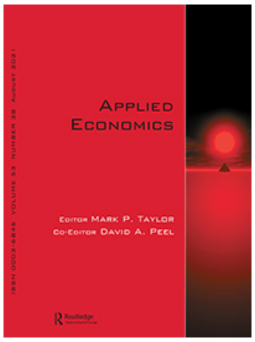

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Income inequality and the volatility of stock prices

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ABSTRACT
We examine the link between income inequality and the price volatility of American Depository Receipts (ADRs). Using a large sample of ADRs across 37 countries, we find that income inequality is negatively associated with ADR volatility. To draw stronger causal inferences, we use the implementation of the French 'Millionaire Tax' as a negative shock to the perceived level of income inequality in France. In difference-in-difference tests, we find that volatility for French ADRs vis-à-vis non-French ADRs increased by at least 4.85 percentage points after the tax change. Therefore, instead of creating political and social uncertainty, income inequality has a stabilizing influence on the volatility of stock prices, which we argue is a result of higher-skilled human capital.

KEYWORDS
Income inequality; volatility; international finance; American depositary receipts

I. Introduction

Few topics have received more attention from researchers, practitioners, and policymakers than economic inequality (see e.g. Piketty 2014; Judge, Fainshmidt, and Brown, 2014; Osberg 2015). To date, much of the literature focuses on the interaction between financial development and income inequality. Some theoretical studies predict that, at earlier stages of financial development, the rich have disproportionate access to financial markets, such as less binding credit constraints, thus benefiting the rich more than the poor (Greenwood and Jovanovic 1990; Claessens and Perotti 2007). In contrast, other studies contend that the accumulation of both physical capital and human capital are likely to increase for the poor relative to the rich (Clarke, Xu, and Zou 2006; Beck, Demirguc-Kunt, and Levine, 2007). The empirical literature seems to support the latter prediction, as the development of financial systems generally reduces inequality.[1] For instance, Burgess and Pande (2005) use exogenous openings of new banks in rural areas of India as a natural experiment and show that financial development reduces poverty.

Instead of focusing on how financial development influences the level of inequality, we attempt to determine whether inequality influences the stability of financial markets. Levine and Zervos (1998) argue that the volatility of stock prices is an important (inverse) measure of financial development. On the one hand, inequality might create both political and social uncertainty that might increase the volatility of markets. For instance, Barro (2000) suggests that when inequality is persistent, political institutions become unstable and subsequently produce uncertain economic policies. In the presence of this type of regulatory uncertainty, firms will likely have difficulty in making sound capital investment decisions (Beaulieu, Cosset, and Essaddam 2005). Therefore, the policy uncertainty associated with inequality could lead to less stable stock prices.

On the other hand, inequality may have a stabilizing influence on stock prices. The theoretical model of Cobb (2016) indicates that compensation structures within firms and the payoff for human capital naturally lead to higher levels of inequality. To the extent that income inequality represents a higher payoff for human capital (Becker and Chiswick 1966; Lucas 1977; Becker and Murphy 2007; Zardkoohi and Bierman 2016), the most highly skilled managers are left to make the most important decisions for the firm. Stated differently, the presence of inequality might signal that human capital is allocated more efficiently and, therefore, firms in countries with greater inequality

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[1]See, for example, Galor and Zeira (1993), Aghion and Bolton (1997), Galor and Moav (2004), Honohan (2004), Claessens and Feijen (2007), Clarke, Xu, and Zou (2006), and Beck, Demirguc-Kunt, and Levine (2007).

could make informed decisions that lead to more stable stock prices. Thus, the effect of inequality on volatility becomes an empirical question.

When assessing whether inequality influences the stability of stock prices across various countries, at least two types of potential biases exist. First, the structure of a country's financial market might be endogenously determined by factors that are related to the level of inequality in that country. Given that financial market structure can affect the level of volatility in stock prices, conclusions about the effects of inequality on volatility might be misguided unless the structure of markets is controlled. Second, determining the correlation between inequality and volatility is not tantamount to determining the direction of causation. Therefore, without an appropriate identification strategy, causal inferences cannot be appropriately made.

We overcome the first potential bias by following the methods of Eleswarapu and Venkataraman (2006), who use a clever research design that properly controls for the structure of financial markets while allowing for variation in the degree of inequality across countries. In particular, we examine the volatility of American Depositary Receipts (ADRs), which are certificates that represent shares of foreign stock but are traded on U.S. exchanges. Therefore, all of the securities in our sample are subject to the same market structure. We overcome the second potential bias by attempting to identify an (arguably) exogenous shock to the perceived level of income inequality in a given country. More specifically, we follow Blau (2018) and use the French Constitutional Court's decision to allow for a dramatic increase in the top marginal tax rate in France. The 'Millionaire Tax', which was first proposed by then French Presidential Candidate Francois Hollande in 2012, taxes salaries above €1 Million at 75%. After initially overruling the proposal in 2012, the Constitutional Court unexpectedly decided to uphold the proposal at the end of 2013. This change in tax policy was likely perceived by markets as reducing the level of inequality in France (Piketty 2014). Accordingly, the passage of the highly progressive Millionaire Tax seems like an appropriate negative shock to inequality.[2] We examine the volatility of French ADRs compared to non-French ADRs surrounding the tax change.

Results from this study show that, after controlling for several ADR-specific and country-specific characteristics, the level of income inequality in a particular country is negatively associated with the volatility of that country's ADRs. We find that a one-unit increase in a country's *GINI* coefficient is associated with a decrease in ADR volatility that ranges from 36 to 43 basis points (bps) depending on the measure of volatility. These results suggest that instead of creating political and social uncertainty, income inequality has a stabilizing influence on the volatility of stock prices.

In additional robustness tests, we use alternative measures of income inequality. More specifically, we examine the proportion of a country's income captured by a subsample of the population – top and bottom quintiles and deciles. Consistent with the results on the *GINI* coefficient, we find that holding all else equal, a percent increase in the fraction of income earned by the top 80% (90%) of the population is associated with a 40 (46) to 46 (53) bp reduction in ADR volatility. Conversely, a unit increase in the percent of income earned by the bottom 20% (10%) of the population is associated with a 165 (366) to 207 (458) bp increase in ADR volatility. These results again support the idea that income inequality has a stabilizing influence on stock prices. We note that these results are slightly more pronounced for less developed countries.

