-setting is a decreasing function

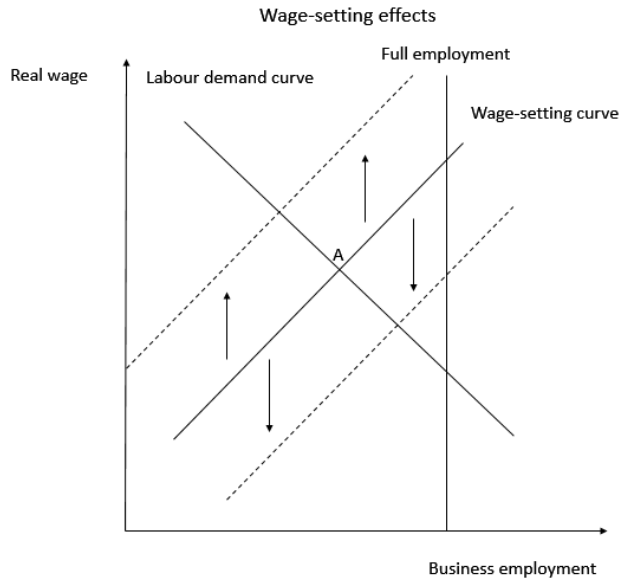

Figure 1: Labour demand effects (adapted from: Estevão, 2003: 5; Scarpetta, 1996: 46; Alogoskoufis & Manning, 1988: 433; Calmfors, 1994: 9)

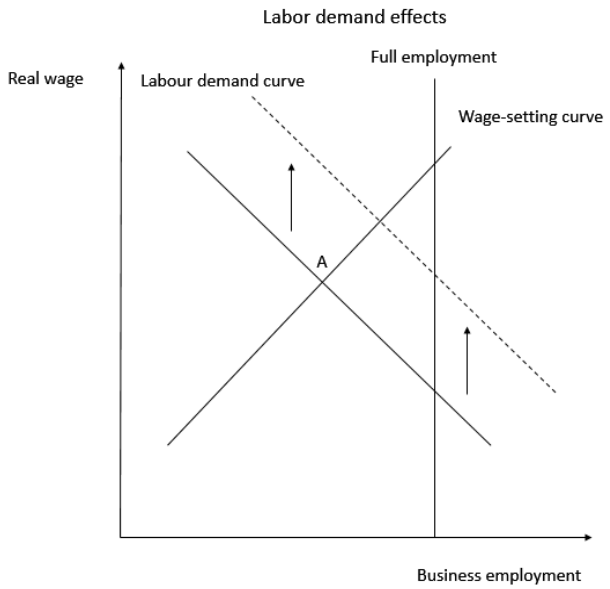

Figure 2: Wage-setting effects (adapted from: Estevão, 2003: 5; Scarpetta, 1996: 46; Alogoskoufis & Manning, 1988: 433 Calmfors, 1994: 9)

of unemployment and an increasing function of wage push factors. Wage push factors are: generosity of unemployment benefits, strength of labour unions, the tax wedge and the degree of mismatch between the skills or geographical location of job seekers and vacancies (see Figure 1 the upward arrows and line). A higher unemployment rate will decrease the wages (see Figure 1 the downward arrows and line) (Scarpetta, 1996: 45-48). Labour unions should realise that demanding higher wages will negatively affect the number of jobs (Alogoskoufis & Manning, 1998: 433). The equilibrium point of employment and wages is the intersection between the labour demand curve and the wage-setting curve, point A in Figure 1 and 2 (Calmfors, 1994: 10). The structural unemployment rate is therefore the rate of unemployment when price and wage expectations are met (the number of unemployed at point A). This is horizontally from point A to the full employment line (Scarpetta, 1996: 47; Calmfors, 1994: 10).

2.2: Factors influencing unemployment

Below the reasons for excluding certain factors affecting unemployment are given. In this thesis a cross-municipality comparison will be conducted, unlike most related research which conduct a cross-country comparison. Factors which are taken into account in these kinds of research are the business cycle, unemployment benefits, employment protection legislation, non-wage labour costs, institutional factors, real interest rates and active labour market policies (Scarpetta, 1996: 50). Most of the factors except active labour market policies are expected to be the same for the whole country. Some of these factors will differ over time (for example the business cycle), but time dummies can be used to control for time-specific fixed effects, on the condition that they are the same for all municipalities.

2.3: ALMP

As described above in the introduction, ALMP can be divided into four categories. The categories the OECD describes are: public employment services and administration, classroom or on-the-job training, public sector job creation and subsidized employment in the private sector (Card, Kluve & Weber, 2017: 897). These ALMP may have a positive effect on the employment by shifting the wage-setting curve mentioned in section 2.1 downwards or shifting the labour-demand curve upwards (Bánociová & Martinková, 2017: 8; Scarpetta, 1996: 51; Estevão, 2003: 5). Estevão describes five channels in which ALMP can affect employment. Firstly ALMP can increase the efficiency of the matching between job-seekers and vacancies. As a result there will be a lower ratio between unemployment and vacancies and more labour

supply. This in turn will reduce the pressure on wages, resulting in a downwards shift of the wage-setting curve and an upwards shift of the labour demand curve. Secondly, the productivity of the labour force can increase due to training programs and on-the-job learning. A higher productivity leads to an upward shift of the labour demand curve. Thirdly, ALMP can integrate unemployed workers into the labour force, even after a longer period of inactivity (this can be accomplished with for example subsidized on-the-job training programs). This will shift the wage-setting curve downwards. Fourthly, wage subsidies can be a substitute for unsubsidized employment. As long as the income effect is larger than the substitution effect, direct subsidies to jobs will shift the labour demand curve upwards. Fifthly, ALMP can also have a negative influence on unemployment by lowering the disutility of being unemployed. Instead of being fully unemployed, ALMP can provide work and the expectation of gaining and keeping labour skills. This can lead to workers demanding higher wages. Shifting the wage-setting curve upwards, leading to more unemployment (Estevão, 2003: 5-6).

Boone and van Ours (2009) distinguish two channels in which ALMP can reduce unemployment. ALMP can increase both the job-finding rate and improve the quality of jobs found. A higher quality job will have a higher wage and a better chance of continuation. Boone and van Ours conclude that the main effect of ALMP on unemployment is through the increased quality of jobs, rather than an increase in the job finding rate (Boone & van Ours, 2009: 296; 309). They came to this conclusion by comparing the effectiveness of the different kinds of ALMP-measures, only training-programs seemed effective in reducing unemployment. Training programs directly influence the quality of the jobs found (Boone & van Ours, 2009; 309).

2.4: Relevant studies on ALMP

Depending on the type of data that is used, three important kinds of studies are conducted on the effectiveness of ALMP: micro-studies, meta-studies and cross-sectional studies. The micro-studies are econometrically the most advanced. Some have experimental designs with random assignment (Martin, 2014: 8). This literature is useful in quantifying what kinds of ALMP work. However, it cannot be used to assess the macroeconomic effects of the ALMP (Martin, 2014: 8). Since the individual effect of ALMP is higher than the aggregate effect, since ALMP may help the participant of an ALMP-program but not necessarily the average job seeker (Jongen, 2010: 157).

Meta-studies evaluate the results of the mixed outcomes from the micro-studies (Vooren, Haelermans, Groot & Brink, 2017; Card, Kluve & Weber, 2010; 2017). Card at al. evaluate the found effects of the 207 micro-studies conducted between 1990 and 2014 (2017). They conclude that subsidized public sector employment programs are least effective in reducing unemployment, and that job search assistance is most effective in the short run. Training programs (on-the-job and classroom) have a larger effect in the medium and long run (Card, et al., 2010: 24-25; Card, et al., 2017: 928). Vooren et al. came to similar conclusions (2017: 201). That is, subsidized public sector employment is least effective, whereas subsidized private sector employment followed by training programs is most effective. Different microstudies use different dependent variables to determine the effectiveness of the ALMP. Micro-studies with the dependent variable time registered in unemployment show more positive results than studies with the dependent variable earnings or probability of employment (Card et al., 2010: 26; Card et al., 2017: 929).

In early cross-sectional research, usually the effect of ALMP-spending on unemployment in a country is examined with Eurostat or OECD data (Scarpetta, 1996; Elmeskov et al., 1998; Boone & van Ours, 2009; Bánociová & Martinková, 2017). In most research, the importance of the endogenous relationship between ALMP and unemployment is highlighted. The effect of ALMP-spending on unemployment is the relationship of interest, but unemployment can influence ALMP-spending in two ways as well. On the one hand, higher unemployment can lead to a higher political demand for ALMP (to reduce the number of unemployed). On the other hand, higher unemployment can also lead to higher costs in maintaining the ALMP-spending on current levels, which can lead to cuts in ALMP-spending and pressure to save money (van Vliet & Koster, 2011: 226). As a result, it is difficult to determine the effect of ALMP-spending on unemployment. Therefore, many researchers try to instrument ALMP-spending to obtain estimates that are more consistent.

Scarpetta (1996) and Elmeskov et al. (1998) take public expenditures for ALMP-programs per unemployed person relative to GDP per capita in percentages as independent variable (relative to GDP per capita is to ensure cross-country comparability) (Bassanini & Duval, 2006: 27-28). As described above this indicator of ALMP-spending is likely to be pro-cyclical. When employment increases, ALMP-spending per unemployed relative to GDP per capita will decrease (Bassanini & Duval, 2006: 27-28). Scarpetta and Elmeskov et al. try to solve the problem of endogeneity by using the average over the entire sample period for each country of the above variable (ALMP-spending per unemployed relative to GDP per capita)

(Scarpetta, 1996: 51; Elmeskov et al., 1998: 213-214). This can still lead to inconsistent estimates because country effects are not independent of other country characteristics (Bassanini & Duval, 2006: 29; Boone & Ours, 2009).

To overcome the problem of endogeneity Boone and van Ours use a different method. They use the shares of separate ALMP categories of the total expenditure as explanatory variables and not the absolute spending or spending per unemployed. They argue that the absolute level of expenditures can be biased by endogeneity, but the shares of the ALMP expenditure are likely to be not. There is no reason why the distribution of ALMP-spending will change when the number of unemployed changes (Boone & van Ours, 2009: 306-307). They find that that labour market training has a large negative effect on the unemployment rate (Boone & van Ours, 2009: 307).

Estevão used, instead of the unemployment rate, the business employment rate in a country to determine the effect of ALMP on employment (2003). He finds a significant effect of ALMP-spending on business employment, and in particular direct employment subsidies seemed to be most effective (Estevão, 2003: 19). In most papers, ALMP has a significant negative impact on unemployment (Martin, 2015: 6: Serres & Murtin, 2013: 16-22). Bakker, Glyn, Howell and Schmitt (2002) did not find a significant effect of ALMP on unemployment, although they used the same variable description as Scarpetta (1996) and Elmeskov et al. (1998).

2.5: ALMP in Dutch municipalities

A few recent studies on the effect of ALMP on the welfare caseload in Dutch municipalities showed that recent reforms on ALMP funds for municipalities were successful in reducing the number of welfare benefit recipients (Kok, Templeman, Koning, Kroon & Berden, 2017: 41). Kok et al. looked at the incentives for municipalities to reduce the welfare caseload. In their research, the dependent variable is the number of welfare benefit recipients and the independent variable is the difference in budgeting base for municipalities. They take advantage of the fact that smaller municipalities get a lump sum based on historical expenses and bigger municipalities receive a budget that is based on a regression block grant (Kok et al., 2017: 33). They used a difference-indifference approach based on individual panel data from administrative records (Kok et al., 2017).

