University of Pretoria
Department of Economics Working Paper Series

Does Inequality Help in Forecasting Equity Premium in a Panel of G7 Countries?
Christina Christou
Open University of Cyprus
Rangan Gupta
University of Pretoria
Fredj Jawadi
University of Evry
Working Paper: 2017-20
March 2017
Does Inequality Help in Forecasting Equity Premium in a Panel of G7 Countries?

Christina Christou*, Rangan Gupta** and Fredj Jawadi***

Abstract
This paper investigates whether the post-tax and transfer growth rate in the Gini index can help in forecasting the equity premium in the G7 countries (Canada, France, Germany, Italy, Japan, United Kingdom (UK), and United States (US)). To this end, we use a panel data-based predictive framework, which controls for heterogeneity, cross-sectional dependence, persistence and endogeneity. When we analyze the annual out-of-sample period of 1990-2011, given an in-sample period of 1967-1989, our results show that: (a) Time series based predictive regression models fail to beat the benchmark of historical average, except for Italy; and, (b) the panel data models beat the benchmark in a statistically significant fashion for all the seven countries. Further, our results highlight the importance of pooling information when trying to forecast excess stock returns based on a measure of inequality.

JEL Codes: C33, C53, G1
Keywords: Equity Premium, Inequality, G7 Countries, Panel Predictive Regressions

* Corresponding author. School of Economics and Management, Open University of Cyprus, 2252, Latsia, Cyprus. Email: christina.christou@ouc.ac.cy.
** University of Pretoria, Department of Economics, Pretoria, 0002, South Africa. Email: rangan.gupta@up.ac.za.
*** University of Evry, Batiment La poste, Office 226, 2, rue du Facteur Cheval - 91025 Évry, France. Email: fredj.jawadi@univ-evry.fr.
1. Introduction

Forecasting stock returns and/or equity premium - that has been in the centre of several studies (see for example, Rapach et al., (2005, 2013), Afonso and Sousa (2011), Sousa (2012), Caporale and Sousa (2016), Sousa et al., (2016), Aye et al., (2017)) - is an interesting question for at least two different reasons. First, practitioners in finance require real-time forecasts of stock returns for asset allocation. Second, forecasting stock returns is relevant for academics in finance, since forecastability has important implications for tests of market efficiency, which in turn, helps to produce more realistic asset pricing models (Rapach and Zhou, 2013).

However, stock return forecasting is highly challenging, since it inherently contains a sizable unpredictable component. Accordingly, a wide array of models (univariate and multivariate; linear and nonlinear), and predictors (domestic and international financial, macroeconomic, institutional and behavioral) have been used (see for example, Rapach et al., (2005, 2013), Rapach and Zhou (2013), Aye et al., (2017) and references cited therein for further details). Not surprisingly, forecasting performances are mixed with the results depending on countries chosen, sample periods, models and predictors. Hence, accurate forecasting of stock returns remains an open and important question, with the need to seek for an answer using other predictors and econometric frameworks.

In this regard, with a steady upward trend in both income and wealth inequality globally (Atkinson et al., 2011; Alvaredo et al., 2013; Piketty and Saez, 2014), a relevant question to ask would be whether inequality plays a role in affecting the equity market? Intuitively, more unequal the society, it is likely to lead to limited participation in the equity market. In other words, higher the inequality can lead to lower stock market investment in a specific country, thus affecting stock prices. A natural follow-up question then would be to look for solid theoretical reasons as to
why should we expect inequality to affect the equity premium?\textsuperscript{1} From Cochrane (2005), when agents have identical constant relative risk-aversion (CRRA) preferences and markets are complete, income inequality cannot affect marginal utilities, and hence, asset prices. But, as shown by Mehra and Prescott (1985), it is well-known that the benchmark model (with identical CRRA preferences and complete market) fails to generate risk premia that match the observed data with a reasonable risk aversion parameter. Recent literature, thus, models heterogeneity amongst investors as one possible solution to this drawback of the benchmark model. Gollier (2001) shows that in a model with complete markets, but with agents having concave risk tolerance (i.e., dropping the assumption of the constant relative risk-aversion (CRRA)), wealth inequality increases the equity premium. Alternatively, Constantinides and Duffie (1996) also keeps the CRRA assumption, but introduce incomplete markets. In this scenario, investors are identical ex ante, but face uninsurable idiosyncratic income shocks, which in turn, lead to ex post dispersion in investor incomes. Given this, investors demand a higher risk premium for assets that provide a poor hedge against idiosyncratic income shocks. In this framework, if inequality is correlated with the magnitude of the uninsurable idiosyncratic income risk and equities are poor hedge against inequality (as shown by Ait-Sahalia et al., (2004)), then, higher inequality would cause a higher equity risk premium.

