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Abstract

This paper analyzes the relationship between women's political empowerment (WPE) and income inequality in a sample of 142 countries between 1990 and 2019. To identify causal effects, we rely on the use of Random Forests techniques and the exogenous variation on ancestral and traditional cultural norms of gender roles within an instrumental variable panel data modeling approach. These tree-based machine learning statistical techniques help us to predict the spatio-temporal distribution of WPE with high accuracy solely using ancestral societal traits. This predicted variable is then used in the second stage of the IV estimation of a panel specification of income inequality including fixed and time-period fixed effects. Our panel-IV regressions show that (i) WPE reduces income inequality and that (ii) this effect is partly transmitted via redistributive policies. In addition, we employ partial identification methods to ensure that our results are not influenced by unobserved confounding variables. Furthermore, we find that the negative link between WPE is robust to the presence of spatial interdependence and time persistence in inequality outcomes, the presence of outliers and influential observations, and an alternative definition of income inequality. Taken together, our results suggest that the observed negative link between WPE and income inequality is likely to be causal.

Keywords: women's political empowerment, income inequality, machine learning, instrumental variables.

JEL codes: C23, C26, C53, D31, D63, I31, J16.

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1 INTRODUCTION

Women's presence in politics has increased significantly over the last few decades. According to data from the Inter-Parliamentary Union, in 2019, 25.5% of parliamentarians in the world were women, representing an increase of 118% over 1997 figures. This improvement in women's political empowerment (WPE hereinafter) has been followed by a growing interest in the subject among scholars, especially concerning its effects on women themselves and on society as a whole. As the World Bank (2001) points out, women's empowerment is not merely an end in itself for reasons of social justice and human development, but also an important means to other ends. In this regard, numerous studies have found empirical evidence of the positive effects of different socio-economic aspects of women empowerment (mainly educational attainment and labor force participation) on democratization (Wyndow et al., 2013) or development (see, e.g., Duflo, 2012 or Klasen and Lamanna, 2006). The political dimension of women empowerment (both in terms of *descriptive* - number of women elected - and *substantive* - effects of women presence in politics- representation) has also received considerable attention in the literature (see Clayton, 2021 and Wangnerud, 2009 for a review). Existing cross-national studies provide compelling evidence of the positive association between a greater presence of women in politics and reduced levels of political corruption (Esarey and Schwindt-Bayer, 2019), economic growth (Dahlum et al., 2022) or human development (Hornset and Soysa, 2022). Women in politics also increase girls and young womens career goals and educational level (Beaman et al., 2012), lower citizens prejudice towards women over time (Beaman et al., 2009), and improve citizens confidence in political institutions (Clayton et al. 2019).

There is also mounting institutional interest in promoting the political role of women, as reflected in the fifth Sustainable Development Goal approved by the United Nations in 2015, which focuses on gender equality and the empowerment of women and girls worldwide. Likewise, numerous international institutions and national governments are adopting measures to promote the presence of women in the political and economic spheres. A greater presence of women in public decision-making is of special importance if we take into account that international empirical evidence confirms the existence of systematic differences in the political behaviour, preferences and priorities of individuals based on sex (Mansbridge, 1999), which points to more collaborative, generous, and altruistic behavior by women in economic decision-making (Eckel and Grossman, 2008; Andreoni and Vesterlund, 2001) as well as a greater preference by women for income redistribution (Keeley and Ming, 2008; Buser et al., 2020), progressivism (Edlund and Pande, 2002), and public spending on social policies (Delaney and O'Toole, 2008). In addition, empirical evidence suggests that more women in politics is followed by increased legislative attention to women's interests and priorities (Wangnerud, 2009). Therefore, in a context of increasing WPE, and given the empirical evidence of their greater preference for redistribution, one would expect that their increased presence among political elites would translate into a reduction in income inequality.

Despite its relevance, this question remains underexplored. Possibly, the main reason for this scarce attention in the literature is the difficulty of providing accurate empirical estimates of the effect of WPE on income inequality, mainly because this relationship is highly endogenous in nature. In this paper we seek to carefully address this potential endogeneity problem to determine the causal long-run effect of WPE on income inequality. For this purpose, we have compiled a large balanced panel dataset with annual information for 142 countries between 1990 and 2019, using various statistical sources that allow us to measure and compare both the differences between countries and the within-country dynamics of inequality and the level of WPE. Unlike in previous studies, our identification strategy relies on the use of tree-based machine learning statistical techniques (as in Atchen and Lessman, 2020) and a set of variables capturing differences in ancestral and traditional cultural norms of gender roles (Brodeur et al., 2020; Alesina et al., 2013) that help us predict actual WPE with high accuracy. Next, this predicted variable is used as an instrument in a panel data specification of income inequality determinants, including country fixed effects and time-period fixed effects. In a second step, we apply the partial identification approach proposed by Oster (2019). This econometric procedure aims to determine the relative importance of unobserved variables with respect to observed variables that would be necessary to explain away the entire effect of WPE on income inequality. Finally, in our empirical analysis, we provide novel evidence showing that redistribution is likely to be an important transmission channel of the impact of WPE on income inequality.

Our paper adds to several strands of the literature. First, it represents a contribution to the literature in public economics analyzing the determinants of income inequality (see, for example, Nolan et al., 2019; Furceri and Ostry, 2019). While some of those papers have focused on the effect of other socio-economic aspects of women empowerment, such as the percentage of female employment (Gonzales et al., 2015), none have directly addressed WPE as an explanatory variable of income inequality. According to recent empirical evidence, a reduction in inequality, particularly among the lowest income groups, improves social justice and boosts economic growth (Islam and McGillivray, 2020, Marrero and Serven , 2021) and development (Easterly, 2007). Therefore, further analysis of the drivers of income inequality could help public policy decision-making for the design of more prosperous and sustainable societies.

Second, it expands the literature on the substantive effects of female representation on policy (see, e.g., Clayton, 2021, Zohal and Fonseca, 2020 or Wangnerud, 2009 for a survey). A review of the literature points to extensive country-based empirical evidence focused on the analysis of how women's preferences and political attitudes translate into the adoption of public policies with a strong social character when they are in office (e.g., Chattopadhyay and Duflo, 2004; Clots-Figueras, 2011; Svaleryd, 2009; Chen, 2013). Yet, despite the growing interest on the policy-related effects of women in politics, still relatively little work has attempted to provide cross-country comparative research on policy outcomes (Wangnerud, 2009). Notable exceptions can be found in Clayton and Zetterberg (2018), Bratton and Ray (2002), Ennser-Jedenastik (2017), Bolzendahl (2011) and De Siano and Chiariello (2021), where the authors find a positive association between a greater presence of women in office and several public social spending programs. Nonetheless, these previous empirical studies have been largely silent on the effectiveness of such policies in terms of income inequality reduction. Quite possibly, the lack of such studies derives from the unresolved endogeneity problems that make it difficult to correctly identify the causal relationship between these two variables.

2 WHY SHOULD WOMEN'S POLITICAL EMPOWERMENT MATTER FOR INCOME INEQUALITY?

As it is well-acknowledged in the literature (Duflo, 2012), a greater presence of women in public decision-making boosts economic empowerment because it both facilitates the entry of women into the labor force and encourages female entrepreneurship (see, e.g., Goltz et al., 2015). The rise in women's relative wages leads to an overall reduction of income inequality in the economy. As noted in Gonzales et al. (2015), narrowing the gender gap in labor force participation is likely to translate into a reduction of the wage gap between sexes, thus reducing income inequality, especially in high-income countries (OECD, 2015).

In addition, greater presence by women in public decision-making can also affect income inequality through differences in women's and men's behavior and priorities and how they translate into different policy outcomes. There is a strand of literature focused on observing gender gaps in important areas of economic decision-making as well as psychological traits (Ranehill and Weber, 2022). According to this literature, women are, on average, less confident and less competitive than men (e.g., Niederle and Vesterlund, 2010). Thus, it seems reasonable to think that these gender differences in confidence and attitudes towards competition would translate into societies governed by women being more equitable, safer and less competitive. Indeed, some authors have documented a gender bias in voters' policy preferences, as studies show a greater preference by women for redistribution (Alesina and La Ferrara, 2005; Funk and Gathmann, 2015; Goerres and Jaeger, 2016; Ranehill and Weber, 2022), progressivism (Keeley and Ming, 2008; Edlund and Pande, 2002), and public spending on social policies (Abrams and Settle, 1999; Aidt and Dallal, 2008; Delaney and O'Toole, 2008). Several plausible behavioral explanations could explain these differences in voting behavior, including gender differences in confidence about the future economic position, risk aversion, and social preferences (Buser et al., 2020). Women are more risk-averse than men (see, e.g., Eckel and Grossman, 2008), and greater aversion to risk leads to greater demand for redistribution (Gartner et al., 2017) as it provides insurance against future economic shocks.

The voting preferences and political attitudes of women toward redistribution have an impact on policy outcomes when they are in office (*substantive* representation). A greater presence of female politicians can affect legislative decisions in several different ways. First, it normalizes women's presence, sends policy cues to all policymakers, and encourages them to pay more attention to women's interests and priorities (Clayton, 2021). Second, women politicians engage more actively in discussions on women's rights and other gendered issue areas than do their male colleagues (Dietrich et al., 2019). Third, women's first-hand experience may enhance discussion and influence men legislators to choose a course of action that better reflects women's preferences (Dietrich et al., 2019, Mansbridge, 1999). Fourth, women legislators can influence policy making to promote shared interests through informal negotiations and bargaining, since a growing body of research suggests that women are more likely to build cross-party alliances and cosponsor legislation (Barnes, 2012). Finally, the increase in the number of women in party leadership bodies also shapes the policy agenda of parties in terms of a greater emphasis on social justice issues (Kittilson, 2011) and, more broadly, a better reflection of the rights and priorities of women as a group (Kerevel and Atkeson, 2013).

A bulk of the literature has devoted attention to analyze the gender bias among public representatives in different countries and conclude that women compel higher public social spending than men in specific areas.[1] As summarized in Clayton (2021) and Zohal and Fonseca (2020), theory-driven and empirical work suggests that women in elected office are most likely to divert legislative attention to issues related to women's rights, education, public health or poverty alleviation, leading to a more generous welfare provision, be it in terms of spending, coverage, or benefit generosity (Ennser-Jedenastik, 2017).

According to existing research, the implementation of such redistributive welfare policies

[1]Chen (2010) uses cross-country data to analyze the impact of gender quotas on policy decisions and concludes that quotas are likely to be translated into an increasing ratio of government expenditures on social welfare. These results are in line with Clayton and Zetterberg (2018)' findings of greater public spending in health due to the adoption of gender quotas. In the same vein, Swiss et al. (2012) report that women's parliamentary presence improves child health outcomes in developing countries, and Kittilson (2008) shows that a large share of women in parliament increases the duration and generosity of family leave as well as on childcare benefits. Likewise, the results of De Siano and Chiariello (2021) indicate that a higher descriptive representation of female politicians increases social spending in health and elderly care in European countries, while Bolzendahl (2011) finds a positive association between women in politics and social spending in twelve OECD democracies. Other country-specific studies include Bratton and Ray (2002),Chattopadhyay and Duflo (2004), Chen (2013), Clots-Figueras (2011), Holman (2014) and Svaleryd (2009), among others.

leads to a reduction of overall income inequality, despite potential offsetting behavioral (second-round) effects.[2] Empirical evidence on this issue is quite compelling. Doerrenberg and Peichl (2014) exploit within-country variations in OECD countries and find evidence of a positive effect of redistribution policies on income inequality. Martinez-Vazquez et al. (2012) use an unbalanced panel data on 150 developed, developing, and transition countries for the period 1970-2009 and find similar results. Therefore, our key hypothesis to be tested in this the paper is whether WPE increases redistribution and, therefore, decreases income inequality.

