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University of Lodz, Department of International Trade (Faculty of Economics and Sociology), POW 3/5, 90-255 Lodz, Poland, room A404, e-mail: tomasz.serwach@eksoc.uni.lodz.pl

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ABSTRACT

Although addressing income inequalities is one of the main challenges in the European Union (EU), whether the EU has influenced income distributions, possibly causing a rise in inequalities, is still a heavily underexplored topic. Using the newest methodological developments associated with the counterfactual estimations, I assessed the distributional effects of the 2004 EU enlargement. The results indicate that EU accession cannot be held responsible for any significant changes in income inequalities in the New Member States. That finding is robust to changes in the method of estimation, and it is also supported by dynamic panel data methods.

JEL: F15, F16, F66, E24

Keywords: European Union, income inequalities, Gini coefficient, counterfactual estimators, panel data

1. Introduction

The European integration process is seen as one of the main contributors to political stability and economic prosperity. In 2012, the European Union (EU) was awarded the Nobel Peace Prize as "for over six decades [it has] contributed to the advancement of peace and reconciliation, democracy and human rights in Europe" (The Nobel Foundation 2012). On economic grounds, some authors argue that European integration means approximately 10% higher income per capita in the first ten years after joining that process (Campos, Coricelli, and Moretti, 2019). With such achievements, membership of the EU should be considered almost as a value in itself.

At the same time, according to Eurobarometer, in 2019, slightly more people tended to distrust the EU as opposed to people who trusted it. 46% of EU citizens declared that they did not trust the EU, while 44% said otherwise (Eurobarometer 2019, Question QA6a.10). Although in only eight then-Member States the majority of respondents declared distrust, it happened in such big countries as the United Kingdom, France, and Italy. Moreover, a distrusting majority was also observed in the newest Member State, Croatia. The prevalence of that attitude also characterized countries such as the Czech Republic and Slovenia, although both of them have benefited from the membership. Campos, Coricelli, and Moretti (2019) calculated that in these countries, GDP per capita would be 5.62% and 10.35% (respectively) lower had they not joined the EU.

In the United Kingdom, this negative view of the EU was the natural origin of the process that eventually led to Brexit. For some, it could also be linked to within-country income inequalities. Bell and Machin (2016) documented that the percentage voting for Brexit was strongly and negatively correlated with the median weekly wage in local authorities in England, Scotland, and Wales, proving that poorer regions voted in favor of leaving the EU. However, such an inequality-populism relationship can also be observed in other Member States. "The revenge of places that do not matter" affected electoral outcomes in the 2016 Austrian presidential election, the 2017 French presidential election, and the 2017 German general elections (Rodriguez-Pose, 2018). As shown by Rodrik (2020), economic dislocation caused by globalization can trigger voting for populist parties through its impact on voters' preferences, party programs and ideology. Other studies that analyzed openness-induced populism include Halla, Wagner, and Zweimüller (2017), Malgouyres (2017), and Colantone and Stanig (2018), to name but a few.

The question that arises is whether European integration has contributed to within-country income inequalities. Although the positive impact of that process on average income is well-documented (see Badinger, 2005, Crespo-Cuaresma, Ritzberger-Grünwald, and Silgoner, 2008, and Campos, Coricelli, and Moretti, 2019, among others), the distributional effects of integration are far from being understood. It is surprising given the current wave of theoretical and empirical studies on the impact of openness on income inequalities (see Section 2). Without any thorough analysis, it could be deduced that European integration widened these inequalities, since regional disparities have been on the increase since the 1980s (see Rosés and Wolf, 2018), and it has coincided with changes in both the intensity (the move from the European Economic Community to the EU) and geographical scope (the EU enlargements) of the integration. However, such correlations could be spurious, and rising inequalities might be caused by other factors, apart from the impact of European integration.

The main aim of this article is to quantitatively assess the effect of the EU on income inequalities within the New Member States from the 2004 EU enlargement. The null hypothesis – no impact of the EU – was tested with the use of the counterfactual methods. The unified framework for these estimators was first introduced by Liu, Wang, and Xu (2019). These data-driven methods allow researchers to compare the trajectories of outcome variables for two scenarios (with and without treatment). The algorithms utilized in the article are the generalizations of other estimators commonly applied in comparative case studies, such as difference-in-differences (DiD) and the synthetic control method (SCM). They differ in the way they generate counterfactual scenarios.

This article is related to the limited literature on the distributional effects of European integration, which includes especially Beckfield (2006), Kuštepeli (2006), Busemeyer and Tober (2015), Bouvet (2021), Kvedaras and Cseres-Gergely (2020), Domonkos, Ostrihoň, and König (2021), and Eaton, Kortum, and Kramarz (2022). Instead of traditional panel data methods such as fixed and random effect models, as in Beckfield (2006) and Busemeyer and Tober (2015), counterfactual estimators are applied. At the same time, while Kuštepeli (2006), Kvedaras and Cseres-Gergely (2020), Domonkos, Ostrihoň, and König (2021) analyzed other issues such as the Kuznets curve, the convergence in income distributions, and the distribution of post-accession economic growth between the poor and the rest of society this article is devoted directly to the causal impact of the EU on inequalities. Eaton, Kortum, and Kramarz (2022) built a quantitative general equilibrium model and simulate the consequences of the 2004 EU accession, including labour market outcomes. A methodologically related paper prepared by Bouvet (2021) used the SCM, which is a special case of one of the methods applied in this article. However, Bouvet's study was focused on the inequality-related effects of the adoption of the euro, while in this paper, the focus is on the distributional consequences of EU membership.

In a broader sense, the article contributes to the literature on the impact of economic openness on within-country income inequalities. Regarding regional integration initiatives, empirical studies usually analyze non-European cases of economic integration processes in the world, most commonly the North American Free Trade Agreement, NAFTA (see Fenstra and Hanson, 1996, 1997, 1999 or more recently Rodriguez-Villalobos, Julian-Arias, and Cruz-Montano, 2019) or focus on the average impact of regional and preferential trade agreements on income inequalities (see J. Lee and Kim, 2016; Mon and Kakinaka, 2020).[1] As far as general openness or globalization are concerned, a detailed review of the literature is provided by Helpman (2010), Harrison, McLaren, and McMillan (2011), Helpman (2016), and Aleman-Castilla (2020).

From the methodological perspective, the article is related to the vast literature that makes use of counterfactual estimators. The SCM, in particular, has become one of the most popular methods in applied econometrics. Its popularity can be illustrated by the fact that as of January 2022, the seminal papers by Abadie and Gardeazabal (2003), Abadie, Diamond, and Hainmueller (2010), and Abadie, Diamond, and Hainmueller (2015), had over 4300, 4400, and 1700 citations, respectively (according to Google Scholar). At the same time, despite the ubiquity of the SCM and related methods in empirical economic literature, it is only recently that new developments regarding ways to (i) allow for multiple treated units, (ii) attenuate the possible cherry-picking problem, and (iii) calculate the p-values have appeared. This article applies these developments, and by doing so, it exploits the new insights from Liu, Wang, and Xu (2019. 2021).

It is worth noting that counterfactual estimators have not been frequently applied to the issues linked to European integration. The exceptions include Wassmann (2016) for the impact of the 2004 EU enlargement on GDP in border regions of the old Member States, Bouvet (2021) for the distributional consequences of Economic and Monetary Union, and Campos, Coricelli, and Moretti (2019) for the growth effects of EU membership. What these

[1] See also Cheong and Jung (2021) who analyse distributional effects of Korean free trade agreements .They do so by utilizing the difference-in-differences estimator, which enabled them to build counterfactual scenarios.

studies have in common is the focus on the SCM-based estimations of single treated cases.[2] However, this study differs from these papers, since it applies methods designed for a multiple unit case. Moreover, the previously mentioned studies do not deal with the cherry-picking problem, nor do they use p-values in their inference.

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 presents the counterfactual estimators, with emphasis on the new developments. Sections 4 and 5 present the data and results, while Section 6 discusses the obtained estimates. The paper closes with the conclusions in Section 7.

2. Literature review

Compared to other consequences of European integration, the impact on income inequalities has only been rarely analyzed in the academic literature. Only a few empirical papers exist, and seemingly there is no theoretical study linking EU accession and within-country income inequalities. Beckfield (2006) was the first to econometrically analyze that issue, applying fixed and random effect models. In most of the considered specifications, it was found that political integration (proxied by the number of cases referred from national courts to the European Court) led to an increase in the post-taxes and post-transfers Gini coefficient. At the same time, economic integration (measured by a percentage of a country's total exports directed to other countries involved in that process) had a non-linear impact on income inequalities. In the preferred specification, an inversely U-shaped relationship was found, with a peak in inequality associated with the level of intra-EU exports equal to around 60%. It should be borne in mind, however, that this analysis was conducted using data for only twelve Western European economies between 1973-1997. Hence, the results pertain to a particular group of rather developed countries and to a period that mostly refers to pre-EU times, when the European Economic Community existed, rather than the more complex and more deeply integrated EU.

Another study, authored by Busemeyer and Tober (2015), also utilized panel data methods (fixed effects models) and analyzed the sample of developed European countries (fourteen out of fifteen of the first EU members, with Luxembourg excluded as a potential outlier) for the years 1999-2010. They used König-Ohr indicators of European integration, which are grouped in four categories, with one proxying economic integration and another –

[2] In these studies, sometimes more units are investigated. However, they are based on separate single-unit estimations for each of the analyzed units.

political integration. According to the results, while political integration significantly increased income inequalities, economic integration was usually insignificant (although one specification suggested a bell-shaped relationship, as in Beckefield, 2006).

The study that share the focus on the 2004 EU enlargement with my analysis is the paper prepared by Eaton, Kortum, and Kramarz (2022). They built a quantitative general equilibrium model with frictions to firm-to-firm matching. Their simulation suggests that after the 2004 accession Poland, Czech Republic, and Hunagry experiences a tertiary workers' shift to the goods sector, while primary and secondary workers moved into services. At the same time, real wages of primary and secondary workers changed only slightl, while real wages of tertiary workers increased, indicating widening inequalities. In this study tertiary, secondary, and primary workers are of high, medium, and low educational attainment, respectively. This distinction corresponds with the assignment to different task, as the most skilled workers are assigned to managerial, administrative, and engineering activities, while medium-skilled workers perform skilled-production tasks, and the least educated workers anre involved in unskilled-production tasks.

Despite the limited number of studies on EU-induced income inequalities, there is a burgeoning literature on the distributional consequences of globalization, especially the increased intensity of international trade and offshoring. The effects of reallocation of production were studied by, among others, Feenstra and Hanson (1996), Zhu and Trefler (2005), Grossman and Rossi-Hansberg (2008), Costinot and Vogel (2010) and Blanchard and Willmann (2016). Studies that analyzed technology-related channel include Dinopoulos and Segerstrom (1999), Yeaple (2005), Verhoogen (2008), Burstein and Vogel (2010), Sampson (2014), and Harrigan and Reshef (2015). The models of trade and unemployment, with consequences for inequalities, are another strand in the literature. The importance of search and matching frictions on the labor markets include Davidson, Martin, and Matusz (1999), Moore and Ranjan (2005), Wälde and Weiss (2006), Artuç, Chaudhuri, and McLaren (2008, 2010), Helpman (2010, 2016), Helpman and Itskhoki (2010), Helpman, Itskhoki, and Redding (2008, 2010, 2013), and Coşar, Guner, and Tybout (2016). The efficiency-wage models of trade were developed by Egger and Kreickemeier (2009, 2012), Egger, Egger, and Kreickemeier (2013), and Davis and Harrigan (2011).

The empirical studies differ in methods and approached, but usually prove that trade and offshoring increase inequalities, although in some cases such an impact may depend on some characteristics of workers, firms, or markets. The empirical literature on that issue include, among others, Feenstra and Hanson (1996, 1997, 1999), Munch and Skaksen (2008), Verhoogen (2008), Artuç, Chaudhuri, and McLaren (2010), Artuç and McLaren (2010), Bustos (2011), Menezes-Filho and Muendler (2011), Amiti and Davis (2012), Frías, Kaplan, and Verhoogen (2012), Ebenstein, Harrison, McMillan, and Phillips (2014), Hummels, Jørgensen, Munch, and Xiang (2014), and Helpman, Itskhoki, Muendler, and Redding (2017).

The distributional effects of the EU can also be seen through the lens of the inequality-related consequence of financial opening, since free capital flows constitute a common market. However, only a few studies that touch on the impact of financial openness on income distribution. The theoretical literature include bargaining models (see Harrison, 2005; Jayadev, 2007), models with financial constraints (see Kunieda, Okada, and Shibata, 2014; Benczúr and Kvedaras, 2021; Larrain, 2015), as well as models that combine technological change and capital rents (Ni, Liu, and Zhou, 2021). The empirical literature mostly supports the notion of financial globalization as an inequality-increasing phenomenon (see Das and Mohapatra, 2003; Harrison, 2005; Jayadev, 2007; Furceri and Loungani, 2015; Larrain, 2015; Cabral, García-Díaz, and Mollick, 2016; Furceri, Loungani, and Ostry, 2018; Eichengreen, Csonto, El-Ganainy, and Koczan, 2021).

The literature on the distributional effects of the EU is also inherently linked to the studies on the effects of migration. That literature covers both migration (see, for instance, Elsner, 2012; Dustmann, Frattini, and Rosso, 2015) and immigration (see Card, 1990; Davies and Wooton, 1992; Borjas, 2003; Peri and Sparber, 2009; Ottaviano and Peri, 2012; Ottaviano, Peri, and Wright, 2013; Kahanec and Zimmermann, 2014; Cattaneo, Fiorio, and Peri, 2015; Peri and Yasenov, 2017; Sebastian and Ulceluse, 2019).