Favilukis (2013) points out that increases in labor income inequality have had relatively moderate effects on wealth inequality, with consumption inequality essentially unchanged. The author also indicates that at the same time, stock market participation has increased and the equity premium has declined. Given these observations, Favilukis (2013) solves a general equilibrium model to show that, when wage inequality increases and in addition, participation costs fall, the model not only predicts changes in wealth and consumption inequality quantitatively similar to those observed in the data, but also a large decline in the equity premium. Increased participation puts middle class households on a level playing field with richer households when it comes to

\textsuperscript{1} For a detailed discussion of the various channels that causes income inequality to drive risk-premium, the reader is referred to Favilukis (2013), and Brogaard et al., (2015).
investing, and hence, counteracts some of the effects caused by increasing wage inequality on wealth and consumption inequalities. At the same time, increased participation raises demand for equity, which causes the price of stocks to rise relative to bonds, and thus, decreases the equity premium. In other words, in this framework inequality and equity premium are negatively related via the participation cost channel.

Finally, a political channel might lead to inequality causing the equity premium in an indirect manner. Persson and Tabellini (1994) indicate that as inequality grows, politicians targeting the median voter have incentives to tax investment for the purpose of wealth redistribution, which in the process causes higher risk premia. This is because, there is widespread evidence which shows that taxes impact risk premia (see for example, McGrattan and Prescott (2003, 2005), Mehra and Prescott (2008), Croce et al, (2012), and Gomes et al., (2012)). Alternatively, Alesina and Perotti (1996) argue that income inequality leads to political uncertainty, which increases the equity premium as described in the works of Pástor and Veronesi (2012, 2013) and Brogaard and Detzel (2015).

Given these theoretical reasons behind the ability of inequality in affecting stock markets, it is important to discuss two recent empirical studies on the stock market of the United States in this regard. First, the paper by Johnson (2012), where the author studies the cross-sectional pricing implications associated with the risk of inequality. The paper shows that stock returns that comove more with inequality attract a negative premium. In other words, investors are willing to pay a higher price for assets which tend to provide a better hedge against the risk of falling income status. Second, Brogaard et al., (2015), who find that, controlling for the dividend-price ratio, higher income inequality (measured by the Gini coefficient), predicts not only a significantly higher equity risk premium, but also risk premia on long-term government and corporate bonds.² More importantly, given that predictive models require out-of-sample validation (Campbell, 2008), Brogaard et al., (2015) show that

² The authors find that a one-standard deviation increase in Gini coefficient is associated with an increase of 8.05% in expected excess log returns.
the inclusion of the Gini coefficient to a one-year stock-return forecasting regression that includes the dividend-price ratio, more than doubles the predictability (with the adjusted-R² increasing from 5.6% to 14.8%). These findings are also shown to be robust to alternative measures of inequality, and other common financial and real-business cycle predictors of returns generally used in this literature.

The objective of this paper is to investigate whether inequality, measured by the Gini index on income after taxes and transfer (i.e., net income), could help in forecasting the equity premium (excess returns) in the G7 countries. For our purpose, we analyze the annual out-of-sample period of 1990 to 2011, given an in-sample period of 1967 to 1989, using panel data-based predictive frameworks. Specifically speaking, for the panel predictive regressions, we adopt the Common Correlated Effects (CCE) estimation method of Pesaran (2006), and the recent updates to it based on 2SLS and GMM estimation methods developed by Neal (2015) to control for possible issues of endogeneity. The issue of endogeneity is important, given that there is wide-spread theoretical and empirical evidence of the role of financial markets in affecting income inequality (see for example, Claessens and Perotti (2007) and Demirgüç-Kunt and Levine (2009), and more recently, de Haan and Sturm (2016) for detailed reviews in this regard). Note that, both the approaches of Pesaran (2006) and Neal (2015), not only allow for slope heterogeneity, but also controls for persistence of predictors and cross-sectional dependence.

