Why Does Equity Trading Activity Vary Across the World? An Empirical Investigation[†]

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Abstract

Equity trading intensity differs widely across countries, shaping market thickness, and, in turn, trade execution risk and price discovery worldwide. We investigate the sources of cross-country variation in trading activity using 20,000 stocks from 66 countries over 2000–2021. Country-level turnover and liquidity are driven by behavioral traits, trading frictions, governance, demographics, and information asymmetry. Individualism and home bias increase trading. Democratic freedom and trading frictions have the opposite effect; natural experiments confirm these relations. Turnover and liquidity diverge through informed trading channels, and illiquidity reinforces the relation between returns and future GDP growth.

JEL Codes: G12; G15

Keywords: International Stock Markets; Trading Activity; Turnover; (Il)liquidity; Amihud Measure; Behavioral Traits; Trading Frictions; Governance; Information Asymmetry; Demographics; Natural Experiments; Mediating Role; GDP Growth

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Abstract

Equity trading intensity differs widely across countries, shaping market thickness, and, in turn, trade execution risk and price discovery worldwide. We investigate the sources of cross-country variation in trading activity using 20,000 stocks from 66 countries over 2000–2021. Country-level turnover and liquidity are driven by behavioral traits, trading frictions, governance, demographics, and information asymmetry. Individualism and home bias increase trading. Democratic freedom and trading frictions have the opposite effect; natural experiments confirm these relations. Turnover and liquidity diverge through informed trading channels, and illiquidity reinforces the relation between returns and future GDP growth.

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1. Introduction

In 2022, share turnover in the Chinese stock market approached 300% per year, while turnover in New Zealand during the same period was a mere 14%.[1] The U.S. occupies a middle ground, with estimates hovering around 100%.[2] Such stark differences illustrate that trading activity varies dramatically across countries, even among well-developed markets. Understanding these differences is important for several reasons. First, trading volume is a central determinant of price discovery (Barclay and Hendershott, 2003), which influences firms' cost of capital and the efficiency of resource allocation (O'Hara, 2003). Second, trading activity is inversely related to market thinness, and the thicker the market, the less is execution risk (Tsoukalas et al., 2019). Hence, trading volume is directly related to the efficacy of international portfolio strategies and, in turn, to global capital flows. Third, trading is accompanied by real monetary costs that represent a wealth transfer from investors to intermediaries (French, 2008). Yet despite its central role, little is known about why some countries exhibit persistently high trading activity while others remain relatively inactive. What explains global differences in this costly economic activity?

A large body of literature examines the relationship between trading volume and returns (e.g., Karpoff, 1987; Schwert, 1989; Gallant et al., 1992; Cookson et al., 2023). Other studies, such as Statman et al. (2006) and Chordia et al. (2007), focus on the cross-sectional determinants of trading volume at the individual stock level within the United States. While these contributions provide important insights, they leave open a more fundamental question: Are international variations in trading activity explained by cultural traits, trading frictions, or demographic differences? To address this issue, we conduct a comprehensive cross-country analysis of trading activity, moving beyond firm-level drivers.

Our empirical framework is motivated as follows. First, we examine whether behavioral and demographic characteristics shown to influence individual investors' trading decisions (Odean, 1998; Barber and Odean, 2001; Ben-Rephael and Izhakian, 2020) aggregate to the country level. Second, we assess whether belief dispersion and information asymmetries, which drive trading at the individual security level (Carlin et al., 2014; Chae, 2005), exert systematic effects on global trading volume. Finally, we investigate the role of trading frictions—including exchange fees and transaction taxes (Colliard and Hoffmann, 2017; Cai et al., 2021)—as well as governance quality (Chung et al., 2010), as proxied by institutional features such as the degree of democracy. Although each of these factors

[1] See https://www.theglobaleconomy.com/rankings/stock_market_turnover_ratio.

[2] The estimates are from CRSP.

has been studied in prior work, we are not aware of any study that systematically links them to global variations in trading activity.

Our investigation proceeds along several dimensions. We begin by constructing a panel of dollar-volume-based turnover (*TURN*) for up to 66 countries (consisting of about 20,000 unique firms) spanning 2000 to 2021, using daily-frequency data from LSEG Datastream. Country-level turnover is defined as the aggregate USD-value of shares traded, scaled by total market capitalization, and then annualized. The cross-country variation in our sample is striking: the time-series average of annualized turnover ranges from 0.08 in Colombia to 2.20 in China, with a cross-country standard deviation of 0.61. The time-series variation is also substantial: aggregate turnover peaked at 1.67 during the 2008 global financial crisis and again rose to 1.39 at the onset of the Covid-19 pandemic in early 2020. This heterogeneity, across countries and time, justifies a rigorous investigation, using a rich set of the underlying forces which shape trading activities in global markets.

Our work merges several datasets, namely Datastream, Worldscope, I/B/E/S, and FactSet, as well as results from psychological studies that measure country-level behavioral traits, to provide a comprehensive picture of the drivers of worldwide trading activity. The specific variables that we use to explain trading activity are organized into four groups for reporting convenience. The first category of variable captures behavioral traits, including individualism (*Indivsm*, a proxy for investor overconfidence), home bias (*HomBias*), ambiguity aversion (*AmbgAvsn*), and risk aversion (*RskAvsn*). The second category reflects trading frictions, measured by the combined burden of financial transaction taxes and exchange fees (*TFriction*). The third category comprises governance and demographic factors, including democratic freedom (*Freedom*), income inequality (*IncIneq*), corruption (*Corrupt*), the female population share (*%Female*), and population age distribution (*%Age0T14* and *%Age65+*). The fourth category captures opinion divergence and information asymmetry, including analyst forecast dispersion (*ForecDisp*), institutional ownership (*InstOwn*), and earnings volatility (*EarnVola*). Finally, we include firm-level characteristics such as firm size (*ln(MCap)*) and short- and long-horizon return momentum (*MOMS* and *MOML*).

We find that behavioral traits play a first-order role in explaining global variations in turnover. Among them, individualism is the most economically significant predictor of turnover: a one-standard-deviation (SD) increase in *Indivsm* is associated with a 0.497-SD increase in *TURN*. This finding is consistent with the well-established link between overconfidence and excessive trading (Odean, 1998; Barber and Odean, 2000; Chui et al., 2010). *HomBias* also strongly increases turnover, reflecting the rebalancing of portfolios concentrated in domestic assets. In contrast, both *AmbgAvsn* and *RskAvsn* are negatively associated with trading activity, consistent with theory (Grossman and Stiglitz, 1980; Easley and O'Hara, 2009). This highlights that trading activity is not solely a function of market conditions, but also of deeply embedded societal preferences. Together, behavioral traits account for roughly 15% of cross-country variation in turnover.

Trading frictions exert a predictable downward effect on trading activity. A one-SD increase in our composite frictions measure (*TFriction*) is associated with a 0.159-SD reduction in *TURN*. Governance and demographic variables add substantially to the model's explanatory power, raising the adjusted R-squared above 40%. *Freedom* is negatively associated with *TURN* — more democratic countries exhibit lower trading intensity. We interpret this finding mainly through the channel that democracy fosters stronger regulatory oversight of financial systems (Bonaparte, 2024), thereby reducing the use of stock trading as a lottery-style vehicle for upward mobility (Gao and Lin, 2015). *IncIneq* has the opposite sign: countries with greater wealth concentration exhibit higher turnover, consistent with speculation being more prevalent when constrained economic opportunities push households toward high-risk investment strategies. The corruption level (*Corrupt*) is also positively related to turnover, suggesting that opaque environments may foster speculative trading activity.

Several demographic variables play notable roles. *%Female* is negatively associated with trading, consistent with evidence that women trade less frequently than men (Barber and Odean, 2001). The share of young population (*%Age0T14*) is also negatively related to turnover, reflecting the hypothesis that childcare burdens restrict the time and resources that households can devote to trading (Jagannathan and Kocherlakota, 1996). By contrast, the share of the elderly population (*%Age65+*) is positively associated with trading, consistent with the view that retirees have lower opportunity costs of time for engaging in speculative trading behavior (Gamble et al., 2015). Variables related to opinion divergence and information asymmetry — including *ForecDisp*, *InstOwn*, and *EarnVola* — are all positively associated with turnover, highlighting the central role of informational environments in shaping trading dynamics across countries.

Our analysis also extends to the firm level, allowing us to bridge the gap between country-level and micro-level evidence. Using a large panel of firm-month observations, we show that the effects identified at the country level largely persist at the firm level. Behavioral traits, trading frictions, governance, and information-related variables all exhibit similar relationships with turnover across firms within countries. This consistency strengthens the interpretation that our country-level findings reflect fundamental economic mechanisms rather than aggregation artifacts.

We further enrich our analyses in several directions. First, we examine the cross-sectional dispersion of turnover across countries, asking why the within-country distribution of trading activity differs substantially across countries. This question is relevant for asset managers who must deal with uneven execution risk within a country when turnover is widely dispersed across stocks. We quantify dispersion using the coefficient of variation (CV) for firm-level turnover, *CV(TURN)*, and for other variables within each country-month, and find that *CV(TURN)* varies widely, from a high of 1.47 in India to a low of 0.55 in Colombia. We show that within-country dispersion in institutional ownership, market capitalization, analyst forecast dispersion, and return momentum collectively explain substantial variation in turnover dispersion across countries.

Second, we investigate the determinants of cross-country variations in illiquidity, proxied by the Amihud (2002) measure (*ILLIQ*). While illiquidity and turnover are related, they capture fundamentally distinct dimensions of trading: turnover reflects the *quantity* of transactions, while illiquidity measures the *quality* (price impact) of those transactions. We find that the determinants of illiquidity (*ILLIQ*) partially mirror those of *TURN*: e.g., greater market capitalization and lower trading frictions are associated with higher liquidity. However, differences emerge. In particular, *AmbgAvsn* reduces turnover but improves liquidity (i.e., reduces *ILLIQ*), consistent with Caskey (2009), who shows that informed investors averse to ambiguity trade less aggressively, reducing information asymmetry. *InstOwn* increases turnover and has the opposite effect on illiquidity, consistent with informed trading (Glosten and Milgrom, 1985). These diverging dynamics justify our joint examination of *TURN* and *ILLIQ* in the remaining analyses.

We next address issues of causality. We acknowledge at the outset that few financial variables can be cleanly classified as exogenous or endogenous. We view our paper as taking a first step by identifying key empirical determinants of international turnover that can serve as building blocks for future research. To further address endogeneity concerns, we implement stacked difference-in-differences (DiD) analyses that exploit plausibly exogenous shocks, allowing us to assess the causal interpretation of our findings on governance quality and trading frictions.

Specifically, for governance quality, we examine three military interventions: two that increased democratic freedom (Thailand in 2006 and Egypt in 2011) and one that reduced it (Turkey in 2016). Because such interventions are typically driven by deep political conflicts rather than stock market conditions, they provide suitable quasi-experimental shocks. We find that positive shocks to democratic freedom significantly reduce turnover in the treated countries, whereas the negative shock in Turkey is associated with a significant increase in *TURN*. For trading frictions, we exploit regulatory changes in transaction taxes in four European countries (Belgium, France, Hungary, and

Italy) between 2012 and 2013. Consistent with our framework, these tax increases significantly reduce turnover in the affected countries, confirming the causal role of frictions in suppressing trading activity.

We further test how the exogenous shocks affect illiquidity in the DiD framework. The military and tax shocks influence illiquidity in a manner broadly consistent with their effects on turnover. For the positive military shocks (Thailand and Egypt), the effect on *ILLIQ* is marginal. By contrast, Turkey's negative shock — the 2016 failed coup and the subsequent restriction of political freedom — significantly reduces *ILLIQ* (improves liquidity) post-event. This indicates that authoritarian consolidation, by concentrating economic power and shifting trading toward a narrower set of market participants, can paradoxically improve short-run price continuity even as it suppresses overall participation. For the four countries subject to increased transaction taxes, the higher trading costs worsen liquidity post-event, consistent with the view that taxing transactions reduces market depth and raises price impact. Taken together, the DiD evidence using illiquidity reinforces the conclusion that governance quality and market frictions have real and causal consequences for both the quantity and quality of trading in equity markets.

We explore the pricing of trading activity across countries. We document that turnover is inversely priced in most countries, providing global confirmation for Datar et al. (1998). That is, high-$TURN$ stocks earn lower returns than low-$TURN$ stocks; however, this pricing effect of $TURN$ is more evident in small stocks, where it is statistically significant in 16 out of the 41 countries in our sample. By contrast, *ILLIQ* is positively priced in almost all countries for both small and large stocks, consistent with Amihud (2002) and Amihud et al. (2015), and significance continues to be stronger in small companies.

In the last part of the analysis, we investigate the macroeconomic implications of turnover and liquidity by examining whether these variables can mediate stock market performance as a leading indicator of economic growth. Allen et al. (2024) suggest that high trading in China, which is primarily driven by retail and noise traders, can play a role in weakening the predictive power of stock prices for future economic growth. We explore this observation rigorously in the global context. Specifically, we run Fama-MacBeth cross-sectional regressions of future GDP growth on the interaction of past quarter's returns (*MOMQ1*) with *ILLIQ* or *TURN*. We find that *ILLIQ* significantly amplifies the predictive power of stock returns for GDP growth, while *TURN* does not. This is consistent with the notion that price movements in a country with less liquid markets reflect informed trading and hence carry more fundamental information about the future state of the economy in that country.

Our paper contributes to several strands of literature. A substantial body of theoretical work examines the relationship between trading volume and information asymmetry (e.g., Grossman and Stiglitz, 1980; Kyle, 1985; Hellwig, 1980; Kim and Verrecchia, 1994; Hong and Stein, 2007), investor overconfidence and speculation (e.g., Odean, 1998; Scheinkman and Xiong, 2003), and the role of frictions (e.g., Epps, 1976; Subrahmanyam, 1998). Empirically, Chordia et al. (2007) study the cross-section of trading activity only in the U.S. market, and Lo and Wang (2000) analyze turnover in the context of portfolio theory. Karolyi et al. (2012) examine the international commonality of liquidity and identify turnover as its leading determinant. Chui et al. (2010) show that individualism explains cross-country momentum patterns. As far as we can see, however, no prior study has undertaken a comprehensive country-level investigation of what drives trading activity globally, whether liquidity is shaped by the same forces, or how these trading characteristics mediate the relationship between financial markets and the real economy. We address the issues related to all three dimensions simultaneously. These findings carry practical implications for portfolio managers seeking to understand global market thinness. They also are relevant to policymakers and regulators, particularly those designing transaction tax regimes or governance reforms aimed at shaping market participation.

The remainder of the paper is organized as follows. Section 2 describes the data and construction of variables, and presents summary statistics. Section 3 presents empirical results at both country and firm levels. In Section 4, we conduct further analyses on turnover dispersion, and on the drivers of illiquidity, highlighting where they diverge from those of turnover. Section 5 conducts natural experiments based on military interventions and tax increases. In Section 6, we examine the pricing of trading-related variables, and investigate the role of trading activity in linking stock market performance to economic growth. Section 7 concludes. We provide supplementary tables in the Appendix.

2. Data and Variable Construction

In this section, we describe our data sources and methods of constructing our variables, and finally present summary statistics. Our study combines several international data sources, namely, Datastream, Worldscope, FactSet, and I/B/E/S (international), and also draws on various psychological studies that measure country-wide behavioral traits, in order to build detailed picture of what drives global trading activity.

2.1. Data on International Stock Markets

This study utilizes a sample of developed and emerging markets as classified by MSCI. Our dataset includes common stocks that are either domiciled in or primarily operate within these jurisdictions.[3] We obtain daily-frequency data from LSEG Datastream, tracking the return index,[4] closing price, and market capitalization, all of which are denominated in U.S. dollars. Additionally, we collect data on trading volume and the number of shares outstanding. We then construct monthly variables by summing daily values and taking daily averages within each month for share volume ($SVol$) and the number of shares outstanding ($NShrs$). We also generate the monthly return index (RI) and monthly market capitalization ($MCap$) from the daily data files by taking the end-of-month values. The monthly stock return (Ret) is calculated as the change in RI.

Following Ince and Porter (2006), we apply the "reversal filter" for our dataset from Datastream, excluding any stock-month with an extreme return reversal.[5] We further require stock-months to have non-missing trading volume and at least 10 trading days within a month. We merge our stock dataset with financial statement data from Worldscope as well as analyst and ownership data from I/B/E/S and FactSet. Using CUSIP and SEDOL identifiers, we construct our firm-level control and explanatory variables. Specifically, we utilize I/B/E/S historical earnings estimates to compute analyst forecast dispersion, and leverage FactSet's comprehensive holdings data to calculate institutional ownership and float-related metrics. These combined sources allow us to account for both the information environment and the shareholder structure of each firm in our global sample.

2.2. Construction of Country-Level Variables

2.2.1. Dollar-Volume-Based Turnover (TURN)

Our primary variable of interest is dollar-volume-based turnover (denoted as $TURN$), which is a widely recognized proxy for aggregate trading activity. We define country-level turnover as the total value of shares traded across all firms within a country, divided by the total market capitalization (in million USD) of those firms at the previous month-end. The value is subsequently annualized

[3]For MSCI market classifications and index methodologies, see https://www.msci.com/indexes/category/market-cap-indexes.

[4]The "return" index is computed by considering the reinvestment of dividends, as opposed to the "price" index.

[5]Specifically, for identifying and removing errors in Datastream, if either Ret_t or Ret_{t-1} exceeds 300% and their combined return $(1 + Ret_t)(1 + Ret_{t-1}) - 1$ is less than 50%, the returns in both periods are set as missing.

by multiplying by 12. Thus, $TURN$ is computed as:

$$TURN_{c,t} = 12 \times \frac{\sum_{i \in c}(SVol_{i,t} \times P_{i,t-1})}{\sum_{i \in c} MCap_{i,t-1}}, \tag{1}$$

where $SVol_{i,t}$ is the number of shares traded for stock i in country c during month t, and $P_{i,t-1}$ and $MCap_{i,t-1}$ denote the stock i's closing price and market capitalization, respectively, both measured at the end of the previous month, $t-1$.[6] To mitigate potential data errors, we follow the approach of Karolyi et al. (2012), excluding stock-month observations when monthly share volume is more than double the shares outstanding. This filter removes less than 0.2% of the sample.[7]

We use $TURN$ as our primary variable to measure trading activity because it reflects both the intensity (share volume) and financial scale (price) of transactions; moreover, it considers cross-country differences in market capitalization. In addition to the country-level analyses, we also conduct analyses at the firm level, for a robustness check, using each firm's share turnover.

2.2.2. Variables Related to Behavioral Traits

Behavioral traits are quite different across countries, and these aspects are likely to affect trading activity (Barber and Odean, 2001; Grinblatt and Keloharju, 2001). We therefore construct a set of country-level behavioral variables to capture the impact of societal preferences and psychological predispositions on trading activity.

(1) Individualism (*Indivsm*): Retail investors often engage in excessive trading due to their overconfidence (Odean, 1998; Barber and Odean, 2000). While overconfidence is not directly observable, in financial contexts, higher individualism is often associated with investor overconfidence (Chui et al., 2010). This trait, one of Hofstede's (1980) most extensively studied dimensions, reflects the degree to which individuals in a society prioritize personal goals over group cohesion. We collect the country-level individualism score from Hofstede's online website.[8]

(2) Home Bias (*HomBias*): The concept of home bias — the empirical phenomenon where

[6] Note that our definition of country-level turnover ($TURN_{c,t}$) is equivalent to the market-capitalization-weighted average of firm-level turnover ($TURN_{i,t}$): that is, $TURN_{c,t} = 12 \times \frac{\sum_{i \in c} SVol_{i,t} \times P_{i,t-1}}{\sum_{i \in c} MCap_{i,t-1}} = 12 \times \frac{\sum_{i \in c} \frac{SVol_{i,t}}{NShr_{i,t-1}} \times MCap_{i,t-1}}{\sum_{i \in c} MCap_{i,t-1}} = 12 \times \sum_{i \in c} TURN_{i,t} \times \frac{MCap_{i,t-1}}{\sum_{i \in c} MCap_{i,t-1}}$. A small number of companies (less than 30) are traded on multiple exchanges under different identifiers. Such companies tend to be multinationals like Royal Dutch Shell, and each of the identifiers for a company records the same market capitalization. Although our analysis includes such companies, we have verified that omitting them has no impact on our results.

