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Income inequality, poverty, and the liquidity of stock markets

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ABSTRACT

Using a broad cross-sectional sample of countries, this study tests whether stock market liquidity affects the level of income inequality. After holding a variety of factors constant – including traditional measures of financial development, results show that liquidity in a country's stock market is negatively related to various measures of inequality. We find that this relationship does not exist in the most developed countries. Instead, our results are stronger in underdeveloped and moderately developed countries. In addition, we find that stock market liquidity is negatively associated with poverty rates. In our final set of tests, we attempt to identify the mechanism through which liquidity reduces inequality. After decomposing wage growth into the portion that is driven by stock market liquidity and the portion that is orthogonal to liquidity, we find strong evidence that liquidity-induced wage growth drives the reduction in both inequality and poverty.

1. Introduction

In the public view, financial markets have, at times, contributed to economic turmoil that has spilled over into all classes of society. Theory, however, is relatively in agreement about the implications of how financial development affects economic growth. As early as Schumpeter (1912), economists have studied how the development of financial markets can influence economic growth rates. More recently, several theoretical and empirical studies seem to confirm the idea that finance matters when attempting to explain economic output, although identifying the direction of causality is difficult (Goldsmith (1969), McKinnon (1973), Pagano (1993), King and Levine (1993), Neusser and Kugler (1998), Rajan and Zingales (1998), Levine et al. (2000), Khan (2001), and Calderon and Liu (2003)).

Levine and Zervos (1998) look beyond general financial development, *per se*, and instead examine whether stock markets promote long-run economic growth. Using data from 47 countries, they find that the liquidity of a country's stock market is positively correlated with a country's economic growth rate. These findings suggest that well-functioning stock markets are, at least, an important correlate of economic output. These results also support endogenous growth theory, which indicates that well-functioning markets allow a greater portion of gross saving to flow into capital investment, thus contributing to economic growth (Romer (1989) and Pagano (1993)). What may be more interesting than identifying the association between stock market liquidity and economic growth is determining whether or not this liquidity disproportionately affects the rich vis-à-vis the poor. The main of objective of this study is to examine this particular question. More specifically, we test whether stock market liquidity influences the level of income inequality using a large sample of nearly 100 countries.

Our tests are motivated by a broad stream of research that examines the interaction between finance, economic development, and the distribution of income. Kuznets (1955) proposes that economic growth can contribute to the level of income inequality in the early stages of development. For those well-developed countries, however, greater economic growth can reduce the level of inequality. Greenwood and Jovanovic (1990) follow Kuznets (1955) and model the growth-inequality framework while accounting for financial structure. Their theory shows that in its infancy, both economic and financial development contribute to greater income inequality while more developed countries, with mature financial structures, tend to have more stability with respect to inequality. To the contrary, Becker and Tomes (1979, 1986) show that the development of the financial system can influence the economic opportunities of the poor and subsequently decrease intergenerational inequality.

Demirguc-Kunt and Levine (2009) provide a thorough and critical review of the theory related to this topic. In their review, they concede that the existing theory that speaks to the association between finance and inequality produces conflicting predictions. The empirical literature, however, seems to lean towards the idea that financial development is associated with a reduction in inequality. For example, Burgess and Pande (2005) show that the Reserve Bank of India's decision to open banks in more rural locations resulted in an increase in the wages of the most disadvantaged workers, thus reducing both poverty and inequality.

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Several similar studies have shown that any relaxation of credit constraints disproportionately benefits the poor who suffer from a lack of both collateral and credit histories (Galor and Zeria (1993), Aghion and Boulton (1997), and Galor and Moav (2004)). More generally, Demirguc-Kunt and Levine (2009) find that financial development helps explain the large portion of the income growth in the poorest quintile of the income distribution.[1]

While our tests of the association between stock market liquidity and income inequality fit nicely in this literature, they are different from more standard studies of financial development, which we review in the next section. It is intuitive to predict that the relaxation of credit constraints (i.e. financial development) might result in a greater benefit for the poor given that the poor are more likely to use credit more than the rich. It might be just as intuitive to predict that lower transaction costs in more liquid stock markets will disproportionately benefit the rich, given that the rich are more likely than the poor to participate in these markets. However, a more subtle, alternative hypothesis exists. Theory in Levine (1991) and Bencivenga et al. (1995) argues that more liquidity in stock markets, where the cost of transacting is lower, reduces the disincentives associated with investing in projects that have longer durations. Firms, therefore, might be more likely to undertake such projects resulting in a greater demand for labor. Whether or not liquidity benefits one class more than another class depends on whether the growth in investment income for the rich – due to the lower transaction costs is greater than the growth in income among the poor – due to the increase in the demand for labor. Determining how the benefits of stock market liquidity are distributed among the various classes of society becomes an empirical question, which we seek to answer below.

Using similar approximations for liquidity as in Levine and Zervos (1998), we find a negative correlation between liquidity and various measures of income inequality. After holding a number of other variables constant, including more traditional measures of financial development, we find that the amount of trading volume on a particular country's stock market is negatively related to the country's Gini coefficient. In economic terms, a one standard deviation increase in trading volume is associated with a 1%–6% reduction in the Gini coefficient, depending on the measure of stock market liquidity. These results suggest that the negative relation between liquidity and inequality is not only statistically significant, but the relation is also economically meaningful.

Admittedly, the results from our tests might simply be driven by the most developed countries. To account for this possibility, we sort our sample of countries into three categories based on GDP per capita. Interestingly, we find that in countries with the highest GDP per capita, stock market liquidity is unrelated inequality. Instead, we find significant results in countries with the least GDP per capita and countries with moderate GDP per capita. These results seem to suggest that our findings are not simply an artifact of the most developed countries.

To further determine whether stock market liquidity influences the inequality in the least developed countries, we test whether liquidity reduces poverty. Here, we find some evidence that stock market liquidity reduces the fraction of the country's population living on less than $1.25 a day – a measure of poverty typically associated with the least developed countries. We also find evidence of a negative relation between liquidity and poverty rates when we examine the fraction of the population that lives below the "nationally-determined" poverty line. Combined with our earlier tests, these findings support the notion that, if anything, stock market liquidity provides more benefit to the poor than to the rich.

As with most of the empirical work in this area, it is difficult to determine the direction of causation in the relationship between liquidity and inequality. In a review of this related literature, Claessens and Perotti (2007) discuss the importance of recognizing the potential for reverse causality – or how inequality can affect financial development. Much of this work revolves around the idea that income inequality creates unequal political influence and can result in some type of control or even regulatory capture of the financial system (Rajan and Zingales (2003) and Perotti and Volpin (2007)).

In our next set of tests, we attempt to strengthen our causal inferences. Doing so is not easy given that identifying a valid instrument is difficult. Finding an appropriate identification strategy may be more problematic. For instance, we would ideally like to use an exogenous shock to the level of market liquidity as a natural experiment where we would then examine inequality during the periods before and after this shock. However, inequality is measured so infrequently (every three to four years in our data), it is naïve to assume that we can properly isolate the effect of a shock to liquidity on the levels of income inequality. Therefore, we take a non-traditional approach and instead of attempting to identify an exogenous shock to liquidity, we attempt to provide some tests that rule out the possibility of reverse causation. In particular, we seek to identify a shock to inequality and then examine market liquidity surrounding this shock in order to make inferences about the possibility that our earlier findings are explained by reverse causation.

In late December 2013, the French Constitutional Court unexpectedly decided to uphold a proposal for a 75% "Millionaire Tax", which would be imposed on employers that compensated an employee more than €1 million per year. This decision came as a surprise given that a year earlier, the same Court rejected a similar proposal. To the extent that reverse causation explains our findings thus far, trading volume in French stocks is expected to increase in response to the Court's decision, which resulted in an (arguably) exogenous reduction in inequality. We face another challenge when trying to compare the liquidity of French stocks to non-French stocks surrounding this particular event. The structure of markets influences liquidity, and inequality, in a particular country, might endogenously determine how financial markets are structured. We therefore recognize the need to control for this potential endogeneity in our tests. Following Eleswarapu and Venkataraman (2006), we examine the liquidity of American Depositary Receipts (ADRs), which are certificates that trade on U.S. exchanges but represent foreign shares of stock. In doing so, we hold constant the structure of the market on which the stock trades while conducting our event study.

Both univariate and multivariate tests show that liquidity in French stocks does not decrease vis-à-vis non-French stocks during the six-month period after the Court's decision. In fact, we find that, if anything, trading volume in French ADRs decreases instead of increases. These results are again robust to controls for other factors that might influence the level of liquidity in the ADR market. Our findings seem to suggest that the negative relation between liquidity and inequality is not explained by reverse causation. We raise caution, however, when drawing strong inferences from these tests. The identification strategy is not ideal, but our tests are intended to begin to speak about the direction of causation. Perhaps a fruitful avenue for future research would be to cleverly tease out causality not only for the liquidity-inequality finding in this paper, but also for the liquidity-economic growth finding in Levine and Zervos (1998).

In our final set of tests, we explore the possible mechanism through which liquidity can adversely affect inequality. Given the theories that suggest that market liquidity can lead to a higher demand for labor (Levine (1991) and Bencivenga et al. (1995)), we test whether wage growth is indeed the link that explains the liquidity/inequality relation. First, we find a strong positive correlation between stock market liquidity and wage growth. We then decompose the wage growth into two portions: the portion of wage growth that is driven by stock market liquidity and the portion of wage growth that is orthogonal to liquidity. After finding a weak, negative relation between (non-decomposed) wage growth and inequality generally, we find strong evidence that liquidity-induced wage growth is negatively related with inequality. These results are both statistically and economically significant. We do not find that the portion of wage growth that is orthogonal to liquidity is related to inequality. Taken together, our findings suggest that stock

[1] For a more thorough review of the literature on finance and income inequality, please see Claessens and Perotti (2007), and Demirguc-Kunt and Levine (2009).

market liquidity is associated with a reduction in income inequality and that wage growth is an important link explains this association.

2. Related literature

Our tests of the association between stock market liquidity and income inequality are most closely related to a broad literature that examines the role that financial development plays in the distribution of income. Both recent theoretical and empirical literature discusses how financial liberalization influences economic inequality (Agnello et al. (2012), Delis et al. (2014), Li and Yu (2014), Jaumotte and Osuorio Buitron (2015), Naceur and Zhang (2016) and Bumann and Lensink (2016)). However, our tests are more concerned with how specific developments in the financial sector influence inequality.

Theory in Demirguc-Kunt and Levine (2009) indicates that how financial development affects economic inequality is ambiguous. On one hand, if credit constraints are relaxed, then the poor should benefit and inequality should be reduced. Similar arguments are made in Galor and Moav (2004) and Beck et al. (2007). On the other hand, if financial development simply improves the quality of existing financial services but does not improve the access to credit markets, then the rich, who are likely using those existing services, should benefit and the distribution of income may widen. Arguments similar to these are made in Greenwood and Jovanovic (1990).[2]

Empirically, the findings in the literature are somewhat mixed. Li et al. (1998) show that financial development – as measured by the ratio of M2 money supply to GDP – is negatively related to income inequality. Similar results are found in Beck et al. (2007), Clarke et al. (2006), and Hamori and Hashiguchi (2012). Naceur and Zhang (2016) find that components for financial development, such as access, efficiency, and stability, are associated with a narrower income distribution. However, mixed results are found in Kappel (2010) and Kim and Lin (2011). In the former study, Kappel (2010) shows that financial development reduces inequality for more developed countries but not for less developed countries. In the latter study, Kim and Lin (2011) find that the reduction in inequality only occurs at a threshold level of financial development. Below that threshold, financial development tends to increase inequality.

