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Do financial reforms help stabilize inequality?

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Abstract

We explore the relationship between financial reforms and income inequality using a panel of 29 countries over 1975-2005. We extend panel unit root tests to allow for the presence of some financial-reform covariates and further suggest an associated but novel, semi-parametric approach. Results demonstrate that although both gross and net Gini indices follow a unit root process, this picture can change when financial reform indices are accounted for. In particular, whilst gross Gini coefcients are generally not stabilized by financial reforms, net measures are (more likely to be). Thus financial reforms enacted in the presence of a strong safety net would seem preferable.
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Non-Technical Summary

In recent decades and across many countries, inequality – as measured by the Gini coefficient – has risen. Over the same period there has been a global push to reform and deregulate the financial sector along various dimensions. In this paper, therefore, we explore the relationship between financial reforms and income inequality. Our particular interest is the extent to which these financial reforms have stabilized income inequality. This concern is close to one of the key justifications for enhanced financial development, namely that it helps again insure against shocks.

For this purpose two datasets are combined. A data set of financial reforms are taken from Abiad et al. (2010) whilst the Gini coefficients measuring (gross and net) income inequality are taken from Solt (2009). The data permit a joint panel sample of 29 developed and emerging economies from the 1970s until 2005.

In examining the link between financial reforms and the stabilization of income inequality, we extend standard panel unit root tests to allow for the presence of some covariates while we suggest a more powerful semi-parametric approach in detecting the null unit root hypothesis. Results suggest that although both gross and net Gini indices follow a unit root process this picture changes when the various financial reforms indices are considered as additional covariates in the standard panel unit root approach. In particular whilst gross Gini coefficients are generally not stabilized by financial reforms, net measures are (more likely to be). Thus financial reforms enacted in the presence of a strong safety net would seem preferable. Our approach can be generalized to the analysis of other types of policy reforms.

1 Introduction

In recent decades and across many countries, inequality – as measured by the Gini coefficient – has risen (e.g., Guest and Swift (2008), Solt (2009)). Over the same period there has been a global push to reform and deregulate the financial sector.

That financial reforms (FRs) and income distribution interact is straightforward to motivate (e.g., Kumhof and Ranciere (2015); Agnello et al. (2012); Claessens and Perotti (2007)). For instance if inequality reflects unequal access to funds by those with poor credit histories or limited collateral, then better functioning, more accessible financial markets might reduce income dispersion. However, if credit flows mirror the (typically uneven) distribution of abilities, then financial deepening might exacerbate inequality. Overall, though, the literature has generally taken a positive perspective on the issue, see the seminal studies of Beck et al. (2007) and Demirgüç-Kunt and Levine (2009).

Our contribution is to re-examine this link – but from a novel and distinct perspective. Using a series of increasingly robust stationarity, covariance stationarity and long-run memory tests, we analyse the univariate properties of the income inequality index taking into consideration the information contained in the FR measures.

A conventional approach to analyzing the reforms-inequality link might be to test for a common trend. But cointegration does not make sense here. First, cointegration between two or more series requires that, although the variables are non-stationary, a linear combination is stationary. Although the stochastic process that represents inequality may be non-stationary (e.g., in the mean and/or covariance), can we say the same of financial reform dummy variables? If FRs have taken place, and are considered unlikely to be implemented again, then these dummy variables are not of that nature.[1] They will take an integer value, say 1, for the specific period(s) during which they were active/implemented. But can one then argue that the proportion of 1's in the sample is an estimator of some underlying probability of the same reforms occurring again at any given future time period? If one cannot make that argument, then linearly combining these dummies with the non-stationary inequality-process will not yield a stationary combination.

Second, and related more intuitively to the first, although FRs will have distributional consequences, it seems unlikely that they were used systematically as an instrument to shape inequality. Yet, if there was an equilibrium relationship between them, this is what we should expect: e.g., inequality rises, policy makers/finance participants respond by promoting FRs, then reversing or stalling them if inequality stops rising. This sequence, though, seems both implausible and counterfactual.[2] More likely, this global trend to-

[1] As we discuss below, our non-parametric approach is independent from the hypothesis that the FR variables are endogenous or exogenous.

[2] In the Abiad et al. (2010) database that we use, for example, FRs were rarely reversed; the amount of significant policy reversals in the sample is put at only 5%.

wards less regulated finance reflected a mixture of historical happenstance and evolving institutional preferences.[3]

Our approach instead relies on a literature claiming that when researchers test for a unit root they typically ignore information contained in other key variables (Hansen (1995)). In fact, even aside from the arguments above, our approach is independent of whether cointegration is present or not between the two variables. Methodologically, our approach also has parallels with the literature on panel unit root tests for conditional, $\beta-$convergence in economic growth (e.g., Barro (1991), Meligkotsidou et al. (2012)).

Accordingly, we ask if, when measures of FRs are incorporated into a unit root Gini regression, might they then lead us to reject the presence of a unit root in inequality? If so, then the information contained in the FR variables affect the power of the unit root test leading to the conclusion that income inequality returns back to its own steady state after a shock occurs (note, not to a common steady-state formed by the covariate and the inequality index, but to its *own* steady state). Indeed, this would be consistent with the 'insurance' objective of financial services; if short-run shocks to inequality persist in the long run, then FRs would not have met that objective.[4]

The paper proceeds as follows. Section 2 discusses the data. The series on international financial reforms are taken from Abiad et al. (2010). The Gini coefficients measuring (gross and net) income inequality are taken from Solt (2009). The data permit a joint sample of 29 developed and emerging economies from the 1970s until 2005.

Section 3 reviews the unit root tests for (unbalanced) panels. We use several tests each with an increasing degree of robustness. First, we use panel Dickey-Fuller (DF) tests using the formulae of Maddala and Wu (1999) and Choi (2001). But we depart from the normal DF test by adding in measures of FRs; the distribution of the unit-root test on inequality is then determined by Monte-Carlo methods. We then use the non-linear IV method of Chang (2002) and Chang and Song (2009) which allows for the presence of cross cointegration, as well as for cross section correlation. This is followed by the Pesaran et al. (2013) test which allows a multi-factor structure of the cross-correlation.

