Does Inequality Help in Forecasting Equity Premium in a Panel of G7 Countries?#

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Abstract

This paper investigates whether the growth rate in the Gini indexes associated with pre- and post-tax and transfer income can help in forecasting the equity premium in the G7 countries over the annual period of 1970-2015. 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 1993-2015, given an in-sample period of 1970-1992, our results show that: (1) Time series-based predictive regression models fail to beat the random walk with drift and autoregressive benchmarks, (2) However, when we consider the panel data models, significant forecasting gains relative to the benchmarks are observed up to five years ahead. Our results highlight the importance of pooling information when trying to forecast long-horizon excess stock returns based on measures of income inequalities, particularly the Gini index associated with post-tax and transfer, and simultaneously accounting for issues of heterogeneity, cross-sectional dependence, persistence and endogeneity. Given that equity market return is considered to be a leading indicator of the overall macroeconomy, our results can assist policymakers to design optimal long-term policies to counteract any possible negative influence.

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1. Introduction

Forecasting stock returns and/or equity premium - which has been in the centre of several studies using both time series and panel data-based approaches (see for example, Rapach et al., (2005, 2013), Sousa (2010), Sousa (2011), Sousa (2015a, 2015b), Afonso and Sousa (2011), Sousa (2012), Rocha Armada et al. (2015), Caporale and Sousa (2016), Sousa et al., (2016), De Castro and Issler (2016), Aye et al., (2017), Costantini and Sousa (2020)) - is an interesting question for at least two 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), Sousa (2010), Sousa (2011), Sousa (2015a, 2015b), Rapach and Zhou (2013), Rocha Armada et al. (2015), Caporale and Sousa (2016), Caporale et al. (2019), 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.

Accordingly, 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? As pointed out by

Aghion et al., (1999), income inequality can impact aggregate saving and investment, but economic theory generates ambiguous predictions of such a relationship. For instance, inequality might foster investment (Kaldor 1955), but it can also hinder it due to credit market imperfections (Stiglitz 1969; Banerjee, 2004). From an empirical point of view, some authors document a negative effect of inequality on investment (Alesina and Perotti, 1996; Alesina and Rodrik 1994; Perotti 1996), while Barro (2000) argues that such negative link accrues to an omitted variable bias. Intuitively, one would expect that more unequal the society, it is likely to lead to limited participation in the equity market. Hence, higher the inequality can lead to lower stock market investment in a specific country, thus affecting stock prices, but as indicated above theoretically this might not necessarily be the case with Kaldor (1955), suggesting higher inequality to result in more overall investment, but this argument can also be extended to the financial market. Naturally, the impact of inequality on stock market is an important empirical question.

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? As pointed out by 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. However, 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) maintain 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. Finally, a political channel can lead to inequality causing the equity premium in an indirect fashion. 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). While all the above theoretical explanations suggest that inequality increases the equity premium, Favilukis (2013) suggests otherwise. The author develops a general equilibrium model to show that, when wage inequality increases and in addition, participation costs fall, the impact on wealth and consumption inequalities are moderate, but there could be large decline in the equity premium. In this framework, increased participation puts middle class households on a level playing field with richer households when it comes to 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. Hence, theoretically, inequality can increase or decrease the equity premium, and thus is more of an empirical issue.

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.[1] More importantly, given that predictive models require out-of-sample validation (Campbell, 2008), Brogaard et al., (2015) show that 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-R^2 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 indexes on income pre- (i.e., market income) and after-taxes and transfer (i.e., disposable 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 1993 to 2015, given an in-sample period of 1970 to 1992, 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

[1] 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.

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), allow not only 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 formally 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., 46 observations, with an out-of-sample of 23 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 categorised 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:

$$ER_{jt} = \alpha_j + B_j' X_{jt-1} + e_{jt} \tag{1}$$

$$e_{jt} = \lambda_j' F_t + u_{jt} \tag{2}$$

where subscript *jt* defines the observation on the j^{th} cross-section unit at time *t*, for $t = 1,2,\dots,T$ and $j = 1,2,\dots,N$. 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.[2] 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, $\overline{ER}_t = \frac{1}{N}\sum_{j=1}^{N} ER_{jt}$ 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:

[2] 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)).

$$ER_{jt} = \alpha_j + B_j' X_{jt-1} + \gamma \overline{ER}_t + \Gamma' \bar{X}_{t-1} + \varepsilon_{jt} \tag{3}$$

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:

$$\hat{B}_{j,CCE-OLS} = \left(\mathcal{X}_j' \bar{D} \mathcal{X}_j\right)^{-1} \mathcal{X}_j' \bar{D} \mathcal{E}\mathcal{R}_j \tag{4}$$

where $\mathcal{X}_j = \left(X_{j1}, X_{j2}, \dots, X_{jT-1}\right)'$, $\mathcal{E}\mathcal{R}_j = \left(ER_{j2}, ER_{j2}, \dots, ER_{jT}\right)'$, $\bar{D} = I_{T-1} - \bar{H}(\bar{H}'\bar{H})^{-1}\bar{H}'$, $\bar{H} = (h_2, h_3, \dots, h_T)'$, $h_t = (1, \overline{ER}_t, \bar{X}_{t-1}')'$, 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:

$$\hat{B}_{CCEMG-OLS} = \sum_{j=1}^{N} \hat{B}_{j,CCE-OLS} \tag{5}$$

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

$$\sqrt{N}(\hat{B}_{CCEMG-OLS} - B) \xrightarrow{d} N(0, \Sigma_{MG}), \tag{6}$$

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

$$\hat{\Sigma}_{CCEMG-OLS} = \frac{1}{N-1} \sum_{j=1}^{N} \left(\hat{B}_{j,CCE-OLS} - \hat{B}_{CCEMG-OLS}\right)\left(\hat{B}_{j,CCE-OLS} - \hat{B}_{CCEMG-OLS}\right)' \tag{7}$$