Another recent study on the effectiveness of Dutch ALMP has been conducted with microdata on Dutch citizens, for every month from 2001 to 2011 (Lammers & Kok, 2017). This

study shows that ALMP have a positive long-term effect on the probability of employment (4 to 7 years), and placement services and short-term training programs outweigh the cost of these programs (Lammers & Kok, 2017: 27). All other programs are not cost effective within 7 years. The long-term programs are less effective in increasing the probability of employment as compared to short-term training programs (Lammers & Kok, 2017: 27). This research suggests that ALMP are more effective for welfare benefit recipients compared to the insured unemployed, since they have a lower probability of finding work without the ALMP (Lammers & Kok, 2017: 27). A study by Lammers, Kok and Wunsch in 2013 already found that insured unemployed have a higher probability of finding work themselves. If they participate in a welfare-to-work program, there is a chance that they will find work later, because they are 'locked-in' to the program (Lammers, Kok & Wunsch, 2013: 49-50; Lammers & Kok, 2014).

2.6: Hypotheses

In this section the hypotheses and justifications are given. As described above in the introduction, the research question in this thesis is: *What is the effect of welfare-to-work programs (ALMP) on the number of* welfare benefit recipients *in the Dutch municipalities?* To test this effect, four hypotheses are constructed and tested. The first hypothesis will be on ALMP-spending, the second on ALMP-programs, the third on the different kinds of ALMP programs in the Netherlands, and the fourth on the shares of the different ALMP-programs.

H1: *The average ALMP-spending per person receiving welfare benefits negatively affects the percentage of welfare benefit recipients in Dutch municipalities between 2008 and 2014.*

H2: *The average number of ALMP-programs per person receiving welfare benefits negatively affects the percentage of welfare benefit recipients in Dutch municipalities between 2008 and 2017.*

H3: *The average number of short-term reintegration programs per person receiving welfare benefits negatively affects the percentage of welfare benefit recipients in Dutch municipalities between 2008 and 2017.*

H4: *A high share of short-term reintegration programs of ALMP in Dutch municipalities negatively affects the percentage of welfare benefit recipients in municipalities between 2013 and 2017.*

For the first hypothesis, the model of Scarpetta (1996) and Elmeskov et al. (1998) will be used to test the effect of ALMP-spending per welfare benefit recipient on the number of

welfare benefit recipients in Dutch municipalities. Scarpetta (1996) and Elmeskov et al. (1998) take public expenditures for active labour market programs per person unemployed relative to GDP per capita in percentages as independent variable. In this theses instead of the number of persons unemployed the number of welfare benefit recipients will be used, this because municipalities are only responsible for this group of unemployed. For cross-municipality comparison, it is also not necessary to take the relative amount of GDP per capita. Therefore, in this thesis ALMP-expenditures per welfare benefit recipient will be used as dependent variable. Because of the endogeneity in the relationship of ALMP-spending and unemployment, it is more difficult to discover an effect and not a correlation between these variables as described above. Various researchers tried to use a proxy for ALMP-spending but they did not seem effective. The most effective way of instrumenting ALMP-spending is taking the average over the whole period (Boone & van Ours, 2009: 307).

This hypothesis will test how useful the spending on ALMP is in reducing unemployment. As can be read above in section 2.1 to 2.5, in most previous research a negative relationship between ALMP-spending and unemployment has been found. That is why this research expects that more spending on ALMP per welfare benefit recipient will result in a lower percentage of welfare benefit recipients in the population.

The second hypothesis will test the relationship between the number of ALMP-programs and the percentage of welfare benefit recipients in the population. The same method as above will be used, but adjusted for the number of welfare-to-work programs instead of spending on ALMP. A longer time period is available for ALMP-programs. This hypothesis will test how useful the number of ALMP-programs is in reducing unemployment. It is expected that a higher number of ALMP-programs per welfare benefit recipient will result in lower unemployment. Since those programs will help more people and the expectation is that the programs are effective in reducing unemployment.

The third hypothesis will test the relationship between the number of the different kinds of ALMP-programs and the percentage of welfare benefit recipients in the population. This is helpful in determining which one of the separate ALMP categories in the Netherlands is most effective in reducing the number of welfare benefit recipients in Dutch municipalities.

Boone and van Ours (2009) tried to circumvent the endogeneity by looking at the effect of the shares of the different categories of ALMP-spending on unemployment. Because unemployment will most likely have an effect on ALMP-spending, but will not likely have an

effect on the distribution of the different categories of ALMP. Training expenditures was found to have the largest negative effect on unemployment (Boone & van Ours, 2009). Training facilities are incorporated into the category 'other reintegration programs'. The expectation is that a high share of this category will have a larger negative effect on the number of welfare benefit recipients in municipalities. For the third hypothesis the same model will be used as for hypothesis 2. Instead of one variable for ALMP-programs per welfare benefit recipient, four variables are included, representing all ALMP-categories.

The fourth hypothesis examines the effect of the relative shares of the different ALMP-programs on the number of welfare benefit recipients. An adjusted model of Boone and van Ours (2009) will be used for this hypothesis, wherein they took the expenditure shares of the different ALMP categories. This was adjusted for the number of programs in each category instead of the spending in each category. With this hypothesis, the effectiveness of the different ALMP-programs is tested.

2.7: Conceptual model

From the research question of this thesis can be extracted that the number of welfare benefit recipients in Dutch municipalities will be the dependent, and ALMP-programs in Dutch municipalities will be the independent variable. The number of welfare benefit recipients in Dutch municipalities will be measured in the percentage of the population receiving welfare benefits in each municipality[2]. ALMP-programs in Dutch municipalities are measured in four ways: ALMP-expenditures per welfare benefit recipient, number of ALMP-programs per welfare benefit recipient, number of ALMP-programs in each category per welfare benefit recipient, and the shares of the different ALMP-programs. They are used for respectively the first, second, third and fourth hypothesis. The four different categories of ALMP together form the total ALMP-spending. ALMP-spending has an influence on the number of welfare benefit recipients, but this in turn can also influence the spending on ALMP. Population characteristics can be important for unemployment. These can vary across municipalities. Kok et al. state that welfare benefit dependency in the Netherlands is higher for migrants (especially refugees) and single parents (2017). In this thesis the control variables which will be used are population size, fraction of population with a non-western-migration background, fraction of women in population, fraction of population under 20 years, fraction of one-parent households and the

[2] The number of welfare benefit recipients below the retirement age is taken, because the welfare-to-work programs are most relevant for this group.

number of jobs in a municipality. Real interest rates can have an influence on unemployment; these will not vary across municipalities but do vary across time. Cyclical factors influence both ALMP-spending and unemployment. This can be controlled for by using time dummies for the different years in the dataset. Cyclical factors are expected to be constant over the municipalities, since all municipalities are in the same country and under same economic conditions. Unemployment influences the variable number of welfare benefit recipients, in this thesis there only will be looked to the number of welfare benefit recipients and not to the unemployment rate. In Figure 3 the conceptual model is depicted.

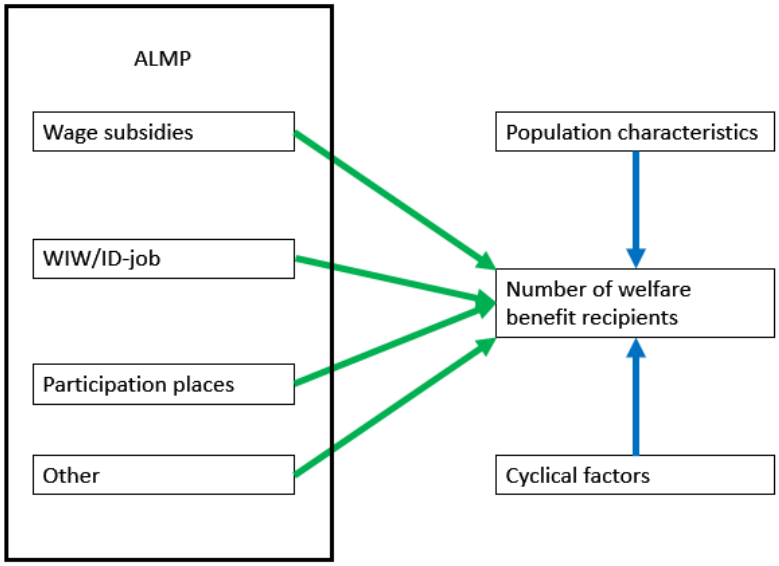

Figure 3: conceptual model

3: Data and Empirical Model

In this section, the data and empirical model will be described. Publicly accessible data obtained from CBS Statline are used for this thesis. The period covered in this dataset is 2008 to 2017, with yearly data for every municipality in the Netherlands. This dataset is used because it has comparable data for a longer period of time for every Dutch municipality. Section 3.1 contains information regarding the development of the dataset. In section 3.2 the descriptive statistics are given, first for the full dataset and afterwards for the specific time periods available for the different hypotheses. In section 3.3 the empirical model is drawn.

3.1: Data

The obtained dataset contains information on the main variables for the period 2008 to 2017. These variables are: the number of welfare benefit recipients, ALMP-programs, population size and all the control variables. For the information on ALMP expenditures, the years 2008 to 2014 are available and for the different ALMP measures the years 2013 to 2017. Therefore, the full dataset can only be used to test the second hypothesis. For the first hypothesis, only the years 2008 to 2014 can be used and for the third and fourth hypothesis, the years 2013 to 2017 can be used. Due to mergers the effective number of municipalities has decreased from 443 in 2008 to 380 in 2018. Account has been taken of this by aggregating the municipalities that have been merged, also for the pre-merger period. Four municipalities are excluded: "Meerlo-Wanssum", "Boarnsterhim", "Maasdonk" and "Littenseradiel". These municipalities were split among multiple new municipalities[3]. For the variables concerning ALMP-programs, only biannual (2013-2014) or monthly (2015-2017) data was available, for these variables the mean over the whole year is taken.

3.2: Descriptive statistics

3.2.1: Information on the full dataset

Table 1 shows the statistics for the main variables of analysis and the control variables for the period 2008 to 2017. The dependent variable for all hypotheses is percentage of welfare

[3] "Meerlo-Wanssum" (7767 citizens when split) and "Maasdonk" (11242 citizens when split) were divided among two municipalities, "Littenseradiel" (10746 citizens when split) was divided among three municipalities and "Boarnsterhim" (19505 citizens when split) was divided among four municipalities. It was unclear how these municipalities exactly where divided in citizen numbers.

benefit recipients. The main independent variable of interest for the second hypothesis is ALMP-programs per welfare benefit recipient.

Table 1: Descriptive statistics 2008 to 2017

	Obs.	Mean	Std. Dev.	Min	Max
Number welfare benefit recipients	3,800	1,039.568	3,273.754	0	42,430
Proportion of welfare benefit recipients	3,800	0.0154	0.00965	0	0.0665
Population size	3,800	43,974.53	65,836.3	919	844,947
ALMP-programs	3,792	586.271	1,686.947	0	29,400
ALMP-programs per welfare benefit recipient	3,776	0.65	0.35	0	2.59
Fraction population non-western migration background	3,800	0.0593	0.0536	0.0073 0	0.379
Fraction population female	3,800	0.503	0.00827	0.465	0.534
Fraction population under 20 years	3,800	0.236	0.0260	0.159	0.411
Fraction of one parent households	3,800	0.0608	0.0120	0.0272	0.123
Number of jobs in 1000	3,800	20.692	43.390	0.3	613.2

The highest number of welfare benefit recipients is 42,430 and the lowest number 0[4]. The percentage of welfare benefit recipients is the number of welfare benefit recipients divided by the population size. The highest number for this variable is 0.066 (6.6%) and the lowest number is zero for the municipalities for which no welfare benefit recipients are registered[5]. The population size is between 919 and 844,947 with a mean of 43,974[6]. The highest number of ALMP-programs is 29,400 and the lowest number 0 was registered for 11 observations, the average number of ALMP-programs is 586.27[7]. For eight observations, the data concerning the

[4] The highest number is observed in Amsterdam in 2014, the lowest number is observed 16 times in: Rozendaal (2008-2015), Vlieland (2008, 2010-2011), Schiermonnikoog (2008-2010) and Ameland (2009-2010).
[5] The highest number is registered for the municipality "Rotterdam" in 2014.
[6] Amsterdam has the most citizens in 2017 and the lowest number of citizens for a municipality are in Schiermonikoog in 2016.
[7] The highest number of ALMP-programs is registered in Amsterdam in 2017 and the lowest number was observed in: Vlieland (2012-2013), Rozendaal (2008-2013), Schiermonnikoog (2008-2009) and Beemster (2010).