[7] Our method is different from that of Karolyi et al. (2012) in that we apply this filter at the monthly level rather than the daily level. Our results are robust when using alternative filters: e.g., equal to the number of shares outstanding (less than 1% of the sample is excluded), and triple the number (less than 0.1% is excluded).

[8] See https://www.theculturefactor.com/country-comparison-tool.

investors hold a disproportionately larger share of domestic assets than predicted by standard portfolio theory—is extensively documented in the literature (French and Poterba, 1991; Cooper and Kaplanis, 1994; Tesar and Werner, 1995). This bias can be attributed to several factors, including information frictions, familiarity effects, and behavioral preferences (Brennan and Cao, 1997; Huberman, 2001). Notably, home bias can also contribute to increased turnover, as investors who overly favor domestic stocks tend to concentrate their rebalancing activities within the local market. As a result, investors substitute one domestic asset for another, thereby generating substantial trading volumes within the home market. Following Wallmeier and Iseli (2022), we use the share of an investor's total holdings allocated to domestic assets as a proxy for *HomBias*. The variable is taken from Table 1 in Wallmeier and Iseli (2022) (where it is labelled as "*SH*"). A larger value of *HomBias* indicates a stronger preference for home-country investments.

(3) Ambiguity Aversion (*AmbgAvsn*), and (4) Risk Aversion (*RskAvsn*): Classical theories suggest that risk aversion negatively affects trading volume (e.g., Grossman and Stiglitz, 1980; Campbell et al., 1993). In addition, ambiguity aversion may reduce investors' participation in risky assets and thus negatively affect trading volume (Easley and O'Hara, 2009; Ben-Rephael and Izhakian, 2020). To capture these effects, we obtain data on both variables from the large-scale international survey conducted by Rieger et al. (2015). Country-level ambiguity aversion (*AmbgAvsn*) is measured as the percentage of respondents in a country who prefer clear probabilistic outcomes (30% of balls in an urn are red; you win if you pick a red) over ambiguous probabilities of outcomes (70% of balls are yellow or blue; you win if you pick a yellow). Risk aversion (*RskAvsn*) is measured by the relative risk premium that individuals require in simple lotteries. As indicated in Rieger et al. (2015), attitudes toward ambiguity and risk are distinct dimensions of preferences. Hence, we include both metrics in our analyses to reflect a country's aversion to uncertainty.

Studies document that psychological traits exhibit commonality across regions of the world (Hofstede, 1980; Kogut and Singh, 1988; House et al., 2001).[9] Therefore, in cases where values for the above four variables are missing, we extrapolate our scores across regions in the following way: missing values for a given country are imputed using the mean values of other countries within the same region (results are robust with median values). The regions considered are East Asia, South Asia (including Kazakhstan, Pakistan, India), Europe, Latin America, North America (USA and Canada), Oceania, North Africa, Sub-Saharan Africa, and the Middle East.[10]

[9]See also https://globeproject.com/results.html#country.

[10]For details, see Tables A3 and A4 in the Appendix, which apply after the sample of countries has been defined in Section 2.3.

2.2.3. Country-Wide Trading Taxes and Exchange Fees (TFriction)

Investors' willingness to trade decreases in the costs that they pay for such transactions, including financial transaction taxes (FTTs) and exchange fees. Such trading costs constitute a vital market friction (Epps, 1976; DeGennaro and Robotti, 2007). FTTs are levied on trading stocks, bonds, and derivatives, whereas exchange fees are charged by market infrastructure providers. Cross-country FTT data are obtained from the Center for Economic and Policy Research (CEPR).[11] Exchange fees include exchange levies, settlement fees, and other mandatory charges associated with executing trades. We obtain exchange fees from J.P. Morgan and Interactive Brokers.[12] When data are not available from these sources, we hand-collect them directly from exchange and regulatory websites. We construct a country-level variable (*TTax&Fee*) by adding the two components: (i) financial transaction taxes (FTTs), and (ii) exchange fees, both of which are measured in basis points (bps). Then, the log transformation, $\ln(1 + \mathit{TTax\&Fee})$ is used to proxy for trading frictions (*TFriction*). Note that the frictions we use emanate from exchange and government authority. We do not use measures that emanate from the trading process such as bid/ask spreads and price impact, as these are susceptible to significant endogeneity with turnover. We recognize that our policy-based measures measures could also be endogenous to turnover, but this endogeneity would likely be over horizons likely longer than the monthly ones we use. Further, the coefficients on our other variables are not appreciably unaltered when we omit the frictions variable. We more fully address endogeneity using identifying events in Section 5.

2.2.4. Variables Related to Governance and Demographic Factors

Governance quality is widely recognized as a key determinant of economic development (e.g., Acemoglu and Johnson, 2005; La Porta et al., 1997). However, the relationship between governance quality and investors' trading activity remains largely unexplored. To address this gap, we employ several proxies for governance, supplemented by variables capturing the demographic conditions of countries. The demographic variables are obtained from the World Bank statistical database (data.worldbank.org), while the sources of the governance variables are described below.

(1) Democratic Freedom (*Freedom*): High democratic freedom provides stronger protection of property rights, greater transparency, and more robust legal systems (Acemoglu and Johnson, 2005;

[11] For CEPR, see https://cepr.net/publications/financial-transactions-taxes-around-the-world.

[12] Since the time-series of trading frictions are not available, we use the most recent available value and, when multiple schedules are available, select the highest applicable cost.

La Porta et al., 1997). These features may promote participation in financial markets and enhance trading volume. However, democracy might also have the opposite effect on turnover. First, democratization introduces the specter of substantial redistribution, which creates risk[13] and might scale down risky positions. Second, democracies typically impose stronger regulatory oversight and transparency on institutions (Bonaparte, 2024). This encourages real-sector opportunities and alternative channels for upward mobility, which reduces reliance on speculative gambling in the stock market (Gao and Lin, 2015). Overall, the impact of democratic freedom on trading activity remains an open question.

We obtain data on *Freedom* from Freedom House,[14] which offers country-level ratings for Political Rights (PR) and Civil Liberties (CL), evaluated on a 1-to-7 scale, where one indicates the highest level of freedom and seven the lowest. These ratings have been updated yearly since 1972. We construct a composite measure of democratic freedom (*Freedom*) as 8 minus the average of the PR and CL ratings, so that higher values of *Freedom* correspond to greater political and civil freedom.

(2) Income Inequality (*IncIneq*): Income inequality may boost trading by inducing greater participation from the wealthy (Mankiw and Zeldes, 1991; Li et al., 2017) or suppress it by excluding lower-income households. Also, households may be incentivized to engage in more lottery-like trades in an attempt to catch up with the privileged (Gao and Lin, 2015), thereby increasing trading activity. The net effect is therefore ambiguous. We use the Gini index to measure income inequality (*IncIneq*).[15] The index ranges from 0 (perfect equality) to 100 (perfect inequality).

(3) Corruption Level (*Corrupt*): High levels of corruption may deter equity investments by undermining trust, reducing trading activity. However, it can also encourage capital to shift away from opaque private ventures, which are more susceptible to corruption, toward more transparent and liquid public markets (Guiso et al., 2008; Wei and Shleifer, 2000), ultimately fostering trading.

We obtain country-level data from Transparency International.[16] The database reports the Corruption Perceptions Index (CPI), which measures perceived levels of public sector corruption based on expert assessments and opinion surveys. The CPI ranges from 0 (highly corrupt) to 100 (very clean). We construct a reverse measure of corruption as (100 − CPI), so that higher values indicate a greater level of corruption.

[13] Miller (2024) shows that following the Catholic Church's endorsement of democracy in the 1960s, risk premia increased.

[14] See https://freedomhouse.org/reports/freedom-world/freedom-world-research-methodology.

[15] The information is extracted from the website at https://data.worldbank.org/indicator/SI.POV.GINI. For Hong Kong, Singapore, and New Zealand, data are not available from the World Bank. We manually collected the relevant figures from the official statistics released by their respective national statistical agencies.

[16] See the related information at https://www.transparency.org/en/.

(4) Female Ratio (*%Female*): Gender differences in financial decision-making are well documented: women tend to exhibit lower overconfidence and therefore are less prone to frequent trading than men (Barber and Odean, 2001). These differences may translate into lower turnover in populations with more women, to the extent that our overconfidence proxy (*Indivsm*) is imperfect. We therefore employ the proportion of females (*%Female*) as one of the explanatory variables.

(5) Youth Share (*%Age0T14*): A higher proportion of children may indicate greater childcare burdens and financial constraints among working-age adults, limiting the time, attention, and resources for active participation in financial markets (Jagannathan and Kocherlakota, 1996). Additionally, households with children may adopt more conservative strategies, reducing stock turnover. We measure the youth share, defined as the percentage of the population aged 0 to 14.

(6) Elderly Share (*%Age65+*): Likewise, older investors may also be related to higher turnover through their lower opportunity costs of time and trading, which can feed into the general tendency to treat risky investments as lotteries (Gamble et al., 2015). We measure the elderly share as the percentage of the population aged 65 and above.

2.2.5. Variables Related to Opinion Divergence and Information Asymmetry

Existing models suggest that opinion divergence and information asymmetry affect trading activity in financial markets. Thus, we construct country-level variables that can reflect these features.

(1) Analyst Forecast Dispersion (*ForecDisp*): Investors' opinion divergence significantly influences trading activity in rational expectations models (e.g., Hellwig, 1980; Kim and Verrecchia, 1994) and behavioral models (e.g., Hong and Stein, 2007). To measure opinion divergence, we use analyst forecast dispersion, for which we obtain analyst EPS forecasts from I/B/E/S and, following Johnson (2004), compute its dispersion as the standard deviation of analyst EPS forecasts for the current fiscal year, scaled by the mean value of forecasts. We then compute country-level dispersion (*ForecDisp*) as the *MCap*-weighted average of firm-level equivalents as follows:

$$ForecDisp_{c,t} = \frac{\sum_{i \in c} ForecDisp_{i,t} \times MCap_{i,t-1}}{\sum_{i \in c} MCap_{i,t-1}}, \tag{2}$$

where $ForecDisp_{i,t}$ is the analyst forecast dispersion for firm i in country c at the end of month t, and $MCap_{i,t-1}$ is the market capitalization (in million USD) of firm i at the end of month $t-1$.[17]

[17] To eliminate the effects of outliers, we winsorize the firm-level analyst forecast dispersion for each month at the 1st and 99th percentiles before value-weighting it at the country level. The same is applied to other firm-level variables (e.g., earnings volatility, past returns, and the Amihud measure) before computing their country-level variables.

(2) Institutional Ownership (*InstOwn*): A large body of theoretical work (e.g., Grossman and Stiglitz, 1980; Kyle, 1985) examines the trading behavior of informed investors. Consistent with this theoretical foundation, extensive empirical evidence shows that the presence of informed traders tends to increase trading volume and liquidity (e.g., Heflin and Shaw, 2000; Rubin, 2007).

To capture the presence and activity of informed traders, we collect firm-level institutional holdings data from FactSet. This database covers professional money managers, including mutual funds, pension funds, bank trusts, and insurance companies (see Ferreira and Matos, 2008). We construct a country-level measure, *InstOwn*, defined as the total value of shares held by institutions across all firms in a country, scaled by the aggregate market capitalization of those firms. Formally,

$$InstOwn_{c,t} = \frac{\sum_{i \in c} \$IO_{i,t}}{\sum_{i \in c} MCap_{i,t-1}}, \tag{3}$$

where $\$IO_{i,t}$ denotes the USD value of shares held by institutions in stock i in country c at month t. For observations with missing monthly values, we carry forward the most recent quarter-end value.[18]

(3) Earnings Volatility (*EarnVola*): In theory, asset volatility stimulates volume because informed traders become more aggressive when there is more uncertainty and more profit potential. Empirically, firms with more volatile earnings tend to exhibit less predictable performance (Dichev and Tang, 2009). Barinov (2014) also documents a positive relationship between turnover and uncertainty. Earnings volatility may also promote speculation by uninformed investors (Kumar, 2009). To capture these effects, we use earnings volatility to proxy for the cash flow uncertainty of firms.

We obtain quarterly earnings data from Worldscope (Item 1551). Following Chordia et al. (2007) and Cao and Narayanamoorthy (2012), we define firm-level earnings volatility as the standard deviation of the most recent eight quarterly earnings, scaled by the average total assets. We then compute the country-level *EarnVola* as the *MCap*-weighted average of firm-level equivalents:

$$EarnVola_{c,t} = \frac{\sum_{i \in c} EarnVola_{i,t} \times MCap_{i,t-1}}{\sum_{i \in c} MCap_{i,t-1}}, \tag{4}$$

where $EarnVola_{i,t}$ is the earnings volatility for firm i in country c at the end of month t. For each month, we assign the most recent available quarter-end earnings volatility.

[18]We acknowledge the potential endogeneity between *InstOwn* and turnover. To mitigate this concern, we lag institutional holdings by one month relative to turnover. In addition, we attempt to instrument institutional holdings via dummies for legal systems (La Porta et al., 1997), but find that the instrument is not significant in the second stage. However, as shown in the next section, our main results are not sensitive to the inclusion of *InstOwn*. We also address endogeneity more generally in Section 5 using natural experiments.

2.2.6. Variables Related to Visibility and Return Momentum

(1) Firm or Market Size [*ln(MCap)*]: Countries with a better-capitalized stock market are more visible and, as a result, can attract more trading activity (Merton, 1987; Li, 2007). To capture this effect, and to account for skewness in market capitalization across countries, we compute the natural logarithm of the aggregate *MCap* of sample firms within a country as:

$$ln(MCap)_{c,t} = \ln\left(\frac{\sum_{i \in c} MCap_{i,t}}{GDP_{c,y-1}}\right), \tag{5}$$

where $MCap_{i,t}$ represents the market capitalization (in million USD) of firm i at the end of month t, and $GDP_{c,y-1}$ is country c's GDP at the end of year $(y-1)$.

(2) Short-Horizon Momentum (*MOMS*): Retail investors are known to chase past returns, causing trading volume to respond to past returns (De Long et al., 1990; Hong and Stein, 1999). On the other hand, liquidity provision under short-selling constraints (Grossman and Miller, 1988) would generate an asymmetric pattern: when returns are low, liquidity providers step in as buyers, driving turnover higher, but when returns are high, they cannot readily take short positions to supply liquidity, muting the turnover response. To capture these effects, we compute the past one-month return (momentum), which is *MCap*-weighted across stocks within a country as follows:

$$MOMS_{c,t} = \frac{\sum_{i \in c}(Ret_{i,t-1} \times MCap_{i,t-1})}{\sum_{i \in c} MCap_{i,t-1}}, \tag{6}$$

where $Ret_{i,t-1}$ is the monthly returns of stock i in country c at the end of month $t-1$.[19]

(3) Longer-Horizon Momentum (*MOML*): In addition to *MOMS*, we also consider a longer-horizon equivalent. Jegadeesh and Titman (1993) show that stocks with high returns over the past three to twelve months continue to outperform low-return stocks in the subsequent months, a pattern that persists across asset classes (Rouwenhorst, 1998; Asness et al., 2013). The phenomenon is typically attributed to investor underreaction to information or gradual diffusion of news (Hong and Stein, 1999). We thus compute a longer-horizon momentum variable as follows:

$$MOML_{c,t} = \frac{\sum_{i \in c}(Ret_{i,t-12 \text{ to } t-2} \times MCap_{i,t-1})}{\sum_{i \in c} MCap_{i,t-1}}, \tag{7}$$

where $Ret_{i,t-12 \text{ to } t-2}$ is the cumulative return of stock i in country c from month $t-12$ to $t-2$.

[19] See, for example, Bajzik (2020) and Liao et al. (2022) for studies on how returns can affect trading volume.

Overall, our study use a mixture of variables that change over time, and those that are held constant throughout the sample period.[20] Specifically, *TFriction* and the behavioral traits (*Indivsm*, *HomBias*, *AmbgAvsn*, and *RskAvsn*) do not vary over time, whereas the governance and demographic variables are measured on an annual basis. The remaining variables vary from month to month.

2.3. Summary Statistics

We compile the list of variables for each of the 47 countries included in the MSCI indices. Due to data-related issues, six countries are excluded from our main analyses.[21] The remaining 41 countries account for an average of 87% of the global GDP during the sample period. Our baseline sample covers the period from 2000 to 2021, consisting of approximately 20,000 unique firms. To test the robustness of our results, we augment the sample by relaxing the MSCI requirements, dropping the requirements about the availability of institutional holdings (*InstOwn*) from FactSet. As *InstOwn* may be endogenous to turnover, this scheme is useful for our robustness check. The expanded sample thus includes 66 countries, accounting for about 93% of global GDP. The 66 countries used in our expanded sample are mapped in Figure 1.[22]

We report the summary statistics for the variables in Table 1. Panel A shows that our primary variable of interest, *TURN*, has a sample mean of 0.78 across the 41 countries, indicating that the annualized trading volume represents 78% of their market capitalization (*MCap*). We also observe substantial variations in *TURN* across countries with a standard deviation (SD) of 0.61.

In Figure 2, we plot the cross-country mean and median (annualized) turnover for the baseline sample. There are significant cross-country variations in *TURN*, with China and the United States exhibiting the highest turnover. Specifically, the average turnover in China is as large as 2.20, and the United States closely trails. By contrast, the mean values of *TURN* in Peru and Colombia are markedly lower, at only 0.13 and 0.08, respectively. In addition, stock market turnover exhibits substantial variations over time. Figure 3 presents the time series of turnover averaged across all 41 countries. While *TURN* seems to exhibit mean-reverting behavior, it is significantly influenced by global financial conditions and systemic shocks. Specifically, *TURN* reached two notable peaks: 1.67 during the 2008 global financial crisis and 1.39 at the onset of the Covid-19 pandemic in March

[20] The most stringent requirement limiting the number of countries is the availability of *InstOwn* from FactSet. We provide analyses with and without this variable. For definitions of the variables, see Table A1 in the Appendix.

[21] These six countries (Egypt, South Africa, the United Arab Emirates, Kuwait, Qatar, and Saudi Arabia) are excluded from the MSCI country universe. The complete list of countries is shown in Table A2 in the Appendix.

[22] The expanded sample adds 27 countries to the 41-country baseline sample. After requiring full data availability for all variables, however, Taiwan and Hong Kong are excluded, yielding a final expanded sample of 66 countries.

2020.[23] Taken together, these results reveal substantial variations in turnover across both intertemporal and geographic dimensions. Such heterogeneity underscores the need to investigate the underlying drivers and motivations behind global trading activity.

In Table 1, we also present statistics for those to be used as the explanatory variables (described by category in the previous section). With the baseline sample in Panel A, we observe significant cross-country variations in some variables. For example, the standard deviation (SD) for past returns (*MOMS* and *MOML*) and earnings volatility (*EarnVola*) are quite large, relative to their mean values. However, most of the other variables, including the behavioral traits (*Indivsm*, *HomBias*, *AmbgAvsn*, and *RskAvsn*), show less dispersion relative to their mean values.[24] The results with the expanded sample in Panel B, we observe by and large similar patterns.

As a preliminary check, we provide an intuitive demonstration of the potential relationship between *TURN* and our explanatory variables, using the variables related to behavioral traits. To this end, each month we divide the dataset for countries into two groups (based on the median) for a given trait. Figure 4 plots turnover (*TURN*) averaged across months for the two groups. It shows that countries with higher values in *Indivsm* and *HomBias* exhibit higher turnover, whereas countries with higher values in *AmbgAvsn* and *RskAvsn* have lower turnover. The plots in Figure 4 broadly suggest that behavioral traits may be important determinants of turnover.

We briefly examine the correlations between the key explanatory variables in Table 2. Discernible in Panel A is that *%Age0T14* is highly negatively correlated with *%Age65+*, which seems natural, while *HomBias* is highly positively correlated with *Corrupt*. The correlation between *Indivsm* and *Freedom* is high (0.67), suggesting that countries with greater levels of individualism enjoy higher levels of democratic freedom. Countries with greater levels of *Indivsm* also show higher levels of *InstOwn* in their stock markets (with a correlation of 0.65). Interestingly, the variable proxying for trading frictions (*TFriction*) tends to exhibit negligible correlations with any of the other variables. With the expanded sample, Panel B shows similar patterns in general.

3. Empirical Results

In this section, we perform formal analyses in a multivariate setting on what factors drive discrepancies in trading activity at the country level as well as the individual stock level.