In section 4 we additionally suggest a novel, semi parametric three-step strategy in checking the existence of a unit root process based on fractional integration (Robinson (1995), Shimotsu and Phillips (2004)). Fractional integration allows the integration parameter to be any real number (and not necessarily an integer). As we know, integrated data do not return to their previous mean after an external shock. But by allowing the

[3]For example, the reduction of financial frictions and obstacles: the breakdown of Bretton Woods; the suspension of dollar-gold convertibility; the establishment of the Eurodollar market; the electoral success of "pro-market" governments; the spontaneous development of financial services etc.

[4]Note, this is *not* the same as saying that financial reforms have worsened or improved inequality. FRs – such as widening credit availability – clearly have great potential for giving, e.g., low-income agents more productive uses for their savings and human capital. Our interest here is in assessing the traditional insurance role for financial markets.

order of integration to take fractional values, we allow data to be mean reverting but to still have long memory in the process.

Our approach, moreover, uses some less restrictive conditions than Phillips (2007) and Phillips and Kim (2007) regarding the behavior of the random variable locally around the origin by using a bounding condition.[5] In addition our non-parametric approach, based on Exact Local Whittle (ELW) estimator, is *independent* from the hypothesis that the FR variables are endogenous or exogenous. According to Velasco (2006), the semi-parametric estimators are not affected asymptotically by the endogeneity of regressors. Further Shimotsu (2012), using a simulation exercise, proved that the stronger the endogeneity the better the ELW estimator performs in terms of root mean squared errors. These tests are also more powerful in detecting unit-root behavior when the actual data generation process (DGP) is unknown, especially in the presence of incidental trends or where some breaks and threshold nonlinearity occur, see Smallwood (2015).

Section 5 summarizes and concludes. All tests demonstrate that a unit root in inequality cannot be rejected. Thus any shocks to income inequality have permanent effects; inequality tends to increase (or decrease) over time in a secular manner. For those at the upper quantiles of the income distribution, this persistence may be regarded as favorable since their current earnings follow past earnings. At the same time, tests also suggest that a unit root in the utilized aggregate FRs index (to be defined later) also cannot be rejected.

However, supplementing those tests with measures of FRs *can* make the series stationary. The extent to which they do so depends on the particular FR considered as well as the particular measure of income inequality. For example, whilst gross Gini coefficients are generally not stabilized by FRs, net measures are (more likely to be). This suggests that FRs can play an important role in stabilizing inequality after a shock. But they may best do so in the presence of a strong social safety net.

2 Data

We employ an unbalanced panel data set for 29 countries, constituting the maximal overlap of the two (financial and inequality) databases. They are: Argentina (1975-2005), Australia (1975-2005), Austria (1975-2005), Belgium (1979-2005), Brazil (1976-2005), Canada (1975-2005), Chile (1980-2005), Colombia (1978-2005), Costa Rica (1977-2005), Denmark (1975-2005), Finland (1975-2005), France (1975-2005), Germany (1975-2004), Greece (1981-2005), India (1975-2005), Israel (1975-2005), Italy (1975-2005), Japan (1975-2005), Mexico (1975-2005), Netherlands (1975-2005), New Zealand (1975-2005), Norway (1975-2005),

[5] Phillips (2007) provides more restrictive conditions than our approach as regards innovations of the unit-root process. In our application, the innovation term is bounded, a mild condition, which yields asymptotics generally relevant for a very wide range of empirical analyses.

Portugal (1981-2005), Spain (1980-2005), Sweden (1975-2005), Switzerland (1975-2005), Turkey (1978-2005), the UK (1975-2005), and the US (1975-2005).

2.1 Gini

Income inequality is captured by the Gini coefficient from the Standardized World Income Inequality Database (SWIID) version 4, Solt (2009).[6] This provides extensive coverage of internationally comparable income inequality data (173 countries, 1960-2009). The SWIID standardizes data comes from multiple sources (e.g. the United Nations University's World Income Inequality Database, the OECD's Income Distribution Database and the Socio-Economic Database for Latin America and the Caribbean by CEDLAS and the World Bank, as well as data from several national statistical offices), and is currently the best suited data set to perform cross-national research on income inequality.[7]

Figure 1 shows the data on gross and net (i.e., when public redistribution is taken into account) Gini measures relating to income inequality. The index lies between 0 and 100; larger values indicate more unequal income distributions. In many cases, both series are trending upwards, and strongly so in proportion terms for some countries (i.e., Australia, Canada, Israel, Portugal, UK). In others, though, there have been sustained reductions in income inequality (e.g., Brazil, Colombia, Denmark, Mexico, Turkey). Further, in most cases, the ratio of average gross-to-net Gini strongly exceeds 1 (especially in Finland, Germany, Sweden) whilst in others, reflecting weak or ineffective redistributive schemes, it is around 1 (e.g., Argentine, Chile, India, Mexico, Turkey).

2.2 Financial Reforms

Data on financial reforms come from the highly comprehensive and internationally comparable Abiad et al. (2010) data set, covering 91 economies over 1973–2005.[8] The database comes with several indices relating to specific financial reforms plus an aggregate index. The latter, $\mathcal{F}$, is the $[0, 1]$ normalized sum of seven (dummy variable) sub indices where $\mathcal{F}_j \in [0, 3], j = 1, \ldots 7$.

[6]Parcero (2015) is a recent example of the use of this data set in economics.

[7]Note, we are constrained to use aggregate measures of the Gini, rather than also particular percentiles (such as the top 10%) since these are not available on an internationally comparable basis.

[8]Laeven (2002) provides an alternative database of financial liberalization, but with a less extensive country coverage.

The j sub-indices are listed below with brief descriptions:

1. **Credit controls**: restrictiveness of reserve requirements; extent to which credit is channeled to certain sectors, and subsidized.
2. **Interest rate controls**: administrative controls and/or bands set for lending interest rates.
3. **Entry barriers/pro-competition measures**: various measures to capture entry of domestic and foreign banks into home economy and regulate their activities;
4. **Banking Supervision**: capital-adequacy rules followed; prudential agency independent of government.
5. **Privatization**: share of banking-sector assets owned by state banks.
6. **International capital flows**: restrictions on international financial transactions and pricing.
7. **Security Markets**: how governments restrict or encourage open domestic securities markets.

