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Estimating the effect of central bank independence on inflation using longitudinal targeted maximum likelihood estimation¹

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Estimating the Effect of Central Bank Independence on Inflation Using Machine Learning

Modern doubly robust estimation techniques applied to an old macroeconomic question

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Abstract

Does an independent central bank (CBI) reduce inflation? Despite numerous articles suggesting it does, this question has not been satisfactorily answered because the complex macroeconomic structure that gives rise to the data has not been adequately incorporated into economic analyses. We develop a causal model that summarizes the economic process of inflation and estimate the effect of CBI on inflation with modern doubly robust effect estimation techniques. We incorporate a large number of variables in our directed acyclic graph and overcome endogeneity issues of previous studies. Our approach includes machine learning algorithms which are tailored to the question of interest and reduce the chance of model misspecification. In this paper, we provide the motivation and give a short summary of our recent study (Baumann, 2021a).

Keywords: macroeconomics, monetary policy, causal inference, doubly robust

JEL classification: C13, C14, C21, C33, E3

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1. Introduction

At least since David Ricardo's days the institutional relationship between central banks and governments has been a subject of considerable interest. Over the past three decades, following a series of events, such as financial liberalization, greater acceptance of long-run inflation as a monetary phenomenon, and rejection of the long-run tradeoff between inflation and unemployment, research on the impact of central bank independence (CBI) on economic outcomes has intensified (Cargill, 2013). It has been claimed that more than 9,000 works have been devoted to this question (Vuletin and Zhu, 2011). After the 2008-09 Global Financial Crisis, the debate on the optimal design of monetary policy authorities has become even more intense.

The traditional case for CBI rests on countering an inflation bias that may occur for various reasons in the absence of an independent central bank (de Haan et al., 2018). One reason for this bias is political pressure to boost output in the short run for electoral reasons. Another reason is the incentive for politicians to use the central bank's power to issue money as a means to finance government spending. Ricardo considered it a great danger to entrust the ministers with the power of issuing paper money. The third reason is the time-inconsistency problem of monetary policy making. When governments have discretionary control over monetary instruments, they can prioritize other policy goals over price stability. For instance, after nominal wages have been negotiated (or nominal bonds purchased), politicians may be tempted to create inflation to boost employment and output (or to devalue government debt).

To overcome an inflation bias, the literature stresses the benefits of enforced commitments (rules). In particular, Rogoff (1985) proposed delegating monetary policy to an independent and conservative central banker to reduce the tendency to produce high inflation. Once central bankers are insulated from political pressures, commitments to price stability can be credible, which helps to maintain low inflation.

Following these ideas, a policy consensus grew around the potential of having independent central banks to promote inflation stability (Bernhard et al., 2002; Kern et al., 2019). Numerous countries followed this policy advice. Between 1985 and 2012, and excluding the creation of regional central banks, there were 266 reforms to the statutory independence of central banks, 236 of which were implemented in developing countries. Most of these reforms (77%) strengthened CBI (Garriga, 2016).

Despite the broad impact of this policy advice, the empirical evidence in support of it remains controversial. Starting with (Bade and Parkin, 1978, 1982, 1988) and extended by (Cukierman et al., 1992), a substantial body of empirical literature evolved claiming the existence of a statistically significant inverse relationship between measures of CBI and inflation. However, the support for more independent central banks has often been based on correlations between CBI measures and inflation over time and across countries, frequently based on single-variable regression models or in models in which several economic and political variables were added as covariates. While many studies have found that an independent central bank may lower inflation (Alesina and Summers, 1993; Arnone and Romelli, 2013; Cukierman et al., 1992; Grilli et al., 1991; Klomp and De Haan, 2010b,a), other studies that have used a broader range of characteristics of a nation's economy have been unable to find such a relationship (Cargill, 1995b; Fuhrer, 1997; Oatley, 1999; Campillo and Miron, 1997; Fujiki, 1996). Other studies suggest that the effect of CBI on inflation can only be seen during

specific time periods (Klomp and De Haan, 2010a) or only in developed countries (Alpanda and Honig, 2014; Klomp and De Haan, 2010b; Neyapti, 2012).