[23] Chiah and Zhong (2020), Gormsen and Koijen (2020), and Khan et al. (2024) also report a spike in trading volume around the Covid-19 pandemic.

[24] As noted earlier, these variables are extrapolated to adjacent regions for missing values. Details are provided in Tables A3 and A4 in the Appendix.

3.1. Analyses at the Country Level

To investigate the dynamics of stock turnover across countries, we adopt the following Fama and MacBeth (1973) regression, run at a monthly frequency:

$$TURN_{c,t+1} = \alpha_t + \sum_{k=1}^{K} \beta_k X_{c,t}^k + \varepsilon_{c,t+1}, \tag{8}$$

where $TURN_{c,t+1}$ is annualized monthly turnover for country c in month $t+1$, and $X_{c,t}^k$ denotes the k-th explanatory variable in month t.[25] To facilitate interpretation, all variables are cross-sectionally standardized each month to have a mean of zero and a standard deviation of one. This allows us to interpret the regression coefficients ("beta coefficients") as the marginal economic impact of each predictor, since the coefficients become dimensionless. Specifically, a one-standard-deviation (SD) increase in a given explanatory variable is interpreted as a change in $TURN$ equal to that variable's estimated coefficient (in units of SD). We also report heteroskedasticity and autocorrelation consistent (HAC) t-statistics computed based on Newey and West (1987, 1994). We take the lag length L to be equal to the integer portion of $4(T/100)^{2/9}$, where T is the number of observations.[26] Along with the t-statistics, we provide the average of the adjusted R-squared (*AdjR-sqr*) for each specification, following Chordia et al. (2007).[27]

3.1.1. With the Baseline Sample

Table 3 reports the regression results, where we incrementally add more sets of variables. In the specifications with the baseline samples from 41 countries (Columns 1 to 4 in Panel A), we first include behavioral traits, followed by the additional sets of variables. The number of country-month observations used in Panel A ranges from 8,465 to 10,062.

[25] In contrast to the contemporaneous regressions in Lo and Wang (2000) and Tkac (1999), the explanatory variables are lagged by one period. The most recent past number is used for those variables that are measured annually. While we report results based on the original variables, we find qualitatively the same results after removing calendar effects and trends from the main variables as in Chordia et al. (2007).

[26] As a robustness check, for the Fama-MacBeth regression, we use the lag length selected by the Akaike Information Criterion, choosing the value that minimizes AIC. The results remain qualitatively unchanged.

[27] We lag all explanatory variables by one month to mitigate endogeneity concerns. More importantly, there is limited scope for reverse causality between *TURN* and most of our explanatory variables, with the main exceptions being *InstOwn* and *TFriction*. We make three observations regarding these variables. First, *InstOwn* evolves gradually over time (Ferreira and Matos, 2008; Duffie, 2010), and it is unclear whether institutional holdings adjust at a monthly frequency in anticipation of country-level turnover. Second, trading frictions are set by policymakers rather than market participants, which reduces concerns about reverse causality. Third, excluding *InstOwn* and *TFriction* from the regressions has little effect on the coefficients of the remaining variables. There is also a possibility of some of our variables like governance quality being jointly determined with turnover. We address such endogeneity in more detail within Section 5.

We observe that many of the variables exhibit significant explanatory power for turnover (*TURN*). Among the behavioral traits, individualism (*Indivsm*) is positively associated with *TURN* across all four specifications. This finding aligns with the notion that overconfidence can stimulate investors' trading incentives. The coefficients on home bias (*HomBias*) are also positive and significant at the 1% level, reflecting the impact of rebalancing portfolios with domestic stocks. Additionally, both ambiguity aversion (*AmbgAvsn*) and risk aversion (*RskAvsn*) are consistently negatively related to *TURN*. These results are significant at any conventional level across the four columns. The economic impact of behavioral traits is also large. Specifically, the full specification in Column 4 shows that a one-SD increase in *Indivsm* and *HomBias* is associated with increases in *TURN* by 0.497 SD and 0.311 SD, respectively. On the other hand, a one-SD increase in *AmbgAvsn* and *RskAvsn* is associated with a decrease of 0.174 SD and 0.084 SD in turnover, respectively. In summary, we find all behavioral traits are significantly related to stock trading activity around the world. These four variables explain about 15% of the variations in cross-country turnover.

Next, we examine the effect of transaction taxes and exchange fees (*TFriction*) on turnover. It seems natural to observe that the coefficient on *TFriction* is negative and significant (at the 1% level). To be specific, Column 4 shows that a one-SD increase in *TFriction* leads to a decrease of *TURN* by 0.159 SD. This negative relation is robust across all three columns in Panel A. In Section 5, we conduct DiD analyses using country-specific exogenous shocks (including military actions and trading tax changes) to establish the causal relations.

When incorporating variables related to governance and demographic aspects, the sample size decreases from 10,062 to 8,465, a nearly 16% reduction.[28] Despite the smaller sample, by adding the variables from this category in Column 3, the explanatory power (*AdjR-sqr*) increases significantly, exceeding 40%. We first find that democratic freedom (*Freedom*) is negatively associated with *TURN*. In Column 4, a one-SD increase in *Freedom* is associated with a 0.514 SD decrease in *TURN*. This results is consistent with the notion that democratic systems create alternative entrepreneurial opportunities and reduce lottery-type stock trading activity viz. Bonaparte (2024) and Gao and Lin (2015); see also Miller (2024).

Interestingly, the impact of the Gini index (*IncIneq*) on *TURN* is positive and significant at any conventional level in Columns 3 and 4. This result aligns with our reasoning that higher income inequality shifts market influence mostly toward wealthier individuals, who tend to trade

[28]This decrease is primarily due to the exclusion of Hong Kong and Taiwan, as well as missing data for certain years in some countries. To align the frequency, we hold these country-year variables constant across months within a year using data from the previous year. Our results remain robust when using current-year data.

more actively. The coefficient on *Corrupt* is also significantly positive: a one-SD move in this variable has a 0.183 SD impact on turnover. This positive impact of *Corrupt* on *TURN* suggests that informational frictions — common hallmarks of opaque, corrupt environments — catalyze speculative trading activity, similarly to the role of income inequality.

As to the effect of *%Female* in Column 4, it has a negative and highly significant coefficient (-0.259: t-statistic = -8.78), consistent with Barber and Odean (2001): women tend to be less prone to overconfidence-driven trading than men. The coefficient on the youth share (*%Age0T14*) is also negative and significant, supporting the view that a higher number of dependents constrains the time and cognitive resources that households can allocate to trading activity.[29] By contrast, *%Age65+* has a positive effect on *TURN*. This suggests that retirees typically possess greater leisure time to monitor financial markets and manage their portfolios actively.

We now include three theory-based variables in Column 4: *ForecDisp*, *InstOwn*, and *EarnVola*. We find in the column that all three variables are positively related to *TURN*. For instance, a one-SD increase in *InstOwn* in a country is associated with a 0.192 SD increase in its turnover. This is consistent with the view that institutional investors trade more frequently than retail participants due to active rebalancing, information processing, and the need to manage fund-level liquidity flows. Likewise, *ForecDisp* is positively associated with *TURN*. As discussed earlier, both rational expectations models (Kim and Verrecchia, 1994) and behavioral models (Hong and Stein, 2007) posit that investors' opinion divergence significantly influences trading activity, which is evidenced in our results. The coefficient on *EarnVola* (0.171: t-statistic = 2.83) is also positive and significant. This is probably because higher earnings volatility leads to a greater divergence of opinion among investors, who trade more frequently in response to uncertain news and information.

With other firm characteristics (aggregated across countries), we find that long-horizon return momentum (*MOML*) is positively associated with *TURN*, whereas the short-horizon equivalent (*MOMS*) plays no role. It is interesting to note that the effect of market size [*ln(MCap)*] is insignificant. As we see in the full specification (Column 4), our variables altogether explain about half of the variations in international turnover.

In Appendix Table A5, we perform a robustness check to ascertain the stability of our cross-sectional results. Specifically, we split our sample into two sub-periods, 2000-2010 and 2011-2021. We find that our turnover determinants, by and large, are consistent in their sign and significance across sub-periods. This lends confidence that we are not merely picking variables that are significant

[29] Alternatively, when we use a country's birth rate, we find that it is negatively associated with turnover.

by chance, but instead are meaningfully describing the cross-section of international turnover.

3.1.2. With the Expanded Sample

For a robustness check, we augment our dataset with more data from additional 27 countries (i.e., 66 countries in total) by dropping the stringent requirements about the availability of *InstOwn* from FactSet. We then repeat the analysis and report the result in Column 5: *InstOwn* is thus excluded in the regression specification. With the expanded sample, the number of country-month observations used in Column 5 substantially increases to 11,077.

We find in Panel B that the effects of the explanatory variables on turnover remain robust in general. Furthermore, their economic impacts are in line with the main findings. For example, Column 5 shows that the economic effect of *TFriction* remains broadly comparable to that reported in Columns 3 and 4. The size of the coefficients on *Indivsm* and *HomBias* is very close to that of their corresponding values in Column 4. Although the magnitude of the coefficients on *Corrupt* and *ForecDisp* and their statistical significance are weakened, the two variables still play a non-trivial role. It is discernible that the effect of the youth share (*%Age0T14*) on *TURN* is muted when the expanded sample is used. Another notable difference is that market size [*ln(MCap)*] is now positively and significantly associated with turnover, even in the cross-country analyses. This aligns with the observation that greater visibility — proxied by market capitalization — attracts increased investor attention and stimulates trading activity.

We summarize in Table 4 the impacts of main explanatory variables that play significant roles in explaining cross-country trading activity (based on Column 5 of Table 3). Given the number of country-month observations, our threshold of significance is a p-value of 1%. We find in Table 4 that the effects of the two variables related to behavioral traits are particularly pronounced: in this category, *Indivsm* exerts the most substantial (positive) influence, followed by *HomBias*. The impacts of the two variables related to governance and demographic factors are also salient, though their effects operate in the opposite direction: *%Age65+* has a positive impact, whereas *Freedom* is negatively associated with trading activity.

3.2. Analyses at the Individual Stock Level

We have examined above what determines trading activity across countries by aggregating firm-specific variables at the country level. However, the vast majority of existing studies on turnover (e.g., Lo and Wang, 2000) focus more on firm-level analyses. To bridge this gap, we use an alternative specification by linking turnover to explanatory variables at the firm level. This approach allows us to verify the robustness of our country-level findings while aligning our method more closely with the existing literature. We therefore estimate the following regression specification:

$$TURN^{firm}_{i,t+1} = \alpha_t + \sum_{k=1}^{K} \beta_k X^k_{i,t} + \varepsilon_{i,t+1}, \tag{9}$$

where $TURN^{firm}_{i,t+1}$ is the annualized monthly turnover for firm i in month $t+1$, which is computed as the trading volume in shares divided by the number of shares outstanding in that month, and annualized by multiplying by 12. $X^k_{i,t}$ denotes the k-th firm-level explanatory variable for firm i in month t. In each month, all firm-level explanatory variables are winsorized at the 1st and 99th percentiles. Again, all variables are standardized, based on the moments in that month.

Table 5 shows that the firm-level sample is substantially larger, ranging from 1.18 million to 1.27 million firm-month observations. For brevity, we report only the results from the full specifications. In Column 1, most of the variables that exert significant effects in the country-level analyses are also strongly related to cross-firm variations in turnover. For example, *Indivsm* continues to exhibit a highly significant effect: a one-SD increase is associated with a 0.286 SD rise in $TURN^{firm}$. *HomBias* remains economically meaningful as well, with a coefficient of 0.100 and a t-statistic of 7.65. As before, *TFriction* has a negative influence on $TURN^{firm}$. For the variables related to governance, we find patterns consistent with our country-level results. That is, *Freedom* plays a significant role: firms located in less democratic environments show more active trading by 0.271 SD, mirroring the cross-country evidence in Table 3. *IncIneq* and *Corrupt* also preserve their positive association with $TURN^{firm}$, with a one-SD increase in them being linked to $TURN^{firm}$ higher by 0.081 SD and 0.137 SD, respectively. Demographic variables behave similarly to the country-level results: larger *%Female* and *%Age0T14* continue to depress turnover (with coefficients of -0.096 and -0.185), while higher *%Age65+* contributes positively to trading activity. The effects of the remaining variables are broadly in line with the country-level evidence.

In Column 2 of Table 5, we report the estimation result using the expanded sample that excludes *InstOwn*, which potentially presents endogeneity with $TURN^{firm}$. The signs of all the remaining variables remain unchanged, and in some cases, their statistical significance increases. For example, the level of significance becomes stronger for *RskAvsn*, *ForecDisp*, and *MOML* in Column 2 than the corresponding values reported in Column 5 of Table 3. In particular, the effect of *MOMS* is now positive and statistically significant at the 5% level. Coupled with our findings in the earlier subsections, our overall conclusions on behavioral traits, trading frictions, forecast dispersion, and return volatility all remain robust.

In Table 5, the *AdjR-sqr* values from the firm-level regressions hover around 22%. This is lower than the corresponding values in Table 3, a result that is not surprising, given the noise inherent in individual stock data. Taken together, the results in Table 5 confirm that the explanatory power of the variables aggregated at the country level largely survives at the firm level.[30]

4. Further Analyses

In this section, we consider two extensions to our main analysis. The first analyzes why turnover exhibits more cross-stock dispersion in some countries relative to others, and the second compares and contrasts the determinants of illiquidity (Amihud, 2002) relative to those of turnover.

4.1. Cross-Sectional Dispersion of Turnover

We next explore why the cross-sectional *dispersion* of turnover (as opposed to *turnover* itself) varies across countries. To motivate our analysis, consider two countries, X and Y. In country X, individual stock turnover levels are tightly clustered around the cross-sectional mean, indicating low dispersion. In contrast, country Y exhibits substantially greater variation in turnover across firms, resulting in high dispersion. What might explain such differences? One possibility is that the drivers of trading are more homogeneous across firms in country X than in country Y. For example, country X may feature a more uniform informational environment, leading to synchronized investor attention and behavior. By contrast, the high dispersion observed in country Y may reflect a segmented market structure, in which a small number of large, widely followed firms coexist with many idiosyncratic small-cap stocks. Global integration may also play a role: if stocks in country X co-move closely with the global market portfolio, their trading activity is likely to be more synchronized. Conversely, if only a subset of stocks in country Y tracks global factors while others respond primarily to local or firm-specific shocks, greater cross-sectional dispersion in turnover will naturally arise.

Understanding cross-sectional turnover dispersion is of considerable practical importance, extending well beyond academic interest. A high level of dispersion implies that trading activity is concentrated in a relatively small subset of stocks, while many others trade infrequently. This

[30]To ascertain if there are meaningful differences in turnover across emerging and developed markets, we try including an emerging market dummy in Table 5. This dummy turns out to be insignificant; results are available on request.

pattern suggests that only a few "popular" stocks—often large-cap firms—dominate trading. Such concentration is relevant for asset managers, who must account for uneven trading frequencies when assessing execution risk in diversified portfolios, and for policymakers concerned with broad market accessibility. Moreover, because corporate access to equity capital is inversely related to market thinness (Butler et al., 2005), high turnover dispersion may signal unequal effectiveness in capital allocation across firms, raising additional concerns for regulators.

While intriguing, the cross-sectional dispersion of turnover across countries has received no attention. We provide an initial characterization of this phenomenon by calculating the monthly standard deviation of turnover across stocks within each country. Note however that standard deviations alone can be misleading if the scales are different.[31] Thus, the standard deviation of turnover is divided by its mean value in that month: i.e., the coefficient of variation (CV) in each month within each country. We denote the CV of turnover as *CV(TURN)*. The most significant advantage of using CV is that it is dimensionless. Moreover, this metric allows us to compare the relative dispersion of trading activity across countries, regardless of their absolute trading volume. We also compute CVs of the explanatory variables that exhibit significant within-country variation and use them to investigate whether they can explain *CV(TURN)* across countries.

We first plot a bar chart in Figure 5 using the time-series mean and median values of *CV(TURN)* for the 41 countries included in the baseline sample. As illustrated in Figure 5, *CV(TURN)* varies considerably across countries. On the far right, India, Malaysia, and Norway exhibit high turnover dispersion exceeding 1.20. This presents a stark contrast to Figure 2, where Turkey, the USA, and China occupy the right-hand tail. Conversely, countries like Israel and Colombia show much lower dispersion, falling below 0.60. Notably, while Peru (PER) and the Philippines (PHL) rank at the lower end of the distribution for mean turnover (in Figure 2), they shift toward the middle of the spectrum when evaluated by CV of turnover (in Figure 5). This shift underscores that a standard deviation of, say, 5% represents a fundamentally different magnitude in a low-turnover market (e.g., PHL) compared to a high-turnover market (e.g., USA). In Figure 6, we also plot the time-series of *CV(TURN)*, after their monthly values are averaged across all the 41 countries in each month over the sample period. As shown in the figure, average *CV(TURN)* rose steeply in the early 2000s before stabilizing and mean-reverting to approximately 0.9.

Given the CVs of the six explanatory variables that exhibit significant within-country varia-

[31] Suppose Stock A has an average turnover of 0.10 with a SD of 0.02. Stock B has an average turnover of 0.50 with a SD of 0.05. While Stock B has a higher absolute SD (0.05 vs. 0.02), Stock A is actually more volatile relative to its mean: i.e., the coefficient of variation (CV) is 20% for A vs. 10% for B.

tion, denoted as *CV(ForecDisp)*, *CV(InstOwn)*, *CV(EarnVola)*, *CV(ln(MCap))*, *CV(MOMS)*, and *CV(MOML)*, respectively,[32] we perform cross-sectional regressions of *CV(TURN)* on them at the country level, using the regression specification similar to Eq. (8). Column 1 in Table 6 shows that the right-hand-side measures account for about 19% of variations in *CV(TURN)* across countries.[33] We find that several right-hand variables show strong explanatory power for *CV(TURN)*. For example, *CV(ForecDisp)*, *CV(InstOwn)*, and *CV(ln(MCap))* are positively associated with *CV(TURN)*. In terms of economic significance, cross-country characteristics in *CV(InstOwn)* and *CV(ln(MCap))* have the largest impact on *CV(TURN)*: a one-SD rise in these measures is associated with an increase in *CV(TURN)* by 0.203 SD to 0.271 SD. We also find that CVs of *ForecDisp* and *MOML* play a significant role. Interestingly, *CV(EarnVola)* is negatively associated with *CV(TURN)*. With the expanded sample in Column 2, the patterns are generally similar.

Overall, the cross-sectional dispersion of turnover is large across countries, and the substantial part of such variation can be explained by the dispersions in our explanatory variables related to opinion divergence and information asymmetry as well as to visibility and return momentum.

4.2. Liquidity vs. Turnover

While stock turnover and liquidity are closely related, the two may represent distinct dimensions of trading activity. Turnover is a measure of trading intensity, indicating how frequently and in what quantities a stock's shares change hands relative to its total shares outstanding. By contrast, liquidity refers to the frictional costs of executing a trade — specifically, the ability to buy or sell an asset quickly without causing a significant movement in its price. The distinction is critical because high turnover does not always guarantee high liquidity. For instance, a stock might have large trading volume (i.e., high turnover) during a period of extreme volatility but suffer from a wide bid-ask spread or high price impact (measured by the Amihud (2002) measure or Kyle (1985)-type lambda), which makes trading expensive. Turnover captures the *quantity* of trading, but liquidity measures the *quality* and *efficiency* of the market environment.

Existing research (e.g., Karolyi et al., 2012; Koch et al., 2016) identifies trading activity as a key determinant of liquidity. Specifically, Karolyi et al. (2012) find that turnover provides a leading explanation for liquidity commonality, suggesting that turnover-related factors influence liquidity. However, informed trading creates a crucial divergence. Although informed traders can increase

[32] To ensure that the two types of past returns (*MOMS* and *MOML*) have positive CVs, gross returns are used.
[33] Since *InstOwn* is potentially endogenous, we again omit the CV of this variable when using the expanded sample.

turnover, they also intensify adverse selection among market participants, which reduces *liquidity* (Glosten and Milgrom, 1985). Consequently, turnover and liquidity do not move in lockstep. This distinction warrants an examination of why illiquidity varies across countries.

