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Abstract:g

Although addressing income inequalities is one of the main challenges in the European Union (EU) Member States, whether the EU has influenced income distributions, even possibly causing a rise in inequalities, is still a heavily underexplored topic. Using the newest methodological developments associated with the counterfactual estimations, I was able to estimate the distributional effects of the 2004 EU enlargement, conduct an inference procedure, as well as escape the problem of cherry-picking. 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.

Keywords: income inequalities, European Union, counterfactual methods, panel data estimation

JEL: F15, F16, F66, E24

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, more people tended to distrust the EU as opposed to people who trusted such an institution. Forty-six percent of EU citizens declared that they did not trust the EU, while 44% said otherwise (Eurobarometer 2019, Question QA6a.10). Although the majority of respondents declared distrust in only eight then-Member States, they included 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 and 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 (2020). 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 commonly applied estimators, 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 (2017), Kvedaras and Cseres-Gergely (2020), and Domonkos, Ostrihoň, and König (2021). 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) analyze 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. A methodologically related paper prepared by Bouvet (2017) uses the SCM, which is a special case of one of the methods applied in this article. However, Bouvet's study is focused on the similar 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, these 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 mention is made regarding the issue of the average impact of regional and preferential trade agreements on income inequality (see J. Lee and Kim, 2016; Mon and Kakinaka, 2020). 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). Available monographs include those by Greenaway, Upward, and Wright (2008), Davidson and Matusz (2009), and Kreickemeier (2017) for a compilation of models linking international trade and labor market outcomes. A more popular treatment of the issue can be found in Helpman (2018).

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 June 2021, the seminal papers by Abadie and Gardeazabal (2003), Abadie, Diamond, and Hainmueller (2010), and Abadie, Diamond, and Hainmueller (2015), had over 3900, 3750, and 1450 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 (2020).

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 (2017) for the distributional consequences of Economic and Monetary Union, and Campos, Coricelli, and Moretti (2019) for the growth effects of EU membership. What these studies have in common is the focus on the SCM-based estimations of single treated cases[1]. 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 inequality 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 engaged in that process) had a non-linear impact on income inequality. 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 mostly 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 – only Luxembourg was not covered by the study) for the years 1999-2010. König-Ohr indicators of European integration were used. These indicators are grouped in four categories, with one that proxied economic integration and another that proxied 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).

Apart from a few empirical studies that directly investigate the impact of the EU on income inequality, there is another that is focused on the effects of EU enlargement on the relation between income inequality and economic growth, named the Kuznets curve (Kuštepeli, 2006). At the same

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

time, Kvedaras and Cseres-Gergely (2020) examined the convergence in income distributions among the EU Member States, while Domonkos, Ostrihoň, and König (2021) investigated the distribution of post-accession economic growth between the poor and the rest of society in the context of the 2004 enlargement of the EU.

Despite the limited number of studies on EU-induced income inequalities[2], there is a burgeoning literature on the distributional consequences of globalization, especially the increased intensity of international trade and offshoring. With the failure of the Stolper-Samuelson theorem, which seems incapable of explaining the increase in the rise of within-country income inequalities in both advanced and developing countries, many theoretical channels have been suggested and explored.

The reallocation of production in the search for cost advantages can be read in such studies as Feenstra and Hanson (1996) or Zhu and Trefler (2005), who speculated that globalization increases the income gap between skilled and /unskilled labor. Grossman and Rossi-Hansberg (2008) present a more nuanced view, since they also analyze the productivity-enhancing effects of globalization, which may outweigh the negative consequences of offshoring[3]. Finally, Costinot and Vogel (2010) and Blanchard and Willmann (2016) introduced the skill-heterogeneity of workers, illustrating that the reallocation of production may lead to job polarization[4].

The trade-induced skill-biased technological change has also been proposed as an explanation for rising inequalities. Studies that analyze such a channel include Dinopoulos and Segerstrom (1999), Manasse and Turrini (2001), Yeaple (2005), Davidson, Matusz, and Shevchenko (2008), Verhoogen (2008), Burstein and Vogel (2010), Monte (2011), Bastos and Straume (2012), Sampson (2014), Harrigan and Reshef (2015), Danziger (2017), Adão, Carrillo, Costinot, Donaldson, and Pomeranz (2020), and Furusawa, Konishi, and Tran (2020). Although some predictions of these analyses differ, they mostly suggest that income inequalities should increase as a consequence of trade opening[5]. Trade itself may be skill-biased since shipping goods abroad

[2] Apart from the studies on the impact of the EU, Baiardi and Morana (2018) investigated the consequences of financial development on income distribution in the euro area.
[3] Davidson, Heyman, Matusz, Sjöholm, and Zhu (2020) also presented ambiguous consequences of globalization. They built a model with productivity heterogeneity among firms and skill heterogeneity among people to investigate the impact of trade on wage distribution and the career paths of workers. Calibrating the model to US data, they found that a reduction in trade costs led to increased wage inequality, wider paths up the jobs ladder, as well as shorter spells of entry level jobs. Meanwhile, Baumgarten, Irlacher, and Koch (2020) analyzed the interaction of productivity and reallocation effects using the GOLE (General Oligopolistic Equilibrium) framework. They showed that the impact of onshoring on employment is non-monotonic across industries. Finally, Acemoglu and Restrepo (2020) studied the interplay between automation and globalization. They found that trade dampens the impact of robotization on employment although that impact was still negative in case of the US economy. Artuç, Bastos, and Rijkers (2018) also found that robotization initially depresses wages through its effect on trade patterns, but as an economy goes closer to robotization frontier higher wages should be observed.
[4] See also E. Lee (2020), who studied trade consequences for between-education-type inequality, and Lee and Yi (2018), who analyzed inequality-related consequences of trade with endogenous labor supply (stemming from the reallocations towards comparative advantages).
[5] However, as shown in Tran (2021), when firms can adopt different technology compositions that are appropriate for its labour composition, the impact of trade on the distribution of wages dampens.

requires promotion and marketing activities, and such activities tend to necessitate skills and competences (Matsuyama, 2007).

Trade may have distributional consequences also through its impact on unemployment. Two important strands exist in the literature. One emphasizes the importance of search and matching frictions on the labor market[6]. Among the examples are Davidson, Martin, and Matusz (1999), Wälde and Weiss (2006), Artuç, Chaudhuri, and McLaren (2008, 2010), Helpman (2010, 2016), Helpman and Itskhoki (2010), Helpman, Itskhoki, and Redding (2008, 2010, 2013), Mitra and Ranjan (2011), Coşar, Guner, and Tybout (2016), and Felbermayr, Impullitti, and Prat (2018). The other combines trade models with efficiency wage theory. Within that strand, Egger and Kreickemeier (2009, 2012), Egger, Egger, and Kreickemeier (2013), and D. Becker (2018) explore worker preference for fair wages. Fairness is also combined with searching-and-matching frictions in Hung and Peng (2019). Meanwhile, Davis and Harrigan (2011) and Paz (2014) focus on shirking[7].

Lastly, some models focus directly on within-firm wage dispersion. For instance, Caliendo and Rossi-Hansberg (2012) analyzed trade-induced organizational changes in firms that take the form of adjusting firms' hierarchies, i.e. the number of layers of management[8]. Ma and Ruzic (2020) showed that trade leads to a wider wage gap within exporting firms, since the pay that accrues to the CEO depends on the size of the firm, while workers' wages are determined in a country's labor market.

The empirical literature related to trade-induced inequalities has developed alongside the theoretical literature. By applying many different methods and approaches, as well as exploiting various datasets, many authors showed that trade can indeed increase income inequalities. For example, Feenstra and Hanson (1996, 1997, 1999) found evidence that trade and offshoring lead to an increased income gap, while Menezes-Filho and Muendler (2011) showed that trade can affect labor market outcomes, such as the spell of unemployment, with an important impact on inequalities. Finally, Frías, Kaplan, and Verhoogen (2012) found that trade may influence within-plant wage dispersion and distributional effects differ across wage percentiles.

A firm's characteristics may also influence how trade affects inequalities. Both Bustos (2011) and Amiti and Davis (2012) obtained results that indicate that wages increase in globalized firms and decrease in firms that are oriented towards domestic markets. At the same time, Verhoogen (2008) and Brambilla, Lederman, and Porto (2012) demonstrated that export destination matters, and trade

[6] Carrère, Fugazza, Olarreaga, and Robert-Nicoud (2020) analyze how the interaction of the pattern of comparative advantage and sector-specific search-and-matching frictions affect unemployment, and showed that specisalization in sectors with more (less) efficient labor markets leads to lower (higher) equilibrium unemployment.

[7] D. Becker (2018) and Paz (2014) also belong to the models that analyze informality. These models, with some implications for labor market adjustments as well as inequalities, include Aleman-Castilla (2006) and Dix-Carneiro, Goldberg, Meghir, and Ulyssea (2021), among others.

[8] Bastos, Monteiro, and Straume (2018) empirically analyzed the consequences of foreign acquisitions and found that they resulted in higher wage inequality across hierarchical layers in Portuguese firms.

tends to be skill-biased, especially when firms export to richer, more economically developed markets. Destination is also important in the context of offshoring. Ebenstein, Harrison, McMillan, and Phillips (2014) showed that reallocating production to low-income countries is associated with a negative change in routine workers' wages in the origin country[9]. Similarly, according to Laffineur and Gazianol (2019), outward FDI reduces wages for workers performing offshorable tasks while raising wages for managers. Munch and Skaksen (2008) found export wage premium, but it accrues to workers hired in skill-intensive firms. Hummels, Jørgensen, Munch, and Xiang (2014) point to workers' occupational characteristics, as occupations may be differently affected by trade and offshoring shocks. They also observed that shocks to offshoring and exporting may lead to different outcomes with implications for inequalities.

Finally, some studies speculate that trade liberalization may affect inequalities in a non-linear way, regarding time. Artuç, Chaudhuri, and McLaren (2010) and Artuc and McLaren (2010) observed that as a labor market adjusts to trade shocks, workers are reallocated from the manufacturing sector to other sectors, and wages in the manufacturing sector first decrease, then increase, while wages in other sectors move in the opposite direction. However, one should bear in mind that during these fluctuations, the real wage of the manufacturing (non-manufacturing) sector is always below (above) that of the pre-liberalization steady state. The nonmonotonic relationship was also found in Helpman, Itskhoki, Muendler, and Redding (2017). They found that, starting from the closed economy, as trade costs decrease, some firms become exporters and offer higher wages, thereby increasing wage inequalities. However, as trade costs continue to fall, more and more firms are engaged in exporting, and gains from trade (in the form of increased wages) are embraced by more workers, leading to lower inequalities. These findings are consistent with the simulations conducted by Egger, Egger, and Kreickemeier (2013), who showed that there is an inverse U-shaped relationship between the share of exporting firms in a country and wage dispersion.