Accordingly, our contribution is primarily twofold: (i) As discussed above, the literature on out-of-sample forecasting of equity premium based on inequality is limited to only Brogaard et al., (2015), with their analysis restricted to the US in a time series structure. Given this, our paper extends the work of Brogaard et al., (2015) to the G7 countries, i.e., we now go beyond the US by looking at simultaneously also six other developed stock markets; (ii) From a methodological perspective, our paper is based on panel data estimation over and
above standard time series-based predictive regression models. As indicated by Rapach et al., (2013) and Aye et al., (2016), panel data regression tends to increase estimation efficiency relative to a time series approach, especially if the sample period is short, which happens to be the case with us, i.e., 45 observations, with an out-of-sample of 22 observations. In addition, given that our panel data estimation allows for slope heterogeneity of inequality, over and above controlling for endogeneity, persistence and cross-sectional dependence, it does not introduce any bias in the estimation either. In sum, our paper is the first paper to analyze the forecasting ability of inequality in forecasting the equity premium of seven major stock markets using time series and robust panel data estimation methods. The remainder of the paper is organized as follows: Section 2 lays out the methodology, while Section 3 presents the data and the empirical results and finally, Section 4 concludes.

2. Methodology

The literature on panel methods can be categorized into those that assume slope homogeneity between panel units and those that do not. In addition, the literature has shown that the presence of cross-sectional dependence in the data leads to inconsistent estimation and can cause severe bias in the estimated coefficients. In this paper we employ panel methods that allow for slope heterogeneity, correct for cross-sectional dependence, and are robust to persistence and endogeneity of the regressors.

To understand this methodology, we refer to Pesaran (2006), where the author introduces a new econometric approach that takes cross sectional dependence into account. This methodology is quite general as it allows individual specific errors to be serially correlated and heteroskedastic. Formally, Pesaran (2006) adopts the following multifactor residual model:

$$ER_{jt} = \alpha_j + B_j'X_{jt-1} + e_{jt}$$  \(1\)
\[ e_{jt} = \lambda_j F_t + u_{jt} \]  \hspace{1cm} (2)

where subscript \(jt\) defines the observation on the \(j^{th}\) cross-section unit at time \(t\), for \(t = 1,2,...,T\) and \(j = 1,2,...,N\). The dependent variable \(ER_{jt}\) measures the excess returns. The variable \(X_{jt-1}\) denotes the \(k \times 1\) regressors vector, which in our case is the Gini index. \(F_t\) denotes the \(m \times 1\) vector of unobserved common factors. Note that in a time-series framework, the predictive regression framework is given by: \(ER_t = \alpha + B'X_{t-1} + e_t\).

To deal with the residual cross-section dependence, Pesaran (2006) uses the cross-sectional averages, \(\bar{ER}_t = \frac{1}{N} \sum_{j=1}^{N} ER_{jt}\) and \(\bar{X}_{t-1} = \frac{1}{N} \sum_{j=1}^{N} X_{jt-1}\) to proxy the common factors \(F_t\).

