

Escaping a Negative Feedback Loop by Becoming Healthier and More Employable

Assessing the Health Outcomes of FINSAM
Social Labor Market Programs

Arian Mosaddegh
Maximilian Onkenhout

October 2023

Abstract

We leverage a natural experiment arising from a policy implementation at the Swedish municipality level aimed at addressing the pressing issue of long-term unemployment. Utilizing a staggered difference-in-differences approach, we assess the impact of social labor market programs on both economic and health outcomes. Our findings reveal a 10 percent reduction in long-term unemployment in the municipalities that implemented the policy. Additionally, we observe mostly positive effects on both physical and mental health. However, we also uncover an increase in alcohol-related deaths and illnesses, suggesting potential unintended consequences of the efforts to reduce long-term unemployment. Our study contributes to the literature by being the first to evaluate the holistic impact of cross-agency Social Labor Market Programs enabled by the Swedish “FINSAM” legislation.

1 Introduction

In Sweden, long-term unemployed individuals make up roughly half of the total unemployment. Many of these individuals lack a high school degree or face mental and physical challenges that hinder their entry into the labor market (Arbetsförmedlingen, 2023). Various labor market programs (LMPs) aim to address unemployment through different strategies, though some face the problem of an overly narrow scope. In a Swedish setting, multiple agencies might simultaneously attempt to assist an individual out of unemployment. This can lead to duplicated efforts or, in the worst case, conflicting actions, such as emphasizing competence-increasing activities when the real need is in recovery and sustainable reintegration, as acknowledged by OECD (2016).

One method to mitigate this risk is through cross-agency collaboration where multiple actors work together toward a combined goal, taking both the labor- and social aspects into account. We refer to these as Social Labor Market Programs (SLMPs). However, a potential concern with these programs is that they may be caught up in buzzwords and political signaling, making them less effective in practice. In Sweden, cross-agency SLMPs governed by financial coordination associations (FCA) were made possible by the FINSAM legislation introduced in 2004 (Riksdagen, 2023), and further rolled out to municipalities over time. The staggered introduction of this policy on the municipality level allows for a natural experiment where we can evaluate the effectiveness of the SLMPs on both economic- and health outcomes, with the use of a staggered difference-in-differences approach.

Our results indicate a reduction of approximately 10 percent in long-term unemployment and an improved overall health in the municipalities, mainly through a 30 percent decrease in socioeconomic-related episodes of care. Additionally, we observe positive effects on both physical and mental health, primarily through a reduction in acute myocardial infarction and suicide rates, decreasing by 13 and 8 percent respectively. However, we also find a rise in alcohol-related deaths and illnesses, pointing to possible unintended side effects of the measures taken to reduce long-term unemployment.

Unemployment is a highly researched topic in economics, often linked to the health implications of income fluctuations, job loss, and prolonged unemployment. A key aspect of this is the effect on health stemming from an income loss. Previous literature finds mixed results regarding the effects of increased income on health outcomes, as shown by Lleras-Muney (2022); Rhum, (2000). However, numerous studies have identified a connection between unemployment and a decline in health, notably Browning and Heinesen (2012) and Kassenboehmer and

Haisken-DeNew (2009). It is also commonly accepted that the connection between health and unemployment stems both from a selection effect and a causation effect, where long-term unemployed are likely to suffer more from both physical and mental health issues (Herbig et.al. (2013), Garcy and Vågerö (2012)). Illness increases the likelihood of unemployment, while unemployment tends to adversely affect one's health. This creates a negative feedback loop, encompassing both selection and causality effects. A key factor in this dynamic is the social isolation that unemployment brings, which is closely linked to deteriorating mental health, as evidenced by Pohlan (2018) and Paul and Moser (2009).

Reducing the unemployment rate through LMPs varies in effectiveness and can impact diverse groups in unique ways, as highlighted by Kluve, Weber, and Card (2018). Recent research has explored the influence of various LMPs on the mental health of the long-term unemployed. These studies suggest that such programs enhance social integration (Ivanov et al., 2020) and, even if they do not yield actual labor market outcomes, benefit the participants' mental health (Bastiaans et.al., 2023).

Thus, previous research suggests that becoming unemployed is detrimental to a person's health. While reduced income might lead some to cut back on unhealthy expenditures like alcohol and fast food, the overwhelming negative health ramifications of losing one's social connections and routine appear to dominate. This impact is particularly pronounced for those facing long-term unemployment, trapping them in a negative feedback loop of illness and reduced employability. While efforts targeting the long-term unemployed have shown mixed results in terms of employment outcomes, they often yield second-order benefits in terms of enhanced health, notably in mental health, by reintroducing social ties and purpose to the participants' lives.