ALMP-programs is missing[8]. The highest number for ALMP-programs per welfare benefit recipient is 2.59[9]. For three observations the number of ALMP-programs per welfare benefit recipient is zero, this because there are no ALMP-programs but there are welfare benefit recipients. For 24 observations the data on ALMP-programs per welfare benefit recipient is missing, this is when the data for ALMP-programs is missing or when the number of welfare benefit recipients is zero. In 13.29 percent of the observations the ALMP-programs per welfare benefit recipient is more than 1 and in 1.38 percent of the observations it was exactly one. Fraction of population with non-western migration background, fraction of population female, fraction population under 20 years, fraction of one parent households and number of jobs are used as control variables. The fraction of non-western, female and under 20 years population are all calculated by dividing the corresponding numbers of the part of the population by the total population. The fraction of one-parent households is calculated by dividing the number of one-parent households by the total number of households. The number of jobs must be multiplied by 1,000.

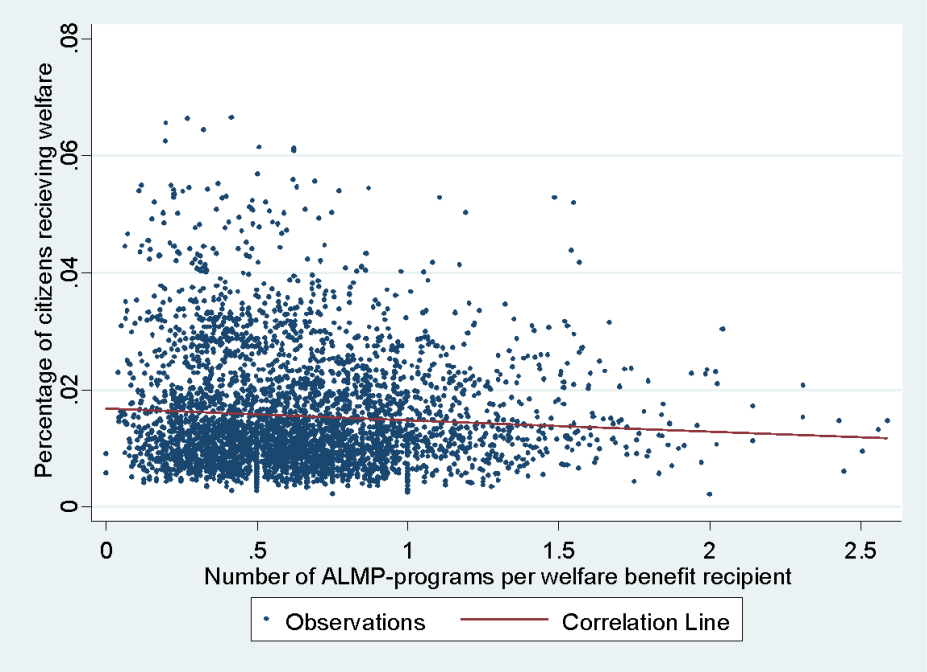

Figure 4: Scatterplot of percentage of citizens receiving welfare benefits and the number of ALMP-programs per welfare benefit recipient.

[8] For the municipalities: Brielle (2008), Kapelle (2009), Nederweert (2009), Opsterland (2009), Borger-Odoorn (2010), Hollands Kroon (2012) and Sûdwest-Fryslân (2011-2012).
[9] in Westerveld there are 725 ALMP-programs registered while only 280 welfare benefit recipients were registered. In ALMP-programs also transport facilities for people otherwise not able to work are included, these kinds of programs can be for people who do not receive welfare benefit.

The full dataset can only be used to test the second hypothesis. In Figure 4 a scatterplot of the percentage of citizens receiving welfare benefits and the number of ALMP-programs per welfare benefit recipient is depicted. They seem to have a slightly negative correlation of -0.0707, significant at the 1% level. On average a higher number of programs corresponds with a lower number of unemployment.

3.2.2: Information on the data 2008 to 2014

Information on the municipality accounts are only available for the years 2008 to 2014. The first hypothesis will be tested with this data. In table 2, the relevant descriptive statistics for the period 2008 to 2014 can be found.

Table 2: Descriptive statistics 2008 to 2014

	Obs,	Mean	Std. Dev.	Min	Max
ALMP-expenditures in 1.000 euro	2,659	12,452.57	32075.18	12	533,287
ALMP-expenditures per welfare benefit recipient in 1000 euro	2,644	17.22	9.51	1.8	101.01
Proportion Welfare benefit recipients of total population	2,660	0.01415	0.00925	0	0.0665
Number of welfare benefit recipients	2,660	970.40	3,154.74	0	42,430
Population size	2,660	43,674.56	64,772.51	932	810,937

ALMP-expenditures are the expenditures on the functions work and income and participation budget measured in 1000 euros, there is one observation missing for this variable[10]. Information on ALMP-expenditures per welfare benefit recipient is missing for 16 observations: this occurs when the ALMP-expenditures are missing or when the number of welfare benefit recipients in a municipality is zero. The main independent variable of interest for the first hypothesis is ALMP-expenditures per welfare benefit recipient. In figure 5, a scatterplot of these two variables is presented. They show a significant (at the 1% level) negative correlation of -0.297. On average municipalities with more expenditures on ALMP

[10] This is the municipality “De Fryske Marren” in 2013. "De Fryske Marren" was created in 2014, but all information about the ALMP-expenditures is missing in 2013 for the municipalities from which it originated.

per welfare benefit recipient have a lower percentage of welfare benefit recipients. This does not necessarily have to be a causal relationship.

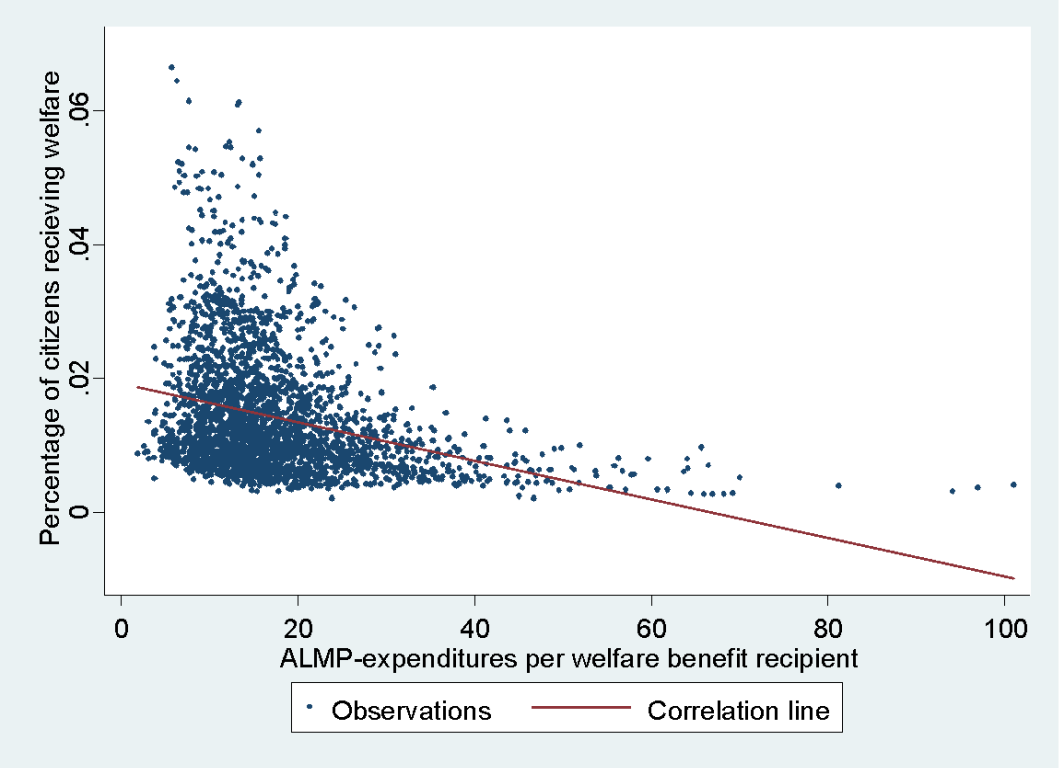

Figure 5: Scatterplot of ALMP-expenditures per welfare benefit recipient and the percentage of citizens receiving welfare benefits

3.2.3: Information regarding the data 2013 to 2017

Information concerning the different ALMP-programs in the Netherlands is only available for the years 2013 to 2017. These years will be used to test the third and fourth hypothesis. Table 3 contains summary statistics for the main variables of interest. This includes the number of ALMP-programs, number of ALMP-programs per welfare benefit recipient, number of ALMP-programs per welfare benefit recipient for the different categories, shares per program, percentage of welfare benefit recipients and population size.

Table 3: Descriptive statistics 2013 to 2017

	Obs.	Mean	Std. Dev.	Min	Max
Number of programs	1900	568.205	1547.388	0	29399.1
Programs per welfare benefit recipient	1897	0.617	0.396	0	2.589
Share per program					
Wage subsidies	1894	0.0340	0.0685	0	1
WIW/ID-job	1894	0.00327	0.0143	0	0.286
Participation places and sheltered work	1894	0.0416	0.0914	0	1
Other	1894	0.921	0.123	0	1
Programs per welfare benefit recipient					
Wage subsidies	1897	0.0153	0.0280	0	0.5
WIW/ID-job	1897	0.00131	0.00507	0	0.0583
Participation places and sheltered work	1897	0.0239	0.0614	0	0.662
Other	1897	0.572	0.384	0	2.407
Proportion of welfare benefit recipients	1900	0.0176	0.00998	0	0.0665
Number of welfare benefit recipients	1900	1165.605	3500.508	0	42430
Population size	1900	44459.96	67544.37	919	844947

For the number of programs per welfare benefit recipient there are 3 missing observations[11]. Regarding information about the shares per program there are 6 missing observations[12] for all other variables all observations are present. The lowest number of ALMP-programs is zero and observed 6 times. The highest number of ALMP-programs is 29,399.1[13]. These four categories; wage subsidies, WIW/ID-job, participation places and other, are chosen because the CBS did only register those four categories in 2013 and 2014. For 2015, 2016 and 2017 the CBS registered more categories, but they are merged with the four main categories, in

[11] This is for Rozendaal in 2013 and 2014.
[12] These observations are missing because the number of programs is 0, this is the case for Vlieland (2013), Rozendaal (2013) and Ameland (2014-2017).
[13] Observed in Amsterdam (2017).

the way described below. In the later dataset three specific types of wage subsidies were registered, these are combined in one group (wage subsidies). Participation places are combined with sheltered work. The other three programs, which were registered in the later dataset, were merged with other programs: Job-coaches, transport provisions, and other provisions for disabled.