Literature on liquidity is extensive, spanning from seminal works by Amihud and Mendelson (1986) to more recent studies by Hasbrouck and Seppi (2001), Chordia et al. (2001), Amihud (2002), Jones (2002), and Næs et al. (2011). Despite this breadth, it is surprising that there has been no empirical study that considers why and how liquidity varies across countries.[34] We address this gap by employing Amihud's (2002) illiquidity measure (*ILLIQ*) as our primary proxy. This choice is supported by Goyenko et al. (2009), who demonstrate its effectiveness in capturing price impact estimated from transaction-level data, as well as by Huh (2014), who identifies it as the only low-frequency-based proxy (available without transaction-level data) that commands a return premium consistently over a long period of time. Moreover, the two studies also suggest that *ILLIQ* captures illiquidity driven primarily by adverse selection or information asymmetry, similarly to the price-impact measure ("lambda") of Glosten and Harris (1988).

To construct the country-level *ILLIQ* each month, we compute the Amihud measure at the stock level as the monthly average of daily values within a month, after calculating the daily measure as the ratio of the absolute daily return to daily trading volume in the local currency. We then derive the country-level *ILLIQ* by computing the *MCap*-weighted average across stocks in each month for each country, similarly to *TURN*. We then run the Fama-MacBeth regressions with *ILLIQ* as the dependent variable in Eq. (8), using the same sets of the explanatory variables.

Table 7 shows that the number of country-month observations is the same as the corresponding specification in Table 3. When *ILLIQ* is used as the dependent variable, the explanatory power (*AdjR-sqr*) decreases below 14%, compared to that in Table 3. We find in Column 1 that countries with larger market size [*ln(MCap)*] and smaller *TFriction* exhibit significantly lower illiquidity (i.e., higher liquidity). This seems natural and consistent with the pattern observed in Table 3.

As for the behavioral traits, *Indivsm* is negatively associated with *ILLIQ*, likely reflecting more active market participation by overconfident investors. However, *RskAvsn* is positively related to *ILLIQ*, suggesting that in more risk-averse societies, investors may trade less aggressively, which in turn leads to thinner markets and higher price impact. Overall, these aspects are in line with the results in Table 3. An intriguing distinction arises from the negative association between *AmbgAvsn*

[34]While Amihud et al. (2015) consider how the return premium for illiquidity varies internationally, they do not directly analyze why liquidity itself varies across countries.

and *ILLIQ*. This finding aligns with the theoretical framework of Caskey (2009), who demonstrates that under high uncertainty (ambiguity), investors prefer coarser, aggregated information over more disaggregated data. By focusing on coarser information, investors can reduce their exposure to "ambiguity risk," mitigating information asymmetry among market participants.

The effect of *EarnVola* on *ILLIQ* is negatively significant in both columns, which accords with the notion that earnings volatility might attract more retail investors who are speculative but uninformed (Kumar, 2009). It is notable in Column 1 that the coefficient on *InstOwn*, our proxy for informed trading, is positively significant at 10%. This underscores the idea that informed trading by institutions may create information asymmetry, thereby increasing illiquidity, although it contributes to turnover (as seen in Table 3). Given the concern that *InstOwn* is potentially endogenous to *ILLIQ*, we omit *InstOwn* in Column 2 and expand the sample to non-MSCI countries. The effects of most variables on *ILLIQ* remain largely similar, although the influence of *HomBias*, *MOML*, and some demographic factors become more pronounced.

Overall, our evidence suggests that liquidity diverges from turnover through an informed-trading channel, where more intensive informed trading drives turnover higher while simultaneously impairing liquidity. Specifically, the variables related to information asymmetry — such as *InstOwn* and *AmbgAvsn* — work differently. That is, higher *InstOwn* tends to contribute positively to turnover and negatively to liquidity, whereas a greater degree of *AmbgAvsn* reduces turnover but improves liquidity. These diverging dynamics motivate a joint examination of both *ILLIQ* and *TURN* in the remaining analyses that follow.

5. Natural Experiments with Exogenous Shocks: Military Actions and Tax Hikes

Unlike investor traits (e.g., risk aversion), governance quality and market freedoms may be jointly determined with economic activity and fundamentals, complicating a clean causal interpretation of their effects on trading activity. More generally, endogeneity remains a concern in our analysis, although we lag all right-hand-side variables by one month relative to turnover. We view our baseline regressions as a first step toward documenting the variables associated with cross-country variation in turnover—an issue that has received limited attention in the literature. Nevertheless, to further mitigate endogeneity concerns, we exploit two sets of political and regulatory shocks as quasi-experiments to identify their causal effects.

The first set of political shocks consists of military interventions, which we source from Jonathan

Powell's global dataset on military interventions to identify the impact of democratic freedom.[35] Such interventions are typically triggered by deep political conflicts or external disruptions rather than by stock-market dynamics. We deliberately exclude many other democracy-related events such as constitutional referenda, changes in voting rules, or gradual legislative reforms because these events tend to be endogenous to prevailing economic conditions. By focusing strictly on military actions and major tax-related shocks, we select events that are (i) sudden, (ii) difficult for investors to anticipate, and (iii) unlikely to be caused by short-term fluctuations in trading activity.

Within this framework, we identify two political transitions that increased democratic freedom (*More-Free* events) in our sample — Thailand in September 2006 and Egypt in February 2011. Although both events involved military forces displacing incumbent governments, the transitions were followed by periods of liberalization, expansion of civil liberties, and increased openness in political participation. In sharp contrast, the July 2016 event in Turkey represents a political shock that significantly reduced democratic freedom (a *Less-Free* event). The failed military coup led to a state of emergency, suspension of constitutional protections, severe media restrictions, and consolidation of executive authority. It is important to note that military actions can either enhance or restrict governance quality (e.g., democratic freedom), and the direction of the change is often difficult to predict, as the process of governance evolution after the intervention is often full of randomness. This unpredictability arises from the complex interplay of factors such as the region's existing political and social dynamics, the nature of the intervention, and external influences, all of which can significantly alter the trajectory of governance outcomes.

Since military actions introduce exogenous shocks to governance, they serve as a valuable testing ground for identifying the impact of governance quality. If strong governance suppresses investor trading (as seen in our results above), these shocks should directly influence trading behavior (inclusion restriction). Furthermore, since market conditions rarely trigger military interventions, the risk of reverse causality is minimal. To avoid potential confounding effects (e.g., immediate market disruption or heightened political uncertainty), we exclude the 12-month period after the events. If the resulting trading patterns align with the direction of changes in democratic freedom rather than general instability, it reinforces the exclusion restriction. This means that the impact on trading is driven by shifts in governance (caused by military actions) rather than extraneous factors.

The second set of shocks concerns regulatory changes (increases) in financial transaction taxes (*Tax-Increase* events), which occurred in four countries: Belgium (January–May 2012), France

[35] For details, see https://jonathanmpowell.com/coups/.

(August 2012), Hungary (January 2013), and Italy (March 2013). We use these shocks to identify the impact of trading frictions.

To estimate the effect of the above events, we employ a stacked difference-in-differences (DiD) design at the firm level. For each event, the treated firms are those headquartered in the affected country, while the control firms come from countries in the same region that did not experience comparable shocks. We construct symmetric 24-month pre- and post-event windows skipping the 12 months around each event. Specifically, our pre-event (post-event) period is from month $m-35$ to $m-12$ ($m+13$ to $m+36$) relative to the event month. We stack the event-specific samples to form a pooled dataset and run the following panel regression:

$$Y_{i,t} = \beta_1 TREAT_{i,c} + \beta_2 POST_t + \delta \cdot (TREAT_{i,c} \times POST_t) + \gamma' \boldsymbol{Z}_{i,t} + \alpha_c + \tau_t + \varepsilon_{i,t}, \qquad (10)$$

where i indexes firms, c indicates countries, and t indexes year-month. $Y_{i,t}$ is either $ln(TURN)_{i,t}$ or $ln(ILLIQ)_{i,t}$,[36] where $TURN$ and $ILLIQ$ are defined in the previous section. $TREAT_{i,c}$ takes a value of 1 for firms from countries that experience the event, and 0 for firms from countries in the same geographic region that do not experience the event. $POST_t$ is set to 1 for the post-event period and 0 otherwise. $\boldsymbol{Z}_{i,t}$ includes all the explanatory variables used in Table 3 except for *Freedom*, which would be affected by the military actions. In addition, α_c and τ_t are the country and year-month fixed effects, respectively. Note that the fixed effects absorb the stand-alone effects of the two dummy variables used in ($TREAT \times POST$), and thus their separate effects are not reported. As an alternative, we estimate the effects of the two stand-alone dummies ($TREAT$ and $POST$) after excluding the fixed effects in Eq. (10).

Panel A of Table 8 reports the stacked DiD estimates with *ln(TURN)*. Columns 1 and 2 in Subpanel A1 focus on the two cases of military actions (*More-Free*: Thailand in 2006 and Egypt in 2011) that increased political freedom. It shows that the coefficient (δ) on ($TREAT \times POST$) is -0.911 (t-statistic $= -4.91$) in Column 1 without the fixed effects, and -1.058 (t-statistic $= -3.14$) in Column 2 with them. This demonstrates that turnover of treated firms from the two countries significantly declines (relative to that of the control group of firms) following the event. By contrast, the *Less-Free* transition in Turkey in 2016 reveals the opposite pattern in Subpanel A2: turnover rises significantly after the event, with the coefficient of 0.199 (t-statistic $= 2.97$) when excluding

[36] We use log-transformations of $TURN$ and $ILLIQ$ for the DiD analyses to satisfy the parallel trends assumption. Unlike baseline regressions with levels in previous sections, log-transformations account for varying market scales by comparing percentage growth trajectories rather than absolute unit changes.

the fixed effects in Column 3, and 0.543 (t-statistic = 2.83) when including them in Column 4.

To ensure that the treatment effect is not driven by any pre-event trends, we plot the dynamic DiD estimates in Figure 7, based on Rambachan and Roth (2023). In the first two panels, which correspond to the cases of *More-Free* and *Less-Free* shocks from military actions, the δ_τ estimates for turnover show that turnover evolves similarly for the treated and control firms prior to the event (i.e., absence of pre-event trends), supporting the parallel-trend assumption. Following the shifts in democratic freedom, however, the δ_τ estimates become more negative on average in Panel A and more positive in Panel B, suggesting that turnover of the treated firms begins to diverge after the events, consistent with the presence of treatment effects. Specifically, military actions resulting in improved vs. deteriorated political freedom have opposite effects on turnover. The direction of the treatment effects is consistent with our baseline analyses in Table 3. As noted earlier, these results are not likely to be explained by reverse causality or confounding factors, lending support to a causal interpretation of the negative relationship between governance quality and turnover.

The last two columns in Panel A of Table 8 examine the impact of the regulatory shocks caused by increased transaction taxes. In Column 6, we find that the coefficient (-0.104) on ($TREAT \times POST$) is negative and statistically significant at the 5% level after accounting for the fixed effects. This is also consistent with the notion that trading frictions indeed suppress trading activity in financial markets. Panel C in Figure 7 also confirms that in the post-event period, turnover of the treated firms begins to diverge from that of the control firms, although the effect is less pronounced.

In Panel B of Table 8, we employ *ln(ILLIQ)* as the dependent variable in Eq. (10). The panel shows that the exogenous shocks caused by military actions and regulatory changes affect liquidity in the treated firms post-event in a manner consistent with turnover. For the military actions leading to improved democratic freedom, however, the effect of such shocks appears less salient, as shown in Subpanel B1. On the other hand, military actions causing negative shocks to democratic freedom have a stronger impact on illiquidity: in Column 4, for instance, the coefficient (-0.958) on ($TREAT \times POST$) is negatively significant at the 5% after accounting for the fixed effects. In addition, Subpanel B3 shows that the regulatory shocks caused by increased trading taxes exacerbate the illiquidity of affected stocks, after controlling for fixed effects.[37]

On balance, the above DiD analyses support our causal interpretation about the impacts of governance quality and market frictions on trading activity.

[37] In unreported tests, we verify parallel trends for the Amihud measure. The results are available upon request.

6. Global Links Between Trading Activity and Asset Prices

In this section, we consider how trading activity is priced in the cross-section of international stock returns, and consider the moderating effect of trading activity on the link between the macroeconomy and stock prices.

6.1. Return Premia on Trading Activity-Related Variables

Do turnover and liquidity affect asset returns? Datar et al. (1998) document that stocks with higher turnover earn lower returns, and attribute this to the notion that high turnover reflects greater uninformed trading, reducing the required return premium. Amihud (2002) provides a similar result for market liquidity. In this subsection, we examine whether turnover and liquidity are priced globally, and whether the strength of this pricing effect varies across countries. Many studies document turnover-related return premia within individual markets. However, little is known about whether the pricing of turnover and liquidity differs across countries and what structural factors shape these variations. Studying trading-related return premia therefore allows us to connect country-level behavioral and governance characteristics not only to trading activity, but also to how information and liquidity embedded in trading activity are reflected in expected returns.

To obtain $TURN$-based return spreads, we follow a standard double-sorting procedure. At the end of month $t-1$, stocks within each country are first sorted into two groups (below/above the median) based on *MCap*. Within each size group, we compute the average of daily share turnover over the previous six months. Then, the sample stocks are sorted on $TURN$ and split again into two portfolios [high (H) and low (L)]. Next, the $TURN$-based return spread (RET^{TURN}_{HML}) is computed as the difference between the equal-weighted return of the high-$TURN$ portfolio and that of the low-$TURN$ portfolio [i.e., (H–L) portfolio return] in month t for each group. The *ILLIQ*-based return spread (RET^{ILLIQ}_{HML}) is constructed using the same procedure.

Panel A in Figure 8 plots the mean $TURN$-based return spread (RET^{TURN}_{HML}) for each country, along with 90% confidence intervals. The figure shows pronounced cross-country heterogeneity in the turnover premium (return spread). The dispersion is particularly striking among small (below-median) stocks, in which RET^{TURN}_{HML} is negative and often statistically significant (i.e., inversely priced), consistent with existing country-specific evidence. However, confidence intervals reveal that the premium is statistically significant in only 19 out of the 41 countries. This suggests that the pricing power of turnover is not globally pervasive. The pattern is also less discernible among big stocks: the premium in this group is generally insignificant and economically negligible.[38]

We find quite a different pattern in Panel B: the *ILLIQ*-based return spread (RET_{HML}^{ILLIQ}) is mostly positive for both large and small stocks. This effect is markedly higher among small stocks, suggesting that liquidity constraints are most binding where information asymmetry is greatest. This global pricing of *ILLIQ* aligns with Amihud (2002) and Amihud et al. (2015). The above findings underscore that while both *TURN* and *ILLIQ* reflect trading activity, they capture distinct dimensions of trading in the global context: i.e., trading intensity vs. price impact.

6.2. Stock Market Performance, Trading Activity, and the Real Economy

Turnover and liquidity are compelling metrics to analyze independently, but what roles do they serve in the real economy? In this section, we investigate how these variables mediate the stock market's function as a leading indicator for economic growth. Given that financial markets can process information pertinent to the future evolution of the real economy and enhance resource allocation (David et al., 2016), one would expect that strong performance in stock markets predicts greater economic growth in the future. Existing studies (Fama, 1990; Schwert, 1990) support this notion by highlighting that stock prices convey information about future economic performance.

Recently, Allen et al. (2024) argue that in the Chinese stock market, extremely high turnover is often driven by retail investors and noise traders rather than informed investors. They observe that when turnover primarily reflects speculative 'churn,' stock prices fluctuate based on investor sentiment and social trends (e.g., as those seen on StockTwits) rather than based on the actual profitability or growth of the underlying companies. Because such price movements are detached from economic fundamentals, the stock market sends a noisy signal and can lose its reliability as a leading indicator of GDP growth. The above observation highlights that high turnover does not necessarily mean more informed trading. If a market has high turnover but low price informativeness, the massive volume of trading does not help financial markets to discover the true value of firms. Motivated by this observation, we analyze the global mediating role of trading-related variables for the stock market-real economy link.

For our analysis, we utilize two trading-related variables: one that increases in both informed and uninformed trading (*TURN*), and another that increases in informed trading (*ILLIQ*) but

[38] Chui et al. (2022) indicate that high turnover represents retail noise and exacerbates reversals, while low turnover allows the underreaction of institutions to be revealed, thus promoting momentum. We confirm these patterns by showing that around the world, momentum profits are significantly lower in high turnover groups relative to low turnover ones. Results appear in Table A6 within the appendix.

decreases in uninformed (noise) trading. We compute quarterly stock performance as well as quarterly percentage changes in total GDP and per-capita GDP in each quarter for each of the countries included in the baseline sample. We then perform Fama-MacBeth cross-sectional regressions, run quarterly, as follows:

$$Y_{c,q+1} = \beta_1 MOMQ1_{c,q} + \beta_2 A_{c,q} + \theta \cdot (MOMQ1_{c,q} \times A_{c,q}) + \gamma' \boldsymbol{Z}_{c,q} + \varepsilon_{c,q}, \tag{11}$$

where $Y_{c,q+1}$ is a total GDP growth rate ($dGDP$) or a per-capita GDP growth rate ($dGDP^{pc}$) (in %) in country c in quarter $q+1$; $MOMQ1_{c,q}$ is the quarterly average of monthly returns of a major stock index in country c in quarter q; $A_{c,q}$ is one of the two trading-activity variables ($ILLIQ$ and $TURN$), which are computed as the quarterly averages of monthly equivalents defined above. $\boldsymbol{Z}_{c,q}$ includes the 11 variables previously known to determine GDP growth, that are used in Barro (2003), which are listed in Table A7 in the Appendix.[39] All variables are again standardized before conducting regressions.

The results are reported in Table 9. In the two panels, past quarter's stock return ($MOMQ1$) indeed has a positive and significant relationship with $dGDP$ as well as $dGDP^{pc}$, confirming the stand-alone role of stock market performance as a leading indicator for future economic growth. In Column 1 of Panel B, for example, the coefficient on $MOMQ1$ indicates that a one-SD increase in the stock returns predicts GDP growth ($dGDP$) higher by 0.177 SD in the following quarter, which is economically meaningful.

More importantly, we examine the mediating role of the trading-related variables. Considering the case with $ILLIQ$ first in Panel B, the coefficient on ($MOMQ1 \times ILLIQ$) is positive and statistically significant at the 5% level in both columns, regardless of the growth metrics ($dGDP$ or $dGDP^{pc}$). The magnitudes are also substantial, at 0.721 and 0.707, respectively. This suggests that the stock market's role as a leading indicator is enhanced in the environments with higher price impact (measured by $ILLIQ$). This is consistent with the view that in less liquid markets across countries, price movements are more likely to be driven by informed investors with fundamental insights into future economic conditions, rather than by noise traders.

By contrast, the two columns in Panel A with $TURN$ show that the coefficient on ($MOMQ1 \times TURN$) is insignificant. This indicates that while turnover reflects trading intensity, it does not dis-

[39] Amihud and Levi (2023) find a positive association between liquidity and economic performance. Chu and Chu (2020) find that this association takes on a U-shape. These studies do not directly address the question of how trading-related variables mediate the informativeness of stock prices for the real economy.

tinguish between informed vs. uninformed trading. Consequently, higher turnover does not necessarily improve the precision of the stock market's signals about future macroeconomic performance.

To summarize, our results in Table 9 demonstrate that at the global level, the interaction of stock market performance (*MOMQ1*) with illiquidity (*ILLIQ*) is a better predictor of economic growth than with turnover (*TURN*). This in turn means that on a global scale, "quiet" but "costly" price movements (reflected in *ILLIQ*) may carry more fundamental information than the noisy high-volume trading (*TURN*), as suggested by Allen et al. (2024) in the Chinese context. All in all, the above findings lend strong support to the notion that the cost of price discovery (measured by *ILLIQ*) is a conditioning variable that is more informative for future economic growth than simple trading intensity (measured by *TURN*).

7. Conclusion

Global trading activity influences market thinness, and thus affects execution quality of international portfolio trades. It also affects price discovery and cost of capital, and thus plays a critical role in linking financial markets to real economic outcomes. Yet, despite its importance, we lack a systematic understanding of why trading intensity differs so widely across countries. This study provides a comprehensive cross-country analysis of equity trading activity—its determinants, asset-pricing implications, and links to the real economy. Using a panel of up to 66 countries (roughly 20,000 firms) from 2000 to 2021, we document large and persistent heterogeneity in turnover and illiquidity across markets. We show that this heterogeneity is systematically explained by a rich set of country-level characteristics.