Given this, the slope coefficients as well as their means, can be consistently estimated in the framework of the auxiliary regression:

\[ ER_{jt} = \alpha_j + B'_j X_{jt-1} + \gamma \bar{ER}_t + \Gamma' \bar{X}_{t-1} + e_{jt} \]  \hspace{1cm} (3)

Pesaran (2006) refers to the resulting OLS estimators \(\hat{B}_{j,CCE-OLS}\) of the individual specific slope coefficients \(B_j\), as the “Common Correlated Effect” (CCE) estimators defined as:

\[ \hat{B}_{j,CCE-OLS} = (X'_j \bar{D} X_j)^{-1} X'_j \bar{D} \varepsilon R_j \]  \hspace{1cm} (4)

where \(X_j = (X_{j1}, X_{j2}, ..., X_{jT-1})'\), \(\varepsilon R_j = (ER_{j2}, ER_{j3}, ..., ER_{jT})'\), \(\bar{D} = I_{T-1} - H (H'H)^{-1} H'\), \(H = (h_2, h_3, ..., h_T)'\), \(h_t = (1, \bar{ER}_t, \bar{X}_{t-1})'\), as the “Common Correlated Effect” (CCE) estimators. The “Common Correlated Effects Mean Group” (CCEMG) estimator corresponds to the average of the individual CCE estimators \(\hat{B}_{j,CCE-OLS}\) and is written as:

\[ \hat{B}_{CCEMG-OLS} = \frac{1}{N} \sum_{j=1}^{N} \hat{B}_{j,CCE-OLS} \]  \hspace{1cm} (5)

It can be shown that this new CCEMG estimator is asymptotically distributed as a standard normal; formally as follows:

---

3 While Pesaran (2006) only focuses on the case of weakly stationary factors, Kapetanios et al. (2011) has recently highlighted that that Pesaran’s (2006) CCE approach is still statistically valid even if common factors are unit root processes (I(1)).
\[
\sqrt{N}(\hat{\beta}_{\text{CCEMG-OLS}} - \beta) \xrightarrow{d} N(0, \Sigma_{MG})
\]

where the asymptotic covariance matrix \( \Sigma_{MG} \) can be consistently estimated using the Newey and West (1987) procedure:

\[
\hat{\Sigma}_{\text{CCEMG-OLS}} = \frac{1}{N-1} \sum_{j=1}^{N} (\hat{\beta}_{j,\text{CCE-OLS}} - \hat{\beta}_{\text{CCEMG-OLS}})(\hat{\beta}_{j,\text{CCE-OLS}} - \hat{\beta}_{\text{CCEMG-OLS}})'
\]

Pesaran (2006) Kapetanios et al. (2011) have shown that the CCE estimators have the correct size, and in general, better small-sample properties than alternatives that are available in the literature. Furthermore, small-sample properties of the CCE estimators are not affected by the residual serial correlation of the errors. Recently, Neal (2015) extends the CCE approach of Pesaran (2006) by replacing OLS by 2SLS/GMM using lags of the regression given in Equation (1) to form the instruments list. The author shows that the resulting CCE estimators (CCE-2SLS, CCE-GMM), and their mean group variants (CCEMG-2SLS, CCEMG-GMM) also share the good properties of the CCE estimators, and are also robust to the presence of endogenous regressors. Furthermore, Neal (2015), based on, shows that his estimators demonstrate better small sample properties when compared to the standard CCE estimators, regardless of whether the regressors are endogenous or not.

3. Data and Results

Our analysis includes two variables, namely, the equity premium or excess returns and the measure of inequality. We look at the G7 countries (Canada, France, Germany, Italy, Japan, UK, and US) over the annual period of 1967 to 2011, with the start and end date being purely driven by data availability of the inequality variable. Equity premium \((EXR)\) is defined
as the stock returns (first-difference of the natural log of the stock index\(^4\)) in excess of a risk-free rate, which in turn, is the three-month Treasury bill rate. The data on stock index and the three-month Treasury bill rate are obtained from the Global Financial Database and the FRED database of the Federal Reserve Bank of St. Louis, respectively.