Trade and offshoring are only one aspect of globalization and economic integration. Another is financial opening. However, as put by Furceri, Loungani, and Ostry (2018), *while the fact that trade generates winners and losers is well recognized, the distributional impacts of financial globalization have received less scrutiny*. Nevertheless, there are a few studies that touch on the impact of financial openness on income inequality. On the theoretical grounds, the literature is scant. There are only a few theoretical models that explain inequality-related consequences of the liberalization of capital flows[10]. Harrison (2005) and Jayadev (2007) built bargaining models in which, after financial opening, labor loses its bargaining power, since it is easier to relocate production abroad.

[9] Geographical aspects of internationalization are also studied by, for instance, Parteka and Wolszczak-Derlacz (2020) who found that the participation of firms in the global value chains resulted in negative pressure on wages in Europe, mostly in Western Europe in manufacturing due to the production links with non-high income countries.
[10] A broader literature touches on the issue of the inequality-linked consequences of domestically oriented financial liberalization. Notable examples include G. Becker and Tomes (1986), Greenwood and Jovanovic (1990), Townsend and Ueda (2006).

Models with financial constraints are another way to examine how financial globalization affects inequality. Kunieda, Okada, and Shibata (2014) and Benczúr and Kvedaras (2021) examined the consequences of relaxing credit constraints. As shown in the former, when an economy is closed, the less-talented agents lend financial capital to the talented ones through the domestic financial market. It means that in a closed economy, talented agents must pay a higher interest rate after the relaxation of credit. However, when capital moves across borders, less-talented agents cannot benefit from the abilities of the talented agents; hence, inequality rises. This model was later extended by Benczúr and Kvedaras (2021), who showed that the impact on inequality depends on the difference between the real interest rate and the economic growth rate. When this difference is positive (negative), credit expansion increases (decreases) income inequality. Financial constraint is also present in Larrain (2015), but this model differs from the two described above. In that paper, constrained firms may raise capital from abroad. Due to capital-skills complementarity, financial globalization leads to both capital accumulation and an increase in the relative demand for skilled labor. As a consequence, inequality rises.

Regarding the empirical literature, Das and Mohapatra (2003), in the context of developing countries, found that capital account liberalization led to shifts in income distribution, which benefited mostly the top quintile's share in income, usually at the expense of the middle class. Harrison (2005) assessed the distributional consequences of capital controls and showed that their intensity causes an increase in labor share. However, closer examination of the results reveals that they could depend on government spending, since they were significant only when these spending-related controls were introduced in the specification. A similar study conducted by Jayadev (2007) showed that capital account openness had a significant and negative impact on labor share in aggregate income[11]. A more detailed analysis shed light on the possible heterogeneity of that impact. When countries were divided into quintiles based on GDP per capita, a significant and negative effect was observed for the top three quintiles, while for the two poorest quintiles, the impact was insignificant. When the grouping was into high, medium, and aggregate average income, the two richest groups experienced significant and negative consequences of capital account openness. Moreover, a significant and negative effect of capital openness was observed for countries with high union density.

Larrain (2015) applied the difference-in-differences method to the analysis of 20 European countries between 1975-2005. According to those results, financial liberalization led to an increase in wage inequality. The sector-level results demonstrated the important role of financial dependence. Capital account opening increases wage inequality in industries with strong complementarity (an industry at the 75th percentile of the complementarity index) by 3% more than in industries with weak complementarity (an industry at the 25th percentile of the complementarity index).

[11] This results was also proved by K. Lee and Jayadev (2005).

The difference-in-difference estimator was also used by Furceri, Loungani, and Ostry (2018). They found that liberalizing capital flows reduced the share of labor income, especially in industries with higher external financial dependence, with a higher natural propensity to use layoffs to adjust to idiosyncratic shocks, and with a higher elasticity of substitution between capital and labor. Additionally, they showed that inequality-magnifying effects are more visible in countries with a low financial depth and inclusion, and where liberalization is followed by a crisis. These findings are backed by Eichengreen, Csonto, El-Ganainy, and Koczan (2021), who also showed that the distributional consequences of financial globalization depend on, among other things, the level of educational attainment. Some conditionality is also present in Zare (2019), who found that globalization tends to worsen income inequality. However, the magnitude of the impact of globalization on income inequality decreases with higher levels of financial development.

Furceri and Loungani (2015) also obtained results that are at least to some extent conditional. Using panel data for 149 countries between 1970-2010, they found that capital account liberalization increased the Gini coefficient by about 0.8%, on average, after one year and by about 1.4% in the five-year period after the reform. The effect was magnified by the depth of capital account liberalization. The authors also checked the consequences of capital account restrictions, as in Harrison (2005), and found that capital account restrictions are insignificant for inequality.

Cabral, García-Díaz, and Mollick (2016) found that financial globalization matters for top income shares, and the largest impact was found for portfolio equity and Foreign Direct Investment (FDI) stocks, which means that globalization affects income inequality mostly through FDI/equity flows. At the same time, Kim, Hsieh, and Lin (2021) analyzed the links between various forms of financial liberalization and income inequalities. According to their results, financial openness alleviates income inequality, particularly for less democratic countries.

In several studies that empirically analyzed the distributional effects of both trade and financial openness, it is the latter that increases income dispersion. Jaumotte, Lall, and Papageorgiou (2013) found that trade reduces income inequalities, while financial globalization – mostly FDI – increases it. Dabla-Norris, Kochhar, Suphaphiphat, Ricka, and Tsounta (2015) see financial globalization as an important driver of inequalities, while trade is seen as insignificant.

Apart from the issues discussed above, a strand exists in the empirical literature on the characteristics of financial liberalization, although without any direct reference to financial globalization or financial openness. Such studies usually focus on inequality-related consequences of financial deregulation and include both case studies and cross-section analyses. Beck, Levine, and Levkov (2010) analyzed the impact of banking sector deregulation in the USA on income inequality and found that such reforms typically reduced inequalities. Meanwhile, the cross-country literature is inconclusive. Agnello, Mallick, and Souza (2012), Delis, Hasan, and Kazakis (2014), and Li and Yu (2014) found that financial liberalization leads to lower inequality, although the opposite findings can be found in Jaumotte and Osuorio Buitron (2015) and Ben Naceur and Zhang (2016). Other studies present results that are conditional, hence dependent on other factors such as financial development, quality of political institutions, the structure of finance, or the level of financial deepening, among others. Examples include Bumann and Lensink (2016), de Hann and Sturm (2016), Brei, Ferri, and Gambacorta (2018), and Čihák and Sahay (2020), to name but a few.

Migration is another globalization-related flow that can influence income inequalities. Since the EU is a common market, which by definition involves the movement of people, it is worth reviewing the scarce literature on the relationship between migration and inequalities. Analyzing the situation in a sending economy, McKenzie and Rapoport (2007) found that such a relationship is inversely U-shaped. Due to the cost of migration, initially, migrants are mostly people from the upper and middle ranges of wealth distribution. It means that remittances then flow to households that occupy the upper and middle parts of the income distribution. However, the costs of migration decrease in time, and in the long run, more people from poorer households emigrate, and remittances are spread more evenly within a society, thus lowering income inequality. In the case of Lithuanian migrants, Elsner (2012) showed that the effects of emigration may be heterogenous – he found that this flow had a positive effect on the men who stayed in Lithuania, but no effect was observed on the women. The results from Dustmann, Frattini, and Rosso (2015) suggest that Polish emigration led to a significant increase in the wages of stayers, especially those with intermediate-level skills. At the same time, low-skilled stayers did not experience any gain, and it is also possible that their wages declined.

Most studies, however, focus on the inflow of people. Some studies demonstrate that the natives adjust to immigration by upgrading their occupation to a higher or unchanged income (see Borjas, 2003, Peri and Sparber, 2009, Cattaneo, Fiorio, and Peri, 2015, Sebastian and Ulceluse, 2019). Other authors find that the effect of immigration on wages in the host country depends on the substitutability between natives and immigrants (see Ottaviano and Peri, 2012, Ottaviano, Peri, and Wright, 2013). Similarly, some papers show that the skills of immigrants matter and that unskilled (skilled) migrants may increase (decrease) income inequalities (see Davies and Wooton, 1992). Both the substitutability and the skill composition of immigrants are accentuated by Kahanec and Zimmermann (2014).

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. However, as another strand of economic literature illustrates, globalization can also influence inequality through its impact on redistribution. Meltzer and Richard (1981), Rodrik (1998), and Gozgor and Ranjan (2017) speculated that governments would more intensely correct the market distribution of income, mostly due to political pressure, since those who lose from globalization may demand more compensation. By contrast, Sinn (2003) claims that openness makes governments adopt the race-to-the-bottom approach towards taxes and regulations, affecting mobile factors (such as capital). Similar assumptions were made by Razin and Sadka (2018a, 2018b, 2019) and Razin, Sadka, and Schwemmer (2019).

Spector (2001) focused on trade, and showed that while in autarky, a government can partially equalize prices and wages through the tax system, but in an open economy, it is impossible, since the prices are determined by world markets. Bjorvatn and Cappelen (2004) showed that the policy response to globalization might be non-linear. Initially, as globalization generates increased pre-tax inequality, the response is first to limit that process by increasing redistribution. Then, as globalization continues, the economy hits a point where the policy response to increased market income inequality is to lower taxes and transfers. Beyond this point, therefore, there will be a sharp increase in disposable income inequality. Apart from these studies, some papers focus on the efficiency costs of the redistribution for gains from trade –recent examples include Antras, de Gortari, and Itskhoki (2017), and Lyon and Wright (2018).

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 forming a counterfactual scenario in which the treated unit (or units) is (are) seen as if 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, *forthcoming*, 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), Abadie and L'Hour (2018), Donohue, Aneja, and Weber (2019) and Ben-Michael, Feller, and Rothstein (2021).

Throughout the study, the counterfactual estimators described by Liu, Wang, and Xu (2020) 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)[12],
3) the Matrix Completion (MC) model – first introduced by Athey, Bayati, Doudchenko, Imbens, and Khosravi (2018)[13].

The applied methods can be illustrated as follows. Consider N units (countries) and T periods, 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 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 (2020) introduced a unified estimation strategy[14]. Denoting the observations under control as $\mathcal{O} = \{(i,t) | D_{it} = 0\}$ and the treatment conditions[15] 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 **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 $\widehat{ATT} = \frac{1}{|\mathcal{M}|} \sum_{\mathcal{M}} \hat{\delta}_{it}$.

[12] 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

[13] See also Athey, Bayati, Doudchenko, Imbens, and Khosravi (forthcoming).

[14] This strategy assumes not only additive separability given by (1), but also low-dimensional decomposition and strict exogeneity. See Section 2 in Liu, Wang, and Xu (2020). 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.

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

The above procedure can be applied to each of the estimators applied in this article. The first one, the FE model, takes the following response surface for $(i,t) \in \mathcal{O}$:

$$Y_{it}^{-} = \mathbf{X}_{it}'\beta + \mu + \alpha_i + \xi_t + \varepsilon_{it},\ \forall i,t, D_{it} = 0 \quad (3)$$

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 1.