Next, we examine the volatility of French ADRs, relative to non-French ADRs, surrounding the Millionaire Tax in a difference-in-difference setting. After holding constant ADR-specific factors, we find that average volatility for French ADRs compared to non-French ADRs increases between 4.85 and 10.08 percentage points after the tax change, depending on the measure of volatility. Combined, our findings suggest that income inequality causes an increase in the volatility of ADR prices. This is consistent with the notion

[2]The French millionaire tax was in effect for the years 2013 and 2014. According to recent data from the World Bank, the average Gini coefficient decreased from 33.2 for the two years prior to the implementation of the tax to 32.4 during the implementation period. This decrease represented a 2.4% decrease in inequality. Similarly, when examining the share of income earned by the highest quintile, the average share in the two years prior to the implementation was 41.3%. This share decreased during the implementation period to 40.7%, which reflects a 1.4% decrease.

that firms in countries with greater inequality might place a greater benefit on higher human capital, which seems to lead to stock stabilizing decision making. In our final set of tests, we provide evidence that human capital, as measured by education, is associated with higher income inequality across countries.

The results from these tests have important implications that relate to the existing literature. First, understanding market volatility is a central tenet in traditional asset pricing theory (Markowitz 1952; Sharpe 1964; Lintner 1965; Black and Scholes 1973). Second, these findings contribute to a large stream of research that attempts to identify factors that influence the volatility of stock prices and how volatility affects firm decision making (Schwert 1989; Minton and Schrand 1999; Bekaert and Wu 2000; Botosan and Plumlee 2002). To the extent that inequality indeed signals a significant payoff to human capital, the findings in this study indicate that inequality may provide the appropriate incentives for the most skilled managers to make important decisions for the firm. Therefore, this type of skilled decision-making can reduce the level of volatility and produce more stable stock prices.

II. Data Description

The data used in this study are obtained from several sources. From the World Bank, we obtain annual country-specific characteristics, such as GDP per capita, gross savings, stock market trading, unemployment, and income inequality. From the Center for Research in Security Prices (CRSP), we gather daily stock-specific characteristics, such as closing prices, shares outstanding, trading volume, exchange listings, and close-to-close returns. From annual Compustat filings, we identify the country where the company headquarters is located. We retain all ADR securities (share codes 30 to 38) from the CRSP database between 2 January 2001, and 31 December 2018. After merging all three databases, we are left with 511 unique ADRs across 37 countries and a total of 2,674 ADR-year observations.[3]

Table 1. Number of ADRs by year.

Year	# of ADRs
2001	63
2002	91
2003	156
2004	211
2005	214
2006	201
2007	155
2008	242
2009	97
2010	226
2011	188
2012	193
2013	198
2014	200
2015	60
2016	72
2017	59
2018	48
Average	148.56

This table reports the number of ADRs by year across 37 countries between 2001 and 2018.

Table 1 reports the total number of ADRs by year across the sample countries. As can be seen, there is substantial variation in the number of ADRs by year. For instance, we find 242 ADRs in the sample in 2008, compared to only 48 in 2018. The average number of ADRs in a sample year is approximately 149, which provides adequate degrees of freedom in our multivariate analysis.

Country characteristics

We proxy income inequality in a particular country using the following measures. *GINI* is the estimated (by the World Bank) GINI coefficient, which directly captures the income inequality for each country. *IncShr80%* (*IncShr90%*) is the share of income earned by the richest 20% (10%) of the population in a particular country. *IncShr20%* (*IncShr10%*) is the share of income earned by the poorest 20% (10%) of the population in a given country. In unreported tests, we find that the pooled correlation coefficient between *IncShr80%* (*IncShr90%*) and *IncShr20%* (*IncShr10%*) is −0.9368 (−0.8741). It is also worth noting that the pooled correlation coefficient between *GINI* and *IncShr80%* (*IncShr90%*) is 0.9946 (0.9829). Therefore, an increase in the *GINI* coefficient, *IncShr80%*, and *IncShr90%* is associated with an increase in country-level income inequality. In

[3]We merge CRSP and Compustat based on 8-digit CUSIPS and then World Bank on 3-digit country codes. Because data are not available for each ADR (or country) for every year, we have an unbalanced panel. For the sample period that we analyse, the average country reports inequality data about every four years.

contrast, an increase in *IncShr20%* and *IncShr10%* corresponds with a decrease in country-level income inequality.

Table 2 displays annual summary statistics for each of the 37 countries. We note that China (131) and the U.K. (50) have the most listed ADRs, while Austria, Colombia, Cyprus, Hungary, Malaysia, Portugal, Turkey, and Venezuela have the least ADRs with one each. There are approximately 14 ADRs in a given country. The average (median) country has a *GINI* coefficient of 37.39 (34.18). Roughly 44.56 (29.19) percent of the average countries' income is earned by those in the richest 20% (10%) of the population. Furthermore, approximately 6.69 (2.57) percent of the average countries' income is earned by the poorest 20% (10%) of the population. When looking at the various inequality measures, we find a good deal of variation across countries. For instance, as measured by the *GINI* coefficient, South Africa (63.65) and Brazil (54) have the highest inequality while Denmark (25.25) and Sweden (25.60) have the lowest inequality. This variation will be important when we attempt to identify a link between inequality and volatility in financial markets.

Recognizing the need to control for other country-specific characteristics, we also include the following variables in our analysis. *GDP/Capita* is the GDP per capita. *Savings* is the annual gross savings (in $billion). *Trading* is the U.S. dollar amount of

Table 2. ADR home country characteristics.