This study adds to the extensive literature on LMPs' economic- and health effects and contributes by being, to our knowledge, the first one to leverage policy implementations of the Swedish financial coordination associations SLMPs. Theoretically, these programs hold particular significance for addressing long-term unemployment, where individuals often find themselves trapped in a negative feedback loop of diminishing health and employability. As these programs target one of the most vulnerable groups of the population, there should exist substantial potential for health improvements. Our insights offer valuable information to policymakers evaluating the holistic impact of strategies aimed at decreasing long-term unemployment.

The remainder of this paper is organized as follows: Section 2 describes the institutional context of the FINSAM legislation and outlines the anticipated implications of establishing an

FCA. Section 3 details the data utilized in this study. The primary and alternative methodological approaches are elaborated in Section 4. Section 5 presents our findings. Finally, Section 6 offers a discussion of these findings and concludes the paper.

2 Background

2.1 Institutional Background of FINSAM

In 2004, the Swedish government introduced the FINSAM law, enabling the formation of cross-agency financial coordination associations. These associations coordinate between municipalities, the Swedish Employment Agency, the Swedish Social Insurance Agency, and their respective regions. The aim is to provide social labor market programs for individuals requiring rehabilitation, enhancing their prospects of joining the labor market (Riksdagen, 2023). Program structures vary across FCAs, but all aim to offer efforts including (1) job-focused, enhancing labor market understanding; (2) competence-boosting, improving general and work skills; (3) social, reducing loneliness and adding structure to personal life; and (4) health-related, targeting physical and mental well-being (FINSAM, 2023b).

Further, the total spending on programs from the FCAs is divided among association members: agencies cover 50 percent, regions 25 percent, and municipalities the remaining 25 percent. This financial structure incentivizes municipalities to join FCAs, allowing them to increase the total spending on programs at the same cost (Riksdagen, 2023). We find that a municipality’s individual spending on these programs stays consistent before and after joining an FCA. Meaning that the total investment rises solely due to agency- and regional contributions. We find no evidence of a changed municipality-level spending on labor market programs after policy implementation, indicating no individual resource allocation, but a genuine increase in total spending on the programs from joining an FCA.

2.2 The expected direct and dynamic effect of the cross-agency SLMP

We anticipate that the cross-agency SLMP will produce three distinct impacts influencing both economic and health outcomes. Firstly, the FCA cross-agency collaboration enables total spending on SLMPs in a municipality to increase. Consequently, we should observe a spending effect, where increased resources lead to enhanced results. We also anticipate a collaboration effect stemming from the coordinated efforts of multiple actors, which should eliminate po-

tential overlaps and conflicting initiatives. Furthermore, given that the SLMPs also focus on rehabilitation of physical- and mental health issues, these efforts should be equipped to break the negative feedback loop of long-term unemployment, we refer to this as the dynamic effect. The dynamic effect implies an increase in returns to scale, producing outcomes that could potentially surpass the direct spending effect. We should therefore expect a greater effect on the long-term unemployed, compared to the pure spending effects of narrower LMPs.

Lastly, even if we observe no impact on economic outcomes from the SLMPs, we will still anticipate a positive influence on participants' health outcomes, particularly mental health. This is because these programs will provide a social context for people who are otherwise running a high risk of social exclusion (FINSAM, 2023b).

3 Data

3.1 Policy Data

FCAs, enabling the formation and joining of municipalities, were introduced in 2004. By 2021, 72 FCAs were established, including 268 of Sweden's 290 municipalities. Although there is available data on FCAs until 2023, this analysis focuses on data up until 2021 due to data-limitations in other variables. A majority of municipalities (197 out of 268) joined an FCA between 2004 to 2011. The data regarding the year each municipality joined an FCA is self-constructed based on information from the FCAs annual reports (FINSAM, 2023b). A geographical representation of what year each municipality joined an FCA is located in Appendix A.1.

3.2 Outcome Variables

Our study measures outcomes using economic and health variables at both municipal and regional levels, that we are expecting to be influenced by policy implementation. We draw data from Statistics Sweden (2021), the National Board of Health and Welfare (2023), and the Swedish Social Insurance Agency (2023), respective open databases.

Economic outcomes include long-term unemployment, defined as individuals who have been unemployed for at least 6 months, labor market participation, defined as individuals who have worked in a given year, and adult education participation, defined as individuals who have been enrolled in non university post-high school education. These variables help assess the effect on economic outcomes in the municipalities that join an FCA and leverage the SLMP to meet their objectives.

Health outcomes are divided into physical-, mental-, and overall health categories, focusing on their correlation with long-term unemployment. Municipal data is more applicable to our analysis, however, due to regional control of healthcare in Sweden, most health data are available at the regional level. We are, therefore, at first hand, including municipality health variables and further complementing the analysis with regional data. For overall health, we analyze municipality-level sickness days while at the regional-level we include total socioeconomic-related episodes of care (EoC). This approach aims to understand the broader health impact, especially on socioeconomically disadvantaged groups, which long-term unemployed are assumed to be a part of.

