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Three Essays in Behavioural Finance

by

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Thesis

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Declarations

I declare that any material contained in this thesis has not been submitted for a degree to any other university. I further declare that both Chapter 2 and Chapter 4 are joint work products with Dr. Constantinos Antoniou, Dr. Carina Cuculiza, and Prof. Alok Kumar. Chapter 3 is my solo work.

Lizhengbo Yang

September, 2021

Abstract

This thesis consists of three essays in behavioural finance. With one essay in chapters 2, 3, and 4, respectively, this doctoral thesis studies the impact of air travel and cultural distance on financial market participants.

Chapter 2 examines whether international tourism affects financial market investments. Using data for more than 40 countries, we demonstrate that recreational travel between countries is associated with higher foreign equity investments. Increased foreign investment leads to a reduction in home bias and improved diversification. The impact of tourism is more potent for countries that are farther apart or when home country residents are more risk-averse. Using predictors of recreational travel as instruments, we show that the relation between foreign travel and foreign equity investments is causal. Collectively, these results suggest that tourism has positive externalities in financial markets.

Chapter 3 examines how air travel affects analyst coverage and forecast accuracy. Using air travel to proxy analysts' information environment with firms, I find air travel from analyst location to firm headquarter location stimulates analyst coverage of firms. This effect is identified with the initiation of new air routes, and the terrorist attacks and mass shootings near firm headquarter city. The results also show that air travel stimulates optimism analyst forecast, confirming the hypothesis that air travel induces recognition heuristic rather than information advantage. However, the interaction effect of shared analyst coverage and air travel has positive externalities on stock comovement and return predictability.

Chapter 4 examines whether the risk preferences of S&P500 CEOs' spouses have a spillover impact on corporate risk-taking, especially when CEOs and their spouses come from different cultural backgrounds. Our hypothesis is motivated by recent research in the social sciences that individual traits can converge over time within closely formed groups. To empirically test the hypothesis, we hand-collect data on CEOs' and spouses' cultural origins and test whether differences in risk-related cultural norms influence corporate risk-taking. We find that firms managed by CEOs married to spouses from relatively more

risk-averse cultures will take on less corporate risk. These results are robust to various econometric specifications, including a model with CEO fixed effects in a sample of CEOs with more than one marriage. Overall, our findings suggest that the cultural composition of a CEO's household affects corporate decisions.

Chapter 1

Introduction

Behavioural finance aims to explain the irrational behaviour and decisions of financial market participants, including households, investors, financial analysts, and corporate managers, under the influence of psychology. Contrary to the traditional assumption of rational market participants, behavioural finance study assumes financial market participants are not always rational. The irrational decisions made by market participants lead to systematic errors which affect stock prices, returns, firm performance, and market inefficiencies. Behavioural finance study is interdisciplinary. Besides psychological principles, the recent popular topics in behavioural finance connect the finance study with the study of geography, politics, culture, social connections, gender, climate, etc., attempting to explain specific financial outcomes with these factors. This thesis comprises three essays in behavioural finance, contributing to the recent literature on how air travel and culture influence financial market participants. Precisely, the paper in Chapter 2 investigates the influence of international tourism on investors' foreign equity holdings. The paper in Chapter 3 examines how air travel impacts analyst forecasts. Chapter 4 includes a paper studying the cultural composition of a CEO's household and corporate risk-taking.

Chapter 2 is joint work with Dr. Constantinos Antoniou, Dr. Carina Cuculiza, and Prof. Alok Kumar. We find that travelling to foreign countries stimulates foreign equity investments. When investors construct their international equity portfolios, they face a complex search problem as they have to select to invest in which countries. As time and other constraints do not allow investors to conduct detailed analyses on all countries, more capital may be allocated to countries that spring more readily to investors' minds. Besides the home country, it is also likely that certain foreign countries that are more recognizable to investors attract more significant equity investments. This conjecture is motivated by experimental research, which shows that people value objects according to a recognition heuristic (Goldstein and Gigerenzer, 2002), where more recognizable objects in a set are ranked higher. One avenue through which foreign countries can become more recognizable is recreational travel between countries. During these travels, tourists will have experienced the country's customs and culture, its general living standard, the quality of its local products and services, and various attitudes of its citizens. We conjecture that these first-hand experiences will make this foreign country more recognizable to foreign visitors. Thus, when they subsequently construct their international equity portfolio, they will be more likely to include these visited countries in their portfolio.