Pesaran (2006) and 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, they have shown that small-sample properties of the CCE estimators are not affected by the residual serial correlation of the errors. Additionally, Kapetanios et al. (2011) showed that the main results of Pesaran (2006) continue to hold in the case of persistent unobserved factors. Their results provide support to the use of the CCE estimators irrespective of the order of integration of the data.

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) share the good properties of the CCE estimators, and are robust to the presence of endogenous regressors. Furthermore, Neal (2015) 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 1970 to 2015, 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 total return (i.e., inclusive of the dividends) index[3]) 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 money market rate are obtained from the Global Financial Database and the Main Economic Indicators Database of the Organisation for Economic Co-operation and Development (OECD), respectively.

The data on inequality involves two Gini indexes associated with inequality in disposable (post-tax, post-transfer) income, and inequality in market (pre-tax, pre-transfer) income obtained from the Standardized World Income Inequality Database (SWIID), available for download from: http://fsolt.org/swiid/. Note that, it is important to compare the predictive

[3] The specific stock indices used are: Canada: SandP/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: SandP 500. Daily, weekly and monthly data as and when available are converted to annual frequency by taking averages over a specific year.

ability associated with these two alternative Gini indexes, because the former measure captures the degree of redistribution effect of fiscal policy, which in turn is important to account for in the two definitions of the Gini index, especially post the global financial and the European sovereign debt crises (Agnello et al., 2013, 2015, 2019; Agnello and Sousa, 2014), 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. 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 (2019). 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, Italy (US) has the highest (lowest) average excess returns, as well as volatility. For all countries except Italy and the UK excess returns are negatively skewed, while France (US) has the highest (lowest) corresponding value for the excess returns median. Further, the Jarque-Bera test rejects the normality null hypothesis for excess returns only in the case of the UK. In terms of the Gini index, US (Germany) has the highest (lowest) average value of the Gini index of disposable income, while UK (Canada) has the highest (lowest) average value of the Gini index of market index. As far standard deviation goes, for both the measures UK (France) has the highest (lowest) variability. The empirical distribution of the Gini index of disposable income demonstrates negative skewness for Canada, Japan, the UK and the US. The empirical distribution of the Gini index of market income is negatively skewed for Italy, Japan, the UK and the US. Finally, the Jarque-Bera test indicates normality of the Gini indexes at the 5% or 10% significance levels for all cases except the UK. 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. Thus, we also summarize the growth rate of the two measures of the Gini indexes in the same table. We find that, Japan (Italy) has the highest (lowest) average value of the growth of the Gini index of disposable income, while UK (Italy) has the highest (lowest) average value of the Gini index of market index. In terms of standard deviation, Canada (US) has the highest (lowest) variance in the growth of the Gini index of disposable income, while UK (Japan) has the highest (lowest) variability of the Gini index of market index. The growth rates of both measures of inequality are normally distributed.

For our empirical analysis, we consider the following model:

$$ER_{jt} = \alpha_j + \beta_j \Delta Gini_{jt-1} + u_{jt}, t.$$

We estimate out model using the panel CCE-OLS and CCE-GMM procedures described in the methodology section. For comparison reasons, we also estimate the time series version of the above model. We start the analysis with the full sample estimation. Since the focus of the paper is the out-of-sample forecasting of excess returns, we report the in-sample results in the Appendix (Table A1). We find that statistically significant estimates are primarily observed at $h = 2$ and 3, with the effect of the growth of inequality being primarily negative, except for the case of the UK, (and in one instance for the US at h=1 under the CCE-GMM estimation method for inequality in market income). In general, our results tend to suggest that inequality tends to reduce the equity premium. This finding is in line with Favilukis (2013), who suggests that, when wage inequality increases and in addition, participation costs fall, the impact on wealth and consumption inequalities are moderate, but there could be large decline in the equity premium. On average, 1 percentage point increase in the growth rate of inequality, can reduce the equity premium between 4 to 5 percentage points.

Next, we focus on the out-of-sample forecasting of excess returns. Next, we focus on the out-of-sample To this end, we split the total sample period into an in-sample period of 1970-1992, and an out-of-sample period of 1993-2015, with the periods essentially trying to ensure a 50 percent split. 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. In addition, increasing inequality trends mainly took over since the late eighties and the early nineties (Atkinson et al., 2011; Alvaredo et al., 2013; Piketty and Saez, 2014; OECD, 2017). Note that following the extant literature (see for example, Rapach et al., (2005), 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.