All the above-mentioned mechanisms of the impact of globalization on inequalities refer to the market-caused distribution of income. Such inequality may be addressed by a redistribution policy through taxes and/or social benefits. Theoretical papers on the impact of globalization on redistribution include Meltzer and Richard (1981), Rodrik (1998), Sinn (2003), Gozgor and Ranjan (2017) Razin and Sadka (2018a, 2018b, 2019), and Razin, Sadka, and Schwemmer (2019). Empirical evidence on the role globalization plays in redistribution policies is inconclusive. Studies that find that globalization positively affects the welfare state include Meinhard and Potrafke (2012), Kauder and Potrafke (2015), Potrafke (2015). The opposite findings are presented by Razin and Sadka (2018a, 2018b, 2019) and Razin, Sadka, and Schwemmer (2019), while some mixed results regarding the impact of globalization on taxation are present in Gozgor and Ranjan (2017).

3. Methodology

The counterfactual estimators are based on the estimation of the average treatment effect on the treated (ATT). In other words, they compare the trajectories of outcome variables for two scenarios (with and without treatment). The main challenge is the creation of a counterfactual scenario in which the treated unit (or units) is (are) seen as if it (they) had not been subjected to a given treatment. The development of these methods reflects different approaches researchers took to build such counterfactuals. Although the counterfactual estimators are typically applied to a setting with only a single treated unit, there are several ways they can be adapted to cases with multiple treated units. For instance, in the context of the SCM, a small but growing amount of literature has emerged (see Section 8 in Abadie, 2021, for the discussion), including Cavallo, Galiani, Noy, and Pantano (2013), Dube and Zipperer (2015), Acemoglu, Johnson, Kermani, Kwak, and Mitton (2016), Gobillon and Magnac (2016), Kreif, Grieve, Hangartner, Turner, Nikolova, and Sutton (2016), Robbins, Saunders, and Kilmer (2017), Xu (2017), Donohue, Aneja, and Weber (2019), Abadie and L'Hour (2021), and Ben-Michael, Feller, and Rothstein (2021).

Throughout the study, the counterfactual estimators described by Liu, Wang, and Xu (2019, 2021) were applied. These were the following:

1) the Fixed Effects (FE) model – it accommodates the DiD estimator as a special case,
2) the Interactive Fixed Effects (IFE) model – it generalizes the algorithms that merge the SCM algorithm with interactive fixed effects (see Gobillon and Magnac, 2016, and Xu, 2017)[3],
3) the Matrix Completion (MC) model – first introduced by Athey, Bayati, Doudchenko, Imbens, and Khosravi (2021).

The applied methods can be illustrated as follows. Consider N units (countries) and T periods (years), and denote Y_{it} the outcome of unit i in period t, D_{it} the treatment status (with treatment being a dichotomous variable which is equal to 0 if there is no treatment and 1

[3] The SCM was introduced by Abadie and Gardeazabal (2003), and since then, it has been significantly elaborated, mostly by Abadie, Diamond, and Hainmueller (2010) and Abadie, Diamond, and Hainmueller (2015). As stated by Athey and Imbens (2017), the SCM is "arguably the most important innovation in the policy evaluation literature in the last 15 years," and has been used in a myriad of studies on a variety of economic and socio-political topics, as well as biomedical disciplines and engineering.

otherwise), $\mathbf{X}_{it}$ a vector of covariates, $\mathbf{U}_{it}$ a vector of unobserved attributes, and ε_{it} an unobserved transitory shock. The functional form of the described models is:

$$Y_{it} = \delta_{it} D_{it} + f(\mathbf{X}_{it}) + h(\mathbf{U}_{it}) + \varepsilon_{it} \tag{1}$$

where δ_{it} is the treatment effect, and $f(\cdot)$ and $h(\cdot)$ are known functions. It means that Y_{it}^{-} and Y_{it}^{+} , i.e. the outcome without any treatment and the outcome with treatment, respectively, are $Y_{it}^{-} = f(\mathbf{X}_{it}) + h(\mathbf{U}_{it}) + \varepsilon_{it}$ and $Y_{it}^{+} = \delta_{it} + f(\mathbf{X}_{it}) + h(\mathbf{U}_{it}) + \varepsilon_{it}$.

The estimand of interest is the ATT, which is given by:

$$ATT = \mathbb{E}(\delta_{it} | D_{it} = 1, \forall i \in \mathcal{T}, \forall t), \mathcal{T} \coloneqq \{i | \exists t, t' \ s.t. D_{it} = 0, D_{it'} = 1\} \tag{2}$$

in which $\mathcal{T}$ is the set of the treatment units.

Liu, Wang, and Xu (2019, 2021) introduced a unified estimation strategy.[4] Denoting the observations under control as $\mathcal{O} = \{(i,t) | D_{it} = 0\}$ and the treatment conditions[5] as $\mathcal{M} = \{(i,t) | i \in \mathcal{T}, D_{it} = 1\}$, the general procedure is as follows:

- **Step 1:** With the functional form assumptions about $f(\cdot)$ and $h(\cdot)$, as well as lower-rank representation of $\mathbf{U}$, fit the model of the response surface Y_{it} to the subset of $\mathcal{O}$. As a result, $\hat{f}$ and $\hat{h}$ are obtained.
- **Step 2:** Predict the counterfactual outcome Y_{it}^{-} for each treated observation with the use of estimates from the previous step, i.e., $\hat{Y}_{it}^{-} = \hat{f}(\mathbf{X}_{it}) + \hat{h}(\mathbf{U}_{it})$ for all $(i,t) \in \mathcal{M}$.
- **Step 3:** For each treated observation $(i,t) \in \mathcal{M}$ estimate δ_{it} using $\hat{\delta}_{it} = Y_{it} - \hat{Y}_{it}^{-}$.
- **Step 4:** Produce estimates for the quantities of interest, taking averages of $\hat{\delta}_{it}$. For ATT it is given by $\widehat{ATT} = \frac{1}{|\mathcal{M}|} \sum_{\mathcal{M}} \hat{\delta}_{it}$.

The above procedure can be applied to each of the estimators applied in this article. The details on each of these methods is given in the Appendix A. Additionally, the applied counterfactual estimators allow for statistical inference that is based on the bootstrap procedure, in which an equal number of units from the original sample is resampled (with replacement). The entire time series of data, including the outcomes, treatment status, and covariates, are replicated for a drawn unit. Then standard errors and confidence intervals are

[4] This strategy assumes not only additive separability given by (1), but also low-dimensional decomposition and strict exogeneity. See Section 2.1 in Liu, Wang, and Xu (2021). Recall that the applied estimation strategy may have a different number of stages, depending on the exact model used in the estimations. However, it still follows the general framework.

[5] $\mathcal{O}$ and $\mathcal{M}$ stand for "Observed" and "Missing", respectively.

obtained with the use of conventional standard deviation and percentiles methods. In what follows, I used the conventional confidence level equal to 0.95.

Other diagnostics are also possible with the use of the applied methods. For example, two tests may be used to verify whether the results are obscured by the existence of time-varying confounders: the Wald test and the equivalence test (both are described in details in the Appendix A). In order to assess the significance of a given treatment, two other tests can be applied. Using the terminology from Abadie, Diamond, and Hainmueller (2015), they are in-time and in-space placebo tests. The former makes it possible to assess the validity of the estimates when the treatment onset is changed to the year (or another time unit) when a treatment did not occur. In other words, the test starts with the assumption that the treatment happened S periods before its actual beginning for each unit in the treatment group. Then the same counterfactual estimator should be applied to obtain estimates of ATT_s for $s = -S, -(S-1), \dots, -1, 0$, as well as an estimate of the overall ATT. When such an estimate of an artificial ATT is statistically different from 0, the in-time placebo test indicates that the estimated treatment effect is invalid. At the same time, when an estimated artificial ATT is indistinguishable from 0, it validates that the treatment effect is indeed generated by the treatment in question. The in-space placebo checks the validity of the results by checking the size of the treatment effect under the assumption that such an intervention happens in units that are not directly exposed to it. By doing so, a researcher may obtain a distribution of placebo effects that can be used to evaluate the estimated treatment effect for the units from the treatment group. The bootstrap procedure that is applied in this study, which generates confidence intervals and corresponding p-values, can be seen as such a placebo test.

The counterfactual methods applied in the study can also alleviate the cherry-picking problem. The tuning parameters are set at values that stem from a rigorous procedure (see Appendix A), instead of any direct interference from the researcher. It should be stressed that the literature related to the specification-searching problem in comparative case studies which also provides some guidance to predictor selection is scarce. It includes, in particular, Dube and Zipperer (2015), and Kaul, Klößner, Pfeifer, and Schieler (2021), who discuss the choice of predictors in the context of the SCM. Ferman, Pinto, and Possebom (2020) show how such a choice affects the possibility of cherry-picking, offering some useful recommendations.

As a robustness check, panel data estimations were also conducted. Since the best counterfactual estimations are those that exploit the dynamics of the time series (see Ferman, Pinto, and Possebom, 2020, for the SCM estimations), it was necessary to apply dynamic panel data models. Both the difference and system generalized method of moments (GMM) were used due to their ability to control for endogeneity. The division of variables into exogenous and endogenous was based on the Granger causality test for panel data, developed by Juodis, Karavias, and Sarafidis (2021) and implemented by Xiao, Karavias, and Sarafidis (2021).[6]

4. Data

The inspiration regarding the choice of variables in the following estimations was the study conducted by Dabla-Norris, Kochhar, Suphaphiphat, Ricka, and Tsounta (2015). In their analysis of the drivers of income inequality (see their Box 1), they considered several measures of income inequality as dependent variables. Specifically, measures such as the market Gini, net Gini, income shares of the top 10%, the 5th income decile, and the bottom 10% were analyzed. In each of the estimations, they used many covariates, referring to the possible impact of globalization and other socio-economic forces on the within-country distribution of income.[7]

I used similar variables, although some data sources are different. The dependent variable in the estimations was the Gini index, and two specific types of that measure were utilized: the market Gini (before taxes and benefits) and the net Gini (after taxes and benefits). The source of the data on the Gini index was the Standardized World Income Inequality Database (SWIID), available at the Harvard Data verse Repository (see Solt, 2020). One feature of these specifications of the dependent variable is important. In the sample, the market Gini was usually higher than the net Gini, indicating that in most countries and most years, fiscal measures were implemented in a way that reduced income inequalities.

[6] The popular Granger causality test for panel data developed by Dumitrescu and Hurlin (2012), later implemented by Lopez and Weber (2017), can suffer from size distortions, when the time dimension is significantly lower than cross-section dimension in the panel data.

[7] These covariates were as follows: (i) *trade* – the sum of exports and imports as a share of a country's GDP, which proxies the trade openness, (ii) *financial* – the sum of foreign assets and liabilities relative to GDP, which illustrates the financial globalization, (iii) *technology* – the share of information and communication technology (ICT) capital in the total capital stock, (iv) *credit* – the ratio of private credit to GDP, which reflects the development of the domestic financial market, (v) *skill premium* – the average years of education in the population aged 15 and older, which is in line with the Mincer wage specification, (vi) *education Gini* – which illustrates the access to education, (vii) *labor flexibility* – taken from the World Economic Forum, (viii) *female mortality* (aged 15-60) – which reflects the quality of and access to the health system, (ix) *government spending* – a proxy for redistributive policies, expressed as a share of a country's GDP, (x) additional controls – lagged GDP growth and share of employment in agriculture and industry, (xi) country and time dummies. In order to capture the varying impact of financial development and skill-biased technological change, two interaction terms were also included – the *credit* and *skill premium* variables were linked with a dummy variable which takes the value of 1 for advanced economies (and zero otherwise).

Regarding the covariates, some data were obtained from the World Bank Data. It was the case of the percentage of trade in GDP (henceforth, *Trade*), the share of domestic credit in GDP (*Credit*), the mortality rate of adult females per 1,000 female adults (*Female mortality*), general government final consumption expenditure, expressed as % of GDP (*Gov consumption*), the share of employment in agriculture and industry in total employment (*Share agriculture* and *Share industry*, respectively), annual GDP growth (with a one-year lag, hence labeled *GDP growth lagged*). The World Bank Data were also used to proxy for *Labor flexibility*. To construct that variable, data on the unemployment rate were used (total unemployment as a percentage of the total labor force), which was then filtered using the Hodrick-Prescott (HP) filter. The obtained trend proxies for the flexibility of the labor market, since it may reflect, at least to some extent, features of a labor market such as structural unemployment, the natural rate of unemployment, or the Non-Accelerating Inflation Rate of Unemployment (NAIRU). The idea is simple: if the value of that measure is high (low), it may indicate long (short) spells of unemployment, which shows how smoothly a labor market absorbs the unemployed. This is exactly what the flexibility of a labor market should characterize; hence the HP-based measure was found to be a relevant measure of such a flexibility.

The *Skill premium* was proxied by mean years of education (in years), defined as the average number of years of education received by people aged 25 and older. The data were provided by the United Nations Development Programme (UNDP), available at the Human Development Reports (HDR) website. Using that measure as a proxy was motivated by the idea that when skill premium rises, a rational response is to adopt such skills, which should be observed as increasing the number of years of education. Financial openness was illustrated by the ratio of total foreign assets and liabilities to GDP (percentage). The measure was calculated using a dataset provided by Lane and Milesi-Ferretti (2018) and labeled *Financial*. In order to assess the impact of skill-biased technological progress (*Technology*), the Economic Complexity Index (ECI) ECI based on the Standard International Trade Classification (SITC) was utilized. The educational Gini index (*Education Gini*) was taken from the Clio Infra project website. This measure was calculated by van Leeuwen, van Leeuwen-Li, and Földvári. It illustrates the inequality of education in the total population of 15 years and older (see van Leeuwen, van Leeuwen-Li, and Földvári, 2012). The only exceptions are the Czech Republic, Slovakia, and Slovenia. Since eliminating these countries would significantly reduce the number of treated units, it was necessary to use another data source for them. I did so by applying Ziesemer's educational Gini index[8] (see Ziesemer, 2016 for details).