	Country	# of ADRs	GINI	IncShr80%	IncShr20%	IncShr90%	IncShr10%	GDP/Cap	Savings ($billions)	Trading ($billions)	Unemployment
[1]	Argentina	17	45.34	49.89	4.16	32.89	1.40	$9,121.71	$74.13	$3.55	10.08
[2]	Australia	20	33.93	41.44	7.43	25.86	2.79	$35,855.43	$192.60	$587.02	5.64
[3]	Austria	1	29.64	38.20	8.48	23.54	3.34	$38,987.72	$88.69	$58.68	5.27
[4]	Belgium	3	28.34	37.12	8.60	22.64	3.34	$43,782.93	$119.47	$115.92	7.91
[5]	Brazil	17	54.00	58.59	3.20	42.65	1.05	$8,934.65	$328.16	$556.31	8.97
[6]	Switzerland	12	32.72	40.55	7.76	25.38	3.12	$68,970.77	$185.90	$737.99	4.09
[7]	Chile	23	47.08	53.39	5.10	38.12	1.93	$11,196.22	$51.90	$29.64	8.36
[8]	China	131	41.64	47.54	5.59	31.28	2.23	$5,602.08	$3,697.77	$6,961.16	4.11
[9]	Colombia	1	52.57	57.30	3.58	41.44	1.21	$6,714.62	$60.12	$18.91	9.56
[10]	Cyprus	1	34.18	42.52	7.94	27.90	3.22	$25,812.75	$3.71	$0.07	14.17
[11]	Germany	26	30.72	39.32	8.41	24.45	3.37	$33,934.02	$714.02	$1,611.71	8.84
[12]	Denmark	2	25.25	35.20	9.85	21.00	4.00	$43,485.19	$64.59	$56.03	5.30
[13]	Spain	9	34.46	40.99	6.38	25.39	2.16	$28,190.53	$292.98	$1,085.00	16.42
[14]	Finland	3	27.80	37.30	9.40	23.10	3.90	$35,278.99	$54.06	$165.54	10.41
[15]	France	29	31.56	40.01	8.17	25.36	3.28	$37,779.14	$539.65	$1,584.43	8.59
[16]	United Kingdom	50	35.05	42.24	6.90	27.06	2.60	$44,154.86	$420.71	$2,399.62	5.02
[17]	Greece	2	33.78	40.92	6.98	25.69	2.59	$24,567.16	$36.60	$58.65	9.69
[18]	Hungary	1	29.24	37.77	8.37	23.44	3.31	$12,696.10	$31.19	$27.99	8.13
[19]	Indonesia	2	35.56	43.95	7.92	28.99	3.40	$2,332.13	$183.43	$65.10	6.04
[20]	Ireland	16	32.63	40.70	7.77	25.67	3.05	$53,396.75	$93.59	$13.00	8.94
[21]	Israel	18	40.34	45.45	5.10	29.03	1.87	$29,629.37	$50.02	$55.10	8.14
[22]	Italy	9	33.96	40.95	6.85	25.84	2.41	$33,130.66	$412.27	$1,194.42	7.46
[23]	Japan	25	33.35	41.05	7.38	26.06	2.81	$41,348.26	$1,215.44	$5,544.94	4.35
[24]	Korea, Rep.	12	31.90	39.35	7.27	24.10	2.63	$22,821.31	$383.59	$1,425.00	3.40
[25]	Luxembourg	7	31.45	39.59	7.95	24.46	3.19	$94,301.67	$23.69	$0.31	4.89
[26]	Mexico	28	48.73	54.35	4.49	38.68	1.60	$8,997.81	$223.93	$80.28	3.94
[27]	Malaysia	1	41.00	47.30	5.80	31.30	2.30	$9,955.24	$99.30	$111.48	3.10
[28]	Netherlands	15	28.95	37.94	8.78	23.46	3.48	$48,603.78	$233.88	$761.83	5.14
[29]	Norway	4	27.97	37.20	9.18	23.19	3.58	$73,934.65	$132.66	$169.36	3.71
[30]	Peru	3	46.57	51.35	4.17	35.23	1.45	$4,942.06	$35.20	$3.06	4.11
[31]	Philippines	2	46.40	52.50	5.23	36.26	2.11	$1,800.30	$28.34	$15.95	3.66
[32]	Portugal	1	38.20	45.58	6.56	30.04	2.44	$19,034.41	$31.05	$60.04	7.13
[33]	Russian Federation	5	39.73	46.67	6.31	30.70	2.51	$8,066.08	$358.06	$380.97	6.87
[34]	Sweden	5	25.60	35.00	9.30	20.48	3.70	$39,384.25	$98.52	$240.20	5.98
[35]	Turkey	1	40.71	46.98	5.70	30.99	2.15	$9,448.43	$174.54	$284.91	10.07
[36]	Venezuela, RB	1	49.40	53.30	3.05	36.30	0.65	$4,343.78	$34.50	$0.62	14.61
[37]	South Africa	8	63.65	69.36	2.54	52.04	0.96	$6,135.87	$62.13	$200.03	25.48
Average	13.81	37.39	44.56	6.69	29.19	2.57	$27,747.88	$292.71	$720.67	7.77	
Median	7.00	34.18	41.44	6.98	26.06	2.60	$25,812.75	$99.30	$115.92	7.13	

This table reports annual summary statistics obtained from the World Bank for 37 ADR home countries between 2001 and 2018. We report the number of ADRs by country. *GINI* is the estimated (by the World Bank) GINI coefficient, which directly captures income inequality. *IncShr80%* (*IncShr90%*) is the share of income held by the richest 20% (10%) of the population. *IncShr20%* (*IncShr10%*) is the share of income held by the poorest 20% (10%) of the population. *GDP/Cap* is the GDP per capita. *Savings* is the annual gross savings in $billions. *Trading* is the amount of stock trading volume in $billions. *Unemployment* is the national unemployment rate.

trading volume (per year) on the stock exchanges of a particular country. *Unemployment* is the national unemployment rate for each of the home countries. In Table 2, we show that the average country has a GDP per capita of 27,747.88, USD gross savings of 292.71 USD billion, stock trading of 720.67 USD billion, and an unemployment rate of 7.77%.