Table 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 (2020).

In the case of the IFE model, the response surface for $(i,t) \in \mathcal{O}$ is given by:

$$Y_{it}^{-} = \mathbf{X}_{it}'\beta + \alpha_i + \xi_t + \lambda_i' f_t + \varepsilon_{it},\ \forall i,t, D_{it} = 0 \quad (4)$$

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

Table 2. The estimation strategy – the IFE model

Step	Description
Step 1	Assuming in round h one has $\hat{\mu}^{(h)}, \hat{\alpha}_i^{(h)}, \hat{\xi}_t^{(h)}, \hat{\lambda}_i^{(h)}, \hat{f}_t^{(h)}$ and $\hat{\beta}^{(h)}$. Denote $\dot{Y}_{it}^{(h)} \coloneqq Y_{it} - \hat{\mu}^{(h)} - \hat{\alpha}_i^{(h)} - \hat{\xi}_t^{(h)} - \hat{\lambda}_i^{(h)\prime} \hat{f}_t^{(h)}$ for the untreated (i.e., $D_{it} = 0$).
Step 2	Update $\hat{\beta}^{(h+!)}$ 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 (2020). a) Step 2 is a five-step algorithm, fully described in Appendix A.1.1 in Liu, Wang, and Xu (2020).

The last estimator applied in this study, the MC model, assumes 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 $\mathbf{L}_{(N\times T)}$:

$$\mathbf{Y}^{-} = \mathbf{X}\beta + \mathbf{L} + \boldsymbol{\varepsilon} \quad (5)$$

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:

$$\hat{\mathbf{L}} = \arg\min_{\mathbf{L}} \left[\sum_{(i,t)\in\mathcal{O}} \frac{(Y_{it} - L_{it})^2}{|\mathcal{O}|} + \lambda_L \|\mathbf{L}\|\right] \quad (6)$$

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:

$$P_{\mathcal{O}}(\mathbf{A}) = \begin{cases} \mathbf{A}_{it}\ (\forall (i,t) \in \mathcal{O}) \\ 0\ (\forall (i,t) \notin \mathcal{O}) \end{cases} \text{ and } P_{\mathcal{O}}^{\perp}(\mathbf{A}) = \begin{cases} 0\ (\forall (i,t) \in \mathcal{O}) \\ \mathbf{A}_{it}\ (\forall (i,t) \notin \mathcal{O}) \end{cases} \quad (7)$$

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 $\text{shrink}_\theta(\mathbf{A}) = \mathbf{S\widetilde{\Sigma}R^T}$, where $\widetilde{\mathbf{\Sigma}}$ 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 3.

Table 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 (2020).

Additionally, the applied counterfactual methods 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 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. The former is based on the following F statistic:

$$F = [\sum_{i\in\mathcal{T}} \sum_{s=m}^{0} \left(\hat{e}_{it}^2 - \left(\hat{e}_{it} - \widehat{ATT}_t\right)^2\right) / (1-m)] / [\sum_{i\in\mathcal{T}} \sum_{t=1}^{T_0} \left(\hat{e}_{it} - \widehat{ATT}_t\right)^2) / (|\mathcal{O}_{\mathcal{T}}| - m + 1)] \quad (9)$$

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 4.

Table 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 $t \leq T_0$. 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).

In the equivalence test, the null hypothesis is:

$$ATT_s < -\theta_2 \text{ or } ATT_s > -\theta_1, \forall s \leq 0 \tag{9}$$

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:

$$-\theta_2 \leq ATT_s \leq \theta_1, \forall s \leq 0 \tag{10}$$

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 (2020) suggest that when the minimum range is within the equivalence range – which is $[-\theta_2, \theta_1]$ – the equivalence test can be considered passed.

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 $s = -S, -(S-1), \ldots, -1, 0$, 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. 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. This way of choosing the tuning parameters allows the model to be selected without any direct interference from the researcher[16].

[16] 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 (2015), who discuss the choice of predictors in the context of the SCM. Ferman, Pinto, and

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 act as a control for endogeneity[17]. The division of variables into exogenous and endogenous are based on the Granger causality test for panel data, which is described in detail in Lopez and Weber (2017). The testing procedure is standard – if the test statistic is larger than a critical value, the conclusion is that the Granger causality exists. The test statistic is:

$$\bar{Z} = \sqrt{\frac{N}{2K}}(\bar{W} - K) \tag{15}$$

and in cases when $T > 5 + 3K$, it should be corrected so that it is given by:

$$\tilde{Z} = \sqrt{\frac{N}{2K}\frac{T-3K-5}{T-2K-3}}\left(\frac{T-3K-3}{T-3K-1}\bar{W} - K\right) \tag{16}$$

T stands for observations per panel (the number of time periods, e.g., years), N is the number of panels (e.g., countries), K is the lag order, and $\bar{W}$ is the average Wald statistic[18]. Under the assumptions described in Lopez and Weber (2017), both statistics follow the standard normal distribution $\mathcal{N}(0, 1)$. With T = 25, in order to meet the condition $T > 5 + 3K$, K should be at least 7, which is an order far beyond what is necessary to determine that a given variable is endogenous in my dynamic panel data estimations. Hence, the applied statistic is given by (15).

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 study 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, many covariates were included that refer to the possible impact of globalization and other socio-economic forces on the within-country distribution of income. These covariates are 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-

Possebom (2020) show how such a choice affects the possibility of cherry-picking, offering some useful recommendations.

[17] The methods are described in detail in Baltagi (2008, Chapter 8).

[18] See Dumitrescu and Hurlin (2012) for the definition of the Wald statistic.

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).

In the estimations, similar variables were used, although some data sources are different. The dependent variable in the estimations is 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.

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 is found to be relevant.

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) was utilized.

The exact measure was the ECI based on the Standard International Trade Classification (SITC). 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[19] (see Ziesemer, 2016 for details).

Two interaction terms (*Credit x advanced* and *Skill premium x advanced*) required country classification. The classification provided by the United Nations was used – 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 WESP classifies 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 the possibility that the treatment was implemented in 1998 was checked. 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 dealing with 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[20], the time coverage varies. It was 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 5.

[19] 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 linear change (as in the case of missing values regarding other variables). 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.

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

Table 5. 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

Nevertheless, the problem that was encountered was missing values. The decision was made to fill all the gaps with the use of the linear trend. In one case – *Gov consumption* for Jamaica in 1992 – it led to interpolation, since the corresponding data for 1991 and 1993 were available. The gap was filled so that the arithmetic progression for the 1991-1993 subperiod was established. In other cases, dealing with missing observations required extrapolation. The linear (arithmetic) change was calculated between the two furthest actual observations, and such a change enabled the calculation of the missing values. Some adjustments were needed, however. 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 6.

Table 6. 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
Credit x advanced	1600	17.089	45.308	0.000	255.310
Skill premium	1600	8.452	2.789	2.000	13.400
Skill premium x advanced	1600	2.859	4.985	0.000	13.400
Education Gini	1600	25.227	13.043	4.578	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 – one 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 A.

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 or continuous treatment effect. These results were also immune to changes in the dependent variable (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 (2020). 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). It also indicates that no anticipation effect was found.

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

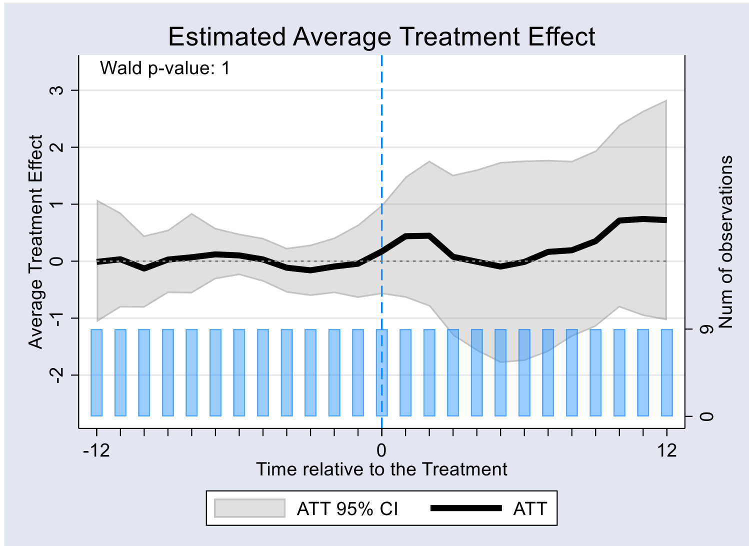


Figure 2. FE model – equivalence test (net Gini)

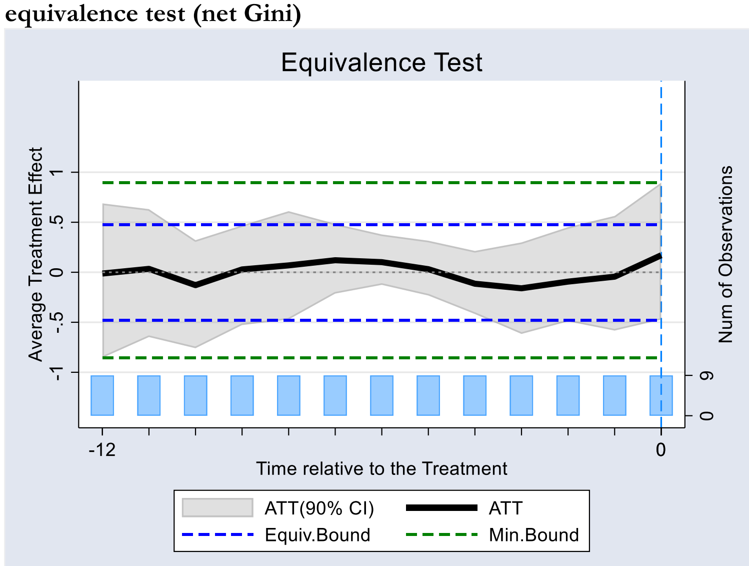
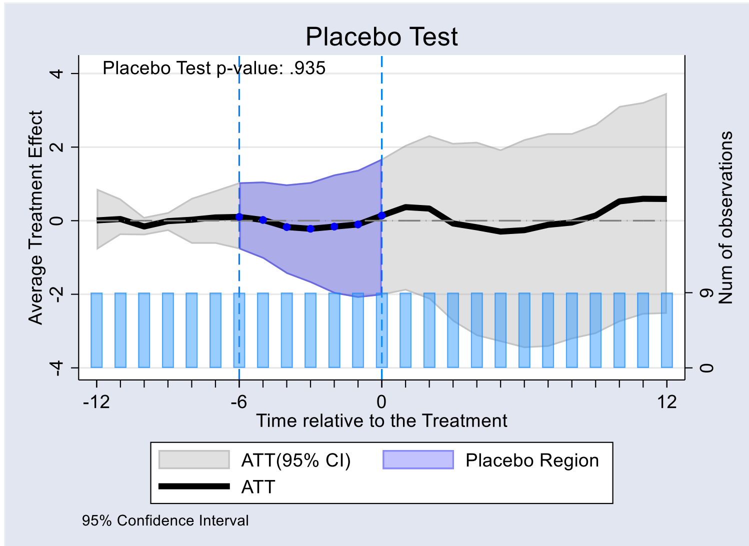


Figure 3. FE model – in-time placebo test (net Gini)



Turning to the IFE model, one should observe that the estimated $ATTs$ were qualitatively and quantitatively similar 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 holds. In the latter case, the minimum bound lies within the equivalence bound (see Figure 5).