The number of welfare benefit recipients per program for the different programs is between 0 and 2.41. The mean for respectively wage subsidies, WIW/ID-jobs, participation places and other is 0.0153[14], 0.00131[15], 0.0239, and 0.572, indicating that by far the most programs are registered in other ALMP-programs and for WIW/ID-job not even one program is registered in 700 welfare benefit recipients on average. Other programs per welfare benefit recipient show a significant (1% level) negative correlation with the percentage citizens receiving welfare benefits, the correlation is - 0.1230. The other three programs per welfare benefit recipient show a slight positive correlation with the percentage of citizens receiving welfare benefits although not all significant. WIW/ID-job has a significant (1% level) correlation of 0.1861, wage cost subsidies 0.0385, significant at the 10% level and participation places 0.0319 but not significant. The scatterplots for these variables can be found in Appendix 1.

The shares per program can be up to 100% (this is for wage subsidies, participation places and sheltered work, and other programs). This implies that in some municipalities all ALMP-programs that are reported are one and the same. The mean for wage subsidies is 0.0340 (3.4%), the highest number registered is 1[16]. In 913 cases there were zero programs registered for wage subsidies (this is in 48% of the cases). The mean for WIW/ID-job is 0.00327 (0.3%), the highest number is 0.2857 and the lowest number 0 was registered in 1706 cases[17] (this is for 90% of the cases). The mean for participation places and sheltered work is 0.04157 (4.2%), the highest number registered is 1 and observed one time, in 1220 cases the number was 0[18] (in 64% of the cases). The mean for other reintegration programs is 0.92116 (92.1%). The number was 0 for two observations[19] (0.1%) and in 658 observations, the number for other ALMP-programs was exactly 1 (in 35% of the cases). The main variables of interest for hypothesis 4

[14] This means that on average if there are 65 welfare benefit recipients, there is 1 program in wage subsidies.
[15] On average if there are 765 welfare benefit recipients only one program in WIW/ID-job is registered.
[16] This was for Ameland in 2013, they had 5 reintegration programs and they were all in the category WIW/ID-job.
[17] The highest number is registered for the municipality Papendrecht in 2013.
[18] This was 1 for the municipality Maasgouw in 2013 all 60 ALMP-programs were registered under this category
[19] Ameland and Maasgouw (2013).

are the shares of the different ALMP-programs of the total number of programs. The mean percentages for these variables are described in table 3. Scatterplots for these variables and the percentage of citizens receiving welfare benefit are depicted in Appendix 2. Other ALMP programs seem to have a significant (at the 1% level) negative relationship with the percentage citizens receiving welfare benefit, the correlation is -0.2048 (see Appendix 2). The other three shares seem to have a slight positive effect on the percentage of citizens receiving welfare benefit. Participation places has a correlation of 0.1229, WIW/ID-job a correlation of 0.2150 and wage cost subsidies 0.1551 all significant at the 1% level.

Table 4: descriptive statistics: mean for the relevant variables of hypothesis 2 for each year

	2013	2014	2015	2016	2017
Proportion of welfare benefit recipients	0.0162	0.0171	0.0179	0.0187	0.0185
Proportion other programs	0.924	0.934	0.933	0.922	0.892
Proportion participation places	0.0413	0.0349	0.0395	0.0456	0.0465
Proportion WIW/ID-job	0.00620	0.00300	0.00300	0.00224	0.00190
Proportion wage subsidies	0.0283	0.0277	0.0248	0.0299	0.0592
Total number of programs	520.290	566.461	548.615	571.911	634.476
Number of programs per welfare benefit recipient	0.570	0.602	0.596	0.616	0.699

In table 4, the relevant variables over time for hypothesis 4 are depicted. A growth of the percentage of welfare benefit recipients can be observed. In 2013 the average percentage of welfare benefit recipients in a municipality was 1.6%, which grew to 1.8% in 2017. The percentages of the different programs are mainly stable over time; two big differences can be noticed. Over time, a big decline of the percentage of WIW/ID-job can be found. In 2013 this percentage was 0.6% compared to 0.2% in 2017. This can be explained by the stop of inflow in this category. In addition, a big increase between 2016 and 2017 for wage subsidies is noticed, from 3.0% to 5.9%. The total number of ALMP-programs and the number of ALMP-programs per welfare benefit recipient is growing.

3.3: Empirical model

In this section, the models will be formulated to be able to test the different hypotheses. The main equation for the tests will be:

Equation 1:

$$Y_{it} = \alpha + \beta 1\ ALMP_{it} + \beta 2\ x_{it} + \beta 3\ Y_t + a_{it} + \varepsilon_{it}$$

- Y_{it} is the proportion of the population receiving welfare benefits in a municipality; this is measured in a number between 0 and 1.
- $ALMP_{it}$ is defined differently for the four hypotheses. Respectively for hypotheses 1, 2, 3 and 4 $ALMP_{it}$ is defined; the ALMP-expenditure per welfare benefit recipient measured in 1,000 euro, the number of ALMP-programs per welfare benefit recipient, the number of the four different ALMP-programs per welfare benefit recipient, and the shares of the different kinds of ALMP-programs.
- x_{it} contains the control variables: population size in 1,000, fraction of population with a non-western-migration background, fraction of women in population, fraction of population under 20 years, fraction of one-parent households the number of jobs in a municipality in 1,000.
- Y_t contains the year dummies for the different years, to control for unobserved year effects.
- a_{it} is a time invariant municipality specific effect.
- ε_{it} is the error term.

Multiple models are used per hypothesis. The first hypothesis will test the effect of ALMP-expenditure per welfare benefit recipient measured in 1,000 euro ($ALMP_{it}$ for this hypothesis) on the percentage of welfare benefit recipients in a municipality. The years 2008 to 2014 are available for this hypothesis, these years are included as a dummy variable with 2008 as a base year. The constant can be interpreted as the percentage of welfare benefit recipients in a municipality when the year is 2008, and all the control variables having the value zero. The tests will be shown in model 1 to 3. Model 1 will have municipality fixed effects with clustered standard errors, since autocorrelation can be detected. For the fixed effects model it is assumed that ε_{it} is independent over time and across municipalities. When doing a Breusch-Godfrey test

for autocorrelation on the first-difference regression there is an indication that ε_{it} is not an independent error term, therefore first differences is preferred. For this reason, model 2 will be a first differences model. For all variables the first differences are taken, in this model the year dummy for 2009 is also excluded. The difference between 2008 and 2009 is the new base level of this model. Model 3 will use instrumental variables (IV), wherein $ALMP_{it}$ will be instrumented with the averages of the separate municipalities over the years. This is similar to the method Scarpetta (1996) and Elmeskov et al. (1998) use; they take the country average for this variable. The idea is that this approach cancels out the potentially biasing impact of local business cycles on both welfare benefit recipiency rates and ALMP expenditure per recipient. Accordingly, this model does not allow for municipality fixed effects.

The second hypothesis will test the effect of the number of ALMP-programs per person receiving welfare benefits (the $ALMP_{it}$ for this hypothesis) on the percentage of the population receiving welfare benefits in a municipality. To test this hypothesis, three comparable models are used, model 4 to 6. The time period used to test this hypothesis is 2008 to 2017. Model 4 will be a fixed effect model, model 5 will be a first difference model and model 6 will use IV, in the same way as described for hypothesis 1, . Only a different variable for $ALMP_{it}$ and a different time period are used.

The third hypothesis will test the effect of the number of the different ALMP-programs per person receiving welfare benefits (the $ALMP_{it}$ for this hypothesis) on the percentage of the population receiving welfare benefits in a municipality. To test this hypothesis, again three models will be used: model 7 to 9. The data for this analysis contains information on the years 2013 to 2017. Four variables are included in $ALMP_{it}$ for this hypothesis:

- Programs in wage subsidies per welfare benefit recipient
- Programs in WIW/ID-job per welfare benefit recipient
- Programs in participation places per welfare benefit recipient
- Programs in other programs per welfare benefit recipient

The models are similar to the models for hypothesis one and two. Model 7 is a fixed effects model, model 8 is a first difference model and model 9 will use IV. For the IV model, all four variables will be instrumented by the average over the whole period, equally as in model 3 and 6, only with four instrumented variables instead of one.

The fourth hypothesis will test which ALMP program is most effective in reducing the percentage of welfare benefit recipients in the population. Two models are used to find out about this hypothesis; a fixed effect model (model 10) and a first difference model (model 11). The variables included in $ALMP_{it}$ for this hypothesis are:

- Proportion wage subsidies of total ALMP programs
- Proportion WIW/ID-job of total ALMP programs
- Proportion participation places of total ALMP programs

The proportion of other ALMP-programs is left out of the equation because this is incorporated in the constant when using fixed effects (including this will cause multicollinearity). The approach of Boone and Ours had to be adjusted; they used the shares of the expenditures as main explanatory variables (2009: 309). In this research, the shares of ALMP-programs are used by taking the number of the specific ALMP-program and dividing it by the total number of ALMP-programs in that municipality. This will reduce the endogeneity problem, since it is expected that the number of welfare benefit recipients has an influence on the ALMP-spending or the number of ALMP-programs but not on the different proportions of the ALMP-categories.

4: Results and analysis

In this section the results will be shown and analysed. The results for hypotheses 1, 2, 3 and 4 are depicted in respectively table 5, 6, 7 and 8. Afterwards the results will be analysed.

4.1: Results for hypothesis 1

The regression results for the first hypothesis are shown in table 5. In the fixed effects model (model 1) and in the first difference model (model 2), a significant relationship between ALMP-expenditures and the proportion of the population receiving welfare benefits is found. In the fixed effect model (model 1) the estimate for $ALMP_{it}$ is -0.0000889. This means that 1000 euro of ALMP-spending per welfare benefit recipient leads to a decrease of 0.0089 percentage point in the percentage of welfare benefit recipients in a municipality. The average spending on ALMP per welfare benefit recipient is 17.2 (see table 2)[20]. According to the model, this will lead to a reduction of welfare benefit recipients by 0.15 percentage point. This seems small, but the average percentage of welfare benefit recipients in a municipality is 1.54% (see table 1). Therefore is a decrease of 0.15 percentage point in this case, a reduction of almost 10%. In model 2 (first difference model) the ALMP-spending on the number of welfare benefit recipients is larger. An increase of ALMP-spending per welfare benefit recipient with 1000 euro will lead to a reduction of number of welfare benefit recipients by 0.0011[21]. This means that an increase of ALMP-spending per welfare benefit recipient with 10,000 euro will lead to a decrease of welfare benefit recipients by 0.11 percentage point. In model 3, with instrumental variables, a significant relationship cannot be found. With this instrumental variable, the average ALMP-spending per welfare benefit recipient over the whole period is used, therefore only the differences between municipalities are taken into account.

In the fixed effects model all control variables except for fraction non-western immigration background are significant. Population size has a significant effect on the percentage of welfare benefit recipients, for every 1000 citizens the percentage of welfare benefit recipients in the population is expected to grow by 0.011 percentage point. The fraction of women in the population also has a significant effect on the percentage of welfare benefit recipients in a municipality. If the population consists 100 percent out of women, the expected percentage of welfare benefit recipients is 7.2 percentage point lower than with a population

[20] The observed values for ALMP-spending per welfare benefit recipient are between 1.8 and 101.1 thousand.
[21] The change in ALMP-expenditure per welfare benefit recipient is between -30,930 and 53,360

consisting 100 percent out of man. Fraction of population under 20 has a significant positive effect on the number of welfare benefit recipients by 0.060. When the fraction of population under 20 is 0.236 (which is the average value) the expectation is that the percentage of welfare benefit recipients in a municipality is 1.4 percentage point higher, than with 0% of the population under 20 years of age. Fraction of one-parent households is positively significant with a value of 0.052; the expectation is that with 1% of the households being a one-parent household the percentage of welfare benefit recipients in a municipality increases by 0.052 percentage point. The effect of number of jobs in a municipality on the proportion of welfare benefit recipients is negative and significant with a value of -0.0013, for each 1000 jobs in a municipality the expected percentage of welfare benefit recipients drops by 0.13 percentage point. All year dummies are significant and positive, which means that in all years a significantly higher percentage of welfare benefit recipients is registered, compared to 2008. In the first difference model, less control variables are significant. Only fraction of population under 20 is significant at the one percent level; a one percent increase in the population under 20 leads to a 0.036 percentage point increase in the percentage of welfare benefit recipients. Most year dummies for model 2 are significant and negative at the 1 percent level, this means that the change in percentage of welfare benefit recipients is significantly lower for the change between 2010/2011, 2011/2012 and 2013/2014 compared to 2008/2009 and the change in the percentage of welfare benefit recipients is significantly higher for 2012/2013 compared to 2008/2009.