2. Motivation

Evaluating the effect of CBI on inflation based on simple cross-sectional regression approaches has some important weaknesses. First, a few researchers question the entire framework of measuring CBI and the statistical results obtained, arguing that these approaches provide misinformation about the fundamental relationship between the central bank and government. They emphasize the difficulty of measuring CBI and the predictive power of the estimated relationship for some countries (Cargill, 1989, 1995a). Second, there is a question as to the direction of causation implied by simple correlations between CBI and inflation (Posen, 1998). A third critique that advises caution in interpreting the results is the focus on *de jure* rather than *de facto* measures of independence (Pollard, 1993). Klomp and De Haan (2010a) combined 59 studies in a meta-regression analysis and concluded that the particular CBI measure used has little effect on the estimated effect and that there is indeed a negative and significant relationship between CBI and inflation. However, echoing the mixed evidence reported in the literature, Parkin (2013) notes that the meta-regression does not control for the amount of data mining undertaken. Nor does the conclusion sit well with the details of the 59 studies included in the analysis. From the 384 regressions included in the studies, 202 exhibit a significant negative relationship while 182 show either no relationship or a significant but “wrong” sign.

In our study (Baumann, 2021a) we offer a solution to two of the major problems encountered by previous empirical work. First, since the problem at hand is longitudinal in nature, only an appropriate panel setup may be suitable to estimate the (long-term) effect of CBI on inflation. Second, the abovementioned cross-sectional regression approaches do not incorporate any causal considerations into their analyses. We propose a novel framework which takes causality explicitly into account. Specifically, we ask what (average) inflation would we observe in 10 years’ time, if from now on each country had an independent central bank compared to a situation in which the central bank were not independent. The data set we use was created specifically for this purpose and extends the data set from Baumann et al. (2021b).

3. Causality in Complex Settings

While evaluating the effect of CBI on inflation requires a longitudinal causal estimation approach, it has been shown repeatedly that standard regression approaches are typically not suitable to answer causal questions, particularly when the setup is longitudinal and when the confounders of the outcome-intervention relationships are affected by previous intervention decisions (Daniel et al., 2013). There are at least three methods to evaluate the effect of longitudinal (multiple time-point) interventions on an outcome in such complex situations: 1) inverse probability of treatment weighted (IPTW) approaches (Robins et al., 2000); 2) standardization with respect to the time-dependent confounders (i.e., g-formula-type approaches (Robins, 1986; Bang and Robins, 2005)); and 3) doubly robust methods, such as targeted

maximum-likelihood estimation (TMLE, Van der Laan and Rose, 2011), which can be seen as a combination and generalization of the other two approaches.

Using causal inference in economics has a long history, starting with path analyses and potential outcome language (Tinbergen, 1930; Wright, 1934) and continuing with regression discontinuity analyses (Hahn et al., 2001), instrumental variable designs (Imbens, 2014), and propensity score approaches in the context of the potential outcome framework (Rosenbaum and Rubin, 1983), among many other methods. More recently, there have been work advocating the use of doubly robust techniques in econometrics (Chernozhukov et al., 2018). From the perspective of statistical inference this is a very promising suggestion because the integration of modern machine learning methods in causal effect estimation is almost inevitable in areas with a large number of covariates and complex data-generating processes (Schomaker et al., 2019).

However, the application of doubly robust effect estimation can be challenging for (macro-)economic data. First, the causal model that summarizes the knowledge about the data-generating process is often more complex for economic than for epidemiological questions, where most successful implementations have been demonstrated so far (Kreif et al., 2017; Decker et al., 2014; Schnitzer, Moodie, van der Laan, Platt and Klein, 2014; Schnitzer, van der Laan, Moodie and Platt, 2014; Schnitzer, Lok and Bosch, 2016; Tran et al., 2016; Schomaker et al., 2019; Bell-Gorrod et al., 2019). The task of representing the causal model in a directed acyclic graph (DAG) becomes particularly challenging when considering how economic variables interact with each other over time. Thus, in order to build a DAG, a thorough review of literature is called for, and economic feedback loops need to be incorporated appropriately. Imbens (2019), who discusses different schools of causal inference and their use in statistics and econometrics, as well as different estimation techniques, emphasizes this point: “[...] a major challenge in causal inference is coming up with the causal model.”

Second, even if a causal model has been developed, the identification of an estimand has been established, and the data have been collected, statistical estimation may be nontrivial given the complexity of a particular data set (Schomaker et al., 2019). If the sample size is small, potentially smaller than the number of (time- varying) covariates, recommended estimation techniques can fail, and the development of an appropriate set of learning and screening algorithms is important. The benefits of LTMLE, which is doubly robust effect estimation in conjunction with machine learning to reduce the chance of model misspecification, can be best utilized under a good and broad selection of learners that are tailored to the problem of interest.