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

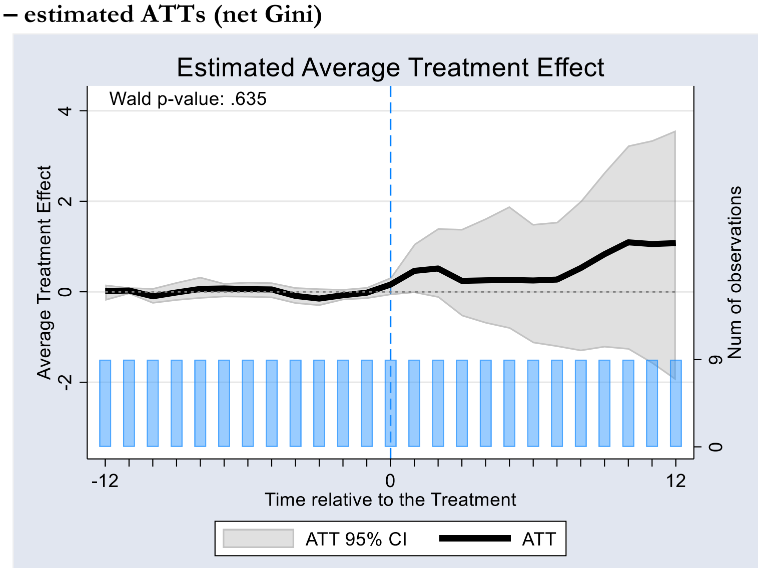


Figure 5. IFE model – equivalence test (net Gini)

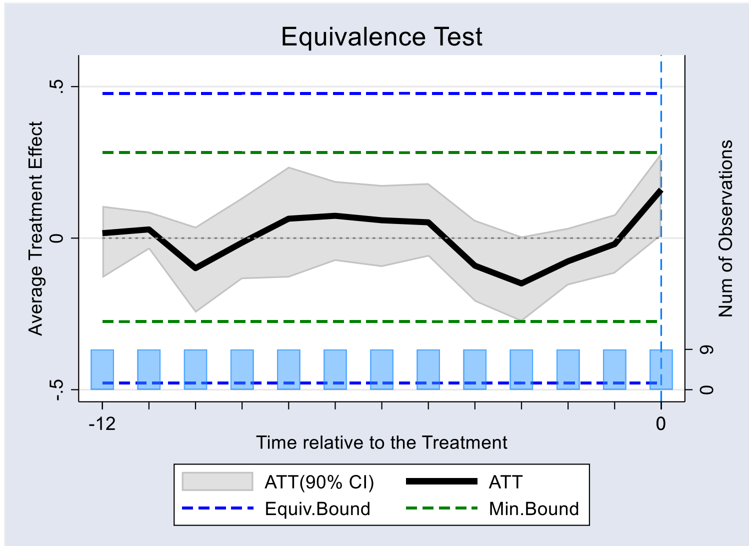
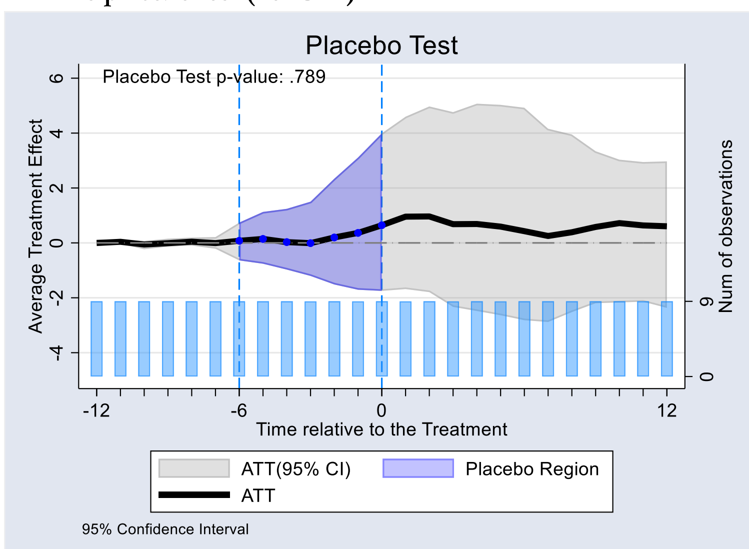


Figure 6. IFE model – in-time placebo test (net Gini)



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)

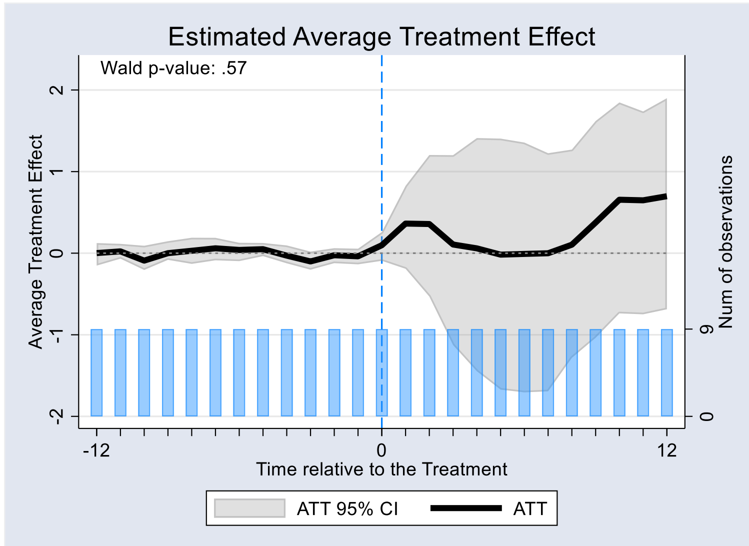


Figure 8. MC model – equivalence test (net Gini)

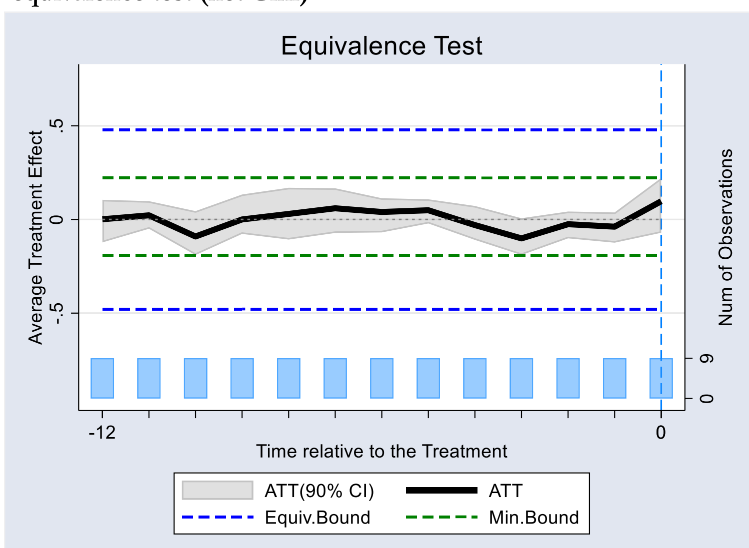
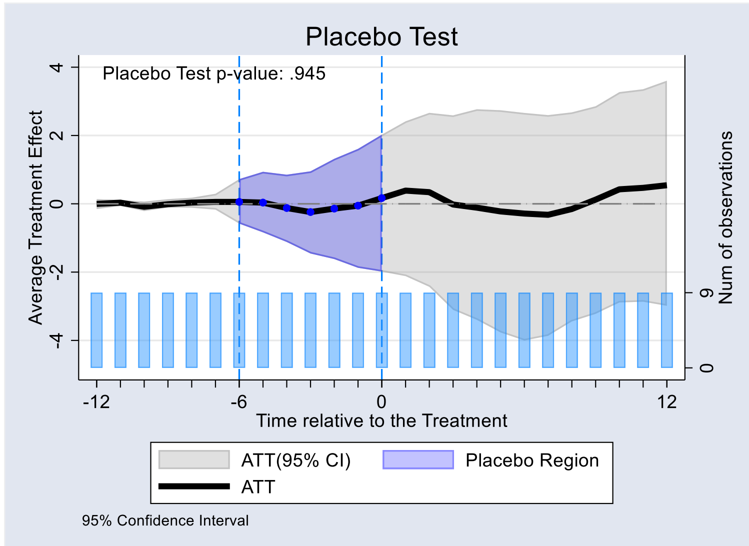


Figure 9. MC model – in-time placebo test (net Gini)



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. For another time, the results obtained from using the FE model were inconclusive regarding 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)

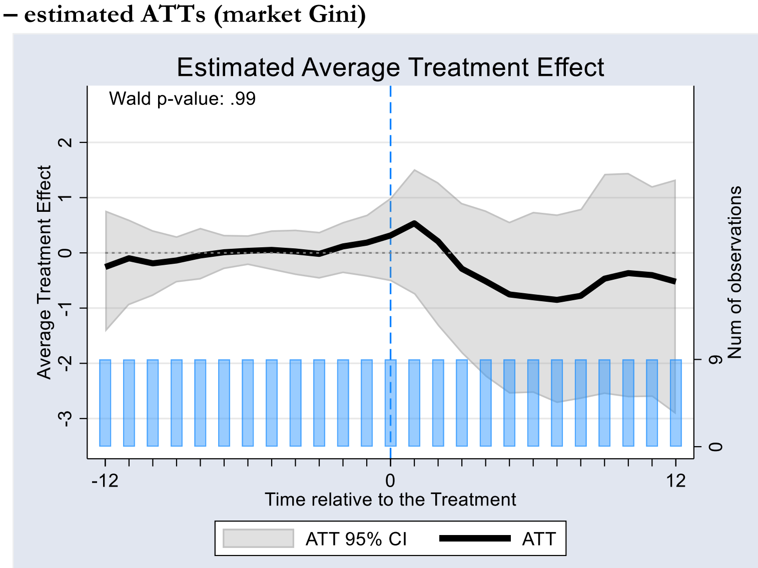


Figure 11. FE model – equivalence test (market Gini)