Regarding interpretation, the higher the value of the reform index (aggregate or individual) the higher degree of financial liberalization. **Figure 2** shows the cross-country pattern of the aggregate FR index.

Although there has been a trend towards generally less regulated financial sectors, there is still a great deal of cross-country heterogeneity. Some countries (e.g., Canada, Germany, Netherlands, Switzerland, UK, US) have traditionally been characterized by a highly liberalized financial sector. For others (e.g., Brazil, Costa Rica, India) there has been steady progress towards higher levels of financial liberalization, but at a level still behind many other countries.

Moreover, **Table 1** shows the correlations between the sub indices and then with the aggregate index. Note, the numbers refer to the Polyserial (rather than Pearson) correlation index. The former index allows us to compute the correlation between a quantitative variable and an ordinal one, based on the assumption that the joint distribution of the quantitative variable and a latent continuous variable underlying the ordinal variable is bivariate Normal.

Given that financial reforms tend to be implemented in a relatively clustered manner both within and (to a lesser extent) across countries, the generally high correlation of the sub-indices is hardly surprising. In some cases, though, a low correlation makes perfect

Table 1: Correlations Between Financial Reforms

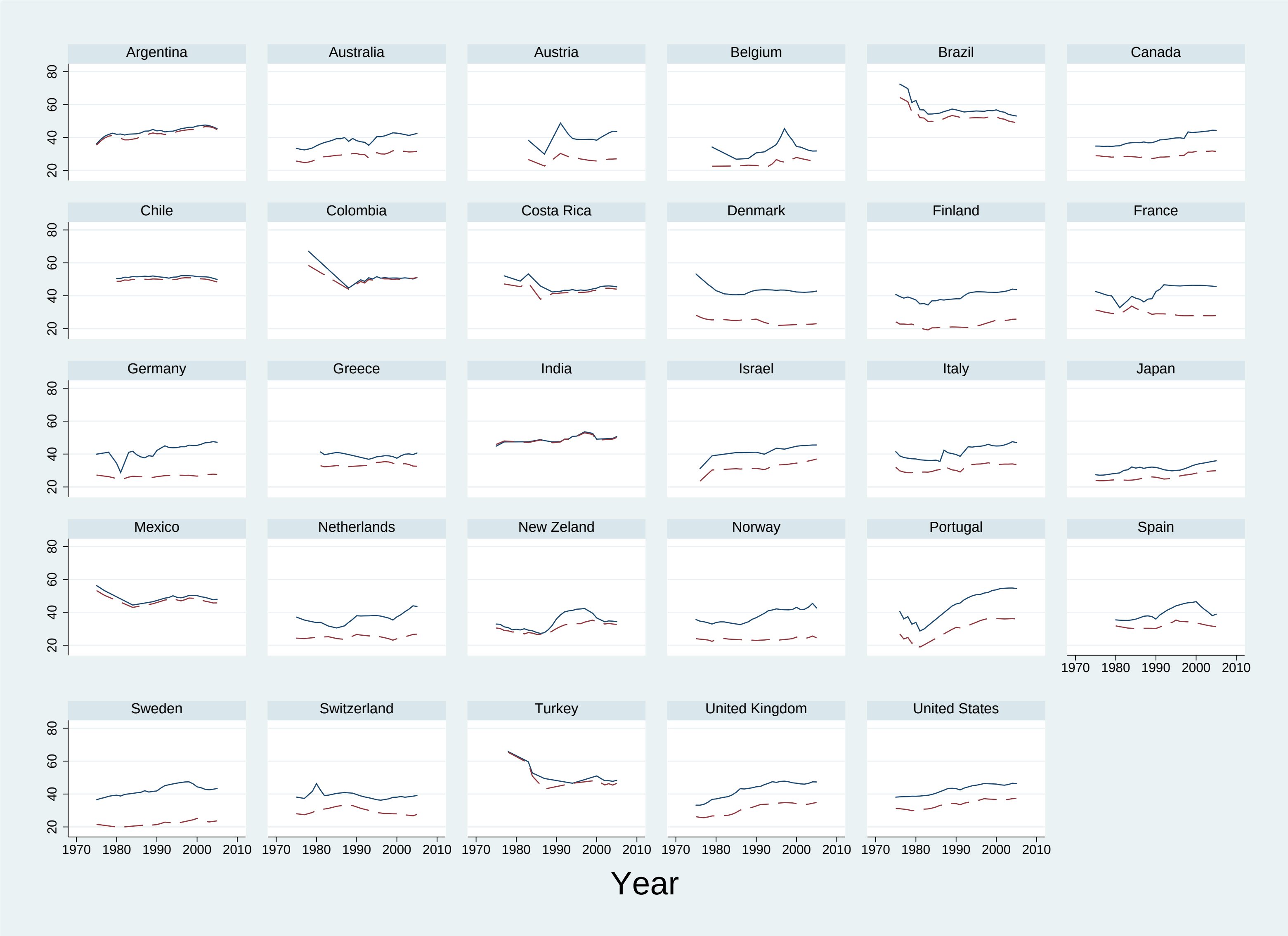
	Interest Controls	Banking Supervision	Security Markets	Privatization	Entry Barriers	International Capital Flows	Credit Controls	Aggregate
Interest Controls	1							0.82
Banking Supervision	0.83	1						0.81
Security Markets	0.73	0.79	1					0.82
Privatization	0.41	0.51	0.47	1				0.63
Entry Barriers	0.73	0.74	0.60	0.44	1			0.77
International Capital Flows	0.72	0.79	0.82	0.55	0.64	1		0.88
Credit Controls	0.78	0.72	0.73	0.53	0.67	0.72	1	0.90

Notes: The (polychoric) correlations reported in this table refer to our 29 country sample.

sense: for example enhanced privatization in financial markets should reduce entry barriers. Ex ante it is difficult to foresee which of these indices should link well with inequality. Inequality in general is non stationary making the correlations somewhat fragile, and in any case our interest lies with the stabilization of income inequality rather than per se its secular trend(s).