Two interaction terms (*Adv Credit* and *Adv Skill premium*) required country classification. I used the classification provided by the United Nations (The Department of Economic and Social Affairs) which is also employed in the World Economic Situation and Prospects (WESP) reports. Advanced economies are those that these reports classify as developed.

Finally, it should be explicitly stated that the treatment here is accession to the EU, and the countries from the 2004 enlargement were analyzed (except for Malta due to many missing observations). Hence, 2004 was set as the year of the treatment (although these countries joined the EU not at the beginning of that year, but in May). However, it is also possible that some socio-economic changes had occurred beforehand due to the anticipation effect. Thus, it required some experimentation with an alternative year of the treatment, which is why I checked the possibility that the treatment was implemented in 1998. By doing so, I followed Campos, Coricelli, and Moretti (2019), who justified this choice by the fact that in 1997 the European Council established the procedures for the eastern enlargement of the EU.

Compiling the database used for subsequent estimations also required addressing the problem of missing values. In order to overcome that difficulty, it was decided to proceed as follows. Firstly, although the SWIID database offers data on 198 countries[9], the time coverage varies. I decided to restrict the timeframe to the years 1991-2015 and include only those countries that had the full Gini coefficient coverage for that period, which reduced the sample to 96 countries. Then, due to the logic of the SCM, all the Old Member States of the EU were omitted, as well as other New Members from subsequent enlargements (Bulgaria, Romania, and Croatia). Lastly, the countries with at least one covariate missing for the entire 1991-2015 period were removed. Kazakhstan was also eliminated since that country had only one observation for *Credit* (for 2015). Ultimately, 64 countries were included in the estimations. Their classification into treated units and the donor pool is presented in Table 1.

[8] The main difference between van Leeuwen, van Leeuwen-Li, and Földvári (2012) and Ziesemer (2016) is that the latter is a five-yearly dataset. I used data for 1995, 2000, 2005, and 2010, and then filled all the missing values with the arithmetic progression. One should bear in mind that the two datasets are relatively similar. Using the data for 58 countries from my analysis that are available in these datasets, one can obtain the following correlation coefficients: 0.91 for 1995, 0.90 for 2000, 0.85 for 2005, and 0.84 for 2010.

[9] For simplicity the term 'country' is used, although the datasets used cover not only countries but also other territories.

Table 1. The list of countries

Treated units (9 countries)	Donor pool (55 countries)
Cyprus, the Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Slovakia, Slovenia	Argentina, Armenia, Australia, Botswana, Brazil, Canada, Chile, China, Colombia, Costa Rica, Cote d'Ivoire, the Dominican Republic, Egypt, El Salvador, Georgia, Ghana, Honduras, India, Indonesia, Iran, Israel, Jamaica, Japan, Kenya, Korea (Republic of), Kyrgyzstan, Malawi, Malaysia, Mauritius, Mexico, Moldova, New Zealand, Nigeria, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Russian Federation, Singapore, South Africa, Sri Lanka, Switzerland, Tajikistan, Tanzania, Thailand, Tunisia, Turkey, Uganda, Ukraine, United States, Uruguay, Venezuela, Zambia

Next, all the gaps were filled with the arithmetic progression. In one case (*Gov consumption* for Jamaica in 1992) it led to interpolation, since the corresponding data for 1991 and 1993 were available. In other cases, dealing with missing observations required extrapolation. In rare cases, the applied procedure led to negative values for *Financial*, *Credit*, and *Gov consumption*, which would be without any reasonable economic meaning. That is why these problematic observations were winsorized – the closest positive value was used. For instance, this was the case of *Financial* for Ukraine in 1991. That observation was cleared by setting it equal to the value for 1992, which was positive.

After all the data preparation activities, a dataset was obtained with 1600 observations, which are described in Table 2.

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
net Gini	1600	40.077	8.708	18.000	63.500
market Gini	1600	46.734	6.962	21.900	72.500
EU	1600	0.068	0.251	0.000	1.00
Trade	1600	79.538	51.126	9.768	437.327
Financial	1600	215.758	544.173	3.344	7864.777
Technology	1600	0.195	0.884	-2.424	2.825
Credit	1600	54.823	50.017	0.031	272.441
Adv Credit	1600	24.137	51.964	0.000	272.441
Skill premium	1600	8.452	2.789	2.000	13.400
Adv Skill premium	1600	2.859	4.985	0.000	13.400
Education Gini	1600	24.937	13.238	2.585	75.049
Labor flexibility	1600	7.833	4.902	0.447	31.338
Female mortality	1600	143.471	110.424	34.322	572.807
Gov consumption	1600	14.642	4.903	0.738	31.554
GDP growth lagged	1600	3.575	4.932	-44.900	18.287
Share agriculture	1600	25.367	20.696	0.080	84.670
Share industry	1600	22.351	7.922	2.620	45.800

Note: all values are rounded to three decimal places.

5. Results

Figures 1-18 show the results obtained by applying different counterfactual methods. The first (last) nine figures are linked to estimations with the net Gini (market Gini) coefficient as the dependent variable. The results of each estimation are grouped into three figures: the first illustrates the estimated $ATTs$, the next presents the findings from the equivalence test, and the last is associated with the in-time placebo test. The bars in each figure represent the number of treated observations used in a given estimation. A detailed summary of each estimation can be found in Appendix B.

The estimated treatment effect was always insignificant, regardless of the applied estimator. The obtained p-values were usually very high, far above the conventional levels of 0.01 or 0.05. This indicates the lack of any permanent treatment effect. These results were also immune to changes in the dependent variable (switch from net Gini to market Gini), which indicates their robustness.

As far as the FE model is concerned, it gave inconclusive results regarding the existence of the pre-trend. The Wald test supported the null hypothesis, while the equivalence test did the opposite. Regarding the latter test, as illustrated by Figure 2, the minimum bound is broader than the equivalence bound, which violates the rule of thumb suggested by Liu, Wang, and Xu (2019, 2021). However, even if a pre-trend existed in this case, it would not lead to any serious bias in the estimates, since such a pre-trend would be captured by the in-time placebo test. On the contrary, that test validated the null hypothesis. It means that the in-time placebo test proved that the estimated $ATTs$ cannot be associated with events other than the 2004 EU enlargement (or, precisely, events prior to the accession to the EU).

Figure 1. FE model – estimated ATTs (net Gini)

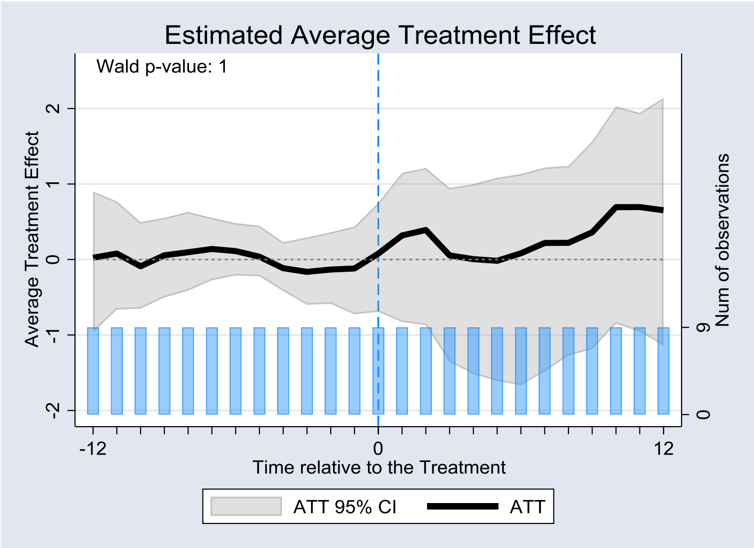


Figure 2. FE model – equivalence test (net Gini)

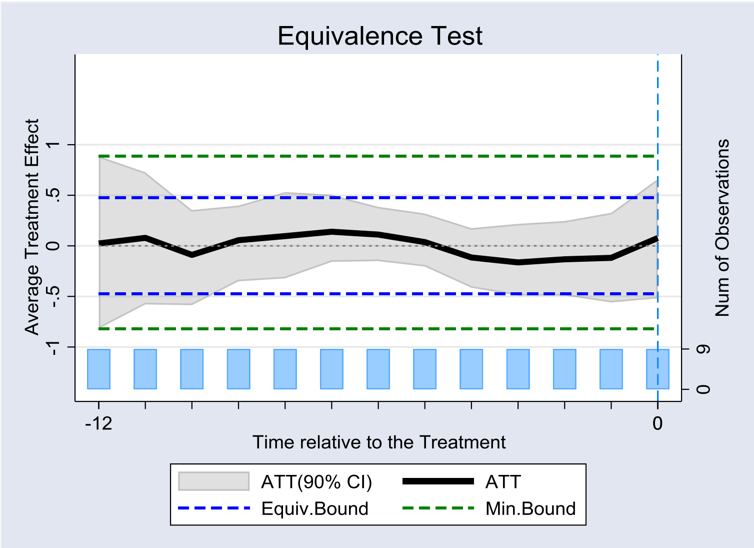
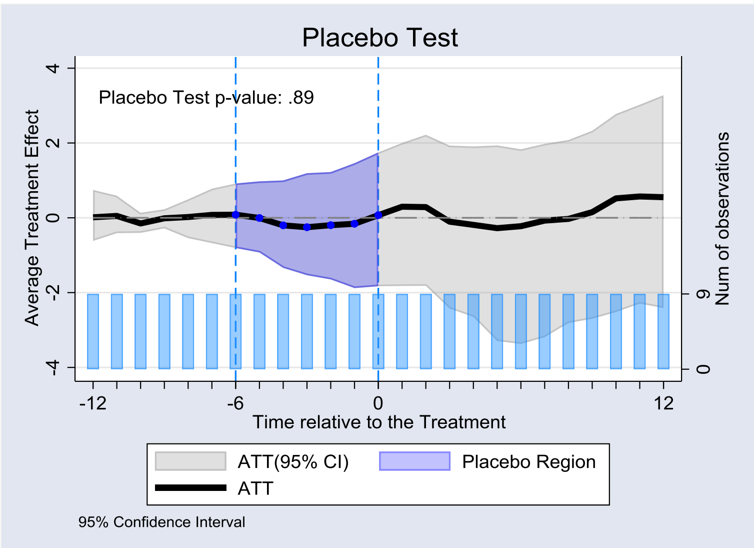


Figure 3. FE model – in-time placebo test (net Gini)



Turning to the IFE model, one should observe that the estimated $ATTs$ were qualitatively and quantitatively close to the results obtained using the FE estimator. Still, the impact of the EU was insignificant (see Figure 4). The placebo test validated the null hypothesis (see Figure 6), as in the FE model. However, this time, unambiguous indications regarding the pre-trend were found. Both the Wald test and the equivalence test proved that the assumption of no-time-varying-confounders held. In the latter case, the minimum bound lied within the equivalence bound (see Figure 5).

Figure 4. IFE model – estimated ATTs (net Gini)

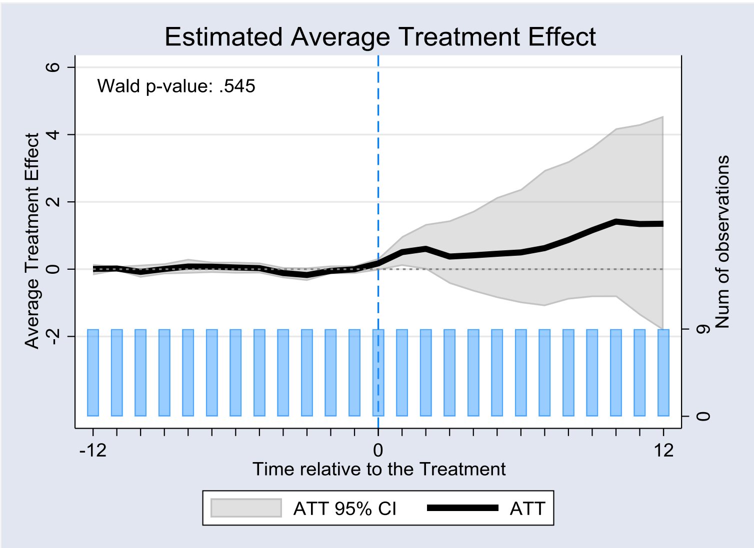


Figure 5. IFE model – equivalence test (net Gini)