Behavioral traits emerge as the most economically powerful drivers of turnover. Individualism and home bias are strongly positively associated with trading intensity, whereas ambiguity aversion and risk aversion significantly dampen it. Trading frictions, as expected, suppress activity. Democratic institutions are negatively associated with turnover, consistent with lower redistribution risk, reduced speculative demand, and broader perceived opportunities for upward mobility than stock trading. In contrast, income inequality and corruption increase trading, consistent with stronger speculative motives in environments characterized by wealth concentration or informational opacity. Demographics also matter: higher female participation and a larger share of young dependents reduce turnover, while older populations trade more actively. Measures of belief dispersion and informational asymmetry are uniformly positively related to turnover. These results hold at both the country and firm levels. To address endogeneity, we implement stacked difference-in-differences designs around military interventions and transaction tax changes, yielding estimates consistent with our baseline findings.

Although turnover and liquidity share common drivers, they diverge in economically meaningful ways. Ambiguity aversion lowers turnover but improves liquidity, consistent with less aggressive trading by uncertainty-averse informed investors and reduced adverse selection. This divergence highlights that turnover and liquidity capture distinct aspects of market activity—quantity versus quality—and should not be conflated. Consistent with this distinction, we find that illiquidity is robustly priced across nearly all countries, whereas the turnover premium is more modest, market-specific, and shaped by factors such as corruption and gender composition.

At the macro level, illiquidity—but not turnover—amplifies the ability of stock returns to predict future GDP growth. This finding suggests that higher price impact implies more informative prices, confirming that the arguments of Allen et al. (2024) in the context of China apply to a wider global setting. Our results carry policy implications: trading frictions and institutional reforms that influence trading intensity can have unintended consequences for the informational efficiency of prices.

Our findings open several avenues for future research. First, can informed and uninformed trading be more cleanly disentangled at the country level, and how does this decomposition map into cross-country differences in price informativeness? Second, do the channels we identify—behavioral traits, governance, and frictions—vary in importance during periods of stress or financial liberalization? Third, do the macroeconomic effects of trading activity operate through corporate investment, as suggested by the price informativeness literature? Addressing these questions would further clarify how global trading activity shapes real economic outcomes.

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Table 1
Summary Statistics for the Variables

This table reports summary statistics [mean, standard deviation (SD), the 25th (P25), 50th (P50), and 75th (P75) percentiles] for each variable computed using the pooled sample. Panel A contains the statistics for the baseline sample of 20,663 stocks from 41 countries, while Panel B does the same for the expanded sample of 22,823 stocks from 66 countries. Variable definitions and data sources are described in Table A1, and the list of countries are reported in Table A2 in the Appendix. The sample period is from 2000 to 2021.

Summary Statistics					
	Panel A: Baseline Sample (N_Stocks = 20,663)				
Variables	Mean	SD	P25	P50	P75
TURN	0.78	0.61	0.38	0.61	1.00
Indivsm	53.23	23.93	30.00	58.00	74.00
HomBias	70.10	21.33	55.29	68.84	92.33
AmbgAvsn	0.59	0.10	0.53	0.60	0.63
RskAvsn	0.71	0.10	0.65	0.67	0.78
TFriction	2.21	1.68	0.31	2.48	3.53
Freedom	6.14	1.33	5.50	7.00	7.00
IncIneq	35.76	7.42	30.40	33.70	41.10
Corrupt	37.00	21.09	18.00	33.00	58.00
%Female	50.49	0.98	50.07	50.54	51.11
%Age0T14	19.65	5.68	15.21	17.99	22.02
%Age65^{+}	13.64	5.43	8.58	14.82	17.72
ForecDisp	0.18	0.23	0.09	0.13	0.19
InstOwn	0.26	0.17	0.15	0.21	0.34
EarnVola	1.21	4.76	0.01	0.02	0.12
ln(MCap)	-15.08	1.03	-15.62	-15.02	-14.30
MOMS	0.91	6.60	-2.53	1.20	4.50
MOML	17.02	29.78	-1.16	14.94	31.41
	Panel B: Expanded Sample (N_Stocks = 22,823)				
TURN	0.66	0.61	0.26	0.52	0.87
Indivsm	50.46	22.85	30.00	54.00	70.00
HomBias	73.40	20.86	58.97	73.07	93.80
AmbgAvsn	0.60	0.10	0.53	0.60	0.65
RskAvsn	0.71	0.09	0.65	0.69	0.78
TFriction	2.29	1.57	0.69	2.48	3.53
Freedom	5.76	1.65	5.00	6.50	7.00
IncIneq	36.09	8.03	30.60	33.90	40.80
Corrupt	41.81	21.92	23.00	42.00	63.00
%Female	50.34	2.41	49.89	50.53	51.19
%Age0T14	21.07	7.39	15.49	18.30	25.83
%Age65^{+}	12.57	5.88	6.82	13.55	17.32
ForecDisp	0.19	0.25	0.09	0.13	0.20
EarnVola	1.76	7.37	0.01	0.03	0.19
ln(MCap)	-15.44	1.32	-16.17	-15.23	-14.47
MOMS	0.85	7.23	-2.81	1.05	4.63
MOML	16.02	32.05	-2.76	13.58	30.91

Table 2
Correlations between International Explanatory Variables

This table reports the correlations between the explanatory variables used in the study. Correlations are calculated using the pooled sample. Panel A contains the result for the baseline sample from 41 countries, while Panel B does the same for the expanded sample from 66 countries. Variable definitions and data sources are described in Table A1, and the list of countries are reported in Table A2 in the Appendix. The sample period is from 2000 to 2021.

Correlations between Explanatory Variables

Panel A: Baseline Sample

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Indivsm	1.00																
2	HomBias	-0.58	1.00															
3	AmbgAvsn	-0.43	0.42	1.00														
4	RskAvsn	0.18	-0.01	-0.23	1.00													
5	TFriction	-0.08	0.17	0.28	0.02	1.00												
6	Freedom	0.67	-0.51	-0.42	0.21	-0.15	1.00											
7	IncIneq	-0.57	0.48	0.14	0.25	0.10	-0.50	1.00										
8	Corrupt	-0.61	0.81	0.49	0.06	0.26	-0.55	0.46	1.00									
9	%Female	0.37	-0.16	-0.20	0.26	-0.08	0.54	-0.27	-0.10	1.00								
10	%Age0to14	-0.38	0.48	0.24	0.14	0.07	-0.38	0.53	0.53	-0.41	1.00							
11	%Age65^{+}	0.57	-0.51	-0.36	-0.04	-0.19	0.63	-0.65	-0.54	0.59	-0.83	1.00						
12	ForecDisp	-0.02	-0.01	-0.09	0.08	0.04	0.05	0.00	0.02	0.08	-0.07	0.07	1.00					
13	InstOwn	0.65	-0.29	-0.43	0.27	0.00	0.44	-0.26	-0.45	0.14	-0.18	0.28	0.01	1.00				
14	EarnVola	-0.35	0.19	0.04	0.01	-0.03	-0.14	0.14	0.26	-0.09	0.17	-0.24	0.02	-0.19	1.00			
15	ln(MCap)	0.12	-0.20	-0.02	-0.16	-0.07	0.05	-0.18	-0.34	-0.21	-0.26	0.20	-0.13	0.19	-0.06	1.00		
16	MOMS	0.00	0.01	0.01	-0.01	0.00	-0.01	0.00	0.02	-0.01	0.03	-0.03	0.01	0.09	0.00	0.00	1.00	
17	MOML	-0.07	0.09	0.05	-0.04	0.02	-0.09	0.04	0.10	-0.08	0.13	-0.13	-0.09	-0.02	0.00	0.03	0.03	1.00

(Table 2: continued)

Correlations between Explanatory Variables

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
		Panel B: Expanded Sample															
1	Indivsm	1.00															
2	HomBias	-0.57	1.00														
3	AmbgAvsn	-0.47	0.44	1.00													
4	RskAvsn	0.12	-0.03	-0.28	1.00												
5	TFriction	-0.02	0.15	0.18	0.03	1.00											
6	Freedom	0.65	-0.60	-0.42	0.15	-0.07	1.00										
7	IncIneq	-0.37	0.41	0.13	0.14	0.14	-0.25	1.00									
8	Corrupt	-0.64	0.79	0.52	0.04	0.21	-0.60	0.37	1.00								
9	%Female	0.19	-0.19	-0.06	0.18	-0.04	0.37	0.02	0.03	1.00							
10	%Age0to14	-0.43	0.53	0.34	-0.01	0.10	-0.46	0.39	0.57	-0.13	1.00						
11	%Age65^{+}	0.55	-0.60	-0.40	0.06	-0.18	0.66	-0.52	-0.57	0.42	-0.81	1.00					
12	ForecDisp	0.01	0.02	-0.05	0.06	0.04	0.03	0.11	0.06	0.10	-0.03	0.04	1.00				
13	EarnVola	-0.29	0.16	0.12	-0.04	-0.06	-0.23	0.05	0.23	0.01	0.11	-0.20	-0.02	1.00			
14	ln(MCap)	0.24	-0.24	-0.07	-0.17	-0.08	0.16	-0.15	-0.46	-0.16	-0.34	0.23	-0.17	-0.03	1.00		
15	MOMS	0.00	0.01	0.01	-0.01	-0.01	-0.01	0.01	0.01	-0.01	0.02	-0.02	0.02	0.02	0.02	1.00	
16	MOML	-0.04	0.07	0.06	-0.03	0.00	-0.06	0.03	0.07	-0.02	0.07	-0.09	-0.10	0.04	0.09	0.03	1.00

Table 3
Cross-Sectional Regressions for International Turnover at the Country Level

This table reports results of monthly Fama-MacBeth cross-sectional regressions (at the country level) using the baseline sample (from 41 countries) in Panel A as well as the expanded sample (from 66 countries) in Panel B. The sample period is from 2000 to 2021. The dependent variable is the annualized monthly turnover (*TURN*). All variables are cross-sectionally standardized each month to have a mean of zero and a standard deviation of one in each sample. Variable definitions and data sources are described in Table A1, and the list of countries are reported in Table A2 in the Appendix. Newey-West (1987) *t*-statistics (with a lag of 4) for the time-series-averaged coefficients are reported in parentheses. The average of the adjusted R-squared (*AdjR-sqr*) across months is reported, together with the numbers of observations (*Obs*) and countries (*N_Country*). The coefficients significantly different from zero at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Fama-MacBeth Regression Results: Dep. Var. = *TURN*					
	Panel A: With Baseline Sample				**Panel B: With Expanded Sample**
Variables	1	2	3	4	5
Indivsm	0.229***	0.229***	0.585***	0.497***	0.491***
	(15.52)	(15.70)	(27.28)	(17.28)	(16.97)
HomBias	0.315***	0.317***	0.384***	0.311***	0.298***
	(12.41)	(12.23)	(17.98)	(18.82)	(16.92)
AmbgAvsn	-0.242***	-0.232***	-0.215***	-0.174***	-0.100***
	(-20.54)	(-18.51)	(-17.56)	(-10.51)	(-6.32)
RskAvsn	-0.255***	-0.251***	-0.088***	-0.084***	-0.053**
	(-21.08)	(-19.96)	(-6.54)	(-5.18)	(-2.49)
TFriction		-0.038***	-0.133***	-0.159***	-0.127***
		(-4.16)	(-10.78)	(-11.36)	(-9.57)
Freedom			-0.487***	-0.514***	-0.403***
			(-13.28)	(-15.04)	(-12.80)
IncIneq			0.175***	0.212***	0.235***
			(10.55)	(9.68)	(6.58)
Corrupt			0.120***	0.183***	0.048*
			(4.70)	(5.37)	(1.74)
%Female			-0.273***	-0.259***	-0.290***
			(-12.07)	(-8.78)	(-4.53)
%Age0T14			-0.246***	-0.207***	-0.021
			(-9.07)	(-5.98)	(-0.52)
%Age65^{+}			0.443***	0.563***	0.523***
			(12.85)	(13.04)	(8.20)
ForecDisp				0.180***	0.091*
				(3.15)	(1.94)
InstOwn				0.192***	
				(9.70)	
EarnVola				0.171***	0.192**
				(2.83)	(2.14)
ln(MCap)				-0.006	0.215***
				(-0.28)	(10.99)
MOMS				0.025	0.025
				(1.17)	(1.25)
MOML				0.181***	0.083**
				(3.75)	(2.26)
Intercept	0.005	0.005	0.015	0.049	0.098
	(0.15)	(0.14)	(0.26)	(0.64)	(1.48)
Country-Month Obs	10062	10062	8465	8465	11077
AdjR-sqr	0.146	0.130	0.429	0.493	0.422
N_Country	41	41	39	39	66

Table 4
Impacts of Explanatory Variables on Turnover

This table summarizes the impacts of some explanatory variables that play significant roles in explaining cross-country trading activities, using Column 5 in Table 3, where the sample is augmented by additional 27 countries (66 countries in total). The dependent variable is the annualized monthly turnover (*TURN*). Variable definitions are described in Table A1 in the Appendix. Given the number of country-month observations, the threshold of significance is a *p*-value of 1% (corresponding to a *t*-value of 2.60). The sample period is from 2000 to 2021. All variables are cross-sectionally standardized each month to have a mean of zero and a standard deviation of one before running the regressions. Thus, the impact (coefficient) in in units of standard deviation (SD). For the time-series-averaged coefficients obtained from the Fama-MacBeth regressions, Newey-West (1987) *t*-statistics are computed with a lag of 4.

The Impact of a One-SD Change in a Variable on *TURN*

Category	Variable	Impact (in Units of SD)
Behavioral Traits	Indivsm	0.49
	HomBias	0.30
	AmbgAvsn	-0.10
Trading Taxes and Fees	TFriction	-0.13
Governance and Demographic Factors	Freedom	-0.40
	IncIneq	0.24
	%Female	-0.29
	$\%Age65^{+}$	0.52
Visibility and Momentum	ln(MCap)	0.22

Table 5
International Turnover at the Individual Stock Level

This table reports results of monthly Fama-MacBeth cross-sectional regressions (at the firm level) using the baseline sample (from 41 countries) as well as the expanded sample (from 66 countries). The sample period is from 2000 to 2021. The dependent variable is the annualized monthly share turnover ($TURN^{firm}$) for each firm. The explanatory variables are measured at a monthly frequency and winsorized at the 1st and 99th percentiles in each month. All variables are cross-sectionally standardized each month to have a mean of zero and a standard deviation of one in each sample. Variable definitions and data sources are described in Table A1, and the list of countries are reported in Table A2 in the Appendix. Newey-West (1987) *t*-statistics (with a lag of 4) for the time-series-averaged coefficients are reported in parentheses. The average of the adjusted R-squared (*AdjR-sqr*) across months is reported, together with the numbers of observations (*Firm-Month Obs*). The coefficients significantly different from zero at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Cross-Sectional Regressions at the Firm Level: Dep. Var. = $TURN^{firm}$		
	With the Baseline Sample	**With the Expanded Sample**
Variables	1	2
Indivsm	0.286***	0.394***
	(18.98)	(27.95)
HomBias	0.100***	0.113***
	(7.65)	(11.21)
AmbgAvsn	-0.078***	-0.049***
	(-9.15)	(-5.68)
RskAvsn	-0.077***	-0.093***
	(-11.35)	(-11.10)
TFriction	-0.080***	-0.089***
	(-18.38)	(-18.19)
Freedom	-0.271***	-0.271***
	(-11.26)	(-9.95)
IncIneq	0.081***	0.122***
	(9.65)	(15.29)
Corrupt	0.137***	0.070***
	(18.35)	(8.71)
%Female	-0.096***	-0.072***
	(-9.72)	(-7.60)
%Age0T14	-0.185***	-0.100***
	(-16.04)	(-8.92)
%Age65^{+}	0.076***	0.086***
	(5.49)	(3.08)
ForecDisp	0.068***	0.058***
	(17.79)	(16.97)
InstOwn	0.170***	
	(12.09)	
EarnVola	0.212***	0.168***
	(5.08)	(5.20)
ln(MCap)	0.002	0.024*
	(0.16)	(1.76)
MOMS	0.002	0.019**
	(0.27)	(2.36)
MOML	0.078***	0.079***
	(5.44)	(5.32)
Intercept	-0.043**	-0.057***
	(-2.43)	(-2.85)
Firm-Month Obs	1182258	1266931
AdjR-sqr	0.223	0.207

Table 6
Regressions for the Country-Wide Dispersion of Turnover [*CV(TURN)*]

This table reports the results of cross-sectional regressions with the coefficients of variation (CVs) using the baseline sample from the 41 countries as well as the expanded sample from the 64 countries. The dependent variable is the coefficient of variation in turnover [*CV(TURN)*]. *CV(TURN)* is defined as the standard deviation of turnover (computed across stocks in each month) divided by the mean value of turnover in that month within each country. CVs for the six explanatory variables are also computed similarly, and each of them is denoted as *CV(X)* for original explanatory variable *X*. For regressions, all CV measures are standardized to have a mean of zero and a standard deviation of one in each sample. To ensure that the two types of past returns (*MOMS* and *MOML*) have positive CVs, gross returns are used. The original definitions of the explanatory variables are described in Table A1 in the Appendix. Newey-West (1987) *t*-statistics (with a lag of 4) for the time-series-averaged coefficients are reported in parentheses. The average of the adjusted R-squared (*AdjR-sqr*) across months is reported, together with the numbers of observations (*Obs*). The coefficients significantly different from zero at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Cross-Sectional Regressions for the Dispersion of Turnover: Dep. Var. = *CV(TURN)*		
	With the Baseline Sample	**With the Expanded Sample**
Variables	1	2
CV(FrecDisp)	0.122***	0.111***
	(6.97)	(8.10)
CV(InstOwn)	0.203***	
	(10.89)	
CV(EarnVola)	-0.082***	-0.119***
	(-4.07)	(-6.06)
CV(MCap)	0.271***	0.271***
	(15.09)	(16.55)
CV(MOMS)	0.015	0.012
	(0.81)	(0.65)
CV(MOML)	0.140***	0.135***
	(5.26)	(6.71)
Intercept	-0.005	-0.001
	(-0.18)	(-0.06)
Country-Month Obs	9646	11688
N_Country	41	64
AdjR-sqr	0.188	0.140

Table 7

Regression Results for the Amihud Illiquidity Measure (*ILLIQ*) across Countries

This table reports results of monthly Fama-MacBeth cross-sectional regressions (at the country level) using the baseline sample (from 39 countries) as well as the expanded sample (from 66 countries). The sample period is from 2000 to 2021. The dependent variable is the monthly Amihud (2002) illiquidity measure (*ILLIQ*), which is aggregated at the country level (market-capitalization-weighted, similarly to *TURN*). All variables are cross-sectionally standardized each month to have a mean of zero and a standard deviation of one in each sample. Variable definitions and data sources are described in Table A1 in the Appendix. Newey-West (1987) *t*-statistics (with a lag of 4) for the time-series-averaged coefficients are reported in parentheses. The average of the adjusted R-squared (*AdjR-sqr*) across months is reported, together with the numbers of observations (*Obs*) and countries (*N_Country*). The coefficients significantly different from zero at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Cross-Sectional Regressions at the Country Level: Dep. Var. = *ILLIQ*		
	With the Baseline Sample	**With the Expanded Sample**
Variables	1	2
Indivsm	-0.189***	-0.064***
	(-4.19)	(-3.83)
HomBias	-0.002	0.073***
	(-0.17)	(4.51)
AmbgAvsn	-0.058***	-0.085***
	(-4.81)	(-7.06)
RskAvsn	0.051***	0.028**
	(5.96)	(2.56)
TFriction	0.059***	-0.001
	(4.91)	(-0.13)
Freedom	0.045	0.010
	(1.39)	(0.41)
IncIneq	-0.080***	-0.113***
	(-5.40)	(-5.10)
Corrupt	-0.047**	-0.136***
	(-2.30)	(-5.22)
%Female	-0.069**	0.125***
	(-2.41)	(3.13)
%Age0T14	0.041	-0.158***
	(1.36)	(-4.47)
%Age65^{+}	0.070	-0.235***
	(1.37)	(-4.76)
ForecDisp	0.011	-0.127***
	(0.52)	(-3.51)
InstOwn	0.046*	
	(1.86)	
EarnVola	-0.125***	-0.114***
	(-5.20)	(-4.10)
ln(MCap)	-0.099*	-0.194***
	(-1.77)	(-5.47)
MOMS	-0.025	-0.012
	(-1.07)	(-0.55)
MOML	-0.040	-0.106***
	(-1.22)	(-3.95)
Intercept	-0.066***	-0.053**
	(-4.58)	(-2.35)
Country-Month Obs	8465	11077
AdjR-sqr	0.116	0.135
N_Country	39	66

Table 8
Results of Stacked Difference-in-Differences Estimates for the Effects of Exogenous Shocks

This table reports the stacked DiD analysis to examine how exogenous country-level events (military actions and tax changes) affect firm-level turnover across countries. The following model is estimated using panel regressions:

$$Y_{i,t} = \beta_1 TREAT_{i,c} + \beta_2 POST_t + \delta \cdot (TREAT_{i,c} \times POST_t) + \gamma' \mathbf{Z}_{i,t} + \alpha_c + \tau_t + \varepsilon_{i,t},$$

where i indexes firms, c indicates countries, and t indexes year-month. The dependent variable, $Y_{i,t}$, is $ln(TURN)_{i,t}$ in Panel A and $ln(ILLIQ)_{i,t}$ in Panel B, where *TURN* and *ILLIQ* are defined previously. $TREAT_c = 1$ for the countries that experience the event, and $TREAT_c = 0$ for the control group of countries that do not experience the event in the same region. $POST_t = 1$ for the post-event window (event month *m*+13 to *m*+36), and $POST_t = 0$ for the pre-event window (*m*-35 to *m*-12). $\mathbf{Z}_{i,t}$ includes all the explanatory variables used in Table 3 except for *Freedom*. α_c and τ_t indicate country and year-month fixed effects (*FE*), respectively. Seven events are considered, which are classified into three categories: (1) *More-Free* events from military actions in Thailand (September 2006) and Egypt (February 2011); (2) a *Less-Free* event from military actions in Turkey (July 2016); and (3) *Tax-Increase* events in Belgium (January-May 2012), France (August 2012), Hungary (January 2013) and Italy (March 2013).