3. Contributions of our Study

Estimating the effect of CBI on inflation is a typical example of a causal inference question that faces all of the challenges described above. Our paper makes five novel contributions to the literature. i) We discuss identification and estimation for our question of interest and estimate the effect of CBI on inflation; ii) develop a causal model that can be applied to other questions related to macroeconomics; iii) demonstrate that it is possible to develop a DAG for economic questions, which is important, as it has been argued that “the lack of adoption in economics is that the DAG literature has not shown much evidence of the benefits for empirical practice in settings that are important in economics.” (Imbens, 2019); iv) demonstrate how to

integrate machine learning into complex causal effect estimation, including how to define a successful learner set when the number of covariates is larger than the sample size and when there is time-dependent confounding with treatment-confounder feedback (Hernan and Robins, 2020); and v) use simulations to study the performance of doubly robust estimation techniques under the challenges described above.

4. Results

As discussed in Baumann et al. 2021a, our main analysis, PlainDAG, shows that if a country had legislated central bank independence for every year between 1998 and 2008, it would have had an average increase in inflation of 0.01 (95% confidence interval: -1.48, 1.50) percentage points in 2010. We conducted a further analysis where a central bank is made independent, if the corresponding country has experienced an inflation rate that is generally considered as too low or too high, respectively. That is, if a country had legislated an independent central bank for every year when the median of the past seven years of inflation had been above 5% or below 0% from 1998 to 2008, it would have led to an average reduction in inflation of -0.07 percentage points only (95% confidence interval: -1.29, 1.15) in 2010 compared to a dependent central bank for the same time span. We conducted two robustness checks with regard to the causal assumptions underlying our model. These two approaches are ScreenLearn and EconDAG. The results suggest somewhat stronger reductions of inflation caused by higher central bank independence (up to -0.61 percentage points). As suggested by the wideness of the confidence intervals, we can exclude neither a strong negative nor a strong positive average treatment effect.

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Introduction

Why a further study on Central Bank Independence (CBI)?

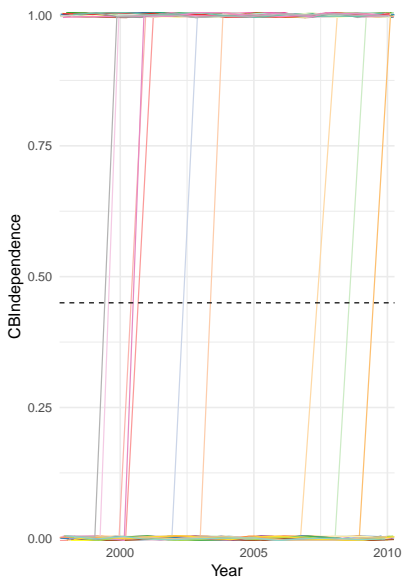
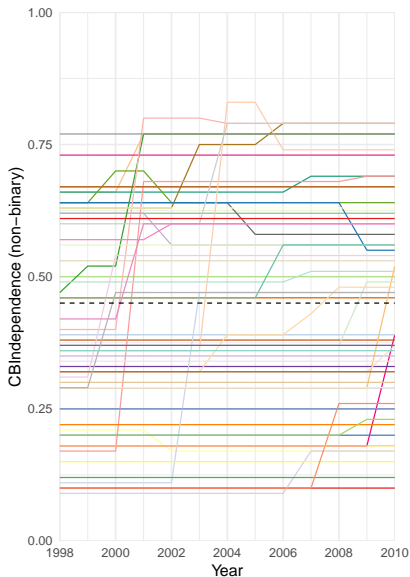
- Models in empirical studies often neglect a holistic causal framework which results in premature causal interpretation.
- Instrumental variable approaches have been proposed to tackle these problems but many authors have been unable to find strong instruments (e.g. Crowe and Meade; 2008).
- Effect estimation in practice: various practical challenges like small sample sizes, too many irrelevant covariates and too restrictive models lead to biased estimators for the causal effect.

Question of our study: What (average) inflation would we observe in 10 years' time, if – from now on – each country's monetary institution had an independent central bank compared to the situation in which the central bank was not independent?