In other studies, Bahmani-Oskooee and Zhang (2015) use time-series tests to determine that the effect of financial development on the distribution of income is a short-term phenomenon and is not persistent across longer time periods. Additionally, others find that the relation between financial development and inequality is sensitive to subsamples of countries, to including different controls, and to how financial development is measured. For instance, Li and Yu (2014) show that in 18 Asian countries, the relation between financial development and inequality is positive. Similar results are found in Denk and Cournede (2015) for OECD countries. In a number of tests, Jauch and Watzka (2012) finds that financial development increases inequality in some econometric specifications. Jaumotte et al. (2013) find that the parts of financial development associated with trade and globalization can increase inequality. In addition, Gimet and Lagoarde-Segot (2011) use multivariate time series methods to determine that development within the banking sector is associated with a widening of the income distribution.[3]

The existing literature, therefore, broadly examines how financial development affects income inequality. Other studies test whether stock markets contribute to economic growth. The objective of our study is to bridge these two streams of research by focusing on tests that determine whether stock markets explains the distribution of income.

3. Data description

The data is gathered from the World Bank. To obtain measures of income inequality, we gather the World Bank's estimate of the Gini Coefficient (Gini), which measures the percentage of the maximum area between the Lorenz curve and a hypothetical line representing perfect equality. The coefficient is bound between zero and 100, where a coefficient equal to zero represents perfect equality while a coefficient equal to 100 represents perfect inequality. We also obtain several other measures that might represent income inequality. IncShr90 is the fraction of income earned by individuals that are in the top decile of the income distribution. Similarly, IncShr80 is the fraction of the income earned by individuals in the top quintile of the income distribution. IncShr20 and IncShr10 are the fractions of income in a particular country earned by individuals in the bottom quintile and bottom decile, respectively. We also gather estimates of poverty for each of our countries. For instance, Poverty1.25 is the fraction of the population that lives on less than $1.25 per day while PovertyGen is the fraction of the population that lives beneath the nationally determined poverty level.

The liquidity measures include the following: Turnover is the ratio of the total amount of trading volume that occurs on a country's stock market to the total amount shares outstanding in a particular country; Volume/GDP is the ratio of the total trading volume on a country's stock market relative to total GDP. The other financial development characteristic is similar to those used in previous studies (Levine (1997), Levine and Zervos (1998), and Demirguc-Kunt and Levine (2009)). For instance, BankCredit is the gross amount of domestic credit provided by banks (relative to GDP).[4] We also gather data on several other macroeconomic characteristics that might be important to control for when determining the association between liquidity and income inequality. GDP is the country's level of GDP while Output Growth is the growth rate of GDP. Savings is the amount of gross savings relative to GDP and Net Exports is the difference between Exports and Imports for a particular country.

From the World Bank, we gather data for the universe of countries from 1960 to 2014. The variables used in the analysis are not populated for each year or for each country. For example, the World Bank began to be reporting income inequality in 1985. Volume/GDP became available in 1988 while Turnover became available in 1989. We also note that, even after 1985, the income inequality measures are not provided for each country in each year. The poverty measures are provided for fewer countries in fewer years. The total number of countries (that have both inequality data and liquidity data in the same year) included in the analysis is 91. The total number of country-year observations ranges from about 400 to 630, depending on the measure in question.

Table 1 reports statistics that summarize the data used in the study. In some of the tests that follow, we analyze subsamples of countries based on per capita GDP. Doing so helps us isolate how stock market liquidity influences inequality for more developed countries and for less developed countries. After taking the average GDP per capita by country, we sort the countries into three subsamples. Panel A reports the summary statistics for the 30 countries with the lowest GDP per capita. Panel B shows the statistics for the 31 countries with GDP per capita ranked in the middle while Panel C reports the summary statistics for the 30 countries with highest GDP per capita. Each of the panels groups the variables of interest into two categories. The first seven variables capture income inequality and poverty by country. The second set of variables examines both the liquidity of countries' financial markets (Turnover and Volume/GDP) and credit market activity. The average country in Panel A has a Gini Coefficient of 39.31 while the share of income earned by the top decile (quintile) is 31.25% (46.49%). The average country in this panel

[2] Rajan and Zingales (2003) suggest that some of the ambiguity associated with how financial development affects inequality might be due to institutional quality. In countries with poor institutional quality, privileged access to finance my only benefit the rich.

[3] Delis et al. (2014) show that the liberalization of banking sectors reduces inequality but this result does not hold across all types of liberalization policies.

[4] In a number of other unreported tests, we also examine how the market capitalization of all publicly traded companies in a particular country, which is also used in Levine and Zervos (1998), influences inequality. The results are available from the authors upon request.

Table 1

Summary Statistics. The table reports statistics that describe the sample of countries used in the analysis. Gini is the World Bank estimate of the Gini coefficient for each country in each year. IncShr90 is the fraction of income earned by the richest 10%. IncShr80 is the fraction of income earned by the richest 20%. IncShr20 is the fraction of income earned by the poorest 20%. IncShr10 is the fraction of income earned by the poorest 10%. Poverty1.25 is the fraction of country i's population that lives on less than $1.25 (U.S. Dollars) in a day during a particular year. PovertyGen is the fraction of country i's population that lives below the poverty line according to that country's definition of the poverty line. Turnover is the total amount of stocks traded on a particular countries stock market scaled by the total amount of shares outstanding that particular country. Volume/GDP is the ratio of the dollar volume of stocks traded on a particular countries stock market to total GDP in that particular country. BankCredit is the gross amount of domestic credit provided by banks. We sort the 91 countries in our sample into three categories based on GDP/Capita. Low GDP/Capita Countries are those 30 countries with the lowest GDP/Capita while Mid GDP/Capita Countries and High GDP/Capita Countries are those 31 and 30 countries with the middle and highest GDP/Capita. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Mean	Std. Deviation	Minimum	Median	Maximum
	[1]	[2]	[3]	[4]	[5]
Panel A. Low GDP/Capita Countries (N = 30)					
Gini	39.31	8.47	24.82	38.40	63.00
IncShr90	31.25	6.29	20.98	29.88	49.00
IncShr80	46.49	6.71	35.17	45.63	65.33
IncShr20	6.59	2.18	0.80	6.56	10.21
IncShr10	2.71	1.08	0.13	2.75	4.52
Poverty1.25	22.00	19.83	0.00	16.22	84.23
PovertyGen	31.36	15.27	5.80	28.60	66.40
Turnover	43.33	86.92	0.04	9.74	580.60
Volume/GDP	8.64	21.83	0.00	0.81	132.95
BankCredit	31.41	25.63	3.76	24.54	127.57
Panel B. Middle GDP/Capita Countries (N = 31)					
Gini	46.62	9.29	26.83	47.64	67.40
IncShr90	36.23	7.66	21.44	35.99	57.54
IncShr80	52.19	7.91	36.17	52.41	72.21
IncShr20	4.70	1.97	1.40	4.23	9.48
IncShr10	1.72	0.94	0.13	1.46	4.04
Poverty1.25	6.11	7.73	0.00	3.80	78.59
PovertyGen	29.60	14.89	2.80	28.65	69.00
Turnover	34.68	120.35	0.27	10.43	1612.94
Volume/GDP	11.54	22.90	0.00	1.79	153.03
BankCredit	41.48	29.36	8.07	31.01	155.90
Panel C. High GDP/Capita Countries (N = 30)					
Gini	33.01	6.17	22.94	32.49	51.99
IncShr90	25.83	4.39	19.65	25.07	41.48
IncShr80	40.83	4.80	33.65	40.26	56.89
IncShr20	7.56	1.63	3.66	7.65	10.80
IncShr10	2.89	0.82	0.75	2.94	4.65
Poverty1.25	0.87	1.80	0.00	0.10	8.62
PovertyGen	22.68	15.36	8.60	17.50	69.00
Turnover	58.62	49.44	0.37	45.49	269.82
Volume/GDP	38.35	61.29	0.02	12.83	348.44
BankCredit	69.19	41.76	12.99	59.35	248.98

also reports that the share of income earned by the bottom quintile (decile) is 6.59% (2.71%). We also show that 22% of the average country's population lives on less than $1.25 per day and 31.36% of the average country's population lives below the poverty level that is determined nationally. The average country has Turnover of 43.33% and trading volume that represents nearly 9% of GDP. Of GDP, about 31.4% is provided as credit by banks in a particular country.

Panels B and C report the summary statistics for the other subsamples. A few results are noteworthy. First, we find that the average country in Panel B has a higher Gini coefficient than the average country in Panel C. We also find that the percent of the population living on less than $1.25 a day is decreases across panels. For instance, Poverty1.25 is 6.11% in Panel B and .87% in Panel C. We also find that PovertyGen is decreasing across panels. To the contrary, Volume/GDP and BankCredit is increasing across each panel.

Fig. 1 through 3 provide a graphical representation of the data that might also help summarize several of the variables of interest. First, Fig. 1 shows the time trend of the two market liquidity variables. The figure reports the equally-weighted, cross-country mean of these measures across our sample time period. In general, we find that both Turnover and Volume/GDP is increasing from the late 1980s to about 2007 with a spike in the year 2000, which is likely to be explained by technology boom. From 2008 to 2012, we observe a decrease in both of our liquidity measures, which is likely in response to the global financial crisis. Given the theory suggesting that liquidity in financial markets is decreasing in the level of asymmetric information, observing a reduction in trading activity is expected as the degree of uncertainty likely surged in response to the crisis and the vast amount of regulation that ensued.

Figs. 2 and 3 show the results for our five inequality measures and two poverty measures, respectively. Specifically, Fig. 2 shows that income inequality decreases for the average country from 1986 to 1988 but has remained relatively stable during the last 20 years. Poverty, on the other hand, has generally been decreasing during the last several years. For the average country, poverty, as defined by national guidelines, reached its maximum level in 1988 at around 65% but obtained its minimum level in 2014 at a level slightly below 20%. Similar inferences can be made when examining the poverty rate, as defined by the fraction of the population living on less than $1.25. A few other results are noteworthy when looking at the figures. First, Fig. 1 shows that Turnover is not available in 1988, and all three measures in the figure conclude in 2012. Therefore, our analysis will extend from 1989 to 2012 when focusing on Turnover and from 1988 to 2012 when focusing on Volume/GDP. Second, Fig. 2 shows that while we have inequality data for a time period similar to our liquidity measures, the data is not available for every country in every year. In fact, the average country only reports inequality data about three times during our sample time period. Third, while data on PovertyGen is missing in 1986 and extends to 2014, we only analyze the effect of liquidity on poverty from 1988 (or 1989 when analyzing Turnover) to 2012 given the data limitation for our liquidity measures.