DiD Analyses with Exogenous Events: Military Actions and Tax Increases in Seven Countries

	Panel A: Dep. Var. = *ln(TURN)*					
Events:	**A1: More-Free**		**A2: Less-Free**		**A3:Tax-Increase**	
Variables	1	2	3	4	5	6
TREAT	1.224		1.363***		0.403*	
	(1.28)		(6.59)		(1.75)	
POST	-0.053		-0.235***		-0.319***	
	(-0.31)		(-3.84)		(-6.92)	
TREAT x POST	-0.911***	-1.058***	0.199***	0.543***	-0.060	-0.104***
	(-4.91)	(-3.14)	(2.97)	(2.83)	(-1.54)	(-2.60)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes
Year-Month & Event FE	No	Yes	No	Yes	No	Yes
Firm-Month Obs	25631	25631	44478	44478	159474	159474
AdjR-sqr	0.466	0.490	0.234	0.253	0.221	0.255

	Panel B: Dep. Var. = *ln(ILLIQ)*					
Events:	**B1: More-Free**		**B2: Less-Free**		**B3: Tax-Increase**	
Variables	1	2	3	4	5	6
TREAT	6.145**		2.325		0.154	
	(2.34)		(1.60)		(0.22)	
POST	-0.098		-0.122		-0.156	
	(-0.21)		(-1.06)		(-1.23)	
TREAT x POST	0.715	0.676*	-0.661**	-0.958**	0.111	0.184**
	(1.27)	(1.70)	(-2.21)	(-2.43)	(0.93)	(1.99)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes
Year-Month & Event FE	No	Yes	No	Yes	No	Yes
Firm-Month Obs	25631	25631	44478	44478	159474	159474
AdjR-sqr	0.831	0.859	0.803	0.852	0.790	0.837

Table 9
Stock Market Performance, Trading Activities, and Economic Growth across Countries

This table reports the results of quarterly Fama-MacBeth (1973) cross-sectional regressions to examine the effects of stock market performance and trading activities on GDP growth across countries, using the baseline sample from 41 countries. For this purpose, the following regressions are run quarterly:

$$Y_{c,q+1} = \beta_1 MOMQ1_{c,q} + \beta_2 A_{c,q} + \theta \cdot \left(MOMQ1_{c,q} \times A_{c,q}\right) + \gamma' \boldsymbol{Z}_{c,q} + \varepsilon_{c,q},$$

where $Y_{c,q+1}$ is total GDP growth (*dGDP*) or per-capita GDP growth ($dGDP^{pc}$) (in %) in country c in quarter $q+1$; $MOMQ1_{c,q}$ is the quarterly average of monthly returns of a major stock index in country c in quarter q; $A_{c,q}$ is one of the two trading activity-related variables (*TURN* in Panel A and *ILLIQ* in Panel B). *TURN* and *ILLIQ* are computed as the quarterly averages of the monthly equivalents defined in previous tables. The set of control variables ($\boldsymbol{Z}_{c,q}$) includes the 11 variables (known to determine GDP growth) used in Barro (2003). All variables are standardized to have a mean of zero and a standard deviation of one. Newey-West (1987) *t*-statistics for the time-series-averaged coefficients are computed in parentheses. The average of the adjusted R-squared (*AdjR-sqr*) across quarters is reported, together with the numbers of observations (*Obs*). The coefficients significantly different from zero at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Stock Market Performance, Trading Activities, and Economic Growth across Countries

	Panel A: Results with *TURN*	
Economic Growth:	**Dep. Var. = *dGDP***	**Dep. Var. = $dGDP^{pc}$**
Variables	1	2
MOMQ1	0.097**	0.090**
	(2.30)	(2.19)
TURN	0.009	0.012
	(0.38)	(0.51)
MOMQ1 x TURN	0.029	0.027
	(0.45)	(0.43)
11 Variables Used in Barro (2003)	Yes	Yes
Country-Quarter Obs	2954	2954
AdjR-sqr	0.157	0.141

	Panel B: Results with *ILLIQ*	
Economic Growth:	**Dep. Var. = *dGDP***	**Dep. Var. = $dGDP^{pc}$**
Variables	1	2
MOMQ1	0.177***	0.171***
	(3.01)	(3.04)
ILLIQ	-0.063	-0.068
	(-0.39)	(-0.45)
MOMQ1 x ILLIQ	0.721**	0.707**
	(2.21)	(2.25)
11 Variables Used in Barro (2003)	Yes	Yes
Country-Quarter Obs	2954	2954
AdjR-sqr	0.158	0.142

Figure 1: World Map for the Countries Covered in the Study

This figure displays all the countries used in the paper. Countries in 'blue' represent the baseline sample (41 countries), while countries in 'green' represent the additionally included countries (another 27 countries) in the expanded sample. The expanded sample includes 66 countries: given the missing values, Taiwan and Hong Kong are excluded from the sample of 68 countries in total). The baseline sample accounts for about 87% of global GDP over the 2000–2021 period, while the expanded sample accounts for about 93%.

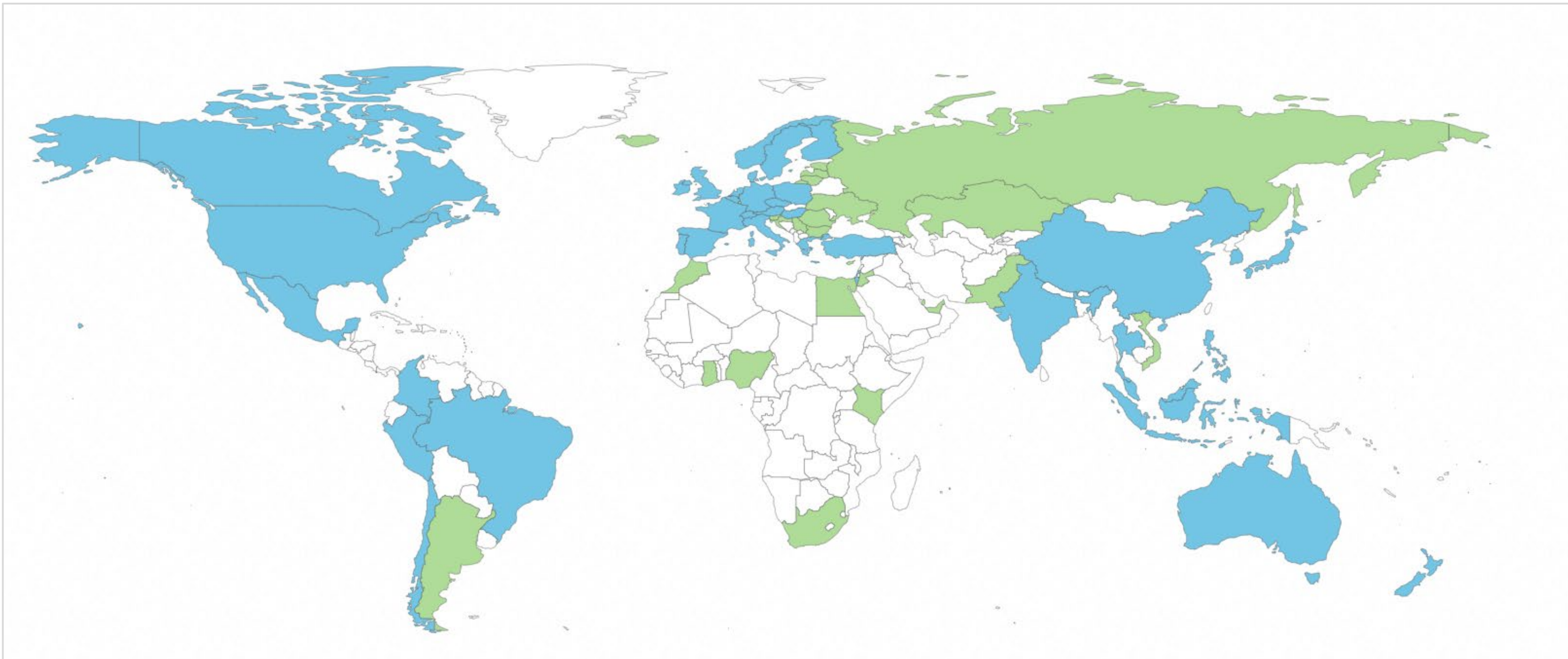


Figure 2: Cross-Country Mean and Median of Turnover (*TURN*)

This figure presents bar charts for the mean and median values of annualized turnover (*TURN*) by country over the sample period (2000-2021) using the baseline sample from 41 countries. *TURN* is defined as the total (US dollar) value of shares traded across firms within a country, divided by the total market capitalization of those firms, and annualized by multiplying by 12. The sample period is from 2000 to 2021. Country names (based on the ISO 3-letter codes) are reported in Table A2 in the Appendix.

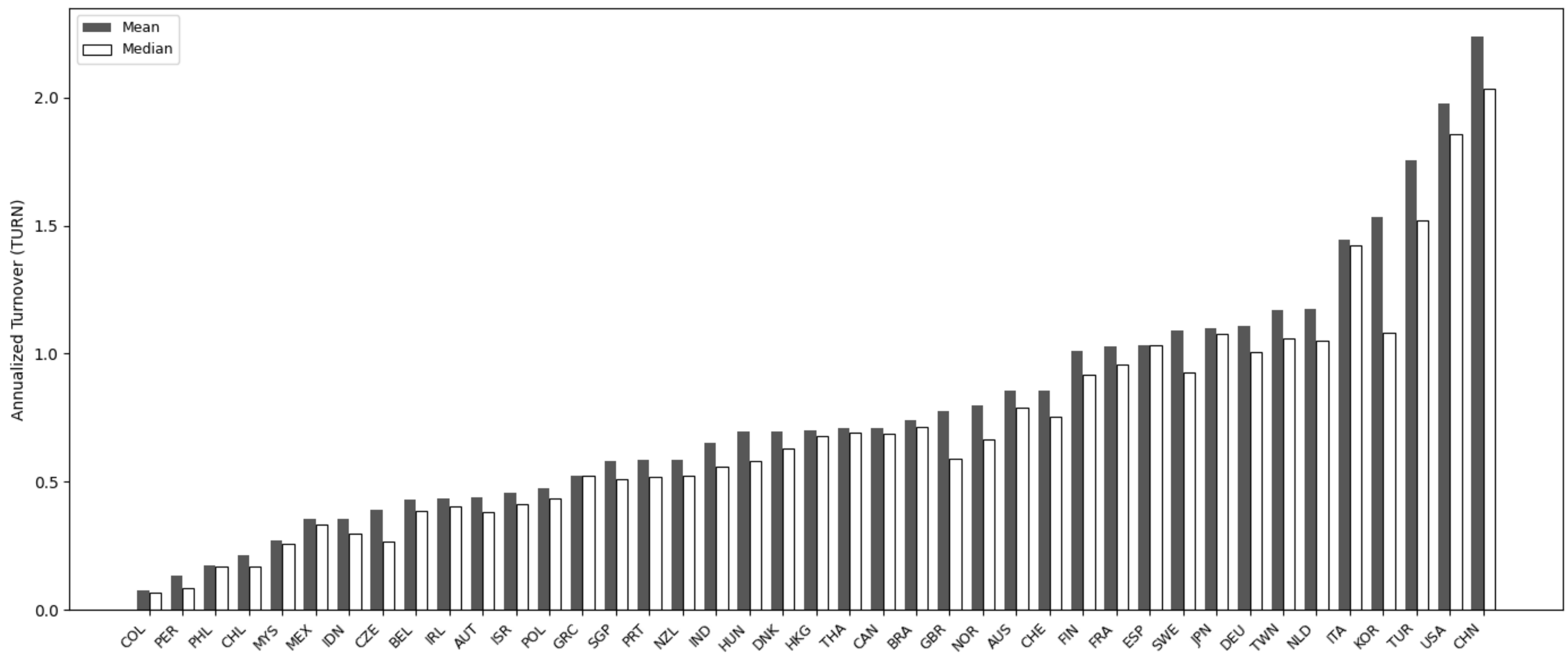


Figure 3: Country-Wide Turnover over Time

This figure presents the time-series of turnover (*TURN*) averaged across all 41 countries included in the baseline sample. *TURN* is defined as the (dollar) value of shares traded across firms within a country, divided by the total market capitalization (in million USD) of those firms, and annualized by multiplying by 12. The sample period is from 2000 to 2021.

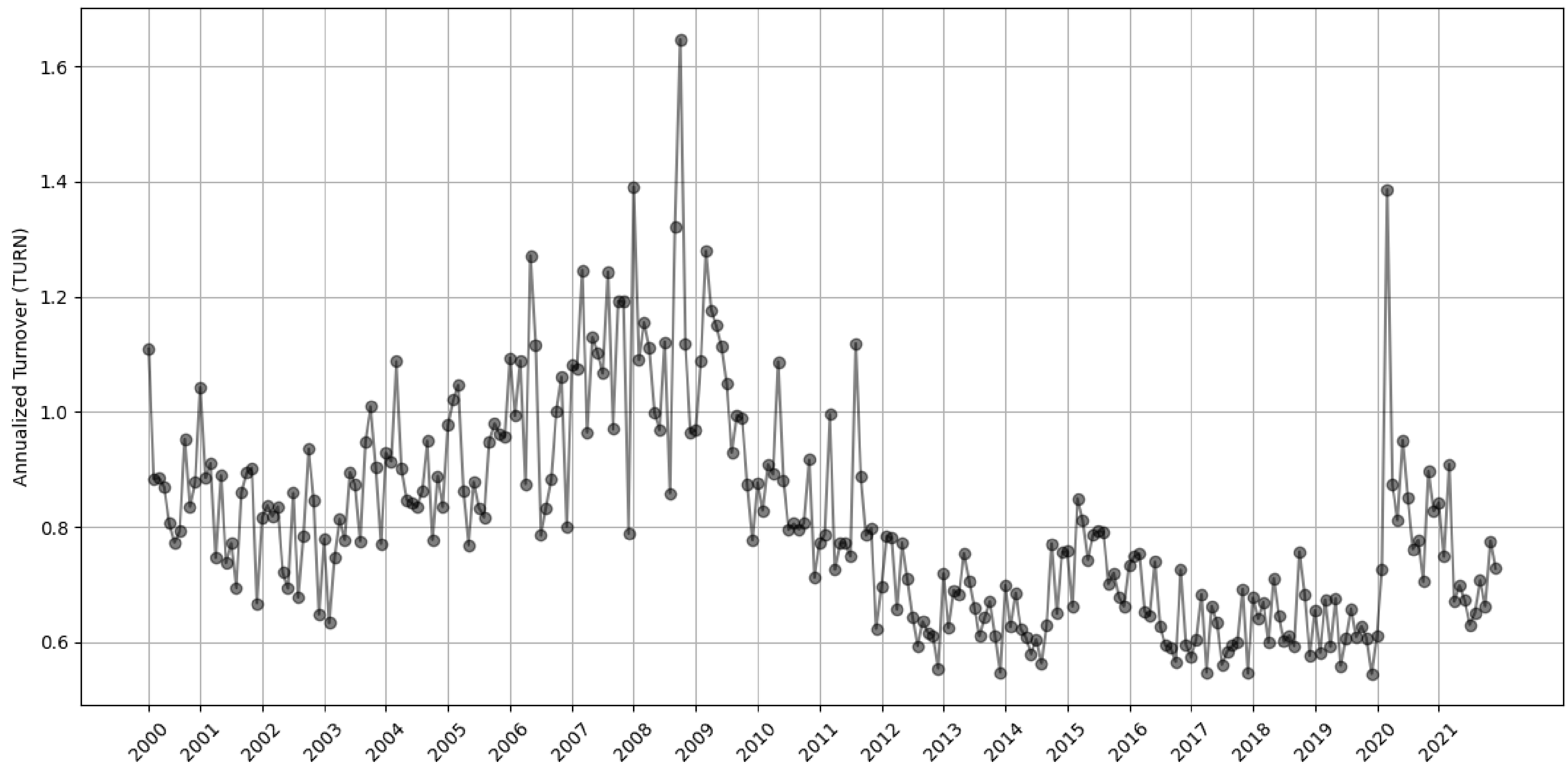


Figure 4: Average Turnover in Behavioral Variables for the Two Groups

This figure plots the level of turnover (*TURN*) averaged across all countries for the variables related to behavioral traits: i.e., individualism (*Indivsm*), home bias (*HomBias*), ambiguity aversion (*AmbgAvsn*), and risk aversion (*RskAvsn*). For each month, countries are first divided into two groups (below the median vs. equal to or above the median) in the above variables before calculating the average values. *TURN* is defined as the total dollar value of shares traded across firms within a country, divided by the total market capitalization (in million USD) of those firms, and annualized by multiplying by 12. The sample period is from 2000 to 2021.