Data

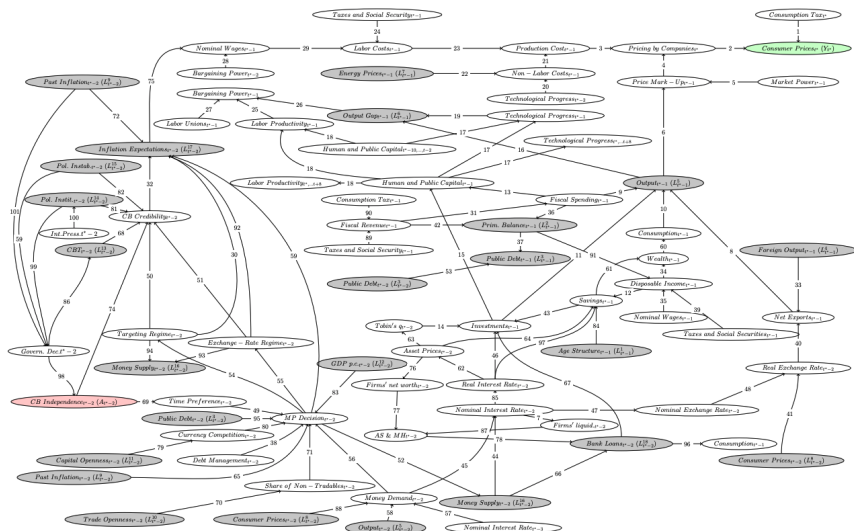
- We accessed databases of the World Bank and the International Monetary Fund to collect annual data for economic, political, and institutional variables.
- Our aim was to include as many countries as possible in our analysis.
- Missing data (2.7%) lead to the use of multiple imputation.
- Finally, we obtained observations for 60 countries and 13 points in time (i.e., calendar years 1998–2010) for 19 measured variables.
- 20% of the 60 countries are low-income countries, 36% belong to the lower-middle-income category, 27% to the upper-middle-income category, and 17% belong to the high-income category.

CBI Index: Dincer and Eichengreen (2014)



The Causal Analysis

The Economy as a DAG



Target Parameters

- Our target parameters are average treatment effects (ATEs)
- Three interventions. Two static and one dynamic.

$\forall t^* \in \{1998, \dots, 2008\}$ and $i \in \{1, \dots, 60\}$

$\bar{d}_{t^*}^1$ = Set every CB i as "independent" for every t^*

$\bar{d}_{t^*}^2$ = Set a CB i as "independent" in t^* when inflation has exceeded 5% or was below 0% in the past seven years. Set "not independent" otherwise.

$\bar{d}_{t^*}^3$ = Set every CB i "not independent" for every t^*

$$\psi_{1,3} = \mathbb{E}(Y_{2010}^{\bar{d}_{t^*}^1}) - \mathbb{E}(Y_{2010}^{\bar{d}_{t^*}^3}), \quad (1)$$

$$\psi_{2,3} = \mathbb{E}(Y_{2010}^{\bar{d}_{t^*}^2}) - \mathbb{E}(Y_{2010}^{\bar{d}_{t^*}^3}). \quad (2)$$

Estimation Method

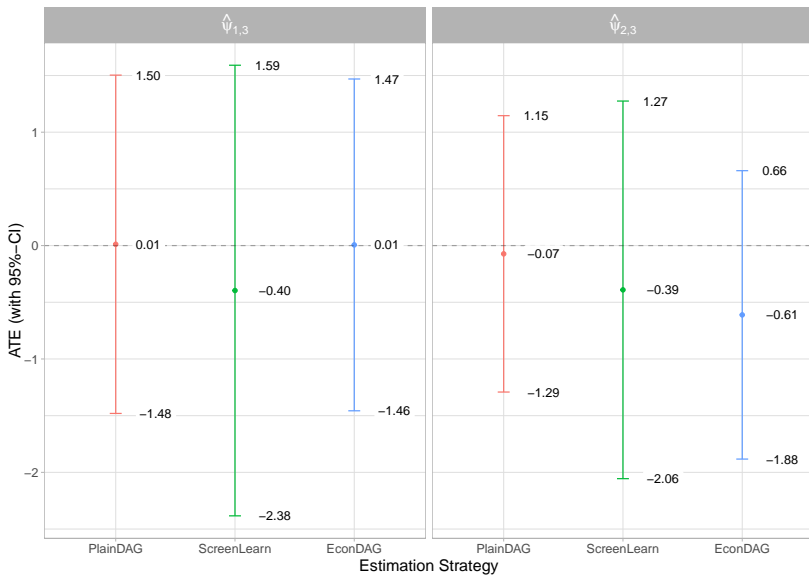
- Longitudinal Targeted Maximum Likelihood Estimation (LTMLE) has been mostly used in the field of bio statistics and epidemiology (van der Laan and Gruber; 2012).
- LTMLE is a doubly robust estimation technique that requires iteratively fitting models for the outcome and intervention mechanisms at each time point.
- LTMLE has the advantage that it can more readily incorporate **machine learning** methods while retaining valid statistical inference.
- Recent research has shown that this is important if correct model specification is difficult, such as when dealing with complex longitudinal data, potentially of small sample size, where relationships and interactions are most likely highly nonlinear and where the number of variables is large compared to the sample size (Tran et al.; 2019).