Interestingly the fraction of the population under 20 years is significant in all three models, but in models 1 and 2 positive and in model 3 negative. This is because in model 3, the differences between municipalities are more important and municipalities with more children generally have a lower percentage of welfare benefit recipients. However, a positive change in the fraction of the population under 20 years leads to higher percentage of the number of welfare benefits recipients.

Within municipalities corrected for time effects and population characteristics, a clear negative effect of the ALMP-spending per person receiving welfare benefits on the percentage of welfare benefit recipients in Dutch municipalities can be found.

Table 5: Regression results for hypothesis 1

Independent variables:	Dependent variable: fraction of citizens receiving welfare benefits			
	Model 1 FE	Model 2 FD	Model 3 IV	First stage Model 3
ALMP-expenditure per welfare benefit recipient in 1000 euro	-0.0000889***	-0.000107***		
	(0.00000)	(0.00002)		
Instrumented ALMP-expenditure per welfare benefit recipient in 1000 euro			-0.0000401	
			(0.00003)	
Mean ALMP-expenditure per welfare benefit recipient in 1000 euro				1.001***
				(0.00883)
Population size in 1000	0.000114***	0.0000499*	0.0000518*	0.000761
	(0.00002)	(0.00003)	(0.00003)	(0.00507)
Fraction of non-western immigrants in population	0.0101	0.0144	0.0167	1.653
	(0.00980)	(0.00970)	(0.0138)	(2.328)
Fraction of women in population	-0.0722***	-0.00374	-0.111***	0.674
	(0.0227)	(0.0174)	(0.0409)	(8.948)
Fraction population under 20 years	0.0602***	0.0361***	-0.106***	0.633
	(0.00928)	(0.0174)	(0.0160)	(2.636)
Fraction one parent households	0.0519***	0.00904	0.292***	-5.337
	(0.0148)	(0.0122)	(0.0509)	(8.845)
Number of jobs in the Municipality in 1000	-0.00134***	-0.0000418*	-0.0000067	-0.00206
	(0.00009)	(0.00002)	(0.00005)	(0.00747)
Years				
2009	0.00107***		0.000660***	-1.605***
	(0.00009)		(0.00008)	(0.233)
2010	0.00215***	-0.0000105	0.00113***	-1.612***
	(0.00011)	(0.00007)	(0.000117)	(0.233)
2011	0.00252***	-0.000765***	0.000901***	-3.707***
	(0.00013)	(0.00007)	(0.00019)	(0.23370)
2012	0.00296***	-0.000633***	0.000637**	-5.548***
	(0.00016)	(0.00007)	(0.00028)	(0.235)
2013	0.00431***	0.000240***	0.00137***	-7.816***
	(0.00020)	(0.00006)	(0.00037)	(0.23748)
2014	0.00522***	-0.000184**	0.00141***	-8.838***
	(0.00023)	(0.00007)	(0.00045)	(0.241)
Constant	0.0291**	0.00108***	0.0748***	3.898
	(0.0118)	(0.00007)	(0.02222)	(4.731)
N	2644	2262	2644	2644
R^2	0.739	0.220	0.612	0.888

Standard errors in parentheses. *** = p < 0.01, ** = p < 0.05, * = p < 0.10

4.2: Results for hypothesis 2

In table 6, the regression results for the second hypothesis are shown. For both the fixed effects model and the first difference model, the number of ALMP-programs per welfare benefit recipient has a significant and negative effect at the 1% level on the proportion of welfare benefit recipients. For model 4 (the fixed effect model) the estimate is -0.0011. This means that if there is one program per welfare benefit recipient, the percentage of welfare benefit recipients is expected to be 0.11 percentage point lower compared to zero programs per welfare benefit recipient. This is a small effect considering that the average number of ALMP-programs per welfare benefit recipient is 0.65 (see table 1); this average number will only reduce the percentage of the population receiving welfare benefits by 0.072 percentage point. The estimate for model 5 (the first difference model) is -0.000798. One additional ALMP-program per welfare benefit recipient will lead to a reduction of 0.080 percentage point in the percentage of the population receiving welfare benefits.

In model 6 ALMP-programs per welfare benefit recipients shows an unexpected positive effect on the percentage of welfare benefit recipients at the 10 percent significance level (0.0020). A problem with this is that the first stage regression only has a R^2 of 0.54, therefore it does not explain the instrumented variable very well. A possible explanation for the unexpected effect is that without using fixed effects or first differences, too much information is lost when looking at (constant) differences between municipalities. Possibly municipalities with more welfare benefit recipients already put more effort in reducing unemployment, for example already offering more ALMP-programs. This will lead to a biased view on the relationship of ALMP on welfare benefit recipients. Pooled OLS is therefore in this specific model not useful.

The interpretation and estimates for the control variables of model 4, 5 and 6 are similar and in the same direction as for models 1, 2 and 3. For the fixed effects model (model 4) all control variables except for the fraction of non-western immigrants in the population are significant at the one percent level.

Table 6: Regression results for hypothesis 2

Independent variables:	Dependent variable: percentage of citizens receiving welfare benefits			
	Model 4 FE	Model 5 FD	Model 6 IV	First stage Model 6
ALMP-programs per welfare benefit recipient	-0.00113***	-0.000788***		
	(0.00009)	(0.00010)		
Instrumented ALMP-programs per welfare benefit recipient			0.00204*	
			(0.00116)	
Mean ALMP-programs per welfare benefit recipient				1.000***
				(0.0157)
Population size in 1000	0.0000895***	0.0000037	0.0000538*	-0.0000998
	(0.00001)	(0.00003)	(0.00003)	(0.00031)
Fraction of non-western immigrants in population	-0.00282	-0.0117	0.0202	-0.0296
	(0.00684)	(0.0111)	(0.0141)	(0.142)
Fraction of women in population	-0.0575***	0.00624	-0.104**	0.361
	(0.0166)	(0.0163)	(0.0406)	(0.529)
Fraction population under 20 years	0.0600***	0.0262***	-0.0984***	-0.00744
	(0.00629)	(0.00988)	(0.0153)	(0.161)
Fraction one parent households	0.0994***	0.0124	0.315***	-.0511
	(0.0113)	(0.0103)	(0.0507)	(0.522)
Number of jobs in the Municipality in 1000	-0.000127***	-0.0000402**	-0.0000102	0.000161
	(0.00001)	(0.00002)	(0.00005)	(0.00045)
Years				
2009	0.00110***		0.000851***	-0.0780***
	(0.00010)		(0.00012)	(0.0174)
2010	0.00212***	-0.000142*	0.00139***	-0.116***
	(0.00011)	(0.00007)	(0.00015)	(0.0174)
2011	0.00263***	-0.000698***	0.00129***	-0.148***
	(0.00012)	(0.00008)	(0.00020)	(0.0174)
2012	0.00309***	-0.000623***	0.00122***	-0.214***
	(0.00014)	(0.00007)	(0.00029)	(0.0175)
2013	0.00459***	0.000324***	0.00209***	-0.227***
	(0.00016)	(0.00007)	(0.00034)	(0.0176)
2014	0.00555***	-0.000183**	0.00205***	-0.195***
	(0.00018)	(0.00008)	(0.00039)	(0.0177)
2015	0.00644***	-0.000355***	0.00235***	-0.201***
	(0.00020)	(0.00007)	(0.00043)	(0.0178)
2016	0.00734***	-0.000261***	0.00257***	-0.181***
	(0.00022)	(0.00008)	(0.00046)	(0.0180)
2017	0.00731***	-0.00131***	0.00188***	-0.0973***
	(0.00024)	(0.00009)	(0.00047)	(0.0180)
Constant	0.0197**	0.00121***	0.0658***	-0.0280***
	(0.00860)	(0.00006)	(0.0206)	(0.271)
N	3776	3388	3776	3776
R^2	0.798	0.225	0.604	0.545

Standard errors in parentheses. *** = p < 0.01, ** = p < 0.05, * = p < 0.10

A clear negative effect of the number of ALMP-programs per person receiving welfare benefits on the percentage of welfare benefit recipients in Dutch municipalities is found when looked at within effects for municipalities. This effect has been corrected for time effects and population characteristics. Although the effect is smaller compared to the effect of ALMP-spending per welfare benefit recipient. When looking at the relationship between the average costs per program and the proportion of welfare benefit recipients, they seem to have a significant and negative correlation of -0.1954 (see Appendix 3 for a scatterplot), but in a fixed effect regression this relationship is not significant.

4.3: Results for hypothesis 3

The regression results for hypothesis 3 on the relationship between the number of specific ALMP-programs per welfare benefit recipient and the proportion of the population receiving welfare benefits are depicted in table 7. For the fixed effects and the first difference model, the number of other programs per welfare benefit recipient indicates a negative and significant (at the 5 percent level) effect on the proportion of the population receiving welfare benefits. For model 7 the estimate for number of other ALMP-programs per welfare benefit recipient is -0.000405, this means that an addition of one ALMP-program in this category for all welfare benefit recipients would reduce the percentage of welfare benefit recipients by 0.041 percentage point. The estimate for model 8 is -0.000813, this means that an addition of one program per welfare benefit recipient will change the percentage of welfare benefit recipients by -0.081 percentage point. Both values are small and therefore their economic impact is limited. For the instrumental variable model, a significant positive effect at the 1 percent level is found for the number of programs in WIW/ID-job per welfare benefit recipient (the first stage regressions for model 9 are depicted in appendix 4). The estimate for this variable is 0.30, indicating that in case every welfare benefit recipient will have a WIW/ID-job, the percentage of welfare benefit recipients will increase by 30 percentage point according to this model. Possible explanations for this high estimate are the missing of within municipalities data in the used pooled OLS and the fact that WIW/ID-job was only registered in 191 observations, while these observations have on average a high percentage of citizens receiving welfare benefits; 2.77% compared to 1.76% for the whole sample. The control variables show similar effects as in models 1, 2 and 3.