ADR characteristics

We use three different measures of ADR return volatility. First, we calculate the standard deviation of daily CRSP close-to-close returns for each ADR by year. We denote this more traditional measure of volatility as *Volt*. Second, we estimate idiosyncratic volatility (*IdioVolt*) by calculating the standard deviation of daily residual returns, $\varepsilon_{i,t}$, for each ADR by year from the following four-factor model:

$$R_{i,t} - R_{f,t} = \alpha + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_{i,t} \quad (1)$$

where the dependent variable is the difference between the daily ADR return (R) and the daily risk-free rate (R_f) obtained from the Wharton Research Data Services. The risk-free rate is approximated by the yield on one-month U.S. Treasury Bills. The independent variables are the four factors found in Fama and French (1996) and Carhart (1997). *MRP* is the daily market risk premium. *SMB* is the daily small-minus-big risk factor. *HML* is the daily high book-to-value minus low book-to-value risk factor. *UMD* is the up-minus-down momentum risk factor explained in Carhart (1997). Third, we account for structure in a more parametric model by fitting daily ADR returns to a Garch(1,1) as follows:

$$\sigma^2_{i,t} = \omega + \alpha\mu^2_{i,t-1} + \beta\sigma^2_{i,t-1} \quad (2)$$

where μ is the residual return. The outcome of this estimation yields parameters for ω, α, and β. We can then construct the square root of conditional expected variance from the Garch(1,1) and average those over each ADR-year. We denote this measure of volatility as *GarchVolt*.

Table 3. ADR summary statistics.

	Mean	Std. Dev.	p25	Median	p75
Volt	0.0307	0.0190	0.0182	0.0255	0.0375
IdioVolt	0.0279	0.0186	0.0160	0.0227	0.0344
GarchVolt	0.0309	0.0176	0.0192	0.0260	0.0375
NYSE	0.7397	0.4389	0.0000	1.0000	1.0000
Price	25.4794	27.7894	7.7595	17.2941	33.8011
MktCap	2.0319	5.6302	0.0742	0.3575	1.5084
Turn	16.2935	46.4072	4.1606	7.7751	15.3107
Spread	0.0090	0.0178	0.0012	0.0031	0.0091

This table provides stock statistics from aggregated daily CRSP files for the sample of 511 unique ADRs across 37 countries annually between 2001 and 2018. *Volt* is the standard deviation of daily returns for each ADR in each year. *IdioVolt* is the standard deviation of daily residual returns for each ADR in each year, where residual returns are obtained from a daily four-factor model. *GarchVolt* is the square root of the conditional expected variance obtained from fitting a Garch(1,1) model to daily returns for each ADR averaged in each year. *NYSE* is an indicator variable equal to one if the ADR is listed on the NYSE and zero otherwise. *Price* is the average daily closing price for each ADR in each year. *MktCap* is the average daily market capitalization for each ADR in each year. *Turn* is the average ratio of daily trading volume scaled by the shares outstanding for each ADR in each year. *Spread* is the average daily relative bid-ask spread, or the difference between the ask price and the bid price scaled by the quote midpoint, for each ADR in each year. The statistics below are obtained from a sample of 2,674 ADR-year observations.

We also include in our analysis several ADR-specific control variables. *NYSE* is an indicator variable equal to one if the ADR is listed on the New York Stock Exchange and zero otherwise. *Price* is the average daily closing price for each ADR in a given year. Similarly, *MktCap* is the average daily market capitalization for each ADR in a given year. *Turn* is the average ratio of daily trading volume scaled by the shares outstanding over a particular ADR-year. *Spread* is the average daily relative (percent) bid-ask spread, which is calculated as the difference between the ask price and the bid price scaled by the quote midpoint, for a given ADR-year. This simple approximation of the spread is shown to be highly correlated with intraday effective spreads (Chung and Zhang 2014).

In Table 3, we report descriptive statistics for the aforementioned ADR measures across the sample of ADR-year observations. The average ADR has a mean *Volt* of 0.0307, an *IdioVolt* of 0.0279, and a *GarchVolt* of 0.0309. Finding that the distributions of *Volt* and *GarchVolt* are similar provides some confidence in our estimates of the sample moments. We also find that 73.97% of ADRs are listed on the NYSE. Additionally, the sample ADRs have, on average, a share price of 25.48, USD a market cap of 2.03 USD billion,

$$LN(Volatility^{j}_{i,c,t}) = \alpha + \beta_1 GINI_{c,t} + \beta_2 LN(GDP/Cap_{c,t}) + \beta_3 LN(Savings_{c,t}) + \beta_4 LN(Trading_{c,t}) + \beta_5 LN(Unemployment_{c,t}) + \beta_6 NYSE_i + \beta_7 LN(Price_{i,t}) + \beta_8 LN(MktCap_{i,t}) + \beta_9 LN(Turn_{i,t}) + \beta_{10} LN(Spread_{i,t}) + \delta_t + \theta_{sic} + \varepsilon_{i,t} \quad (3)$$

turnover of 16.29%, and a bid-ask spread of 0.9%.

III. Empirical results

In this section, we discuss our empirical methods and results. We begin by examining the cross-country association between income inequality and ADR volatility in a panel regression setting. Recognizing that determining the relation between these variables is not tantamount to identifying a causal link, we then exploit an exogenous change in French tax law that might have been perceived as a reduction in income inequality in France. We then examine whether volatility for French ADRs, relative to all other ADRs, increases surrounding this change in legislation. Last, we examine whether greater human capital is associated with an increase in income inequality.