The data on inequality is net income (i.e., after tax and transfer)-based Gini index obtained from the Standardized World Income Inequality Database (SWIID), available for download from: [http://fsolt.org/swiid/](http://fsolt.org/swiid/). SWIID is appropriate in our context, as it is designed to meet the needs of cross-national research by maximizing the comparability of income inequality data while maintaining the widest possible coverage across countries and over time. It incorporates data from the United Nations University’s World Income Inequality Database, the OECD Income Distribution Database, the Socio-Economic Database for Latin America and the Caribbean generated by CEDLAS and the World Bank, Eurostat, the World Bank’s PovcalNet, the UN Economic Commission for Latin America and the Caribbean, national statistical offices around the world, and academic studies while minimizing reliance on problematic assumptions by using as much information as possible from proximate years within the same country. A full description of the SWIID, the procedure used to generate it, and an assessment of the SWIID’s performance in comparison to the available alternatives is presented in Solt (2016). While, excess returns are mean-reverting by design, we work with growth rate (i.e., the first-difference of the natural log) of the Gini index (\(\Delta Gini\)) to ensure stationarity of the variable. As can be seen from the summary statistics in Table 1, Japan (UK) has the highest average excess returns (inequality), and Italy has the lowest average excess returns and inequality. Italy (France) has the highest standard deviation for the equity premium (inequality), while US has the lowest corresponding values of the standard

\(^4\) The specific stock indices used are: Canada: S&P/TSX 300 Composite; France: CAC All-Tradable Index; Germany: CDAX Composite Index; Italy: Banca Commerciale Italiana Index; Japan: Nikkei 225; UK: FTSE All Share Index, and; US: S&P 500. Daily, weekly and monthly data as and when available are converted to annual frequency by taking averages over a specific year.
deviation for the excess returns and inequality. Further, all excess returns are normally distributed except for UK, while non-normality is observed for Canada, France and Germany in the context of the Gini index. The data on excess returns and the growth rate of the Gini index have been plotted in Figure 1.

Next, we focus on the out-of-sample forecasting of excess returns. To this end, we split the total sample period into an in-sample period of 1967-1989, and an out-of-sample period of 1990-2011, with the periods essentially trying to ensure a 50 percent split – a popular approach in the literature (Rapach et al., 2005). Our out-of-sample period also includes important events in the history of stock markets such as the Black Wednesday, Asian financial crisis, the Dot-com bubble, financial market effects due to the terror attacks in September of 2001, stock market downturn of 2002, the recent global financial crisis of 2007-2008, and also the European Sovereign debt crisis, to name a few. Note that, following the extant literature (see for example, Rapach and Zhou (2013)), the predictive regression models are estimated recursively over the out-of-sample period, and hence is able to accommodate for structural breaks in the predictive regression framework arising due to the above mentioned major events that affected global stock markets.

We consider the following model: $ER_{jt} = \alpha_j + \beta_j \Delta Gini_{jt-1} + u_{jt}$, with the benchmark being a time series random walk model with drift, i.e., historical average. We also, estimate the time series version of the above model, but since the focus is the panel predictive regressions, we report the time series results of these two models in the Appendix (Table A1) of the paper. To compare the out-of-sample forecasting ability of two models, this study focuses on the relative root mean-squared error (RRMSE), i.e., the RMSE of a specific model relative to the time series random walk with drift model. To statistically assess whether the performance of alternative forecasting models outperform the historical average, we employ the
McCracken’s (2007) MSEF test for country $j = 1,2, ..., N$. The $MSE-F$ statistic is formally defined as:

$$MSEF_j = (T - 1 - R) \left[ \frac{MSE_{b,j}}{MSE_j} - 1 \right],$$

where $R$ is the number of observations in the first in-sample portion, and $MSE_{b,j}$ and $MSE_j$ are MSEs for the benchmark and the alternative forecasting models, respectively. The $MSEF$ statistic is a one-sided test for equal forecast accuracy. More specifically, $MSEF$ is formulated under the null that the forecast error from the alternative model ($MSE_j$) is equal to or larger than the forecast error from the benchmark ($MSE_{b,j}$). A rejection of the null indicates that the alternative model has superior forecast performance than the benchmark. Moreover, it is well known that the asymptotic distribution is a pure approximation of the true distribution of a test statistic. As a remedy to this problem, we compute the finite sample $p$-values by applying the technique of Monte Carlo tests (see Dwass (1957); Barnard (1963); Dufour and Khalaf (2001)) which allows one to replace the unknown theoretical finite sample distribution $f(MSEF/\theta)$, where $\theta = (\pi, k_2)$ are the parameters of the distribution, by its sample analogue based on the statistics $MSEF_1(\theta), MSEF_2(\theta), \ldots, MSEF_N(\theta)$ simulated under null hypothesis $H_0$. The Monte Carlo test procedure can be summarized in the following steps:

(a) Based on actual data, we calculate the relevant test statistic denoted as $MSEF_0(\theta);

(b) Using draws under $H_0$, we generate $N$ samples of the relevant statistic:

$$MSEF_1(\theta), MSEF_2(\theta), \ldots, MSEF_N(\theta);$$

(c) Using these simulations, we compute the simulated $p$-value, $\hat{p}_N$ is

$$\hat{p}_N = \{1 + \sum_{i=1}^{N} I[MSEF_i(\theta) - MSEF_0(\theta)]\}/(N + 1),$$

where $I(\cdot)$ the indicator function;

(d) Then, the null hypothesis is rejected at level $\alpha$ if $\hat{p}_N \leq \alpha$.

The forecasting results are presented in Table 2. The results reported from the panel predictive regression based on the growth rate of inequality provide strong evidence of predictability for the equity premium relative to the random walk model. When the CCE-OLS method is used, most of the RRMSRs are less than unity. Specifically, in the case of the CCE-OLS with individual specific coefficients (INDIV), all countries except Japan and the
UK demonstrate RRMSEs less than unity, with four of them being statistically significant. Specifically, the $MSEF$ test rejects the null hypothesis of equal MSEs for Canada, France, Italy and the US. In the case of the CCE-OLS with mean group coefficients (MG), all countries have RRMSEs less than unity and statistically significant. The only exception is Italy for which the $MSEF$ statistic indicates equal MSEs at all reasonable levels of significance. Additionally, the CCE-GMM mean group (MG) estimated coefficients significantly improve the forecasting ability of the model. Specifically, CCE-GMM with individual estimated coefficients, results in less than one and statistically significant RRMSEs for two (Canada and the US). In the case of CCE-GMM with mean group coefficients (MG), all countries demonstrate less than one and statistically significant RRMSEs. This is not surprising given the possible endogeneity of the regressor as discussed above. In general, the model CCE-GMM with mean group coefficient estimates (MG) performs better relative to the other panel predictive regression models. When we compare these results with Table A1, where we estimate the time series based predictive regression model with the growth rate of the measure of inequality, we observe that, barring the case of Italy, the RRMSE is greater than one in all cases. More importantly, the $MSEF$ statistic is significant in this case. However, unlike Brogaard et al., (2015), we do not observe inequality to provide forecasting gains for the US equity premium. In sum, our results highlight, to a certain degree, the importance of pooling information, using a panel data approach, and accounting for possible endogeneity of the predictor.

---

5 This should not be surprising given that our sources of the measure of inequality is different from that of Brogaard et al., (2015), who uses the Gini based on data from the Annual Census Population Survey. Further, and perhaps, more importantly, our sample periods also differ, with Brogaard et al., (2015) using the period of 1947 to 2013.

6 In a recent paper, Blau (2015) showed that inequality can affect stock market volatility. Given this, we also tested whether the growth rate of the Gini can forecast (realized) volatility of the stock returns of the G7 countries. Note that, realized volatility was calculated as the sum of squared returns over a year based on daily, weekly or monthly data as per data availability over the sample period. However, while our panel data models failed to beat the benchmark model, we observed that inequality can forecast realized volatility of the UK significantly better than the benchmark at the ten percent level of significance. Complete details of these results are available upon request from the authors.
4. Conclusion

Theory suggests that inequality tends to affect the stock market directly and indirectly. Against this backdrop, the objective of this paper is to investigate whether post-tax and transfer-based measure of income inequality, i.e., the Gini index, could help in forecasting the equity premium in the G7 countries. For our purpose, we analyze the annual out-of-sample period of 1990-2011, given an in-sample period of 1967-1989, using panel data-based predictive frameworks that allows for heterogeneity of parameter estimates across the panels, and also account for possible issues of cross-sectional dependence, persistence and endogeneity of the predictors. Our results show that, time series based predictive regression models fail to beat the benchmark random walk with drift, except in the case of Italy. But, when we consider the panel data models, significant forecasting gains relative to the benchmark are observed for all countries in our sample. Our results highlight the importance of pooling information when trying to forecast long-horizon excess stock returns based on a measure of income inequality, and simultaneously accounting for issues of heterogeneity, cross-sectional dependence, persistence and endogeneity. As part of future research, it would be worthwhile to study the role of inequality in forecasting stock returns of developing countries using the panel predictive regression framework used in this paper.