To test this conjecture, we obtain annual bilateral data on foreign equity holdings from the Co-ordinated Portfolio Investment Survey (CPIS) and tourism data from the World Tourism Organization (UNWTO). To capture the foreign equity investment, we measure foreign ownership which is the ratio of equity investments by residents of a given home country in a given foreign country over the total foreign investments made by residents of this home country. Then we take the natural logarithm of the number of citizens of this home country travelling to the given foreign country in the previous year as the primary explanatory variable of international tourism.

We find that the coefficient on international tourism is positive and statistically significant. International tourism between countries is associated with higher levels of foreign equity investments. This result continues to hold when we instrument travel using variables shown to predict recreational tourism. The effect of travel is more potent when the distance between the home and the foreign country is farther and when the population in the home country exhibits higher uncertainty avoidance. On the home country level, more outward tourism is associated with a reduction in the home bias. Collectively, our results suggest that tourism has positive externalities: inward tourism stimulates an inflow of investments in local equities, and outward tourism helps local investors construct better diversified portfolios.

These findings in Chapter 2 contribute to several strands of finance, especially behavioural finance literature. First, it complements the literature that examines the determinants of foreign equity investments and the home bias puzzle. Second, our work combines tourism and finance study by examining the effect of tourism on equity investments in an international setting. Finally, Our study complements the literature that examines the effect of familiarity on international portfolio choice.

After documenting the influence of international tourism on investors' foreign equity holdings in Chapter 2, Chapter 3 turns to examine whether travel can impact the decisions of other financial market participants, especially sell-side financial analysts. Sell-side analysts provide specialized information to other market participants helping them make financial decisions. However, because little is known about the "black box" how analysts acquire information, analyst forecasts can be biased (Ramnath, Rock, and Shane, 2008). Some determinants of information processing and forecast accuracy of analysts are documented in previous behavioural finance literature like geographical proximity (Malloy, 2005), political contribution (Jiang, Kumar, and Law, 2016), culture distance (Du, Yu, and Yu, 2017), and education connections (Fang and Huang, 2017). Chapter 3 complements these studies by finding that air travel can drive analyst coverage and forecast accuracy. Air travel breaks the obstruct of geographical distance and improves the information environment between analysts and companies. On the one hand, it allows analysts to access some firm-specific information quickly. On the other hand, it makes firms at the destination become more familiar and recognized to local analysts.

To explore the effect of air travel on analyst coverage and forecast accuracy, I firstly obtain data on quarterly analyst earnings forecasts for U.S. firms traded on NYSE, AMEX, or NASDAQ from Thomson Reuters' Institutional Brokers Estimate System (IBES). Based on these data, I can compute each firm's analyst coverage and analyst forecast errors. Then I obtain air travel data from the U.S. Department of Transportation (DOT), including airports' location and the number of passengers between two airports. To match the analyst forecast data and air travel data, I obtained the location of companies and analysts from multiple databases, including Compustat, IBES, Thomson Reuters, and FINRA.

I firstly find air travel is positively and significantly correlated with analyst coverage. To address the endogenous concerns and identify the causal effect, I pick up two instrumental variables regarding exogenous shocks on air travel from the literature and find that results still hold. This chapter then shows that air travel is also positively associated with analyst forecast errors, specifically, more optimistic forecasts. These findings confirm the hypothesis that air travel leads to a recognition heuristic and induces more biased expectations rather than information advantage. Finally, the market reaction results document that the interaction of air travel and shared analyst coverage has positive predictability on stock comovements and future returns.