For out-of-sample forecasting analysis we consider two different benchmark models, a time series random walk model with drift, i.e., historical average, and an autoregressive model of order one (AR(1)). Furthermore, we perform the forecasting analysis for five forecasting horizons h (1, 2, 3, 4, 5 years).

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 $j = 1,2, \dots, N$. The *MSE-F* statistic is formally defined as:

$$MSEF_j = (T - 1 - R)\left[\frac{MSE_{b,j}}{MSE_j} - 1\right], \tag{8}$$

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 for example, Dwass (1957), Barnard (1963), Dufour and Khalaf (2001)).

The forecasting analysis results against the historical average benchmark are presented in Tables 2-6, while the corresponding results against the AR(1) benchmark are reported in the Appendix (Tables A3-A8). In each table, we report the results for two measures of inequality: the inequality in disposable income (Panel A) and the inequality in market income (Panel B).

Table 2 presents the one-year ahead forecasting analysis against the random walk with drift benchmark. The results reported in Panel A suggest that the panel predictive regressions based on the growth rate of inequality in disposable income provide strong evidence of predictability for the equity premium relative to the random walk model. Specifically, when the CCE with mean group (MG) coefficients methods are used, most of the RRMSEs are less than unity. In the case of the CCE-OLS with MG coefficients, all countries except Italy demonstrate RRMSEs less than unity, which are also statistically significant. Specifically, the $MSEF$ test fails to rejects the null hypothesis of equal MSEs only for Italy. Additionally, the CCE-GMM with MG estimated coefficients also highlight the significant forecasting ability of the model. When CCE-GMM with MG estimated coefficients are used, all countries demonstrate less than one and statistically significant RRMSEs. The only exception is Italy for which the $MSEF$ statistic indicates equal MSEs at all reasonable levels of significance. On the other hand, our results suggest that the CCE methods with individual specific (INDIV) coefficients provide limited forecasting ability of the model. Specifically, CCE-GMM with INDIV (country specific) estimated coefficients, results in less than one and statistically significant RRMSEs for three countries (Canada, France and the US). In the case of CCE-OLS with INDIV coefficients, Canada and France demonstrate less than one and statistically significant RRMSEs. In general, CCE models with mean group coefficient estimates (MG) perform better relative to the other panel predictive regression models. When we compare panel regression forecasting results with the results based on time series predictive regression model, we observe that, barring the case of France, the RRMSE is greater than one in all cases. However, unlike Brogaard et al., (2015), we do not observe inequality to provide forecasting gains for the US equity premium.[4]

The one-year-ahead forecasting results for the case of inequality in market income are reported in Panel B of Table 2. Surprisingly, both panel and time series predictive models suggest that inequality in market income does not help forecasting excess returns. The only exception is Canada for which the RRMSE is less than one and statistically significant for the case of CCE-OLS with country specific coefficients (INDIV).

Let us now examine the forecasting ability of the model at longer horizons. Tables 3-6 report the forecasting analysis results for horizons 2-5 years ahead against the historical average benchmark. Panel A of each table reports the results for inequality in disposable income while Panel B reports the results of inequality in market income. From the inspection of Tables 2-6 we can easily verify that the forecasting regularities observed in the case 1-year-ahead forecasting are also observed at the longer forecasting horizons of 2-, 3-, 4-, and 5-year-ahead. Specifically speaking, we find that, (1) The best forecasting ability can be achieved by panel predictive regression models; (2) panel CCE models with mean group coefficients (MG)

[4] 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.

provide strong forecasting ability in the case of inequality in disposable income; (3) forecasting ability of all models is reduced in the case of inequality in market income, and; (4) time series models fail to beat the benchmark in all cases.

Additionally, some very interesting patterns are present when we forecast at longer horizons using our model and methods. First, panel forecasting regressions seem to maintain their forecasting ability even at longer forecasting horizons. For example, in the case of inequality in disposable income (Panel A of Tables 2-6), CCE-OLS with MG coefficients returns statistically significant and less than one RRMSEs for five countries for one-, two-, three- and four-years-ahead forecasts. This pattern is even stronger in the case of CCE-GMM with MG coefficients that returns statistically significant and less than one RRMSEs for all countries except Italy at all forecasting horizons.

This is not surprising given the possible endogeneity of the regressor. In general, the model CCE-GMM with mean group coefficient estimates (MG) performs better relative to the other panel predictive regression models at all horizons. The second interesting pattern observed when the forecasting horizon is getting longer, is the forecasting ability in the case of inequality in market income (Panel B of Tables 2-6). It is evident that in longer horizons the forecasting ability of inequality in market income is increasing. For example, the CCE-OLS with MG coefficients fail to return a statistically significant and less that one RRMSE for any country when forecasting one-year ahead. However, it returns statistically significant and less that one RRMSEs for two, three and four countries when forecasting two-, three- and five-years-ahead, respectively.

In order to examine to robustness of our results, we repeat the forecasting analysis using a different benchmark model. Specifically, Tables A3-A8 in the Appendix present the forecasting results against the AR(1) benchmark. From the inspection of Tables A3-A8 it is evident that forecasting analysis results against the AR(1) model benchmark are qualitatively similar to those we obtain against the historical average benchmark. Furthermore, all regularities observed in the case of the historical average benchmark are also present in the case of the AR(1) benchmark.