Physical health variables explore the impact of unemployment on cardiovascular diseases and alcohol-related issues, as suggested in studies by Herbig et al. (2013) and Browning and Heinesen (2012). We include municipality-level data on addiction and abuse, and regional data on alcohol-related EoCs, alcohol poisoning fatalities, and acute myocardial infarction (AMI) incidents. Variables on mental health focus on the effects of unemployment on suicide rates, depressive symptoms, and stress, as used in research by Browning and Heinesen (2012), Garcy and Vågerö (2012), and Vinokur et al. (2000). We incorporate municipality-level data on stress-induced sick leaves and suicide rates, along with regional data on depression-related EoCs.

3.3 Covariates and Time Period

The covariates controlling for municipal and regional observable characteristics include mean income, working-age population share (aged 20-64), share of high school dropouts, foreigner share, and population size. These are assumed to be linked to economic well-being, which is likely to influence policy decisions. Further, the income- and population variables have been logarithmically transformed to reduce the skewness of the distribution. We are analyzing the period from 1997 to 2021 due to the availability of Swedish municipality-level data on the desirable variables (SCB, 2021). This range affords a substantial pre- and post-treatment period, enabling us to assess parallel trends and dynamic treatment effects using an event-study approach. Thus, the panel data tracks 290 municipalities over 25 years.

4 Method

4.1 Main Empirical Method

The policy’s staggered rollout from 2004 to 2021 means municipalities received treatment at different times. A binary treatment variable is used to isolate the policy’s effect, indicating a municipality as treated at a given year with a value of one, and never- or not yet treated with zero. Typically, the average treatment effect of a policy is estimated using two-way fixed effect regression (TWFE), comparing outcomes of groups under different treatments and at the same time controlling for both group and time-fixed effects. However, TWFE assumes constant treatment across groups and time. Estimating a TWFE on a staggered treatment includes estimates of all 2x2 difference-in-differences comparisons. This can produce biased outcomes, as indicated by Goodman-Bacon (2019) and de Chaisemartin and D’Haultfoeuille (2020).

To address this issue, we will adopt the methodology suggested by Callaway and Sant’Anna (2021). The core idea of this approach is to only compare those who are treated at a given year, with those who are not yet treated. Initially, the differences in outcome between a post-treatment year and the year prior to treatment initiation is compared with the differences in outcome, to those not yet treated at the post-treatment year, over the same period. The average treatment effect (on treated) (ATT) is subsequently calculated using the doubly robust estimation technique as suggested by Callaway and Sant’Anna (2021). Further, the ATTs for each combination of treatment and outcome years are aggregated to derive an event-study estimate, showing the dynamic effects of the treatment over time. From the event-study, the average ATTs for all pre-treatment periods and all post-treatment periods are calculated.

The event-study window is limited to 10 pre-treatment and 15 post-treatment periods for municipalities. This ensures a balanced count of treated municipalities in pre-treatment ATTs and captures dynamic effects post-treatment. We will apply the Callaway and Sant’Anna (2021) method at the municipality-level, using a binary treatment variable for the staggered policy implementation, termed Method A. Further, we will focus on the average post-treatment ATTs (ATT_{APT}) as a measure of the policy effect, while using the less preferred simple ATTs (ATT_{simple}), which tend to put more weight on earlier treated municipalities, as discussed by Callaway and Sant’Anna (2023), as an indicator of robustness. The model specification for the event-study model follows:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{e=-10}^{t-2} \delta_e D_{it}^e + \sum_{e=0}^{15} \beta_e D_{it}^e + \lambda X_{it}' + \epsilon_{it} \quad (1)$$

Where Y_{it} is the outcome for the municipality i at year t , α_i are the group fixed effects and γ_t are the time fixed effects, X'_{it} is a vector of municipality observed characteristics, D_{it}^e is an indicator for a municipality i being e periods away from the initial treatment at year t , and ϵ_{it} are the robust standard errors. The coefficient of interest that estimates the average post-treatment ATTs is β_e where $e > 0$.

4.2 Alternate Empirical Method

Due to most health data being unavailable on the municipality-level, we will proceed by conducting an alternate analysis using Swedish regions. Swedish regions comprise multiple municipalities which are not always treated simultaneously, therefore the choice of treatment variable can yield varied results. To address this, we will use three treatment variables and compare their outcomes. Method B uses a binary treatment variable that indicates when the region's first municipality is treated, capturing early policy effects but has a risk of misclassifying untreated groups as treated. Method C activates when over 50 percent of the region's population receives treatment, preventing Method B's overgeneralization but potentially missing early effects and misclassifying treated groups as untreated. Both methods have disadvantages, but if we assume uniform effectiveness in policy implementation across all municipalities, Method B is more likely to provide an accurate estimate of the policy's impact. We will therefore use Method B as our main method. Both methods will be estimated using the Callaway and Sant'Anna (2021) method with a window of 10 pre- and post-treatment periods.