4. Empirical tests

In this section, we begin by first examining univariate correlations between the income inequality measures and our variables capturing stock market liquidity. Second, we report our multivariate tests that attempt to isolate the effect of market liquidity on inequality while holding other important factors constant. Third, we provide some additional analysis in order to begin to make causal inferences. Fourth, we attempt to identify the mechanism through which stock market liquidity influences inequality.

4.1. Univariate correlations

We begin by estimating simple univariate correlations between the income inequality measures, poverty measures, and our independent variables of interest. Table 2 reports the Pearson correlation coefficients along with the corresponding p-values (in brackets) for our entire sample of 91 countries. In the first row, we find that the first five measures of inequality are heavily correlated. We also find that Gini is also positively correlated with Poverty1.25 and PovertyGen. Consistent with the idea that market liquidity is negatively associated with inequality, we find that by Turnover and Volume/GDP are negatively related to income inequality. The correlation coefficients in first row of columns [8] and [9] are also reliably different from zero (p-values = <.0001, <.0001). We also find some evidence that Gini and BankCredit are negatively correlated (coefficient = −0.065, p-value = 0.038), which supports finding in Demirguc-Kunt and Levine (2009).

A few other results reported in Table 2 are noteworthy. First, we are able to draw similar conclusions when looking at the four income share variables. More specifically, IncShr90 and IncShr80 are negatively related to both Turnover and Volume/GDP while IncShr10 and IncShr20 are positively related the market liquidity variables. Second, we also find some evidence of cross-country correlation between our market liquidity

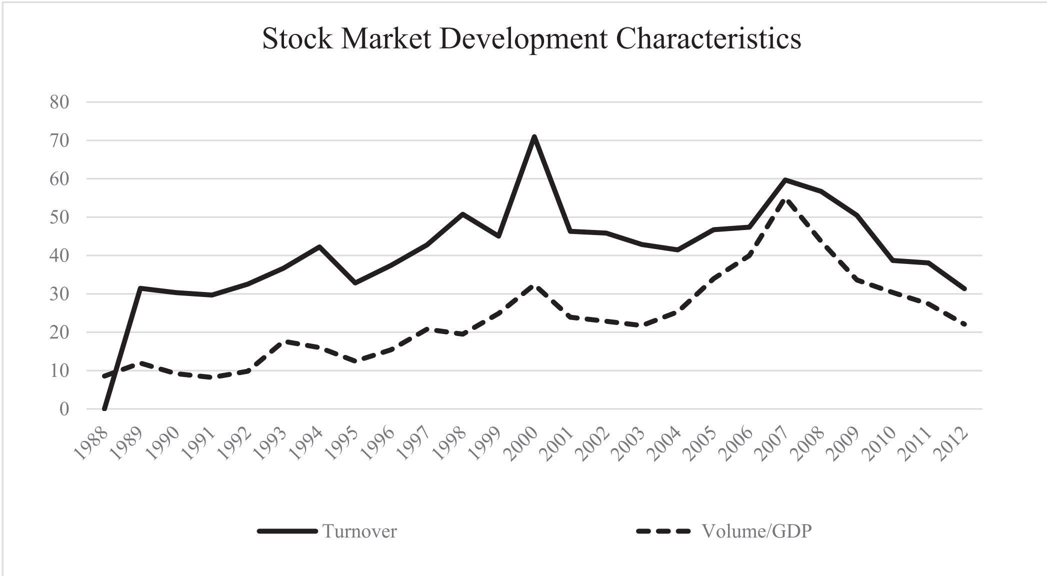

Fig. 1. The figures shows the Stock Market Development characteristics for the average country in our sample across the time period when the data was available.

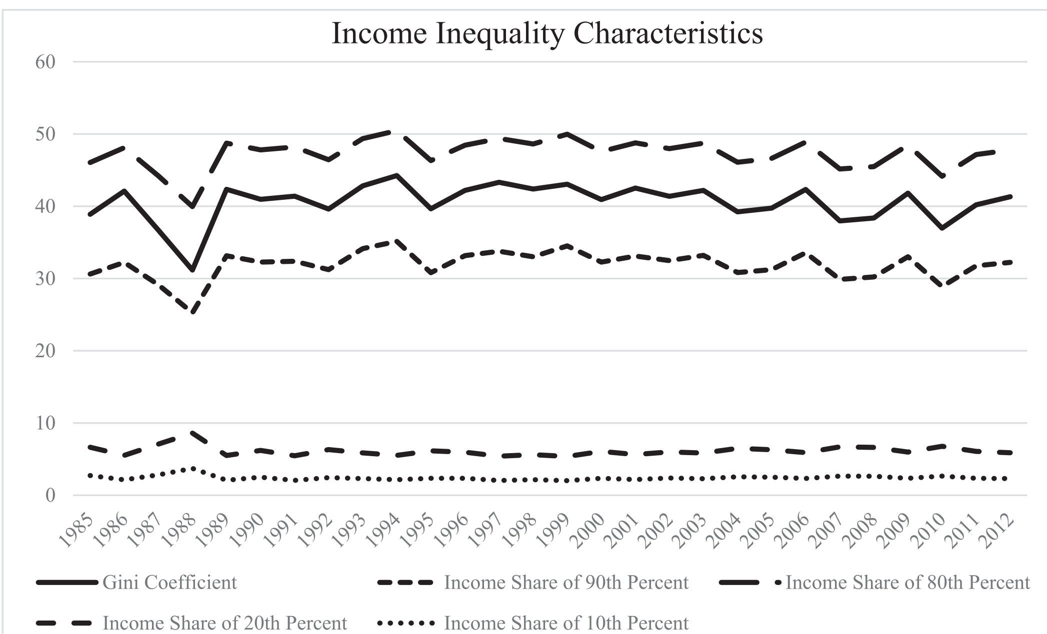

Fig. 2. The figures shows the Income Inequality characteristics for the average country in our sample across the time period when the data was available.

measures and our poverty measures. In particular, column [8] shows that Turnover relates inversely with PovertyGen while Volume/GDP is negatively associated with both Poverty1.25 and PovertyGen. We are able to draw similar conclusions when examining the correlation coefficients for BankCredit.

4.2. *Multivariate tests – inequality and liquid stock markets*

In this subsection, we report the bulk of our multivariate tests. We first examine the association between our five income inequality measures and our two market liquidity variables. We do so while holding constant other factors including financial development and other macroeconomic characteristics. Second, we conduct a subsample analysis to determine how liquidity influences inequality for those countries that are least developed and those that are most developed (according to per capita GDP). Third, we explore the relationship between poverty variables and our liquidity measures.

We begin by estimating the following equation using pooled country-year observations in an unbalanced panel.

$$\begin{aligned} Ln\left(Inequality_{i,t}\right) = {} & \beta_1 Ln(Turnover_{i,t}) + \beta_2 Ln(BankCredit_{i,t}) \\ & + \beta_3 Output\ Growth_{i,t} + \beta_4 Ln\left(Saving_{i,t}\right) \\ & + \beta_5 Net\ Exports_{i,t} + \alpha + \varepsilon_{i,t} \end{aligned} \tag{1}$$

The dependent variables include the natural log of our five measures of inequality. Gini is the World Bank estimate of the Gini coefficient for each country in each year. IncShr90 is the fraction of income earned by the richest 10%. IncShr80 is the fraction of income earned by the richest 20%. IncShr20 is the fraction of income earned by the poorest 20%. IncShr10 is the fraction of income earned by the poorest 10%. The

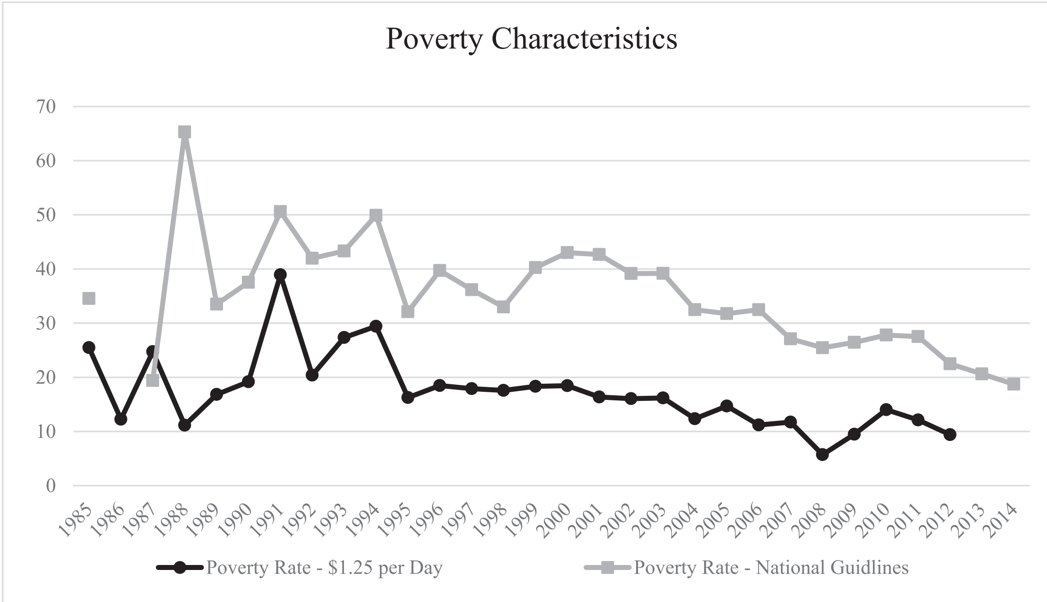

Fig. 3. The figures shows the Poverty characteristics for the average country in our sample across the time period when the data was available.

Table 2

Correlation Matrix for the Entire Sample. The table reports the Pearson correlation coefficients along with corresponding p-values (in brackets). Gini is the World Bank estimate of the Gini coefficient for each country in each year. IncShr90 is the fraction of income earned by the richest 10%. IncShr80 is the fraction of income earned by the richest 20%. IncShr20 is the fraction of income earned by the poorest 20%. IncShr10 is the fraction of income earned by the poorest 10%. Poverty1.25 is the fraction of country i's population that lives on less than $1.25 (U.S. Dollars) in a day during a particular year. PovertyGen is the fraction of country i's population that lives below the poverty line according to that country's definition of the poverty line. Turnover is the total amount of stocks traded on a particular countries stock market scaled by the total amount of shares outstanding that particular country. Volume/GDP is the ratio of the dollar volume of stocks traded on a particular countries stock market to total GDP in that particular country. BankCredit is the amount of domestic credit provided by banks as a percent of GDP.