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] In addition, we find that whether inequality is measured on disposable or market income matters. Specifically speaking the growth of the Gini index associated with post-tax and transfer income is a relatively stronger predictor of the stock market than the pre-tax and transfer version of the same. This should not be surprising since fiscal policy decisions have been shown to strongly impact inequality (Agnello and Sousa, 2014). Thus, the more appropriate measure of inequality shock that capture its information content and association with stock market, should be the one based on disposable rather than market income, as at the end of the day agents make investment decisions based on net income.

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 Gini indexes associated with pre- and post-tax and transfer-based measures of income inequality, could help in forecasting the equity premium in the G7 countries. For our purpose, we analyze the annual out-of-sample period of 1993-2015, given an in-sample period of 1970-1992, 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

[5] 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.

of the predictors. Our results show that time series based predictive regression models fail to beat the random walk with drift and autoregressive benchmarks. Contrary, when we consider the panel data models, significant forecasting gains relative to the benchmarks are observed. We find that the use of Gini index of disposable income as a predictor within a panel Common Correlated Effect (CCE) framework with GMM corrections for possible endogeneity, ensures the forecastability of excess stock returns up to five years ahead. Our results highlight the importance of pooling information when trying to forecast long-horizon excess stock returns based on measures of income inequalities, particularly the Gini index associated with post-tax and transfer, and simultaneously accounting for issues of heterogeneity, cross-sectional dependence, persistence and endogeneity.

Our results have important implications for researchers, investors and policymakers. Academics can utilize our findings to explain deviations from asset-pricing models by embedding growth of inequality in their pricing kernels of equity market returns. Moreover, Investors can improve their investment strategies by exploiting the role of growth in inequality in their prediction models, while risk managers can develop asset allocation decisions conditional on the level of inequality shocks. Finally, given that stock markets are historically considered to be a leading indicator of output growth and inflation (Stock and Watson, 2003), the future path of the equity market conditional on measures of inequality, can provide long-term forecast for macroeconomic variables, and help policy authorities design appropriate monetary and fiscal policies to counteract any possible negative impact of equity market behavior on the overall economy.

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.

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Table 1. Summary Statistics

Statistic	Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque-Bera	p-value
Panel A: Excess returns									
Canada	0.0148	0.0199	0.0941	-0.0824	0.0367	-0.4598	3.4577	2.0663	0.3559
France	0.0204	0.0271	0.1474	-0.1090	0.0521	-0.5586	3.5648	3.0690	0.2156
Germany	0.0138	0.0226	0.1029	-0.0886	0.0383	-0.6690	3.6376	4.3023	0.1163
Italy	0.0249	0.0207	0.1448	-0.0818	0.0528	0.2649	2.6285	0.8200	0.6636
Japan	0.0131	0.0174	0.0941	-0.1050	0.0415	-0.5330	3.5100	2.7351	0.2547
UK	0.0168	0.0144	0.1587	-0.0660	0.0399	0.7931	5.4231	16.4255	0.0003
US	0.0100	0.0091	0.0880	-0.0703	0.0335	-0.1402	3.2975	0.3272	0.8491
Panel B: Gini index of disposable income									
Canada	29.5894	29.8000	31.6000	27.1000	1.4713	-0.2712	1.4895	5.0443	0.0803
France	29.1872	29.2000	31.4000	27.8000	0.9946	0.2393	2.2193	1.6422	0.4399
Germany	26.7319	26.5000	29.0000	24.8000	1.2985	0.3024	1.6935	4.0591	0.1313
Italy	33.2638	33.0000	37.6000	30.5000	1.7298	1.1379	3.9950	12.0819	0.0024
Japan	28.4553	29.0000	32.3000	24.6000	2.8391	-0.1496	1.3936	5.2285	0.0732
UK	30.9553	32.8000	34.1000	25.7000	3.1782	-0.6029	1.5269	7.0973	0.0287
US	34.5021	34.9000	38.1000	30.8000	2.3983	-0.2519	1.6463	4.0856	0.1296
Panel C: Gini index of market income									
Canada	42.9149	42.6000	46.1000	39.4000	2.4374	0.0366	1.2255	6.1767	0.0455
France	47.7830	47.6000	49.2000	46.1000	0.7938	0.2452	2.2804	1.4850	0.4759
Germany	45.4298	45.0000	52.2000	38.3000	4.4460	1.1561	1.5925	4.0705	0.1306
Italy	47.3106	47.7000	52.2000	43.0000	2.4909	-0.0066	2.3184	0.9101	0.6344
Japan	40.4809	40.8000	45.7000	35.5000	3.8271	-0.0507	1.4240	4.8840	0.0870
UK	48.3319	52.2000	54.0000	38.3000	5.7183	-0.7043	1.7158	7.1151	0.0285
US	46.2638	46.9000	51.0000	41.4000	3.1679	-0.2348	1.7189	3.6458	0.1615
Panel D: Gini index of disposable income growth rate									
Canada	-0.0004	0.0000	0.0267	-0.0324	0.0136	-0.4170	3.0860	1.3473	0.5098
France	0.0006	0.0017	0.0169	-0.0170	0.0090	-0.4406	2.3928	2.1951	0.3337
Germany	0.0009	0.0017	0.0288	-0.0199	0.0094	0.4655	3.8749	3.1284	0.2093