Chapter 4 is also co-authored with Dr. Constantinos Antoniou, Dr. Carina Cuculiza, and Prof. Alok Kumar. We turn to recent studies of peer effects and culture with financial outcomes. Research in social science shows that, within closely formed groups, individual traits can converge over time. A natural question is whether CEOs' spouses' preferences affect corporate decisions. On the one hand, CEOs are hired for their specific skills, knowledge and preferences. Thus, the preferences of their spouses should not enter corporate decisions. On the other hand, evidence suggests that in closely related groups such as marriages, individuals' traits such as risk preferences can become more similar over time (Serra-Garcia, 2021). Such convergence in preferences between CEOs and their spouses may lead to spouses indirectly influencing corporate decisions. The risk preferences of CEOs and their spouses are not directly observed, but to some extent, shaped by cultural heritage (Falk et al., 2018). Thus, to empirically test our hypothesis, we examine whether culturally related differences in the propensity to take risks between CEOs and their spouses affect corporate decisions. Various studies in finance show that the culture of the CEO matters for corporate risks (e.g., Ahern, Daminelli, and Fracassi, 2015; Pan, Siegel, and Wang, 2017; Nguyen, Hagendorff, and Eshraghi, 2018). However, no study examines whether differences in risk-related culture norms between CEOs and their spouses affect corporate risk-taking.

To construct our variable, we first manually collect data on the cultural origins of CEOs of S&P500 firms and their spouses from multiple databases, measuring their risk attitude using the Hofstede Uncertainty Avoidance Index (UAI) for their country of origin. We use the difference between spouse's UAI and CEO's UAI, then scaled by CEO's UAI as our primary measure of cultural distance. To measure corporate risk-taking, we use the industry-adjusted volatility of return on assets.

Consistent with our conjecture, we find that cultural distance has a negative and statistically significant effect on a firm's operation risk. This finding suggests that, in the cross-section of CEO-spouse pairs, firms headed by a CEO whose spouse is relatively more risk-averse adopt relatively safer corporate policies. We conduct two additional tests to address the endogenous concern that the choice of spouse reflects the CEO's own risk attitudes instead of the marriage spillover effect. First, we conduct a placebo test where we randomly match a CEO to a different spouse in our sample. We repeat this random match

1,000 times and find the coefficient is centred around zero, which means our findings are not capturing the effect of CEOs' risk attitude. Second, we estimate a model with CEO fixed effects, which absorb CEO-level personal characteristics, including risk attitude. Our results still hold. We also perform a propensity score matching exercise to compare similar firms whose only difference is whether their CEOs share a similar cultural background with their spouses. We then try another two measures of corporate risk-taking, R&D expenditure and litigation suits. We find our results still hold. Finally, we find that the effect of cultural distance is stronger if CEOs come from low individualism culture and if CEOs are first-, second- or third-generation of immigrants.

In the end, Chapter 5 concludes with a discussion of the findings and contributions of this thesis and discusses future potential research questions.

Chapter 2

Seeing is Believing: Tourism and Foreign Equity Investments

2.1 Introduction

Investors face a difficult search problem when constructing their international equity portfolios. Given the various constraints, more capital is likely to be allocated to countries that come more easily to the mind of investors. Consequently, investor portfolios would exhibit a home bias as investors would be naturally drawn towards their home countries (French and Poterba, 1991). It is also likely that certain foreign countries that are more recognizable to investors attract more equity investments.

Experimental research shows that people value objects according to a *recognition heuristic* (Goldstein and Gigerenzer, 2002), where more recognizable objects in a set are ranked higher. For example, Kilka and Weber (2000) find that German individuals are more optimistic about German companies than American companies, while American subjects display the opposite pattern. Further, in a portfolio choice setting, households who are more aware of the stock market are more likely to invest in equities (Dimmock et al., 2016). Investors also overweight recognizable assets in their portfolios (French and Poterba, 1991; Huberman, 2001), including their employers' stocks (Benartzi, 2001). These findings suggest that awareness about a specific topic may induce a positive bias in investor expectations, and recognizable assets are likely to be viewed more favourably.