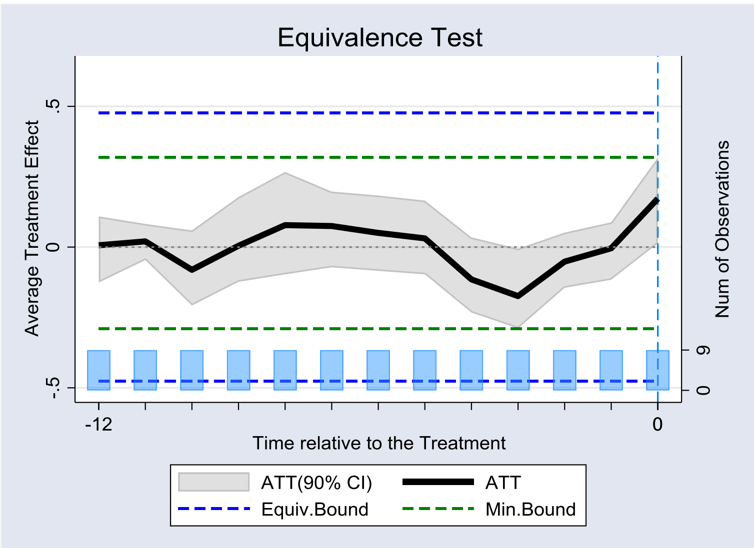
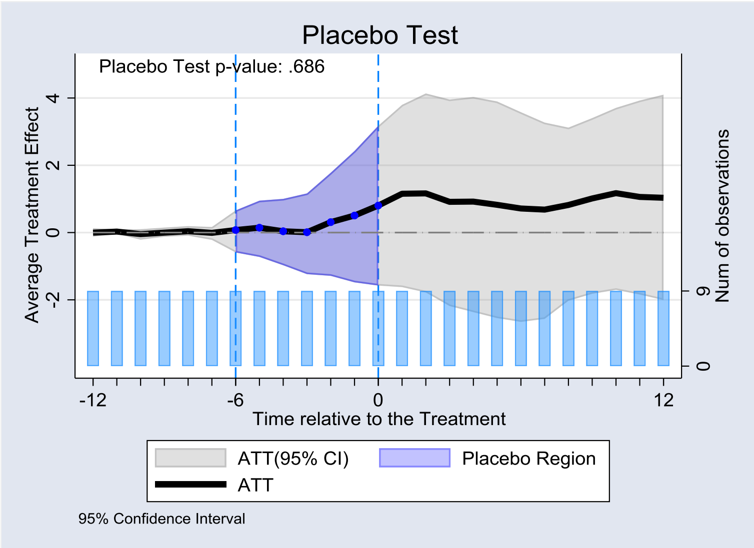


Figure 6. IFE model – in-time placebo test (net Gini)



Substantially similar results were obtained by the MC estimator. Once again, the $ATTs$ were insignificant (see Figure 7). Both null hypotheses in the diagnostics were validated, i.e., the one associated with the existence of the pre-trend (the Wald tests and the equivalence test – see Figure 8) and the other one of no impact of other prior potential interventions (the in-time placebo test – see Figure 9).

Figure 7. MC model – estimated ATTs (net Gini)

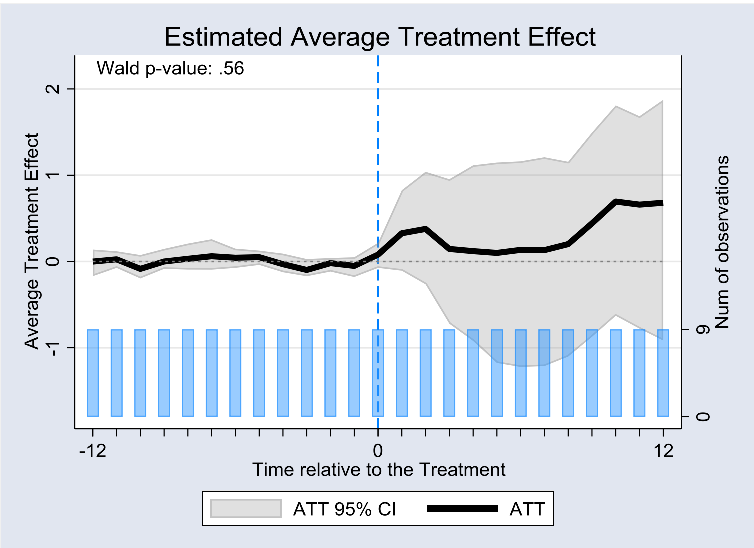


Figure 8. MC model – equivalence test (net Gini)

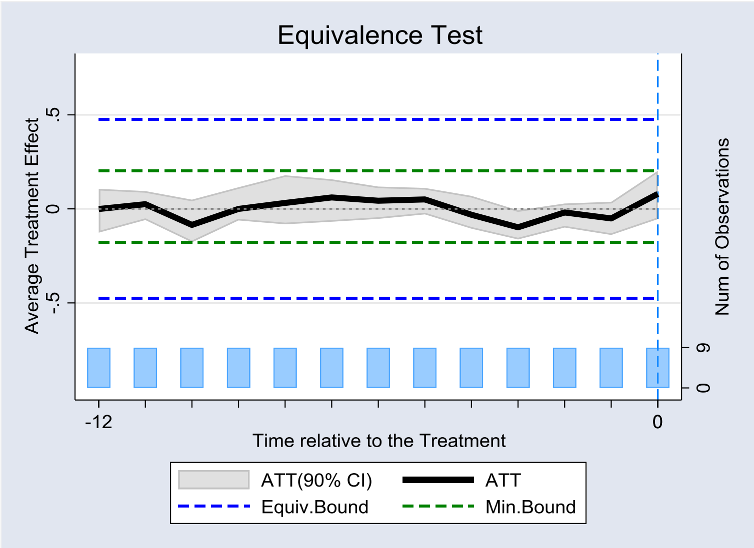
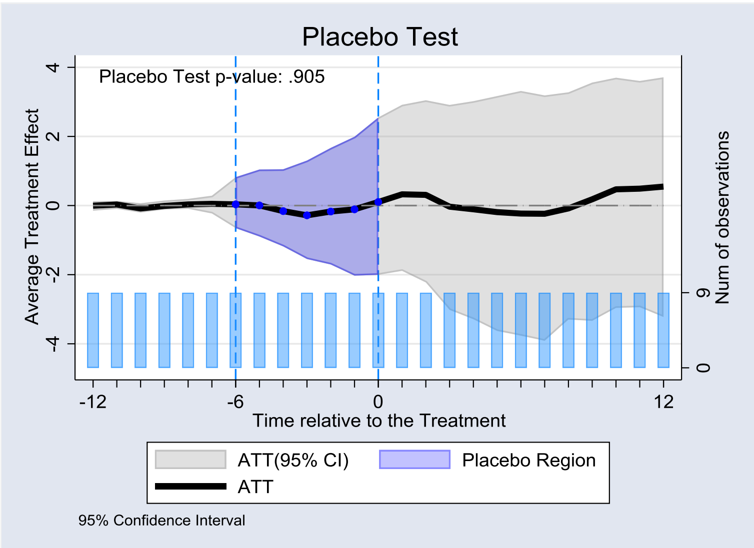


Figure 9. MC model – in-time placebo test (net Gini)



As far as market Gini is concerned, similar conclusions could be drawn. No estimator generated the $ATTs$ that were significant. Once again, the EU accession can be considered neutral in terms of its possible impact on income inequalities in the New Member States. For another time, the results obtained from using the FE model were inconclusive in terms of the existence of the pre-trend. The Wald test validated the null hypothesis, which, at the same time, was rejected by the equivalence test (see Figure 11). The placebo test in the FE estimator proved that the estimated $ATTs$ were associated with the analyzed treatment rather than any other prior intervention (see Figure 12).

Figure 10. FE model – estimated ATTs (market Gini)

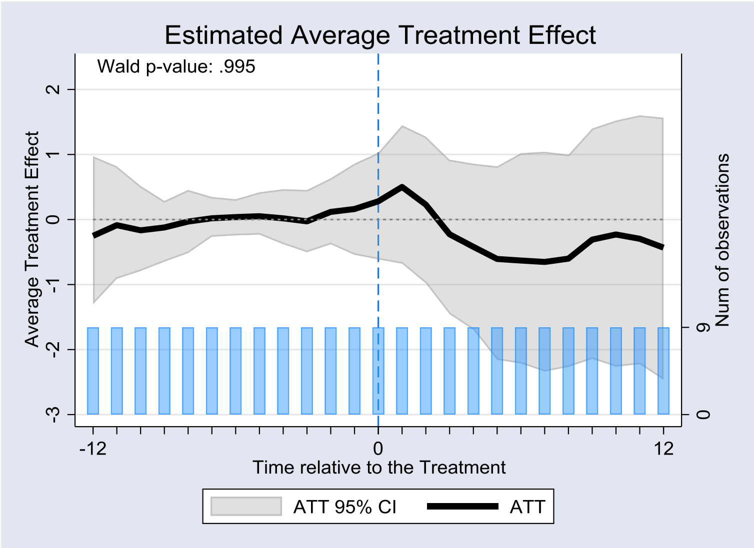


Figure 11. FE model – equivalence test (market Gini)

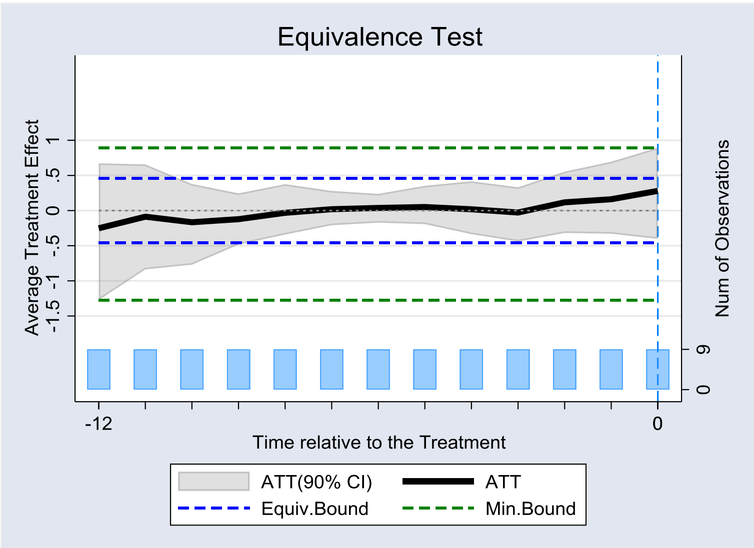
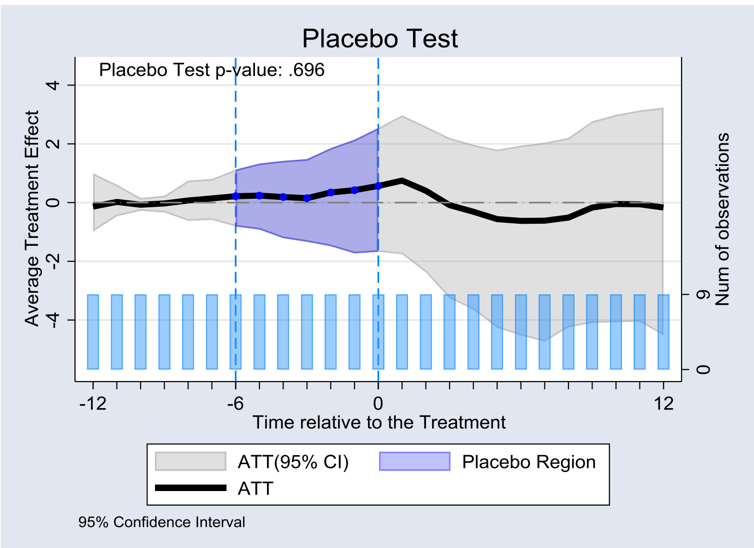


Figure 12. FE model – in-time placebo test (market Gini)



Both the IFE and MC models outperformed the FE estimator in terms of the conclusiveness of the diagnostic tests for the no-time-varying-confounders assumption. Other results were qualitatively and quantitatively similar. It proved once again that the 2004 EU engargement cannot seen as an event that increased income inequalities within the New Member States.

Figure 13. IFE model – estimated ATTs (market Gini)

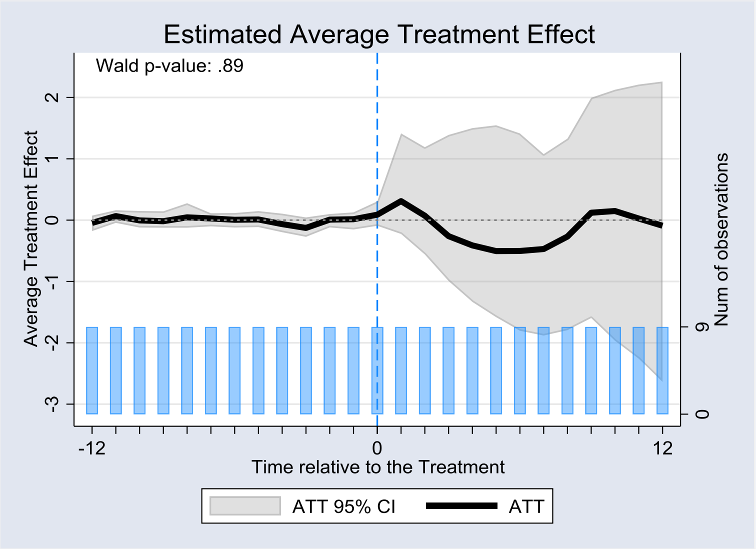


Figure 14. IFE model – equivalence test (market Gini)

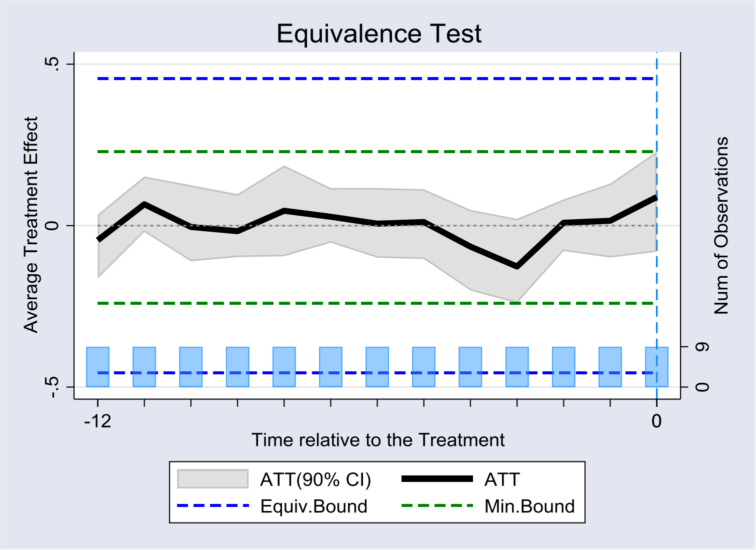


Figure 15. IFE model – in-time placebo test (market Gini)