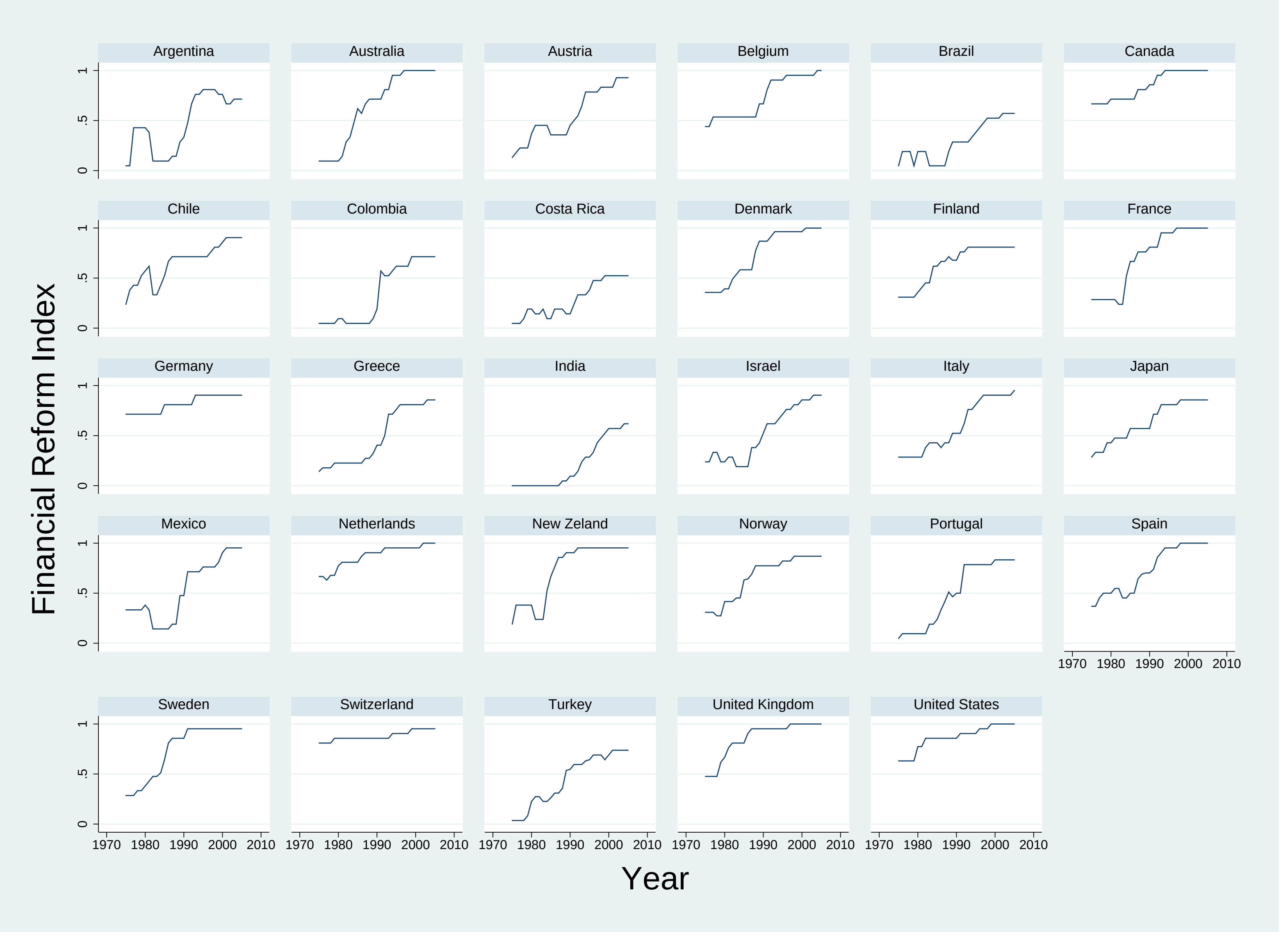
Nonetheless, perhaps it is most obvious that credit and interest rate controls as well as entry barriers should be highly linked with inequality. Ever there, the net effect is unclear. Credit-constrained or sub-prime borrowers may benefit from wider access to finance. On the other hand, those at the upper end of the income and wealth scale with capital holdings will likely find better and more sable use for their assets and savings. If there are shocks to income inequality, it is not clear how these benefits will net out.

Figure 1: Gini Coefficients, Gross and Net



Notes: Solid (dashed) line indicates Gross (Net) Gini coefficients.
Source: Solt (2009).

Figure 2: Financial Reforms Index, Normalized Aggregate



Source: Abiad et al. (2010).

3 Methodology

In the following sections, we examine (unbalanced) panel unit root tests following Maddala and Wu (1999), Choi (2001), Chang (2002) and Chang and Song (2009) and Pesaran et al. (2013). Each of these procedures builds in an increasing degree of robustness in the testing for a unit root, and allows us to add covariates into the associated test.

3.1 Panel Unit Root Tests *Allowing For Covariates*

To test the stationarity properties of the Gini index in a panel data setting, we modify the test proposed by Maddala and Wu (1999) (hereafter MW) by incorporating into the fitted model some stationary covariates. This test can be employed in an unbalanced data set contrary to other well known (symmetric) panel unit roots such as Harris and Tzavalis (1999) and Levin et al. (2002).

To make these tests appropriate for our approach we include the FR index as an additional regressor. Thus the MW Dickey-Fuller regression for each i^{th} cross section unit (i.e., country) is,

$$\Delta Gini_{it} = \alpha_i + \beta_i t + \phi_i Gini_{it-1} + \sum_{p=1}^{P} \delta_{ip} \Delta Gini_{it-p} + \theta_i \mathbb{F}_{it} + e_{it}, \quad i = 1, \ldots N, t = 1, \ldots T \tag{1}$$

where $\mathbb{F}$ is a stationary covariate and denotes the particular index of the FR under consideration (be it the aggregate, $\mathcal{F}$, or a sub-index, $\mathcal{F}_j$) where $\mathbb{F} = \left\{ \begin{array}{c} \mathcal{F}_j \\ \Delta\mathcal{F} \end{array} \right.$.[9] Scalar P denotes (here as elsewhere in the paper) the lags required to ensure white noise errors in e_{it}.