One avenue through which foreign countries can become more recognizable to investors is international travel, especially *recreational travel* between countries. During international visits, individuals can experience a country's customs and culture. These first-hand experiences can make a foreign country more recognizable, than other unvisited countries. Therefore, international tourism across countries can increase awareness about a country, lower international stock market participation costs, and stimulate foreign equity investments. When investors with greater international travel experience pick foreign firms, they are more likely to include firms from these visited countries and reduce home bias. In this paper, we focus on recreational travel rather than business trips. Compared with business trips that are endogenously related to economic activities, the primary purpose of recreation travel is to enjoy foreign countries' weather or local customs that are more exogenous to foreign investments.

To test this conjecture, we obtain annual data on foreign equity holdings from the Co-ordinated Portfolio Investment Survey (CPIS) and tourism data from the World Tourism Organization (UNWTO). Our sample period is from 2001 to 2016 and covers around 40 countries. The dependent variables in our empirical models capture the equity holdings in a specific foreign country by the citizens of another home country in a specific year. We use two different dependent variables in our analysis. The first measure is *Foreign Ownership*, which is the ratio of equity investments by residents of the home country i in the foreign country j over the total foreign investments made by residents of the home country i. The second variable is *Adjusted Foreign Ownership*, which adjusts ownership according to the weight that country j receives in the world market portfolio.

The key independent variable in our models is *Travel*, defined as the natural logarithm of the number of citizens of a home country travelling to a foreign country in the previous year. We expect for the coefficient on *Travel* to be positive and statistically significant, suggesting that more recreational travel is associated with greater equity investment in a country.

Our empirical models control for several variables that could affect foreign equity investments, which we divide into four categories: (i) *General country characteristics,* (ii) *Financial variables,* (iii) *Links between the two countries,* and (iv) *Transaction costs.* Overall, we control for 28 variables that may influence foreign equity investment decisions. In addition, we include various fixed effects in order to absorb time-invariant unobservable variables that may bias our estimates (i.e., home and foreign country fixed effects, home-year and foreign-year fixed effects, or country-pair fixed effects).

Our results are consistent with our key conjecture, as we find that the coefficient on *Travel* is positive and statistically significant. In economic terms, a one standard deviation increase in *Travel* is associated with a 1.25% increase in *Foreign Ownership* and a 13.45% increase in *Adjusted Foreign Ownership.* This evidence suggests that international tourism generates positive externalities, where host countries that become more recognizable to investors attract greater foreign equity capital.

Travel may capture the effect of an economic variable that is omitted from our specifications. For example, someone travels abroad for international business cooperation, searching for investment opportunities, or engaging in other economic activities. As we cannot ensure all tourists only travel for leisure, these business-related trips may be endogenously related to foreign investments. To address these potential endogeneity concerns, we test our main hypothesis using an instrumental variable estimation framework. Our instruments are tourism-related variables that capture the decision of a recreational traveller to visit a specific country for the holidays rather than business trips.

Specifically, motivated by the evidence in the tourism literature, we use the following two instruments: *Holiday Climate Index,* which captures the appeal of the climate of a particular country for foreign tourists (e.g., Scott et al., 2016) and a *Scenery Index,* which reflects the number of sites in a country that are included in the World Heritage List. These two variables are known to be positively related to the number of tourists visiting a specific country (e.g., Arezki, Cherif, and Piotrowski, 2009; Culiuc, 2014; Saha and Yap, 2014; Scott et al., 2016). We consider the relative difference between the indices for the foreign country and the indices for the home country, expecting that more tourism will flow into countries with relatively better weather and more interesting sites.

Consistent with the findings from the tourism literature, we find that, in the first stage regression where the dependent variable is *Travel*, these indices are both positive and statistically significant. Outbound tourists fly to foreign countries with better weather for outdoor activities, or to foreign countries with more famous sites, than their home countries. In the second stage of the estimation, the results show that the coefficient on (instrumented) *Travel* is positive and statistically significant for all the regression specifications. These findings provide causal evidence that recreational tourism drives foreign equity investments.

Our results are similar when we consider alternative definitions for *Travel* and exclude economically large countries from our dataset (China, France, Germany, Japan, U.K., and the U.S.). The findings are also robust to augmenting our main specification with control variables that capture migration flows, remittance levels, and the general public attention that citizens of a home country pay to another foreign country. Additionally, we examine whether our findings are affected by reverse causality, i.e., the possibility that people travel more to countries where they have higher investments. The evidence does not support this alternative story, as we find that *Foreign Ownership* and *Adjusted Foreign Ownership* cannot predict *Travel*.