	Gini	IncShr90	IncShr80	IncShr20	IncShr10	Pov.125	Pov.Gen	Turnover	Vol./GDP	BankCredit
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Gini	1.000	0.986 [<.0001]	0.997 [<.0001]	−0.968 [<.0001]	−0.924 [<.0001]	0.161 [<.0001]	0.490 [<.0001]	−0.196 [<.0001]	−0.149 [<.0001]	−0.065 [0.038]
IncShr90	–	1.000	0.995 [<.0001]	−0.913 [<.0001]	−0.857 [<.0001]	0.192 [<.0001]	0.491 [<.0001]	−0.197 [<.0001]	−0.156 [<.0001]	−0.071 [0.024]
IncShr80	–	–	1.000	−0.944 [<.0001]	−0.892 [<.0001]	0.178 [<.0001]	0.492 [<.0001]	−0.197 [<.0001]	−0.154 [<.0001]	−0.065 [0.039]
IncShr20	–	–	–	1.000	0.986 [<.0001]	−0.101 [0.002]	−0.457 [<.0001]	0.181 [<.0001]	0.126 [0.001]	0.033 [0.300]
IncShr10	–	–	–	–	1.000	−0.047 [0.150]	−0.420 [<.0001]	0.164 [<.0001]	0.090 [0.016]	−0.014 [0.664]
Pov.1.25	–	–	–	–	–	1.000	0.579 [<.0001]	0.019 [0.652]	−0.072 [0.085]	−0.402 [<.0001]
Pov.Gen	–	–	–	–	–	–	1.000	−0.200 [<.0001]	−0.219 [<.0001]	−0.464 [<.0001]
Turnover	–	–	–	–	–	–	–	1.000	0.464 [<.0001]	0.186 [<.0001]
Vol./GDP	–	–	–	–	–	–	–	–	1.000	0.402 [<.0001]
BankCredit	–	–	–	–	–	–	–	–	–	1.000

independent variable of interest is the natural log of Turnover. The other control variables include the following: the natural log of domestic credit provided by banks as a percent of GDP (BankCredit); the natural log of the GDP (GDP); the growth rate of GDP (Output Growth); the natural log of gross savings relative to GDP (Savings); and the difference between exports and imports (Net Exports). In response to a Hausman test and additional F-tests, we include year fixed effects. Below each estimate, we report t-statistics that are obtained from standard errors that cluster across both countries and years.

In column [1] of Table 3, the dependent variable is Ln(Gini). Consistent with the idea that financial development results in lower levels of inequality, we find that the estimate for Ln(BankCredit) is −0.0376 (t-statistic = −3.23). In economic terms, a one standard deviation increase in BankCredit is associated with an reduction in the Gini coefficient of about 1.35% suggesting that the results are not only statistically significant, but the they are also economically meaningful. These results further support the findings in Demirguc-Kunt and Levine (2009). We also find that GDP and Net Exports are positively associated with Gini coefficients while the level of savings is generally negatively related to the Gini coefficient. In fact, the control variables produce qualitatively similar coefficients in columns [2] and [3]. In columns [4] and [5], when the dependent variable is the share of income earned by

Table 3
Multivariate Regressions – Income Inequality and Stock Market Turnover. The table reports the results from estimating the following equality using our pooled (Country-Year) sample.

$$Ln(Inequality_{i,t}) = \beta_1 Ln(Turnover_{i,t}) + \beta_2 Ln(BankCredit_{i,t}) + \beta_3 Output\ Growth_{i,t} + \beta_4 Ln(Saving_{i,t}) + \beta_5 Net\ Exports_{i,t} + \alpha + \varepsilon_{i,t}$$

The dependent variables include the natural log of our five measures of inequality. Gini is the World Bank estimate of the Gini coefficient for each country in each year. IncShr90 is the fraction of income earned by the richest 10%. IncShr80 is the fraction of income earned by the richest 20%. IncShr20 is the fraction of income earned by the poorest 20%. IncShr10 is the fraction of income earned by the poorest 10%. The independent variable of interest is the natural log of total amount of stocks traded on a particular countries stock market scaled by the total amount of shares outstanding that particular country (Turnover). The other control variables include the following: the natural log of the gross amount of domestic credit provided by banks (BankCredit); the natural log of the GDP (GDP); the growth rate of GDP (Output Growth); the natural log of gross savings relative to GDP (Savings); and the difference between exports and imports (Net Exports). In response to a Hausman test and additional F-tests, we include year fixed effects. In parentheses, we also report t-statistics that are obtained from standard errors that cluster across countries and years. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Ln(Gini)	Ln(IncShr90)	Ln(IncShr80)	Ln(IncShr20)	Ln(IncShr10)
	[1]	[2]	[3]	[4]	[5]
Ln(Turnover)	−0.0667***	−0.0608***	−0.0451***	0.1358***	0.1911***
	(−10.15)	(−10.05)	(−10.19)	(10.88)	(10.50)
Ln(BankCredit)	−0.0376***	−0.0359***	−0.0248***	0.0164	−0.0108
	(−3.23)	(−3.20)	(−3.05)	(0.73)	(−0.33)
Ln(GDP)	0.0292***	0.0217***	0.0172***	−0.0548***	−0.0807***
	(4.65)	(3.51)	(3.87)	(−4.74)	(−5.04)
Output Growth	0.0006	0.0006	0.0004	−0.0010	−0.0012
	(0.86)	(0.84)	(0.83)	(−1.13)	(1.06)
Ln(Savings)	−0.0520*	−0.0450*	−0.0352*	0.1605***	0.2313***
	(−1.81)	(−1.66)	(−1.75)	(2.66)	(2.79)
Net Exports	0.0028***	0.0029***	0.0022***	−0.0075***	−0.0098***
	(2.64)	(2.89)	(2.99)	(−3.79)	(−3.60)
Constant	3.3906***	3.2915***	3.7087***	2.2948***	1.7535***
	(19.00)	(19.34)	(29.87)	(6.66)	(3.72)
Adjusted R^2	0.2171	0.2082	0.2136	0.2699	0.2779
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Robust Std. Errors	Yes	Yes	Yes	Yes	Yes
N	633	630	630	630	629

the poorest quantiles, we generally find estimates for the control variables of the opposite sign with two notable exceptions. For instance, the coefficient on Ln(BankCredit) is statistically close to zero.

When focusing on the variable of interest, we find in column [1] that Ln(Turnover) produces a negative estimate that is both statistically and economically significant (estimate = −0.0667, t-statistic = −10.15). In economic terms, a one standard deviation increase in Turnover is associated with a 6.4% reduction in the Gini coefficient. In columns [2] and [3], when the dependent variable is the income share earned by richest 10% or 20%, we find similar coefficients for Ln(Turnover). Specifically, a one standard deviation increase in Turnover is associated with a reduction in IncShr90 of 5.8% and a decrease in IncShr80 of 4.3%.

Columns [4] and [5] show a relatively stronger affect for IncShr20 and IncShr10. For instance, the estimate for Ln(Turnover) is 0.1358 in column [4], suggesting that a one standard deviation increase in Turnover is associated with a 13% increase in IncShr20. Likewise, the estimate for Ln(Turnover) is 0.1911, indicating that for every percent increase in Turnover, IncShr10 increases more than 18%. These findings in the latter two columns again provide strong support for a negative relationship between stock market liquidity and income inequality.[5]

It is possible that the results in Table 3 are simply driven by the most developed countries. To consider this possibility, we replicate our analysis in Table 3 for each subsample based on GDP per capita. Said differently, we estimate Equation (1) for each of our three subsamples and report the results in Table 4. Columns [1] through [3] show the results for countries with lowest GDP per capita. For brevity, we exclude the two specifications when the dependent variable is defined as either Ln(IncShr90) or Ln(IncShr10). Therefore, we only include as dependent variables Ln(Gini), Ln(IncShr80), and Ln(IncShr20).[6] In the first three columns, we find results that are qualitatively similar to those in the previous table as the coefficient on Ln(Turnover) is negative in columns [1] and [2] and positive in column [3]. In economic terms, a one standard deviation increase in Turnover is associated with 2.7% decrease in the Gini coefficient and a 1.9% decrease in IncShr80. In column [3], our results show that a one standard deviation increase in Turnover is associated with a 6.7% increase in IncShr20.

We are able to find even stronger results in columns [4] through [6] for the subsample of countries with moderate GDP per capita. The coefficients in these columns are at least twice as large (in absolute value) as the corresponding coefficients in the previous three columns. These results again support the idea that stock market liquidity reduces inequality in countries with the lowest GDP per capita and countries with moderate GDP per capita. When examining the final three columns of Table 4, we do not find coefficients that are reliably different from zero. While the signs are similar to those in the previous columns, the t-statistics are not sufficiently large. We therefore conclude that the liquidity-inequality relationship is not driven by the most developed countries and instead is driven by moderately developed and, to a lesser extent the least developed countries.

Next, we examine and alternative measure of liquidity measure. In particular, we estimate the following equation with our unbalanced panel.

[5] Perhaps our findings thus far are simply capturing a reduction in inequality with broad measures of financial development that have been discussed in the existing literature. To determine to the merit of this assertion, we conduct a series of unreported tests to determine whether the observed reduction in inequality associated with stock market liquidity can be attributed to a broader measure of financial development using in the literature. We replicate our analysis but instead of examining liquidity measures, we examine how the market capitalization of all publicly traded companies in a particular country influences inequality. We follow Levine and Zervos (1998) by using market capitalization as a general measure of financial development. In these unreported tests, we do not find that countries with higher market capitalization have lower levels of inequality. If anything, the correlation is positive. These results indicate that liquidity specifically is associated with a reduction in inequality.

[6] In unreported tests, we replicate the analysis in Table 4 when the dependent variable is defined as Ln(IncShr90) and Ln(IncShr10), respectively. The conclusions that we are able to draw is similar to those in Table 4.

Table 4
Multivariate Regressions – Income Inequality and Stock Market Turnover. The table reports the results from estimating the following equality using our pooled (Country-Year) sample.

$$Ln\left(Inequality_{i,t}\right) = \beta_1 Ln(Turnover_{i,t}) + \beta_2 Ln(BankCredit_{i,t}) + \beta_3 Output\ Growth_{i,t} + \beta_4 Ln\left(Saving_{i,t}\right) + \beta_5 Net\ Exports_{i,t} + \alpha + \varepsilon_{i,t}$$