The null hypothesis of a unit root ($H_0 : \phi_i = 0 \; \forall i$ against $H_1 : \phi_i < 0 \; \forall i$) can be tested using the formulae suggested by Maddala and Wu (1999) and Choi (2001):

$$MW : -2 \sum_{i=1}^{N} \log(\pi_i) \quad \xrightarrow{d} \chi^2(2N) \tag{2}$$

$$Choi : N^{-0.5} \sum_{i=1}^{N} \Phi^{-1}(\pi_i) \xrightarrow{d} N(0,1) \tag{3}$$

where π_i is the probability value from the term $t_{\varphi_i} = \frac{\hat{\varphi}_i}{se(\hat{\varphi}_i)}$ while Φ^{-1} is the cdf of a standard Normal.

To derive the Dickey-Fuller distribution in the case where a dummy variable is included in the baseline regression 40,000 simulations were generated. The steps of the

[9]We use the first difference operator only in the case where FR variable is a continuous one (namely, the aggregate series) to make it stationary.

simulations are the following:

1. We generate for every single country a random walk with a drift process,

$$x_{it} = \alpha + a_1 x_{it-1} + e_{it} \tag{4}$$

where $\alpha = \alpha_1 = 1, x_0 = 0, e_{it} \sim (0,1), t = 1, \ldots T$.

2. We generate y_t conditional on the set of stationary covariates $\mathbb{F}_t$, that is

$$y_{it} = x_{it} + \theta \mathbb{F}_{it} + \omega_{it} \tag{5}$$

where $\omega_{it} \sim (0,1)$ with a sample equal to that of the data.

3. We perform $40,000$ replications to each realization and compute a set of simulated t-statistics for each sample. The probability value of the unit root test can be obtained as the proportion of times the generated t-ratios is smaller than t_{φ_i}.

3.2 Chang-Song Panel Unit Root Test

In order to construct more powerful unit root tests appropriate for small samples, designed either for symmetric or asymmetric panels, Chang (2002) and Chang and Song (2009) suggest unit root tests allowing for the presence of cross cointegration, as well as for cross section correlation. Failure to account for cross section correlation lead to large size distortions in panel unit root tests, e.g., O'Connell (1998). In addition this test can be extended to allow for covariates. Thus, we have the regression,

$$Gini_{it}^{\mu t \mathbb{F}} = \rho_i Gini_{it-1}^{\mu t \mathbb{F}} + \eta_{it} \tag{6}$$

where η_{it} is an error term and $Gini_{it}^{\mu t \mathbb{F}}$ stands for the demeaned-detrended Gini series (μt):

$$Gini_{it}^{\mu t \mathbb{F}} = Gini_{it} - \widehat{\alpha_i^*} - \widehat{\beta_i^*} t - \widehat{\gamma_i^*} Gini_{it-1} - \sum_{p=1}^{\widetilde{P}} \widehat{\delta_{ip}^*} \Delta Gini_{it-p} - \widehat{\theta_i^*} \mathbb{F}_{it}$$

To test the null unit root hypothesis $H_0 : \rho_i = 1 \; \forall i$ against $H_1 : \rho_i < 1 \; \forall i$ in a panel data setting they have shown that equation (6) can be estimated by non linear IV OLS using as instruments non linear transformations of the lagged levels, that is:

$$\Pi_i(Gini_{it-1}) = Gini_{it-1}e^{-\sigma_i|Gini_{it-1}|} \tag{7}$$

where $\sigma_i = KT_i^{-0.5}\psi^{-1}(\Delta Gini_{it})$, and $\psi^2(\Delta Gini_{it}) = T_i^{-1}\sum_{t=1}^{T}(\Delta Gini_{it})^2$ and where K is a constant for every $i = 1,...N$ and then using the standardized sum of the individual t-ratios to generate the following statistic:

$$S = N^{-1/2}\sum_{i=1}^{N} t_{\rho_i} \xrightarrow{d} N(0,1) \tag{8}$$

where $t_{\rho_i} = \frac{\widehat{\rho}_i - 1}{se(\widehat{\rho}_i)}$.

Parameter σ_i is crucial for the properties of the test as $\Pi_i(Gini_{it-1}) \in [-(\sigma_i e)^{-1}, (\sigma_i e)^{-1}]$ with $Gini_{it-1} \in [-\frac{1}{\sigma_i}, \frac{1}{\sigma_i}]$. Accordingly σ_i must be proportional to the inverse of the standard deviation of the $\Delta Gini_{it}$. To avoid over rejection of the null hypothesis of a unit root when the time dimension is small we follow Chang (2002) and use a larger K to correct for the size distortions. Finally this test is robust against cross section dependence and cross cointegration.

3.3 Pesaran-Smith-Yamagata test

Although the Chang and Song (2009) test allows for both the presence of cross sectional correlation and cross cointegration it does not assume a multi factor structure of the cross-correlation. This leads to size distortions and potentially misguided inference. In addition this test is appropriate for small panels with relatively large T.

To this end, Pesaran et al. (2013) have proposed a panel unit root test, $CIPS$, adapted to take into account the multifactor structure of the errors. In doing this, they utilize the information contained in a number of additional covariates that together are assumed to share the common factors of the series of interest. Thus, the resulting augmented DF regression is augmented with the cross sectional averages of the series of interest and the additional covariates. In particular they specify the following ADF regression:

$$\Delta Gini_{it} = \alpha_i^* + \beta_i^* t + \phi_i^* Gini_{it-1} + \sum_{p=1}^{P}\delta_{ip}^*\Delta Gini_{it-p} + v_{it} \tag{9}$$

where,

$$v_{it} = \boldsymbol{\gamma'_{i,Gini}\zeta_t} + w_{i,Gini,t} \tag{10}$$

where $\boldsymbol{\zeta}$ is a $q \times 1$ vector of unobserved common effects following a covariance stationary process ($q \geq 1$ denotes the number of additional covariates, here the FR variable); $\gamma_{i,Gini}^{'}$, is a vector of factor loadings; and $w_{i,Gini,t}$ is an idiosyncratic component.