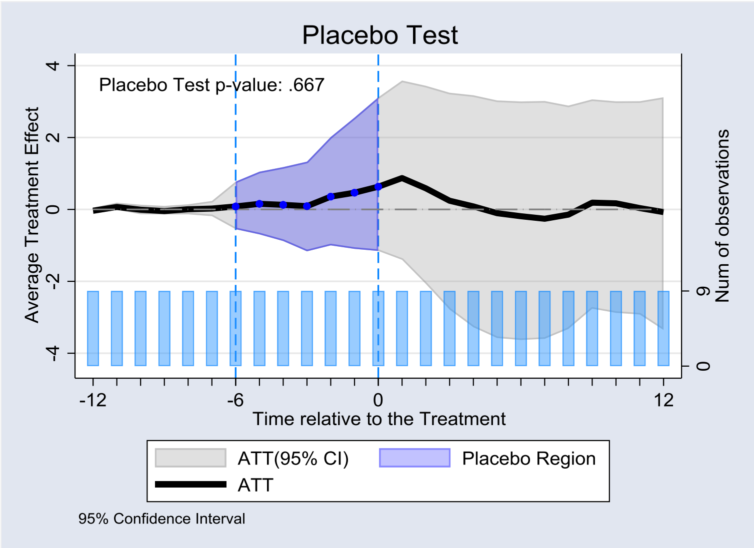


Figure 16. MC model – estimated ATTs (market Gini)

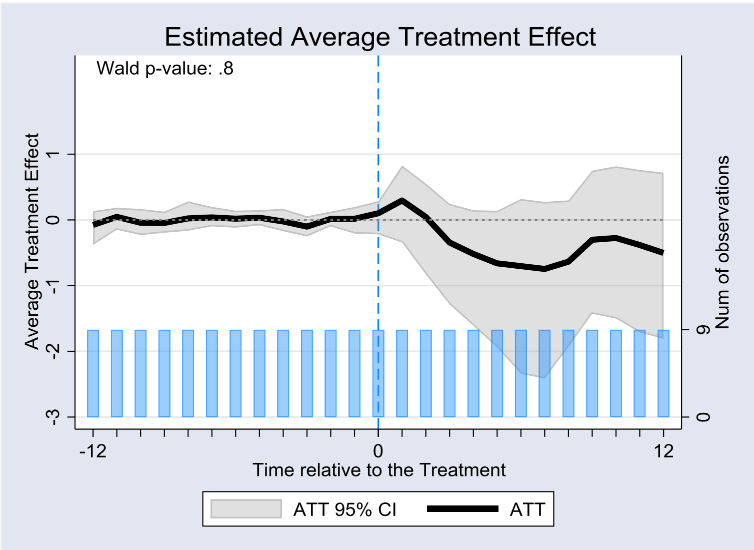


Figure 17. MC model – equivalence test (market Gini)

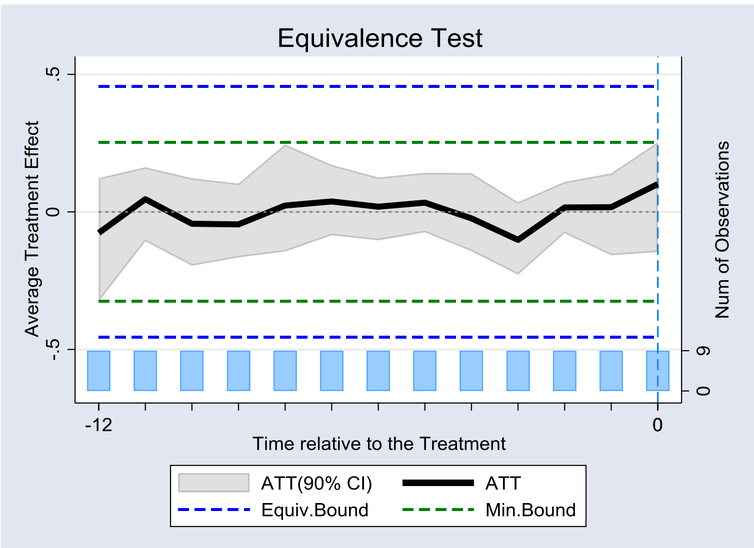


Figure 18. MC model – in-time placebo test (market Gini)

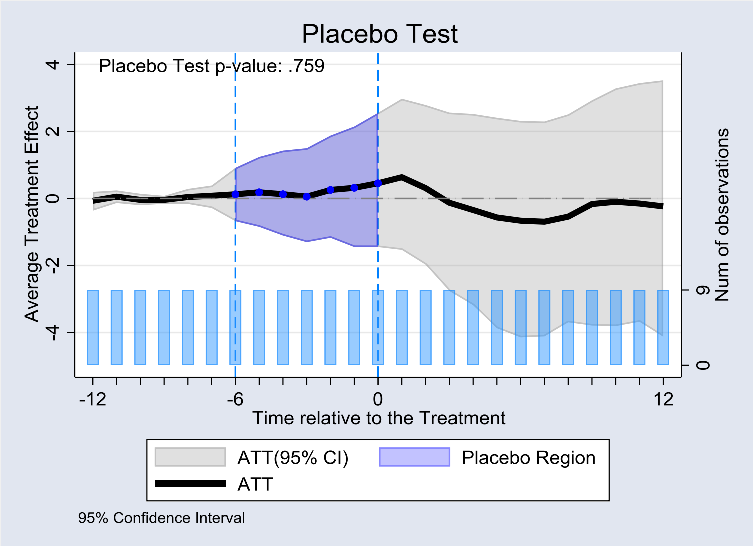


Table 3 summarizes the results obtained with the use of the three counterfactual methods. It includes findings on both the EU distributional effects and the diagnostics of the estimated models.

Table 3. The summary of the results

Variable	Estimator	ATTs	Wald Test	Equivalence Test	In-time Placebo Test
net Gini	FE	Insignificant	Passed	Failed	Passed
	IFE	Insignificant	Passed	Passed	Passed
	MC	Insignificant	Passed	Passed	Passed
market Gini	FE	Insignificant	Passed	Failed	Passed
	IFE	Insignificant	Passed	Passed	Passed
	MC	Insignificant	Passed	Passed	Passed

As described in Section 3, as a robustness check, dynamic panel data methods were also applied. To determine endogenous variables through a typical Granger causality test, a two-way relationship should be checked. However, since the regressors used in this study are seen in the empirical literature as possible determinants of Gini coefficients (see Dabla-Norris, Kochhar, Suphaphiphat, Ricka, and Tsounta, 2015), the endogeneity may be tested by checking the causality running in the opposite direction. The idea is straightforward: assuming that a given variable may cause inequalities, the endogeneity may be observed, when there is also a link from Gini coefficients to that variable. Table 4 summarizes the results of the Granger test for panel data.

Table 4. Granger causality test for panel data (Juodis-Karavias-Sarafidis approach)

Variable (X)	net Gini → X	market Gini → X

	Coeff.	p-value	Coeff.	p-value
Trade	-0.139	0.456	0.486	0.014
Financial	2.205	0.511	4.348	0.207
Technology	-0.002	0.422	-0.000	0.864
Credit	0.212	0.067	0.543	0.000
Skill premium	0.025	0.000	0.030	0.000
Education Gini	0.018	0.132	0.024	0.061
Labor flexibility	-0.123	0.000	-0.115	0.000
Female mortality	-0.381	0.033	0.078	0.667
Gov consumption	-0.036	0.152	-0.006	0.803
GDP growth lagged	-0.221	0.001	-0.278	0.000
Share agriculture	-0.222	0.000	-0.140	0.000
Share industry	0.067	0.000	0.034	0.052

Note: all values are rounded to three decimal places

The results indicated that some of the variables should be treated as endogenous. *Credit*, *Skill premium*, *Labor flexibility*, *GDP growth lagged*, *Share agriculture*, and *Share industry* should be treated as engoneous in each of the dynamic panel estimations, regardless the exact specification of the dependent variable. At the same time, it was whown that *Female mortality* (*Trade* and *Education Gini*) should be considered endogenous in estimations with net Gini (market Gini) coefficient. The hypothesis of Granger causality for other variables could not be tested, since they are invariant in case of some countries. Since the empirical literature is silent on the impact of within-country inequalities upon EU accession and there is probably no anticipation effect in the estimations (see Figures 3, 6, 9, 12, 15, and 18), I decided to consider the *EU* variable exogenous. *Adv Credit* and *Adv Skill premium* were treated as engogenous, because they were derived from other endogenous variables (*Credit* and *Skill premium*).

Table 5 presents the results of the panel data estimations. Once again, it was confirmed that EU membership did not influence income inequalities in the analyzed countries. The coefficients associated with the EU were statistically insignificant. The details of these estimations can be found in Appendix C.

Table 5. Dynamic panel data estimation – results

Variable	diff. GMM	system GMM	diff. GMM	system GMM
net Gini (lagged)	0.942	0.805		
market Gini (lagged)			0.712	1.004
EU	-0.589	-0.413	0.010	-1.099
Trade	0.003	0.003	0.000	-0.003
Financial	0.000	0.000	0.000	0.001
Technology	-0.539	-0.408	-0.299	0.651
Credit	0.001	0.006	0.001	-0.007
Adv Credit	-0.003	0.001	-0.003	0.002
Skill premium	0.016	0.013	-0.019	0.045

Adv Skill premium	-0.050	-0.142	0.069	-0.026
Education Gini	0.009	0.030	-0.028	0.004
Labor flexibility	0.015	0.071	0.030	0.004
Female mortality	0.000	0.004	0.012	0.005
Gov consumption	0.016	0.010	-0.007	0.008
GDP growth lagged	-0.001	-0.000	0.001	0.003
Share agriculture	0.012	-0.009	-0.005	0.008
Share industry	0.025	-0.018	-0.009	0.054
Constant		6.037		-2.535

Note: all values rounded to three decimal places; lag order: 1

6. Discussion

The results of the estimations suggest that the EU accession has had no impact on income inequalities in the New Member States. This finding is in line with some other studies on the distributional consequences of regional integration. Beckfield (2006) showed that while the political part of the European integration was responsible for an increase in income inequalities in Western European countries, economic integration decreased such inequalities when the share of intra-EU exports in total exports was higher than 60%. In other words, with significant trade integration, the impact of both parts of the European integration may be nullified. Although the results stated in this paper refer to a different set of economies, it may be the case that the findings from Beckfield (2006) may apply to the New Member States as well. According to Eurostat, all the countries analyzed in this study reported in 2015 that their share of intra-EU exports in total exports was higher than 60%. It varied from 61% (Lithuania) to even 85% (Slovakia). The mean intra-EU share for these eight countries was around 76%. Mon and Kakinaka (2020) examined the consequence of regional trade agreements and showed that neither bilateral nor plurilateral RTAs show significant effects on income distribution in developed countries. Since all the countries from the 2004 EU enlargement were classified as high-income economies, that result is similar to the findings from this study.

The no-effect finding from this analysis may also be the result of the averaging out of the heterogenous effects across treated units. Eaton, Kortum, and Kramarz (2022) found that due to the EU accession Poland, Czech Republic, and Hungary experienced an increase in relative real wages of tertiary workers (in relation to primary and secondary workers). Domonkos, Ostrihoň, and König (2021) suggested that the negative consequences of the transmission of the financial and economic crisis to the income of the poor were especially evident in the cases of Hungary and Slovenia. At the same time, other countries avoided such substantial propagation. Similarly, Bouvet (2021) found that the adoption of the euro had a heterogenous effect on income inequalities in the first 12 members of the eurozone. Since New Member States were also engaged in the process of monetary integration within the EU – and some of them eventually adopted the euro – a similar pattern may be behind the main conclusion of this study.

Having observed the above-mentioned heterogeneity in empirical studies, the analysis of the single-unit cases may be a promising area for future research. The same applies to the mechanisms and/or channels of the impact of European integration on income inequality. One thing should be clearly stated. The comparison between the treatment effects for the market and net Gini indicates that the reason why the null hypothesis could not be rejected is not based on the attenuating effects of income redistribution. It could be argued that the EU led to rising market-based inequalities in the New Member States, which were then tackled by fiscal measures. However, according to this study's results, it was not the case. In fact, not only did the EU have no impact on income distribution post-taxes and post-transfers, but also it did not affect the market distribution of income.

Although a more thorough analysis is needed to assess the impact of different channels on income inequalities in the analyzed economies, some remarks can still be given. Firstly, there are forces that drive income distribution more equally. For instance, in the year of accession, as well as in the last year of the analysis, all the treated units had a ratio of capital stock to population significantly lower than the mean or median for the EU-15 (see Table 6). A similar finding refers to the ratio of capital stock to the employed, with the exception of Cyprus. With the logic of the Stolper-Samuelson theorem, one can infer that more trade with the Old Member States should lead to rising wages (compared to capital earnings) and lower inequalities.