The dependent variables include the natural log of three measures of inequality. Gini is the World Bank estimate of the Gini coefficient for each country in each year. IncShr80 is the fraction of income earned by the richest 20%. IncShr20 is the fraction of income earned by the poorest 20%. The independent variable of interest is the natural log of total amount of stocks traded on a particular countries stock market scaled by the total amount of shares outstanding that particular country (Turnover). The other control variables include the following: the natural log of the gross amount of domestic credit provided by banks (BankCredit); the natural log of the GDP (GDP); the growth rate of GDP (Output Growth); the natural log of gross savings relative to GDP (Savings); and the difference between exports and imports (Net Exports). In response to a Hausman test and additional F-tests, we include year fixed effects. In parentheses, we also report t-statistics that are obtained from standard errors that cluster across countries and years. We report the results for three different subsamples. We sort the 91 countries in our sample into three categories based on GDP/Capita. Low GDP/Capita Countries consist of those 30 countries with the lowest GDP/Capita. Mid GDP/Capita Countries consist of those 31 countries GDP/Capita in the middle. High GDP/Capita Countries are those 30 countries with the highest GDP/Capita. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Low GDP/Capita Countries			Mid GDP/Capita Countries			High GDP/Capita Countries		
	Ln (Gini)	Ln (IncShr80)	Ln (IncShr20)	Ln (Gini)	Ln (IncShr80)	Ln (IncShr20)	Ln (Gini)	Ln (IncShr80)	Ln (IncShr20)
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Ln(Turnover)	−0.0313***	−0.0214***	0.0770***	−0.0750***	−0.0528***	0.1633***	−0.0213	−0.0139	0.0294
	(−3.52)	(−3.57)	(4.56)	(−7.80)	(−7.67)	(7.25)	(−1.37)	(−1.46)	(1.43)
Ln(BankCredit)	0.0651**	0.0463**	−0.2276***	0.0661***	0.0578***	−0.1099***	−0.0613**	−0.0539***	0.0612*
	(2.19)	(2.27)	(−3.16)	(3.93)	(4.68)	(−2.89)	(−2.28)	(−3.08)	(1.66)
Ln(GDP)	−0.0388***	−0.0278***	0.1090***	0.0605***	0.0444***	−0.1233***	0.0582***	0.0335***	−0.0853***
	(−2.75)	(−2.81)	(3.51)	(4.60)	(4.57)	(−4.61)	(6.47)	(5.87)	(−7.00)
Output Growth	−0.0011	−0.0008	0.0003	0.0009	0.0005	−0.0002	−0.0003	−0.0001	0.0008
	(−1.40)	(−1.60)	(0.24)	(0.28)	(0.21)	(−0.04)	(−0.62)	(−0.26)	(1.12)
Ln(Savings)	0.0094	0.0039	0.0504	−0.0112	−0.0102	0.0520	−0.0804	−0.0556*	0.0683
	(0.25)	(0.16)	(0.67)	(−0.24)	(−0.30)	(0.61)	(−1.59)	(−1.74)	(1.07)
Net Exports	0.0042**	0.0030***	−0.0099***	0.0017	0.0011	−0.0031	−0.0077***	−0.0037**	0.0114***
	(2.46)	(2.60)	(−2.77)	(0.77)	(0.68)	(−0.78)	(−3.28)	(−2.56)	(4.17)
Constant	4.4389***	4.3921***	−0.3754	2.1316***	2.6683***	4.7062***	2.7465***	3.4324***	3.4720***
	(14.38)	(20.50)	(−0.57)	(5.37)	(9.22)	(5.96)	(9.17)	(18.08)	(8.46)
Adjusted R^2	0.3616	0.3710	0.4726	0.2865	0.2850	0.3257	0.3849	0.3947	0.3780
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust Std. Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	167	164	164	276	276	276	190	190	190

Table 5
Multivariate Regressions – Income Inequality and Stock Market Volume to GDP. The table reports the results from estimating the following equality using our pooled (Country-Year) sample.

$$Ln\left(Inequality_{i,t}\right) = \beta_1 Ln(Volume/GDP_{i,t}) + \beta_2 Ln(BankCredit_{i,t}) + \beta_3 Output\ Growth_{i,t} + \beta_4 Ln\left(Saving_{i,t}\right) + \beta_5 Net\ Exports_{i,t} + \alpha + \varepsilon_{i,t}$$

The dependent variables include the natural log of our five measures of inequality. Gini is the World Bank estimate of the Gini coefficient for each country in each year. IncShr90 is the fraction of income earned by the richest 10%. IncShr80 is the fraction of income earned by the richest 20%. IncShr20 is the fraction of income earned by the poorest 20%. IncShr10 is the fraction of income earned by the poorest 10%. The independent variable of interest is the natural log of the ratio of the dollar volume of stocks traded on a particular countries stock market to total GDP in that particular country (Volume/GDP). The other control variables include the following: the natural log of the gross amount of domestic credit provided by banks (BankCredit); the natural log of the GDP (GDP); the growth rate of GDP (Output Growth); the natural log of gross savings relative to GDP (Savings); and the difference between exports and imports (Net Exports). In response to a Hausman test and additional F-tests, we include year fixed effects. In parentheses, we also report t-statistics that are obtained from standard errors that cluster across countries and years. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Ln(Gini)	Ln(IncShr90)	Ln(IncShr80)	Ln(IncShr20)	Ln(IncShr10)
	[1]	[2]	[3]	[4]	[5]
Ln(Volume/GDP)	−0.0285***	−0.0238***	−0.0183***	0.0706***	0.1095***
	(−4.62)	(−4.05)	(−4.30)	(6.29)	(7.03)
Ln(BankCredit)	−0.0178	−0.0196	−0.0121	−0.0344	−0.0905**
	(−1.24)	(−1.43)	(−1.22)	(−1.22)	(−2.25)
Ln(GDP)	0.0166**	0.0084	0.0079	−0.0402***	−0.0689***
	(2.13)	(1.09)	(1.43)	(−2.93)	(−3.74)
Output Growth	0.0000	0.0001	0.0000	0.0002	0.0006
	(0.04)	(0.11)	(0.07)	(0.15)	(0.41)
Ln(Savings)	−0.0769**	−0.0690**	−0.0525**	0.2019***	0.2824***
	(−2.53)	(−2.39)	(−2.45)	(3.27)	(3.40)
Net Exports	0.0041***	0.0042***	0.0031***	−0.0096***	−0.0123***
	(3.63)	(3.95)	(4.00)	(−4.46)	(−4.17)
Constant	3.6199***	3.5609***	3.8891***	2.1821***	1.8768***
	(15.08)	(15.47)	(23.28)	(5.03)	(3.28)
Adjusted R^2	0.1334	0.1280	0.1314	0.1817	0.1991
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Robust Std. Errors	Yes	Yes	Yes	Yes	Yes
N	663	630	630	630	630

$$Ln(Inequality_{i,t}) = \beta_1 Ln(Volume/GDP_{i,t}) + \beta_2 Ln(BankCredit_{i,t}) + \beta_3 Output\ Growth_{i,t} + \beta_4 Ln(Saving_{i,t}) + \beta_5 Net\ Exports_{i,t} + \alpha + \varepsilon_{i,t} \tag{2}$$

Equation (2) is identical to the previous equation with one exception. Instead of Ln(Turnover), the independent variable of interest is Ln(Volume/GDP). As before, we include year fixed effects and report t-statistics from standard errors that account for clustering across by countries and years. Table 5 reports the results. In general, the control variables produce coefficients that are similar in sign to the corresponding coefficients in the previous table. However, we do not find that Ln(BankCredit) produces a reliable estimate in columns [1] through [4]. Focusing on the estimates for Ln(Volume/GDP), we again find support for the idea that market liquidity reduces income inequality across each of the columns. For instance, column [1] shows that Ln(Volume/GDP) produces a coefficient that is −0.0285 (t-statistic = −4.62) and suggests that a one standard deviation increase in Volume/GDP is associated with a 1.16% decrease in the Gini coefficient. Column [5] suggests that for every one standard deviation increase in Volume/GDP, the share of income earned by the poorest 10% increases by 4.44%. These results again confirm our findings from the previous table.

Similar to Table 4, Table 6 reports the results from estimating Equation (2) for the three subsamples that are established based on GDP per capita. Focusing on the independent variable of interest, Ln(Volume/GDP) produces negative coefficients in columns [1] and [2] and a positive coefficient in column [3]. We note, however, that the coefficients in columns [1] and [2] are not reliably different from zero (coefficients = −0.0115, −0.0086; t-statistics = −1.23, −1.37). Therefore, we find only weak evidence of a negative relation between Volume/GDP and Gini (or IncShr80) in countries with the lowest per capita GDP. We do find that the positive coefficient on Ln(Volume/GDP) in column [3] is statistically significant (coefficient = 0.0434, t-statistic = 2.55).

As before, we find stronger results when we estimate Equation (2) for countries with moderate per capita GDP. Columns [4] and [5] show that Ln(Volume/GDP) produces reliably negative coefficients while, in column [6], Ln(Volume/GDP) produces a significant positive coefficient. In the remaining three columns, we again find that our liquidity measure does not reliably affect inequality in countries with the most GDP per capita. Combined, these results indicate that the results in Table 5 seem to be driven by countries with moderate GDP per capita. We only find weak evidence that trading volume relative to GDP is associated with a reduction in inequality in countries that are least developed.

To provide some additional insight into how stock market liquidity influences the poor, we examine how measures of poverty are affected by stock market liquidity. We do so by estimating the following equation that consists of an unbalanced panel of country-year observations.

$$Ln(Poverty_{i,t}) = \beta_1 Ln(Liquidity_{i,t}) + \beta_2 Ln(BankCredit_{i,t}) + \beta_3 Output\ Growth_{i,t} + \beta_4 Ln(Saving_{i,t}) + \beta_5 Net\ Exports_{i,t} + \alpha + \varepsilon_{i,t} \tag{3}$$

The dependent variables include the natural log of our two measures of poverty. Poverty1.25 is the fraction of country i's population that lives on less than $1.25 (U.S. Dollars) a day during a particular year. This measure of poverty is generally attributed to the least developed countries. PovertyGen is the fraction of country i's population that lives below the poverty line according to that country's definition of the poverty line. The independent variables of interest is the natural log of Liquidity, which consist of the following two variables: Turnover and Volume/GDP, which have been defined previously. The other control variables have also been defined earlier. As before, we include year fixed effects and t-statistics that account for clustering across countries and years.

Table 7 reports the results from estimating Equation (3). Columns [1] and [2] show the results when the dependent variable is defined as

Table 6
Multivariate Regressions – Income Inequality and Stock Market Volume to GDP. The table reports the results from estimating the following equality using our pooled (Country-Year) sample.

$$Ln(Inequality_{i,t}) = \beta_1 Ln(Volume/GDP_{i,t}) + \beta_2 Ln(BankCredit_{i,t}) + \beta_3 Output\ Growth_{i,t} + \beta_4 Ln(Saving_{i,t}) + \beta_5 Net\ Exports_{i,t} + \alpha + \varepsilon_{i,t}$$