For another approach, Method D introduces a continuous treatment variable based on the proportion of the treated population within a region. Specifically, this variable adopts a value of zero when none of the population in that region is treated, and gradually increases to one as 100 percent of the population in that region is treated. Since a continuous treatment variable is not functional when using the Callaway and Sant'Anna (2021) method, this will be analyzed through a TWFE model. However, as discussed by Callaway, Sant'Anna, and Goodman-Bacon (2021), the results from this approach may be biased and should be analyzed with caution. Thus, we have reasons to assume that the results from Method D may be unreliable on their own, but we argue that when combined with the findings from Method B and C, they enhance the overall robustness of our conclusions.

5 Results

5.1 Identifying Assumptions

In a difference-in-differences analysis, the parallel trends assumption is essential. It implies that without treatment, the treated group's outcome would follow the untreated group's trend, emphasizing that no other factor but the treatment influences the treated group. While impossible to validate by definition, proving no significant differences in pre-trends can strengthen its validity. We will assess this using Callaway and Sant'Anna (2021) event-study estimates of average pre-treatment ATTs and graphical analysis.

Table 1: Outcomes of FCA using Region-level Data

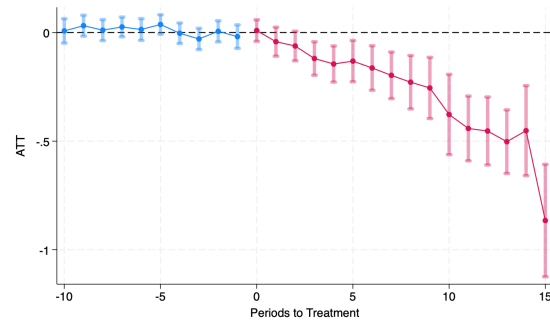
	Method (A) Municipality	Method (B) 1 = t	Method (C) 50% = t
VARIABLES	Pre-treat Average	Pre-treat Average	Pre-treat Average
Long-term Unemployment	−0.0083 (0.0062)		
Labor Market Participation	−0.043** (0.017)		
Adult Education Participation	0.0000416 (0.0000559)		
Addiction and Abuse	0.6279 (2.770)		
Sickness-days	0.0483 (0.032)		
Suicide-rate	0.277*** (0.117)		
Stress-related Sickness	−.00046* (0.0002)		
EoC (total)		52.49 (79.20)	18.216 (49.411)
EoC (socioeconomic)		−0.928 (1.565)	3.6801** (2.009)
EoC (alcohol related)		−1.658 (8.004)	−10.1245 (13.599)
EoC (depression)		0.702 (2.469)	0.7176 (1.7235)
Death from Alcohol Poisoning		0.457 (1.402)	−0.9454 (0.7515)
AMI		−8.60e0 (−8.60e0)	−6.61e6 (0.00001)

Note: Coefficients are gathered from a staggered difference-in-differences using the method proposed by Callaway and Sant'Anna (2021). Pre-treat Average coefficient shows the average pre-treatment ATTs. All estimates control for municipality-observed characteristics. Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

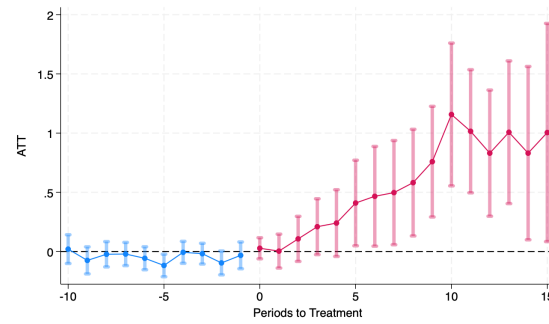
The insignificant average pre-treatment ATTs in Table 1 suggests that the parallel trends assumptions hold for all variables except for labor market participation, suicide-rate, stress-related sickness, and EoC due to socioeconomic reasons. Evaluating the pre-treatment point estimates for these in Figure 1 (a-g) and Figure 2 (a-f) shows some variation but with 95-confidence bounds around zero. Based on this evidence, we argue that the parallel assumption holds for all variables allowing us to pursue the difference-in-differences analysis.

Another crucial assumption is that there should not be any compositional changes pre- and post-treatment, ensuring the policy does not alter municipality characteristics beyond its intent. The policy should not cause the long-term unemployed to migrate from policy-free- to policy municipalities, or vice versa. We tested this with a Callaway and Sant’Anna (2021) event-study regression using net domestic migration per municipality as the outcome. The results showed no significant migration patterns due to the policy, further supported by non-mandatory program participation.