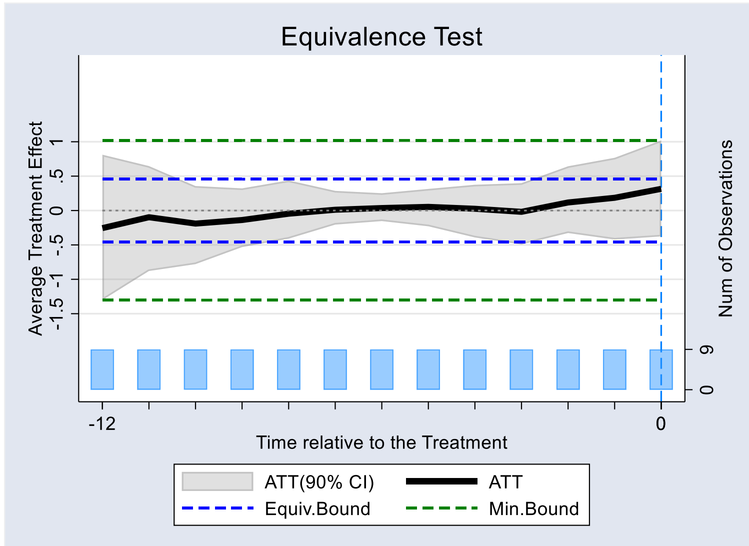
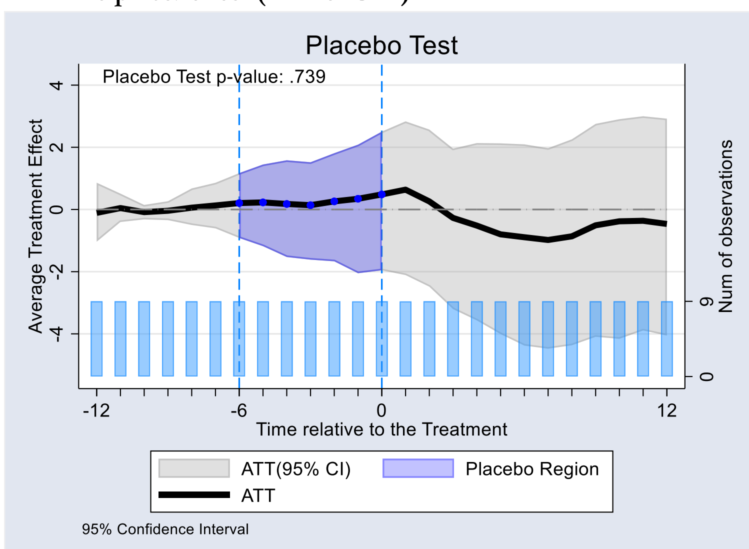


Figure 12. IFE model – in-time placebo test (market Gini)



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.

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

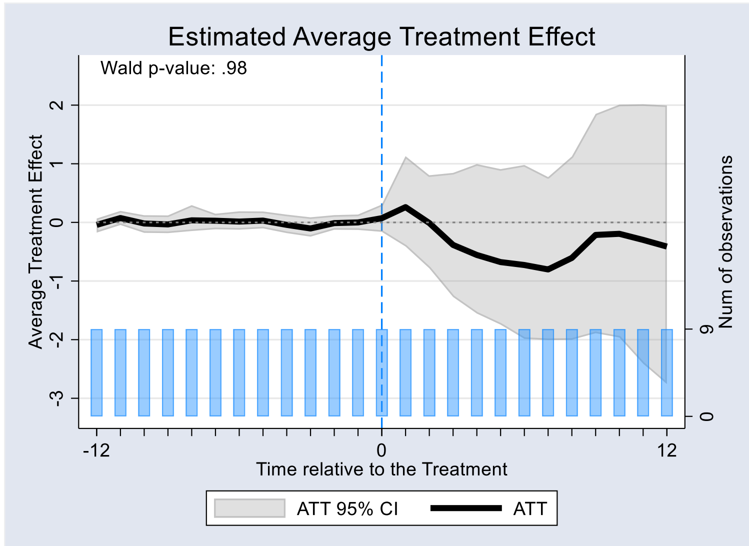


Figure 14. IFE model – equivalence test (market Gini)

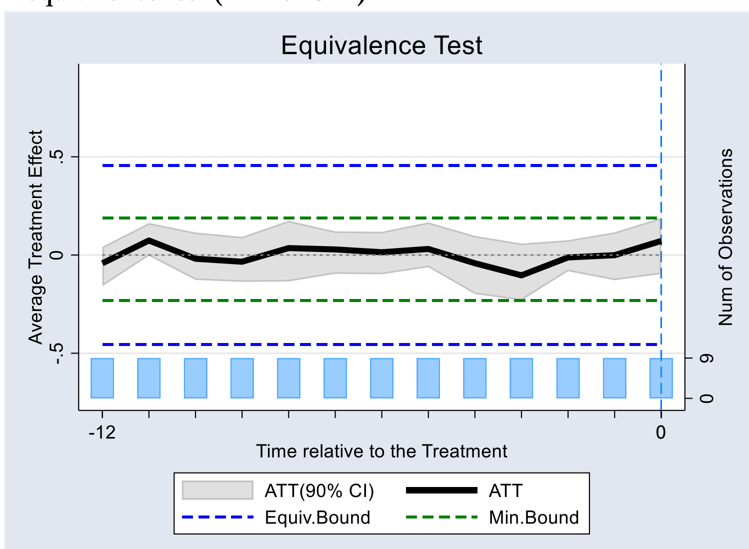


Figure 15. IFE model – in-time placebo test (market Gini)

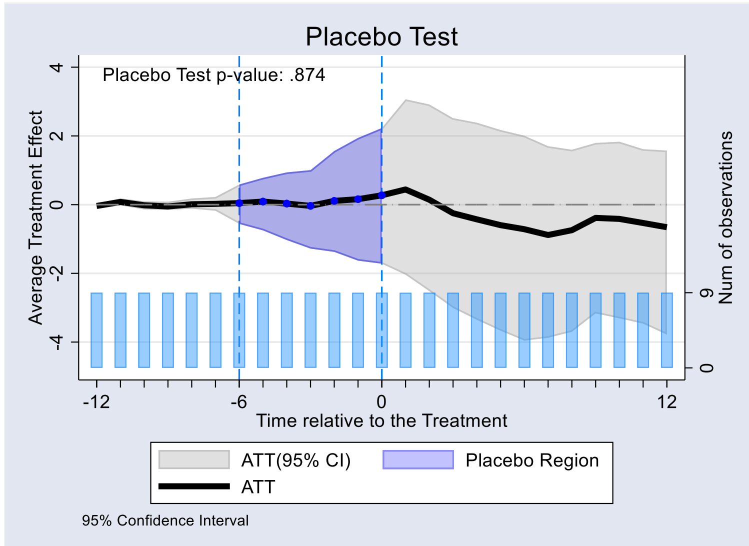
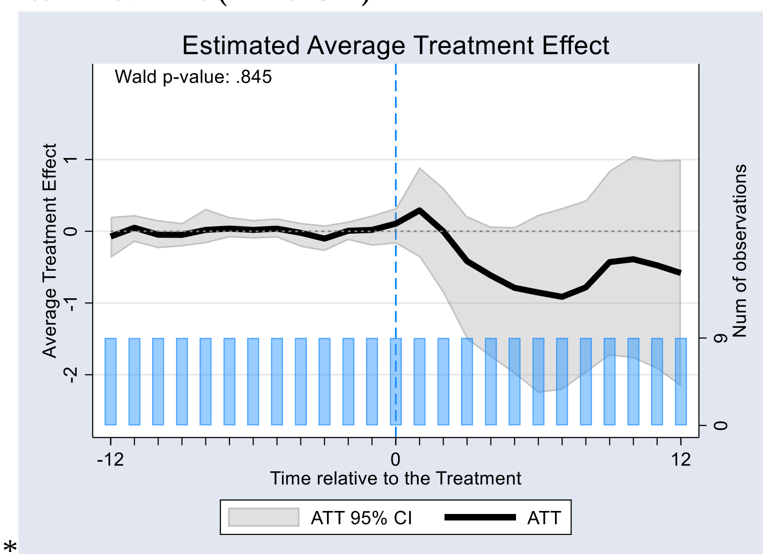


Figure 16. MC model – estimated ATTs (market Gini)



*

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

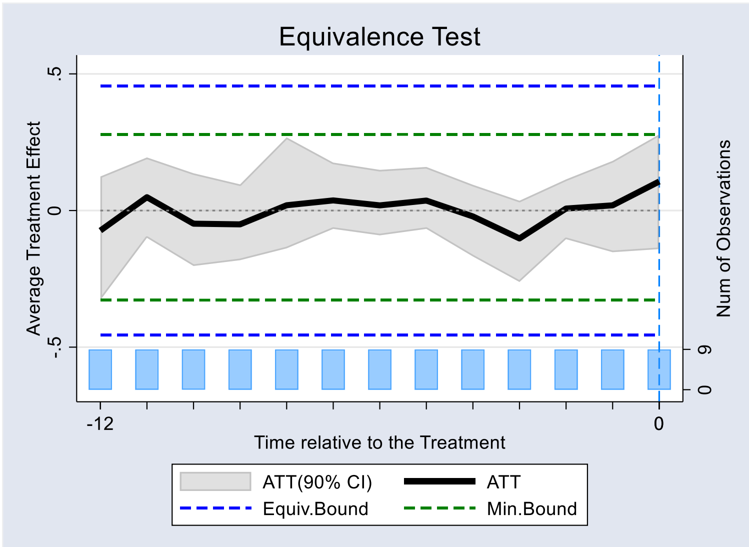


Figure 18. MC model – in-time placebo test (market Gini)

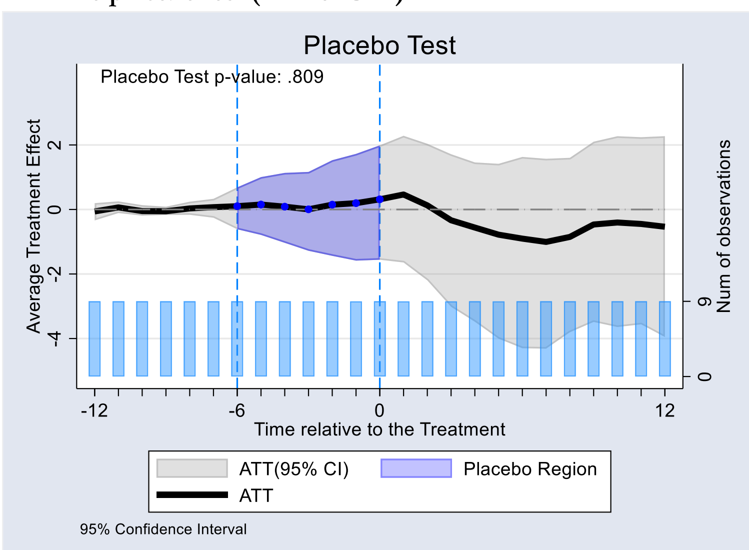


Table 7 summarizes the results obtained with the use of the three counterfactual methods.