In our next set of tests, we examine whether the effect of tourism on foreign equity investments differs in the cross-section of country pairs. The first variable we consider is the geographical distance between two countries. Since people are in general more knowledgeable about countries that are located closer to them, *Travel* may be more impactful in making a foreign country more recognizable to investors if this foreign country is geographically distant. To examine this possibility, we divide our sample of countries into two groups based on the geographical distance between the home and foreign countries and perform our analysis separately in each group. In line with our hypothesis, we find that the effect of *Travel* on foreign equity investments is more potent for countries that are located farther away.

Motivated by the observation that cultural attributes affect economic exchange (e.g., Guiso, Sapienza, and Zingales, 2006), we also examine whether the effect of travel on international equity investments interacts with the general risk-taking propensity of foreign visitors. However, it is difficult to determine the direction of the effect ex-ante. On the one hand, it is possible that people travelling from more risk-averse cultures are less willing to invest internationally. Thus, travel may have a weaker effect on their foreign equity investments. On the other hand, travellers from more risk-averse countries are also likely to be less familiar with international countries because they are less likely to gather information about them. As a result, travel could have a more significant effect on their investments since it will induce a larger positive "shock" in the recognizability of a foreign country.

To test this conjecture, we split our sample into two groups based on the degree of uncertainty avoidance in a home country defined using Hofstede's (2001) cultural dimensions. We find that travel has a significant effect on foreign equity investments only if the Uncertainty Avoidance Index of the home country is high. Overall, the results from our cross-sectional tests suggest that travel is more impactful on foreign equity investments when the degree to which a specific foreign country is recognizable is ex-ante lower.

In the next set of tests, we directly investigate whether international tourism affects home bias, i.e., the tendency of investors to overweight their home countries in their portfolios (e.g., French and Poterba, 1991; Karolyi and Stulz, 2003). Due to international travels, investors in a home country may decrease the weight of their home country in their portfolio and increase the weights assigned to foreign countries that they visit.

We test this hypothesis using a country-level model. The dependent variable is the portfolio weight of home country equities relative to their size in the world market, i.e., home bias. The main independent variable of interest is the *Total Travel* variable, which is defined as the natural logarithm of the total number of people from the host country who travel abroad in a given year. Consistent with our conjecture, we find that *Total Travel* is associated with a decrease in home bias. The economic effect is meaningful, as a one standard deviation increase in *Total Travel* is associated with a 9.8% reduction in home bias.

In our last test, we examine whether tourists can better extract value-relevant information through their travels. We estimate a country-level regression, where the dependent variable is the return of the foreign equity portfolio held by the residents of a specific country in a given year. The key independent variable is *Total Travel.* If travellers extract value-relevant information in their travels, we would expect the coefficient on *Total Travel* to be positive and statistically significant. Contrary to this prediction, we find that the coefficient on *Total Travel* is insignificant in all models. This evidence suggests that the effect of international travel on foreign equity investments is unlikely to be information related.

These empirical findings contribute to several strands of finance and economics literature. First, it complements the literature that examines the determinants of foreign equity investments and the home bias puzzle. Previous studies on this topic indicate that international investments are affected by transaction costs (Glassman and Riddick, 2001), real exchange rate risks (Fidora, Fratzscher, and Thimann, 2007), information-related factors (Ahearne, Griever, and Warnock, 2004; Van Nieuwerburgh and Veldkamp, 2009; Andrade and Chhaochharia, 2010; Choi et al., 2017; Dumas, Lewis, and Osambela, 2017), corporate governance (Dahlquist et al., 2003), and cross-listings (Ammer et al., 2012).

Other work emphasizes the effect of behavioural variables such as culture and trust (Guiso, Sapienza, and Zingales, 2009; Beugelsdijk and Frijns, 2010; Aggarwal, Kearney, and Lucey, 2012). Our results contribute to this literature and demonstrate that tourism can positively affect international investment decisions and reduce home bias.