Which covariates need to be included?

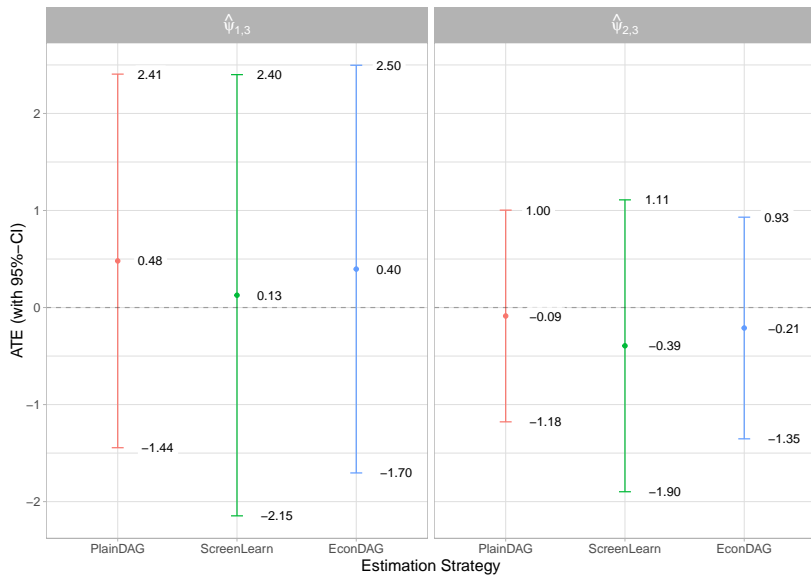
- **Main analysis – PlainDAG:** Models contain only the relevant baseline variables from 1998 that were measured prior to the first CBI intervention.
- **Robustness check No. 1 – ScreenLearn:** All measured variables are taken into account by the models with respect to the temporal ordering.
- **Robustness check No. 2 – EconDAG:** Models includes only variables that are measured during a particular 2-yearly transmission cycle, as defined by our DAG.

Results

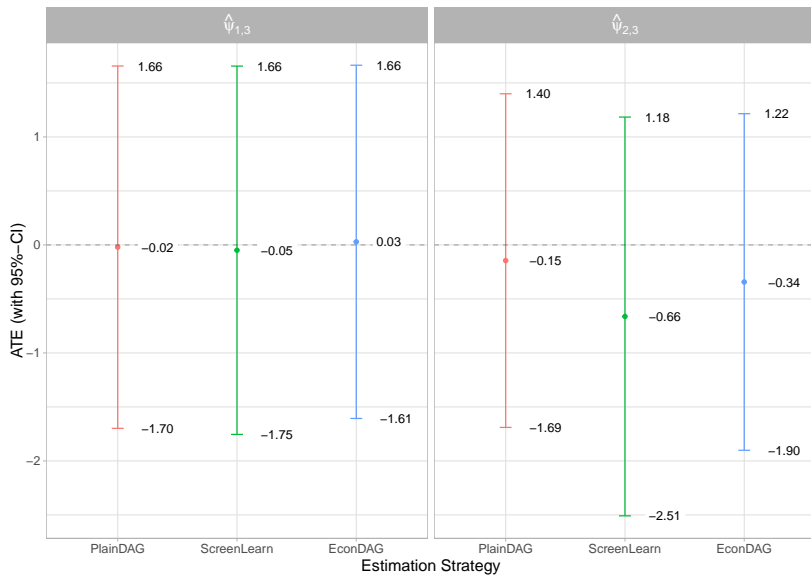
Results: Full Sample (n = 60)



Results: High income (n = 26)



Results: Low income (n = 34)



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