References


Table 1. Summary Statistics

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Jarque-Bera</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>EXR CANADA</td>
<td>-0.9328</td>
<td>-0.0419</td>
<td>27.1977</td>
<td>-43.0962</td>
<td>14.9578</td>
<td>-0.4294</td>
<td>3.0713</td>
<td>1.3926</td>
<td>0.4984</td>
</tr>
<tr>
<td>EXR FRANCE</td>
<td>-0.9099</td>
<td>-0.2271</td>
<td>43.2606</td>
<td>-42.4584</td>
<td>19.0627</td>
<td>-0.0955</td>
<td>2.4068</td>
<td>0.7281</td>
<td>0.6948</td>
</tr>
<tr>
<td>EXR GERMANY</td>
<td>-0.4687</td>
<td>1.5740</td>
<td>29.0617</td>
<td>-32.5006</td>
<td>18.0717</td>
<td>-0.1436</td>
<td>1.8688</td>
<td>2.5540</td>
<td>0.2789</td>
</tr>
<tr>
<td>EXR ITALY</td>
<td>-4.8029</td>
<td>-8.6542</td>
<td>58.5305</td>
<td>-41.7038</td>
<td>24.1202</td>
<td>0.4891</td>
<td>2.7335</td>
<td>1.9276</td>
<td>0.3814</td>
</tr>
<tr>
<td>EXR JAPAN</td>
<td>1.4464</td>
<td>3.2459</td>
<td>40.6448</td>
<td>-34.5888</td>
<td>17.9468</td>
<td>-0.1943</td>
<td>2.6004</td>
<td>0.5824</td>
<td>0.7473</td>
</tr>
<tr>
<td>EXR UK</td>
<td>-0.4495</td>
<td>2.7695</td>
<td>27.9196</td>
<td>-66.3213</td>
<td>16.2873</td>
<td>-1.5339</td>
<td>7.1345</td>
<td>49.6974</td>
<td>0.0000</td>
</tr>
<tr>
<td>EXR US</td>
<td>-0.1350</td>
<td>2.6338</td>
<td>20.8251</td>
<td>-36.3162</td>
<td>13.9186</td>
<td>-0.5722</td>
<td>2.5968</td>
<td>2.7605</td>
<td>0.2515</td>
</tr>
<tr>
<td>ΔGINI CANADA</td>
<td>0.8341</td>
<td>0.1688</td>
<td>10.3858</td>
<td>-3.9404</td>
<td>2.8777</td>
<td>1.8013</td>
<td>6.1387</td>
<td>42.8064</td>
<td>0.0000</td>
</tr>
<tr>
<td>ΔGINI FRANCE</td>
<td>-0.1883</td>
<td>-0.0989</td>
<td>17.6164</td>
<td>-22.4750</td>
<td>6.5683</td>
<td>-0.4804</td>
<td>6.7462</td>
<td>28.0439</td>
<td>0.0000</td>
</tr>
<tr>
<td>ΔGINI GERMANY</td>
<td>0.1902</td>
<td>-0.0118</td>
<td>8.4833</td>
<td>-12.8800</td>
<td>3.9030</td>
<td>-1.3590</td>
<td>6.4843</td>
<td>36.6150</td>
<td>0.0000</td>
</tr>
<tr>
<td>ΔGINI ITALY</td>
<td>-0.2884</td>
<td>-0.3751</td>
<td>6.3411</td>
<td>-5.6204</td>
<td>2.4528</td>
<td>0.5609</td>
<td>3.8554</td>
<td>3.7315</td>
<td>0.1548</td>
</tr>
<tr>
<td>ΔGINI JAPAN</td>
<td>0.4183</td>
<td>0.2001</td>
<td>8.7609</td>
<td>-5.6402</td>
<td>3.3588</td>
<td>0.6636</td>
<td>3.2572</td>
<td>3.4270</td>
<td>0.1802</td>
</tr>
<tr>
<td>ΔGINI UK</td>
<td>0.5972</td>
<td>0.3483</td>
<td>4.2537</td>
<td>-2.1103</td>
<td>1.4146</td>
<td>0.5012</td>
<td>2.8155</td>
<td>1.9482</td>
<td>0.3775</td>
</tr>
<tr>
<td>ΔGINI US</td>
<td>0.2661</td>
<td>0.3118</td>
<td>3.5433</td>
<td>-2.9770</td>
<td>1.2139</td>
<td>-0.1718</td>
<td>3.9767</td>
<td>2.0098</td>
<td>0.3661</td>
</tr>
</tbody>
</table>