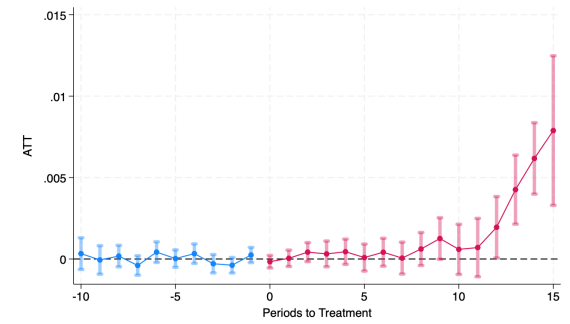
Figure 1: Event-study Graphs for Method A (Municipality)



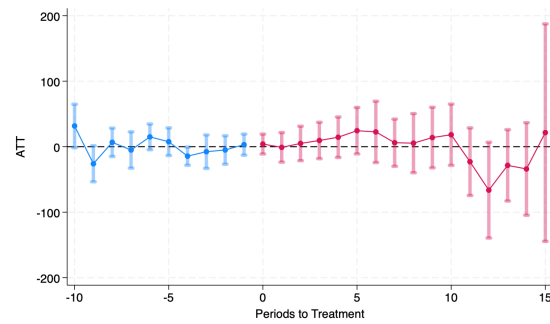
(a) Long-term Unemployment



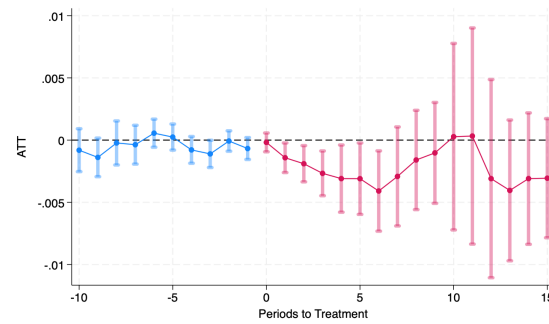
(b) Labor-market Participation



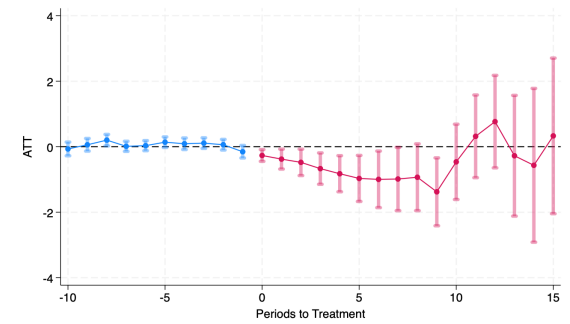
(c) Adult Education Participation



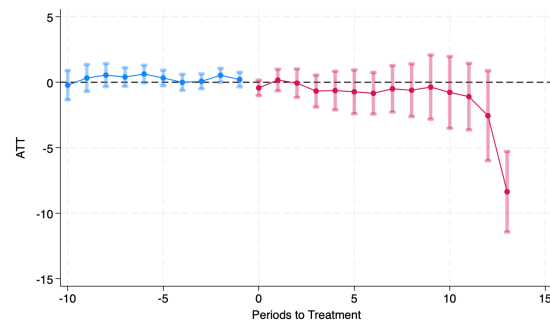
(d) Adicition and Abuse



(e) Stress-related Sickness

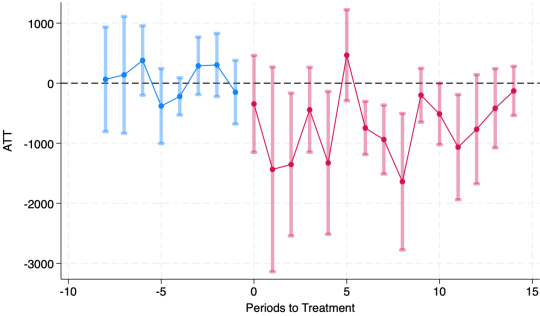


(f) Sickness-days

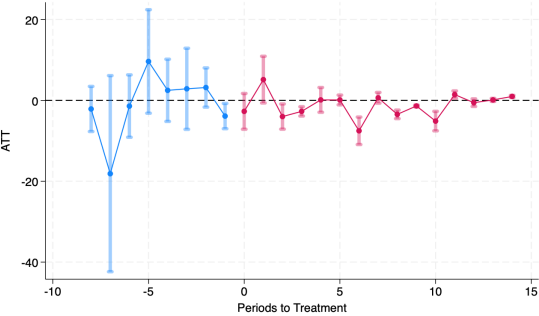


(g) Suicide Rate

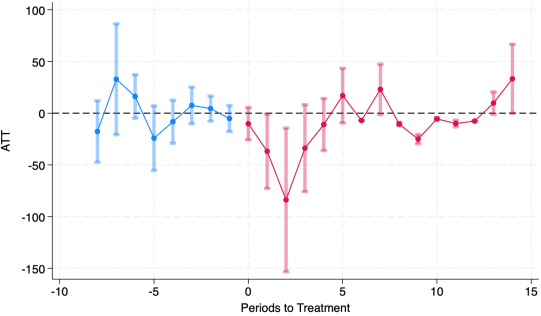
Figure 2: Event-study Graphs for Method B (Region)