The dependent variables include the natural log of three measures of inequality. Gini is the World Bank estimate of the Gini coefficient for each country in each year. IncShr80 is the fraction of income earned by the richest 20%. IncShr20 is the fraction of income earned by the poorest 20%. The independent variable of interest is the natural log of the ratio of the dollar volume of stocks traded on a particular countries stock market to total GDP in that particular country (Volume/GDP). The other control variables include the following: the natural log of the gross amount of domestic credit provided by banks (BankCredit); the natural log of the GDP (GDP); the growth rate of GDP (Output Growth); the natural log of gross savings relative to GDP (Savings); and the difference between exports and imports (Net Exports). In response to a Hausman test and additional F-tests, we include year fixed effects. In parentheses, we also report t-statistics that are obtained from standard errors that cluster across countries and years. We report the results for three different subsamples. We sort the 91 countries in our sample into three categories based on GDP/Capita. Low GDP/Capita Countries consist of those 30 countries with the lowest GDP/Capita. Mid GDP/Capita Countries consist of those 31 countries GDP/Capita in the middle. High GDP/Capita Countries are those 30 countries with the highest GDP/Capita. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Low GDP/Capita Countries			Mid GDP/Countries			High GDP/Countries		
	Ln (Gini)	Ln (IncShr80)	Ln (IncShr20)	Ln (Gini)	Ln (IncShr80)	Ln (IncShr20)	Ln (Gini)	Ln (IncShr80)	Ln (IncShr20)
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Ln(Volume/GDP)	−0.0115	−0.0086	0.0434**	−0.0317***	−0.0209***	0.0798***	0.0055	0.0037	−0.0068
	(−1.23)	(−1.37)	(2.55)	(−3.80)	(−3.34)	(4.68)	(0.54)	(0.60)	(−0.50)
Ln(BankCredit)	0.0910***	0.0635***	−0.2823***	0.0882***	0.0715***	−0.1725***	−0.0737**	−0.0621***	0.0775*
	(2.95)	(2.99)	(−3.64)	(4.02)	(4.46)	(−3.62)	(−2.43)	(−3.19)	(1.89)
Ln(GDP)	−0.0500***	−0.0343***	0.1188***	0.0414***	0.0293**	−0.0941***	0.0466***	0.0259***	−0.0697***
	(−3.07)	(−3.03)	(3.47)	(2.68)	(2.52)	(−3.28)	(4.97)	(4.42)	(−5.36)
Output Growth	0.0016*	−0.0012**	0.0018	−0.0005	−0.0006	0.0022	−0.0004	−0.0002	0.0010
	(−1.82)	(−2.06)	(1.10)	(−0.15)	(−0.22)	(0.32)	(−0.90)	(−0.53)	(1.37)
Ln(Savings)	−0.0092	−0.0081	0.0835	−0.0373	−0.0292	0.1035	−0.0796	−0.0551	0.0669
	(−0.24)	(−0.32)	(1.05)	(−0.72)	(−0.77)	(1.14)	(−1.49)	(−1.64)	(0.99)
Net Exports	0.0052***	0.0037***	−0.0115***	0.0035	0.0025	−0.0064	−0.0085***	−0.0042***	0.0125***
	(2.91)	(3.02)	(−3.08)	(1.51)	(1.47)	(−1.54)	(−3.44)	(−2.74)	(4.32)
Constant	4.6529***	4.5080***	−0.4286	2.5064***	2.9818***	4.2879***	3.0223***	3.6153***	3.1052***
	(12.10)	(17.09)	(−0.56)	(4.94)	(7.90)	(4.61)	(8.84)	(16.93)	(6.55)
Adjusted R^2	0.3184	0.3272	0.4292	0.1958	0.1963	0.2285	0.3771	0.3864	0.3694
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust Std. Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	167	164	164	276	276	276	190	190	190

Table 7

Multivariate Regressions – Poverty and Stock Market Liquidity. The table reports the results from estimating the following equality using our pooled (Country-Year) sample.

$$Ln(Poverty_{i,t}) = \beta_1 Ln(Liquidity_{i,t}) + \beta_2 Ln(BankCredit_{i,t}) + \beta_3 Output\ Growth_{i,t} + \beta_4 Ln(Saving_{i,t}) + \beta_5 Net\ Exports_{i,t} + \alpha + \varepsilon_{i,t}$$

The dependent variables include the natural log of our two measures of poverty. Poverty1.25 is the fraction of country i's population that lives on less than $1.25 (U.S. Dollars) in a day during a particular year. PovertyGen is the fraction of country i's population that lives below the poverty line according to that country's definition of the poverty line. The independent variables of interest is the natural log of the following variables: Turnover is the total amount of stocks traded on a particular countries stock market scaled by the total amount of shares outstanding that particular country; Volume/GDP is the ratio of the dollar volume of stocks traded on a particular countries stock market to total GDP in that particular country. The other control variables include the following: the natural log of the gross amount of domestic credit provided by banks (BankCredit); the natural log of the GDP (GDP); the growth rate of GDP (Output Growth); the natural log of gross savings relative to GDP (Savings); and the difference between exports and imports (Net Exports). In response to a Hausman test and additional F-tests, we include year fixed effects. In parentheses, we also report t-statistics that are obtained from standard errors that cluster across countries and years. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Ln(Poverty1.25)		Ln(PovertyGen)	
	[1]	[2]	[3]	[4]
Ln(Turnover)	−0.2005***		−0.0958***	
	(−3.37)		(−4.72)	
Ln(Volume/GDP)		−0.0556		−0.0626***
		(−1.13)		(−3.86)
Ln(BankCredit)	−0.5538***	−0.5044***	−0.3397***	−0.3038***
	(−5.42)	(−4.74)	(−7.17)	(−6.46)
Ln(GDP)	−0.0291	−0.1042	−0.0418*	−0.0454*
	(−0.45)	(1.48)	(−1.83)	(−1.77)
Output Growth	0.0262***	0.0255***	0.0062***	0.0051***
	(3.77)	(3.88)	(5.32)	(5.19)
Ln(Savings)	0.5893***	0.4370**	0.1247***	0.0976**
	(2.75)	(2.16)	(3.00)	(2.56)
Net Exports	−0.0069	0.0018	−0.0018	−0.0006
	(−0.65)	(0.20)	(−0.62)	(−0.23)
Constant	2.3401	4.6509**	4.9332***	4.8049***
	(1.26)	(2.32)	(7.99)	(6.66)
Adjusted R^2	0.1897	0.1787	0.3918	0.3803
Year Fixed Effects	Yes	Yes	Yes	Yes
Robust Std. Errors	Yes	Yes	Yes	Yes
N	491	521	399	413

Ln(Poverty1.25) while columns [3] and [4] present the results when the dependent variable is Ln(PovertyGen). Regarding the coefficients on the control variables, a few results are noteworthy. First, the estimate for Ln(BankCredit) is negative and significant in each of the specifications suggesting that the amount of credit provided by banks is negatively related to poverty rates. This result extend the findings in Levine and Zervos (1998) among others (Galor and Zeria (1993), Aghion and Boulton (1997), Galor and Moav (2004), Honohan (2004), Clarke et al. (2006), Burgess and Pande (2005), and Demirguc-Kunt and Levine (2009)). Second, we also find that Output Growth and Savings are positively related to poverty rates.

When focusing on our variables of interest, we find in column [1] that, after holding a number of variables constant, Turnover is negatively correlated with poverty rates. In economic terms, a one standard deviation increase in Turnover is associated with an 18% reduction in the fraction of a country's population that lives on less than $1.25 a day. This measure of poverty is generally associated with the least developed countries. In fact, in Table 1 we showed that Poverty1.25 was 22% in countries with the least GDP per capita and only .87% in countries with the most per capita GDP. Our findings indicate that stock market liquidity can alieve true poverty in these countries and support of our results in previous tests that show that the effect of stock market liquidity on inequality is not simply driven by the most developed countries.

In column [2], we do not find that Ln(Volume/GDP) produces a reliably negative estimate (coefficient = −0.0556, t-statistic = −1.13). However, both Ln(Turnover) and Ln(Volume/GDP) produce significant, negative estimates in columns [3] and [4]. In economic terms, we find that a one standard deviation increase in Turnover is associated with an 8.6% reduction in PovertyGen while a one standard deviation increase in Volume/GDP is associated with a 2.5% reduction in PovertyGen. These findings indicate that stock market liquidity has a positive effect on the poor.

4.3. *Identification strategy*

While Levine and Zervos (1998) show a correlation between stock market liquidity and long-term economic growth, their analysis does not attempt to identify a causal link. This is likely due to the difficulty of identifying an valid instrument or an exogenous shock to market liquidity that might allow for a natural experiment. We face the same difficulty in this study given that exogenous instruments and/or exogenous shocks to cross-country market liquidity are difficult to identify. However, as mentioned above, we take an unusual approach to try to rule out the possibility of reverse causality. The models that have been estimated in earlier tables suggest that liquidity will affect the level of income inequality and poverty rates. As mentioned previously, it is intuitive to think of how liquidity can reduce income inequality given that liquidity can eventually lead to a greater level of investment in long-duration capital projects (Levine (1991) and Bencivenga et al. (1995)). However, it is possible that causality runs the other way. That is, higher levels of inequality lead to a reduction in market liquidity. This might be true if, in countries with the highest levels of inequality, fewer investors (the rich) are willing to trade in equity markets.

With this idea in mind, we begin to take a step in the direction of determining causality by using a natural experiment as our identification strategy. In the framework of our tests, it would be most useful to identify an exogenous shock to market liquidity and then examine inequality surrounding this shock. The difficulty in these tests is that inequality data is not widely available at higher frequencies. Said differently, we cannot isolate the effect of exogenous shocks to market liquidity on inequality, given that inequality is only measured every few years for our sample of countries and we cannot be sure that the shock to liquidity is indeed causing the reduction in inequality. Instead, we take a non-traditional approach and attempt to rule out the possibility of reverse causation by examining an exogenous shock to inequality and we then isolate the effect of this shock on the liquidity of financial markets. Admittedly, our approach is not testing whether liquidity causes a reduction inequality, but instead, we test whether a reduction in inequality causes an increase in liquidity.

To conduct these tests, we first identify an exogenous shock to income inequality. As explained earlier, the French Constitutional Court decided to uphold France's newly proposed “Millionaire Tax” near the last day of 2013. The Millionaire Tax was proposed by French President, Francois Hollande, during his campaign in 2012. An initial proposal was taken before the same court at the end of 2012 and was rejected thus leading to a revised proposal that, in a surprising and unexpected turn of events, was upheld by the court the end of 2013. The Millionaire Tax was applied for two years – 2013 and 2014. Before simply examining the trading activity of French stocks surrounding this event, we recognize another potential draw back. We need to identify a control group of stocks outside of France and, in doing so, we recognize the possibility that structure of the financial market on which these stocks trade may be endogenously determined by some characteristics that are related to differing levels of income inequality between France and other countries, whose stocks are in the control group. Therefore, we examine the volatility of ADRs, which are certificates that trade on U.S.

Table 8

Stock Market Trading Activity and Shocks to Income Inequality – Univariate Tests. The table reports the results from univariate tests that examine trading activity of French ADRs surrounding the French Constitutional Court decision to uphold the Millionaire tax. On December 29th, 2013 the Court allowed for the Millionaire Tax, which provides an exogenous shock to income inequality in France. Using this decision as a natural experiment, we examine several measures of trading activity during the one-year (252 trading day) period surrounding this event. In column [1], we examine daily share turnover for French ADRs. In column [2], we focus on daily trading volume for French ADRs. Column [3] shows the results for Ab-Turnover, which is the difference between daily share turnover for French ADRs and daily share turnover of non-French ADRs. Column [4] presents the results for Ab-Volume, which is the difference between daily trading volume for French ADRs and daily trading volume for non-French ADRs. We reports the averages for the French ADRs that existed during this period and the abnormal measures of trading activity which account for the average trading activity of all non-French ADRs. *,**, *** denote statistical significance at the 0.10, 0.05, and the 0.01 levels, respectively.

	Turnover	Volume	Ab-Turnover	Ab-Volume
	[1]	[2]	[3]	[4]
Pre-Decision	9.611	2,857,281	−55.959	1,432,384
Post-Decision	8.485	1,705,266	−64.719	267,396
Difference	1.126***	1,152,014***	8.760***	1,164,988***
	(2.59)	(4.33)	(4.28)	(4.40)

exchanges but represent foreign shares of stocks. ADRs, therefore, allow us to hold constant the structure of the financial market on which these securities trade, while isolating the effect of the Court's decision on the liquidity of French ADRs vis-à-vis non-French ADRs. From the Center for Research on Security Prices (CRSP), we obtain the universe of ADRs from France and countries other than France.