Substituting (10) into (9) yields:

$$\Delta Gini_{it} = \alpha_i^* + \beta_i^* t + \phi_i^* Gini_{it-1} + \sum_{p=1}^{P} \delta_{ip}^* \Delta Gini_{it-p} + \boldsymbol{\gamma_{i,Gini}'\zeta_t} + w_{i,Gini,t} \tag{11}$$

The null of a unit root,

$$H_0 : \phi_i^* \ = \ 0 \ \forall i = 1, \ldots N$$

is tested against the alternative,

$$\begin{aligned} H_1 : \phi_i^* &< 0 \text{ for } i = 1, \ldots N_1, \\ \phi_i^* &= 0 \text{ for } i = 1, \ldots N_1 + 1, \ldots N \end{aligned}$$

where $N_1/N \rightarrow c \in (0,1]$ as $N \rightarrow \infty$.

Next we assume that additional to the original inequality series ($Gini_{it}$) FR variable ($\mathbb{F}_{it}$) depends on at least the same set of common factors (ζ_t) although with different factor loadings:

$$\mathbb{F}_{it} = \alpha_{i,\mathbb{F}}^{**} + \beta_{i,\mathbb{F}}^{**} t + \boldsymbol{\omega_{i\mathbb{F}}'\zeta_t} + w_{i,F,t} \tag{12}$$

Combining (11) and (12) a test of the panel unit root hypothesis can be based on the individual t-ratio t_{ϕ_i} derived from OLS estimation of,

$$\Delta Gini_{it} = \alpha_i^* + \beta_i^* t + \phi_i^* Gini_{it-1} + \sum_{p=1}^{P} \delta_{ip}^* \Delta Gini_{it-p} + \zeta_i' \overline{\mathbf{x}}_{it-1} + g_i' \Delta \overline{\mathbf{x}}_{it} + \varpi_{it} \tag{13}$$

where $\mathbf{x}_{it} = \left(Gini_{it}, \mathbb{F}_{it}'\right)$ and where ϖ is an error term.

The resulting panel unit root test is simply the average of the average ratios:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} t_{\phi_i} \left(N, T\right) \tag{14}$$

This test by allowing the case of a multifactor structure of the errors is shown to have the stable size for all combinations of cross section units and time series dimensions considered. Critical values are provided in Pesaran et al. (2013).

3.4 Results

Table 2 shows the stationarity tests for the aggregate financial reform index as well as gross and net Gini (alone, and then with covariates). The tests do not allow us to reject the null of a unit root in the level of either unconditional inequality measure. The same also applies to the level of the aggregate FR index, $\mathcal{F}$.[10]

Regarding the covariate *gross* Gini case, there is mixed evidence that FRs stabilize inequality. In fact there are only two reforms – relating to (i) entry barriers and pro-competition policies and (ii) reforms of securities markets – that suggest such an effect across all the four tests. If we were to consider the last two tests alone (S, $CIPS$), there is evidence that reforms in international capital flows and interest rates controls also stabilize inequality, although only at 10% significance.

By contrast, there is stronger evidence that the unit root in the *net* Gini can be removed by the addition of the aggregate and individual FR indices. This is except for the financial privatization reform covariate (for which $CIPS$ cannot reject a unit root) and in securities markets reforms (which $Choi$ rejects, and MW accepts only at 10%).

In the next section, we assess the robustness of these results using fractional unit root test, which are robust to whether or not we know the true DGP for the series. Nonetheless, the message from this section seems to be that the distributional and stabilizing properties of FRs are ambiguous. That they may best play this role in the net Gini case, suggests that a fiscal safety net is required to cushion some of the immediate impacts of FR, and support the take up of new financial services and instruments.

Finally, **Table 3** shows the half lives derived from equation (1): where applicable, these suggest that after some shock to inequality, reversion to the 50% pre-shock level will occur in around 3-4 years. Thus, in practical terms, if there is, say, a fall in demand (or a particular fall in the demand for low-skilled employees) then it would take two times this time frame for those affected to have, for example, access to supporting bank credit, or for the financial sector to have recapitalized and resumed normal business. Note, there is no marked differences in adjustment times for the shock to dissipate across net and gross Gini measures.

[10] Note, that contrary to the aggregate FR index, the FR indices are dummy variables and cannot be tested for stationarity.

Table 2: Panel Unit Root Tests With Financial Indices

Variable	Covariate	*MW*	*Choi*	*S*	*CIPS*
$\mathcal{F}$	–	28.60	2.93	-0.65	–
Gini-Gross	–	68.11	-1.11	-1.58	–
	$\Delta\mathcal{F}$	69.01^{*}	-2.30^{**}	-3.53^{***}	-2.61
	$\mathcal{F}_{Entrybarriers,pro\text{-}competition\ measures}$	73.96^{**}	-1.77^{*}	-2.15^{**}	-2.69^{*}
	$\mathcal{F}_{Privatization}$	71.32^{*}	-1.53	-1.37	-2.54
	$\mathcal{F}_{International\ Capital\ flows}$	62.88	-1.25	-1.79^{*}	-2.74^{*}
	$\mathcal{F}_{Credit\ Controls}$	66.03	-1.20	-1.46	-2.87^{**}
	$\mathcal{F}_{Interest\ Rates\ Control}$	69.37^{*}	-1.85^{*}	-1.71^{*}	-2.73^{*}
	$\mathcal{F}_{Banking\ Supervision}$	75.82^{**}	-1.94^{**}	-1.99^{**}	-2.54
	$\mathcal{F}_{Security\ Markets}$	69.01^{*}	-1.78^{*}	-1.87^{*}	-2.80^{**}
Gini-Net	–	65.03	-1.63	-1.52	–
	$\Delta\mathcal{F}$	84.95^{**}	-2.36^{***}	-2.71^{**}	-3.28^{**}
	$\mathcal{F}_{Entrybarriers/pro\text{-}competition\ measures}$	84.13^{***}	-2.47^{**}	-1.86^{*}	-2.90^{**}
	$\mathcal{F}_{Privatization}$	90.36^{***}	-2.39^{**}	-3.23^{***}	-2.34
	$\mathcal{F}_{International\ Capital\ flows}$	81.38^{**}	-2.03^{**}	-3.58^{***}	-3.07^{***}
	$\mathcal{F}_{Credit\ Controls}$	77.96^{**}	-2.02^{**}	-3.64^{**}	-3.29^{***}
	$\mathcal{F}_{Interest\ Rates\ Control}$	77.18^{**}	-1.78^{*}	-1.74^{*}	-3.26^{***}
	$\mathcal{F}_{Banking\ Supervision}$	80.52^{**}	-2.08^{**}	-1.98^{**}	-3.11^{***}
	$\mathcal{F}_{Security\ Markets}$	70.30^{*}	-1.43	3.40^{***}	-3.20^{***}

