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Rethinking Policy Evaluation – Do Simple Neural Nets Bear Comparison with Synthetic Control Method?

With the advent of big data in economics machine learning algorithms become more and more appealing to economists. Despite some attempts of establishing artificial neural networks in the early 1990s, only little is known about their ability of estimating causal effects in policy evaluation. We employ a simple forecasting neural network to analyze the effect of the construction of the Oresund bridge on the local economy. The outcome is compared to the causal effect estimated by the proven Synthetic Control Method. Our results suggest that – especially in so-called prediction policy problems – neural nets may outperform traditional approaches.

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JEL codes: C45, O18

Keywords: Artificial Neural Nets, Machine Learning, Synthetic Control Method, Policy Evaluation.

1 Introduction

Machine learning methods such as artificial neural networks (ANN) were introduced in economics in the early 1990s, but did not become accepted by a wide range of economists (see e.g. Lee et al. 1993 and Kaastra and Boyd 1996). Their failure was not a cause of bad performance, instead classical methods of nonparametric estimation of treatment effects such as propensity-score-matching, k-nearest-neighbor matching, kernel methods performed well due to the small number of available covariates. Moreover these approaches also allow to estimate heterogeneous treatment effects, which had been hard to achieve with machine learning methods (see e.g. Crump et al. 2008). Today, more data becomes available and datasets are getting increasingly bigger. Especially the use of geocoded data, the need for image classification or the use of language data in economics cause classical approaches to fail due to e.g. the curse of dimensionality or the need for high non-linearity (see Jean et al. 2016, Wager and Athey 2017). Whereas there has been much effort to overcome this issue in computer science, it has been largely ignored in economics. However, starting with Athey's approaches to use machine learning techniques for estimating (heterogeneous) causal effects there is a gain of recognition (see e.g. Athey 2017 and Athey and Imbens 2016, 2017). Nevertheless, machine learning techniques remain fundamentally different from classical approaches of policy evaluation such as Regression Discontinuity Design or Instrumental Variables because their goal is prediction – not causal inference (Athey and Imbens 2017). Kleinberg et al. (2015) argue, that this feature is rather an asset than an issue since many policy evaluation problems

require the prediction of the outcome instead of drawing causal inference about the effect of treatment on the outcome. As a consequence machine learning techniques may provide additional insights into policy evaluation.

We contribute to the policy evaluation literature by assessing the practical relevance of ANN in ex-post policy evaluation in comparison to the new quasi-gold-standard Synthetic Control Method (SCM) which was introduced by Abadie and Gardeazabal (2003). This comparison is of high relevance because according to Athey and Imbens (2017) SCM has been “*arguably the most important innovation in the policy evaluation literature in the last 15 years*”. However, SCM fails when applied to big datasets.

We proceed in two steps. First, we describe the identification strategy of SCM and the nonlinear regression framework of simple forecasting ANNs. Afterwards, we evaluate the performance of ANN compared to the state-of-the-art SCM by estimating the causal effect of the construction of the Oresund-Bridge, that connects the metropolitan regions of Malmo (Sweden) and Copenhagen (Denmark). We focus on Oresund because of two reasons. First, it is a very large infrastructure investment (more than one billion Euro were spent until opening in 2000) that may stimulate economic performance through improved market access, network effects and increased firm productivity. Therefore, we expect to find large positive effects on economic development on local (Malmo) and regional (Södra Sverige) level (see e.g. Aschauer 1989a,b and Cantos et al. 2005). Second, in a recently published study by Achten et al. (2018) SCM was applied on solely publicly available data to estimate the causal effect of the construction of the bridge. As a consequence, we can feed our ANN with the same data and use the results from Achten et al. (2018) as standard of comparison.

Our ANN finds treatment effects on local and regional level that are similar to those estimated by SCM. Therefore, it seems to be suitable method in ex-post evaluation. Considering that policy intervention must also be evaluated a priori and that a priori evaluation implies prediction, ANN are more advantageous than SCM due to their easy to implement prediction capability. Thus, machine learning techniques such as ANN need to be adapted by econometricians.

2 Methods and Data

In our study, we aim to estimate treatment effects. Therefore, we need to have a closer look at the potential outcome framework in a first step (Rubin 1974). In the so called Rubin causal model, a treatment effect TR_i is defined as the difference between two potential outcomes Y_i^I and Y_i^N , where Y_i^I denotes the outcome of individual i in a state with treatment and Y_i^N is the potential outcome of individual i without treatment:

$$TR_i = Y_i^I - Y_i^N \quad (1)$$

Unfortunately, we never directly observe TR_i because Y_i^N cannot be realized in a state where individual i is exposed to treatment (vice versa). This phenomenon is called ‘‘Hollands (1986) fundamental problem of causal inference’’. In order to calculate the treatment effect, we need to predict Y_i^N via ANN or SCM.