Table 7: Regression results hypothesis 3

Independent variables:	Dependent variable: proportion of citizens receiving welfare benefits		
	Model 7	Model 8	Model 9
	FE	FD	IV
Programs in wage subsidies per welfare benefit recipient	-0.00103 (0.00153)	0.0000528 (0.00101)	0.00815 (0.0184)
Programs in WIW/ID-job per welfare benefit recipient	0.00371 (0.0166)	-0.00405 (0.0103)	0.300*** (0.0862)
Programs in Participation places per welfare benefit recipient	-0.000171 (0.000645)	-0.000486 (0.000493)	-0.000918 (0.00699)
Programs in other programs per welfare benefit recipient	-0.000405** (0.000159)	-0.000813*** (0.000123)	-0.000129 (0.000922)
Population size in 1000	-0.000644* (0.000377)	-0.00113*** (0.000284)	0.000520 (0.000332)
Fraction population with a non-western migration background	0.00751 (0.0162)	-0.0271** (0.0133)	0.0267* (0.0151)
Fraction population female	-0.00491 (0.0279)	0.0333 (0.0207)	-0.115** (0.0447)
Fraction population under 20 years	0.0402*** (0.0135)	0.0349*** (0.0116)	-0.0955*** (0.0154)
Fraction of one parent households	0.0637*** (0.0184)	0.0275** (0.0138)	0.314*** (0.0537)
Number of jobs in a municipality in 1000	-0.0000176 (0.0000229)	0.00000156 (0.0000173)	-0.0000129 (0.0000566)
Year dummies			
2014	0.000958*** (0.0000784)		0.000361** (0.000168)
2015	0.00181*** (0.000132)	-0.000142** (0.0000624)	0.000774*** (0.000235)
2016	0.00268*** (0.000186)	-0.0000604 (0.0000690)	0.00108*** (0.000275)
2017	0.00253*** (0.000234)	-0.00110*** (0.0000793)	0.000458 (0.000435)
Constant	0.00823 (0.0149)	0.00106*** (0.0000684)	0.0726*** (0.0221)
Observations	1897	1517	1897
R^2	0.614	0.273	0.573

Standard errors in parentheses. *** = p < 0.01, ** = p < 0.05, * = p < 0.10

The hypothesis cannot be answered clearly, because of insufficient information. The only significant and negative effect on the percentage of welfare benefit recipients in a municipality can be found by the number of ALMP-programs in the category other, which is comprehensible because most programs fall within this category.

4.4: Results for hypothesis 4

The regression results for hypothesis 2 on the relationship between the proportions of ALMP-programs and the percentage of welfare benefit recipients are depicted in table 8. The different proportions of ALMP-programs do not show a significant effect on the percentage of citizens receiving welfare benefits. Only in model 10 (the fixed effects model), the percentage of participation places shows a significant effect on the 10 percent significance level. The estimate for this variable is 0.00067.his means that if 100% of the ALMP-programs were in the category participation places, the expectation is that the percentage of welfare benefit recipients will be 0.067 percentage point higher compared to the category other, which is the base level in this model.

A smaller amount of control variables are significant compared to the previous models. There is no evidence that a high share of short-term reintegration programs of ALMP in Dutch municipalities negatively affects the number of welfare benefit recipients in municipalities.

Table 8: Regression results hypothesis 4

Independent variables:	Dependent variable: percentage of citizens receiving welfare benefits	
	Model 10	Model 11
	FE	FD
Proportion wage subsidies	0.000338	0.000775
	(0.000665)	(0.000540)
Proportion WIW/ID-job	-0.000118	-0.00207
	(0.00348)	(0.00199)
Proportion Participation places	0.000666*	0.000402
	(0.000367)	(0.000307)
Population size in 1000	-0.000614	-0.00109***
	(0.000381)	(0.000288)
Fraction citizens migration background in population	0.00555	-0.0300**
	(0.0154)	(0.0130)
Fraction female citizens in population	-0.00959	0.0395*
	(0.0286)	(0.0220)
Fraction population under 20	0.0389***	0.0360***
	(0.0139)	(0.0117)
Fraction of one parent households	0.0669***	0.0242*
	(0.0189)	(0.0143)
Number of jobs in a municipality in 1000	-0.0000185	0.00000258
	(0.0000231)	(0.0000176)
Year dummies		
2014	0.000934***	0.000775
	(0.0000785)	(0.000540)
2015	0.00178***	-0.000116*
	(0.000133)	(0.0000644)
2016	0.00266***	-0.0000383
	(0.000184)	(0.0000700)
2017	0.00245***	-0.00115***
	(0.000228)	(0.0000780)
Constant	0.0104	0.00105***
	(0.0152)	(0.0000687)
N	1894	1514
R^2	0.608	0.253

Standard errors in parentheses. *** = p < 0.01, ** = p < 0.05, * = p < 0.10

5: Conclusion

In this research, a regression analysis of the effect different ALMP variables have on the percentage of the population receiving welfare benefits within Dutch municipalities is conducted. First an answer on the research question will be formulated, guided by the different hypotheses. Afterwards the strengths and weaknesses of this thesis will be discussed and recommendations for further research will be given.

5.1: Effect of ALMP on welfare benefit recipients

The research question of this thesis is: *What is the effect of welfare-to-work programs (ALMP) on the number of* welfare benefit recipients *in the Dutch municipalities?* To be able to answer this research question, four hypothesis have been formulated.

The first hypothesis is: *The average ALMP-spending per person receiving welfare benefits negatively affects the percentage of welfare benefit recipients in Dutch municipalities between 2008 and 2014.* Evidence has been found in support of this hypothesis. More spending on ALMP per welfare benefit recipient reduces the percentage of welfare benefit recipients in a municipality. Spending 1000 euro more on ALMP per welfare benefit recipients will reduce the percentage of welfare benefit recipients by approximately 0.01 percentage point. However, no significant relationship between the two variables could be found when using an instrumental variable, too much variation has been lost when using the average over time as the instrument.

The second hypothesis is**:** *The average number of ALMP-programs per person receiving welfare benefits negatively affects the percentage of welfare benefit recipients in Dutch municipalities between 2008 and 2017.* Evidence in support of this hypothesis has been found. Having one ALMP-program per person receiving welfare benefits reduces the percentage of welfare benefits between 0.08 and 0.11 percentage point. In an average municipality with a population size of 40,000 and an average number of welfare benefits 1.54%, 616 people receive welfare benefits. With focus on the cost of reintegration divided by the number of ALMP-programs in a municipality, the average costs of a program are 33,000 euro. If an average municipality, with an average number of welfare benefit recipients, wants to provide every welfare benefit recipient with an ALMP-program, and the costs for the programs stay constant, this will cost 20,328,000 euro (616*32,000). It will result in a decrease in the welfare caseload by approximately 44 people (616/1.54*0.11). This does not seem

economically viable. However, when more programs are provided, a reduction of price per program can be expected due to scale benefits. Similar to the findings of hypothesis 1 no significant relationship between the ALMP variable and the percentage of welfare benefit recipients has been found with help of an instrumental variable.

The third hypothesis is: *The average number of short-term reintegration programs per person receiving welfare benefits negatively affects the percentage of welfare benefit recipients in Dutch municipalities between 2008 and 2017.* Not a clear relationship between short-term programs and a reduction of the percentage of welfare benefit recipients in Dutch municipalities has been found. Only the category other ALMP programs shows a significant and negative relationship with the percentage of the population receiving welfare benefits. However, this is a very wide category and therefore gives limited information about the included programs.

The fourth hypothesis is**:** *A high share of short-term reintegration programs of ALMP in Dutch municipalities negatively affects the percentage of welfare benefit recipients in municipalities between 2013 and 2017.* No evidence could be found in support of this hypothesis; the different shares for the different reintegration programs do not seem to have any significant effect on the percentage of the population receiving welfare.

In conclusion, a small significant effect of ALMP on the percentage of the population receiving welfare benefits has been found. Both spending on ALMP and number of ALMP-programs have, in a fixed effect and in a first difference model, a significant effect on the percentage of the population receiving welfare. This is in accordance with most previous research on ALMP, which is summarized in the theoretical framework of this research. For ALMP-spending an effect of approximately 0.01 percentage point per 1,000 euro per welfare benefit recipient has been found. Moreover, for the number of ALMP-programs an effect of approximately 0.1 percentage point has been found in case all welfare benefit recipients are provided with an ALMP-program. No relationships of the different shares of the four categories of ALMP-programs have been found. A possible explanation is that information has been lost due to the large category other ALMP programs. The models with instrumental variables do not give any significant results. The variable by which it is instrumented is the value average over the time period; with this variable, a lot of information is lost and no fixed effects or first differences can be used.

5.2: Limitations

An objective in this thesis has been to correct for the endogeneity by using instrumental variables and the shares of the different ALMP-categories. However, no significant relationship was found after using these methods. In the fixed effects and the first differences model, time dummies have been used to correct for fixed effects over time. The assumption is that these time fixed effects (for example the business cycle) are constant over all municipalities. In this way, the expectation is also that the effect of the number of welfare benefit recipients on the ALMP-spending will be constant over the municipalities and therefor taken out by the time fixed effects.

Due to municipality reorganisations during the observed time period, municipalities were merged, split or decomposed. Account has been taken for this by adding together the municipalities which were merged for the whole period observed. But for some municipalities this was not possible because they were divided among multiple other municipalities. This were small municipalities, however results can be biased by this information gap.

A limitation of this thesis is the lack of available information on the distribution of the expenditures of the different ALMP-programs in the Netherlands. Another problem is that many ALMP-programs are label "Other" this is 92% of the total ALMP-programs. When more divisions would be made, a more accurate estimation could be conducted. According to the literature, training is good instrument in reducing unemployment. In the division CBS made, training is included in the category other and therefore it is difficult to measure the effect of this category in Dutch municipalities. For the ALMP-expenses in this thesis the functions of the municipal accounts on work and income and participation budget are taken, not all the budgets spent in these functions are on ALMP-programs. Nevertheless, the budgets in the categories are all used to promote employment opportunities in the municipality (encouraging employment).

5.3: Recommendations for further research

When more exact data is available or gathered, a better estimation of the effect the different ALMP-categories have on the reduction of the number of welfare benefit recipients in Dutch municipalities can be made. It is especially interesting to take a closer look at more specific ALMP categories. In this research, conclusions could not give specific efficiency details as a result of a large sum of other ALMP-programs. To the extent of this research, more insights can be found with more specific ALMP-program designs. Conducting the same research with the ALMP-categories the OECD has developed might lead to results that are more

relevant and precise. Further research should also be looking into new methods of instrumentation of the ALMP-variables, or using an ALMP-variable that is not expected to have an endogenous relationship with the unemployment rate.

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Appendix 1

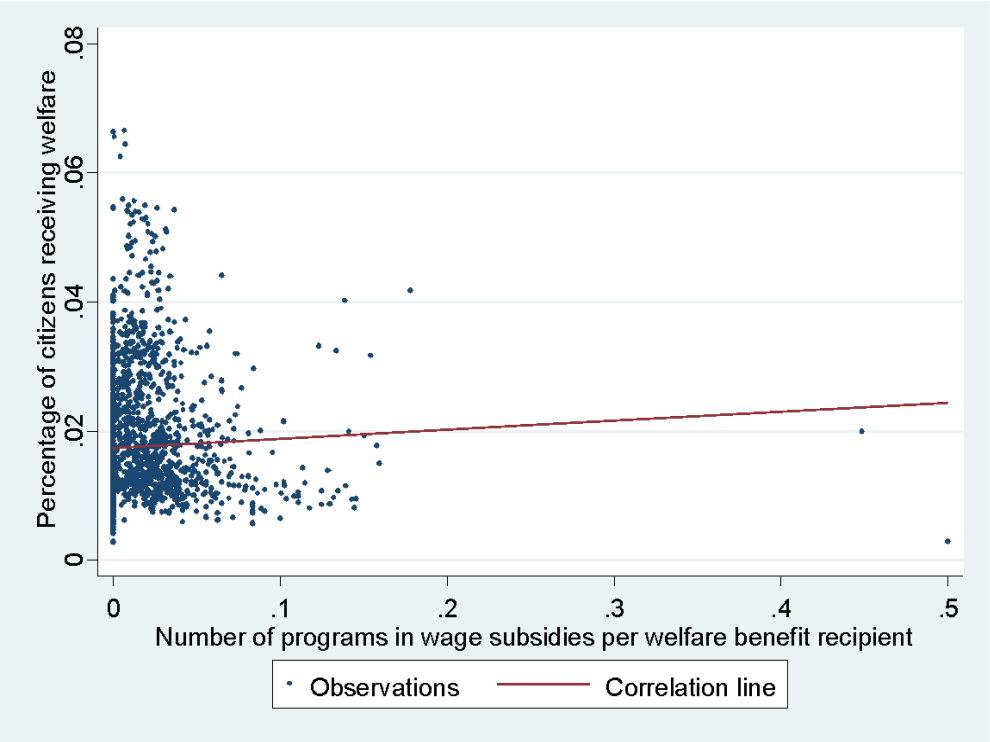

Figure 6: Scatterplot of number of programs in wage subsidies per welfare benefit recipient and the percentage of citizens receiving welfare benefit