Table 6. Capital stock to the number of persons engaged and population

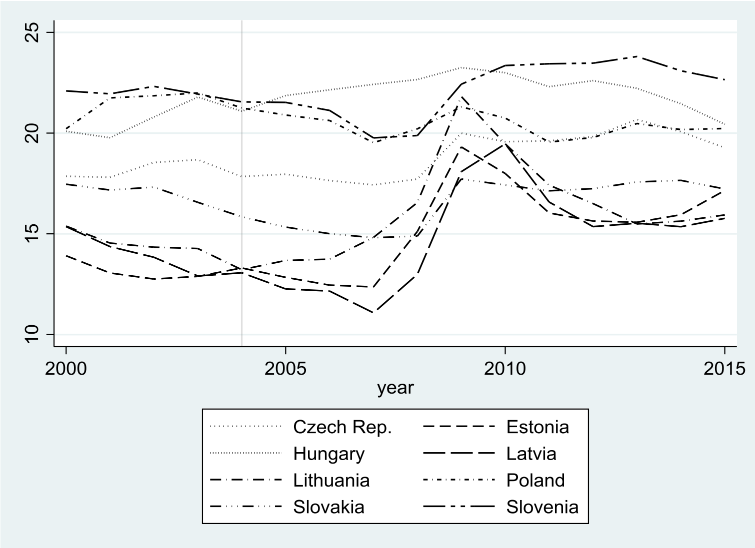
Country	K/E (2004)	K/E (2015)	K/L (2004)	K/L (2015)
EU-15 (mean)	533,143.3	596,083.6	251,272.8	277,432.7
EU-15 (median)	512,101.2	621,376.2	241,702.4	267,486.5
Cyprus	532,661.9	643,772.9	220,210.8	238,593.6
Czech Republic	449,424.8	444,212.7	213,319.6	218,773.0
Estonia	234,929.2	313,437.4	105,629.9	151,880.4
Hungary	.260,535.5	307,807.6	107,052.7	134,895.5
Latvia	410,717.5	500,792.1	174,307.2	225,094.7
Lithuania	195,854.2	256,915.1	81,845.5	118,725.8
Poland	134,474.0	176,601.2	47,962.2	73,479.2
Slovakia	287,950.3	319,166.8	110,951.3	134,336.0
Slovenia	451,566.6	512,634.6	212,0184.4	235,297.8

Note: author's own calculations based on the Penn World Tables (version 10.0; see Feenstra, Inklaar, and Timmer, 2015). Capital stock (K) is measured at constant 2017 national prices (in millions 2017 USD). The number of people engaged (E) and population (L) are expressed in millions.

At the same time, the New Member States might experience greater income inequalities generated by trade openness in the presence of labor market frictions. The 2016 Index of Economic Freedom (with data for 2015) illustrates that the labor markets of the eight analyzed countries were quite rigid. In the subcategory 'Labor Market Freedom,' the average score for these economies was 60.5, with the median at 58.2. The lowest score was received by Slovakia (55.0), with the highest by the Czech Republic (77.7). The maximum value of that category was 100; hence, a relatively significant distance from 100 indicates labor market rigidity in the countries of the 2004 EU enlargement.

Another important issue is that no treatment effect was found for both the net and market Gini indices. This precludes the negative correlation between the impact of the EU on the market distribution of income and the corrective actions of governments. In other words, the EU did not affect market-based income inequalities, nor did it stimulate the governments to address that problem. As a result, the net Gini index in the New Member states was not determined by the 2004 enlargement. The apparent lack of impact of the EU on fiscal redistribution of income is not surprising given the patterns of the ratio of public spending to GDP in the analyzed economies. In general, this ratio was unresponsive to the accession (see Figure 19). These results can be assessed in two ways. On the one hand, it shows that the EU is not responsible for any rise in inequality in the New Member States, and on the other hand, it means that the EU is limited in the actions it can take to combat the unequal division of income. This is crucial, since inequality-driven populism may undermine the process of European integration. The interplay between the lack of proper instruments and the lack of political willingness to address this issue may seriously (and adversely) affect the functioning of the EU.

Figure 19. Public social spending to GDP (in %)



Note: author's own calculations based on the OECD database.

7. Conclusions

The results of the estimations suggest that EU accession has had no impact on income inequalities in the New Member States. This finding is robust to changes in the type of the measure of income inequalities (net Gini vs. market Gini), the applied counterfactual estimator, and the onset of the treatment, as well as the application of the dynamic panel data methods. The results are also consistent with the findings from the scarce empirical literature on the distributional consequences of economic integration.

The article is one of only a few economic studies that take a holistic approach to counterfactual estimation, as many papers report only the estimation results without adequate inference. In this article, however, the estimates are assessed on the basis of the p-values, which illustrate their statistical significance. Moreover, the cross-validation enabled the model selection without any direct intervention from the researcher, which helped to deal with the possible specification-searching problem.

Not only does the article touch on the underexplored topic of the inequality-related consequences of EU accession, but it also poses important questions which open up new directions for further research. Firstly, while the main goal of the analysis was to detect the average treatment effect for the New Member States, there may also be significant heterogeneity across countries and/or regions. An associated issue is the importance of certain preconditions that may influence how a given economy is affected by EU accession (regarding inequalities). The next important direction for further analysis is to identify the mechanisms and/or channels of the impact of the EU on within-country income inequalities. It may be the case that neither mechanism (channel) contributes to these inequalities. However, it may also be that they cancel each other out. In this case, identifying whether it is possible to strengthen these inequality-reducing mechanisms (channels) would be worth exploring, making European integration more immune to populistic tendencies within the Member States.

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Appendix A: The methodology

A1. FE model

Assume the following response surface for $(i,t) \in \mathcal{O}$:

$$Y_{it}^{-} = \mathbf{X}_{it}'\beta + \mu + \alpha_i + \xi_t + \varepsilon_{it},\ \forall i,t, D_{it} = 0 \tag{A1}$$

The identification is achieved by imposing constraints on the fixed effects: $\sum_{D_{it}=0} \alpha_i = 0$ and $\sum_{D_{it}=0} \xi_t = 0$. The details of the estimation strategy are presented in Table A.1.

Table A.1. The estimation strategy – the FE model

Step	Description
Step 1	Estimate a two-way fixed effect model with the use of non-treated observations only $Y_{it}^{-} = \mathbf{X}_{it}'\beta + \mu + \alpha_i + \xi_t + \varepsilon_{it},\ \forall i,t, D_{it} = 0$ ($\sum_{D_{it}=0} \alpha_i = 0$ and $\sum_{D_{it}=0} \xi_t = 0$. $\hat{\mu}, \hat{\alpha}_i, \hat{\xi}_t, \hat{\beta}$ are obtained.
Step 2	Estimate $\hat{Y}_{it}^{-}$ obtaining $\hat{Y}_{it}^{-} = \mathbf{X}_{it}'\hat{\beta} + \hat{\mu}+\hat{\alpha}_i+ \hat{\xi}_t$ for all $i, t, D_{it} = 1$
Step 3	Obtain the estimates of ATT as $\widehat{ATT} = \frac{1}{\sum_{\forall i,t} D_{it}=0} \sum_{D_{it}=1} \hat{\delta}_{it}$.

Source: Author's elaboration based on Liu, Wang, and Xu (2021.

A2. IFE model

Assume the following response surface for $(i,t) \in \mathcal{O}$:

$$Y_{it}^{-} = \mathbf{X}_{it}'\beta + \alpha_i + \xi_t + \lambda_i' f_t + \varepsilon_{it},\ \forall i,t, D_{it} = 0 \tag{A2}$$

The estimation strategy for this class of models is summarized in Table A.2.

Table A.2. The estimation strategy – the IFE model

Step	Description
Step 1	Assuming in round h one has $\hat{\mu}^{(h)}$, $\hat{\alpha}_i^{(h)}$, $\hat{\xi}_t^{(h)}$, $\widehat{\lambda}_i^{(h)}$, $\hat{f}_t^{(h)}$ and $\widehat{\beta}^{(h)}$. Denote $\dot{Y}_{it}^{(h)} \coloneqq Y_{it} - \hat{\mu}^{(h)} - \hat{\alpha}_i^{(h)} - \hat{\xi}_t^{(h)} - \widehat{\lambda}_i^{(h)\prime}\hat{f}_t^{(h)}$ for the untreated (i.e., $D_{it} = 0$.
Step 2	Update $\widehat{\beta}^{(h+!)}$ using Expectation-Maximization algorithm with treated counterfactuals as missing values[a].
Step 3	Estimate $\hat{Y}_{it}^{-}$ obtaining $\hat{Y}_{it}^{-} = \mathbf{X}_{it}'\hat{\beta} + \hat{\alpha}_i + \hat{\xi}_t + \hat{\lambda}_i'\hat{f}_t$ for all i, t, $D_{it} = 1$
Step 4	Obtain the estimates of ATT as $\widehat{ATT} = \frac{1}{\sum_{\forall i,t} D_{it}=0}\sum_{D_{it}=1}\hat{\delta}_{it}$.

Source: Author's elaboration based on Liu, Wang, and Xu (2021. a) Step 2 is a five-step algorithm, fully described in Appendix A.1.1 in Liu, Wang, and Xu (2021.

A3. MC model

Assume that the matrix of $[h(\mathbf{U}_{it})]_{i=1,2,\dots,N,t=1,2,\dots,T}$ can be approximated by a lower-rank matrix $\mathbf{L}_{(N\times T)}$:

$$\mathbf{Y}^{-} = \mathbf{X}\beta + \mathbf{L} + \boldsymbol{\varepsilon} \tag{A3}$$

where $\mathbf{Y}^{-}$ is a matrix of untreated outcomes, $\mathbf{X}$ is an array of covariates, and $\boldsymbol{\varepsilon}$ is a matrix of idiosyncratic errors. The matrix $\mathbf{L}$ can be estimated by solving the minimization problem:

$$\hat{\mathbf{L}} = \arg\min_{\mathbf{L}}\left[\sum_{(i,t)\in\mathcal{O}}\frac{(Y_{it}-L_{it})^2}{|\mathcal{O}|} + \lambda_L\,||\mathbf{L}||\right] \tag{A4}$$

where λ_L is a tuning parameter and $||\cdot||$ is a matrix norm.

In what follows, it is useful to define $P_{\mathcal{O}}(\mathbf{A})$ and $P_{\mathcal{O}}^{\perp}(\mathbf{A})$ for any matrix $\mathbf{A}$ as:

$$P_{\mathcal{O}}(\mathbf{A}) = \begin{cases}\mathbf{A}_{it}\ (\forall(i,t)\in\mathcal{O})\\ 0\ (\forall(i,t)\notin\mathcal{O})\end{cases} \text{ and } P_{\mathcal{O}}^{\perp}(\mathbf{A}) = \begin{cases}0\ (\forall(i,t)\in\mathcal{O})\\ \mathbf{A}_{it}\ (\forall(i,t)\notin\mathcal{O})\end{cases} \tag{A5}$$

One can obtain $\mathbf{A} = \mathbf{S\Sigma R^T}$ through singular value decomposition on matrix $\mathbf{A}$. Then the matrix shrinkage operator is defined as $\text{shrink}_\theta(\mathbf{A}) = \mathbf{S\tilde{\Sigma}R^T}$, where $\tilde{\mathbf{\Sigma}}$ is equal to $\mathbf{\Sigma}$ with the i-th singular value $\sigma_i(A)$ being replaced by $\max(\sigma_i(A) - \theta, 0)$. The estimation algorithm is shown in Table A.3.

Table A.3. The estimation strategy – the MC model

Step	Description
Step 0	Given tuning parameter θ, start with the initial value $\mathbf{L}_0(\theta) = P_{\mathcal{O}}(\mathbf{Y})$.
Step 1	For $h = 0,1,2,\dots$ calculate $\mathbf{L}_{h+1}(\theta)$ with the use of the formula: $\mathbf{L}_{h+1}(\theta) = \text{shrink}_\theta\{P_{\mathcal{O}}(\mathbf{Y}) + P_{\mathcal{O}}^{\perp}(\mathbf{L}_h(\theta))\}$
Step 2	Repeat Step 1 until the sequence $\{\mathbf{L}_h(\theta)\}_{h\geq 0}$ converges.
Step 3	With $\hat{Y}_{it}^{-} = \hat{L}_{it}$, obtain the estimates of ATT as $\widehat{ATT} = \frac{1}{\sum_{\forall i,t} D_{it}=0}\sum_{D_{it}=1}\hat{\delta}_{it}$.

Source: Author's elaboration based on Liu, Wang, and Xu (2021.

A4. Cherry-picking issue

The counterfactual methods applied in the study can also alleviate the cherry-picking problem. In the case of the IFE model, Step 2 is repeated to choose tuning parameter r. This time, that step is performed on a training set of untreated observations until $\hat{\beta}$ converges. The optimal r is selected based on minimizing the Mean Squared Prediction Error (MSPE) using a k-fold cross-validation scheme. By analogy, in the case of the MC estimator, a similar procedure is applied to select the λ_L.

A5. The Wald test

The Wald test is based on the following F statistic:

$$F = {[\sum_{i\in\mathcal{T}}\sum_{s=m}^{0}\left(\hat{e}_{it}^2 - \left(\hat{e}_{it} - \widehat{ATT}_t\right)^2\right)/(1-m)]} \Big/ {\sum_{i\in\mathcal{T}}\sum_{t=1}^{T_0}\left(\hat{e}_{it} - \widehat{ATT}_t\right)^2)/|\mathcal{O}_{\mathcal{T}}| - m + 1} \tag{A6}$$

in which $\mathcal{O}_{\mathcal{T}} = \{(i,t)|D_{it} = 0, i \in \mathcal{T}\}$ and $1 - m$ is the total number of pre-treatment periods (with $m < 0$. The algorithm for the Wald test is presented in Table A.4.