3 DATA

3.1 Income inequality

To analyze the effect of WPE on the distribution of income, we need recourse to income inequality data at the country level. With this aim, we rely on the Standardized World Income Inequality Database v.9 (SWIID) developed and assembled by Solt (2020). This database combines the data collected by the Luxembourg Income Study (LIS) with the World Inequality Indicators Database (WIID) to create comprehensive income inequality measures with broad cross-national and temporal coverage that are standardized across sources, welfare definitions, and equivalence scales.

As its country-year coverage and comparability far exceeds those of alternate datasets, the SWIID seems the best option to carry out cross-national research on income inequality.However, one issue with SWIID inequality data is that the number of missing country-year observations over time is well above 50% for 57 of the 198 countries for which there is any inequality measurement. For this reason, we drop from our sample countries with a $> 50\%$ share of missing country-year values. This leaves us with a global sample of $N = 142$

[2]Indeed, economic agents can adjust their labor supply or investment decisions due to more progressive taxes or social cash benefits, which ultimately depend on the labor supply and taxable income elasticities. Recent empirical evidence suggests that this behavioral response to progressive tax rates is higher among taxpayers in the upper tail of the income distribution, and increases as tax avoidance becomes more feasible (see Saez et al. (2012) for a survey). Employers can also condition their wage-setting behavior to the level of redistribution in their country, as they might shift away from any social responsibility if they expect the government to ensure equity and fairness.

countries, with 13% of missing data values at annual frequency and 7.6% of missing data observations at 5-year frequency.

In a second step, to obtain a balanced panel structure, annual missing data are interpolated using penalized smooth cubic spline methods and then averaged over 5-year periods to fill in the 7.6% of missing data values at 5-year frequency.[3] Thus, our final data set consists of a balanced panel of 852 observations with $N = 142$ countries and $T = 6$, as we average over the following 5-year windows: 1990-1994, 1995-1999, 2000-2004, 2005-2009, 2010-2014, 2015-2019.[4] We employ 5-year window averages of the SWIID net Gini index to minimize measurement errors and to maximize the comparability of our findings with previous studies, as this is now the convention of the literature in cross-country inequality differentials (Acemoglu et al., 2015; Furceri and Ostry, 2019).

3.2 Women's Political Empowerment

To carry out our analysis, we also need data on WPE. Thus, we resort to the WPE index developed by Sundstrom et al. (2017) within the Varieties of Democracy (V-Dem) project.[5] The WPE index is based on the definition of empowerment as "a process of increasing capacity for women, leading to greater choice, agency, and participation in decision-making" (Sundstrom et al., 2017). This definition has three dimensions that encompass the three most significant strands of empowerment: choice, agency and participation. Accordingly, the V-Dem WPE index relies on three components:

- The *Women's civil liberties* (WCL) index is intended to capture the dimension of freedom of choice, as it emphasizes individuals' ability to make choices over areas of their lives. This is closely related to formal legal frameworks based on human rights, as well as to

[3] For details on the interpolation approach of the missing values of the SWIID Gini index, see Appendix B. The results of the procedure are illustrated in Figure B.1.

[4] Appendix C provides the detailed list of countries included in the sample.

[5] To date, the *Gender-Related Dev elopment Index* and the *Gender Empowerment Measure* developed within the context of the United Nations Development Programme (UNDP) have been the most commonly used indicators for measuring women's empowerment in empirical analysis. Other authors such Branisa et al. (2014) and Cingranelli and Richards (2010) have proposed alternative measures. However, all these indexes have been criticized for (i) having an elite bias (Klasen, 2006; Cueva-Beteta, 2006) and for (ii) their relatively low geographical and temporal coverage, which is especially pressing in developing countries, thus making it difficult to study female empowerment and equal opportunity in non-Western societies.

informal culture as currently operating. It considers as fundamental aspects of choice the following indicators for women: (1) freedom of domestic movement; (2) freedom from forced labor; (3) property rights; and (4) access to justice.

- The *Women's civil society participation* (WCSP) index is constructed with the aim of capturing the dimension of agency, which focuses on women's ability to be an active agent of change through the ability to engage freely in public debate. This pillar consists of three additional indicators: (5) freedom of discussion for women; (6) participation in civil society organizations; and (7) representation by women in the ranks of journalists.
- The *Women's political participation*(WPP) index relates to the extent to which women engage in political decision-making, in both the executive branch and the legislature, and this is measured by combining (8) the legislative presence of women and (9) the political power distribution by gender indicator.

Except for the legislative presence of women in parliaments in the WPP component, which comes from historical data sources, all the indicators of the three components are constructed using rating information provided by more than 2,600 local and cross-national country experts. Then, these experts' ratings are aggregated through a Bayesian item response theory model. We then use the point estimate coinciding with the median value of the resulting probability distribution as our measure of WPE (see Sundstrom et al., 2017 for further details).

The resulting WPE index ranges from 0 to 1, and the higher the value, the greater the WPE. Overall, the key advantage of this metric with respect to other indicators used in the literature [6] is that its country-year coverage is much greater when compared to prior measures, and it is much less likely to be biased.

[6]Previous indicators of women's empowerment include those provided by Cingranelli and Richards (2010) (CIRI) project on human rights (CIRI), the Gender-Related Development Index (GDI), and the Social Institutions and Gender Index (SIGI) developed by Branisa et al. (2014)

3.3 Preliminary evidence

We begin our empirical analysis by studying the cross-sectional distribution of our variables of interest during the period 1990-2019. Figure (1) plots the cross-sectional distribution of income inequality, whereas Figure (2) depicts the distribution of WPE. In both cases, the darkening of colors in each figure increases with the score of the indexes[7].

Observation of Figures (1) and (2) reveals substantial cross-country variation in the two variables as well as a negative overlap in their cross-sectional distribution. For example, focusing on the lower 10% of the distribution of income inequality, with Gini coefficients below the 0.26 mark, we find Northern European countries such as Sweden, Norway, Belgium and Finland. Similarly, in the top 10% of WPE scores, we find the majority to be Northern European along with other Western countries such as Canada. On the other hand, the highest levels of income inequality, with Gini indexes well above the 0.49 threshold, are all found in Africa and Latin America. In the lower 10% of the distribution of the WPE index scores, we find countries such as Yemen, Qatar, Sudan, Ethiopia, and Iran; in the lower 10% to 25% percentiles, with scores from 0.52 to 0.66, we find a myriad of African and Asian countries including Kenya, Angola, Sierra-Leone, Pakistan, Indonesia, and Cambodia. Latin American countries also tend to obtain relatively low scores in the WPE index. In sum, developing and middle-income countries exhibit both lower levels of WPE and higher levels of income inequality.

INSERT FIGURE (1) ABOUT HERE

INSERT FIGURE (2) ABOUT HERE

To further investigate the links between our variables of interest, Figure (3) provides a graphical illustration on the association between the average level of income inequality, measured by the Gini index, and the average WPE score across the world during the period

[7]The color scale reflects the following percentiles: light yellow stands for the 0-10% percentile, yellow for the 10-25% percentile, orange for the 25-50% percentile, dark orange for the 50-75% percentile, red for the 75-90% percentile, and dark red for the last 90-100% percentile.

1990-2019. The negative and statistically significant relationship ($\rho = -0.371$ with p-value $= 0.00$) depicted in the scatter plot suggests that that countries with higher WPE tend to have more egalitarian distributions of income, while those countries where women are less politically empowered are characterized, on average, by higher levels of income inequality.

INSERT FIGURE (3) ABOUT HERE

Nonetheless, this information should be treated with caution, as the observed relationship between these two variables may simply be a spurious correlation resulting from the omission of other variables affecting both WPE and income inequality. Moreover, the problem of endogeneity due to reverse causality is likely to be present in this setting, as numerous theorists have argued that for women to reach a certain level of political and socio-economic empowerment, it is necessary to have achieved a certain economic equality in the first place (Collins et al., 1993). To avoid this problem, in the next section we develop an econometric strategy to precisely analyze the relationship between WPE and income inequality.

4 EMPIRICAL STRATEGY

Theory offers little guidance on the appropriate framework from which to investigate the effect of WPE on income inequality. For this reason, we use a Random Forest Two-Stage-Least-Squares (RF-TSLS) panel data model to make inference in this context. Specifically, the empirical framework is based on the following panel data specification:

$$I_{i,t:t+5} = \alpha_i + \gamma_t + \psi Y_{i,t:t+5} + \sum_j \beta_j X_{j,t:t+5} + \epsilon_{i,t:t+5} \tag{1}$$

$$Y_{i,t:t+5} = \delta_0 + \delta_1 \hat{Y}^{RF}_{i,t:t+5}\left(Z_i\right) + \sum_j \beta_j X_{j,t:t+5} + \upsilon_{i,t:t+5} \tag{2}$$

$$\hat{Y}^{RF}_{i,t:t+5} = \hat{f}\left(Z_i\right) + u_t \tag{3}$$

where $I_{i,t:t+5}$ denotes the average level of income inequality over the period $[t : t+5]$, $Y_{i,t:t+5}$ is the 5-year average score of WPE, and α_i and γ_t are country and time-period fixed effects. Country-fixed effects control for all country-specific time invariant variables whose omission could bias the estimates in a cross-sectional study, while time-period fixed effects control for all time-specific, space-invariant variables whose omission could lead to biased estimates in a time series analysis. $\epsilon_{i,t:t+5}$ and $\upsilon_{i,t:t+5}$ are heteroskedastic error terms with zero mean and variances given by $\sigma_\epsilon^2 \Omega_\epsilon$ and $\sigma_\upsilon^2 \Omega_\upsilon$, respectively. $\hat{Y}^{RF}_{i,t:t+5}(Z_i)$ denotes the forecast of empowerment scores using Random Forests and Z, which is an $N \times p$ matrix containing information on ancestral cultural characteristics of each country (see Section (4.1)).

Finally, X is the set of exogenous variables that, according to previous empirical literature, help in explaining income inequality at the country level which might be correlated with WPE outcomes (Dabla-Norris et al., 2015; Furceri and Ostry, 2019; Nolan et al., 2019). This set of regressors includes: (i) economic and financial development variables (per capita GDP, urbanization, educational level, financial inclusion); (ii) demographic and institutional characteristics (age dependency ratio, past fertility rates, share of Muslim population, and liberal democracy index); (iii) technological and globalization levels (i.e., the relative price of investment, trade and financial globalization indexes); and (iv) economic policies and macroeconomic conditions (share of government consumption in GDP and unemployment rate). Definitions, descriptive statistics and data sources of the variables used in the paper are presented in Table (1).