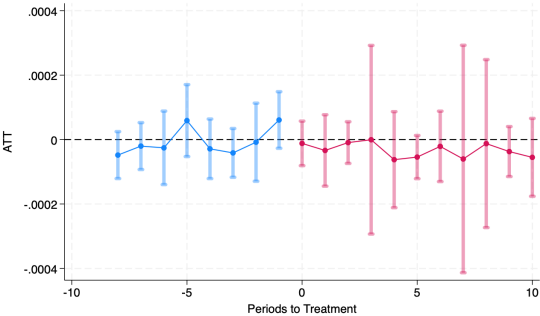
(a) Episodes of Care



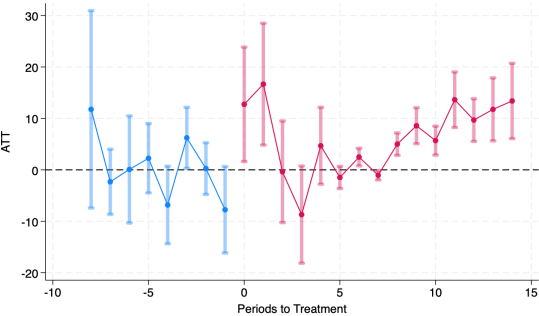
(b) Episodes of Care (socioeconomic)



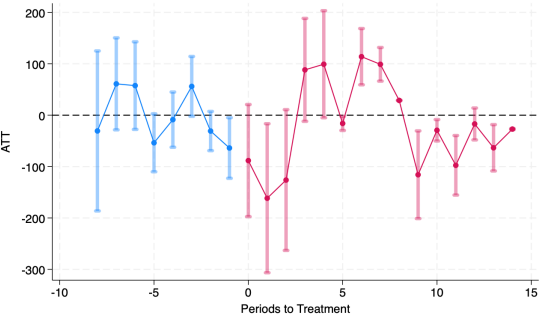
(c) Episodes of Care (depression)



(d) Acute Myocardial Infraction



(e) Death from alcohol



(f) Episodes of Care (alcohol)

5.2 Main Results

Having provided evidence towards the validity of the identifying assumptions, the subsequent results will show how joining an FCA, and thereby increasing the intensity of SLMPs, impacts economic- and health outcomes. Table 2 shows significant results for all economic outcomes. The effects of long-term unemployment and adult education participation are most substantial, decreasing- respectively increasing with approximately 10 percent when comparing the coefficients with the mean. Figure 1 (a-c) show the policy’s escalating impact over time, confirming previous findings of delayed effects. Supported by the ATT_{simple} coefficients, the results fulfill the policy’s primary objective of positively affecting the economic outcomes.

Table 2: Outcomes of FCA using Municipality-level Data

Method (A): Municipality	ATT_{APT}	ATT_{simple}	Mean	Obs.
ECONOMIC OUTCOMES				
Long-term Unemployment	−0.155*** (0.037)	0.233*** (0.3684)	1.401	7, 208
Labor Market Participation	0.572*** (0.153)	0.505*** (0.142)	77.98	7, 226
Adult Education Participation	0.001567*** (0.0004375)	0.00112*** (0.000376)	0.0154	7, 226
HEALTH OUTCOMES				
Addiction and Abuse	−0.443 (15.262)	1.088 (13.41)	199.95	5, 490
Sickness-days	−0.485 (0.377)	−1.557** (0.769)	37.224	7, 226
Suicide-rate	−1.251** (0.591)	−0.560 (0.571)	16.185	4, 929
Stress-related Sickness	−0.00216 (0.0016)	−0.00204 (0.00142)	0.0277	4, 895

Note: Coefficients are gathered from a staggered difference-in-differences using the method proposed by Callaway and Sant’Anna (2021). ATT_{APT} coefficient shows the average post-treatment ATTs. The ATT_{simple} coefficients show the ATT for all groups across all periods. All estimates control for municipality-observed characteristics. Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In examining the effects on health outcomes, we observe some contradictory results when comparing the ATT_{APT} with the ATT_{simple} coefficients. Our analysis reveals significant effects on the suicide rate in the ATT_{simple} estimate, resulting in an 8 percent decrease, however, this significance vanishes in the ATT_{simple} estimate. Conversely, for the ‘Sickness Days’ variable, we observe an inverse relationship. Notably, the variables ‘Addiction and Abuse’ and ‘Stress-related Sickness’ remain insignificant in both analyses.