Table A.4. The algorithm for the Wald test

Step	Description
Step 1	Fit a model with the use of observations under the control condition ($D_{it} = 0$) with a tunning parameter (for instance, r or θ. Obtain the residuals for each observation $\hat{e}_{it}$.
Step 2	Estimate the ATT for each pre-treatment period for treated units ($i \in \mathcal{T}$), averaging the residuals at period t: $\widehat{ATT}_t = \sum_{i\in\mathcal{T}}\hat{e}_{it}/N_{tr}$ for $t \le T_0$. Obtain an F statistic: $F^{obs} = [\sum_{i\in\mathcal{T}}\sum_{t=1}^{T_0}(\hat{e}_{it}^2 - (\hat{e}_{it} - \widehat{ATT}_t)^2)/T_o]/[\sum_{i\in\mathcal{T}}\sum_{t=1}^{T_0}\left(\hat{e}_{it} - \widehat{ATT}_t\right)^2)/(N_{tr} \times T_o - T_o)]$
Step 3	Construct the h^{th} bootstrap sample by randomly assigning unit i the weight $w_i^{(h)} = 1$ with probability 0.5, and generating new pseudo-residuals $\tilde{e}_{it}^{(h)} = \hat{e}_{it} \times w_i^{(h)}$ as well as the new outcomes: $y_{it}^{(h)} = \hat{Y}_{it}^{-} + \tilde{e}_{it}^{(h)}$.
Step 4	Use of the method from Steps 1 and 2 with the bootstrapped sample. Obtain an F statistic: $F^{(h)}$.
Step 5	Repeat Steps 3 and 4 for B times. Obtain an empirical distribution of the F statistic under H0: $F^{(1)}$, $F^{(2)}$, $F^{(B)}$.
Step 6	Calculate the p-value with the use of the formula: $p = \sum_{h=1}^{B}\mathbb{1}\left[F^{(h)} > F^{obs}\right]/B$

Source: Author's elaboration based on Liu, Wang, and Xu (2019.

A6. The equivalence test

Define the null hypothesis as:

$$ATT_s < -\theta_2 \text{ or } ATT_s > -\theta_1, \forall s \le 0 \tag{A7}$$

in which $-\theta_2 < 0 < \theta_1$ are pre-determined equivalence thresholds. Rejection of the null hypothesis means that the following condition is met with high probability:

$$-\theta_2 \le ATT_s \le \theta_1, \forall s \le 0 \tag{A8}$$

It means that the no-time-varying-confounder assumption is validated when the pre-treatment residual averages lie within a pre-determined narrow range. It is also useful to calculate the minimum range, which is the smallest symmetric bound within which the null hypothesis can be rejected. Liu, Wang, and Xu (2019, 2021) suggest that when the minimum range is within the equivalence range – which is $[-\theta_2, \theta_1]$ – the equivalence test can be considered passed.

Appendix B: Counterfactual Estimations

B1. Estimation results – dependent variable: net Gini

Table B.1. FE model – results (ATTs)

Year	ATT	Standard Deviation	p-value	Lower Bound	Upper Bound
Pre-treatment period					
1991	0.023	0.471	0.960	-0.967	0.901
1992	0.079	0.393	0.840	-0.664	0.771
1993	-0.090	0.326	0.784	-0.652	0.496
1994	0.056	0.258	0.829	-0.503	0.552
1995	0.096	0.278	0.729	-0.413	0.630
1996	0.139	0.205	0.496	-0.275	0.552
1997	0.111	0.173	0.520	-0.212	0.482
1998	0.037	0.166	0.824	-0.222	0.448
1999	-0.115	0.177	0.514	-0.419	0.230
2000	-0.164	0.221	0.458	-0.600	0.293
2001	-0.133	0.241	0.581	-0.587	0.360
2002	-0.119	0.317	0.708	-0.723	0.438
2003	0.078	0.382	0.839	-0.692	0.752
Post-treatment period					
2004	0.318	0.493	0.519	-0.829	1.148
2005	0.391	0.548	0.476	-1.359	1.213
2006	0.055	0.612	0.929	-1.516	0.949
2007	0.005	0.682	0.994	-1.610	0.998
2008	-0.017	0.751	0.982	-1.664	1.083
2009	0.082	0.761	0.914	-1.484	1.132
2010	0.219	0.752	0.771	-1.274	1.218
2011	0.221	0.687	0.748	-1.186	1.239
2012	0.360	0.713	0.613	-0.851	1.567
2013	0.693	0.725	0.339	-0.956	2.027
2014	0.694	0.741	0.349	-0.962	1.942
2015	0.652	0.815	0.423	-1.142	2.140

Note: all values are rounded to three decimal places. ATT (average treatment effect on the treated) is the difference between the actual and the counterfactual (estimated) outcome.

Table B.2. FE model – results (covariates)

Variable	Coef.	Standard Deviation	p-value	Lower Bound	Upper Bound
Constant	58.540	5.290	0.000	46.771	67.506
Trade	0.002	0.007	0.741	-0.012	0.014
Financial	0.000	0.001	0.874	-0.002	0.003

Technology	-0.068	0.471	0.886	-0.976	0.852
Credit	0.017	0.010	0.079	-0.001	0.037
Adv Credit	-0.018	0.015	0.246	-0.050	0.011
Skill premium	-1.364	0.312	0.000	-1.989	-0.674
Adv Skill premium	1.243	0.306	0.000	0.552	1.774
Education Gini	-0.176	0.074	0.018	-0.307	-0.004
Labor flexibility	0.128	0.073	0.084	0.002	0.294
Female mortality	0.000	0.003	0.925	-0.005	0.006
Gov consumption	-0.031	0.040	0.439	-0.126	0.041
GDP growth lagged	0.032	0.012	0.009	0.006	0.050
Share agriculture	-0.114	0.048	0.019	-0.198	-0.021
Share industry	-0.144	0.092	0.117	-0.313	0.046

Note: all values are rounded to three decimal places.

Table B.3. IFE model – results (ATTs)

Year	ATT	Standard Deviation	p-value	Lower Bound	Upper Bound
Pre-treatment period					
1991	0.007	0.080	0.935	-0.181	0.155
1992	0.020	0.038	0.560	-0.055	0.090
1993	-0.081	0.091	0.373	-0.252	0.132
1994	0.005	0.084	0.955	-0.152	0.172
1995	0.078	0.120	0.517	-0.133	0.305
1996	0.075	0.084	0.371	-0.110	0.221
1997	0.050	0.079	0.525	-0.130	0.218
1998	0.031	0.080	0.698	-0.125	0.197
1999	-0.115	0.081	0.154	-0.268	0.061
2000	-0.174	0.101	0.084	-0.349	0.050
2001	-0.052	0.057	0.367	-0.146	0.107
2002	-0.004	0.066	0.949	-0.140	0.111
2003	0.172	0.089	0.053	-0.037	0.328
Post-treatment period					
2004	0.507	0.265	0.056	0.098	0.978
2005	0.605	0.361	0.094	-0.011	1.340
2006	0.375	0.490	0.444	-0.435	1.449
2007	0.412	0.607	0.497	-0.663	1.731
2008	0.458	0.688	0.506	-0.857	2.141
2009	0.498	0.753	0.508	-1.010	2.382
2010	0.626	0.853	0.463	-1.100	2.947
2011	0.870	0.955	0.362	-0.903	3.207
2012	1.157	1.130	0.306	-0.832	3.639
2013	1.415	1.289	0.272	-0.830	4.187
2014	1.342	1.415	0.343	-1.373	4.310
2015	1.351	1.559	0.386	-1.831	4.556

Note: all values are rounded to three decimal places. ATT (average treatment effect on the treated) is the difference between the actual and the counterfactual (estimated) outcome.

Table B.4. IFE model – results (covariates)

Variable	Coef.	Standard Deviation	p-value	Lower Bound	Upper Bound

Constant	56.946	5.438	0.000	46.347	66.792
Trade	-0.003	0.002	0.143	-0.008	0.002
Financial	-0.000	0.001	0.972	-0.002	0.000
Technology	-0.130	0.158	0.408	-0.435	0.197
Credit	-0.001	0.005	0.869	-0.011	0.010
Adv Credit	0.002	0.010	0.876	-0.021	0.020
Skill premium	-1.039	0.278	0.000	-1.577	-0.524
Adv Skill premium	1.033	0.290	0.000	0.480	1.602
Education Gini	-0.153	0.065	0.019	-0.267	-0.036
Labor flexibility	0.012	0.062	0.844	-0.110	0.130
Female mortality	-0.003	0.004	0.471	-0.012	0.006
Gov consumption	-0.003	0.017	0.853	-0.041	0.029
GDP growth lagged	0.002	0.006	0.694	-0.009	0.013
Share agriculture	-0.113	0.040	0.004	-0.206	-0.038
Share industry	-0.166	0.069	0.015	-0.310	0.034

Note: all values are rounded to three decimal places.

Table B.5. MC model – results (ATTs)

Year	ATT	Standard Deviation	p-value	Lower Bound	Upper Bound
Pre-treatment period					
1991	-0.001	0.073	0.992	-0.171	0.138
1992	0.025	0.047	0.591	-0.074	0.119
1993	-0.085	0.067	0.204	-0.197	0.074
1994	-0.000	0.056	0.998	-0.085	0.146
1995	0.032	0.082	0.701	-0.094	0.208
1996	0.061	0.079	0.443	-0.095	0.258
1997	0.043	0.054	0.419	-0.074	0.149
1998	0.050	0.054	0.249	-0.040	0.126
1999	-0.031	0.041	0.559	-0.124	0.091
2000	-0.098	0.051	0.057	-0.171	0.028
2001	-0.019	0.041	0.647	-0.117	0.040
2002	-0.051	0.054	0.343	-0.180	0.049
2003	0.080	0.075	0.281	-0.074	0.216
Post-treatment period					
2004	0.327	0.235	0.164	-0.107	0.826
2005	0.377	0.347	0.277	-0.265	1.040
2006	0.145	0.456	0.750	-0.721	0.954
2007	0.120	0.565	0.832	-0.921	1.115
2008	0.100	0.636	0.875	-1.176	1.147
2009	0.134	0.661	0.839	-1.223	1.161
2010	0.132	0.654	0.840	-1.212	1.208
2011	0.201	0.596	0.735	-1.102	1.156
2012	0.442	0.610	0.469	-0.873	1.494
2013	0.695	0.614	0.258	-0.630	1.809
2014	0.659	0.616	0.285	-0.778	1.684
2015	0.681	0.672	0.311	-0.917	1.874

Note: all values are rounded to three decimal places. ATT (average treatment effect on the treated) is the difference between the actual and the counterfactual (estimated) outcome.

Table B.6. MC model – results (covariates)

Variable	Coef.	Standard Deviation	p-value	Lower Bound	Upper Bound
Constant	57.117	5.119	0.000	46.082	65.822
Trade	0.002	0.004	0.665	-0.006	0.009
Financial	0.000	0.006	0.787	-0.001	0.002
Technology	-0.039	0.315	0.902	-0.633	0.675
Credit	0.013	0.007	0.068	-0.005	0.025
Adv Credit	-0.014	0.012	0.241	-0.034	0.013
Skill premium	-1.330	0.303	0.000	-1.862	-0.740
Adv Skill premium	1.213	0.324	0.000	0.602	1.850
Education Gini	-0.172	0.069	0.013	-0.293	-0.026
Labor flexibility	0.124	0.056	0.027	0.006	0.229
Female mortality	-0.000	0.003	0.889	-0.007	0.004
Gov consumption	-0.023	0.020	0.241	-0.064	0.019
GDP growth lagged	0.009	0.004	0.012	0.003	0.017
Share agriculture	-0.112	0.041	0.006	-0.189	-0.025
Share industry	-0.148	0.090	0.101	-0.292	0.056

Note: all values are rounded to three decimal places.

B2. Estimation results – dependent variable: market Gini

Table B.7. FE model – results (ATTs)

Year	ATT	Standard Deviation	p-value	Lower Bound	Upper Bound
Pre-treatment period					
1991	-0.252	0.576	0.992	-1.305	0.974
1992	-0.087	0.418	0.591	-0.913	0.818
1993	-0.166	0.336	0.204	-0.793	0.518
1994	-0.122	0.242	0.998	-0.649	0.286
1995	-0.032	0.256	0.701	-0.518	0.455
1996	0.020	0.184	0.443	-0.266	0.347
1997	0.037	0.149	0.419	-0.245	0.313
1998	0.051	0.173	0.249	-0.233	0.419
1999	0.019	0.220	0.559	-0.381	0.466
2000	-0.028	0.234	0.057	-0.504	0.454
2001	0.117	0.267	0.647	-0.382	0.635
2002	0.161	0.359	0.343	-0.544	0.860
2003	0.280	0.438	0.281	-0.613	1.028
Post-treatment period					
2004	0.501	0.585	0.164	-0.680	1.450
2005	0.229	0.613	0.277	-0.982	1.276
2006	-0.227	0.669	0.750	-1.457	0.921
2007	-0.420	0.727	0.832	-1.696	0.859
2008	-0.607	0.815	0.875	-2.158	0.819
2009	-0.630	0.865	0.839	-2.215	1.020
2010	-0.652	0.883	0.840	-2.339	1.042
2011	-0.602	0.877	0.735	-2.269	0.997
2012	-0.209	0.968	0.469	-2.144	1.400
2013	-0.230	1.026	0.258	-2.263	1.522
2014	-0.260	1.066	0.285	-2.225	1.602
2015	-0.432	1.126	0.311	-2.465	1.565

Note: all values are rounded to three decimal places. ATT (average treatment effect on the treated) is the difference between the actual and the counterfactual (estimated) outcome.