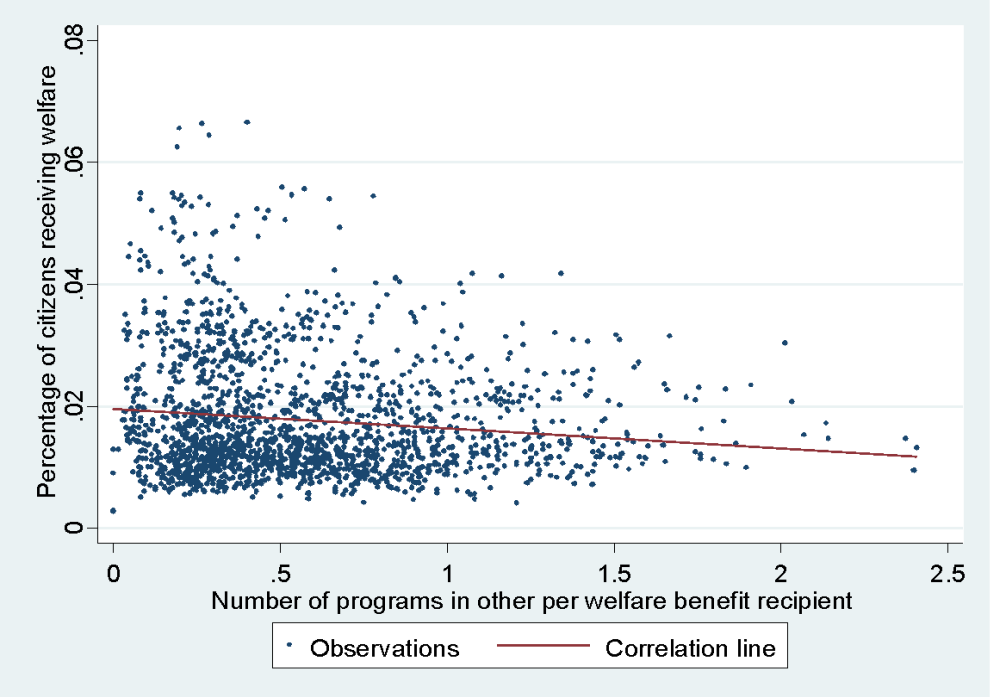

Figure 7: Scatterplot of number of programs in category other per welfare benefit recipient and the percentage of citizens receiving welfare benefit

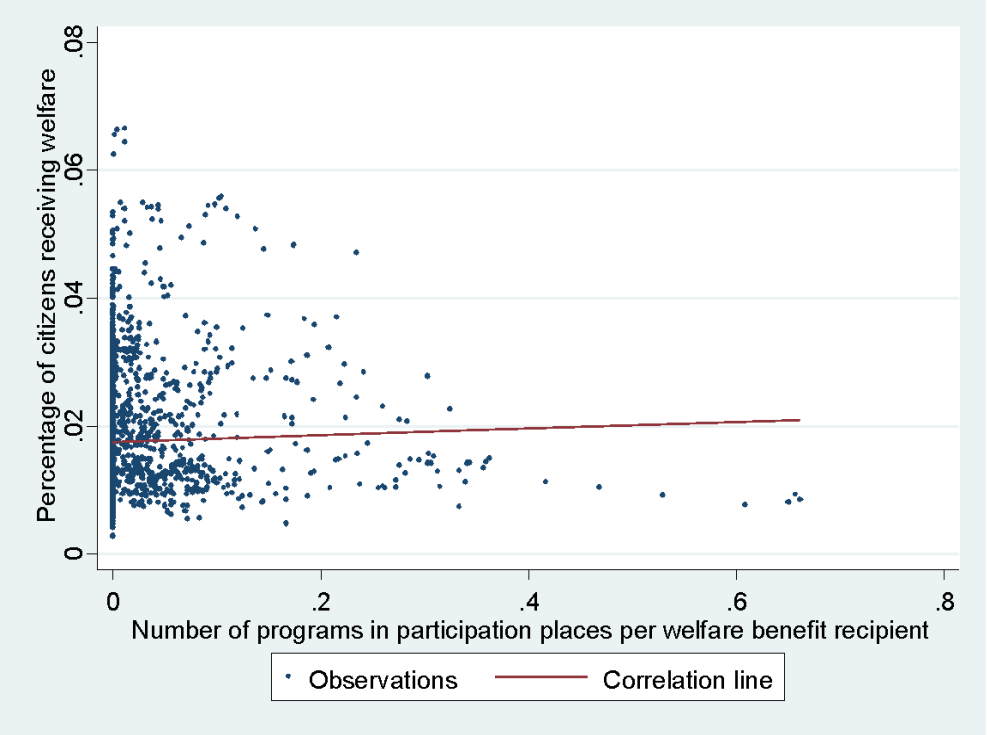

Figure 9: Scatterplot of number of programs in category participation places per welfare benefit recipient and the percentage of citizens receiving welfare benefit

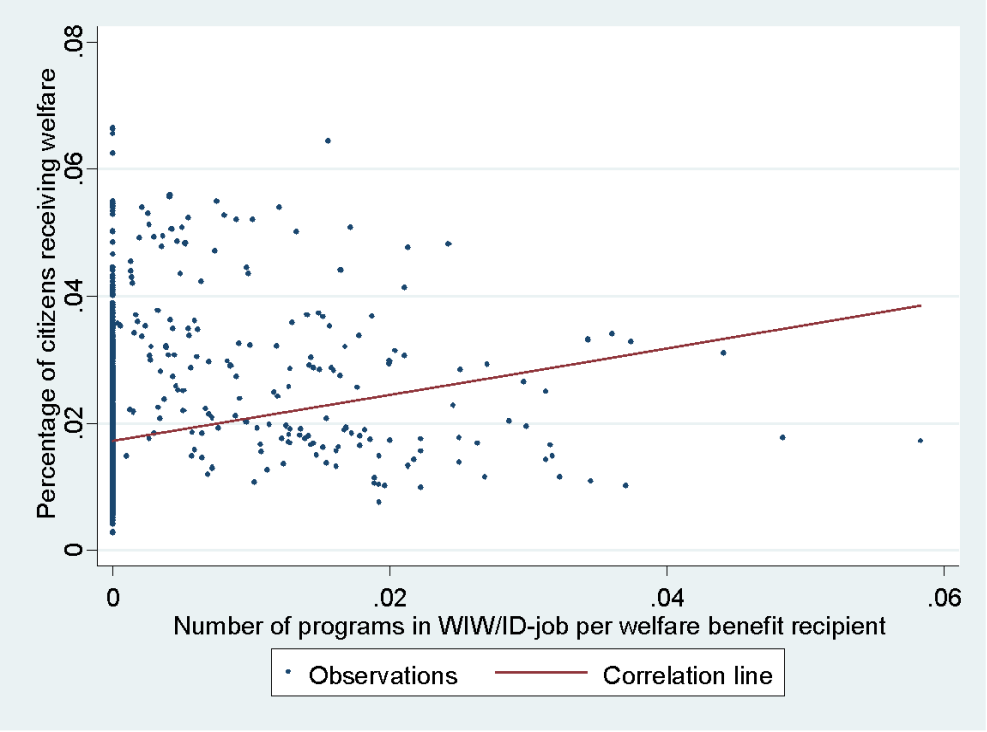

Figure 10: Scatterplot of number of programs in WIW/ID-job per welfare benefit recipient and the percentage of citizens receiving welfare benefit

Appendix 2

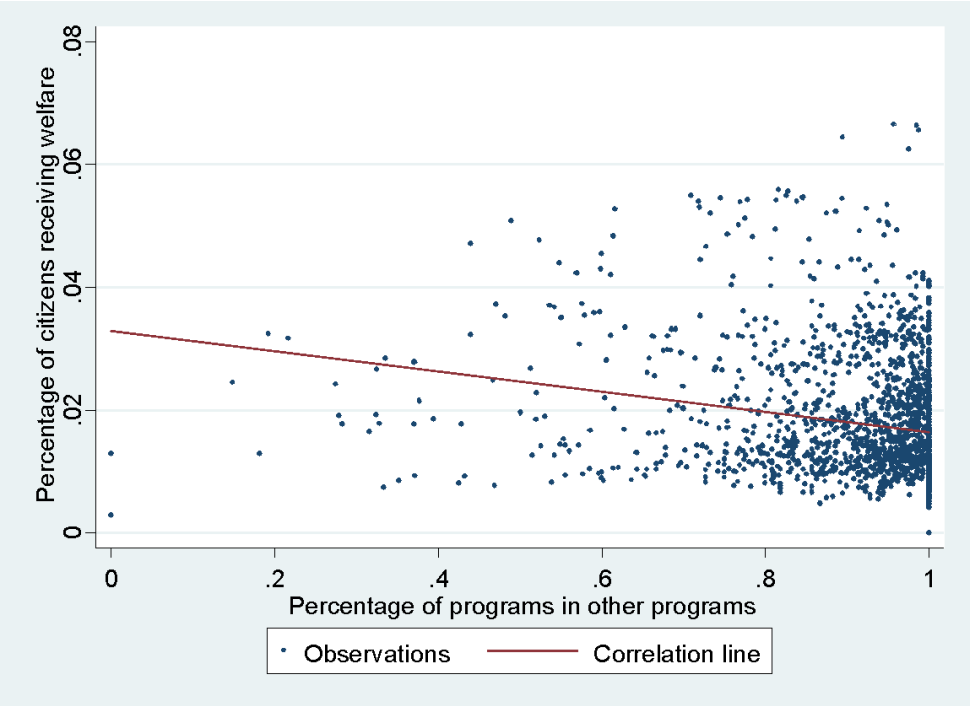

Figure 11: Scatterplot of percentage of programs in category other and the percentage of citizens receiving welfare benefit

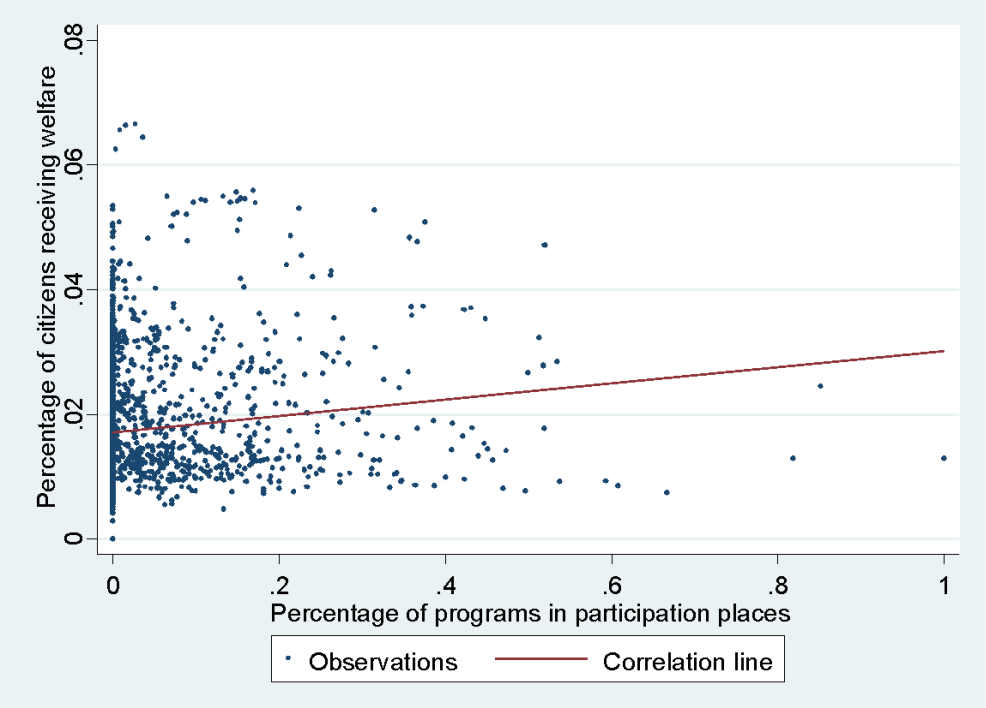

Figure 12: Scatterplot of percentage of programs in category participation places and the percentage of citizens receiving welfare