Notes: The critical values for the MW test at the 1%, 5% and 10% statistical level are 82.77, 73.66 and 68.89, respectively. Superscripts ***, ** and * indicate rejection of the null hypothesis of a unit root at the 1%, 5% and 10% statistical level respectively. "–" denotes not applied.

Table 3: Half Lives

Variable	Covariate	
Gini-Gross	–	
	$\Delta\mathcal{F}$	3.60
	$\mathcal{F}_{\textit{Entry barriers, pro-competition measures}}$	2.94
	$\mathcal{F}_{\textit{Privatization}}$	
	$\mathcal{F}_{\textit{International Capital flows}}$	
	$\mathcal{F}_{\textit{Credit Controls}}$	
	$\mathcal{F}_{\textit{Interest Rates Control}^{\dagger}}$	3.14
	$\mathcal{F}_{\textit{Banking Supervision}}$	2.55
	$\mathcal{F}_{\textit{Security Markets}}$	3.14
Gini-Net	–	
	$\Delta\mathcal{F}$	3.27
	$\mathcal{F}_{\textit{Entry barriers/pro-competition measures}}$	3.01
	$\mathcal{F}_{\textit{Privatization}}$	2.95
	$\mathcal{F}_{\textit{International Capital flows}}$	2.51
	$\mathcal{F}_{\textit{Credit Controls}}$	2.97
	$\mathcal{F}_{\textit{Interest Rates Control}}$	2.57
	$\mathcal{F}_{\textit{Banking Supervision}}$	2.91
	$\mathcal{F}_{\textit{Security Markets}}$	2.97

Notes: Half lives derived from model (1). A blank entry denotes that the half life is not defined given that a unit root in the series cannot be rejected.

4 A Semi-Parametric and Fractional Approach

Standard panel unit root tests (such as those considered above) have lower power in detecting the null unit root hypothesis when the true DGP is unknown. To overcome this, we propose a *three step* unit root strategy:

(1) We check for the existence of a unit root process based on the long memory approach in fractional integrated series advanced by Robinson (1995) and Shimotsu and Phillips (2004). The fractional integration approach is more general than the standard

parametric unit root tests in the sense that the integration parameter, d can be any real number. The fractional integration tests used are also more powerful in detecting unit-root behavior when the true data generating process is unknown or some breaks and threshold nonlinearity occur, see Smallwood (2015). In this context semi-parametric estimation is more appropriate because of its general treatment of the short memory component.

To illustrate, consider the process X_t :

$$(1-L)^d X_t = \epsilon_t \tag{15}$$

where L is the lag operator and ϵ_t is stationary with zero mean (the short memory process). If $d = 1$ then X_t is a random walk and integrated of order one, $I(1)$. If $d = 0$, X_t is white noise and weakly stationary, $I(0)$.

In what follows we use the Exact Local Whittle (ELW) estimator of Shimotsu and Phillips (2004) to estimate d. The ELW estimator is consistent, asymptotically Normal and robust even for a non stationary process. The estimate of d can be obtained by using the Whittle likelihood function:

$$Q_m(G,d) = -\frac{1}{m}\sum_{j=1}^{m}[\log(G\omega_j^{-2d}) + \frac{1}{G}I_{(1-L)^d Gini_t}(\omega_j)],\ j = 1,\ldots m. \tag{16}$$

where $I_{(1-L)^d Gini_t}(\omega_j)$ is the periodogram of the fractional difference of the Gini; ω_j are the set of Fourier frequencies, $2\pi j/T$; and where G is $f(\omega)$, the spectral density; as $\omega \to 0$ and $m < T$ is the bandwidth parameter which must satisfy $\frac{1}{m} + \frac{m}{T} \to 0$ as $T \to \infty$ (and thereby focuses attention on the long run).

The estimated integration parameter is then given by:

$$\widehat{d} = \arg \underset{d \in [\Delta_1, \Delta_2]}{minR(d)} \tag{17}$$

where

$$-0.5 < \Delta_1 < \Delta_2 < \infty$$
$$R(d) = \log(\widehat{G}(d)) - \frac{2d}{m}\sum_{1}^{m}\log(\omega_j)$$
$$\widehat{G}(d) = \frac{1}{m}\sum_{1}^{m}\omega_j^{2d} I_{Gini}(\omega_j)$$

(2) We regress the *Gini* inequality index on the FR index including a constant and a

trend in the fitted model and generate the residuals:

$$Res_{t,\mathbb{F}_i} = Gini_{it} - \widehat{\gamma_0} - \widehat{\gamma_1}t - \widehat{\gamma_2}\mathbb{F}_{it} \tag{18}$$

(3) We estimate the long memory parameter ($\hat{d}_{Res_{\mathcal{F}_i}}$) for the residuals of step two. If it is significantly smaller than the estimated long memory parameter of the *Gini* inequality series ($\widehat{d}_{\text{Gini}}$), then this would be an indication that FRs stabilize the inequality index over time.

Finally, let d^i_{Res} be the estimated long memory parameter for cross section unit i, we construct a panel version of this test by simply taking the average value of the cross section units, that is $d^{Panel}_{\text{Res}} = \frac{1}{N}\sum_{i=1}^{N} d^i_{\text{Res}}$.