2.1 Artificial Neural Network

Due to the fact that ANN belongs to the supervised learning regimes of machine learning labelled training data is mandatory. Therefore, we employ a forecasting version of an ANN that uses economic growth predictor variables of several regions at time t for training in order to forecast the regions outcome at time $t + 5$.¹ This approach also safeguards against possible simultaneity issues. Thus, our ANN learns how growth predictors forecast economic outcome. Afterwards, we employ the trained network on pre-treatment predictor data of Malmo and Södra Sverige. The forecasted outcomes serves as a proxy for Y_i^N . This approach is motivated by Foster et al. (2010) who aim to identify heterogeneous treatment effects along the covariate space X by estimating $\mathbb{E}(Y_i^I|X_i = x)$ and $\mathbb{E}(Y_i^N|X_i = x)$ separately via random forests and by Sokolov-Mladenović et al. (2016) who feed an ANN with trade data to predict economic growth.

To be more specific a neural network is a nonlinear regression technique that is modelled by an unobserved set of so-called hidden nodes. Suppose X_i is a $(P + 1 \times 1)$ vector of P observed predictor variables and one bias term that serves as the ANN equivalent of the intercept in a regression. This vector enters the $P + 1$ input nodes of our artificial brain. Weighted combinations of the input nodes are then transferred as inputs to the hidden nodes:

$$H_{i,input} = W_{input,hidden} \cdot X_i \quad (2)$$

¹ We consider a five year forecast because they roughly span one business cycle.

where $W_{input,hidden}$ is a $(R \times P + 1)$ weight-matrix and $H_{i,input}$ denotes a $(R \times 1)$ vector that enters the R hidden nodes. At the hidden nodes input signals are transformed by a sigmoidal function:² (3)

$$H_{i,output} = \frac{1}{1 + e^{-H_{i,input}}}.$$

The output of the hidden nodes $H_{i,output}$ is weighted by the $(1 \times R)$ vector $W_{hidden,output}$ and transformed by the sigmoidal function again. Thus the predicted outcome \hat{Y}_i is given by:

$$\hat{Y}_i = \frac{1}{1 + e^{-(W_{hidden,output} \cdot H_{i,output})}} \quad (4)$$

Initially, the elements of the weight-matrices are randomly drawn from a normal distribution with mean zero and standard deviation \sqrt{R} and 1 respectively. The subsequent training of the neural network employs the so-called back-propagation technique (BP) on the training sample that contains approx.. 90 % of all available data (see Rumelhart et al. 1986). We chose BP because it is the standard approach in forecasting settings. In a first step, the squared prediction error E_{output} is calculated in a textbook like fashion as $(Y_i - \hat{Y})^2$ and backward distributed across the hidden nodes in order to calculate the hidden error E_{hidden} :

$$E_{hidden} = W_{hidden,output}^T \cdot E_{output} \quad (5)$$

In a second step, we need to update the elements of both weight-matrices in order to minimize the error terms using gradient descent method. At this stage the advantage of the sigmoid function becomes obvious because of it is continuously differentiable and its deviation is easy to implement.³ Thus the updated matrices are given by:

$$W_{hidden,output(m+1)} = W_{hidden,output(m)} + \varphi \cdot E_{output} \cdot \hat{Y} \cdot (1 - \hat{Y}) \cdot H_{output}^T \quad (6a)$$

$$W_{input,hidden(m+1)} = W_{input,hidden(m)} + \varphi \cdot E_{hidden} \cdot H_{output} \cdot (1 - H_{output}) \cdot X^T \quad (6b)$$

Where the index m denotes the training stage and φ is the learning rate. The final matrices can be employed to forecast the outcome variable of interest.

Several approaches for choosing the optimal number of hidden nodes as well as the learning rate such as fixed, constructive and destructive exist. Most of them got in common that they aim to minimize the mean squared prediction error in the test sample. Therefore, we refuse from reporting these methods in detail and point to Kaastra and Boyd 1996 who provide a detailed overview.

Due to their ability to learn patterns and to approximate almost any nonlinear function, ANN can also be used in recognition and classification. Moreover, in many cases they are more advantageous than classical econometric approaches because they can tolerate fat tails and noise, do not require strong assumptions regarding the error term, can adapt to new patterns and even incorporate observations with missing variables by including dummy nodes (Masters 1993, Kaastra and Boyd 1996, Tkáč and Verner 2016). On the contrary, although ANN provide just another way to solve the least squares problem, their black-box character remains immanent. Thus, it is hard to provide a convincing story regarding causality when ANN are applied.

2.2 Synthetic Control Method

The basic idea behind SCM is to build on classical difference in differences estimation but to select comparison units and assign weights based on a data driven approach. This feature is advantageous in comparison to ANN because results claim causality by construction. Therefore, in SCM, as introduced by Abadie and Gardeazabal (2003), Abadie et al. (2010), and Abadie et al. (2015), it is assumed that $Y_{i,t}^N$ is given by the following factor model:

$$Y_{i,t}^N = \delta_t + \Theta_t Z_i + \lambda_t \mu_i + \varepsilon_{i,t}, \quad (7)$$

where δ_t denotes an unknown common factor, Θ_t is a $(1 \times r)$ vector of unknown parameters, Z_i is a $(r \times 1)$ vector of observed but unaffected predictors, λ_t denotes a time varying $(1 \times F)$ vector of unobserved common factors, μ_i is a $(F \times 1)$ vector of unknown factor loadings and $\varepsilon_{i,t}$ are zero mean unobserved shocks. Suppose that our sample consists of $i = 1, \dots, J$ units of which only the first unit is exposed to the treatment and all other units serve as possible donors. All units are observed at dates $t = 1, \dots, T$. $[1, T_0]$ denotes the entire pre-treatment period so that $T_0 \in [1, T[$. Consider a $(J - 1 \times 1)$ vector of non-negative weights $W = (w_2, \dots, w_J)$, whose elements sum up to one. Each realisation of W represents a potential synthetic control unit. The resulting synthetic control units come with the following value of their outcome variable:

$$\sum_{j=2}^J w_j Y_{j,t} = \delta_t + \Theta_t \sum_{j=2}^J w_j Z_j + \lambda_t \sum_{j=2}^J \mu_j + \sum_{j=2}^J \varepsilon_{j,t} \quad (8)$$

² Other transfer-function such as arc-tan, step or linear exists but are seldom employed.