Italy	-0.0025	-0.0030	0.0323	-0.0250	0.0122	0.4477	3.4463	1.9181	0.3832
Japan	0.0055	0.0065	0.0229	-0.0130	0.0082	-0.1215	2.6335	0.3706	0.8308
UK	0.0047	0.0034	0.0309	-0.0192	0.0115	0.4129	2.6848	1.4975	0.4730
US	0.0046	0.0054	0.0186	-0.0112	0.0063	-0.1990	3.0741	0.3143	0.8546
Panel E: Gini index of market income growth rate									
Canada	0.0022	0.0000	0.0275	-0.0153	0.0108	0.6879	2.7158	3.7829	0.1509
France	0.0009	0.0000	0.0124	-0.0086	0.0060	0.2302	2.0739	2.0500	0.3588
Germany	0.0055	0.0048	0.0309	-0.0178	0.0085	-0.3316	5.3213	11.1707	0.0038
Italy	-0.0011	0.0021	0.0201	-0.0200	0.0100	-0.2398	2.5245	0.8742	0.6459
Japan	0.0053	0.0069	0.0177	-0.0044	0.0053	0.0648	2.1287	1.4871	0.4754
UK	0.0067	0.0075	0.0357	-0.0207	0.0118	-0.0743	3.0601	0.0493	0.9757
US	0.0045	0.0044	0.0200	-0.0146	0.0069	-0.4666	4.2240	4.5410	0.1033

Table 2: Forecasts of equity premium based on panel and time series predictive regressions

h	One-year-ahead				Two-years-ahead				Three-years-ahead			
	CCE OLS		CCE GMM		CCE OLS		CCE GMM		CCE OLS		CCE GMM	
Panel A: The case of inequality in disposable income												
	INDIV	*MG*	*INDIV*	*MG*	*INDIV*	*MG*	*INDIV*	*MG*	*INDIV*	*MG*	*INDIV*	*MG*
Canada	0.9456**	0.9524**	0.9222***	0.9910*	0.9524**	0.9443**	0.9524**	0.9743**	0.9522**	0.9411***	0.9333**	0.9691**
France	0.9620**	0.9695**	0.9835*	0.9652**	0.9715**	0.9715**	0.9822*	0.9723**	0.9760**	0.9727**	0.9854*	0.9765**
Germany	1.0078	0.9702**	1.2903	0.9509**	0.9974	0.9711**	1.1452	0.9611**	0.9938	0.9715**	1.0859	0.9679**
Italy	1.0213	1.0101	1.0699	1.0485	1.0016	1.0120	1.0093	1.0472	1.0054	1.0131	1.0161	1.0611
Japan	1.0229	0.9852*	1.2263	0.9491**	1.0174	0.9859*	1.2073	0.9521**	1.0072	0.9865*	1.0742	0.9548**
UK	0.9910	0.9804**	1.0690	0.9881*	0.9763**	0.9810*	1.0053	0.9887*	0.9768**	0.9816**	1.0228	0.9896*
US	1.0254	0.9771**	0.9883*	0.9457**	0.9925	0.9787**	0.9807**	0.9481**	0.9937	0.9793**	0.9985	0.9537**
Panel B: The case of inequality in market income												
	INDIV	*MG*	*INDIV*	*MG*	*INDIV*	*MG*	*INDIV*	*MG*	*INDIV*	*MG*	*INDIV*	*MG*
Canada	0.9401**	0.9930	1.0164	1.1227	0.9371**	0.9538**	0.9896*	0.9634**	0.9368**	0.9501**	0.9899*	0.9531**
France	0.9946	1.0013	0.9954	1.0504	0.9935	0.9953	1.0025	1.0309	0.9929	0.9918	0.9979	1.0201
Germany	1.0245	0.9932	1.0103	1.0251	1.0043	0.9817*	0.9906	0.9964	0.9974	0.9778**	0.9749**	0.9875*
Italy	1.1039	1.0224	1.1060	1.0643	1.0999	1.0152	1.1195	1.0428	1.0967	1.0094	1.0965	1.0264
Japan	1.1272	1.0040	1.3406	1.0446	1.1036	1.0006	1.3399	1.0355	1.0858	0.9979	1.2565	1.0285
UK	1.0522	1.0201	1.1454	1.1254	1.0257	1.0065	1.0945	1.0834	1.0111	1.0010	1.0493	1.0716
US	1.0701	1.0208	1.0962	1.1336	1.0643	0.9743	1.0082	0.9853*	1.0647	0.9702**	1.0181	0.9733**

Notes: The table reports the RRMSE, defined as the ratio of RMSE of a linear forecasting model ($ER_{jt} = \alpha_j + \beta_j \Delta\, Gini_{jt-1} + u_{jt}$) 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: In-sample estimation results.