Table 8 reports some univariate statistics. We examine four measures of liquidity of French ADRs. Turnover is the share turnover for each ADR and is the ratio of daily trading volume relative to shares outstanding (in percent). Volume is the amount of daily trading volume for each ADR. We then calculate two abnormal measures of trading activity. Ab-Turnover is the difference between Turnover for French ADRs and the average Turnover for non-French ADRs on a particular day. Similarly, Ab-Volume is the difference between Volume for French ADRs and the average Volume for non-French ADRs.

Given the negative relationship between liquidity and inequality in our earlier tests, if reverse causality explains our findings, then we should observe an increase in French-ADR liquidity surrounding this negative shock to income inequality. However, results in Table 8 show the opposite. For instance, in column [1], the average daily Turnover decreases from 9.611% during the six-month period before the court decision to 8.485% during the six-month period after the court decision. The difference is 1.126% and statistically significant at the 0.01 level. Similarly, column [2] shows that daily trading volume in French ADRs decreases during the Post-Decision period. The reduction in volume is 1.15 million and is also reliably different from zero (t-statistic = 4.33). In economic terms, the reduction in Turnover (column [1]) represents an 11.7% decrease while the reduction in Volume (column [2]) represents a 40.3% decline. These findings seem to indicate that instead of increasing trading activity, the decision to uphold the Millionaire Tax resulted in less trading activity during the post-event period.

Using a Difference-in-Difference type approach, columns [3] and [4] show the results for our two abnormal measures of liquidity. These measures capture the change in liquidity for French ADRs relative to the change in liquidity for non-French ADRs. Similar to our findings in the previous two columns, we again find a significant reduction in both Ab-Turnover and Ab-Volume. The pre-post differences are both economically and statistically significant and suggest that not only does liquidity decrease (instead of increase) for French ADRs during the post-decision period, but French ADR liquidity also decreases relative to non-French ADRs during the period.

We recognize the need to control for the other factors that may be influencing the level of trading activity in French ADRs. Therefore, we estimate the following equation using pooled ADR-day observations.

$$Trading_{i,t} = \beta_1 DECISION_t + \beta_2 \ln(ADR\ Cap)_{i,t} + \beta_3 \ln(Price)_{i,t} + \beta_4 \ln(Spread)_{i,t} \ \beta_5 \ln(GARCH)_{i,t} + \beta_6 NYSE_i + \alpha + \varepsilon_{i,t} \tag{4}$$

The dependent variable is one of following four measures of ADR liquidity: the natural log of share turnover for French ADRs; the natural log of daily trading volume for French ADRs; Ab-Turnover, which is the difference between daily share turnover for French ADRs and the average of daily share turnover of non-French ADRs; and Ab-Volume, which is the difference between daily trading volume for French ADRs and the average of daily trading volume for non-French ADRs. The independent variable of interest is DECISION, which is an indicator variable that captures the 6-month period after the French Constitutional Court upheld the Millionaire tax (December 29th, 2013 to June 30th, 2014). As other control variables, we include the following: ln(ADR Cap) is the natural log of market capitalization for each ADR on each day; Ln(Price) is the natural log of the closing price for each ADR on each day; ln(Spread) is the natural log of average daily bid-ask spread in percent; ln(GARCH) is the natural log of daily conditional expected volatility obtained from fitting daily security returns to a Garch(1,1) model; NYSE is an indicator variable equal to one if the ADR is listed on the NYSE – zero otherwise. We do not include stock fixed effects or day fixed effects given that the indicator variable NYSE (DECISION) does not vary across the time series (cross section). We do, however, report t-statistics that are robust to two-dimensional clustering (across ADRs and days) in parentheses. The time period includes the one-year (252 trading day) period surrounding the court decision.

Table 9 reports the results from estimating Equation (4). Columns [1] through [4] show the results for each of the four dependent variables used in this analysis. Regarding the control variables, we generally find larger ADRs – in terms of market capitalization – have more trading activity than smaller ADRs. Further, lower priced, more volatile ADRs also have higher turnover and volume. We also find some evidence that ADRs listed on the NYSE and ADRs will smaller bid-ask spreads have more trading activity. All of these results are fairly intuitive and support prior research regarding market liquidity (Karpoff (1987), McInish and Wood (1992), Christie and Schultz (1994), Christie et al. (1994), among others).

Focusing now on our independent variables of interest, we do not find that DECISION produces an estimate that is reliably different from zero in either column [1] or column [2]. These results suggest that, after controlling for a number of factors that affect trading activity, the Court's decision to uphold the Millionaire Tax in France had no effect on the level of liquidity in French ADRs. We note, however, that in columns [3] and [4], the coefficients on DECISION are both negative and statistically significant (estimates = −8.9043, −1.2288; t-statistics = −4.19, −6.77). These findings suggest that instead of an increase in trading activity, which would be consistent with a reverse causality explanation in our previous results, we find that the liquidity of French ADRs, relative to non-French ADRs, significantly decreases during the post-decision period. The combined results tend to rule out the idea that, at least for this particular event, the inverse relationship between inequality and liquidity, which we observe in previous tables, is explained by causality flowing from inequality to liquidity instead of the other way around. Again, we raise caution in drawing strong inferences from our tests in this subsection. This natural experiment is not ideal, but the results from our event study surrounding this (arguably) exogenous shock to income inequality are intended to begin to speak about the direction of causation.

4.4. *The mechanism explaining the liquidity-inequality relationship*

The findings thus far are somewhat surprising. Given that the rich are most likely the participants in stock markets around the world, it would seem that more liquidity – and subsequently lower transaction costs –

Table 9

Stock Market Liquidity and Shocks to Income Inequality – Multivariate Tests. The table reports the results from estimating the following equation using pooled ADR-day data.

$$Trading_{i,t} = \beta_1 DECISION_t + \beta_2 \ln(ADR\ Cap)_{i,t} + \beta_3 \ln(Price)_{i,t} + \beta_4 \ln(Spread)_{i,t}\ \beta_5 \ln(GARCH)_{i,t} + \beta_6 NYSE_i + \alpha + \varepsilon_{i,t}$$

The dependent variable is one of four variables. In column [1], the dependent variable is the natural log of share turnover for French ADRs. In column [2], the dependent variable is the natural log of daily trading volume for French ADRs. Column [3] shows the results for Ab-Turnover, which is the difference between daily share turnover for French ADRs and daily share turnover of non-French ADRs. Column [4] presents the results for Ab-Volume, which is the difference between daily trading volume for French ADRs and daily trading volume for non-French ADRs. The independent variable of interest is DECISION, which is an indicator variable that captures the 6-month period (December 29th, 2013) after the French Constitutional Court upheld the Millionaire tax. As other control variables, we include the following: ln(ADR Cap) is the natural log of market capitalization for each ADR on each day; Price is the closing price for each stock on each day; $\ln(Spread)_{i,t}$ is the natural log of average daily bid-ask spread in percent; ln(GARCH) is the natural log of daily conditional expected volatility obtained from fitting daily security returns to a Garch(1,1) model; NYSE is an indicator variable equal to one if the ADR is listed on the NYSE – zero otherwise. We do not include stock fixed effects or day fixed effects given that the indicator variable NYSE (DECISION) does not vary across the time series (cross section). We do, however, report t-statistics that are robust to two-dimensional clustering in parentheses. The time period includes the one-year (252 trading day) period surrounding the court decision. *,**, *** denote statistical significance at the 0.10, 0.05, and the 0.01 levels, respectively.

	Ln(Turnover)	Ln(Volume)	Ab-Turnover	Ab-Volume
	[1]	[2]	[3]	[4]
DECISION	0.0320	−0.0381	−8.9043***	−1.2288***
	(0.95)	(−1.05)	(−4.19)	(−6.77)
Ln(ADR Cap)	0.2675***	1.4590***	2.5148***	3.1286***
	(17.70)	(91.93)	(2.61)	(22.80)
Price	−0.0387***	−0.0828***	−0.3599***	−0.1500***
	(−21.04)	(−41.56)	(−3.15)	(−19.01)
Ln(Spread)	−0.3809***	−0.2861***	−1.4199	0.6747***
	(−11.83)	(−8.19)	(−0.88)	(7.91)
Ln(GARCH)	0.1820**	0.4963***	0.6772	6.3038***
	(2.27)	(6.07)	(0.13)	(13.70)
NYSE	0.5519***	0.1282*	4.7997	4.3180***
	(8.22)	(1.69)	(1.35)	(17.67)
Constant	−3.2296***	−5.2828***	−92.2840***	−12.3843***
	(−9.94)	(−15.63)	(−4.61)	(−14.05)
Adj. R^2	0.4168	0.8413	0.0209	0.5636
Day Fixed Ef	No	No	No	No
Robust SEs	Yes	Yes	Yes	Yes
N	2016	2016	2016	2016

would disproportionately benefit the rich relative to the poor. However, our results show that opposite. In this subsection, we attempt to identify the mechanism through which stock market liquidity reduces inequality and poverty rates. To do so, we rely on the theoretical literature that posits that liquidity stock markets incentivizes investors to invest in longer-duration projects, which will result in a higher demand for labor (Levine (1991) and Bencivenga et al. (1995)). In the framework of our study, we test whether (i) stock market liquidity is positively correlated with higher wage growth in countries and (ii) whether the liquidity-induced wage growth helps explain the reductions in both inequality and poverty.

We gather wage data, which is not widely available, from two sources. First, from the OECD, we gather average wages for 26 OECD countries. From the World Bank, we obtain total wage bills in 14 countries in our sample. Therefore, we are only able to obtain wage data for 40 out of the 91 countries in our sample. Furthermore, the years that the wage data is available does not cover our entire sample time period. For instance, the World Bank wage bill data only extends from 2001 to 2008. The average wage data from the OECD only begins in 1991. After calculating the growth (in percent) in either average wages (OECD data) or the total wage bill (World Bank data), we first estimate the univariate correlation between Turnover and Wage Growth and find a correlation coefficient of .1218 (p-value = 0.093). These results suggest that the growth in wages is positively associated with stock market liquidity. We then attempt to cleverly tease out how liquidity-induced wage growth influences inequality and poverty by estimating the following simple regression.

$$Wage\ Growth_{i,t} = \beta Ln(Turnover_{i,t}) + \alpha + \varepsilon_{i,t} \tag{5}$$

The dependent variable includes the Wage Growth for each country in the years that the data is available. The independent variable has been defined previously. We note that the results from this regression, which includes 191 country-year observations. The coefficients from the regression are reported in Equation (6) with corresponding t-statistics below each estimate:

$$Wage\ Growth_{i,t} = \underset{(1.70)}{0.581 Ln(Turnover_{i,t})} + \underset{(-0.04)}{-0.048} \tag{6}$$

Again, the results from estimating Equation (5) show that the percent growth in wages is positively related to stock market liquidity. Using the results from estimating Equation (5), we decompose Wage Growth into two portions. The first is the portion of Wage Growth that is associated with stock market liquidity. In particular, we calculate the predicted values, which we denote as P(Wage Growth) from the results of the regression above. The second is the portion of Wage Growth that is orthogonal to stock market liquidity. From the estimation of Equation (5), we obtain the residual, which we denote as R(Wage Growth). If the growth in wages is indeed a link that explains the relationship between liquidity and inequality/poverty, then we expect that the portion of Wage Growth that is associated with liquidity will help reduce inequality and poverty. To test this assertion, we estimate the following equation.

$$Ln\left(Inequality/Poverty_{i,t}\right) = \beta_1 Wage\ Growth_{i,t} + \beta_2 Ln(BankCredit_{i,t}) + \beta_3 Output\ Growth_{i,t} + \beta_4 Ln\left(Saving_{i,t}\right) + \beta_5 Net\ Exports_{i,t} + \alpha + \varepsilon_{i,t} \tag{7}$$

The dependent variables include the natural log of three measures of inequality and two measures of poverty. Gini is the World Bank estimate of the Gini coefficient for each country in each year. IncShr80 is the fraction of income earned by the richest 20%. IncShr20 is the fraction of income earned by the poorest 20%. Poverty1.25 is the fraction of country i's population that lives on less than $1.25 (U.S. Dollars) in a day during a particular year. PovertyGen is the fraction of country i's population that lives below the poverty line according to that country's definition of the poverty line. There are three independent variables of interest. WageGrowth is the raw wage growth of a particular country during a particular year. P(WageGrowth) is the predicted value from a regression of WageGrowth on Ln(TradeTurn). R(WageGrowth) are the residuals from the simple regression. Therefore, P(WageGrowth) is portion of wage growth that driven by stock market liquidity while R(WageGrowth) is the portion of wage growth that is orthogonal to stock market liquidity. The other control variables have been discussed previously. As before, we include year fixed effects in response to a Hausman test and additional F-tests. We also report t-statistics that are obtained from standard errors that cluster across both countries and years.