INSERT TABLE (1) ABOUT HERE

An approach widely used in economics to identify causal effects is to employ the TSLS estimator and the use of instrumental variables (IVs) by assuming a linear function f in Equation (2) to model $Y = \delta_0 + \sum_{j=1}^{p} Z_j \delta_j + \sum_{j=1}^{p} X_k \beta_k$ in the so-called first stage; being its main advantage that the estimated coefficients are easy to interpret. This approach is useful if instruments are valid, which requires the fullfilment of two criteria: *(i) instrument relevance* ($cov(Z, Y) \neq 0$) and *(ii) instrument exogeneity* ($cov(\epsilon, Z) = 0$). Nevertheless, the trade-off between instrumental variable exogeneity and its predictive strength poses challenges to inference when using the TSLS approach since a higher degree of exogeneity often comes at the cost of weaker instruments. On the other hand, stronger instruments face a higher risk of being endogenous.[8]

Statistical machine learning methods designed to exploit non-linearities and inter-dependencies among predictors are more standard in other research areas such as computer science. In many cases, and depending on the research question, the goal of the machine learning method is not to identify individual parameters and interpret them, but to fit the complete function f that represents the relationship between the dependent and independent variables of interest (in this case, the link between Z and Y). These methods outperform linear regression analysis in terms of predictive ability, in the presence of nonlinearities between the variables of interest, or when interaction effects are important (James et al., 2013).

Given that the aim of this study is not to identify the effect of instrumental factors Z on WPE, but rather to find a good prediction of the spatial and time dynamics of WPE scores based solely on exogenous information, we follow the RF-TSLS approach used by Atchen and Lessman (2020). This approach is particularly suitable for our goal of performing causal inference, as it addresses the trade-off between instrument exogeneity and instrument strength. Another advantage of the Random Forest approach is that, given a set of predetermined characteristics Z, where all variation occurs over the cross-sectional domain, the function $\hat{f}$ can produce spatially time-varying predictions of empowerment outcomes $\hat{Y}_{it}$. Thus, in our empirical analysis we opt for a two-step method to investigate the impact of WPE on inequality. The first step uses Random Forests developed by Breiman (2001) to produce an estimate of $\hat{Y}^{RF}$ (i.e, it estimates Equation (3)), whereas the second step is the IV regression itself based on the TSLS algorithm (Equations (2) and (1)).

However, as discussed in Angrist and Pischke (2008), if a theoretical justification is absent, the instruments may simply be an artifact of the dataset, increasing the probability of finding a spurious association between the variables of interest. Thus, we base our identification strategy on the theory and evidence that suggest that societies hold beliefs

[8] Stock et al. (2002) (p. 518) points out: "Finding exogenous instruments is hard work, and the features that make an instrument plausibly exogenous, such as occurring sufficiently far in the past to satisfy a first-order condition or the *as-if random* coincidence that lies behind a quasi-experiment, can also work to make the instrument weak."

about women's roles and have rules of social behavior that are deeply rooted in cultural values that were originated in pre-industrial socio-economic arrangements. In this regard, there is evidence that despite changes in economic conditions, ancestral cultural norms of subsistence modes and marriage traditions have persisted over time, resulting in significant socio-economic and political consequences, driving current differences in women's socio-economic status (Alesina et al., 2013). Thus, we use exogenous data on ancestral cultural norms of gender roles to predict contemporary WPE scores. These IV's are correlated to women's status but are not directly associated to the contemporary level of income inequality. In fact, it is very unlikely that these socio-cultural characteristics will exert any effect on inequality other than through their impact on WPE. However, even if this were the case, in our TSLS regressions we also control for many potential variables that correlate with both inequality and WPE, which decreases the likelihood of not having blocked alternative causal pathways running from our Random Forest forecast ($\hat{Y}^{RF}(Z)$) towards our measurement of income inequality.

We now provide the rationale for using historical societal traits Z as exogenous sources of variation in this context, and we describe the procedure to construct our instrument $Y^{RF}(Z)$ using the Random Forest approach.

4.1 Building the instrument: Ancestral cultural norms of gender roles

Ancestral subsistence modes and traditional agricultural practices are linked to current contemporary beliefs around the role of women in society. In past societies, the increased presence of women in agricultural subsistence activities gave them greater economic value and fostered the development of more gender equal social norms (Boserup, 1970). Alesina et al. (2013) tests the hypothesis developed by Boserup (1970) finding that differences in traditional agricultural practices, such as the use of plough and non-plough (shifting cultivation), are relevant to explain the gender division of labor, and that these differentials promoted long-lasting unequal gender norms. Specifically, they find that female descendants of societies that engaged in plough agriculture are less likely to participate in activities outside the home, such as the workplace, politics, and entrepreneurial activities (Brodeur et al., 2020).

The intuition of this result is that in pre-industrial societies employing the plough in agriculture (which requires substantial physical strength), men had a comparative physiological advantage over women, which in turn led to a gender-based specialization of production where men tended to work in activities outside the home, while women specialized in activities within the home. This division of labor had the effect of generating long-lasting cultural norms and views about the role of women in society, that contributed to women's being relegated to the domestic sphere. To capture cross-country differentials in traditional agricultural practices we use an indicator of the use of ploughs, taken from Alesina et al. (2013). These authors use information from the Ethnographic Atlas database to develop a dummy variable for traditional plough-based agriculture that takes the value one if the plough was present and zero otherwise.

According to the literature, traditional marriage practices also prove to be a key factor in shaping gender roles (Ashraf et al., 2020;Brodeur et al., 2020). We consider two main marriage variables that have received considerable attention in recent research: (i) post-marital residence rules and (ii) marriage payments. Post-marital residence rules distinguish between two main social rules that define the place where married couples live after marriage, patrilocality and matrilocality. In patrilocal societies, the married couple resides with or near the husband's parents, whereas in matrilocal societies the couple settles with or near the wife's parents. Previous empirical studies have found, in general, greater gender differentials in parental investment in child quality in patrilocal societies (Malhotra et al., 1995). Our data on the degree of matrilocality or patrilocality of societies comes from Alesina et al. (2013), who develop two indicators that measure the proportion of a country's ancestors with patrilocal and matrilocal post-marital residence rules.

As regards marriage payment systems, the bride price is the most common marriage practice that consists of either a cash payment or an in-kind transfer that is made at marriage from the groom or his family to the bride's parents (Giuliano and Nunn, 2018). Empirical evidence on the consequences of this tradition is inconclusive. On the one hand, this payment can improve girls' years of schooling, as it incentivates parents to invest in their daughters' education (Ashraf et al., 2020). On the other hand, this cultural practice is also related to the acquisition of women's labor rights and reproductive ability and, therefore, can lead to the commodification of women (Anderson, 2007). In addition, as explained in Brodeur et al. (2020), bride-price payment can incentivize parents to sell their daughters early, increasing the probability of early marriage of women, with negative impacts on their education and lifetime reproductive health. We use data on bride price and other transaction practices at marriage (bride-service, token bride-price, female exchange and dowry) to capture cross-country differences in marriage customs. The data on these variables are taken from the database developed by Giuliano and Nunn (2018).

Our last group of historical predictors considers pre-industrial historical family features, given that these might be correlated to contemporary inequality in gender roles and gender gaps in employment. In particular, we capture variation in family structures with three different indicators: polygyny, nuclear family, and extended family types. In this regard, there are empirical studies suggesting that women living in a polygynous union and in extended families have less autonomy, face a higher levels of physiscal, sexual or emotional violence, exhibit worse educational outcomes, and have lower employment rates when compared to those in Western nuclear families (see Pesando, 2021 for a review). To the contrary, in societies where nuclear families predominate, there is a more equal distribution of employment and housework between men and women (Algan et al., 2005) and lower education gender gaps (Bertocchi and Bozzano, 2015). Definitions, descriptive statistics, and data sources of the instrumental variables described above are reported in Table (2).

INSERT TABLE (2) ABOUT HERE

4.2 Forecasting women's political empowerment with Random Forests

We now investigate the relationship between ancestral cultural norms of gender roles and contemporary women's empowerment using a Random Forest approach (Breiman, 2001). Random Forest is supervised machine learning classifier algorithm based on averaging individual regression trees to produce predictions, which assumes a model of the form $Y = \sum_{j=1}^{p} c_j 1_{Z \in R_j}$ where $R_1, \ldots, R_p$ represent divisions of the predictor space. The general idea of a regression tree is to partition the sample data according to the values of the different explanatory variables, thus creating more homogeneous subgroups/regions R_j of observations of the dependent variable. The regression tree is constructed through an iterative process that splits the data into nodes or branches into smaller groups. The regression tree is composed of different branches, internal nodes and terminal leafs or nodes (see James et al., 2013).

The functioning of trees can be explained with the following example. Initially, all observations are placed in the same group. Next, the data are allocated into two partitions/branches, using every possible split point on a random sample of the available predictors. To start the process of partitioning the predictor space, the tree algorithm may divide the data into two subregions (branches) that deliver - according to one of the randomly selected explanatory factors (like the use of ploughs) - the greatest possible group homogeneity in actual WPE. This can occur if WPE scores are efficiently divided by whether the ancestors in a country used the plough in agriculture or not. This first partition creates an internal node that is further partitioned based on the value s of another variable (for example, patrilocality) which will attempt to divide the subsample into the most homogeneous subgroups possible. This procedure is repeated many times, and the algorithm only stops branching the data when either a predetermined number of observations within a terminal leaf is reached or when the number of internal nodes grows up to a predetermined threshold. In the final forecast, an observation receives the mean value of the terminal leaf in which it ended up being classified.

One key feature of Random Forests is that the regression trees are trained independently, and the forecasts of each tree are then averaged to generate the final predictions. The steps of the Random Forest approach are described in James et al. (2013) and Yoon (2021) as follows:

Step 1. For $m = 1$ to M, where M denotes the number of iterations:

- (1.a) Stack the observations of Y_{it} and Z_{it} over time to produce $NT \times 1$ and $NT \times p$ matrices $\mathbf{Y}, \mathbf{Z}$ and create a bootstrapped sample set $\tilde{Y}, \tilde{Z}$ from the training data.
- (1.b) Grow a Random Forest tree T_m for the bootstrapped data $(\tilde{Y}, \tilde{Z})$ by repeating the

following steps until the minimum leaf size of observations n_{min} is reached:

1.b.1 Select randomly l predictors from the set of p explanatory variables in $\tilde{Z}$

1.b.2 Pick the best predictor z_h and split point s among the l predictors

1.b.3 Split the parent leaf into two daughter leaves in such way that it minimizes the Mean Squared Error (MSE), defined as follows:

$$MSE\left(z\right)=\frac{1}{n}\left[\sum_{n=1:z_n\in R_{1,(h,s)}}^{NT}\left(\tilde{Y}_n-\hat{Y}_{R_1}\right)^2+\sum_{n=1:z_n\in R_{2,(h,s)}}^{NT}\left(\tilde{Y}_n-\hat{Y}_{R_2}\right)^2\right] \tag{4}$$

where Y_n is the observed value of WPE and $\hat{Y}_{R_j}$ is the predicted value for the training observations within the *h-th* division of the predictor space (i.e, $R_{1,sh}=\left[\tilde{Z}|z_h<s\right]$ and $R_{2,sh}=\left[\tilde{Z}|z_h\geq s\right]$ are the regions/subdivisions that reduce the most the sum of squared residuals.[9]

Step 2: Average the forecasts of the individual trees $(T_m)_{m=1}^{M}$:

$$\hat{Y}^{RF}=\frac{1}{M}\sum_{m=1}^{M}\left(T_m\left(z\right)\right) \tag{5}$$

In other words, in building a Random Forest, at each split in the mth-tree T_m, the algorithm is not allowed to use most of the ancestral predictors of size p, thus decorrelating the forecasts of individual trees. This precludes the algorithm to produce trees that are very similar to each other in cases where there is a very strong predictor. On average, because we only allow a random subset of size $l=\sqrt(p)=3.4$ at each split, only a fraction $\frac{p-l}{p}$ of the splits will not consider the strong predictor, and so other predictors will have more of a chance. The effect of decorrelating the forecasts of individual trees makes the resulting aggregate prediction more robust, especially when forecasting out-of-sample.