4.1 Results

The results of the long memory parameters d's, employing the semi-parametric ELW estimator, alongside the 95% confidence intervals (CI) for each variable involved in the estimation procedure are presented in **Table 4**.

Consistent with table 2, the fractional tests confirm a unit root in the two Gini series, as well as in aggregate financial index: the confidence intervals traverse unity, as do the central estimates $\hat{d} > 1$.

For the *gross* Gini conditional on the aggregate and component FRs indices, the null hypothesis of a unit root cannot be rejected for all but the banking supervision reform index. In the latter case, to illustrate, d is smaller that the unconditional fractional parameter, $\hat{d} = 0.76 < 1.03$, while the corresponding CI does not include unity, $\{0.95 : 0.57\}$. According to Shimotsu and Phillips (2004) large differences in the estimated long memory parameter is an indication that the two series have different stationary properties.

The fact that, irrespective of the inequality measure considered, reforms related to banking supervision stabilize income inequality is a particularly interesting finding. The extent and quality of supervision have been widely discussed as a contributor to the recent financial crisis. It has also been emphasized in the policy reforms enacted in its aftermath, e.g., Fischer (2014).

This set of results therefore strengthens and sharpens the earlier conclusion that FRs may not stabilize income inequality if the latter is measured in gross terms. For the *net* measures, there is firmer evidence that FRs help stabilize inequality. All series, possibly barring the privatization reform index (whose CI includes unity), are characterized by values and confidence intervals below unity, and well below $\hat{d}_{Gini\ Net} = 1.13$.

Table 4: Estimated Long Run Memory Parameter $\hat{d}$

Variables	$\hat{d}$	95% CI
$\mathcal{F}$	1.17	1.37 : 0.97
Gini Gross	1.03	1.23 : 0.80
$Res_{\mathcal{F}}$	1.17	1.35 : 0.99
$Res_{\mathcal{F}_{\text{Entry barriers/pro-competition measures}}}$	0.89	1.09 : 0.69
$Res_{\mathcal{F}_{\text{Privatization}}}$	0.92	1.12 : 0.73
$Res_{\mathcal{F}_{\text{International Capital flows}}}$	0.91	1.10 : 0.71
$Res_{\mathcal{F}_{\text{Credit Controls}}}$	0.91	1.11 : 0.70
$Res_{\mathcal{F}_{\text{Interest Rates Control}}}$	0.92	1.12 : 0.72
$Res_{\mathcal{F}_{\text{Banking Supervision}}}$	0.76	0.95 : 0.57
$Res_{\mathcal{F}_{\text{Security Markets}}}$	0.89	1.10 : 0.70
Gini Net	1.13	1.33 : 0.93
$Res_{\mathcal{F}}$	0.73	0.91 : 0.55
$Res_{\mathcal{F}_{\text{Entry barriers/pro-competition measures}}}$	0.80	0.98 : 0.60
$Res_{\mathcal{F}_{\text{Privatization}}}$	0.81	1.00 : 0.59
$Res_{\mathcal{F}_{\text{International Capital flows}}}$	0.75	0.90 : 0.53
$Res_{\mathcal{F}_{\text{Credit Controls}}}$	0.74	0.94 : 0.54
$Res_{\mathcal{F}_{\text{Interest Rates Control}}}$	0.80	0.99 : 0.60
$Res_{\mathcal{F}_{\text{Banking Supervision}}}$	0.74	0.93 : 0.54
$Res_{\mathcal{F}_{\text{Security Markets}}}$	0.80	0.97 : 0.55

These results are consistent with those in table 2 given that we find broad stationarity in the net series with FRs compared to the gross series. Though there are some differences, the fractional integration approach is more powerful when the true DGP is unknown lead us to lean more towards it. Both sets of tests, though, constitute a useful robustness and cross checking exercise.

5 Conclusions

Generally, the literature has suggested a positive connection between FRs and inequality. When viewed through the lens of covariance stationary tests, our evidence is a little more mixed.

Our first result is that, across a battery of tests, a unit root in both gross and net income inequality cannot be rejected. The same holds true for the aggregate FR measure. However, supplementing those tests with FR covariates *can* make the series stationary. The extent to which they do depends on the particular FR considered, as well as the particular measure of income inequality.

For the gross Gini, FRs appear not to have stabilized income inequalities. Thus shocks to inequality become permanent. One exception appears to relate to reforms to banking supervision; this suggests that recent emphasis on strengthening prudential polices, see Fischer (2014), though implemented to improve financial stability, will also help stabilize income inequality. For the net Gini case, there is more positive evidence across the board.

How might we rationalize these differences? If the insurance function offered by private financial markets is imperfect, then it may not fully stabilize income inequality in the face of shocks. Likewise, pro-cyclicality in credit flows suggest that during downturns or financial crises,[11] those on low incomes may be denied funds (or receive less favorable terms) (with possible long-term consequences). A redistributive and progressive fiscal system may thus bolster and complement economy-wide insurance mechanisms. It may also be that progressive fiscal systems are capturing (or instrumenting for) more general "institutional" features that underpin the success of large policy reforms.[12] Thus countries with a weak redistributive mechanism that wish to benefit from a more active, deregulated financial sector may have difficulty doing so.[13]

Finally, an open question is whether there is a positive relationship between FRs and the probability of financial crises. For instance, if reforms are such as to make the financial sector too big, too interconnected, too crisis-prone. If so, and allied to the fact that financial crises are highly regressive (see Reinhart and Rogoff (2009)), then fiscal preconditions (e.g., an average gross-to-net Gini above unity) may be required to realize the gains from FRs. If this is not the case, then pursuit of FRs may generally place less burden on fiscal systems.

[11] Laeven and Valencia (2013) provide a comprehensive chronology of financial crises.

[12] See Acemoglu et al. (2008) for the case of central-bank reforms.

[13] In this respect, the so-called Washington Consensus, (for discussions see Williamson (1989), Rodrik (2006)), which tended to favor rapid liberalization of financial flows may be unsuited to countries with weak fiscal capacity.

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