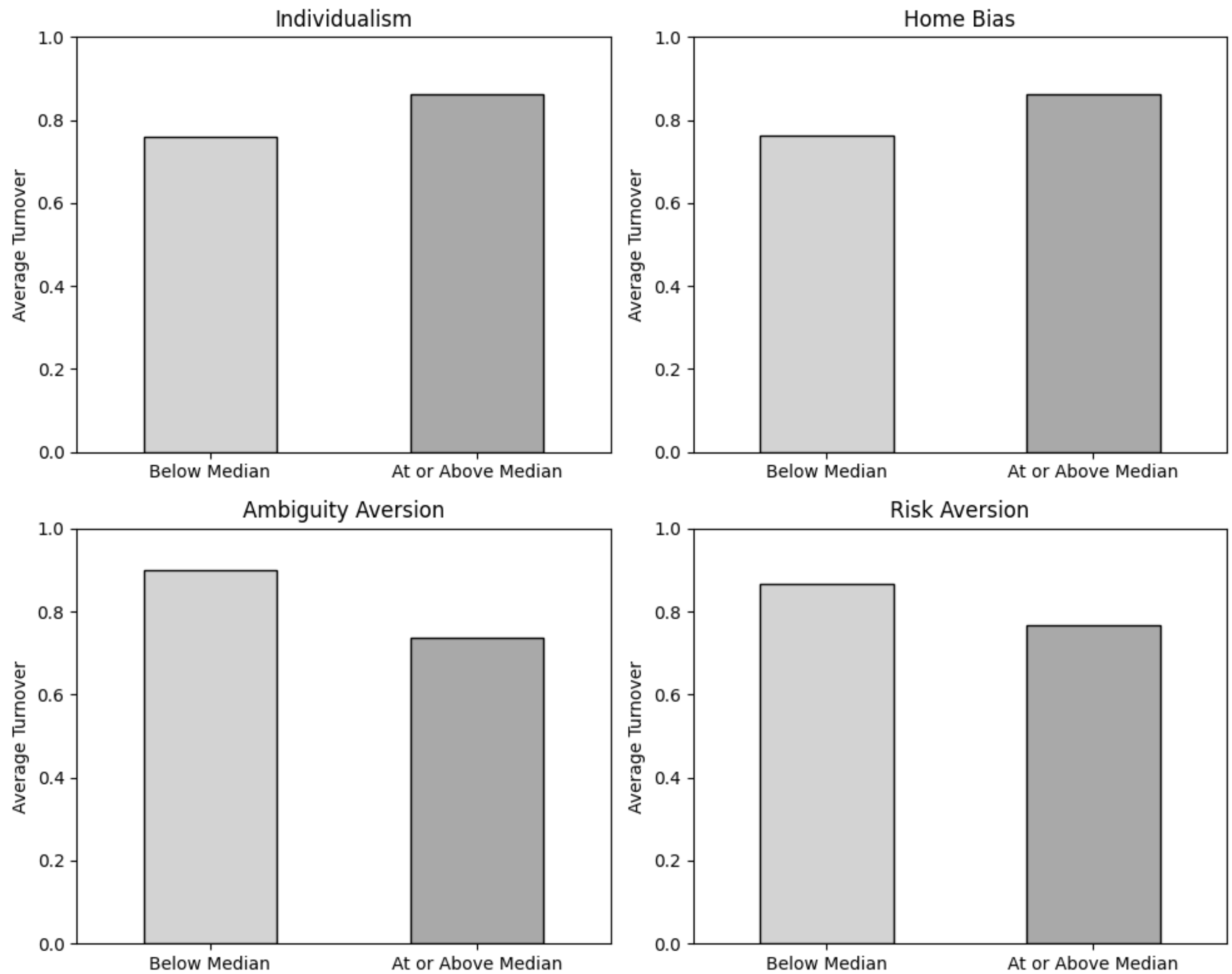


Figure 5: Mean and Median Values of the Coefficient of Variation for Turnover [*CV(TURN)*] across Countries

This figure plots a bar chart for the mean and median values of the monthly coefficient of variation in turnover [*CV(TURN)*] over the sample period (2000-2021) for the 41 countries included in the baseline sample. To compute *CV(TURN)*, the standard deviation of annualized turnover ($TURN^{firm}$) across stocks within each month is divided by the mean value of $TURN^{firm}$ in that month. For the chart, the time-series mean and median values are then computed within each country.

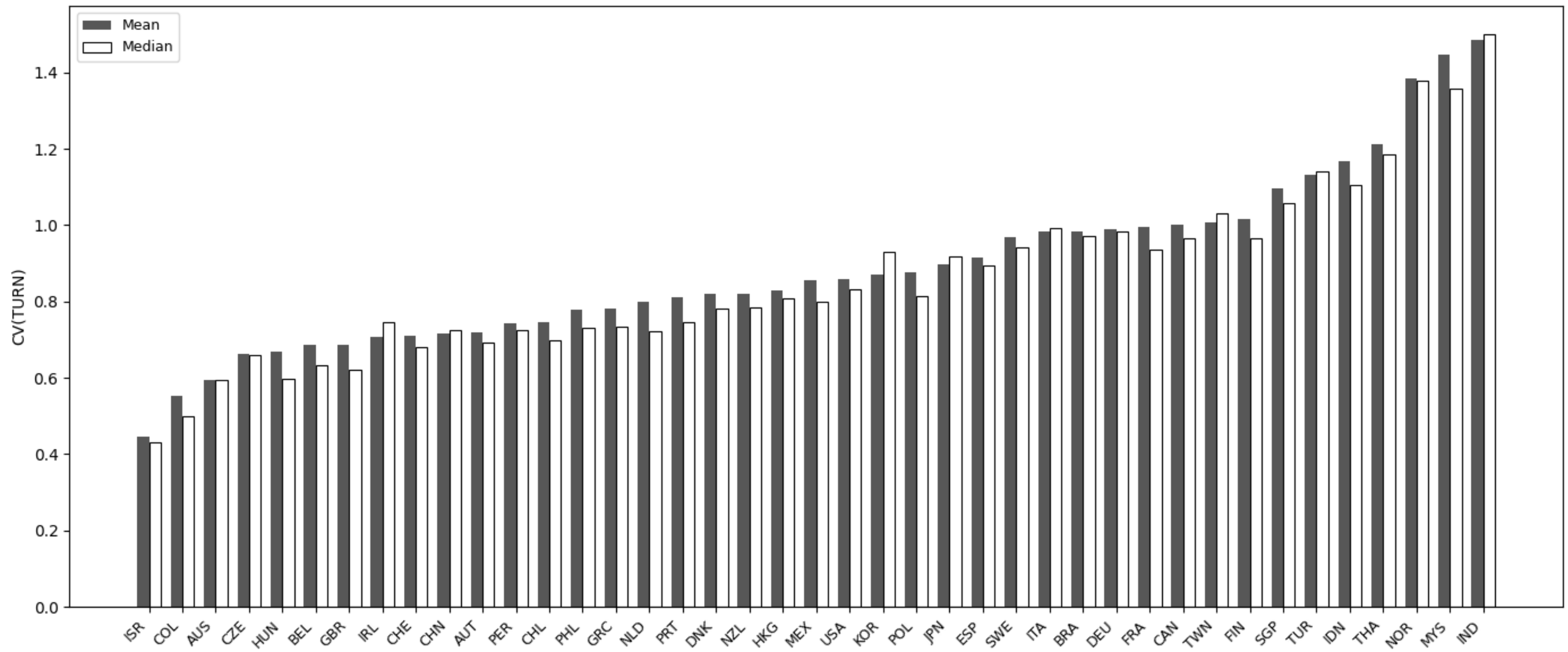


Figure 6: Country-Wide Coefficient of Variation in Turnover over Time

This figure plots the time-series of the coefficient of variation in turnover [*CV(TURN)*] over time using the baseline sample from 41 countries. To compute *CV(TURN)*, the standard deviation of annualized turnover ($TURN^{firm}$) across stocks within each month is divided by the mean value of $TURN^{firm}$ in that month. For this plot, the values of monthly *CV(TURN)* are averaged across all the 41 countries in each month over the sample period (2000-2021).

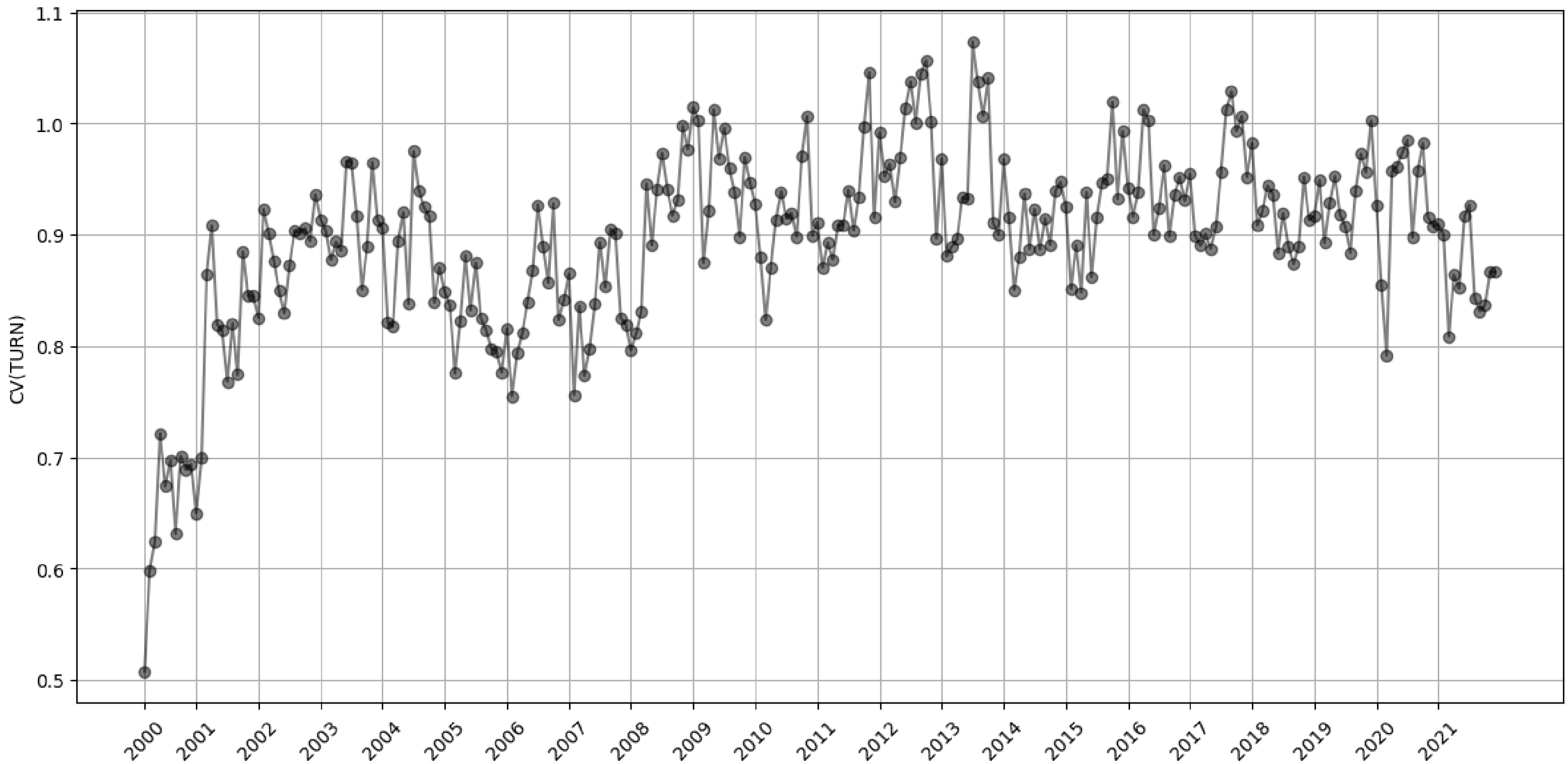


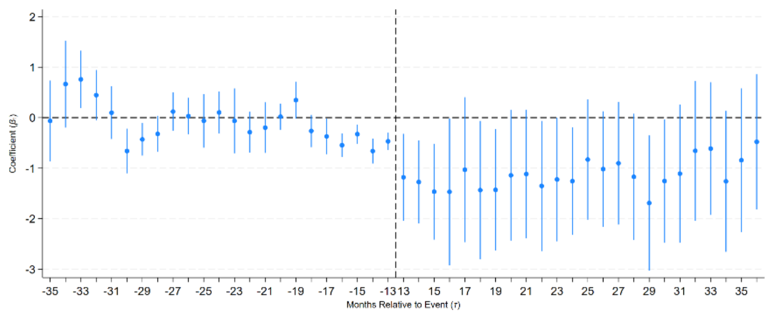
Figure 7: Analyses of Parallel Trends for Turnover

This figure evaluates the validity of the parallel trend assumption, using a dynamic difference-in-differences approach based on Rambachan and Roth (2023). Specifically, to examine how firm-level international turnover changes around the exogenous events, we utilize country-level shocks caused by military actions *(More-Free* cases) in Thailand (September 2006), Egypt (February 2011), and (*Less-Free* case) in Turkey (2016) (for Panels A and B), as well as by increases in trading taxes (*Tax-Increase* case) in Belgium (January-May 2012), France (August 2012), Hungary (January 2013), and Italy (March 2013) (for Panel C). For this purpose, the following specification is estimated:

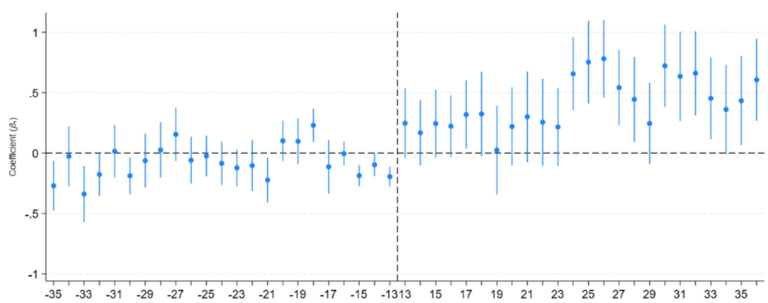
$$Y_{i,t} = \sum_{\tau\neq\tau_0} \delta_\tau \cdot \left(TREAT_{i,c} \times 1\{EventTime_{i,t} = \tau\}\right) + \gamma' \boldsymbol{Z}_{i,t} + \alpha_c + \omega_t + +\varepsilon_{i,t},$$

where i indexes firms, c indexes countries, and t indexes year-month. $Y_{i,t}$ is *ln(TURN)* for firm i and in month t. $TREAT_{i,c}$ takes a value of 1 for firms from countries experiencing the events, and 0 otherwise. α_c and ω_t are country and year-month fixed effects. The control variables ($\boldsymbol{Z}$) include the explanatory variables used in Table 3 (except for *Freedom*). Standard errors are clustered at the country and year-month level. The coefficient estimates, δ_τ (measured by the vertical axis), capture the dynamic treatment effects for event-time bin τ, where τ ranges from months *m*–35 to *m*–12 for the pre-event period and from *m*+13 to *m*+36 for the post-event period; and the reference period τ_0 is set at month *m*–12.

Panel A: With the *More-Free* Event from Military Actions



Panel B: With the *Less-Free* Event from Military Actions



Panel C: With the *Tax-Increase* Event

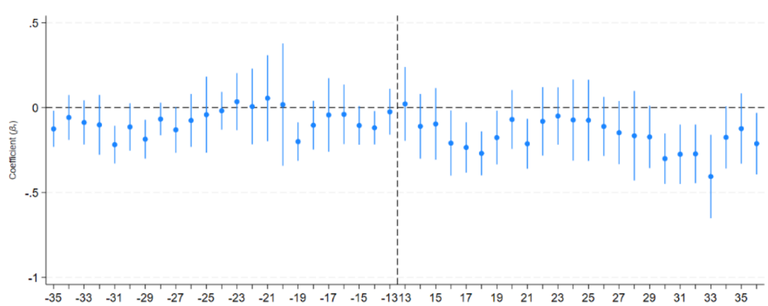
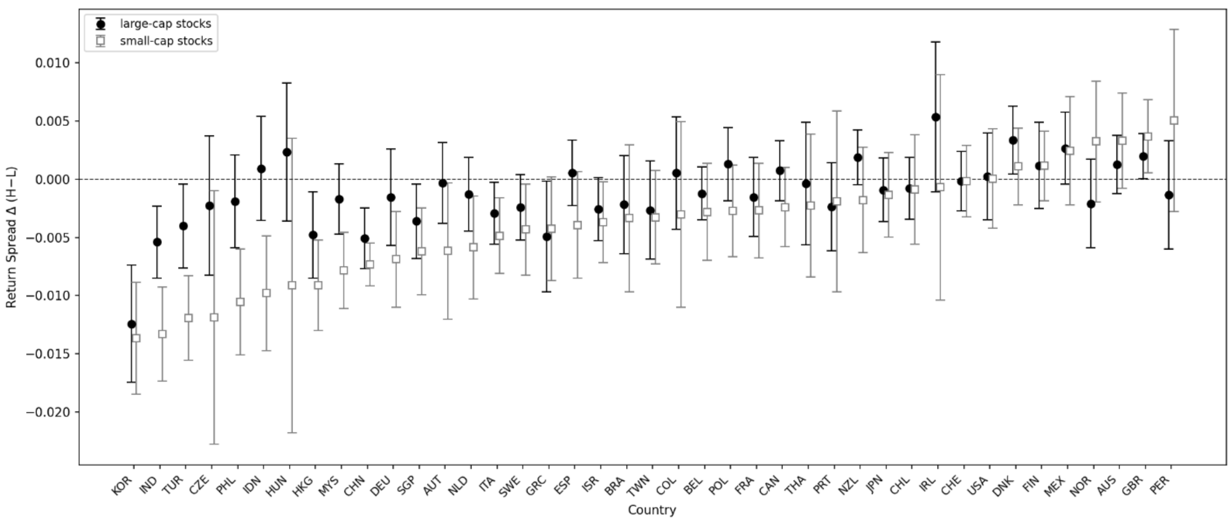


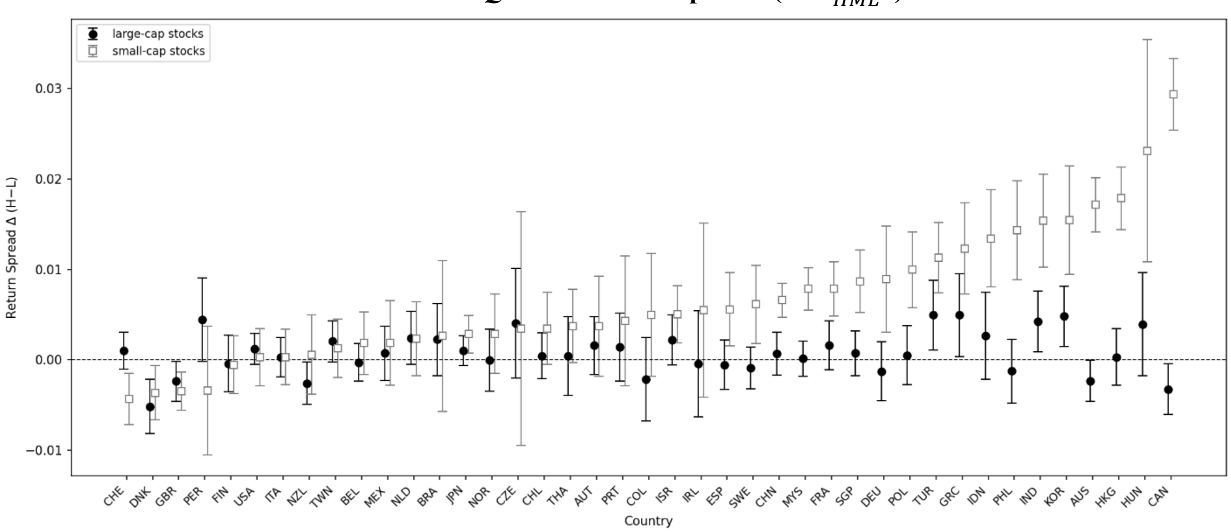
Figure 8. Trading Variable-Sorted Return Spreads Across Countries

This figure plots the mean and the 90% confidence interval of the *TURN*-based return spread (RET_{HML}^{TURN}) in Panel A and *ILLIQ*-based return spread (RET_{HML}^{ILLIQ}) in Panel B for each country. RET_{HML}^{TURN} and RET_{HML}^{ILLIQ} are obtained as follows: At the end of each month $t-1$, stocks within each country are sorted into two groups (small vs. big based on the median of *MCap*) in each country; Within each size group, the average of daily share turnover (*TURN*) or the Amihud measure (*ILLIQ*) over the previous six months is calculated; The sample stocks are then sorted on *TURN* or *ILLIQ* and split into two portfolios [high (H) and low (L)]; Finally, the (H – L) portfolio return or the return premium [i.e., RET_{HML}^{TURN} and RET_{HML}^{ILLIQ}] is computed as the difference in the equal-weighted average returns for each country. The confidence intervals are calculated as (Mean ± $Z_{0.95}$ × Standard Error). The gray line represents the plot for the group of below-median (small) stocks, while the black line is for the group of above-median (big) stocks within each country. The charts are plotted using the baseline sample from 41 countries over the sample period from 2000 to 2021.