Table B.8. FE model – results (covariates)

Variable	Coef.	Standard Deviation	p-value	Lower Bound	Upper Bound
Constant	60.417	5.313	0.000	49.307	68.800
Trade	0.004	0.007	0.547	-0.012	0.015
Financial	0.000	0.001	0.877	-0.001	0.003
Technology	0.189	0.423	0.655	-0.694	1.066
Credit	0.022	0.010	0.022	0.004	0.043
Adv Credit	-0.010	0.016	0.528	-0.041	0.025
Skill premium	-1.161	0.325	0.000	-1.838	-0.509
Adv Skill premium	1.791	0.340	0.000	1.210	2.688
Education Gini	-0.176	0.074	0.018	-0.334	-0.041
Labor flexibility	0.090	0.071	0.208	-0.021	0.247
Female mortality	0.002	0.004	0.652	-0.005	0.008
Gov consumption	0.009	0.037	0.809	-0.073	0.074
GDP growth lagged	0.020	0.014	0.173	-0.009	0.045
Share agriculture	-0.097	0.044	0.026	-0.177	-0.003
Share industry	-0.160	0.094	0.090	-0.321	0.034

Note: all values are rounded to three decimal places.

Table B.9. IFE model – results (ATTs)

Year	ATT	Standard Deviation	p-value	Lower Bound	Upper Bound
Pre-treatment period					
1991	-0.045	0.061	0.459	-0.178	0.073
1992	0.066	0.049	0.176	-0.045	0.161
1993	-0.004	0.069	0.952	-0.121	0.149
1994	-0.017	0.066	0.793	-0.124	0.144
1995	0.046	0.096	0.631	-0.123	0.275
1996	0.027	0.052	0.598	-0.102	0.112
1997	0.006	0.061	0.921	-0.121	0.116
1998	0.011	0.068	0.870	-0.113	0.147
1999	-0.065	0.078	0.407	-0.197	0.105
2000	-0.127	0.084	0.132	-0.272	0.044
2001	0.009	0.051	0.862	-0.119	0.100
2002	0.015	0.067	0.821	-0.152	0.127
2003	0.089	0.099	0.372	-0.092	0.306
Post-treatment period					
2004	0.310	0.400	0.437	-0.225	1.414
2005	0.073	0.440	0.869	-0.560	1.189
2006	-0.261	0.570	0.648	-0.993	1.389
2007	-0.411	0.700	0.557	-1.333	1.500
2008	-0.504	0.757	0.505	-1.582	1.546
2009	-0.503	0.780	0.519	-1.804	1.414
2010	-0.471	0.739	0.524	-1.881	1.076
2011	-0.268	0.794	0.736	-1.794	1.329
2012	0.121	0.919	0.895	-1.596	1.996

2013	0.149	1.043	0.887	-1.967	2.126
2014	0.026	1.139	0.982	-2.259	2.211
2015	-0.091	1.246	0.942	-2.263	2.260

Note: all values are rounded to three decimal places. ATT (average treatment effect on the treated) is the difference between the actual and the counterfactual (estimated) outcome.

Table B.10. IFE model – results (covariates)

Variable	Coef.	Standard Deviation	p-value	Lower Bound	Upper Bound
Constant	59.250	4.894	0.000	48.728	67.638
Trade	-0.002	0.002	0.393	-0.005	0.003
Financial	-0.000	0.001	0.975	-0.002	0.000
Technology	-0.067	0.112	0.546	-0.253	0.190
Credit	0.003	0.005	0.552	-0.006	0.015
Adv Credit	0.003	0.010	0.740	-0.018	0.023
Skill premium	-0.867	0.247	0.000	-1.446	-0.366
Adv Skill premium	1.664	0.333	0.000	1.129	2.415
Education Gini	-0.155	0.060	0.010	-0.258	-0.030
Labor flexibility	0.014	0.046	0.764	-0.082	0.094
Female mortality	-0.002	0.004	0.528	-0.011	0.004
Gov consumption	0.002	0.015	0.909	-0.036	0.023
GDP growth lagged	0.001	0.004	0.897	-0.006	0.009
Share agriculture	-0.096	0.037	0.009	-0.175	-0.025
Share industry	-0.157	0.072	0.029	-0.285	-0.008

Note: all values are rounded to three decimal places.

Table B.11. MC model – results (ATTs)

Year	ATT	Standard Deviation	p-value	Lower Bound	Upper Bound
Pre-treatment period					
1991	-0.076	0.132	0.562	-0.382	0.135
1992	0.046	0.086	0.589	-0.150	0.186
1993	-0.043	0.100	0.667	-0.231	0.166
1994	-0.045	0.077	0.564	-0.196	0.126
1995	0.023	0.118	0.844	-0.165	0.282
1996	0.038	0.077	0.624	-0.098	0.198
1997	0.019	0.068	0.781	-0.119	0.141
1998	0.034	0.064	0.597	-0.083	0.149
1999	-0.023	0.092	0.800	-0.173	0.170
2000	-0.101	0.082	0.214	-0.252	0.056
2001	0.016	0.059	0.783	-0.099	0.126
2002	0.017	0.094	0.856	-0.208	0.196
2003	0.101	0.118	0.391	-0.220	0.286
Post-treatment period					
2004	0.295	0.290	0.309	-0.345	0.828
2005	0.046	0.332	0.891	-0.828	0.555
2006	-0.344	0.381	0.367	-1.288	0.247
2007	-0.517	0.436	0.236	-1.611	0.148
2008	-0.661	0.512	0.197	-1.944	0.138
2009	-0.703	0.601	0.242	-2.341	0.319

2010	-0.746	0.621	0.230	-2.417	0.274
2011	-0.635	0.581	0.275	-1.935	0.297
2012	-0.302	0.629	0.632	-1.429	0.750
2013	-0.275	0.648	0.671	-1.502	0.816
2014	-0.382	0.660	0.563	-1.714	0.760
2015	-0.502	0.704	0.476	-1.811	0.719

Note: all values are rounded to three decimal places. ATT (average treatment effect on the treated) is the difference between the actual and the counterfactual (estimated) outcome.

Table B.12. MC model – results (covariates)

Variable	Coef.	Standard Deviation	p-value	Lower Bound	Upper Bound
Constant	59.337	5.154	0.000	48.718	69.315
Trade	0.001	0.003	0.727	-0.005	0.009
Financial	0.000	0.001	0.873	-0.002	0.002
Technology	0.132	0.225	0.556	-0.260	0.597
Credit	0.012	0.006	0.036	0.001	0.024
Adv Credit	-0.005	0.012	0.674	-0.025	0.022
Skill premium	-1.030	0.296	0.000	-1.710	-0.452
Adv Skill premium	1.759	0.337	0.000	1.279	2.561
Education Gini	-0.163	0.068	0.016	-0.309	-0.049
Labor flexibility	0.075	0.048	0.096	-0.009	0.172
Female mortality	-0.000	0.003	0.877	-0.008	0.005
Gov consumption	-0.003	0.018	0.854	-0.045	0.023
GDP growth lagged	0.007	0.004	0.090	-0.002	0.015
Share agriculture	-0.095	0.047	0.044	-0.186	0.001
Share industry	-0.161	0.081	0.046	-0.317	0.009

Note: all values are rounded to three decimal places.

Appendix C: Dynamic Panel Data Estimations

C1. Estimation results – difference GMM

Table C.1. Two-step difference GMM estimation – dependent variable: net Gini

Variable	Coefficient	Standard Error	t-value	p-value
net Gini (lagged)	0.942	0.044	21.62	0.000
EU	-0.589	0.496	-1.19	0.235
Trade	0.003	0.003	0.88	0.381
Financial	0.000	0.000	0.84	0.401
Technology	-0.539	0.441	-1.22	0.222
Credit	0.001	0.001	0.73	0.465
Adv Credit	-0.003	0.003	-0.86	0.390
Skill premium	0.016	0.037	0.43	0.668
Adv Skill premium	-0.050	0.102	-0.49	0.628
Education Gini	0.009	0.021	0.43	0.665
Labor flexibility	0.015	0.014	1.06	0.290
Female mortality	0.000	0.001	0.43	0.669
Gov consumption	0.016	0.023	0.70	0.483
GDP growth lagged	-0.001	0.002	-0.29	0.774
Share agriculture	0.012	0.008	1.55	0.120

Share industry	0.025	0.016	1.53	0.126
Number of observations	1472			
Number of groups	64			
Number of instruments	32			
Wald chi2(15)	1870.23			
Prob > chi2	0.000			
Arellano-Bond test for AR(1) in first differences: z = -2.95				Pr > z = 0.003
Arellano-Bond test for AR(2) in first differences: z = -2.30				Pr > z = 0.022
Sargan test of overid. restrictions: chi2(16) = 13.47				Pr > chi2 = 0.638
(Not robust, but not weakened by many instruments)				
Sargan test of overid. restrictions: chi2(16) = 9.22				Pr > chi2 = 0.904
(Robust, but weakened by many instruments)				

Table C.2. Two-step difference GMM estimation – dependent variable: market Gini

Variable	Coefficient	Standard Error	t-value	p-value
market Gini (lagged)	0.712	0.116	6.16	.000
EU	0.010	0.308	0.03	0.975
Trade	0.000	0.001	0.17	0.868
Financial	0.000	0.000	1.10	0.270
Technology	-.0299	0.450	-0.66	0.507
Credit	0.001	0.002	0.83	0.408
Adv Credit	-0.003	0.003	-1.06	0.290
Skill premium	-0.019	0.032	-0.59	0.554
Adv Skill premium	0.069	0.099	0.70	0.485
Education Gini	-0.028	0.014	-2.08	0.038
Labor flexibility	0.030	0.014	2.10	0.036
Female mortality	0.012	0.006	1.99	0.047
Gov consumption	-0.007	0.022	-0.30	0.763
GDP growth lagged	0.001	0.001	0.87	0.383
Share agriculture	-0.005	0.010	-0.45	0.654
Share industry	-0.009	0.014	-0.61	0.543
Number of observations	1472			
Number of groups	64			
Number of instruments	33			
Wald chi2(15)	887.49			
Prob > chi2	0.000			
Arellano-Bond test for AR(1) in first differences: z = 0.05				Pr > z = 0.957
Arellano-Bond test for AR(2) in first differences: z = 0.81				Pr > z = 0.416
Sargan test of overid. restrictions: chi2(17) = 24.04				Pr > chi2 = 0.118
(Not robust, but not weakened by many instruments)				
Sargan test of overid. restrictions: chi2(17) = 13.99				Pr > chi2 = 0.668
(Robust, but weakened by many instruments)				

C2. Estimation results – system GMM

Table C.3. Two-step system GMM estimation – dependent variable: net Gini

Variable	Coefficient	Standard Error	t-value	p-value
net Gini (lagged)	0.805	0.128	6.30	0.000
EU	-0.413	0.629	-0.66	0.511
Trade	0.003	0.007	0.41	0.685

Financial	0.000	0.001	0.18	0.859
Technology	-0.408	0.558	-0.73	0.465
Credit	0.006	0.009	0.59	0.554
Adv Credit	0.001	0.012	0.08	0.936
Skill premium	0.013	0.404	0.03	0.974
Adv Skill premium	-0.142	0.172	-0.83	0.409
Education Gini	0.030	0.110	0.28	0.781
Labor flexibility	0.071	0.064	1.10	0.269
Female mortality	0.004	0.006	0.66	0.508
Gov consumption	0.010	0.065	0.15	0.880
GDP growth lagged	0.000	0.007	-0.02	0.987
Share agriculture	-0.009	0.039	-0.23	0.817
Share industry	-0.018	0.071	-0.26	0.797
Constant	6.037	7.764	0.78	0.437
Number of observations	1536			
Number of groups	64			
Number of instruments	34			
Wald chi2(16)	1140.95			
Prob > chi2	0.000			

Arellano-Bond test for AR(1) in first differences: z = -0.92 Pr > z = 0.360
Arellano-Bond test for AR(2) in first differences: z = -0.39 Pr > z = 0.696
Sargan test of overid. restrictions: chi2(21) = 42.89 Pr > chi2 = 0.000
(Not robust, but not weakened by many instruments)
Sargan test of overid. restrictions: chi2(21) = 4.58 Pr > chi2 = 0.999
(Robust, but weakened by many instruments)

Table C.4. Two-step system GMM estimation – dependent variable: market Gini

Variable	Coefficient	Standard Error	t-value	p-value
market Gini (lagged)	1.004	0.132	7.58	0.000
EU	-1.099	0.748	-1.47	0.142
Trade	-0.003	0.004	-0.71	0.476
Financial	0.001	0.001	0.86	0.389
Technology	0.651	0.697	0.93	0.351
Credit	-0.007	0.008	-0.93	0.353
Adv Credit	0.002	0.009	0.20	0.845
Skill premium	0.045	0.130	0.35	0.730
Adv Skill premium	-0.026	0.101	-0.26	0.796
Education Gini	0.004	0.027	0.16	0.875
Labor flexibility	0.004	0.045	0.09	0.926
Female mortality	0.005	0.007	0.68	0.495
Gov consumption	0.008	0.048	0.17	0.866
GDP growth lagged	0.003	0.010	0.36	0.716
Share agriculture	0.008	0.033	0.24	0.808
Share industry	0.054	0.039	1.39	0.164
Constant	-2.535	7.209	-0.35	0.725
Number of observations	1536			
Number of groups	64			
Number of instruments	35			
Wald chi2(16)	1846.95			
Prob > chi2	0.000			

Arellano-Bond test for AR(1) in first differences: z = -1.99 Pr > z = 0.047
Arellano-Bond test for AR(2) in first differences: z = -0.88 Pr > z = 0.376

Sargan test of overid. restrictions: chi2(21) = 69.66	Pr > chi2 = 0.000
(Not robust, but not weakened by many instruments)	
Sargan test of overid. restrictions: chi2(21) = 12.04	Pr > chi2 = 0.845
(Robust, but weakened by many instruments)	