Table 7. 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 used. To determine endogenous variables through a typical Granger causality test, a two-way relationship should be checked. However, since my panel data estimations verified whether a given variable determines Gini indices or not, in order to treat it as endogenous, one should only check whether it is Granger-caused by a given Gini index. The covariates are treated as potential determinants of income inequalities (see Dabla-Norris, Kochhar, Suphaphiphat, Ricka, and Tsounta, 2015), and if the Granger causality test also indicates that a given variable is affected by inequalities, then it is treated as endogenous in the following estimations. Table 7 summarizes the results of the Granger test for panel data. Each row presents the statistics associated with the impact of the Gini indices on a given variable. The test was conducted using the *xtgcause* command in Stata.

Table 7. Granger causality test for panel data

Variable	net Gini		market Gini	
	$\bar{Z}$	$\tilde{Z}$	$\bar{Z}$	$\tilde{Z}$
Trade	11.007 (0.000)	8.685 (0.000)	13.466 (0.000)	10.731 (0.000)
Financial	18.363 (0.000)	14.820 (0.000)	17.077 (0.000)	13.748 (0.000)
Technology	12.358 (0.000)	9.812 (0.000)	11.122 (0.000)	8.781 (0.000)
Skill premium	6.891 (0.000	5.252 (0.000)	6.638 (0.000)	5.040 (0.000)
Education Gini	7.140 (0.000)	5.459 (0.000)	7.931 (0.000)	6.119 (0.000)
Labor flexibility	74.598 (0.000)	61.729 (0.000)	50.994 (0.000)	42.040 (0.000)
Female mortality	93.415 (0.000)	77.425 (0.000)	98.133 (0.000)	81.361 (0.000)
Gov Consumption	11.283 (0.000)	8.916 (0.000)	13.492 (0.000)	10.758 (0.000)
GDP growth lagged	7.799 (0.000)	6.009 (0.000)	5.505 (0.000)	4.095 (0.000)
Share agriculture	28.766 (0.000)	23.498 (0.000)	23.507 (0.000)	19.112 (0.000)
Share industry	17.473 (0.000)	14.078 (0.000)	18.461 (0.000)	14.902 (0.000)

Note: all values are rounded to three decimal places; p-values are given in parentheses

The results confirm that each of the analyzed variables should be treated as endogenous. The *xtgcause* command collapses for other variables. However, since it is documented in the empirical literature that income inequalities may affect economic phenomena such as financial deregulation, which may lead to credit expansion (see Dabla-Norris, Kochhar, Suphaphiphat, Ricka, and Tsounta, 2015), I decided to consider *Credit* and *Adv_Credit* as endogenous as well. Moreover, since *Skill_premium* was Granger-caused by the Gini indices, it was reasonable to consider that *Adv_Skill_premium* is determined by income inequalities. Lastly, 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.

Table 8 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 are provided in Appendix B.

Table 8. Dynamic panel data estimation – results

Variable	diff. GMM	system GMM	diff. GMM	system GMM
net Gini (lagged)	0.923**	0.764**		
market Gini (lagged)			0.911**	1.045**
EU	-0.000	0.484	-0.361	-2.877
Trade	-0.000	-0.000	-0.000	0.000
Financial	0.000	-0.000	0.000	0.000
Technology	-0.018	-0.006	0.013	0.111
Credit	0.000	0.007	0.001	-0.002
Credit x advanced	-0.001	-0.002	-0.001*	0.000
Skill premium	-0.025	-0.280	0.007	0.057
Skill premium x advanced	0.001	-0.169*	0.124	0.055
Education Gini	-0.005	-0.032	-0.010	0.009
Labor flexibility	0.025*	0.087**	0.021	0.005
Female mortality	0.000	0.005	0.000	-0.001
Gov Consumption	0.005	-0.028	0.001	0.008
GDP growth lagged	0.000	0.004	-0.000	-0.007
Share agriculture	0.005	-0.024	-0.006	0.023
Share industry	0.003	-0.079*	-0.005	0.062
year	-0.007	0.001	-0.021**	0.003
Constant		13.129		-9.857

Note: all values rounded to three decimal places. legend: * $p<0.05$; ** $p<0.01$

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. 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 (2017) claims 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 9). 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).

Table 9. Capital stock to the number of persons engaged and population

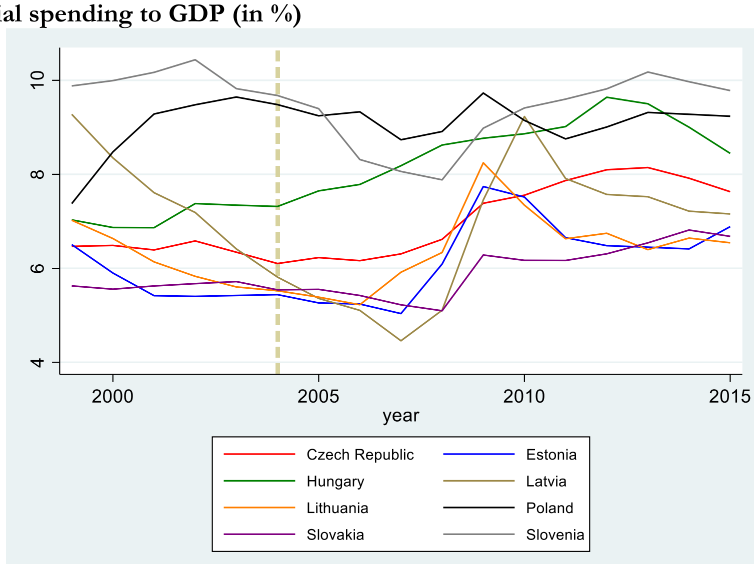
Country	K/E (2004)	K/E (2015)	K/L (2004)	K/L (2015)
EU-15 (mean)	533,143.3	596,083.6	251,272.8	277,432.7
EU-15 (median)	512,101.2	621,376.2	241,702.4	267,486.5
Cyprus	532,661.9	643,772.9	220,210.8	238,593.6
Czech Republic	449,424.8	444,212.7	213,319.6	218,773.0
Estonia	234,929.2	313,437.4	105,629.9	151,880.4
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.

The result is consistent with the results from Beņkovskis, Tkačevs, and Yashiro (2019), Pasimeni and Riso (2019), and Crescenzi and Giua (2020), who documented limited EU capacity to challenge many socio-economic issues. Beņkovskis, Tkačevs, and Yashiro (2019) used data on Latvian firms and showed that larger and more productive companies are more likely to receive EU funds. It means that the possibility that the EU fund could address income (wage) inequalities through support given to smaller, weaker firms is debatable. Pasimeni and Riso (2019) showed that the EU budget is not very responsive to income differences across the EU. They found that for every 1000 EUR difference in income per capita across the Union, 9 EUR is offset by reduced contributions to the budget, and 3 EUR is offset by higher budget expenditures. The main conclusion is the small equalizing effect of the EU budget. Thus, the negligible EU effect on between-country income inequalities corresponds with my finding that the effect on within-country inequalities has also been insignificant. Finally, using data for regions in Germany, France, Spain, and the UK, Crescenzi and Giua (2020) found that the impact of the EU Cohesion Fund on economic growth and employment has been heterogenous and depends on national-level strategic choices. It indicates that the EU's impact on within-country inequalities through the impact on regional successes and failures is also hampered by the national environment (mostly institutional).

Lastly, the results place the analysis alongside those other studies that indicate no impact of a given treatment. For instance, Kaul, Klößner, Pfeifer, and Schieler (2015) question the findings of Billmeier and Nanncini (2013) and show that – contrary to the latter's findings – economic liberalization had no effect on the GDP per capita in countries such as Guinea-Bissau, Barbados, or the Gambia. Similarly, Ferman, Pinto, and Possebom (2020) documented that the discovery of natural resources had no impact on the GDP per capita in Ecuador (in contrast to Smith, 2015).

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: Counterfactual Estimations

Estimation results – dependent variable: net Gini

Table A.1. FE model – results (ATTs)

Year	ATT	Standard Deviation	p-value	ATT Lower Bound	ATT Upper Bound
Pre-treatment period					
1991	-0.013	0.547	0.982	-1.071	1.082
1992	0.034	0.418	0.935	-0.813	0.856
1993	-0.129	0.331	0.697	-0.817	0.453
1994	0.028	0.269	0.916	-0.561	0.553
1995	0.069	0.325	0.823	-0.566	0.847
1996	0.120	0.230	0.601	-0.317	0.585
1997	0.101	0.175	0.562	-0.245	0.484
1998	0.031	0.186	0.868	-0.360	0.409
1999	-0.115	0.199	0.565	-0.554	0.235
2000	-0.160	0.245	0.513	-0.611	0.290
2001	-0.093	0.247	0.705	-0.561	0.416
2002	-0.044	0.332	0.894	-0.646	0.644
2003	0.170	0.495	0.675	-0.579	0.989
Post-treatment period					
2004	0.439	0.520	0.399	-0.642	1.486
2005	0.447	0.627	0.476	-0.796	1.767
2006	0.076	0.691	0.911	-1.309	1.519
2007	-0.009	0.764	0.990	-1.576	1.611
2008	-0.094	0.866	0.914	-1.787	1.742
2009	-0.013	0.887	0.988	-1.751	1.768
2010	0.163	0.871	0.851	-1.592	1.779
2011	0.192	0.781	0.806	-1.327	1.762
2012	0.353	0.814	0.665	-1.151	1.944
2013	0.714	0.818	0.383	-0.813	2.399
2014	0.741	0.841	0.378	-0.962	2.643
2015	0.721	0.935	0.441	-1.038	2.838

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 A.2. FE model – results (covariates)

Variable	Coefficient	Standard Deviation	p-value	Lower Bound	Upper Bound
Constant	58.099	5.274	0.000	47.658	67.928
Trade	0.003	0.007	0.661	-0.012	0.015
Financial	0.000	0.001	0.877	-0.003	0.003
Technology	-0.023	0.489	0.963	-0.890	1.102
Credit	0.011	0.008	0.156	-0.005	0.024
Credit x advanced	-0.002	0.005	0.700	-0.013	0.008
Skill premium	-1.277	0.340	0.000	-1.946	-0.603
Skill premium x advanced	1.158	0.345	0.001	0.330	1.793
Education Gini	-0.175	0.073	0.016	-0.336	-0.038
Labor flexibility	0.134	0.079	0.087	-0.011	0.290
Female mortality	0.000	0.003	0.962	-0.006	0.006
Gov Consumption	-0.026	0.043	0.544	-0.123	0.047
GDP growth lagged	0.034	0.013	0.011	0.002	0.053

Share agriculture	-0.121	0.045	0.007	-0.190	-0.016
Share industry	-0.150	0.100	0.132	-0.338	0.067

Note: all values are rounded to three decimal places.