Table 10 reports the results from estimating Equation (7). Columns [1] through [5] show the results when the independent variable of interest is raw (non-decomposed) Wage Growth. In each of the columns, we find that while coefficients on Wage Growth are negative in columns [1], [2], [4] and [5] and positive in column [3], the estimates are statistically close to zero. Therefore, the results in the first set of tests do not allow us to speak to how Wage Growth influences inequality and poverty.

In columns [6] through [10], we report the results when we include the decomposed measures of Wage Growth. Interestingly, we find that coefficients on P(Wage Growth) are negative and statistically significant in columns [6], [7], [9] and [10]. Furthermore, the estimate for P(Wage Growth) is reliably positive in column [8]. These results suggest that the

Table 10
Multivariate Regressions – Income Inequality, Poverty and Wage Growth. The table reports the results from estimating the following equality using our pooled (Country-Year) sample.

$$Ln\left(Inequality/Poverty_{i,t}\right) = \beta_1 Wage\ Growth_{i,t} + \beta_2 Ln\left(BankCredit_{i,t}\right) + \beta_3 Output\ Growth_{i,t} + \beta_4 Ln\left(Saving_{i,t}\right) + \beta_5 Net\ Exports_{i,t} + \alpha + \varepsilon_{i,t}$$

The dependent variables include the natural log of three measures of inequality and two measures of poverty. Gini is the World Bank estimate of the Gini coefficient for each country in each year. IncShr80 is the fraction of income earned by the richest 20%. IncShr20 is the fraction of income earned by the poorest 20%. Poverty1.25 is the fraction of country i's population that lives on less than $1.25 (U.S. Dollars) in a day during a particular year. PovertyGen is the fraction of country i's population that lives below the poverty line according to that country's definition of the poverty line. There are three independent variables of interest. WageGrowth is the wage growth of a particular country during a particular year. P(WageGrowth) is the predicted value from a regression of WageGrowth on Ln(TradeTurn). R(WageGrowth) are the residuals from the simple regression. Therefore, P(WageGrowth) is portion of wage growth that driven by stock market liquidity while R(WageGrowth) is the portion of wage growth that is orthogonal to stock market liquidity. The other control variables include the following: the natural log of the gross amount of domestic credit provided by banks (BankCredit); the natural log of the GDP (GDP); the growth rate of GDP (Output Growth); the natural log of gross savings relative to GDP (Savings); and the difference between exports and imports (Net Exports). In response to a Hausman test and additional F-tests, we include year fixed effects. In parentheses, we also report t-statistics that are obtained from standard errors that cluster across countries and years. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Ln (Gini)	Ln (IncShr80)	Ln (IncShr20)	Ln (Pov1.25)	Ln (PovGen)	Ln (Gini)	Ln (IncShr80)	Ln (IncShr20)	Ln (Pov1.25)	Ln (PovGen)
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
WageGrowth	−0.0031	−0.0022	0.0065	−0.0209	−0.0048					
	(−1.18)	(−1.28)	(1.34)	(−1.22)	(−0.82)					
P(WageGrowth)						−0.1539***	−0.1056***	0.2851***	−0.9268***	−0.2537***
						(−8.71)	(−8.72)	(7.05)	(−5.56)	(−4.29)
R(WageGrowth)						0.0007	0.0004	−0.0005	0.0061	0.0011
						(0.27)	(0.23)	(−0.10)	(0.31)	(0.15)
Ln(BankCredit)	−0.0730***	−0.0534***	0.0546	−1.1770***	−0.4519***	−0.0916***	−0.0661***	0.0889***	−1.6912***	−0.5082***
	(−2.78)	(−2.95)	(1.18)	(−4.14)	(−3.89)	(−4.80)	(−5.04)	(2.80)	(−6.72)	(−4.80)
Ln(GDP)	0.0222**	0.0107*	−0.0208	−0.6996***	−0.0821**	0.0609***	0.0373***	−0.0923***	−0.5038***	0.0157
	(2.40)	(1.72)	(−1.19)	(−4.60)	(−2.08)	(8.48)	(7.64)	(−7.45)	(−4.03)	(0.42)
Output Growth	0.0005	0.0003	−0.0005	0.0218**	0.0019	0.0010**	0.0007**	−0.0014*	0.0207*	0.0019
	(0.88)	(0.90)	(−0.54)	(2.32)	(1.49)	(2.09)	(2.17)	(−1.71)	(1.93)	(1.42)
Ln(Savings)	−0.1563***	−0.0988**	0.2663**	−1.1890*	−0.0088	−0.0953*	−0.0570*	0.1537*	−0.5869	0.1287
	(−2.71)	(−2.55)	(2.42)	(−1.81)	(−0.05)	(−1.88)	(−1.70)	(1.73)	(−0.98)	(0.67)
Net Exports	0.0008	0.0014	−0.0040	0.0470**	0.0135**	−0.0012	0.0001	−0.0004	0.0307	0.0053
	(0.32)	(0.89)	(−0.90)	(2.47)	(2.35)	(−0.57)	(0.09)	(−0.12)	(1.55)	(1.01)
Constant	3.9525***	4.1566***	1.1777*	26.630***	7.6302***	3.0320***	3.5254***	2.8783***	22.628***	5.1283***
	(11.79)	(18.31)	(1.82)	(5.69)	(6.16)	(12.26)	(21.22)	(6.67)	(5.60)	(4.81)
Adjusted R^2	0.2182	0.2263	0.1350	0.6048	0.5579	0.4615	0.4759	0.4728	0.7091	0.6684
Year Fixed Efs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust Std. Ers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	191	191	191	88	79	191	191	191	88	79

portion of Wage Growth that is explained by stock market liquidity is negatively associated with the Gini coefficient, the fraction of income earned by the richest 80%, and our two measures of poverty. On the other hand, P(Wage Growth) is positively associated with the fraction of income earned by the poorest 20% in a particular country. These results are not only statistically significant, but the results are economically meaningful. For instance, a one percent increase in P(Wage Growth) is associated with a 15.39% decrease in the Gini coefficient.

Perhaps just as interesting is that the coefficients on R(Wage Growth) are not reliably different from zero. Combined with the results for P(Wage Growth), these findings seem to indicate that while the decomposed portion of Wage Growth that is explained by stock market liquidity is associated with a reduction in inequality and poverty, the portion of Wage Growth that is orthogonal liquidity is entirely unrelated to both inequality and poverty. Taken together, this last set of tests seem to suggest that our earlier findings that show that liquid stock markets are associated with lower levels of inequality and poverty, can be attributed to the growth in wages that is explained by liquidity.

5. Conclusion

This paper studies the effect of stock market liquidity on the level of income inequality. While Levine and Zervos (1998) show that stock market liquidity is directly associated with economic growth, we seek to determine whether liquidity-induced growth disproportionately affects the poor vis-à-vis the rich. Using a broad cross-sectional sample of nearly 100 countries, both univariate and multivariate tests show that liquidity in a particular country's stock market is negatively related to a country's Gini coefficient. Said differently, liquidity and inequality are negatively correlated. We also find that the share of income earned by those in the top of the income distribution is negatively affected by the level of stock market liquidity. Similarly, we find that the share of income earned by those in the bottom part of the income distribution is positively associated with stock market liquidity. These findings seem to suggest that, indeed, liquidity in financial markets disproportionately affects the income of poor relative to the rich.

We continue to address this research question by determining whether the relationship between liquidity and inequality is simply driven by the most developed countries. Instead we find that the negative relation between stock market liquidity and inequality is found in countries with moderate GDP per capita and, to a lesser extent, countries with the least GDP per capita. For those countries with the highest GDP per capita, we do not find a reliable correlation between liquidity and inequality. In other tests, we find that liquidity is negatively correlated with poverty rates in our sample of countries. Again, these findings support the idea that liquidity has an important effect on the incomes of the poor.

Finding a negative correlation between liquidity and inequality/poverty is not tantamount to observing that liquidity *causes* a reduction in inequality/poverty. Research in this area (Levine and Zervos (1998) and Demirguc-Kunt and Levine (2009)) has had difficulty drawing strong causal inferences about how finance affects economic growth and/or inequality. We face a similar difficulty given that exogenous instruments are hard to come by. Additionally, examining shocks to liquidity and attempting to isolate the effect of these shocks on inequality is even more problematic given that inequality is measured so infrequently (three to four times per country during our sample time period from 1988 to 2012). Instead, we take a non-traditional approach and try to rule out the possibility of reverse causality by examining an exogenous shock to inequality and then isolating its effect on liquidity. Using the recent French Court decision to uphold the Millionaire Tax as a (negative) shock to inequality, we find that, relative to non-French stocks, liquidity of French stocks decrease in response to this event. Admittedly, this event study is not ideal as we are not able to infer that causation flows from liquidity to inequality. However, to the extent that this particular event is indeed exogenous and an appropriate natural experiment, the event allows us to rule out that causation flows from inequality to liquidity and begins to speak about the direction of causality in a financial development/economic outcome framework.

In our final set of tests, we explore the potential mechanism that explains our findings. Relying on the theoretical literature that suggests that liquidity stock markets provide the proper incentives for investment in longer duration projects and can therefore increase the demand for labor, we decompose wage growth into two portions – the first is the portion that is explained by liquidity in stock markets. The second is the portion of wage growth that is orthogonal to liquidity. Consistent with the idea that wage growth is the mechanism that explains the liquidity/inequality relationship, we find strong evidence that liquidity-induced wage growth significantly reduces both inequality and poverty while the portion of wage growth that is orthogonal to liquidity is unrelated to inequality and poverty.

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