³The deviation is given by: $\frac{d \frac{1}{1+e^{-x}}}{dx} = \frac{1}{1+e^{-x}} \cdot \left(1 - \frac{1}{1+e^{-x}}\right)$

Since SCM aims to assign weights to donors according to their similarity to the treated unit, we need to find the optimal set of weights W^* such that pre-intervention matching:

$$\sum_{j=2}^J w_j Y_{j,t} = Y_{1,t} \quad \forall t = 1, \dots, T_0 \quad (9)$$

$$\sum_{j=2}^J w_j Z_j = Z_1 \quad (10)$$

is achieved at least approximately. Such a W^* does exist if $(Y_{1,1}, \dots, Y_{1,T_0}, Z_1')$ is not too far away from the convex hull of $\{(Y_{2,1}, \dots, Y_{2,T_0}, Z_2'), \dots, (Y_{J,1}, \dots, Y_{J,T_0}, Z_J')\}$. In this case, and under standard conditions $\sum_{j=2}^J w_j^* Y_{j,t}$ can be used as an estimator of Y_1^N for $T_0 < t \leq T$.

A suitable procedure to obtain W^* is described as follows. Define X_1 as a $(M \times 1)$ vector of pre-intervention values of predictor and outcome variables for the treated unit 1. Let X denote a $(M \times J - 1)$ matrix of the same variables for the $J - 1$ units from the donor pool. The optimal weights W^* are chosen to minimize the weighted distance between X_1 and X :

$$W^* = \operatorname{argmin}_W (X_1 - XW)'V(X_1 - XW), \quad (11)$$

where V is a non-negative semidefinite $(M \times M)$ matrix whose diagonal elements reflect the importance of each considered predictor variable. At this step, the optimal $W^*(V)$ depends on the choice of the relative predictor importance. Among all possible matrices V , V^* is chosen to minimize the residual mean squared prediction error (RMSPE) of the outcome variable during the pre-intervention period:

$$V^* = \operatorname{argmin}_V (Y_1 - YW^*(V))'(Y_1 - YW^*(V)), \quad (12)$$

where Y_1 is a $(T_0 \times 1)$ vector of pre-treatment outcomes for unit 1 and Y is a $(T_0 \times J)$ matrix that contains the pre-treatment outcomes for the donor units. Since there are infinitely many collinear solutions of V^* , the Euclidean norm of V^* is normalized to one. The optimal weights are given by $W^*(V^*)$. This synthetic control unit, which comes as a weighted average of units from the donor pool, is the best to reproduce unit 1's trajectory in the absence of treatment. Thus, SCM provides a synthetic counterfactual as a convex combination of control regions.

In contrast to ANN, the procedure of SCM allows us to perform so-called placebo studies to test the significance of the treatment effect (Abadie et al. 2010, and Abadie et al. 2015, Munasib and Rickman 2015). The in-space placebo test produces inferences by computing a distribution

of a test statistic in the following manner. It assumes that treatment is assigned across units at random. Thus, a synthetic counterfactual is calculated for each unit in the donor pool producing a distribution of placebo treatment effects. Let us denote the actual treatment effect by TR_1 and the cumulative density function of placebo effects by $F(TR)$. Following the argumentation of Munasib and Rickman (2015), the p -value of a one-tailed test of a null-hypothesis that $TR_1 \leq 0$ can easily be calculated by $p = 1 - F(TR_1)$.

This procedure is advantageous over other identification strategies such as OLS based DiD estimations. First, the data-driven weighting approach allows to abstract from the subjective choice of comparison units. Second, the restriction of the weights to be non-negative and sum to one makes the counterfactual very realistic and supports causality. Third, this procedure is robust against time-trends and against the violation of strict exogeneity in time series data that both lead to biased results in DiD. Fourth, by applying *placebo tests in space* and *in time*, one can test the significance of the results and control for endogeneity issues (for more detailed description of the advantages also see Buchmueller et al., 2011, Munasib and Rickman, 2015 and Pinotti, 2015).

However, when applied to real world data, SCM suffers from the following three shortcomings: First, Kaul et al. (2016) argue that pre-treatment matching is often achieved only if pre-treatment outcome variables are included as additional predictor variables. This procedure turns the other predictor variables irrelevant and reduces the credibility of the final results. Second, SCM suffers from severe reproducibility problems. Klößner et al. (2017) show that the choice of software package as well as the order of observations in the dataset are influential factors in determining the estimated treatment effect. Third, when it comes to big datasets or many control units, the execution of SCM is inefficient, causes standard computers to run into RAM limits and does not necessarily provide efficient estimates. By and large, these features diminish the practical relevance and plausibility of SCM.