Table A.3. IFE model – results (ATTs)

Year	ATT	Standard Deviation	p-value	ATT Lower Bound	ATT Upper Bound
		Pre-treatment period			
1991	0.016	0.086	0.850	-0.054	0.160
1992	0.029	0.038	0.444	-0.262	0.100
1993	-0.099	0.089	0.265	-0.198	0.082
1994	-0.015	0.098	0.879	-0.153	0.215
1995	0.064	0.123	0.603	-0.120	0.331
1996	0.074	0.087	0.397	-0.127	0.195
1997	0.059	0.084	0.481	-0.141	0.220
1998	0.052	0.087	0.546	-0.266	0.208
1999	-0.091	0.086	0.291	-0.314	0.101
2000	-0.149	0.097	0.121	-0.188	0.076
2001	-0.076	0.061	0.213	-0.158	0.061
2002	-0.020	0.069	0.776	-0.075	0.104
2003	0.160	0.096	0.094	-0.028	0.319
		Post-treatment period			
2004	0.462	0.282	0.101	-0.028	1.060
2005	0.515	0.394	0.191	-1.132	1.405
2006	0.241	0.486	0.620	-0.541	1.390
2007	0.253	0.585	0.665	-0.701	1.624
2008	0.262	0.624	0.675	-0.817	1.890
2009	0.251	0.652	0.701	-1.137	1.499
2010	0.270	0.724	0.709	-1.219	1.546
2011	0.525	0.821	0.522	-1.313	2.010
2012	0.831	0.956	0.384	-1.230	2.646
2013	1.094	1.089	0.315	-1.278	3.234
2014	1.055	1.221	0.388	-1.589	3.349
2015	1.076	1.379	0.435	-1.959	3.569

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 A.4. IFE model – results (covariates)

Variable	Coefficient	Standard Deviation	p-value	Lower Bound	Upper Bound
Constant	56.498	5.075	0.000	46.766	65.144
Trade	-0.004	0.002	0.122	-0.008	0.002
Financial	-0.000	0.000	0.965	-0.001	0.000
Technology	-0.133	0.165	0.421	-0.411	0.244
Credit	0.001	0.004	0.829	-0.007	0.009
Credit x advanced	0.005	0.003	0.126	-0.003	0.010
Skill premium	-0.996	0.244	0.000	-1.504	-0.480
Skill premium x advanced	1.066	0.343	0.002	0.492	1.814
Education Gini	-0.154	0.055	0.005	-0.261	-0.028
Labor flexibility	0.025	0.059	0.679	-0.111	0.121
Female mortality	-0.003	0.004	0.472	-0.013	0.005
Gov Consumption	-0.004	0.016	0.823	-0.040	0.027
GDP growth lagged	0.002	0.006	0.673	-0.010	0.012
Share agriculture	-0.117	0.037	0.002	-0.192	-0.050
Share industry	-0.171	0.071	0.016	-0.310	-0.038

Note: all values are rounded to three decimal places.

Table A.5. MC model – results (ATTs)

Year	ATT	Standard Deviation	p-value	ATT Lower Bound	ATT Upper Bound
		Pre-treatment period			
1991	0.001	0.066	0.985	-0.152	0.124
1992	0.022	0.047	0.634	-0.067	0.114
1993	-0.091	0.075	0.224	-0.205	0.091
1994	0.000	0.063	0.997	-0.082	0.147
1995	0.030	0.080	0.710	-0.131	0.189
1996	0.060	0.072	0.405	-0.087	0.188
1997	0.040	0.055	0.466	-0.098	0.127
1998	0.049	0.042	0.240	-0,036	0.125
1999	-0.030	0.056	0.592	-0.124	0.095
2000	-0.101	0.060	0.090	-0.203	0.019
2001	-0.025	0.046	0.580	-0.122	0.609
2002	-0.038	0.051	0.451	-0.137	0.055
2003	0.097	0.084	0.245	-0.093	0.259
		Post-treatment period			
2004	0.363	0.269	0.177	-0.191	0.825
2005	0.357	0.411	0.385	-0.531	1.203
2006	0.106	0.529	0.841	-1.126	1.201
2007	0.059	0.646	0.927	-1.447	1.411
2008	-0.018	0.731	0.981	-1.672	1.404
2009	-0.009	0.738	0.990	-1.705	1.356
2010	-0.001	0.721	0.999	-1.693	1.225
2011	0.104	0.653	0.873	-1.283	1.270
2012	0.375	0.667	0.574	-1.037	1.620
2013	0.655	0.676	0.332	-0.734	1.848
2014	0.648	0.684	0.344	-0.749	1.737
2015	0.698	0.761	0.359	-0.687	1.899

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 A.6. MC model – results (covariates)

Variable	Coefficient	Standard Deviation	p-value	Lower Bound	Upper Bound
Constant	56.646	5.188	0.000	47.095	67.163
Trade	0.002	0.004	0.600	-0.008	0.009
Financial	0.000	0.001	0.820	-0.002	0.001
Technology	-0.034	0.302	0.910	-0.548	0.626
Credit	0.009	0.006	0.117	-0.005	0.020
Credit x advanced	-0.001	0.003	0.808	-0.006	0.006
Skill premium	-1.245	0.290	0.000	-1.803	-0.667
Skill premium x advanced	1.149	0.346	0.001	0.522	1.916
Education Gini	-0.171	0.070	0.014	-0.315	-0.033
Labor flexibility	0.131	0.060	0.028	0.005	0.223
Female mortality	-0.001	0.003	0.858	-0.009	0.005
Gov Consumption	-0.021	0.020	0.298	-0.068	0.018
GDP growth lagged	0.010	0.004	0.005	0.003	0.017
Share agriculture	0.119	0.041	0.004	-0.198	-0.394
Share industry	-0.153	0.088	0.080	-0.340	0.006

Note: all values are rounded to three decimal places.

Estimation results – dependent variable: market Gini

Table A.7. FE model – results (ATTs)

Year	ATT	Standard Deviation	p-value	ATT Lower Bound	ATT Upper Bound
		Pre-treatment period			
1991	-0.256	0.575	0.657	-1.436	0.770
1992	-0.097	0.411	0.813	-0.948	0.603
1993	-0.190	0.319	0.552	-0.780	0.411
1994	-0.138	0.217	0.526	-0.535	0.301
1995	-0.046	0.230	0.841	-0.482	0.454
1996	0.012	0.167	0.945	-0.293	0.327
1997	0.036	0.143	0.800	-0.220	0.319
1998	0.053	0.173	0.757	-0.311	0.408
1999	0.026	0.222	0.908	-0.402	0.421
2000	-0.019	0.229	0.935	-0.467	0.381
2001	0.117	0.243	0.630	-0.368	0.560
2002	0.185	0.305	0.542	-0.432	0.691
2003	0.315	0.395	0.425	-0.514	0.999
		Post-treatment period			
2004	0.536	0.574	0.351	-0.754	1.518
2005	0.209	0.639	0.744	-1.328	1.279
2006	-0.288	0.689	0.676	1.825	0.905
2007	-0.513	0.755	0.497	-2.244	0.769
2008	-0.753	0.856	0.379	-2.549	0.564
2009	-0.804	0.915	0.380	-2.535	0.743
2010	-0.851	0.917	0.353	-2.720	0.696
2011	-0.778	0.855	0.363	-2.645	0.798
2012	-0.467	0.931	0.616	-2.556	1.431
2013	-0.366	0.972	0.706	-2.616	1.448
2014	-0.403	1.003	0.688	-2.609	1.209
2015	-0.521	1.068	0.625	-2.925	1.332

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 A.8. FE model – results (covariates)

Variable	Coefficient	Standard Deviation	p-value	Lower Bound	Upper Bound
Constant	60.105	5.070	0.000	49.109	70.052
Trade	0.004	0.007	0.543	-0.011	0.019
Financial	0.000	0.001	0.896	-0.003	0.002
Technology	0.218	0.495	0.659	-0.729	1.312
Credit	0.018	0.007	0.010	0.005	0.031
Credit x advanced	0.001	0.006	0.813	-0.011	0.013
Skill premium	-1.096	0.306	0.000	-1.708	-0.525
Skill premium x advanced	1.729	0.368	0.000	1.158	2.645
Education Gini	-0.176	0.076	0.021	-0.327	-0.021
Labor flexibility	0.094	0.067	0.159	-0.029	0.217
Female mortality	0.002	0.004	0.674	-0.005	0.008
Gov Consumption	0.013	0.015	0.766	-0.062	0.089
GDP growth lagged	0.021	0.015	0.174	-0.015	0.047
Share agriculture	-0.102	0.042	0.015	-0.172	0.004
Share industry	-0.164	0.089	0.065	-0.310	0.039

Note: all values are rounded to three decimal places.

Table A.9. IFE model – results (ATTs)

Year	ATT	Standard Deviation	p-value	ATT Lower Bound	ATT Upper Bound

Pre-treatment period					
1991	-0.042	0.056	0.457	-0.174	0.066
1992	-0.074	0.059	0.211	-0.045	0.196
1993	-0.019	0.077	0.806	-0.178	0.122
1994	-0.034	0.077	0.660	-0.183	0.119
1995	0.035	0.106	0.738	-0.147	0.294
1996	0.029	0.066	0.664	-0.118	0.148
1997	0.014	0.069	0.836	-0.125	0.189
1998	0.031	0.078	0.694	-0.102	0.186
1999	-0.042	0.081	0.607	-0.183	0.132
2000	-0.103	0.084	0.216	-0.243	0.087
2001	-0.012	0.060	0.840	-0.126	0.124
2002	-0.001	0.068	0.991	-0.128	0.134
2003	0.072	0.110	0.514	-0.161	0.305
Post-treatment period					
2004	0.260	0.391	0.505	-0.412	1.130
2005	-0.011	0.427	0.980	-0.783	0.803
2006	-0.385	0.522	0.461	-1.272	0.844
2007	-0.555	0.588	0.344	-1.555	0.994
2008	-0.677	0.663	0.307	-1.744	0.908
2009	-0.727	0.736	0.324	-1.986	0.979
2010	-0.802	0.734	0.275	-2.006	0.773
2011	-0.606	0.759	0.425	-2.002	1.125
2012	-0.214	0.857	0.803	-1.890	1.850
2013	-0.195	0.946	0.837	-1.964	2.008
2014	-0.299	1.031	0.772	-1.410	2.015
2015	-0.412	1.137	0.717	-2.757	1.994

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 A.10. IFE model – results (covariates)

Variable	Coefficient	Standard Deviation	p-value	Lower Bound	Upper Bound
Constant	58.939	4.719	0.000	51.251	69.547
Trade	-0.002	0.002	0.397	-0.006	0.003
Financial	-0.000	0.001	0.974	-0.002	0.000
Technology	-0.062	0.135	0.642	-0.278	0.218
Credit	0.005	0.004	0.234	-0.004	0.013
Credit x advanced	0.004	0.003	0.210	-0.001	0.014
Skill premium	-0.833	0.236	0.000	-1.425	-0.417
Skill premium x advanced	1.695	0.394	0.000	0.933	2.620
Education Gini	-0.157	0.060	0.008	-0.277	-0.044
Labor flexibility	0.020	0.045	0.649	-0.093	0.097
Female mortality	-0.002	0.004	0.601	-0.011	0.005
Gov Consumption	0.001	0.016	0.936	-0.034	0.029
GDP growth lagged	0.000	0.004	0.921	-0.008	0.009
Share agriculture	-0.0099	0.037	0.008	-0.176	-0.031
Share industry	-0.162	0.070	0.020	-0.304	-0.034

Note: all values are rounded to three decimal places.