The divergence between the ATT_{simple} and the ATT_{APT} effects can be attributed to the

Simple ATT placing greater weight on earlier treated municipalities. This is evident in Figure 1 (g), which shows that the effects on suicide rates are primarily influenced by later post-treatment periods. Furthermore, the absence of significant effects in stress-related sickness and sickness days, as observed in Figure 1 (e-f), interestingly appears to be due to initial decreasing effects being offset over time. As we assume the ATT_{APT} to be the more rigorous estimate its result should be the focus.

5.3 Results on Region-level

While municipality-level health effects appeared mostly insignificant, an examination at the region-level may offer deeper insights. In Table 3, the coefficients for Method B and C are presented. The coefficients for Method D are presented in Table B.1. Methods B and C provide coefficients for ATT_{APT} and ATT_{simple} , while Method D presents the TWFE coefficient. To evaluate the effect based on the results of the different methods, with Method B being the main method, we will categorize the significance of the effect as strong- if both Model B and C show significance, moderate- if only B shows significance, and weak- if only C shows significance. We will further use the results in Model D as a robustness indicator of the results in Models B and C. The only strong significant result is an annual decrease in socioeconomic-related

Table 3: Pre-Treatment Period Average ATT for all Outcome Variables

VARIABLES	Method (B) $1 = t$		Method (C) $50\% = t$		Mean	Obs.
	ATT_{APT}	ATT_{simple}	ATT_{APT}	ATT_{simple}		
EoC (total)	-723.8*** (206.6)	-880.81** (401.66)	339.4 (229.2)	241 (202.6)	11956.46	504
EoC (socioeconomic)	-1.269*** (0.260)	-0.298*** (0.0746)	-3.595*** (1.059)	-3.112** (1.27)	3.89	504
EoC (alcohol)	-20.91 (18.08)	0.132 (0.302)	107.8*** (41.82)	77.04* (45.05)	572.89	504
EoC (depression)	-10.56* (6.157)	0.217 (0.154)	-5.846 (8.383)	-5.324 (6.96)	78.87	504
Death from Alcohol Poisoning	6.180*** (1.518)	0.505*** (0.142)	2.289 (2.756)	2.03 (2.384)	21.27	525
AMI	-0.000085** (0.00003)	-0.00011** (0.00004)	-0.00003 (0.00004)	-0.00003 (0.000028)	0.0007	525

Note: Coefficients are gathered from a staggered difference-in-differences using the method proposed by Callaway and Sant'Anna (2021). ATT_{APT} coefficient shows the average post-treatment ATTs. The ATT_{simple} coefficients show the ATT for all groups across all periods. All estimates control for municipality-observed characteristics. Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

EoC, approximately 30 percent (looking at Method B). We can identify moderately significant

results for both total- and depression-related EoCs, and for the number of AMI incidents and deaths from alcohol. The total and depression-related EoC decreased by 6 percent respectively 13 percent, while AMI incidents decreased by 13 percent and the number of deaths from alcohol poisoning increased by 29 percent. Lastly, we identify a weak significant increase in alcohol-related EoC of approximately 19 percent.

As stated previously, the results from Method D (presented in Table B.1) should be interpreted with caution due to bias problems with the TWFE method. Comparing the results from Method B and D, we can however see similar patterns regarding depression and deaths from alcohol. Which could be seen as further evidence for the robustness of the results.

6 Discussion

Our results indicate that joining an FCA has significant effects on economic outcomes, aligning with the policy’s aims. Long-term unemployment decreases by 10 percent in municipalities that introduce SLMPs. This contrasts with the zero economic outcomes effect observed by Bastiaans et.al. (2023), suggesting an advantage of the SLMPs compared to obligatory activation programs. However, the implementation of an SLMP also had an increased spending effect which naturally should lead to an effect on the outcome variable. We are unable to disentangle the spending effect from the collaboration and dynamic effect of the SLMP. This is of interest when determining the efficacy of the SLMP and should be the subject for future studies. However, an argument supporting the collaboration and dynamic effect is the impact of the SLMP on the long-term unemployed. This group often faces barriers to entering the labor market that are not solely competence related. Therefore, merely increasing spending on competence enhancing LMPs might not be as effective as SLMPs that also improve other vital factors.

Given the strong- and moderate significant results we see overall health benefits of a decrease in EoC, particularly socioeconomic-related ones. This is what we should expect since people who have been long-term unemployed likely are in a more socioeconomic vulnerable situation. We also find both physical- and mental health benefits. The physical benefits of a decrease in AMI cases are in line with previous findings of a link between unemployment and cardiovascular illnesses. The mental health benefits are most clearly observed with a decrease in suicide rate and a decrease in depression-related EoC which also corroborates previous findings. Most variables are measures of severe health issues and should *prima facie* indicate meaningful benefits on an individual’s health. An in-depth comparison between previously established health

benefits of other LMPs should be the subject of future studies in order to evaluate the relative importance of the health benefits of SLMPs.