Also note that it is possible to grow highly parameterized trees that produce almost perfect fits by *(i)* using a large number of branches/splits in each tree or *(ii)* reducing the minimum leaf size n_{min} allowed. However, this configuration would lead to overfit, and

[9] Here, $[Z|z_h<s]$ refers to the subregion of the predictor space where the predictor Z_h has a value lower than s.

because our prediction would replicate the original data, this would cause our instrument to become endogenous (Atchen and Lessman, 2020). To avoid such a situation, we follow the convention of restricting the training data to 63% of the sample, whereas the remaining 37% is considered as an *out-of-bag sample* (OOB) (Atchen and Lessman, 2020) . In addition, to deal with potential over-parameterization concerns, we only allow for a maximum of $2\sqrt{NT}$ branch nodes in each individual tree and we set the minimum leaf size n_{min} to 10 observations. Finally, the size of individual trees making up the Random Forest is set to $M = 5,000$.

In Table (3) we report the results of our prediction analysis using both standard regression models and the Random Forest approach for each of the indicators that comprise the WPE index. We evaluate the forecasts of linear regression and Random Forests using three different accuracy metrics: *(i)* the R-squared; *(ii)* the Mean Absolute Percentage Error (MAPE); and *(iii)* the Root Mean Squared Percentage Error (RMSPE). These forecast accuracy metrics are calculated as follows:[10]

$$
\begin{aligned}
&R^2 = \\
&MAPE = \frac{1}{NT}\sum_n \frac{\left|Y_n - \hat{Y}_n\right|}{Y_n} \\
&RMSPE = \sqrt{\frac{1}{NT}\sum_n \left(\frac{\left(Y_n - \hat{Y}_n^{RF}\right)}{Y_n}\right)^2}
\end{aligned}
\tag{6}
$$

As shown in Table (3), the Random Forest approach is superior to the linear regression framework when forecasting all the empowerment indexes as well as for all the accuracy metrics considered. Looking at the results of the R-squared, we find that the Random Forest approach captures 71.9% of variation of the WPE over space and time. The quality of the fit is even higher for the WCL and WCSP components, ranging between 78% and 75.9%, respectively. As regards the WPP, the quality of the forecast is relatively modest, as it captures only 50% of the variability observed in the data. However, these results imply

[10]Besides the R-squared, which is the common goodness-of-fit metric of empirical models in economics, we employ two metrics widely used in forecasting. The RMSPE is a quadratic scoring rule that gives a relatively higher weight to large errors than the MAPFE does. This means the MSFE is most useful when large errors are particularly undesirable. However, we also report the MAPE, which is among the most commonly employed metrics in forecasting due to its interpretability.

that Random Forests outperform linear regression by a factor of about 1.8 to 2.2 times, depending on the index, as they capture much successfully the differences across countries and time periods. As for the MAPE, we find that when forecasting the WPE with Random Forests, the average error is 11.6%, whereas linear regression produces a MAPE of 17.3%. When looking at performance across the components, we find that the reduction in the size of the forecast error with respect to linear regression is in the range of 20% to 42%, producing significantly lower MAPEs. The entries in the table that correspond to the results of the RMSPE tells us the same story: Random Forests produce much better forecasts than regression models.[11]

INSERT TABLE (3) ABOUT HERE

To complement previous results, Table (4) provides information on the relative importance of the various pre-industrial social characteristics when forecasting women's political empowerment. The term 'relative importance' is defined as the contribution of each variable to the prediction of women's empowerment both by itself and in combination with other predictor variables. This definition clearly differs from classical statistical inference, where a variable can be considered very meaningful even when it explains a small proportion of predictable variance (Johnson and LeBreton, 2004). To assess relative importance, within the linear regression framework we employ the following R^2 variance decomposition measures: (i) the LMG metric (see Gromping, 2007); (ii) the Proportional Marginal Variance Decomposition (PMVD) metric proposed by Feldman (2005); (iii) the Genizi (1993); and (iv) CAR scores (Zuber and Strimmer, 2010; Zuber and Strimmer, 2011). The assessment of predictor importance within the Random Forest approach is based on the Mean Decrease Impurity (MDI) and the Permutation Importance Metric (PIM) (Breiman, 2001).[12] Colored entries in Table (4) correspond to the "top predictors" depending on the specific relative importance metric under consideration.

[11]In Figures (A1) and (A2) in the Appendix, we plot the fit produced by the conventional linear regression framework and the Random Forest to allow for a visual inspection when predicting WPE index scores using ancestral data.

[12]For more details on the computation and interpretation of the various relative importance metrics in Table (4), see Appendixes D1 and D2.

INSERT TABLE (4) ABOUT HERE

As can be observed, both linear regression and Random Forest techniques suggest that key pre-industrial societal characteristics to predict actual WPE scores include the extent to which societies *(i)* practiced the bride-price and *(ii)* had patrilocal post-marital residence rules. They also agree in attributing a low importance to family structures. However, the two methods present some differences in the way they rank and attach importance to other factors. Relative importance metrics obtained using linear regressions point to a significant role of additional marriage payment systems features (i.e., token bride-price and the dowry), whereas the PIM and MDI metrics calculated from the random forest give a higher importance to traditional agricultural practices such as the use of a plough. This latter result is more in line with the theory of Boserup (1970) and the findings of Alesina et al. (2013). Taken together, these findings suggest that most of the information needed to construct a strong instrument of current WPE comes from the differences in pre-industrial post-marital rules, marriage payments, and agricultural practices, while the different patterns of family structure are less relevant to this purpose.

5 RESULTS AND DISCUSSION

5.1 Baseline results

We estimate different versions of the model specification given by Equation (1) using data for 142 countries during the period 1990-2019. The TSLS results with heteroskedasticity robust standard errors are reported in Columns (4) to (7) of Table (5). In addition, for the purposes of comparison, we also present the results when the same specifications are estimated using OLS with heteroskedasticity robust standard errors (Columns 1 to 3). Specifically, the OLS and TSLS results reported in Table (5) correspond to (i) the pooled panel data model (which assumes $\alpha_i = \alpha_t = 0$) in Equation (1); (ii) the "between-effects" panel data model based on the regression on the group means; and (iii) the panel data model including both country-fixed effects and time-period fixed effects (i.e, the "within-effects").

These last two specifications are especially useful in this context as they allow us to better understand which drivers exert a higher impact on the cross-sectional variability and which of them act on the within-country time variation of income inequality, respectively.

We begin our discussion of results by noting that the findings in Table (5) include several important diagnostic tests of the RF-TSLS approach. For TSLS regressions in Columns (4) to (7), we present the F-statistic for the joint significance of excluded instruments for the first stage of each model. This test establishes the strength of the variables being used to instrument for WPE. However, to assess the strength of our instrument, we depart from the rule of thumb proposed by Staiger and Stock (1997)) of $F > 10$, as recent studies of Andrews et al. (2019) and Young (2022) suggest that applied researchers should increase considerably that threshold to perform valid inferences. In this regard, the results of simulation studies in Young (2022) and Kean and Neal (2021) point to the use of a new F-test statistic threshold such that $F > 105$, which should guarantee that t-tests in TSLS overperform OLS estimates. Thus, we take this F-test value as the new benchmark to guide us in the assessment of the strength of our instruments.

Secondly, note that in the TSLS specifications presented in Columns (4) to (6), we use only our instrument of WPE based on ancestral cultural traits and the Random Forest algorithm, whereas in Column (7), together with our core instrument we include its spatial lag (i.e., the neighbors' average Random Forest prediction of WPE calculated with a 5-nearest neighbors' row standardized spatial weights matrix). We add this instrument to the specification of Equation (2) following the strand of spatial econometrics literature on STSLS/GMM estimation (see Kelejian et al., 2013), as this allows us to perform the Sargan/Hansen J test on instrument validity.[13] [14]

Finally, we carry out Durbin-Wu-Haussman endogeneity tests in all our TSLS specifications. The rejection of its null hypothesis implies that $cov(\epsilon|X) = 0$ can no longer be

[13]We proceed in this way as the Sargan/Hansen J test for over-identifying restrictions requires the number of instruments to be greater than the number of endogenous variables.

[14]The justification for employing this instrument, which captures differences in neighbor's average preindustrial societal traits, rests on the notion that as values and norms gradually permeate and spill across neighboring countries, they impact citizens' perspectives on the role of women in society and politics, which ultimately matters for women's status. As noted in Ezcurra and Zuazu (2022): "these spatial spillovers are more likely between neighboring countries, as they often share similar cultural and historical backgrounds and present closer informational links."

accepted and that we must estimate our model using IV instead of OLS.

INSERT TABLE (5) ABOUT HERE

The results reported in Columns (4) to (7) of Table (5) show that our RF-TSLS approach produces F-tests well above the 105 threshold in all cases and a non-significant Sargan/Hansen J test with p-value of 0.45 (in Column 7), suggesting that our instruments are both valid and strong. In addition, we find for the pooled and between-effects model specifications that the endogeneity of WPE is a concern and that TSLS results are preferable over OLS results. Nonetheless, in models already including country fixed and time-period effects, we cannot reject the null of consistency of the OLS estimates at the 5% level or lower. These results suggest that the endogeneity of WPE after controlling for unobserved heterogeneity by means of fixed effects is not strongly biasing the OLS estimates.

Turning to the main aim of the paper, our results indicate that the estimated parameter of WPE is negative and statistically significant at the 1% or 5% levels in most of the cases, the only exception being that of the OLS between-effects regression, where the negative effect is significant at the 10% level. Therefore, our estimates suggest that higher levels of WPE are associated with lower levels of income inequality, a result that is in line with the hypothesis presented in Section (2) and the preliminary evidence provided by Figure (3). More precisely, the results from our preferred TSLS specification in Column (7) suggest that increasing the index of WPE by one standard deviation reduces the Gini index of around 0.012 points. Let's consider the case of China as an example to better understand the magnitude of the effect of WPE on income inequality. China is a country that exhibits an intermediate degree of income inequality (Gini = 0.395), whereas its WPE index is below the sample median (WPE = 0.64). According to our findings, if China had a WPE index equal to that registered for example by New Zealand (WPE = 0.94), its Gini index would decrease by 6.5% (0.025 points). On the other hand, the between-effects model TSLS estimates in Column (5) suggest a causal effect that is even more pronounced, as the impact of WPE on cross-country inequality differences is much stronger. In this case, if China had the WPE index score of New Zealand, its average Gini index over the study period would have been at

0.327, very close to the averages of European countries like Spain (0.32) and Italy (0.33) or advanced Asian economies like South Korea (0.31) and Japan (0.31). These figures suggest that changes in WPE can exert a quantitatively relevant impact on both the cross-country differentials of income inequality and on its time-variation. Taken together, our results suggest that WPE is a robust driver of income inequality. However, the explanation of why some countries are more unequal than others, or why some countries may be experiencing a higher concentration of income over time, is far more complex. This is because of the factors driving variation over space and time are different from each other and, sometimes, a given variable may produce opposite effects depending on the type of variation under consideration.