	CCE OLS			CCE GMM		
h	1	2	3	1	2	3
Panel A: The case of inequality in disposable income						
			INDIV			
Canada	0.8736	-6.5591	-9.5477*	4.9827	-6.7249	-7.6993***
France	-1.5286	-2.0417	-2.0961*	-1.6787	-2.6645***	-1.9936**
Germany	0.1170	3.8588	-0.0267	0.8230	2.3957*	0.4147
Italy	2.3543	1.4263	-1.7458	3.0470	1.3835	0.4135
Japan	2.2726	-6.8085	6.3191	0.7398	-2.9621	3.9143
UK	-1.5481	0.2394	2.9037*	-0.8973	0.8918	2.5997***
US	-2.5280	9.3797	-12.8971*	-4.0482	8.3577	-12.5838***
			MG			
	0.0018	-0.0721	-2.4415	0.4227	0.0967	-2.1335
Panel B: The case of inequality in market income						
			INDIV			
Canada	1.9161	-14.4283	-13.1631	4.1816	-14.6024	-15.1103**
France	-1.8716	-2.3029	-0.5047	-6.0021	-1.9230*	0.0827
Germany	2.7567	-8.1057*	-9.4651*	-2.3577	-6.9547**	-7.2513***
Italy	1.1039	-1.0771	-3.0731	0.3331	-0.2856	-1.5138
Japan	0.9197	-11.0004	4.1448	2.5393	-5.2293	6.4568
UK	7.2710	-3.5080	0.4933	0.0155	-3.3413	0.2981
US	-2.7764	8.2689	-6.3173	6.6814**	7.1970	-3.5370
			MG			
	1.2771	-4.5933*	-3.9836*	0.7702	-3.5913	-2.9393

Notes: The table reports the estimation results of the linear forecasting model $ER_{jt} = \alpha_j + \beta_j \Delta\, Gini_{jt-1} + u_{jt}$; "INDIV" indicates the CCE individual (country) specific slope coefficients; "MG" indicates the average of the CCE individual (country) slope coefficients. '***', "**" and "*" denote the statistical significance at the 1%, 5% and 10% levels, respectively. *h* is the in-sample forecasting horizon.

Figure 1: In-sample recursive CCE-INDIV estimates for inequality in disposable income

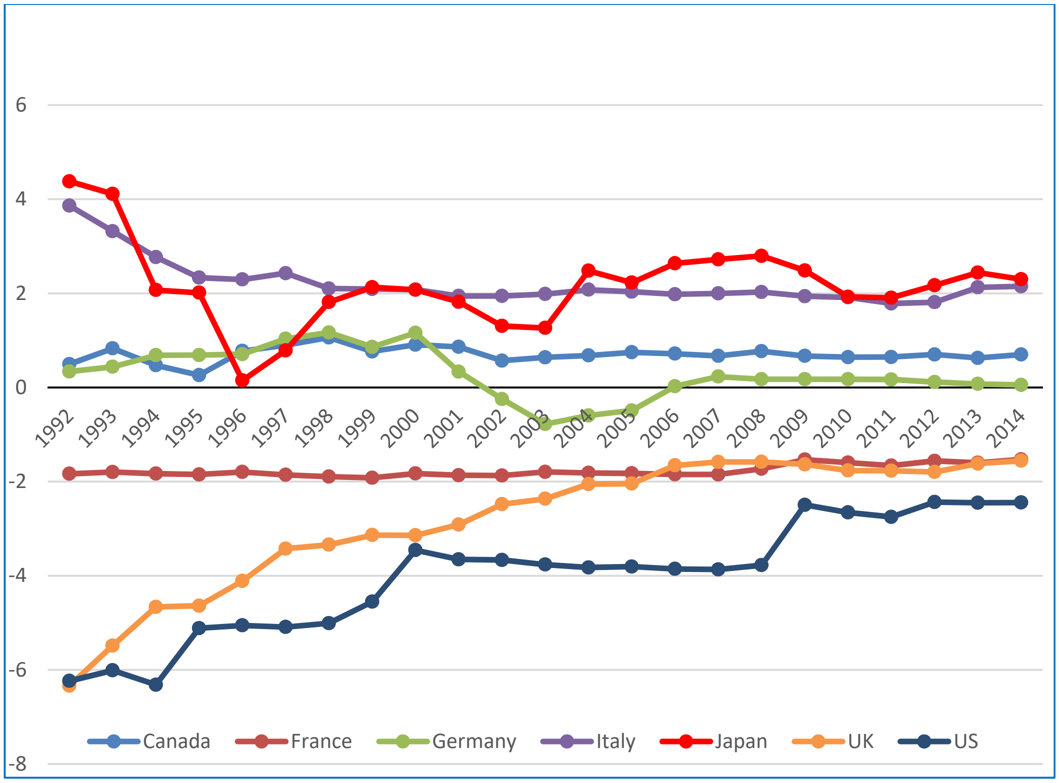

Figure 2: In-sample recursive CCE-GMM-MG estimates for inequality in disposable income