Income inequality and ADR volatility

To determine the association between income inequality and ADR volatility, we estimate the following equation on a sample of 2,674 ADR-year observations:

where the dependent variable is the natural log of one of the following three previously defined volatility measures: *Volt*, *IdioVolt*, or *GarchVolt*. *GINI* is the income inequality variable of interest obtained from the World Bank. We include both country-level and ADR-level control variables, which have previously been defined. We also include year fixed effects, δ_t, and two-digit SIC industry fixed effects, θ_{sic}. We report t-statistics in parentheses obtained from robust standard errors.[4]

The results from estimating equation (3) are reported in Table 4. We find that savings, market capitalization, share turnover, and bid-ask spreads all positively affect the level of ADR volatility. Conversely, GDP per capita, trading volume, share prices, and NYSE exchange listing inversely affect the level of ADR volatility. In column [1], we show the results when *Volt* is the dependent variable in equation (3). We find that holding other variables constant, the coefficient on *GINI* is negative and reliably different from zero (estimate = −0.0039, *t*-statistic = −3.19). In economic terms, a one-unit increase in the *GINI* coefficient is associated with a decrease in volatility of roughly 39 bps. In column [2], we display the results when *IdioVolt* is the dependent variable in equation (3). The estimate on *GINI* is −0.0043 (*t*-statistic = −3.39). Therefore, a one-unit increase in the *GINI* coefficient is associated with a 43 bp decrease in idiosyncratic volatility. In column [3], we report the results when *GarchVolt* is the dependent variable in equation (3). Again, the estimated coefficient on *GINI* is negative, −0.0036, and significant at the 0.01 level. Here, a one-unit increase in the

$$LN(Volatility^{j}_{i,c,t}) = \alpha + \beta_1 IncShr\%^{j}_{c,t} + \beta_2 LN(GDP/Cap) + \beta_3 LN(Savings_{c,t}) + \beta_4 LN(Trading_{c,t}) + \beta_5 LN(Unemployment_{c,t}) + \beta_6 NYSE_i + \beta_7 LN(Price_{i,t}) + \beta_8 LN(MktCap_{i,t}) + \beta_9 LN(Turn_{i,t}) + \beta_{10} LN(Spread_{i,t}) + \delta_t + \theta_{sic} + \varepsilon_{i,t} \quad (4)$$

[4]We do not include ADR fixed effects as the independent variable of interest only varies by country and not firm.

Table 4. Income inequality (GINI) and ADR volatility.

	LN(Volt)	LN(IdioVolt)	LN(GarchVolt)
	[1]	[2]	[3]
GINI	−0.0039***	−0.0043***	−0.0036***
	(−3.19)	(−3.39)	(−3.27)
LN(GDP/Cap)	−0.0383***	−0.0681***	−0.0382***
	(−3.86)	(−6.78)	(−4.32)
LN(Savings)	0.0816***	0.0891***	0.0861***
	(6.97)	(7.69)	(8.10)
LN(Trading)	−0.0383***	−0.0480***	−0.0395***
	(−7.10)	(−8.81)	(−8.00)
LN(Unemployment)	0.0245	0.0064	0.0213
	(1.60)	(0.41)	(1.50)
NYSE	−0.1285***	−0.1477***	−0.1723***
	(−6.77)	(−7.56)	(−9.84)
LN(Price)	−0.1024***	−0.1111***	−0.1182***
	(−12.76)	(−13.72)	(−16.64)
LN(MktCap)	0.0763***	0.0599***	0.0627***
	(12.22)	(9.42)	(11.02)
LN(Turn)	0.1850***	0.1680***	0.1605***
	(23.56)	(20.70)	(22.53)
LN(Spread)	0.2947***	0.3071***	0.2594***
	(23.03)	(23.40)	(22.73)
Constant	−3.9968***	−3.1944***	−3.8946***
	(−14.06)	(−11.22)	(−15.37)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Adj. R^2	0.7391	0.7564	0.7506
N	2,674	2,674	2,674

This table reports the results from estimating the following regression on a sample of 2,674 ADR-year observations between 2001 and 2018: where the dependent variable is the natural log of one of the following three volatility measures: *Volt, IdioVolt*, or *GarchVolt*. *GINI* is the income inequality variable of interest obtained from the World Bank. We include both country-level and ADR-level control variables, which have previously been defined. We also include year fixed effects, δ_t, and two-digit SIC industry fixed effects, θ_{sic}. We report t-statistics in parentheses obtained from robust standard errors. *, **, and *** denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

GINI coefficient is associated with a 36 bp decrease in Garch(1,1) volatility. The results from Table 4 suggest that instead of a positive effect, inequality negatively influences stock market volatility, thus lending support for our alternative hypothesis.

Next, we attempt to provide some robustness to the conclusions that we draw in Table 4 by estimating the following equation on the same sample of 2,674 ADR-year observations:

The model in equation (4) is identical to that in equation (3) with one exception. Instead of measuring income inequality via the *GINI* coefficient, we use the proportion of a country's income captured by a subsample of the population, $IncShr\%^{j}_{c,t}$. *IncShr80%* (*IncShr20%*) captures the share of income held by the richest (poorest) 20% of the population. Similarly, *IncShr90%* (*IncShr10%*) captures the share of income held by the richest (poorest) 10% of the population. To avoid multicollinearity issues, we do not include two of the income inequality measures in the same model specification. As before, we include both country-level and ADR-level control variables, which have previously been defined. We also include year fixed effects, δ_t, and two-digit SIC industry fixed effects, θ_{sic}. For brevity, we do not report the output for the control variables or fixed effects.[5] We

$$\begin{aligned} LN(Volatility^{j}_{i,c,t}) = {} & \alpha + \beta_1 GINI_{c,t} + \beta_2 Developed_c + \beta_3 GINI_{c,t} \times Developed_c + \beta_4 LN(GDP/Cap_{c,t}) \\ & + \beta_5 LN(Savings_{c,t}) + \beta_6 LN(Trading_{c,t}) + \beta_7 LN(Unemployment_{c,t}) + \beta_8 NYSE_i \\ & + \beta_9 LN(\Pr ice_{i,t}) + \beta_{10} LN(MktCap_{i,t}) + \beta_{11} LN(Turn_{i,t}) + \beta_{12} LN(Spread_{i,t}) + \delta_t + \theta_{sic} + \varepsilon_{i,t} \end{aligned} \quad (5)$$

[5]The control variables produce seemingly identical estimates to those in Table IV.

Table 5. Income inequality (income share) and ADR volatility.