5.2 Partial identification analysis

One issue with the RF-TSLS approach is that the identification of a causal effect of WPE on income inequality is necessarily conditional on our set of controls, since preindustrial societal traits may have additional effects on factors other than womens status (i.e, economic development). Nevertheless, we argue that once we account for differences in economic, social, and demographic attributes, the exclusion restriction is likely to be met. In any case, we acknowledge that we cannot be absolutely certain that we have eliminated all possible causal relationships between our instruments and the dependent variable, nor that our results are not influenced by confounding factors.

In this regard, a common practice for assessing sensitivity to omitted variable bias is to observe how the inclusion of different controls affects the magnitude of the estimated parameters. In a rigorous econometric study, Oster (2019) shows that omitted variable bias analysis should account for both coefficient and R-squared movements. Thus, we now adopt a different approach to evaluate whether unobserved heterogeneity may introduce a bias in our estimates that is large enough to change our research conclusions. Specifically, we use Oster (2019) partial identification method to assess (i) how relevant unobservables would have to be relative to our observable controls in X to explain away the entire causal effect of womens political empowerment on income inequality ($\hat{\delta}$), and to verify (ii) how the bias-adjusted coefficient (ψ^*) changes when assuming different maximum R-squared values.

Specifically, we compute the following statistics:

$$\psi^* = \psi_L - (\psi_S - \psi_L)\,\delta \left(\frac{R^2_{max} - R^2_L}{R^2_L - R^2_S}\right) \tag{7}$$

$$\delta = \left(\frac{\psi_L}{\psi_S - \psi_L}\right)\left(\frac{R^2_{max} - R^2_L}{R^2_L - R^2_S}\right) \tag{8}$$

where ψ^* stands for the bias-adjusted coefficient, ψ_S and R^2_S denote the corresponding coefficient estimate and the R-squared of a short regression (without controls) of inequality on WPE, and ψ_L and R^2_L are the coefficient estimates and the R-square of a long regression including all controls (observables). R^2_{max} stands for the maximum possible value assumed for R^2. If $\delta < 1$, selection on observables account for more than half of all selection whereas a value of $\delta = 1$ indicates that observable and unobservable variables are equally important. After assuming a value for R^2_{max}, the convention in the literature is to consider that the results are robust to confounding if $\delta \geq 1$.

The results of this procedure are reported in Table (6) for our preferred specification of Table (5) including both country-fixed effects and time-period fixed effects. As observed, for an R-squared of 0.975, which is very close to that of the baseline model, the degree of selection on unobservables relative to observables is about 3.09. This suggests that in order to explain away the impact of WPE on income inequality, unobservables would have to be 3.09 times more important than the set of observable regressors in X. Although for higher R_{max} thresholds this quantity falls, even in the most stringent case of assuming $R_{max} = 1$ we find that $\hat{\delta} > 1$. As refers to the bias-adjusted point estimate, we find that it is always negative and that identified bounded intervals never contain the possibility of a zero effect. Thus, this partial identification analysis suggests that potential biases arising due to confounding factors are not strong enough to modify our main result of WPE driving down income inequality.

INSERT TABLE (6) ABOUT HERE

5.3 Robustness checks

We now investigate whether our finding that WPE is a key driver of income inequality reduction is robust to changes in the set-up of our analysis. One concern with previous static models, which only account for heterogeneity, is that inequality might be quite persistent over time, which may require the inclusion of a time-lag of this variable in the right-hand side of the specification. Thus, we consider a dynamic panel data specification of inequality, estimated using the system-GMM approach of Blundell and Bond (2000):

$$I_{i,t:t+5} = \alpha_i + \gamma_t + \rho I_{i,t-5:t} + \psi Y_{i,t:t+5} + \sum_j \beta_j X_{j,t:t+5} + \epsilon_{i,t:t+5} \tag{9}$$

The system-GMM estimator combines moment conditions for the model in levels with moment conditions for the differenced version of the model. All predictors $[I_{t-5:t}, Y_{t:t+5}, X_{t:t+5}]$ are instrumented with their second and higher order time lags together with $[\Delta I_{t-5:t}, \Delta Y_{t-5:t}, \Delta X_{t-5:t}]$ as additional instruments in the levels equation. This model is useful as it allows us to capture the inertia in the distribution of income while controlling for other sources of endogeneity.

However, a weakness of this approach is that it ignores weak cross-sectional dependence. In view of this, our third and fourth specifications focus on the issue of cross-sectional dependence in the data. Simple Moran's I statistics reveal that income inequality exhibits important spatial dependence (I=0.7, zstat=35.4, pval=0.00). This cross-sectional dependence may emerge through cross-country interactions among the error term, the dependent variable, and/or the explanatory variables. As explained by Kelejian et al. (2013), if these interactions occur through the dependent variable, non-spatial estimates might be biased. Therefore, we consider both a spatial error specification and a more general Spatial AutoRegressive model with AutoRegressive disturbances (SARAR) of order (1,1):

$$I_{i,t:t+5} = \alpha_i + \gamma_t + \psi Y_{i,t:t+5} + \sum_k \beta_k X_{k,i,t:t+5} + \upsilon_{i,t:t+5} \tag{10}$$

$$I_{i,t:t+5} = \alpha_i + \gamma_t + \delta \sum_j w_{ij} I_{j,t:t+5} + \psi Y_{i,t:t+5} + \sum_k \beta_k X_{k,i,t:t+5} + \upsilon_{i,t:t+5} \tag{11}$$

where the disturbance term is spatially autocorrelated $\upsilon_{i,t:t+5} = \rho W_n \upsilon_{j,t:t+5} + \epsilon_{i,t:t+5}$ and ϵ_t is an $N \times 1$ vector of heteroskedastic disturbances, and w_{ij} represents the element of an $N \times N$ non-negative matrix W of known constants describing the connectivity among countries the sample. These two spatial specifications are estimated using the panel STSLS-GMM estimator developed by Kelejian and Prucha (2010). We use as instruments $H_{i,t:t+5} = [\hat{Y}^{RF}_{i,t:t+5}(Z_i), \sum_j w_{ij} X_{j,t:t+5}]$.

Table (7) reports the results obtained when using these alternative estimation approaches. Column (1) reports the results of the dynamic panel specification using the system-GMM estimator. As observed, the estimated coefficient of -0.0733 is significant at the 1% level, with a weakly significant time lag. The consistency of this parameter estimate depends on whether the instruments are valid in this context. To assess the validify of the instruments we implement the Sargan over-identifying restrictions test and check for the serial correlation of the error term. Given that our model contains only one time lag of the dependent variable in the regression ($I_{t-5,t}$), one expects first-order serial correlation in the error term but not second-order serial correlation, as this would suggest the model is miss-specified. We find that the instruments used are valid and that there is only weak first-order serial correlation in the first-order residuals. Overall, these results suggest that controlling for the time-dynamics in income inequality does not affect our previous findings.

Looking at the spatial specifications in Columns (2) and (3), we find that the parameter estimate of WPE in the spatial models ranges from -0.0680 to -0.0707. Thus, the overall negative link seems to be robust to the presence of spatial interdependence in inequality outcomes. Nevertheless, one should note that in the SARAR (1,1) specification, a change in a single country i associated with any given explanatory variable will affect the dependent variable in the country itself (*direct effect*) and potentially affect other countries indirectly (*indirect effect*). The sum of both effects leads to the so-called *total effect*. The results are presented in Table A1 in the Appendix, where indirect effects are shown to be quite substantial and amplify the observed negative effect with respect non-spatial models. Given that the total effect remains negative and significant, the qualitative evidence does not change. Taken together, the results obtained in all these alternative specifications corroborate the existence of a statistically significant and negative relationship between income inequality and WPE.

INSERT TABLE (7) ABOUT HERE

Finally, note that our results are also robust to a variety of changes to the set-up of our analysis in addition to those discussed throughout this section (i.e. income dynamics and the role of space). In particular, we further check whether our results may be biased by the presence of (i) the presence of outliers and influential observations and (ii) the specific definition of income inequality employed through the paper. In order to save space, a brief discussion of each additional robustness check and its results is presented in Appendix E and Tables E.1 and E.2.

5.4 Zooming in the transmission mechanism

5.4.1 Which component of WPE index is driving the results?

As explained in Section (3.2), the WPE index relies on three components (women's civil liberties, women's civil society participation, and women's political participation) that are designed to capture different aspects of WPE. Next, we examine each of these separately, so as to determine which component drives the effect of the WPE index on income inequality outcomes. The results are shown in Table (8). As observed, the component that seems to be driving the negative effect at the aggregate scale is that of political participation (WPP), which is again negative and significant at the 5% level with a parameter estimate value of -0.0605. In this regression, the TSLS diagnosis tests reveal again that endogeneity might bias OLS and that our instruments are both strong and valid. We also find that the dimensions of empowerment related to the civil society participation of women or to civil liberties do not seem to exert any statistical effect on income inequality. This latter result suggests that the impact of women's empowerment on the distribution of income mainly occurs via legislation or policies, which is in line with the theoretical considerations laid down in Section (2).

INSERT TABLE (8) ABOUT HERE

5.4.2 The role of redistribution as a transmission channel

So far, our empirical analysis has shown that WPE decreases the levels of income inequality and that this occurs via parliamentary representation and legislation or policies. As explained in Section (2), the most likely transmission channel of females political empowerment on income inequality is through progressive redistributive policies that increase taxes to the rich and extend the reach of welfare spending policies.

To measure progressive redistribution, we calculate a new variable using the SWIID: the Gini coefficient based on gross income (i.e., before taxes and other forms of redistribution are considered). This gross Gini index measures income inequality at the market level pre-government intervention. We operationalize our measure of redistribution as $R = \frac{(Gini_{Gross} - Gini_{Net})}{Gini_{Gross}}$, so that higher values of R reflect a stronger variation in the distribution of income after intervention (i.e, the numerator increases the lower the net inequality compared to gross inequality).[15] To examine if the observed effect of WPE on inequality is explained by redistribution we proceed as follows. First, we provide evidence that both WPE and WPP exert a positive effect on the degree of redistribution of income during government intervention. In column (1) of Table (9) we report the estimates of the aggregate WPE index on redistribution, whereas column (2) reports the effect of WPP. The two models are estimated using the RF-TSLS approach outlined before, as both redistribution and our proxies of female empowerment may display reverse causality. We find that in both cases the coefficients are negative and statistically significant. Secondly, in column (3), we provide the results of redistribution on income inequality within a heteroskedastic panel setting including fixed and time-period effects. As observed, a higher level of redistribution reduces net income inequality. Finally, in columns (4) and (5) we regress inequality on WPE (and on WPP), the transmission variable (redistribution) and the set of controls, using again the RF-TSLS approach. We find a negative and statistically significant effect

[15]This proxy measurement of redistribution based on the variation of the market Gini and the net Gini is similar to that employed by Berg et al. (2018) and Krieger and Meierrieks (2019). We employ this data given that the geographical and time coverage of other proxies of redistributive policies like tax revenues, transfers received by households, social security benefits or social expenditure is much lower.

of both WPE/WPP and redistribution. In this regard, a feature that stands out from this analysis is that the coefficients of WPE and WPP, although negative, are closer to zero than in column (7) of Table (5) (-0.068 vs -0.081) and in column (3) of Table (8) (-0.052 vs -0.059), respectively.