2.3 Data

To be consistent with the approach of Achten et al. (2018) we feed our ANN with data from the Cambridge Econometrics European Regional Database (ERD). Although it provides economic indicators over a period between 1980 and 2014, we limit the period of investigation to the year 2005 – five years after the opening of the bridge. We do so because our ANN gives us a five year forecast of Gross Domestic Product per Capita (GDPpC) and using post-treatment predictor variables would cause severe endogeneity issues. We employ investment share,

sectoral shares of value added, population density, compensation of employees and the pre-treatment level of the GDPpC as predictors for economic growth following Barro (1991).

As in Achten et al. (2018), we also consider only those regions in our training and test sample for which data is available from 1980 onwards. If spillover effects are relevant in fact, the inclusion of Germany and Scandinavia would induce biased estimates. Therefore and due to the fact that Jean et al. (2016), who focus on convolutional neural networks and satellite imagery, argue that the exclusion of the states of interest reduces predictive power only modestly, we exclude all German and Scandinavian regions. To make the outcome of SCM and ANN comparable and to guarantee causality, we also drop all observations that were exposed to large infrastructure investment during entire period. Our final sample consists of nearly 6.000 suitable observations. However, since we employ ten-fold cross-validation to avoid overfitting, our training- and test-samples contain 5.400 and 600 observations respectively

3 Results

Based on the pyramids rule (see Master 1993) and due to the fact that we use the ANN to densify information across the layers, we assume the optimal number of hidden nodes to be between 11 and 2. Therefore, we use the fixed approach to choose the number of hidden nodes as well as the learning rate. Since this procedure examines (almost) all available combinations, we select the configuration that minimizes the mean of squared residuals in the test-samples using ten-fold cross-validation. A graphical illustration of the results can be seen in Figure 1.

< Insert Figure 1 about here >

Our final network contains 6 hidden nodes and is endowed with a learning rate of 1. At this stage, we need to mention that the BP algorithm – although it converges – does not necessarily find the global optimum solution and may stuck in local optima. However, we aim to overcome this problem, by using randomly chosen initial weights, repeating the algorithm several times and averaging the outcomes. Despite this shortcoming, we employed this algorithm because it is easy to implement, highly efficient and does not require strong assumptions regarding the error term. Similar to other machine learning techniques ANN also tend to overfit. However, the number of weights in the network is small compared to the number of observations and we find good results in our cross-validation approach. Thus, refuse from pruning high weights and model complexity. In a robustness check, we also considered a deep neural network consisting of two hidden layers. We refuse from reporting the results, because it seemed to memorize instead of learning patterns so that it showed severe overfitting.

To avoid the above mentioned local optima issue we repeat the forecasting of Malmo's (local level NUTS⁴ 2) and Södra Sverige's (regional level NUTS 1) GDPpC trajectories one hundred times and calculate the averages. Afterwards, we also calculated the treatment effects as the differences between the actual outcomes and the forecasted versions. The results are shown in Figure 2 and 3. To compare the results of our ANN with the SCM approach, the outcome of SCM is shown in Figures 4 and 5.

< Insert Figure 2 about here >

< Insert Figure 3 about here >

< Insert Figure 4 about here >

< Insert Figure 5 about here >

It becomes obvious that both estimation strategies reveal a distinct positive treatment effect around the year 2000. Additionally, the ANN confirms the previous results of a more pronounced effect at the regional level (Södra Sverige) that arises from potential spill-over effects. Since neither our ANN nor the SCM of Achten et al. (2018) do perfectly replicate the pre-treatment path of GDPpC, we apply the difference-in-differences treatment estimator TR as suggested by Bohn et al. 2014:

$$TR = (\overline{Y_{post}^I} - \overline{Y_{post}^N}) - (\overline{Y_{pre}^I} - \overline{Y_{pre}^N}) \quad (13)$$

where Y_{post}^I is the actual post-intervention outcome, Y_{post}^N is the counterfactual post-treatment outcome, Y_{pre}^I denotes the actual and Y_{pre}^N the counterfactual pre-treatment outcome. Considering Malmo our ANN TR amounts to 1.489 € (in 2005 terms) and is very close to the SCM estimate (1.680 €). For Södra Sverige the ANN TR (4.133 €) is approximately 38 % larger than the SCM TR (2.988 €). However, the discrepancy may arise from the fact that the period of consideration in the SCM approach is 2 years longer and our ANN counterfactual indicates a decrease in treatment effect starting in 2005.

As a robustness checks, we exclude the year of prediction as input variable in our training procedure to prevent the network from memorizing Europe-wide exogeneous economic shocks. Instead, it now has to learn more general patterns from the economic predictor variables. The results are reported in the appendix and confirm our prior results.

⁴ Nomenclature of territorial units for statistics.

4 Conclusion

In this study we showed that ANNs are powerful tools for solving the least squares problem in a highly nonlinear fashion. Moreover, by applying a simple forecasting ANN to a case study, namely the construction of the Oresund bridge, we find that this single-layer feed forward neural network yields similar results as the much more advanced and appreciated SCM. Considering that ANNs are said to perform notably well in settings where there are many covariates relative to the number of observations, this result becomes even more astonishing.