Table A.11. MC model – results (ATTs)

Year	ATT	Standard Deviation	p-value	ATT Lower Bound	ATT Upper Bound
Pre-treatment period					
1991	-0.073	0.138	0.594	-0.375	0.202
1992	0.049	0.093	0.601	-0.152	0.227

1993	-0.048	0.101	0.634	-0.238	0.157
1994	-0.050	0.085	0.554	-0.213	0.116
1995	0.019	0.125	0.877	-0.169	0.314
1996	0.037	0.075	0.620	-0.086	0.200
1997	0.019	0.069	0.785	-0.103	0.159
1998	0.036	0.068	0.590	-0.090	0.182
1999	-0.022	0.085	0.800	-0.219	0.118
2000	-0.102	0.089	0.249	-0.277	0.083
2001	0.007	0.067	0.913	-0.125	0.138
2002	0.019	0.103	0.853	-0.203	0.221
2003	0.106	0.131	0.417	-0.174	0.325
Post-treatment period					
2004	0.291	0.333	0.381	-0.365	0.894
2005	-0.001	0.359	0.998	-0.866	0.609
2006	-0.417	0.408	0.307	-1.509	0.213
2007	-0.616	0.456	0.177	-1.756	0.068
2008	-0.789	0.537	0.142	-1.989	0.061
2009	-0.854	0.610	0.162	-2.255	0.232
2010	-0.914	0.618	0.140	-2.212	0.326
2011	-0.782	0.607	0.198	-1.976	0.433
2012	-0.429	0.710	0.545	-1.734	0.848
2013	-0.390	0.749	0.603	-1.771	1.050
2014	-0.475	0.777	0.541	-1.921	0.988
2015	-0.582	0.833	0.485	-2.164	1.001

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 A.12. MC model – results (covariates)

Variable	Coefficient	Standard Deviation	p-value	Lower Bound	Upper Bound
Constant	59.014	4.953	0.000	50.538	68.708
Trade	0.001	0.003	0.728	-0.005	0.009
Financial	0.000	0.001	0.878	-0.002	0.001
Technology	0.134	0.225	0.550	-0.256	0.582
Credit	0.011	0.005	0.015	0.002	0.020
Credit x advanced	0.001	0.003	0.772	-0.006	0.007
Skill premium	-0.971	0.259	0.000	-1.621	-0.569
Skill premium x advanced	1.737	0.359	0.000	1.240	2.588
Education Gini	-0.164	0.065	0.012	-0.303	-0.051
Labor flexibility	0.077	0.043	0.074	0.001	0.164
Female mortality	-0.000	0.003	0.890	-0.006	0.007
Gov Consumption	-0.003	0.018	0.852	-0.044	0.024
GDP growth lagged	0.008	0.004	0.050	-0.001	0.014
Share agriculture	-0.099	0.042	0.019	-0.194	-0.027
Share industry	-0.166	0.082	0.043	-0.320	-0.007

Note: all values are rounded to three decimal places.

Appendix B: Dynamic Panel Data Estimations

Estimation results – difference GMM

Table B.1. Difference GMM estimation – dependent variable: net Gini

Variable	Coefficient	Corr. Std. Err.	*z*	P>|*z*|
net Gini (lagged)	0.923	0.035	26.28	0.000

EU	-0.000	0.288	-0.00	1.000
Trade	-0.000	0.001	-0.61	0.539
Financial	0.000	0.000	0.37	0.709
Technology	-0.018	0.038	-0.47	0.639
Credit	0.000	0.001	0.25	0.805
Adv_Credit	-0.001	0.001	-0.72	0.472
Skill_premium	-0.025	0.045	-0.55	0.580
Adv_Skill_premium	0.001	0.091	0.01	0.990
Education_Gini	-0.005	0.005	-1.09	0.278
Labor_flexibility	0.025	0.011	2.21	0.027
Female_mortality	0.000	0.000	0.94	0.350
Gov_Consumption	0.005	0.003	1.56	0.118
GDP_growth_lagged	0.000	0.001	0.16	0.872
Share_agriculture	0.005	0.007	0.72	0.473
Share_industry	0.003	0.009	0.29	0.771
year	-0.007	0.006	-1.09	0.275
Number of observations	1472			
Number of groups	64			
Number of instruments	38			
Wald chi2(15)	2086.98			
Prob > chi2	0.000			

Arellano-Bond test for AR(1) in first differences: z = -2.90 — Pr > z = 0.004

Arellano-Bond test for AR(2) in first differences: z = -2.20 — Pr > z = 0.028

Sargan test of overid. restrictions: chi2(21) = 49.95 — Pr > chi2 = 0.000

(Not robust, but not weakened by many instruments)

Sargan test of overid. restrictions: chi2(21) = 18.27 — Pr > chi2 = 0.632

(Robust, but weakened by many instruments)

Table B.2. Difference GMM estimation – dependent variable: market Gini

Variable	Coefficient	Corr. Std. Err.	*z*	P>|*z*|
market Gini (lagged)	0.911	0.035	25.64	0.000
EU	-0.361	0.313	-1.15	0.248
Trade	-0.000	0.000	-0.02	0.987
Financial	0.000	0.000	0.50	0.615
Technology	0.013	0.035	0.37	0.709
Credit	0.001	0.001	0.75	0.452
Adv_Credit	-0.001	0.000	-1.97	0.048
Skill_premium	0.007	0.030	0.24	0.814
Adv_Skill_premium	0.124	0.068	1.82	0.068
Education_Gini	-0.010	0.005	-1.85	0.065
Labor_flexibility	0.021	0.011	1.94	0.052
Female_mortality	0.000	0.000	0.56	0.577
Gov_Consumption	0.001	0.002	0.51	0.607
GDP_growth_lagged	-0.000	0.001	-0.14	0.885
Share_agriculture	-0.006	0.007	-0.82	0.415
Share_industry	-0.005	0.009	-0.53	0.594
year	-0.021	0.006	-3.36	0.001
Number of observations	1472			
Number of groups	64			
Number of instruments	38			
Wald chi2(15)	2520.10			
Prob > chi2	0.000			

Arellano-Bond test for AR(1) in first differences: z = -3.27 — Pr > z = 0.001

Arellano-Bond test for AR(2) in first differences: z = -1.38 — Pr > z = 0.168

Sargan test of overid. restrictions: chi2(21) = 63.91 — Pr > chi2 = 0.000

(Not robust, but not weakened by many instruments)
Sargan test of overid. restrictions: chi2(21) = 22.31 Pr > chi2 = 0.382
(Robust, but weakened by many instruments)

Estimation results – system GMM

Table B.3. System GMM estimation – dependent variable: net Gini

Variable	Coefficient	Corr. Std. Err.	*z*	P>|*z*|
net Gini (lagged)	0.764	0.075	10.20	0.000
EU	0.484	0.550	0.88	0.379
Trade	-0.000	0.003	-0.04	0.969
Financial	-0.000	0.000	-1.42	0.156
Technology	-0.006	0.251	-0.02	0.981
Credit	0.007	0.005	1.30	0.193
Adv_Credit	-0.002	0.005	-0.37	0.711
Skill_premium	-0.280	0.180	-1.55	0.121
Adv_Skill_premium	-0.169	0.083	-2.03	0.043
Education_Gini	-0.032	0.022	-1.47	0.142
Labor_flexibility	0.087	0.032	2.74	0.006
Female_mortality	0.005	0.003	1.52	0.128
Gov_Consumption	-0.028	0.031	-0.90	0.366
GDP_growth_lagged	0.004	0.005	0.82	0.413
Share_agriculture	-0.024	0.021	-1.12	0.261
Share_industry	-0.079	0.044	-1.78	0.074
year	0.001	0.018	0.03	0.976
constant	13.129	34.541	0.38	0.704
Number of observations	1536			
Number of groups	64			
Number of instruments	40			
Wald chi2(16)	3267.40			
Prob > chi2	0.000			

Arellano-Bond test for AR(1) in first differences: z = -1.15 Pr > z = 0.249
Arellano-Bond test for AR(2) in first differences: z = -0.31 Pr > z = 0.758
Sargan test of overid. restrictions: chi2(21) = 1333.58 Pr > chi2 = 0.000
(Not robust, but not weakened by many instruments)
Sargan test of overid. restrictions: chi2(21) = 16.19 Pr > chi2 = 0.807
(Robust, but weakened by many instruments)

Table B.4. System GMM estimation – dependent variable: market Gini

Variable	Coefficient	Corr. Std. Err.	*z*	P>|*z*|
market Gini (lagged)	1.045	0.090	11.62	0.000
EU	-2.877	1.687	-1.71	0.088
Trade	0.000	0.002	0.11	0.915
Financial	0.000	0.000	0.78	0.437
Technology	0.111	0.204	0.54	0.587
Credit	-0.002	0.006	-0.36	0.717
Adv_Credit	0.000	0.005	0.07	0.944
Skill_premium	0.057	0.104	0.55	0.585
Adv_Skill_premium	0.055	0.062	0.89	0.372
Education_Gini	0.009	0.015	0.64	0.522
Labor_flexibility	0.005	0.036	0.13	0.895
Female_mortality	-0.001	0.003	-0.26	0.797
Gov_Consumption	0.008	0.020	0.41	0.684
GDP_growth_lagged	-0.007	0.005	-1.54	0.124

Share_agriculture	0.023	0.023	1.00	0.316
Share_industry	0.062	0.047	1.32	0.188
year	0.003	0.012	0.21	0.832
constant	-9.857	25.751	-0.38	0.702
Number of observations	1536			
Number of groups	64			
Number of instruments	40			
Wald chi2(16)	2483.27			
Prob > chi2	0.000			

Arellano-Bond test for AR(1) in first differences: z = -3.06 Pr > z = 0.002

Arellano-Bond test for AR(2) in first differences: z = -1.81 Pr > z = 0.070

Sargan test of overid. restrictions: chi2(21) = 441.94 Pr > chi2 = 0.000
(Not robust, but not weakened by many instruments)

Sargan test of overid. restrictions: chi2(21) = 19.46 Pr > chi2 = 0.617
(Robust, but weakened by many instruments)