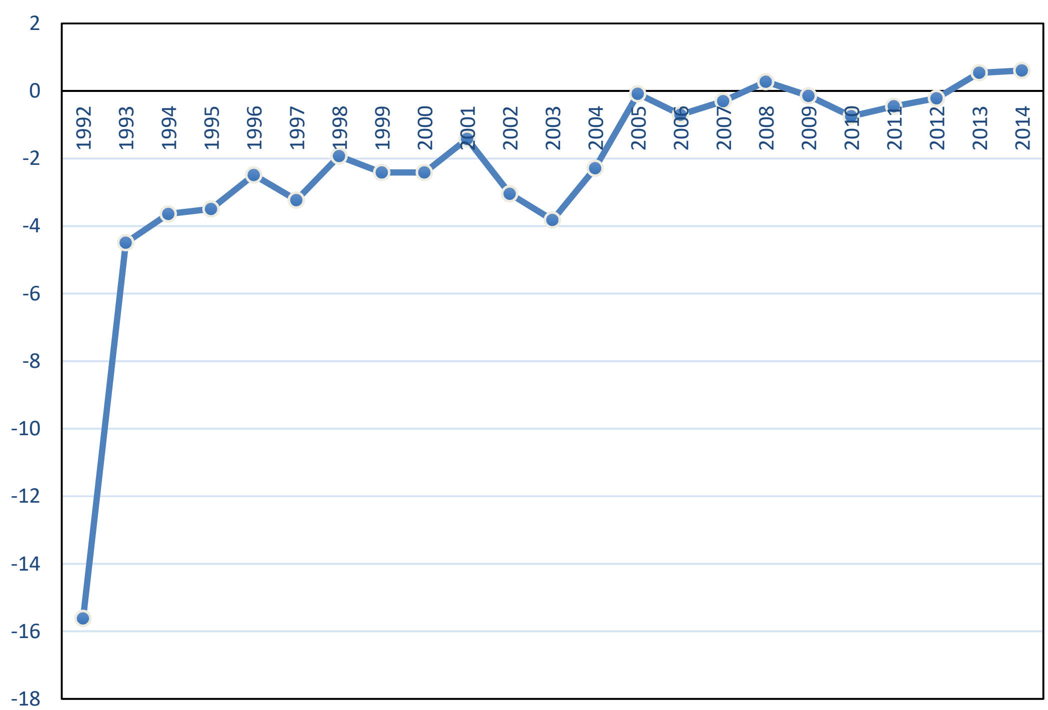

Figure 3: In-sample recursive CCE-GMM-INDIV estimates for inequality in market income

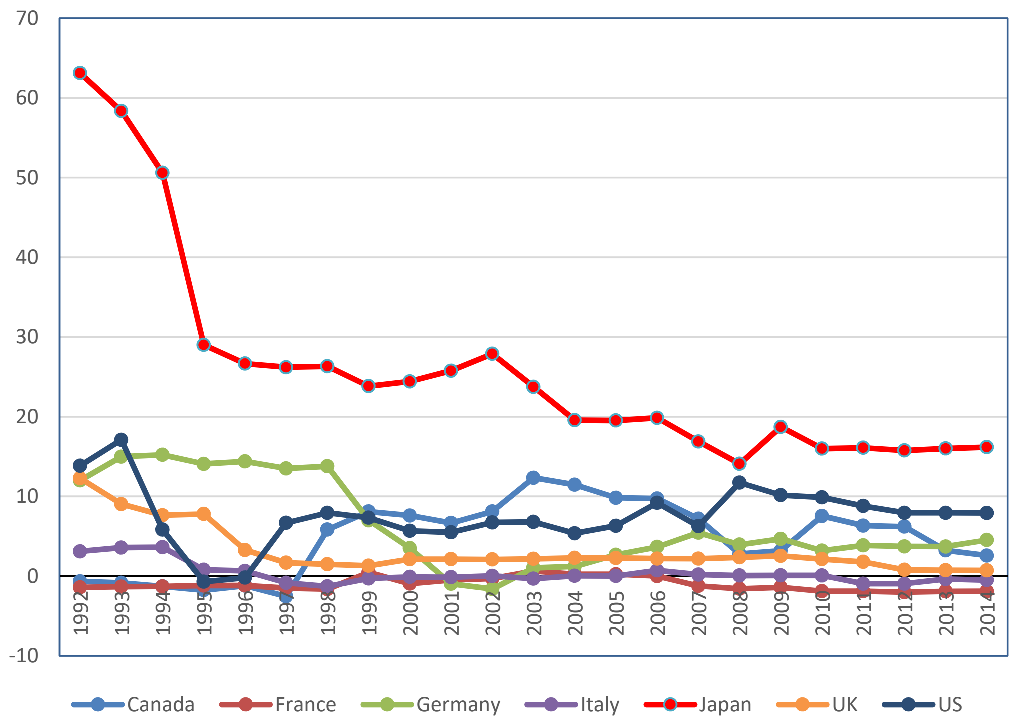

Figure 4: In-sample recursive CCE-GMM-MG estimates for inequality in market income