Lastly, we observed a positive effect on alcohol-related deaths and EoCs, which undoubtedly indicates a negative health effect. Consistent with the findings of Garcy & Vågerö (2012) where long-term unemployment likely has a negative effect on alcohol consumption, this is likely due to both an income effect and an improved social dynamic. Gaining employment increases income, which has been linked to heightened alcohol consumption, as noted by Rhum (2000). Moreover, alcohol is often consumed in social contexts, and one of the intended outcomes of the SLMP is to enhance social integration. This could potentially influence participants' alcohol consumption habits and should be considered when evaluating the health effects of this policy.

From a policy perspective, our findings indicate that SLMPs are a viable strategy to address long-term unemployment and other economic outcomes. However, we cannot draw conclusions about cost-effectiveness, as various spending factors might influence the results. Additionally, our research emphasizes the significance of considering the secondary health effects of economic policies. We mostly find positive effects on both physical and mental health outcomes however there is reason to suspect an increase in alcohol consumption which should be a part of the overall evaluation of policy structure. Including a greater emphasis on alcohol awareness in the social labor market programs could be a beneficial modification to reduce alcohol related risks.

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A Appendix

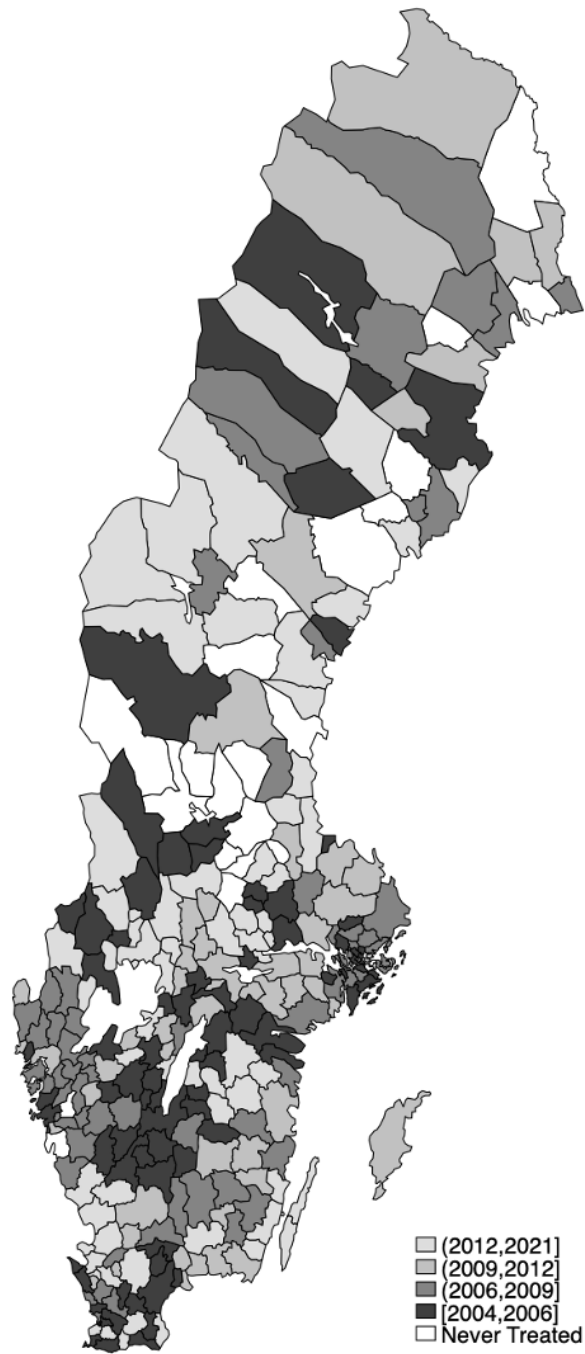


Figure A.1: Graphical representation of municipalities joining a financial coordination association from 2004-2021

B Appendix

Table B.1: Outcomes of FCA using Region-level Data

Method (D) TWFE			
VARIABLES	TWFE	Mean	Obs.
EoC (total)	−13.26 (112.4)	11956.46	504
EoC (socioeconomic)	4.197*** (1.334)	3.89	504
EoC (alcohol)	−8.639 (18.71)	572.89	504
EoC (depression)	−7.496** (3.076)	78.87	504
Death from Alcohol Poisioning	3.568*** (1.002)	21.27	525
AMI	0.00004* (0.00002)	0.0007	525

Note: TWFE coefficients show the two-way fixed effects coefficients of a continuous treatment. All estimates control for municipality observed characteristics. Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.