Panel A. Income Shares 80% and 20%						
	LN(Volt) [1]	LN(IdioVolt) [2]	LN(GarchVolt) [3]	LN(Volt) [4]	LN(IdioVolt) [5]	LN(GarchVolt) [6]
IncShr80%	−0.0040***	−0.0046***	−0.0040***			
	(−2.85)	(−3.13)	(−3.10)			
IncShr20%				0.0195***	0.0207***	0.0165***
				(3.65)	(3.75)	(3.39)
Constant	−4.0018***	−3.1819***	−3.8717***	−4.2765***	−3.5107***	−4.1738***
	(−13.67)	(−10.84)	(−14.81)	(−17.24)	(−14.27)	(−18.97)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.7389	0.7563	0.7505	0.7394	0.7567	0.7506
N	2,674	2,674	2,674	2,674	2,674	2,674
Panel B. Income Shares 90% and 10%						
	LN(Volt) [1]	LN(IdioVolt) [2]	LN(GarchVolt) [3]	LN(Volt) [4]	LN(IdioVolt) [5]	LN(GarchVolt) [6]
IncShr90%	−0.0046***	−0.0053***	−0.0047***			
	(−3.11)	(−3.48)	(−3.48)			
IncShr10%				0.0422***	0.0458***	0.0366***
				(3.78)	(3.98)	(3.58)
Constant	−4.0280***	−3.2021***	−3.8810***	−4.2792***	−3.5081***	−4.1711***
	(−14.38)	(−11.43)	(−15.49)	(−17.32)	(−14.31)	(−19.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.7391	0.7565	0.7507	0.7395	0.7568	0.7508
N	2,674	2,674	2,674	2,674	2,674	2,674

This table reports the results from estimating the following regression on a sample of 2,674 ADR-year observations between 2001 and 2018 where the dependent variable is the natural log of one of the following three volatility measures: *Volt*, *IdioVolt*, or *GarchVolt*. *IncShr80%* (*IncShr20%*) captures the share of income held by the richest (poorest) 20% of the population. *IncShr90%* (*IncShr10%*) captures the share of income held by the richest (poorest) 10% of the population. We include both country-level and ADR-level control variables, which have previously been defined. We also include year fixed effects, δ_t, and two-digit SIC industry fixed effects, θ_{sic}. We report t-statistics in parentheses obtained from robust standard errors. *, **, and *** denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

report t-statistics in parentheses obtained from robust standard errors.

Table 5 reports the results from estimating equation (4). In Panel A of Table 5, we report the results when examining the income held by the richest (columns [1] – [3]) and poorest (column [4] – [6]) 20% of the countries' populations. In the first three columns, we find that the estimated coefficients on *IncShr80%*, which is positively correlated with income inequality, are between −0.0040 and −0.0046, all of which are significant at the 0.01 level. In economic terms, these results imply that a unit increase in *IncShr80%* is associated with a 40 to 46 bp decrease in volatility, depending on the volatility measure. In the final three columns, we show that the coefficients on *IncShr20%*, which is inversely related to income inequality, are all positive and significant, ranging from 0.0165 to 0.0207. These results suggest that a unit increase in *IncShr20%*, which is inversely related to income inequality, is associated with a 165 to 207 bp increase in volatility.

In Panel B of Table 5, we report the results when examining the share of income held by the richest (columns [1] – [3]) and poorest (column [4] – [6]) 10% of the countries' populations. In the first three columns, we find that the estimated coefficients on *IncShr90%*, which is positively correlated with income inequality, are negative and significant at the 0.01 level. In economic terms, the results show that a unit increase in *IncShr90%* is associated with a 46 to 53 bp decrease in volatility, depending on the model specification. In the final three columns, we find that the estimated coefficients on *IncShr10%*, which is inversely correlated with income inequality, are positive and significant, ranging from 0.0366 and 0.0458. In other words, a unit increase in *IncShr10%* is accompanied by a 366 and 458 bp increase in volatility, depending on the measurement of volatility.

The results in Table 5 show as a greater percentage of income is earned by the top (bottom) 20% and 10% of the population, volatility significantly decreases (increases). The findings to this point provide support for the notion that income inequality is negatively associated with equity market volatility. Therefore, instead of creating more volatility, inequality has a stabilizing influence on stock prices.

Table 6. Income inequality and ADR volatility by country development.

	LN(Volt)	LN(IdioVolt)	LN(GarchVolt)
	[1]	[2]	[3]
GINI	−0.0042***	−0.0045***	−0.0039***
	(−2.60)	(−2.72)	(−2.73)
Developed	−0.1458	−0.2083	−0.1959*
	(−1.15)	(−1.62)	(−1.77)
GINI × *Developed*	0.0045	0.0067*	0.0061**
	(1.33)	(1.94)	(2.06)
Constant	−3.9704***	−3.1353***	−3.8496***
	(−13.36)	(−10.59)	(−14.58)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Adj. R^2	0.7392	0.7568	0.7509
N	2,674	2,674	2,674

This table reports the results from estimating the following regression on a sample of 2,674 ADR-year observations between 2001 and 2018 where the dependent variable is the natural log of one of the following three volatility measures: *Volt, IdioVolt*, or *GarchVolt. GINI* is the income inequality variable obtained from World Bank. *Developed* is an indicator variable equal to one if the country is classified as developed and zero if developing. The interaction term between *GINI* and *Developed* is the independent variable of interest. We include both country-level and ADR-level control variables, which have previously been defined. We also include year fixed effects, δ_t, and two-digit SIC industry fixed effects, θ_{sic}. We report t-statistics in parentheses obtained from robust standard errors. *, **, and *** denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Income inequality and ADR volatility – country development

Since financial development affects both the distribution of income across countries (Demirgüç-Kunt and Levine 2009) and cross-listing decisions (Sarkissian and Schill 2016), we examine whether the relation between inequality and volatility is more pronounced in developed or developing countries. To do so, we estimate the following equation on the same sample of 2,674 ADR-year observations:

where all variables have previously been defined, except for *Developed*, which is an indicator variable equal to one if the country did not receive official development assistance (ODA) and zero otherwise.[6] The interaction term between the income inequality *GINI* coefficient and *Developed* is the independent variable of interest. Again, we include both country-level and ADR-level control variables, year fixed effects (δ_t), and two-digit SIC industry fixed effects (θ_{sic}). For brevity, we suppress the output of the control variables and fixed effects as they produce their expected signs. We report t-statistics in parentheses obtained from robust standard errors.