INSERT TABLE (9) ABOUT HERE

Overall, these results show that (i) WPE affects redistribution in a statistically significant way and that (ii) redistribution influences income inequality. Furthermore, the smaller coefficients of the impact of WPE and WPP on income inequality after controlling for the degree of redistribution, and the significant effect of redistribution (netting out WPE and WPP) suggest that (iii) the effect of WPE/WPP on income inequality is (partly) transmitted via redistribution. Although these results should be interpreted with caution, as they are only suggestive of the underlying mechanism, overall, they tend to confirm some of the theoretical intuitions provided in Section (2).

6 CONCLUSIONS

Over recent decades, the political empowerment of women has increased considerably and, as the literature points to a gender bias in preferences and political attitudes, a greater presence by women does indeed matter for public policy. Women exhibit more collaborative, generous, and altruistic behavior in economic decision-making as well as a greater preference for income redistribution and public spending on social policies. Therefore, in a context of increasing political empowerment of women, one would expect that their greater presence among political elites would translate into a reduction in income inequality.

To test this hypothesis, we have drawn a balanced sample of 142 countries for the period 1990-2019. Providing accurate empirical estimates of the effect of WPE on inequality is a notoriously difficult task, chiefly because this relationship is highly simultaneous in nature. To address this endogeneity problem, we use a Random Forest Two-Stage-Least-Squares (RF-TSLS) panel data model. We base our identification strategy on previous literature which suggests that societies possess certain beliefs about women's roles in the society and rules of social behavior that are deeply rooted in cultural values originated in pre-industrial socio-economic arrangements. Accordingly, we use exogenous data on ancestral and traditional cultural norms of gender roles (i.e. traditional agricultural practices, marriage practices and family features) to predict current WPE scores, as these variables are expected to be correlated to WPE but not to the actual figures of income inequality.

We use both Random Forest techniques and the standard linear regression approach to build the instrument and evaluate the resulting forecasts using three different accuracy metrics. The results indicate that (i) the Random Forest prediction outperforms the linear regressions, as it captures the 72% of variation of the WPE over space and time with a lower forecast error, and (ii) most of the information needed to construct a strong instrument of current WPE scores comes from differences in three key pre-industrial societal characteristics: patrilocal post-marital residence rules, marriage payments (bride-price), and agricultural practices (the use of ploughs).

In a second step, we use panel IV regressions, finding that WPE is one of the key robust drivers reducing income inequality over space and time. This result also holds in both dynamic and spatial panel data model specifications, indicating that our findings are robust to the presence of spatial interdependence and time persistence in inequality outcomes. Additional robustness checks allow us to confirm that our findings are not driven by unobserved heterogeneity and that they are robust to omitted variables bias and sample selection bias.

A disaggregated analysis of the three components of the WPE index on income inequality indicates that the component that seems to be driving the negative effect at the aggregate scale is the political participation index (WPP), as we find that the dimensions of womens political empowerment related to the participation of women in civil society (WCSP) or to civil liberties (WCL) do not exert a statistically significant effect on income inequality. Finally, we provide evidence of redistribution being a transmission channel through which female political empowerment operates.

Overall, these results suggest that the impact of WPE on the distribution of income occurs mainly via legislation or the implementation of public policies and provide an additional argument for countries to promote WPE, which is an end in itself but also a means to achieve more egalitarian income distributions. Encouraging countries to lead the process towards women's political leadership would be particularly effective in developing and middle-income countries, as they exhibit a combination of low levels of WPE and high income inequality figures.

An additional avenue of research worth pursuing is to verify whether there are nonlinearities or threshold effects where the impact of women in politics becomes apparent.

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Figures and Tables

Figure 1: Average Gini index, 1990-2019

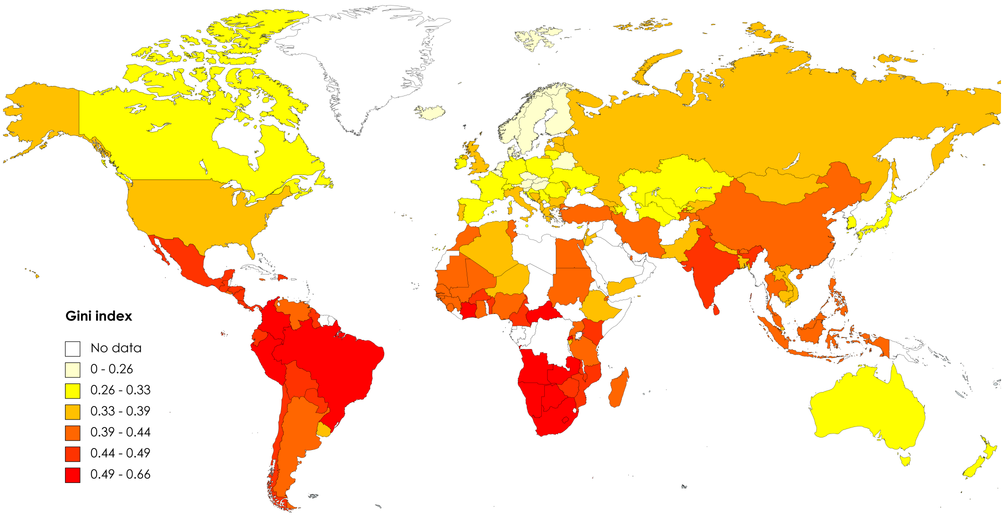

Figure 2: Average women's political empowerment index, 1990-2019

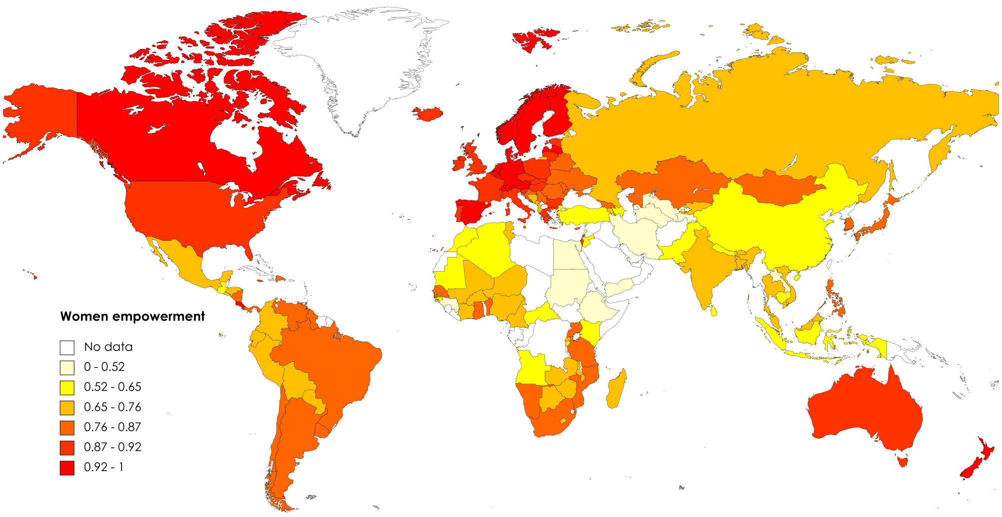

Table 1: Descrptive statistics, data sources, and definitions of the variables

Variable	Mean	Std. dev	Missing data (%)	Data Source	Definition
Dependent variable					
Income inequality	38.90	8.62	7.6%	SWIID	Gini index calculated using data on household disposable income (post taxes and transfers).
Women's empowerment					
Women's political empowerment (WPE)	0.738	0.167	0.82%	V-DEM	Composite index that consists of three dimensions: women's fundamental civil liberties, women's participation in civil society, and women's participation in politics.
Women's civil liberties (WCL)	0.722	0.17	0.82%	V-DEM	Freedom of choice for women, including: (i) freedom of domestic movement, (ii) freedom from forced labor, (iii) property rights, and (iv) access to justice.
Women's civil society partic. (WCSP)	0.715	0.180	0.82%	V-DEM	Ability to engage in public debate freely, including: (i) freedom of discussion, (ii) participation in civil society organizations, and (iii) representation of women in the ranks of journalists.
Women's political partic. (WPP)	0.794	0.190	0.82%	V-DEM	Women's engagement in political decision-making, including: (i) legislative presence of women and (ii) the political power distribution by gender indicator.
Economic Development					
GDP per capita	8.34	1.51	0.00%	IHME	Natural logarithm of GDP per capita (constant US $ 2020).
Urbanization	55.34	22.36	0.00%	WDI	Urban population (% of total population) .
Education	7.71	3.49	0.00%	IHME	Age Standardized Years of education per capita (population > 25 years old).
Financial access	0.25	0.26	1.40%	IMF	Average of the financial institutions' depth and financial institutions' access composite indexes.
Demographics and Institutions					
Liberal democracy	0.44	0.27	0.82%	V-DEM	Composite indicator that measures the extent to which the ideal of liberal democracy is achieved protecting individual and minority rights against the tyranny of the state and the tyranny of the majority.
Muslim	0.24	0.35	0%	WRD	Share of population that follows the Islam religion.
Fertility lag	3.25	1.77	0.00%	WD	Five years lagged average fertility rate (births per woman): the number of children that would be born to a woman if she were to live to the end of her childbearing years in accordance with age-specific fertility rates.
Age dependency ratio	63.91	19.08	0.00%	WDI	Age dependency ratio (% of working-age population) calculated as the ratio of dependents (people younger than 15 or older than 64) to the working-age population.
Technology and Globalization					
Technology	0.76	0.83	0.00%	PWT	Defined as the product of the (i) ratio of the relative price of investment of country i to US times (ii) the ratio of the investment price deflator to the personal consumption expenditure deflator for the US.
Trade Globalization	52.64	17.71	0.00%	KOF	Composite indicator of trade in (i) goods and services, (ii) trade partner diversity, (iii) trade regulations, (iv) taxes, (v) tariffs, and (vi) trade agreements .
Financial Globalization	56.28	17.63	0.00%	KOF	Composite indicator of (i) foreign direct investment, (ii) portfolio investment, (iii) international debt, (iv) international reserves, (v) international income payments, (vi) investment restrictions, (vii) capital account openness, and (viii) international investment agreements .
Policy and economic conditions					
Government spending	0.19	0.08	0.00%	PWT	Share of government consumption (% of GDP) at current PPPs.
Unemployment rate	8.13	6.06	0.00%	ILOSTAT	Unemployment. total (% of total labor force) (modeled ILO estimate).

Notes: SWIID Standardized World Income Inequality Database, WDI World development indicators, IHME Institute for Health Metrics and Evaluation, V-DEM Varieties of Democracy, IMF International Monetary Fund, WRD World Religion's Database, KOF ETH Zurich/KOF, ILOSTAT International Labor Organization Statistics.