Note: Std. Dev. stands for standard deviation; Probability corresponds to the Jarque-Bera test with the null hypothesis of normality; $EXR_i$ corresponds to excess returns of country $i$; $ΔGini_i$: is the growth rate of the Gini index for country $i$, with $i$ = Canada, France, Germany, Italy, Japan, UK and US.
Figure 1. Data Plots:

1(a). Excess Returns ($EXR$):
1(b). Growth rate of the Gini Index ($\Delta Gini$):
Table 2: One-year-ahead forecasts of equity premium based on panel predictive regressions

<table>
<thead>
<tr>
<th>Country</th>
<th>CCE OLS</th>
<th>CCE GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>INDIV</td>
<td>MG</td>
</tr>
<tr>
<td>Canada</td>
<td>0.9794**</td>
<td>0.9515**</td>
</tr>
<tr>
<td>France</td>
<td>0.9894*</td>
<td>0.9840**</td>
</tr>
<tr>
<td>Germany</td>
<td>0.9970</td>
<td>0.9809**</td>
</tr>
<tr>
<td>Italy</td>
<td>0.9879*</td>
<td>0.9974</td>
</tr>
<tr>
<td>Japan</td>
<td>1.0150</td>
<td>0.9196***</td>
</tr>
<tr>
<td>UK</td>
<td>1.0017</td>
<td>0.9857*</td>
</tr>
<tr>
<td>US</td>
<td>0.9790**</td>
<td>0.9651**</td>
</tr>
<tr>
<td>median RRMSE</td>
<td>0.9894</td>
<td>0.9809</td>
</tr>
<tr>
<td>average RRMSE</td>
<td>0.9927</td>
<td>0.9691</td>
</tr>
</tbody>
</table>

Notes: The table reports the RRMSE, defined as the ratio of RMSE of a linear forecasting model ($ER_t = \alpha_i + \beta_i \Delta Gini_{t-1} + u_t$) to that of the benchmark model (time series random walk with drift); “INDIV” indicates that forecasting is based on country specific model’s coefficients; “MG” indicates that forecasting is based on the average of country specific model’s coefficients; “***” and “**” denote rejection of the null of equal MSEs according to the McCracken’s (2007) $MSEF$ statistic at the 5% and 10% levels, respectively; finite sample critical values are calculated through Monte Carlo simulations.

Appendix:

Table A1. One-year-ahead forecasts of equity premium based on time series predictive regressions:

<table>
<thead>
<tr>
<th>Country</th>
<th>RRMSE:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canada</td>
<td>1.0011</td>
</tr>
<tr>
<td>France</td>
<td>1.0009</td>
</tr>
<tr>
<td>Germany</td>
<td>1.0131</td>
</tr>
<tr>
<td>Italy</td>
<td>0.9580**</td>
</tr>
<tr>
<td>Japan</td>
<td>1.0082</td>
</tr>
<tr>
<td>UK</td>
<td>1.0219</td>
</tr>
<tr>
<td>US</td>
<td>1.0056</td>
</tr>
</tbody>
</table>

Note: See Notes to Table 2.