The results from estimating equation (5) are reported in Table 6. We find that the estimated coefficients on the interaction term are positive and significant in the *IdioVolt* and *GarchVolt* model specifications, but indifferent from zero in the *Volt* model. Therefore, we find limited evidence that the effects of income inequality on volatility are stronger for less developed countries. It is important to note, however, the estimates on the *GINI* coefficient remain negative and significant in all specifications even after controlling for country development.

French ADR volatility around the millionaire tax

The results in this study surprisingly suggest that income inequality is negatively associated with volatility in financial markets. However, identifying this relation is not necessarily indicative of causality. It is possible that the volatility of stock prices can influence income inequality. A potential mechanism that might explain this type of reverse causation is the link between stock market participation and excess volatility (see e.g. Allen and Gale 1994). While empirical tests have not been able to link stock market participation to income inequality (Bilias, Georgarakos, and Haliasson, 2017), the possibility exists.

In this subsection, we attempt to find an appropriate identification strategy to make stronger causal inferences. On December 29th, 2013, the French Constitutional Court unexpectedly approved the Millionaire Tax proposed by French President Francois Hollande, which taxes salaries of €1 million at 75% during the 2013 and 2014 tax years. One year earlier, the same court rejected an

[6]Our list of developed and developing countries also aligns with the 2014 World Economic Situation and Prospects country classification, available at: https://www.un.org/en/development/desa/policy/wesp/wesp_current/2014wesp_country_classification.pdf.

Table 7. French ADR volatility around the millionaire tax.

	LN(RangeVolt)	LN(GarchVolt)
	[1]	[2]
Court	0.0540	0.1773***
	(1.12)	(6.42)
Treat	−0.1173***	0.0049
	(−8.59)	(0.64)
Court × *Treat*	0.1008***	0.0485***
	(5.55)	(4.83)
Constant	−3.7493***	−2.2853***
	(−85.58)	(−96.37)
Controls	Yes	Yes
Day FE	Yes	Yes
Industry FE	Yes	Yes
Adj. R^2	0.4756	0.5694
N	144,901	145,676

This table reports the results from estimating the following regression on a sample of ADR-day observations between 2 January 2013, and 31 December 2014: where the dependent variable is the natural log of one of the following two daily volatility measures: *RangeVolt* or *GarchVolt. RangeVolt* is the natural log of the daily high ask price minus the natural log of the daily low bid price. *GarchVolt* is the square root of the conditional expected variance obtained from fitting a Garch(1,1) model to daily returns for each ADR. *Court* is an indicator variable equal to one after the French Constitutional Court upheld the Millionaire Tax on December 29th, 2013 and zero otherwise. *Treat* is a categorical variable equal to one if the ADR is from France, and zero otherwise. The interaction term between *Court* and *Treat* is the independent variable of interest. We include ADR-level control variables, which have previously been defined. We also include day fixed effects, δ_t, and two-digit SIC industry fixed effects, θ_{sic}. We report t-statistics in parentheses obtained from robust standard errors. *, **, and *** denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

earlier proposal based on the argument that the implementation of the tax rate was unfair. In a surprising turn of events, the Constitutional Court revisited a revised proposal and collectively decided to approve the new tax rate. This decision by the court is arguably an exogenous shock to the perceived level of income inequality in France and seems to be an appropriate identification strategy. Therefore, we examine the volatility of French ADRs vis-à-vis other country ADRs surrounding this tax change in a difference-in-difference setting. To the extent that inequality reduces volatility as described in the analysis above, we would expect that the exogenous reduction in inequality in response to the court's decision would lead to an increase in volatility in French ADRs, relative to non-French ADRs. Accordingly, we estimate the following equation on a sample of ADR-day observations:

$$\begin{aligned} LN\left(Volatility^{j}_{i,c,t}\right) = \alpha &+ \beta_1 Court_t + \beta_2 Treat_c \\ &+ \beta_3 Court_t \times Treat_c \\ &+ \beta_4 NYSE_i + \beta_5 LN\left(Price_{i,t}\right) \\ &+ \beta_6 LN\left(MktCap_{i,t}\right) \\ &+ \beta_7 LN\left(Turn_{i,t}\right) \\ &+ \beta_8 LN\left(Spread_{i,t}\right) + \delta_t + \theta_{sic} \\ &+ \varepsilon_{i,t} \end{aligned} \tag{6}$$

where the dependent variable is the natural log of one of two daily measures of volatility. *RangeVolt* is the range-based volatility measure of Alizadeh, Brandt, and Diebold (2002), which is the natural log of the daily high ask price minus the natural log of the daily low bid price. *GarchVolt* is the square root of the conditional expected variance obtained from fitting a Garch(1,1) model to daily returns for each ADR. *Court* is an indicator variable equal to one after the French Constitutional Court upheld the Millionaire Tax on December 29th, 2013 and zero otherwise. *Treat* is a categorical variable equal to one if the ADR is from France, and zero otherwise. The interaction term between *Court* and *Treat* is the difference-in-difference term and the independent variable of interest. All other control variables have previously been defined. For brevity, we suppress the output for the control variables, year fixed effects (δ_t), and industry fixed effects (θ_{sic}). We report t-statistics in parentheses obtained from robust standard errors.

Table 7 reports the results from estimating equation (6). The estimated daily correlates on the controls are identical to those in the previous tables. Therefore, we focus our attention exclusively on the variables of interest. After holding other factors constant, we find that the interaction term, *Court* x *Treat*, produces a positive and significant coefficient in both columns [1] and [2]. For instance, the estimate for the interaction term in column [1] is 0.1008 (t-statistic = 5.55) suggesting that, after holding the other independent variables constant, the average daily volatility for French ADRs,

Table 8. Human capital and income inequality.