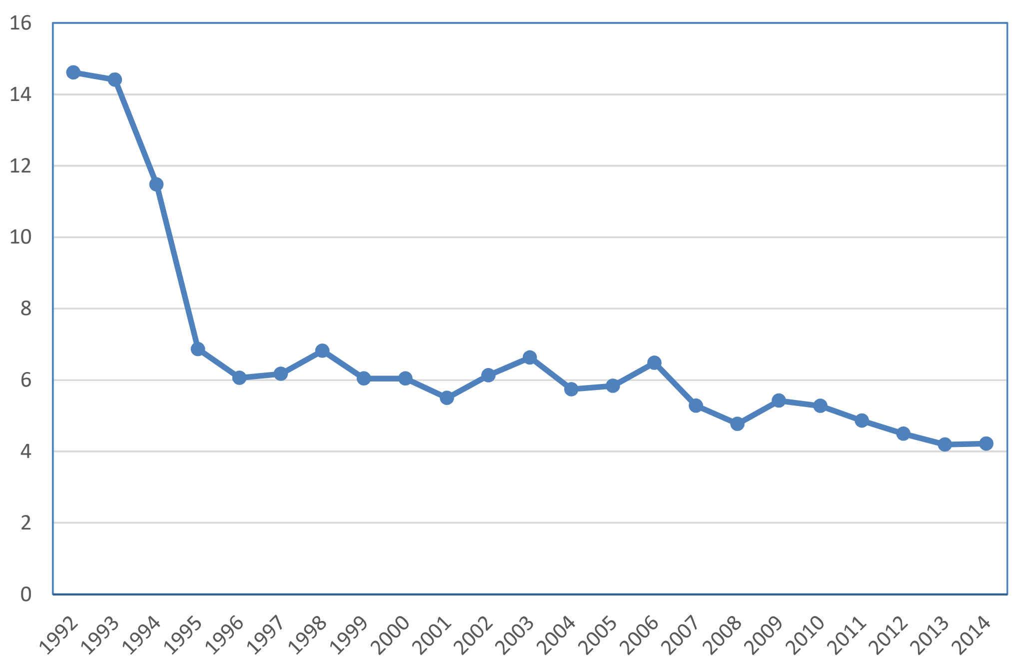

Table A2: One-year-ahead forecasts of equity premium based on panel and time series predictive regressions: The case of AR(1) benchmark.

h	**One-year-ahead**				**Two-years-ahead**				**Three-years-ahead**			
	CCE OLS		**CCE GMM**		**CCE OLS**		**CCE GMM**		**CCE OLS**		**CCE GMM**	
Panel A: The case of inequality in disposable income												
	INDIV	*MG*	*INDIV*	*MG*	*INDIV*	*MG*	*INDIV*	*MG*	*INDIV*	*MG*	*INDIV*	*MG*
Canada	0.9186***	0.9252**	0.8959***	0.9690**	0.9521**	0.9440**	0.9521**	0.9741**	0.9494**	0.9383**	0.9305**	0.9663**
France	0.9854*	0.9901*	1.0075	0.9887*	0.9769**	0.9770**	0.9877*	0.9778**	0.9788**	0.9755**	0.9882*	0.9793**
Germany	1.0273	0.9890*	1.3153	0.9693**	1.0049	0.9784**	1.1538	0.9683**	0.9980	0.9756**	1.0904	0.9719**
Italy	1.0552	1.0436	1.1054	1.0833	1.0187	1.0292	1.0265	1.0651	1.00083	1.0160	1.0191	1.0642
Japan	1.0999	1.0593	1.3186	1.0206	1.0549	1.0222	1.2517	0.9872*	1.0184	0.9975	1.0862	0.9654**
UK	1.0396	1.0285	1.1214	1.0576	0.9855*	0.9902	1.0147	1.0080	0.9783**	0.9831**	1.0245	0.9942
US	1.0287	0.9803**	0.9915	0.9487**	0.9853*	0.9716**	0.9736**	0.9412**	0.9865*	0.9722**	0.9913*	0.9468**
	0.9186***	0.9252**	0.8959***	0.9690**	0.9521**	0.9440**	0.9521**	0.9741**	0.9494**	0.9383**	0.9305**	0.9663**
Panel B: The case of inequality in market income												
	INDIV	*MG*	*INDIV*	*MG*	*INDIV*	*MG*	*INDIV*	*MG*	*INDIV*	*MG*	*INDIV*	*MG*
Canada	0.9132***	0.9646**	0.9874*	1.0906	0.9369**	0.9535**	0.9616**	0.9631**	0.9341**	0.9473**	0.9870**	0.9503**
France	1.0189	1.0254	1.0196	1.0760	0.9991	1.0009	1.0212	1.0367	0.9957	0.9947	1.0008	1.0230
Germany	1.0443	1.0124	1.0298	1.0449	1.0118	0.9891*	1.0022	1.0039	1.0016	0.9818**	0.9789**	0.9916
Italy	1.1405	1.0564	1.1427	1.0996	1.1187	1.0325	1.1373	1.0606	1.0999	1.0124	1.0997	1.0294
Japan	1.2120	1.0796	1.4415	1.1233	1.1443	1.0374	1.3895	1.0737	1.0978	1.0089	1.2704	1.0399
UK	1.1038	1.0702	1.2016	1.1806	1.0354	1.0160	1.1375	1.0936	1.0127	1.0026	1.0509	1.0733
US	1.0737	1.0241	1.0997	1.1373	1.0565	0.9671**	1.0189	0.9781**	1.0570	0.9632**	1.0107	0.9662**

Notes: The table reports the RRMSE, defined as the ratio of RMSE of a linear forecasting model ($ER_{jt} = \alpha_j + \beta_j \Delta\ Gini_{jt-1} + u_{jt}$) to that of the benchmark model (autoregressive of order 1 (AR(1)) model); "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.