Panel A: *TURN*-Based Return Spreads (RET_{HML}^{TURN})



Panel B: *ILLIQ*-Based Return Spreads (RET_{HML}^{ILLIQ})



APPENDIX

Table A1: Variable Definitions and Sources

Category	Variable	Definition	Source
Trading Activity	*TURN*	Turnover computed as the dollar value of shares traded in a month, divided by total market capitalization. The ratio is calculated monthly and annualized by multiplying by 12.	Datastream
Behavioral Traits	*Indivsm*	Individualism (as opposed to collectivism) as a proxy for overconfidence.	Hofstede (1980)
	HomBias	Home bias computed as the proportion of investors' total holdings allocated to domestic assets.	Wallmeier and Iseli (2022)
	AmbgAvsn	Ambiguity aversion defined as the percentage of market participants who choose an unambiguous offer vs. an ambiguous one.	Rieger et al. (2015)
	RskAvsn	Risk aversion defined as the deviation of market participants' certainty equivalents from expected value of proposed lotteries.	Rieger et al. (2015)
Trading Taxes and Fees	*TFriction*	Trading frictions, for which *TTax&Fee* is computed as the sum of financial transaction taxes, exchange fees, and brokerage commissions (in bps). Then, its logarithmic transformation, *ln*(1+ *TTax&Fee*), is used for analyses.	J.P. Morgan, exchange websites, Interactive Brokers, and CEPR
Governance and Demographic Factors	*Freedom*	Democratic freedom based the average rank of political rights (PR) and civil liberties (CL) from the database, computed as 8 − (PR rank + CL rank)/2. The original ranks range from 1 (most free) to 7 (least free). Thus, higher values of *Freedom* indicate greater political and civil freedom.	Freedom House
	IncIneq	Measure proxied by the Gini index. The index captures the extent to which income distribution deviates from perfect equality, ranging from 0 (perfect equality) to 100 (perfect inequality); thus higher values of *IncIneq* indicate greater inequality.	World Bank
	Corrupt	Corruption level, based on the Corruption Perceptions Index (CPI) from the database, calculated as (100 – CPI). The original CPI captures the perceived levels of public sector, ranging from 0 (highly corrupt) to 100 (very clean). Thus, higher values of *Corrupt* indicate higher degree of corruption.	Transparency International
	%Female	The proportion of females in the total population.	World Bank
	%Age0T14	The proportion of population aged 0 to 14.	World Bank
	%Age65^{+}	The proportion of population aged 65 or older.	World Bank
Belief Divergence and Information Asymmetry	*ForecDisp*	Analyst forecast dispersion computed as the standard deviation of analysts' EPS forecasts for a firm for the current fiscal year, scaled by the mean value of forecasts. Country-level values are computed as market-capitalization-weighted averages across firms within a country.	IBES
	InstOwn	Institutional ownership, which is the value of shares held by all institutions within a country, scaled by the total market capitalization.	Factset
	EarnVola	Earnings volatility computed as the standard deviation of the most recent eight quarterly earnings (including the current one), scaled by average total assets. Country-level values are computed as market-capitalization-weighted averages.	Worldscope
Visibility and Return Momentum	*ln(MCap)*	Firm size is first obtained as the natural logarithm of month-end market value of each stock (in million USD). Then country-level market size is computed as the natural logarithm of the total market value of all sample stocks within a country, scaled by the previous year's GDP.	Worldscope
	MOMS	Past return or short-horizon (month *t-1*) return momentum, computed as the market-capitalization-weighted average return (in %) across sample stocks within a country.	Worldscope
	MOML	Long-horizon (from month *t-12* to month *t-2*) momentum, computed as the market-capitalization-weighted average return (in %) across sample stocks within a country.	Worldscope

Table A2: List of Included Countries

This table lists the countries and regions included in the study. Countries 1–41 constitute the baseline sample (consistent with Table 3, Column 1), while countries 1–68 comprise the expanded sample (consistent with Table 3, Column 5). Due to missing values, Taiwan and Hong Kong are excluded from the expanded set, resulting in a final count of 66 countries for that sample.

No.	ISO 3	Country Name	Region	No.	ISO 3	Country Name	Region
1	CHN	China	East Asia	42	GHA	Ghana	Sub-Saharan Africa
2	HKG	Hong Kong	East Asia	43	KEN	Kenya	Sub-Saharan Africa
3	IDN	Indonesia	East Asia	44	MUS	Mauritius	Sub-Saharan Africa
4	JPN	Japan	East Asia	45	NGA	Nigeria	Sub-Saharan Africa
5	KOR	South Korea	East Asia	46	ZAF	South Africa	Sub-Saharan Africa
6	MYS	Malaysia	East Asia	47	EGY	Egypt	North Africa
7	PHL	Philippines	East Asia	48	MAR	Morocco	North Africa
8	SGP	Singapore	East Asia	49	KAZ	Kazakhstan	South Asia
9	THA	Thailand	East Asia	50	PAK	Pakistan	South Asia
10	TWN	Taiwan	East Asia	51	VNM	Vietnam	East Asia
11	IND	India	South Asia	52	BGR	Bulgaria	Europe
12	AUT	Austria	Europe	53	CYP	Cyprus	Europe
13	BEL	Belgium	Europe	54	EST	Estonia	Europe
14	CHE	Switzerland	Europe	55	HRV	Croatia	Europe
15	CZE	Czech Republic	Europe	56	ISL	Iceland	Europe
16	DEU	Germany	Europe	57	LTU	Lithuania	Europe
17	DNK	Denmark	Europe	58	LUX	Luxembourg	Europe
18	ESP	Spain	Europe	59	LVA	Latvia	Europe
19	FIN	Finland	Europe	60	ROU	Romania	Europe
20	FRA	France	Europe	61	RUS	Russia	Europe
21	GBR	United Kingdom	Europe	62	SRB	Serbia	Europe
22	GRC	Greece	Europe	63	SVN	Slovenia	Europe
23	HUN	Hungary	Europe	64	UKR	Ukraine	Europe
24	IRL	Ireland	Europe	65	ARG	Argentina	Latin America
25	ITA	Italy	Europe	66	QAT	Qatar	Middle East
26	NLD	Netherlands	Europe	67	JOR	Jordan	Middle East
27	NOR	Norway	Europe	68	ARE	United Arab Emirates	Middle East
28	POL	Poland	Europe				
29	PRT	Portugal	Europe				
30	SWE	Sweden	Europe				
31	TUR	Turkey	Europe				
32	BRA	Brazil	Latin America				
33	CHL	Chilé	Latin America				
34	COL	Colombia	Latin America				
35	MEX	Mexico	Latin America				
36	PER	Peru	Latin America				
37	ISR	Israel	Middle East				
38	CAN	Canada	North America				
39	USA	United States	North America				
40	AUS	Australia	Oceania				
41	NZL	New Zealand	Oceania				

Table A3: Extrapolation of Missing Values in the Four Variables Related to Behavioral Traits for the Baseline Sample

This table describes how to extrapolate missing values in the four behavioral variables [individualism (*Indivism*), home bias (*HomBias*), ambiguity aversion (*AmbgAvsn*), and risk aversion (*RskAvsn*)] to obtain our baseline sample for the 47 countries defined by MSCI. Letter "A" in the table indicates that the value for the variable is directly available (so no need to extrapolate), while "E" indicates that the value for the variable is extrapolated (the corresponding region and specific countries used for extrapolation are shown in the parentheses). "n.a." indicates that the value for the variable is still missing. The regions considered are: East Asia, South Asia (including Kazakhstan, Pakistan, India), Europe, Latin America, North America (USA and Canada), Oceania, North Africa, Sub-Saharan Africa, and Middle East. After applying the procedure, the countries which still have missing values in the variables are excluded for the analyses. The finalized baseline sample includes up to 41 countries (as indicated in Table 3, Column 1).

	ISO 3	Country Name	Continent	*Indivsm*	*HomBias*	*AmbgAvsn* and *RskAvsn*
1	EGY	Egypt	Africa (North)	A	A	n.a.
2	ZAF	South Africa	Africa (Sub-Saharan)	A	A	n.a.
3	CHN	China	Asia (East)	A	A	A
4	HKG	Hong Kong	Asia (East)	A	E (East Asia: CHN, IDN, JPN, KOR, MYS, PHL, SGP, THA)	A
5	IDN	Indonesia	Asia (East)	A	A	E (East Asia: CHN, HKG, JPN, KOR, MYS, THA, TWN)
6	JPN	Japan	Asia (East)	A	A	A
7	KOR	South Korea	Asia (East)	A	A	A
8	MYS	Malaysia	Asia (East)	A	A	A
9	PHL	Philippines	Asia (East)	A	A	E (East Asia: CHN, HKG, JPN, KOR, MYS, THA, TWN)
10	SGP	Singapore	Asia (East)	A	A	E (East Asia: CHN, HKG, JPN, KOR, MYS, THA, TWN)
11	THA	Thailand	Asia (East)	A	A	A
12	TWN	Taiwan	Asia (East)	A	E (East Asia: CHN, IDN, JPN, KOR, MYS, PHL, SGP, THA)	A
13	IND	India	Asia (South)	A	A	A
14	AUT	Austria	Europe	A	A	A
15	BEL	Belgium	Europe	A	A	A
16	CHE	Switzerland	Europe	A	A	A
17	CZE	Czech Republic	Europe	A	A	A
18	DEU	Germany	Europe	A	A	A
19	DNK	Denmark	Europe	A	A	A
20	ESP	Spain	Europe	A	A	A
21	FIN	Finland	Europe	A	A	A

(Table A3: continued)

22	FRA	France	Europe	A	A	A
23	GBR	United Kingdom	Europe	A	A	A
24	GRC	Greece	Europe	A	A	A
25	HUN	Hungary	Europe	A	A	A
26	IRL	Ireland	Europe	A	E (Europe: Country No.14-33)	A
27	ITA	Italy	Europe	A	A	A
28	NLD	Netherlands	Europe	A	A	A
29	NOR	Norway	Europe	A	A	A
30	POL	Poland	Europe	A	A	A
31	PRT	Portugal	Europe	A	A	A
32	SWE	Sweden	Europe	A	A	A
33	TUR	Turkey	Europe	A	A	A
34	BRA	Brazil	Latin America	A	A	E (Lain America: CHL, COL, MEX)
35	CHL	Chile	Latin America	A	A	A
36	COL	Colombia	Latin America	A	A	A
37	MEX	Mexico	Latin America	A	A	A
38	PER	Peru	Latin America	A	E (Lain America: BRA, CHL, COL, MEX)	E (Lain America: CHL, COL, MEX)
39	ARE	United Arab Emirates	Middle East	A	n.a.	n.a.
40	ISR	Israel	Middle East	A	A	A
41	KWT	Kuwait	Middle East	A	n.a.	n.a.
42	QAT	Qatar	Middle East	A	n.a.	n.a.
43	SAU	Saudi Arabia	Middle East	A	n.a.	n.a.
44	CAN	Canada	North America	A	A	A
45	USA	United States	North America	A	A	A
46	AUS	Australia	Oceania	A	A	A
47	NZL	New Zealand	Oceania	A	A	A

Table A4: Extrapolation of Missing Values in the Four Variables for the Extended Sample

This table describes how to extrapolate missing values in the four behavioral variables [individualism (*Indivsm*), home bias (*HomBias*), ambiguity aversion (*AmbgAvsn*), and risk aversion (*RskAvsn*)] to obtain our extended sample, allowing the institutional ownership variable (*InstOwn*) to be missing. Similarly to Table A3, letter "A" in the table indicates that the value for the variable is directly available (so no need to extrapolate), while "E" indicates that the value for the variable is extrapolated (the corresponding region and specific countries used for extrapolation are shown in the parentheses). "n.a." indicates that the value for the variable is still missing. The regions considered are: East Asia, South Asia (including Kazakhstan, Pakistan, India), Europe, Latin America, North America (USA and Canada), Oceania, North Africa, Sub-Saharan Africa, and Middle East. After applying the procedure, the countries which still have missing values in the variables are excluded for the analyses. Thus, the finalized extended sample includes up to 66 countries (as indicated in Table 3, Column 5). To include as many countries as possible, a few minor adjustments are made: (i) ambiguity aversion (*AmbgAvsn*), and risk aversion (*RskAvsn*) are extrapolated from Lebanon (LBN) and Azerbaijan (AZE) to all Middle East countries (except Israel); (ii) ambiguity aversion (*AmbgAvsn*) and risk aversion (*RskAvsn*) are extrapolated from the Middle East (except Israel) to all North African countries. For expositional convenience, a short form is used: i.e., For *Indivsm*, "E (Europe)" in the table stands for E (Europe: AUT, BEL, BGR, CHE, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HRV, HUN, IRL, ITA, LTU, LUX, LVA, NLD, NOR, POL, PRT, ROU, RUS, SRB, SVN, SWE, TUR); For *HomBias*, "E (Europe)" stands for E (Europe: AUT, BEL, CHE, CZE, DEU, DNK, ESP, FIN, FRA, GBR, GRC, HUN, ITA, NLD, NOR, POL, PRT, RUS, SWE, TUR); and For *AmbgAvsn* and *RskAvsn*, "E (Europe)" stands for E (AUT, BEL, CHE, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HRV, HUN, IRL, ITA, LTU, LUX, NLD, NOR, POL, PRT, ROU, RUS, SVN, SWE, TUR). For brevity, only the 27 countries (not included in the baseline sample above) are listed in this table.

No.	ISO 3	Country Name	Continent	***Indivsm***	***HomBias***	***AmbgAvsn* and *RskAvsn***
1	EGY	Egypt	Africa (North)	A	A	E (LBN, AZE)
2	MAR	Morocco	Africa (North)	A	E (EGY)	E (LBN, AZE)
3	GHA	Ghana	Africa (Sub-Saharan)	A	E (ZAF)	E (NGA)
4	KEN	Kenya	Africa (Sub-Saharan)	A	E (ZAF)	E (NGA)
5	MUS	Mauritius	Africa (Sub-Saharan)	A	E (ZAF)	E (NGA)
6	NGA	Nigeria	Africa (Sub-Saharan)	A	E (ZAF)	A
7	ZAF	South Africa	Africa (Sub-Saharan)	A	A	E (NGA)
8	VNM	Vietnam	Asia (East)	A	E (CHN, IDN, JPN, KOR, MYS, PHL, SGP, THA)	A
9	KAZ	Kazakhstan	Asia (South)	E (IND, PAK)	E (IND)	E (IND)
10	PAK	Pakistan	Asia (South)	A	E (IND)	E (IND)
11	BGR	Bulgaria	Europe	A	E (Europe)	E (Europe)
12	CYP	Cyprus	Europe	E (Europe)	E (Europe)	E (Europe)
13	EST	Estonia	Europe	A	E (Europe)	A
14	HRV	Croatia	Europe	A	E (Europe)	A

(Table A4: continued)

15	ISL	Iceland	Europe	E (Europe)	E (Europe)	E (Europe)
16	LTU	Lithuania	Europe	A	E (Europe)	A
17	LUX	Luxembourg	Europe	A	E (Europe)	A
18	LVA	Latvia	Europe	A	E (Europe)	E (Europe)
19	ROU	Romania	Europe	A	E (Europe)	A
20	RUS	Russia	Europe	A	E (Europe)	A
21	SRB	Serbia	Europe	A	E (Europe)	E (Europe)
22	SVN	Slovenia	Europe	A	E (Europe)	A
23	UKR	Ukraine	Europe	E (Europe)	E (Europe)	E (Europe)
24	ARG	Argentina	Latin America	A	E (BRA, CHL, COL, MEX)	A
25	ARE	United Arab Emirates	Middle East	A	E (EGY)	E (LBN, AZE)
26	JOR	Jordan	Middle East	A	E (EGY)	E (LBN, AZE)
27	QAT	Qatar	Middle East	A	E (EGY)	E (LBN, AZE)

Table A5: Cross-Sectional Regressions for International Turnover at the Country Level, by Sub-Period

This table reports results of monthly Fama-MacBeth cross-sectional regressions (at the country level) using the baseline sample (from 41 countries) in Panel A as well as the expanded sample (from 66 countries) in Panel B. The sample period is from 2000 to 2021, and split into two sub-periods, 2000-2010, and 2011-2021. The dependent variable is the annualized monthly turnover (*TURN*). All variables are cross-sectionally standardized each month to have a mean of zero and a standard deviation of one in each sample. Variable definitions and data sources are described in Table A1, and the list of countries are reported in Table A2 in the Appendix. Newey-West (1987) *t*-statistics (with a lag of 4) for the time-series-averaged coefficients are reported in parentheses. The average of the adjusted R-squared (*AdjR-sqr*) across months is reported, together with the numbers of observations (*Obs*) and countries (*N_Country*). The coefficients significantly different from zero at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Fama-MacBeth Regression Results: Dep. Var. = *TURN*		
Variables	2000-2010	2011-2021
Indivsm	0.584***	0.428***
	(11.44)	(18.42)
HomBias	0.240***	0.369***
	(9.78)	(24.97)
AmbgAvsn	-0.190***	-0.161***
	(-9.66)	(-6.44)
RskAvsn	-0.008	-0.146***
	(-0.33)	(-10.52)
TFriction	-0.197***	-0.128***
	(-7.25)	(-15.72)
Freedom	-0.589***	-0.452***
	(-10.24)	(-12.63)
IncIneq	0.120***	0.288***
	(3.98)	(13.09)
Corrupt	0.102*	0.253***
	(1.72)	(7.59)
%Female	-0.189***	-0.318***
	(-3.26)	(-17.43)
%Age0T14	-0.095	-0.299***
	(-1.60)	(-10.28)
%Age65$^+$	0.668***	0.478***
	(8.18)	(14.61)
ForecDisp	0.378***	0.015
	(4.09)	(0.29)
InstOwn	0.159***	0.219***
	(5.30)	(8.74)
EarnVola	0.374***	0.004
	(3.14)	(0.44)
ln(MCap)	0.075**	-0.071***
	(2.14)	(-3.73)
MOMS	0.045	0.011
	(1.59)	(0.34)
MOML	0.125**	0.226***
	(2.54)	(2.95)
Intercept	0.464***	-0.292***
	(5.14)	(-4.77)
Country-Month Obs	3498	5004
AdjR-sqr	0.444	0.533
N_Country	38	39

Table A6: Turnover Sorts for Momentum Spreads across Countries

This table reports the results for how momentum profits vary by share turnover across the world, for both the baseline and extended samples, which are described in Table A2. Each month, all global stocks are sorted into quintiles by their share turnover, and within each share turnover quintiles, into five momentum quintiles, where momentum is the compound return from two to twelve months ago. For each turnover quintile, the next-month equal-weighted return differential is computed across the momentum quintiles, and these five returns are also averaged across the turnover quintiles. Variable definitions are described in Table A1 in the Appendix. Newey-West (1987) *t*-statistics (with a lag of 4) for the time-series-averaged coefficients are reported in parentheses. The coefficients significantly different from zero at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

With the Baseline Sample

Group	Mean H-L (%)	NW t-stat
TURN Q1	1.26	3.41***
TURN Q2	0.51	1.21
TURN Q3	0.21	0.51
TURN Q4	0.25	0.56
TURN Q5	-0.16	-0.28
Q5 - Q1	-1.42	-4.03***

With the Expanded Sample

Group	Mean H-L (%)	NW t-stat
TURN Q1	1.32	3.56***
TURN Q2	0.53	1.25
TURN Q3	0.29	0.69
TURN Q4	0.28	0.64
TURN Q5	-0.10	-0.18
Q5 - Q1	-1.42	-3.98***

Table A7: National Characteristic Variables Used in Barro (2003)

This table reports the country-level variables used in Barro (2003, Table 3), who models them as the determinants of GDP growth. These variables include the following 11 variables: (1) male upper-level schooling (to measure educational attainment); (2) inverse of life expectancy at age 1 (to measure health capital); (3) natural logarithm of the total fertility rate (to measure population growth); (4) the ratio of government consumption to GDP (to measure public finance); (5) a subjective score on the rule of law (to measure enhancement of property rights); (6) openness ratio (the ratio of exports plus imports to GDP); (7) the change in terms of trade (measured by the annual change in the ratio of import to export prices); (8) the ratio of domestic investment to domestic GDP; (9) inflation rate (to measure macroeconomic stability); (10) a subjective indicator of democracy; and (11) the squared version of democracy (both to measure political power). Changes in terms of trade occasionally take on extreme values. To mitigate the influence of outliers/errors, we truncate this variable at ±200%. The middle column lists the exact or closest measures identified from the corresponding databases (sources). For details, please see Barro (2003). All variables are measured at an annual frequency.

No.	Variables	Exact or Closest Measures	Source
1	Male Upper-Level Schooling	Human Capital Index	Penn World Table
2	1/(Life Expectancy at Age 1)	Life Expectancy at Birth, total (in years)	World Bank
3	Log(Total Fertility Rate)	Fertility Rate, total (births per woman)	World Bank
4	Govt. Consumption/GDP	General Govt. Final Consumption Expenditure (% of GDP)	World Bank
5	Rule of Law	Rule of Law: Estimate	World Bank
6	Openness Ratio	Trade (% of GDP)	World Bank
7	Change in Terms of Trade	Terms of Trade Adjustment (constant LCU)	World Bank
8	Investment Ratio	Share of Gross Capital Formation at Current PPPs	Penn World Table
9	Inflation Rate	Inflation in Consumer Prices (annual %)	World Bank
10	Democracy	*Freedom* as defined in Table A1	Freedom House Dataset
11	Democracy Squared	Square of *Freedom*	Freedom House Dataset