	GINI	IncShr80%	IncShr90%	IncShr20%	IncShr10%
	[1]	[2]	[3]	[4]	[5]
AdvEduc	0.3197***	0.2495***	0.2230***	−0.0814***	−0.0412***
	(3.64)	(3.40)	(3.32)	(−3.99)	(−4.28)
LN(GDP/Cap)	−5.1276***	−4.3543***	−4.0308***	1.0240***	0.4052***
	(−10.20)	(−10.81)	(−10.95)	(8.21)	(6.79)
LN(Savings)	0.6297	0.3916	0.1568	−0.2017	−0.0810
	(0.96)	(0.72)	(0.31)	(−1.26)	(−1.06)
LN(Trading)	−0.3271	−0.1898	−0.0663	0.1123**	0.0402
	(−1.45)	(−0.98)	(−0.37)	(2.10)	(1.61)
LN(Unemployment)	2.9888***	2.3795***	1.9415**	−0.8441***	−0.4405***
	(3.48)	(2.96)	(2.57)	(−5.06)	(−5.72)
Constant	42.0653**	52.7891***	40.9168***	8.9962*	4.7366**
	(2.14)	(3.28)	(2.79)	(1.92)	(2.16)
Year FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.4866	0.4840	0.4708	0.4370	0.3723
N	293	293	293	293	293

This table reports the results from estimating the following regression on a sample of 293 ADR-year observations with education data between 2001 and 2018 where the dependent variable is one of five measure of inequality: *GINI, IncShr80%, IncShr90%, IncShr20%*, or *IncShr10%. AdvEduc* is the independent variable of interest obtained from the World Bank and is defined as the percent of the labour force in a particular country with advanced education. As control variables, we include the natural log of *GDP/Cap, Savings, Trading*, and *Unemployment*, which have previously been defined. We also include year fixed effects, δ_t. We report t-statistics in parentheses obtained from robust standard errors. *, **, and *** denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

relative to non-French ADRs, increases by about 10.08 percentage points after the court decided to allow the Millionaire Tax. Similarly, the estimate on the interaction term in column [2] is 0.0485 (t-statistic = 4.85), which suggests that the average daily *GarchVolt* for French ADRs vis-à-vis non-French ADRs, increases by 4.85 percentage points post-tax. Taken together, the results from this analysis provide strong support for the hypothesis that income inequality is associated with less ADR volatility.

Robustness – human capital and income inequality

To this point, our results indicate a strong inverse relation between income inequality and market volatility. To explain these results, we lean on the literature that suggests that income inequality represents a higher payoff for human capital, which means that the most highly skilled managers are the more important decision-makers for firms (Becker and Chiswick 1966; Lucas 1977; Becker and Murphy 2007; Cobb, 2016). Therefore, firms in countries with greater inequality (higher-skilled labour) could make decisions that lead to more stable stock prices. In our final set of tests, we ensure that there is a positive relation between income inequality and human capital across our sample countries. To do so, we estimate the following regression equation on a sample of 293 country-year observations:

$$\begin{aligned} Inequality^j_{c,t} = \alpha &+ \beta_1 AdvEduc_{c,t} \\ &+ \beta_2 LN\left(GDP/Cap_{c,t}\right) \\ &+ \beta_3 LN\left(Savings_{c,t}\right) \\ &+ \beta_4 LN\left(Trading_{c,t}\right) \\ &+ \beta_5 LN\left(Unemployment_{c,t}\right) + \delta_t \\ &+ \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where the dependent variable is the World Bank *GINI* coefficient for country c in year t. To proxy human capital, we obtain from the World Bank the percent of the labour force with advanced education (*AdvEduc*).[7] The control variables have previously been defined. We also include year fixed effects, δ_t. We report t-statistics in parentheses obtained from robust standard errors.

The results from estimating equation (7) are reported in Table 8. The control variables indicate that economic output is negatively associated with inequality, while unemployment is positively associated with inequality. In the first three columns, the dependent variables are positively associated with income inequality. As expected, we find that the coefficients on *AdvEduc* are positive and significant in each of the model specifications, ranging from

[7]We also looked at the percent of the labour force with intermediate and basic education and find similar results.

0.2230 and 0.3197. In the final two columns, the dependent variables are inversely related to income inequality. We find that the estimated coefficients on *AdvEduc* are negative and significant, ranging between −0.0412 and −0.0814. Therefore, holding other factors constant, we find that a more educated population (i.e. greater human capital) is associated with higher inequality in a given country.

IV. Conclusion

While prior research finds that the development of financial markets leads to a reduction in income inequality (see e.g. Demirgüç-Kunt and Levine 2009), few if any studies have examined the effect of inequality on the stability of financial markets. On the one hand, inequality might create social and political uncertainty that could be reflected in higher volatility in stock prices. On the other hand, inequality might reflect a higher payoff to human capital so that highly skilled individuals are making the most important investment decisions for the firm, which might lead to a reduction in the volatility of stock prices.

In this study, we examine a large sample of ADRs across 37 countries to test whether inequality influences the volatility of stock prices. By focusing on ADRs, we at least partially control for the possibility that the structure of a country's financial market is endogenously determined by factors associated with income inequality. Our multivariate tests show that, after controlling for several ADR-specific and country-specific characteristics, inequality is negatively associated with volatility. Our results are robust to various measures of volatility and inequality. The results are most pronounced in countries that have the highest percentage of income held by the poorest parts of the population and in developing economies.

To make stronger causal inferences, we use the December 29th, 2013 French Constitutional Court decision to enforce a Millionaire Tax, which taxes salaries of €1 Million per year at 75%, as a negative shock to the perceived level of income inequality in France. We then examine the volatility of French ADRs, relative to non-French ADRs, around the implementation of this policy in a difference-in-difference setting. We find that volatility of French ADRs vis-à-vis non-French ADRs increases between 4.85 and 10.08 percentage points around the change in tax policy.

Combined, our findings provide strong support for the notion that income inequality leads to higher stock volatility. We also document that greater human capital is positively correlated with income inequality across countries. Therefore, the more skilled labour force in high-income inequality countries (Becker and Chiswick 1966; Lucas 1977; Becker and Murphy 2007; Adam Cobb 2016) might help stabilize the prices of stocks in those countries.

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No potential conflict of interest was reported by the authors.

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