Table 2: Descrptive statistics, data sources, and definitions of the instruments

Variable	**Mean**	**Std. dev**	**Missing data** (%)	**Data Source**	**Definition**
Traditional agricultural practices:					
Plough	0.546	0.470	0.00%	Alesina et al. (2013)	Indicator variable that equals 1 if the plough was present, 0 otherwise.
Ancestral post-marital residence rules:					
Matrilocality	0.036	0.121	0.00%	Alesina et al. (2013)	Proportion of a country's ancestors with patrilocal post-marital residence rule (i.e. newly wed couple lives with/near the husband's family).
Patrilocality	0.693	0.408	0.00%	Alesina et al. (2013)	Proportion of a country's ancestors with matrilocal post-marital residence rule (i.e. newly wed couple lives with/near the wife's family).
Ancestral marriage payment systems:					
Bride-price	0.403	0.442	0.00%	Giuliano and Nunn (2018)	Fraction of a population's ancestors who traditionally practiced bride-price (i.e., transfer of money and/or other assets from the gromm and/or his parents to the bride's parents).
Bride service	0.026	0.100	0.00%	Giuliano and Nunn (2018)	Fraction of a population's ancestors who traditionally practiced bride service at marriage (i.e., labor or other services).
Token bride-price	0.063	2.212	0.00%	Giuliano and Nunn (2018)	Fraction of a population's ancestors who traditionally practiced token bride-price at marriage (i.e., small or symbolic payment only).
Female exchange	0.032	0.148	0.00%	Giuliano and Nunn (2018)	Fraction of a population's ancestors who traditionally practiced female exchange at marriage (i.e., transfer of a sister or other female relative of the groom in exchange for the bride).
Dowry	0.249	0.401	0.00%	Giuliano and Nunn (2018)	Fraction of a population's ancestors who traditionally practiced dowry at marraige (i.e., transfer of a substantial amount of property from the bride's relatives to the bride, the groom, or the kinsmen of the latter).
Pre-industrial family features:					
Polygyny	0.087	0.222	0.00%	Alesina et al. (2013)	Proportion of a country's ancestors with polygynous families
Nuclear family	0.266	0.352	0.00%	Alesina et al. (2013)	Proportion of a country's ancestors with nuclear families
Extended family	0.610	0.386	0.00%	Alesina et al. (2013)	Proportion of a country's ancestors with extended families

Notes: The plough variable has been constructed by Alesina et al (2013) using information coming from the FAOs Global Agro-Ecological Zones (GAEZ) v3.0 database. All the other variables have been calculated by Alesina et al. (2013) and Giuliano and Nunn (2018) using information from the Ethnographic Altas (variable v12 for post-marital residence rules; variable v6 for pre-industrial marriage systems; variable v8 for pre-industrial historical family features).

Figure 3: The association between WPE and income inequality

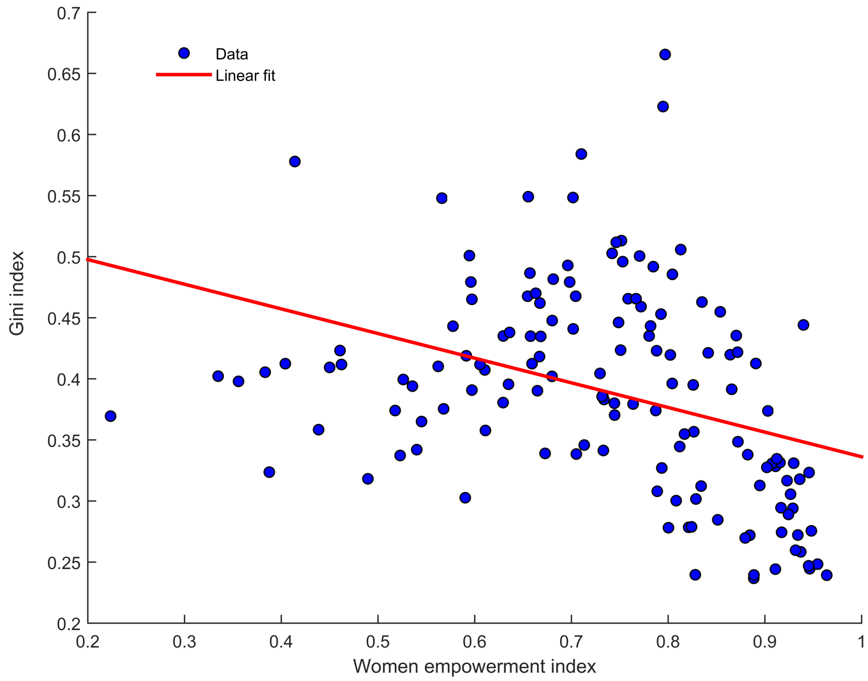

Table 3: Forecast Accuracy Metrics

	Women's Political Empowerment (WPE)	Women's Civil Liberties (WCL)	Women's civil society participation (WCSP)	Women's political participation (WPP)
	R-squared			
Random forest	0.719	0.781	0.759	0.500
Linear regression	0.401	0.356	0.368	0.259
	Mean Absolute Percentage Error (MAPE)			
Random forest	0.116	0.194	0.122	0.178
Linear regression	0.173	0.328	0.208	0.220
	Root Mean Squared Percentage Error (RMSPE)			
Random forest	0.201	0.554	0.233	0.373
Linear regression	0.288	0.848	0.355	0.429

Notes: Entries in this table represent average forecast accuracy calculated over the entire sample of countries and periods. Higher values for the R-squared represent a higher ability to capture variability in the data, whereas higher values of the MAPE and the RMSPE signify a deterioration of the accuracy of the forecast.

Table 4: Ancestral Characteristics: Importance Analysis

	Linear regression R-squared decomposition					**Random forest importance**	
	LMG	PMVD	Genizi	CAR	Average	MDI [$\times$1000]	PIM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bride-Price	49.0	60.2	49.0	57.4	53.9	0.187	4.758
Patrilocal	12.4	6.0	13.6	12.8	11.2	0.105	1.792
Token bride-price	9.4	13.9	9.7	9.1	10.5	0.097	1.480
Dowry	14.6	1.4	14.1	11.7	10.4	0.100	0.764
Extended family	4.5	5.8	4.9	6.3	5.3	0.108	1.679
Matrilocal	2.8	3.9	2.3	1.9	2.7	0.046	0.760
Polygyny	2.4	3.4	1.7	0.2	1.9	0.054	0.791
Nuclear family	2.5	1.8	2.9	0.3	1.9	0.086	1.589
Plough	1.6	2.4	1.0	0.0	1.3	0.173	3.485
Bride service	0.5	0.9	0.5	0.3	0.5	0.043	1.007
Female exchange	0.4	0.4	0.4	0.0	0.3	0.046	0.600

Notes: Entries in Columns (1) to (4) represent the percentage of variability in women's political empowerment scores that can be explained by a specific ancestral determinant given a particular R-squared decomposition metric. Column (5) reports the average across metrics. Entries in Columns (6) and (7) provide the Mean Decrease Impurity (MDI) and the Permutation Importance Metric (PIM) calculated within the random forest approach.

Table 5: Baseline results

	Pooled panel	Between effects	Fixed effects	Pooled panel TSLS	Between effects TSLS	Fixed effects TSLS	Fixed effects TSLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WPE	-0.0513**	-0.0972*	-0.0778***	-0.4213***	-0.2273**	-0.0808***	-0.0817***
	(-2.10)	(-1.67)	(-5.27)	(-7.24)	(-2.52)	(-4.28)	(-4.33)
GDP per capita(logs)	-0.0210***	-0.0172*	0.0131***	-0.0380***	-0.0231**	0.0132***	0.0132***
	(-5.24)	(-1.69)	(4.02)	(-7.48)	(-2.47)	(4.02)	(4.02)
Urbanization	0.0310*	0.0314	-0.0079	0.0474**	0.0356	-0.0078	-0.0077
	(1.94)	(0.82)	(-0.38)	(2.53)	(0.94)	(-0.37)	(-0.37)
Financial Dev.	0.0496***	0.0556*	-0.0291**	0.0527***	0.0572	-0.0292**	-0.0292**
	(3.69)	(1.71)	(-2.53)	(2.79)	(1.48)	(-2.53)	(-2.54)
Technology	-0.0071***	-0.0292**	-0.0005	-0.0052	-0.0255**	-0.0005	-0.0005
	(-2.81)	(-2.20)	(-0.71)	(-0.99)	(-2.07)	(-0.71)	(-0.71)
Financial Glob.	0.0013***	0.0017**	0.0004***	0.0014***	0.0017**	0.0004***	0.0004***
	(5.45)	(2.38)	(3.97)	(5.24)	(2.38)	(3.96)	(3.96)
Trade Glob.	-0.0014***	-0.0024***	0.0000	-0.0011***	-0.0023***	0.0000	0.0000
	(-6.73)	(-3.88)	(0.19)	(-5.14)	(-4.37)	(0.20)	(0.21)
Democracy	-0.0450***	-0.0262	0.0253***	0.1114***	0.0320	0.0262***	0.0265***
	(-2.73)	(-0.61)	(2.77)	(4.12)	(0.66)	(2.66)	(2.69)
Gov. spending	-0.1331***	-0.0923	-0.0155	-0.1642***	-0.0924	-0.0156	-0.0157
	(-4.49)	(-0.94)	(-1.30)	(-4.67)	(-0.90)	(-1.31)	(-1.31)
Education	-0.0066***	-0.0070**	0.0002	-0.0037***	-0.0061**	0.0002	0.0001
	(-5.53)	(-2.40)	(0.09)	(-2.90)	(-2.34)	(0.06)	(0.06)
Fertility lag	2.0311***	3.2340***	-0.4665	0.7936	2.9323**	-0.4777	-0.4810
	(3.96)	(2.33)	(-1.58)	(1.40)	(2.42)	(-1.60)	(-1.61)
Muslim	-0.0868***	-0.1064**	0.0009***	-0.0011***	-0.0026***	-0.0445*	-0.0445*
	(-11.53)	(-5.99)	(4.52)	(-2.70)	(-2.80)	(-1.85)	(-1.85)
Age Dependency	-0.0015***	-0.0026***	-0.0444*	-0.1187***	-0.1187***	0.0009***	0.0009***
	(-3.74)	(-2.24)	(-1.84)	(-12.11)	(-6.12)	(4.52)	(4.53)
Unemployment	0.4256***	0.5319***	0.0460*	0.3578***	0.5110***	0.0456*	0.0454*
	(11.57)	(5.74)	(1.90)	(6.64)	(4.20)	(1.87)	(1.87)
Country fixed effects	No	No	Yes	No	No	Yes	Yes
Time-period effects	No	No	Yes	No	No	Yes	Yes
Countries	142	142	142	142	142	142	142
Observations	852	852	852	852	852	852	852
R^2	0.54	0.64	0.97	0.41	0.62	0.97	0.97
No. Instruments	0	0	0	1	1	1	2
F-test (1st stage)				274.9	925.2	1307.1	659.1
Sargan							0.34
Sargan pval							[0.55]
DWH				363.28	49.71	0.01	0.02
DWH pval				[0.00]	[0.00]	[0.91]	[0.87]

Notes: The dependent variable in all regressions is the SWIID Gini index calculated over 5 years intervals from 1990 to 2019. All regressions include a constant (omitted). Robust-heteroskedastic tstats in parenthesis. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level. The instrumental variable employed in TSLS regressions in Columns (4) to (6) is the prediction of women's political empowerment based on ancestral societal characteristics $\hat{Y}^{RF}_{i,t:t+5}(Z_i)$ from Equation (3). Column (7) reports the results from a modified version of Equation (2) with two instrumental variables, such that the first stage regression is given by: $Y_{i,t:t+5} = \delta_0 + \delta_1 \hat{Y}^{RF}_{i,t:t+5}(Z_i) + \delta_2 \sum_{j \neq i} W_{ij} \hat{Y}^{RF}_{j,t:t+5}(Z_j) \sum_k \beta_k X_{k,t:t+5} + v_{i,t:t+5}$ where W_{ij} is a 5-nearest neighbor's geographical row-normalized matrix.