As pointed out by Kleinberg et al. (2015) most policy evaluation problems are rather prediction than causal inference problems. Therefore, ANNs – which provide excellent prediction capabilities – should find their way into the toolbox of any econometrician. This claim can easily be verified if one considers that each policy intervention needs to be evaluated *ex ante* and *ex post*. Whereas SCM and the backward looking forecasting ANN – as employed above – are both suitable for *ex post* identification of causal effects, pure forecasting machine learning techniques also allow a status-quo prediction of future outcomes. This feature is of high relevance because the effect of a policy often depends on the relevant outcome itself. The following example illustrates this statement. The net return of a large infrastructure investment such as the Oresund bridge is a function of the future economic prosperity itself. In detail, the construction of the bridge would cause more and more intense network and spillover effects in a hypothetical situation where there is a high future GDPpC. Consequently, there would be a high treatment effect in terms of GDPpC. On the contrary, if the future GDPpC is low, the construction of the bridge has merely short term government spending effect on GDPpC because network effects will not occur.

With the advent of big data in economics the importance of ANN will continue to rise. Specifically, since SCM and other popular approaches such as LASSO or elastic nets either become inefficient or hard to interpret as the number of covariates increases, there is a need in economics to borrow machine learning techniques from computer scientist in order to adapt them for policy evaluation purposes. However, up to now, an ANN remains a black box without a well-understood sampling distributions what makes it really hard to test hypotheses. Although, there remains much work to establish causal ANN in economics we are confident that this paper excites economists and econometricians to explore the field of machine learning.

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Figures:

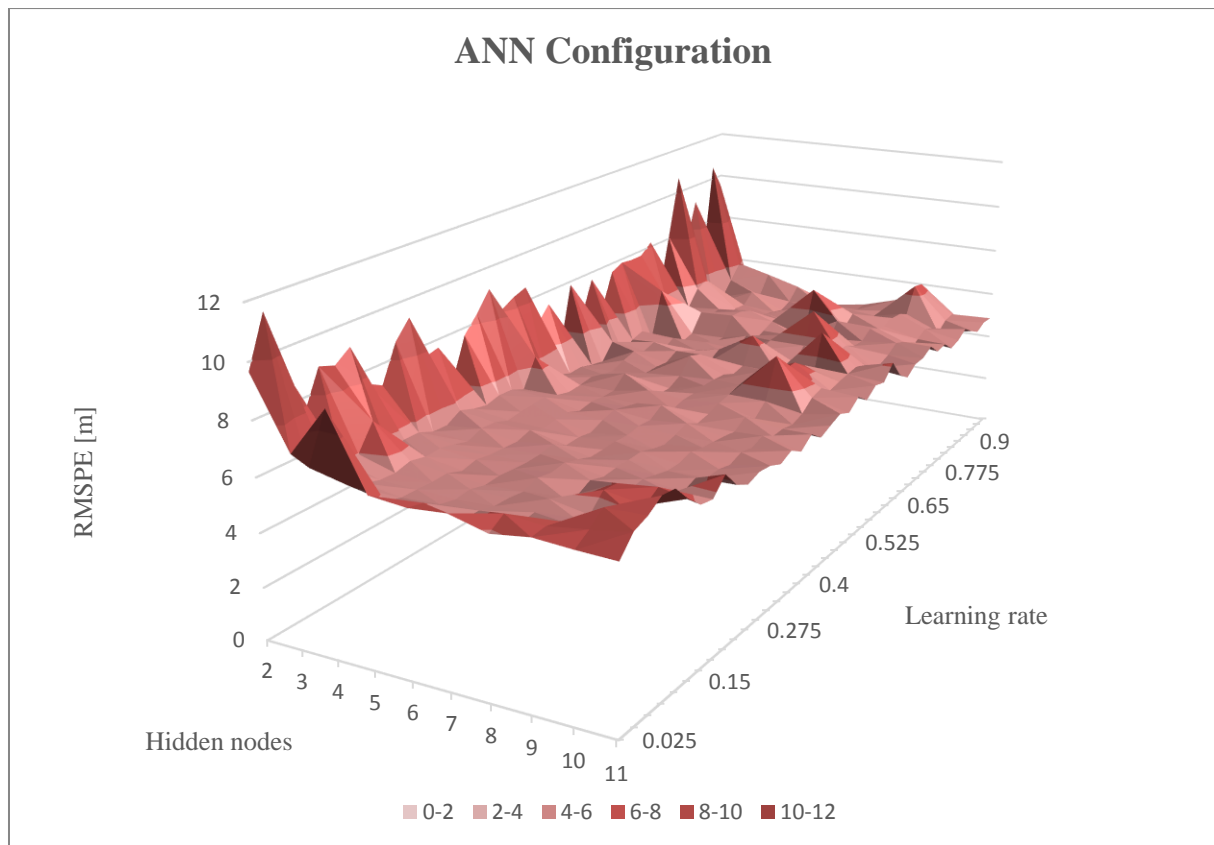


Figure 1: Results of fixed approach

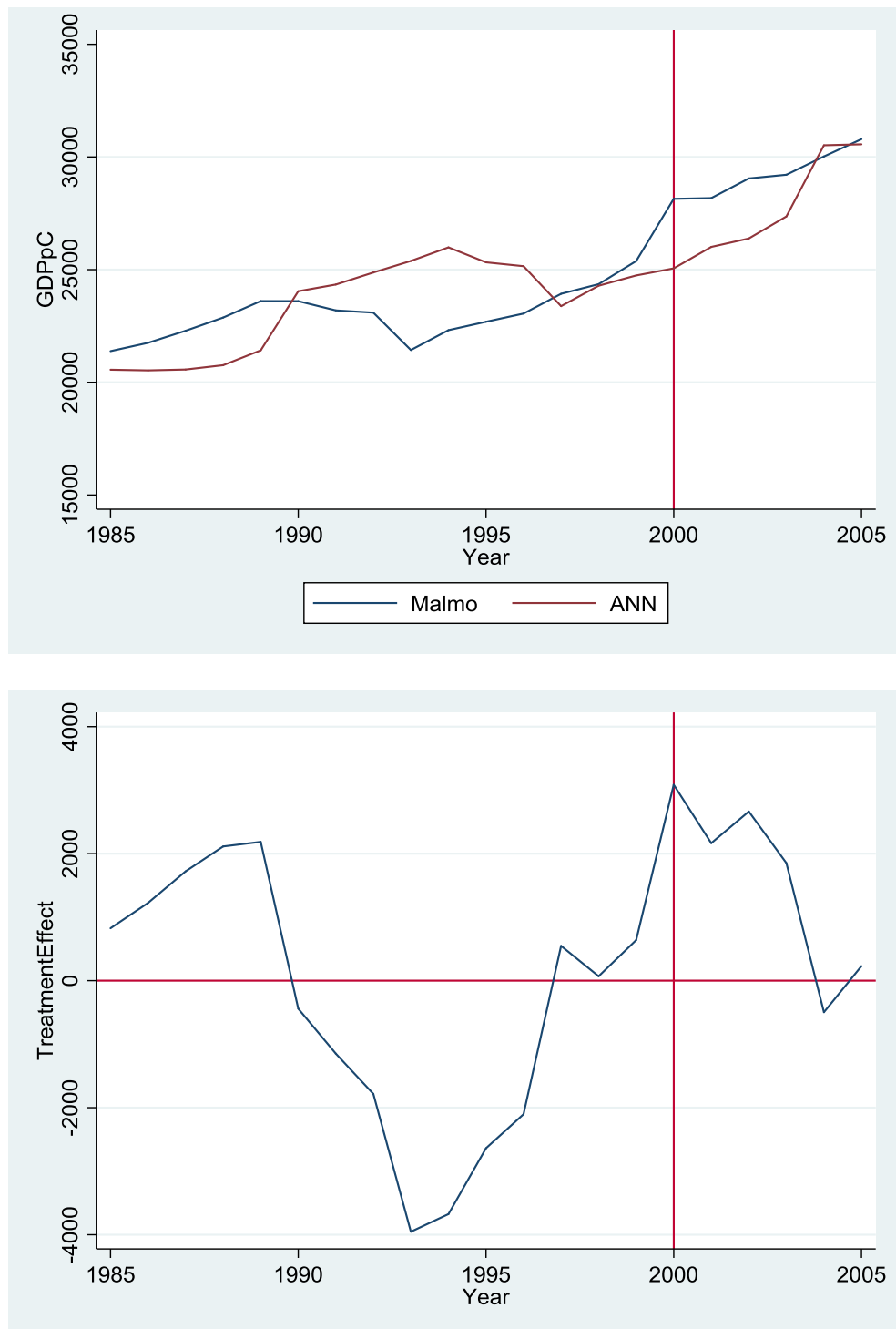


Figure 2: ANN forecast of Malmo and treatment effect

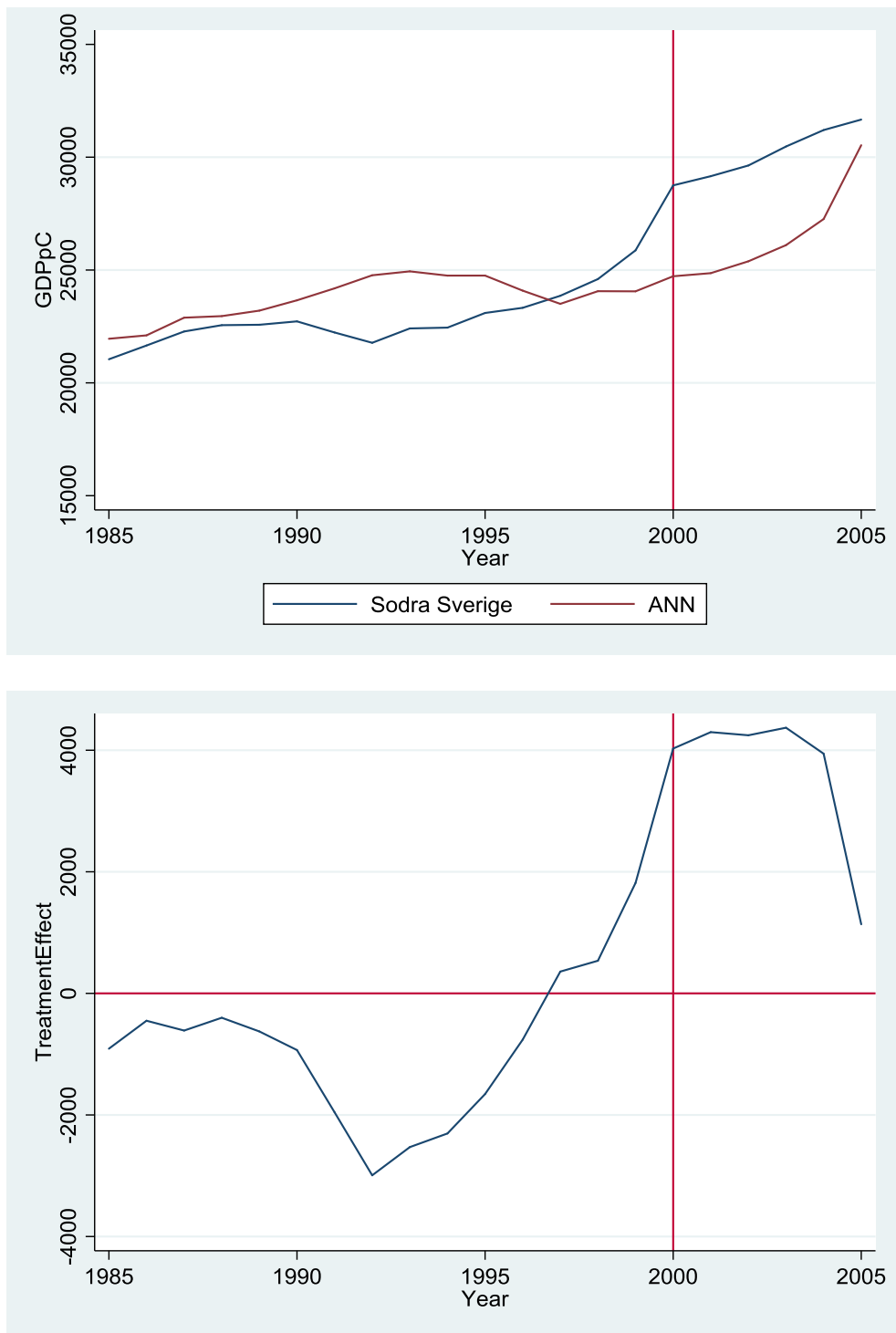