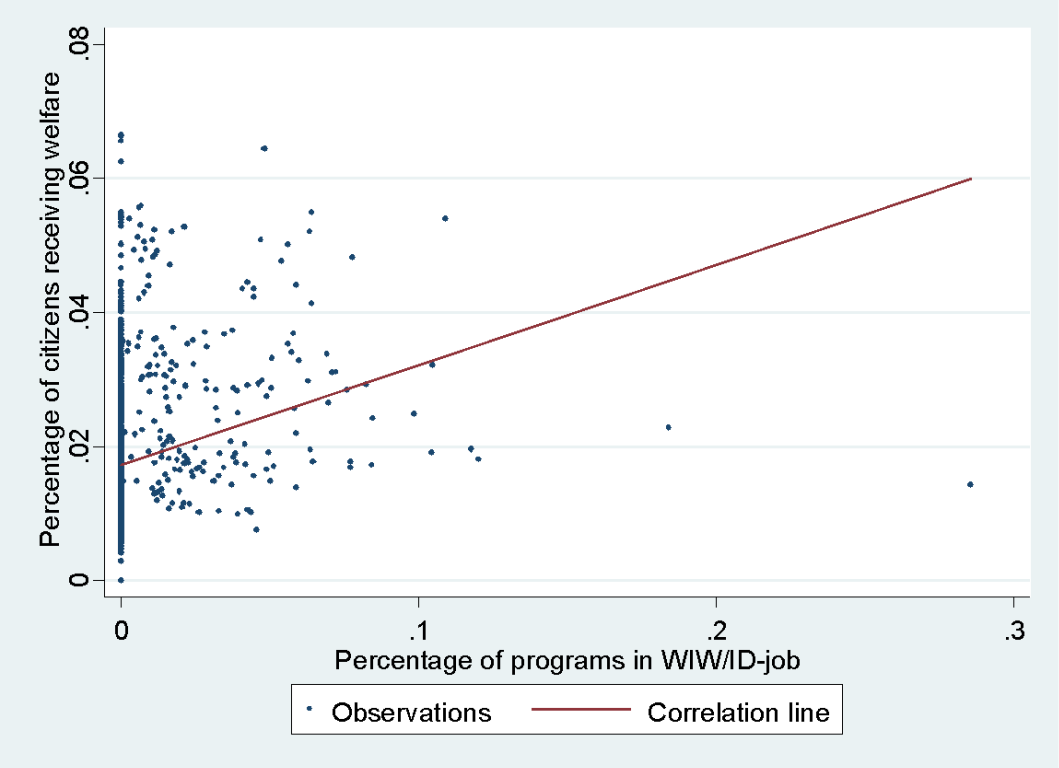

Figure 13: Scatterplot of percentage of programs in category WIW/ID-job and the percentage of citizens receiving welfare benefit

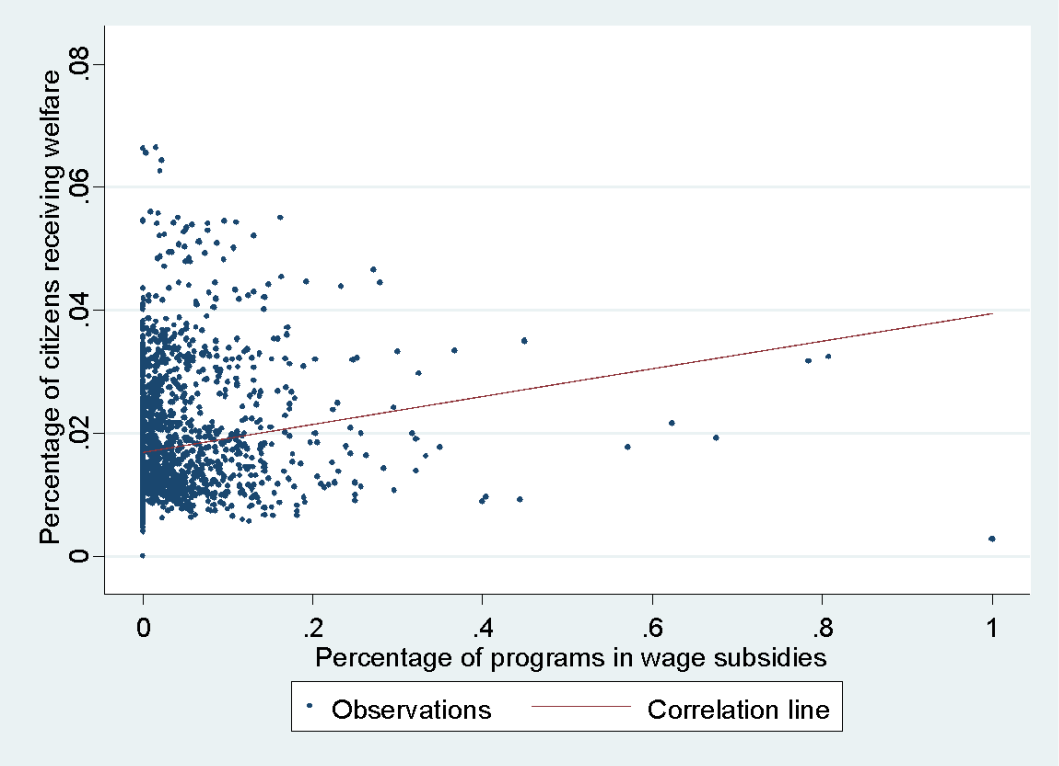

Figure 14: Scatterplot of percentage of programs in category wage cost subsidies and the percentage of citizens receiving welfare benefit

Appendix 3

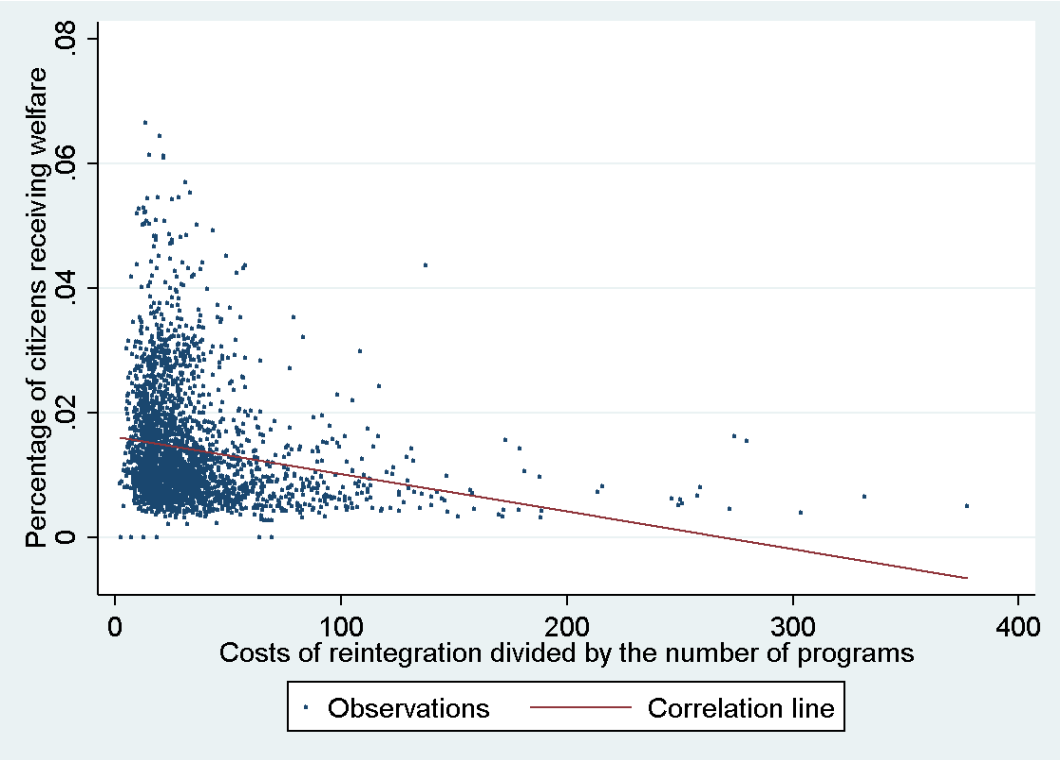

Figure 15: Scatterplot of cost of reintegration divided by the number of programs and the percentage of citizens receiving welfare benefit

Appendix 4

Table 10: First stage equations of Model 11

Independent variables:	Dependent variables:			
	Fraction wage subsidies	Fraction WIW/ID-job	Fraction participation places	Fraction other reintegration programs.
Population size in 1000	0.0000939 (0.000355)	0.0000204 (0.0000450)	0.000104 (0.000677)	0.000394 (0.00278)
Fraction population with migration background	0.00168 (0.0167)	0.000300 (0.00211)	-0.00260 (0.0318)	0.0272 (0.131)
Fraction population female	0.0000920 (0.0626)	0.00185 (0.00794)	0.0361 (0.120)	0.0189 (0.491)
Fraction population under 20 years	-0.00427 (0.0192)	-0.000585 (0.00244)	-0.00880 (0.0367)	-0.0111 (0.151)
Fraction of one parent households	-0.0159 (0.0593)	-0.00305 (0.00752)	-0.0124 (0.113)	-0.131 (0.465)
Number of jobs in a municipality in 1000	-0.0000146 (0.0000510)	-0.00000330 (0.00000647)	-0.0000145 (0.0000974)	-0.0000743 (0.000400)
Year dummies				
2014	-0.00131 (0.00145)	-0.000990*** (0.000184)	0.000192 (0.00277)	0.0337*** (0.0114)
2015	-0.00470*** (0.00146)	-0.00136*** (0.000185)	0.00202 (0.00278)	0.0292** (0.0114)
2016	-0.00178 (0.00146)	-0.00160*** (0.000186)	0.00406 (0.00279)	0.0438*** (0.0115)
2017	0.0166*** (0.00147)	-0.00177*** (0.000186)	0.00914*** (0.00280)	0.102*** (0.0115)
Mean fraction wage subsidies	1.000*** (0.0253)	-0.000169 (0.00321)	0.0000261 (0.0483)	-0.00449 (0.198)
Mean fraction WIW/ID-job	-0.00311 (0.108)	0.999*** (0.0137)	-0.00856 (0.207)	0.00404 (0.849)
Mean Fraction participation places	-0.000346 (0.00984)	-0.0000627 (0.00125)	0.999*** (0.0188)	0.000816 (0.0772)
Mean fraction other reintegration programs.	-0.0000348 (0.00135)	-0.00000817 (0.000171)	-0.0000797 (0.00258)	1.000*** (0.0106)
Constant	-0.00000671 (0.0317)	0.000511 (0.00402)	-0.0184 (0.0605)	-0.0421 (0.249)
Observations	1897	1897	1897	1897
R^2	0.498	0.754	0.618	0.835

Standard errors in parentheses. *** = p < 0.01, ** = p < 0.05, * = p < 0.10