Table 6: Omitted variable bias and coefficient stability

	$\hat{\delta}$ for $\psi = 0$ given $R^2 max$	Bias-corrected ψ^*	Identified set
$R^2_{max} = 0.975$	3.09	-0.0763	[-2.29, -0.071]
$R^2_{max} = 0.99$	2.27	-0.0757	[-2.16, -0.062]
$R^2_{max} = 1.00$	1.93	-0.0754	[-2.08, -0.056]

Notes: Higher values of δ for $\psi = 0$ indicate greater robustness against confounding and omitted variable bias. A value of δ above 1 is deemed to be more robust while a value of $\delta < 1$ implies that the estimated treatment effect could vary more easily if unobservable variables were taken into account in the model. The identified set is bounded below by ψ_L (the coefficient with all controls included) and above by ψ^* (the bias-adjusted treatment effect), and is computed based on the R^2_{max} threshold specified in the row of each panel and $\delta = \hat{\delta}$.

Table 7: Robustness checks: Alternative estimation strategies

	Dynamic Panel (System-GMM) (1)	Spatial Error (STSLS-GMM) (2)	SARAR(1.1) (STSLS-GMM) (3)
Gini index (t-1)	0.2815*		
	(1.73)		
WPE	-0.0733***	-0.0763***	-0.0680***
	(-3.49)	(-4.318)	(-4.38)
GDP per capita(logs)	-0.0128***	0.0121***	0.0079***
	(-3.69)	(3.78)	(3.09)
Urbanization	0.0002*	0.001	-0.0073
	(1.79)	(0.089)	(-0.44)
Financial.Dev	0.0348***	-0.017	-0.0209**
	(3.41)	(-1.56)	(-2.46)
Technology	-0.0020*	-0.0001	-0.0005
	(-1.71)	(-0.24)	(-0.88)
Financial Glob.	0.0004***	0.0002**	0.0002***
	(2.63)	(2.27)	(2.65)
Trade Glob.	-0.0009***	0.0001	0.000
	(-3.69)	(0.93)	(0.05)
Democracy	-0.0048	0.0224***	0.0267***
	(-0.53)	(2.77)	(3.15)
Education	-0.0056***	-0.0001	-0.003**
	(-3.62)	(-0.02)	(-1.93)
Gov.Spending	-0.0618**	-0.0192*	-0.008
	(-2.41)	(-1.68)	(-0.87)
Fertility	0.0151***	-0.0308	-0.007
	(3.62)	(-0.10)	(-0.03)
Muslim	-0.0713***	-0.0638***	-0.048**
	(-4.24)	(-2.84)	(-2.34)
Age dependency	-0.0011***	0.0005***	0.0001
	(-3.52)	(2.77)	(1.10)
Unemployment	0.0030***	0.0252	0.0295
	(4.42)	(1.08)	(1.54)
Spatial error		0.355	-0.734***
		(25.54)	(-58.40)
Spatial lag			0.790***
			(16.96)
R-squared	0.990	0.975	0.979
Countries	142	142	142
Observations	852	852	852
AR(1)	1.75[0.08]		
AR(2)	0.74[0.45]		
F-stat (1st stage)		651.67	651.67
No Instruments	33	28	28
Sargan	11.68	10.25	7.49
Sargan p-val	[0.55]	[0.74]	[0.99]

Notes: The dependent variable in all regressions is the SWIID Gini index calculated over 5 years intervals from 1990 to 2019. All regressions include a constant (omitted). tstats in parenthesis. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Column (1) reports the results of the a dynamic non-spatial fixed-effects model estimated using the System-GMM estimator. Column (2) reports the reports the results of a static spatial error fixed-effects model estimated using the STSLS-GMM estimator. Column (3) reports the reports the results of a static SARAR(1,1) fixed-effects model estimated using the STSLS-GMM estimator. The instrumental variables in the STSLS-GMM regressions in Columns (2) and (3) are the prediction of women's political empowerment based on ancestral societal characteristics $\hat{Y}^{RF}_{i,t:t+5}(Z_i)$ and the spatial lag of exogenous regressors WX_t.

Table 8: Estimation results for the three dimensions of WPE

	Civil liberties (WCL) (1)	Civil participation (WCSP) (2)	Political participation (WPP) (3)
Women's empowerment	-0.012	-0.009	-0.059***
	(-0.72)	(-0.48)	(-6.78)
GDP per capita (logs)	0.014***	0.014***	0.014***
	(3.35)	(3.35)	(3.63)
Urbanization	-0.009	-0.009	-0.011
	(-0.35)	(-0.38)	(-0.46)
Financial Dev.	-0.033**	-0.033**	-0.028**
	(-2.53)	(-2.54)	(-2.26)
Technology	0.000	0.000	0.000
	(-1.21)	(-1.07)	(-0.36)
Financial Glob.	0.000***	0.000***	0.000***
	(4.05)	(3.98)	(3.98)
Trade Glob.	0.000	0.000	0.000
	(-0.07)	(0.01)	(0.26)
Democracy	0.007	0.005	0.015*
	(0.67)	(0.50)	(1.68)
Gov. Spending	-0.016	-0.015	-0.020
	(-1.21)	(-1.13)	(-1.49)
Education	0.002	0.002	0.001
	(0.83)	(0.78)	(0.22)
Fertility lag	-0.166	-0.138	-0.309
	(-0.57)	(-0.48)	(-1.15)
Muslim pop.	0.001***	0.001***	0.001***
	(4.02)	(4.07)	(4.26)
Age dependency	-0.040	-0.040*	-0.037
	(-1.63)	(-1.65)	(-1.44)
Unemployment	0.058***	0.057***	0.057***
	(2.66)	(2.59)	(2.59)
Country fixed effects	Yes	Yes	Yes
Time-period effects	Yes	Yes	Yes
Countries	142	142	142
Observations	852	852	852
R^2	0.976	0.975	0.976
No. Instruments	2	2	2
F-statistic (1st stage)	826.6	710.14	1155.6
Sargan	3.36	0.004	1.49
Sargan pval	[0.07]	[0.94]	[0.22]
DWH	0.29	2.40	13.97
DWH pval	[0.58]	[0.12]	[0.00]

Notes: The dependent variable in all regressions is the SWIID Gini index calculated over 5 years intervals from 1990 to 2019. All regressions include a constant (omitted). Robust-heteroskedastic tstats in parenthesis. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Column (1) reports the effect of the effect of the (WCL) component of the WPE index on inequality. Column (2) reports the effect of the effect of the (WCSP) component of the WPE index on inequality whereas Column (3) reports the effect of the effect of the (WPP) component of the WPE index on inequality. The instrumental variables employed in TSLS regressions in Columns (1) to (3) are the prediction of women's political empowerment based on ancestral societal characteristics $\hat{Y}^{RF}_{i,t:t+5}(Z_i)$ from Equation (3) and its spatial lag $\sum_{j\neq i} W_{ij}\hat{Y}^{RF}_{j,t:t+5}(Z_i)$ where W_{ij} is a 5-nearest neighbor's geographical row-normalized matrix.

Table 9: The redistribution transmission channel

	Dependent variable: Redistribution		Dependent variable: Income inequality		
	RF-TSLS	RF-TSLS	HOLS	RF-TSLS	RF-TSLS
	(1)	(2)	(3)	(4)	(5)
WPE	0.0326**			-0.0684***	
	(2.06)			(-3.18)	
WPP		0.0162**			-0.0521***
		(2.16)			(-6.28)
Redistribution			-0.5005***	-0.4851***	-0.4895***
			(-11.43)	(-11.50)	(-11.85)
GDP per capita (logs)	0.0018	0.0018	0.0135***	0.0140***	0.0141***
	(0.42)	(0.43)	(3.46)	(3.78)	(3.81)
Urbanization	0.0000	0.0000	-0.0001	-0.0001	-0.0001
	(-0.20)	(-0.11)	(-0.50)	(-0.48)	(-0.50)
Financial Dev.	0.0191	0.0192	-0.0180	-0.0200*	-0.0212*
	(1.36)	(1.37)	(-1.57)	(-1.77)	(-1.89)
Technology	-0.0005	-0.0006	-0.0008***	-0.0007**	-0.0005*
	(-1.00)	(-1.20)	(-2.00)	(-2.33)	(-1.67)
Financial Glob.	-0.0003***	-0.0003***	0.0003***	0.0003***	0.0003***
	(-3.02)	(-3.02)	(3.00)	(3.00)	(3.01)
Trade Glob.	-0.0001	-0.0001	-0.0001	0.000	0.000
	(-0.86)	(-0.78)	(-0.59)	(-0.18)	(-0.22)
Democracy	-0.0281***	-0.0214***	-0.0081	0.0137	0.0036
	(-3.35)	(-3.06)	(-0.85)	(1.25)	(0.37)
Education	-0.0010	-0.0012	0.0010	-0.0004	-0.0004
	(-0.36)	(-0.44)	(0.36)	(-0.13)	(-0.14)
Gov. Spending	0.0764***	0.0761***	0.0254**	0.0211*	0.0205*
	(4.47)	(4.40)	(2.13)	(1.85)	(1.78)
Fertility lag	0.0009	0.0002	-0.0019	-0.0045*	-0.0036
	(0.38)	(0.08)	(-0.68)	(-1.67)	(-1.38)
Muslim pop.	-0.0523	-0.0533	-0.0697***	-0.0699***	-0.0673***
	(-1.54)	(-1.55)	(-3.30)	(-3.08)	(-2.96)
Age dependency	0.000	0.0001	0.0008***	0.0009***	0.0008***
	(0.20)	(0.41)	(4.00)	(4.50)	(4.00)
Unemployment	0.0001	0.0000	0.0006***	0.0005**	0.0006**
	(0.17)	(0.03)	(3.00)	(2.50)	(3.00)
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Time-period fixed effects	Yes	Yes	Yes	Yes	Yes
Countries	142	142	142	142	142
Observations	852	852	852	852	852
R^2	0.99	0.99	0.97	0.97	0.97
No Instruments	2	2		2	2
F-statistic (1st stage)	481.4	1401.1		1279.0	236.6
Sargan	2.98	0.61		0.27	2.04
Sargan p-val	0.08	0.43		0.61	0.15
DWH	0.01	6.41		0.71	13.34
DWH p-val	0.90	0.01		0.40	0.00

Notes: The dependent variable in Column (1) and (2) is the level of redistribution whereas in Columns (3) to (5) is the SWIID Gini (net) index calculated over 5 years intervals from 1990 to 2019. Robust-heteroskedastic tstats in parenthesis. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level. The instrumental variables employed in TSLS regressions in Columns (1), (2), (4) and (5) are the predictions of WPE and WPP respectively, based on ancestral societal characteristics $\hat{Y}^{RF}_{i,t:t+5}\,(Z_i)$ from Equation (3) and its spatial lag $\sum_{j\neq i} W_{ij}\hat{Y}^{RF}_{j,t:t+5}\,(Z_i)$ where W_{ij} is a 5-nearest neighbor's geographical row-normalized matrix.