Figure 3: ANN forecast of Södra Sverige and treatment effect

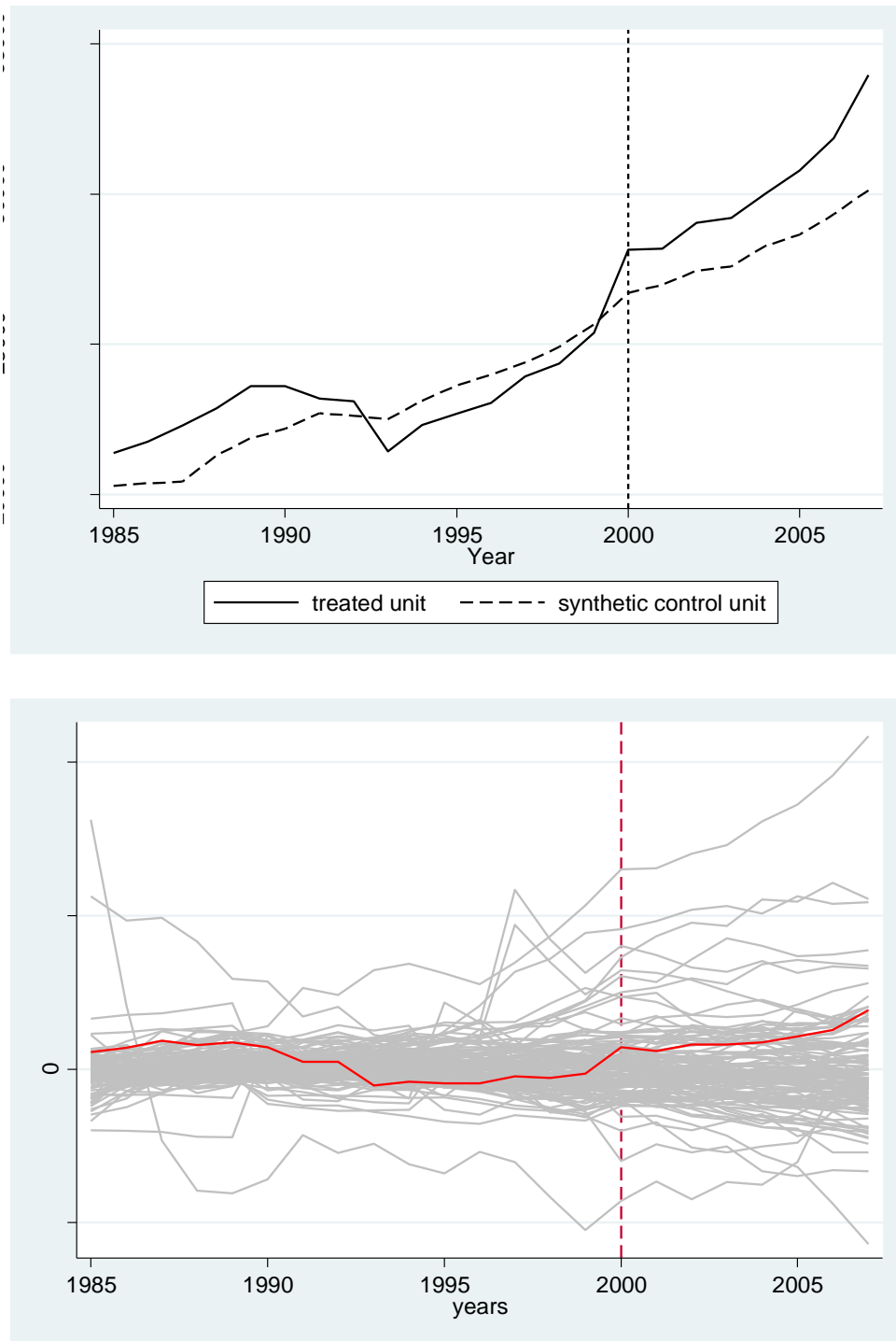


Figure 4: SCM results of Malmo - taken from Achten et al. 2018

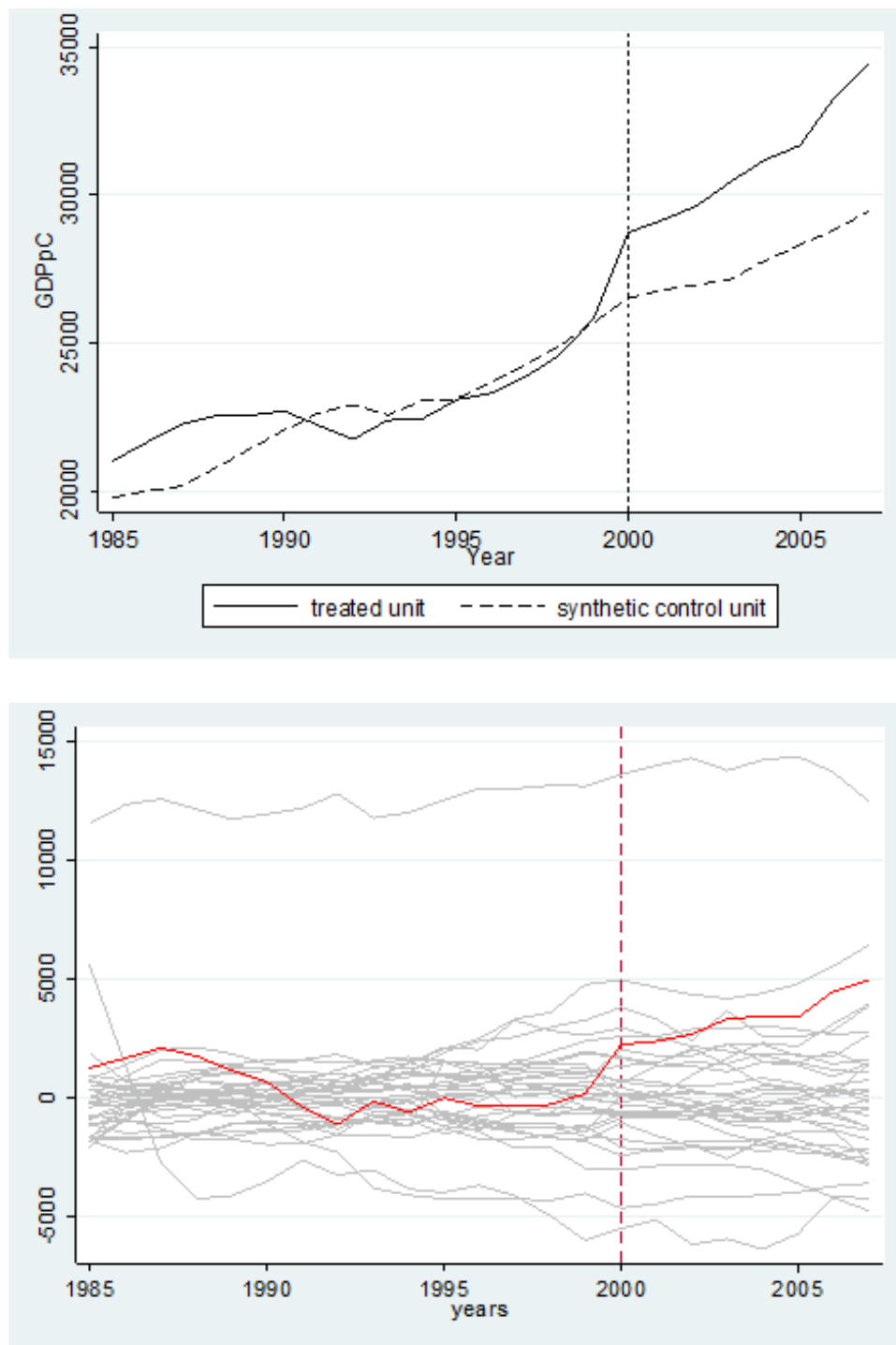


Figure 5: SCM results of Södra Sverige - taken from Achten et al. 2018

Appendix



Figure A 1: ANN forecast of Malmo and treatment effect – Year excluded from set of predictors: TR: 1.583 €



Figure A 2: ANN of Södra Sverige and treatment effect – Year excluded from set of predictors: TR: 3.863 €