In a related paper, Giroud (2013) uses air travel data to show that the exogenous introductions of airline routes increase the proximity between the headquarters of companies and their manufacturing plants, leading to better firm performance.[1] Da et al. (2021) show that travel within the U.S. increases cross-state institutional investments. Our work extends this literature and examines the effect of tourism on equity investments in an international setting. We study a comprehensive sample of foreign investments in over 40 countries spanning 21 years, focusing on the effect of tourism on foreign equity investments and the home bias.

Our analysis identifies two positive externalities of tourism that are novel to the international finance literature. First, for the home country, more outward travel is associated with an increase in investments abroad, a reduction in the home bias, and better diversification. Second, for recipient countries, an influx of tourism is associated with an increase in foreign capital invested in local equities. Our instrumental variables model suggests that these effects of tourism are causal. Further, because we study a large sample of countries with different characteristics, we are able to identify cross-sectional differences in the effect of tourism. Travel matters most when the distance between the two countries is greater or when the population in the home country is more risk-averse.

Our study also complements the literature that examines the effect of familiarity on international portfolio choice (e.g., Portes and Rey, 2005; Guiso, Sapienza, and Zingales, 2009; Beugelsdijk and Frijns, 2010; Aggarwal, Kearney, and Lucey, 2012). In these studies, familiarity is typically captured by variables that are "fixed" at the country pair level, such as geographical or cultural distance. Our results highlight the effect of familiarity in a more dynamic setting, since our models focus on the effect of variation in tourism while accounting for fixed country characteristics that are known to be related to familiarity.

The rest of the paper is organized as follows: Section 2 describes the data and the methodology, Section 3 presents the main results, Section 4 presents the results from various robustness checks, Section 5 presents additional results, and Section 6 concludes.

[1] Other studies that emphasize the economic implications of improved monitoring as a result of air travel include Bernstein, Giroud, and Townsend (2016) and Chemmanur, Hull, and Krishnan (2014).

2.2 Data and Methodology

In this section, we briefly describe the data used in our empirical analysis, as well as the empirical methodology.

2.2.1 Foreign Equity Holdings and Tourism Data

We collect foreign equity holdings data from the Co-ordinated Portfolio Investment Survey (CPIS) conducted by the International Monetary Fund (IMF). CPIS provides the data of year-end equity holdings in each foreign country by resident investors in a given home country every December from 2001 to 2016. The survey includes both end-investors (e.g., banks, security dealers, pension funds, insurance companies, mutual funds, households, etc.) and custodians who hold or manage securities on behalf of others. All holdings are expressed in U.S. dollars.

We obtain outbound travel data from the World Tourism Organization (UNWTO). UNWTO provides statistics on the annual number of residents from each home country travelling to each foreign country from 1995 to 2016.

There are 90 home countries in the CPIS dataset and 223 home countries in the UNWTO dataset. From the merged database of these two sources, we further exclude some countries that are defined as offshore financial centres or tax havens by the IMF, such as Luxembourg, Ireland, and the Caribbean countries. We then require that a country has available data to estimate our models: data from CPIS and UNWTO, data on the instruments used in our instrumental variable model (discussed in the next section), and the various control variables (see Appendix Table 2.A1). From the resulting sample, we keep all developed countries and large developing countries (with more than 100 billion U.S. dollars GDP). Our final dataset is comprised of 37 home countries (22 developed countries and 15 developing countries) and 41 foreign countries (23 developed countries and 18 developing countries), which are listed in Table 2.1.

[Insert Table 2.1 here]

2.2.2 Variable Definitions

We use two different measures to capture foreign equity investments. The first measure, Foreign Ownership (W_{ijt}), is the dollar value of the equity holdings in a foreign country j

by investors of the home country i in year t, scaled by the total foreign equity holdings by investors of home country i in year t:

$$W_{ijt} = \frac{FEH_{ijt}}{\sum_{j=1}^{n} FEH_{ijt}} \tag{1}$$

where FEH_{ijt} is the dollar value of equity holdings in foreign country j by investors of home country i in year t.

The second measure, *Adjusted Foreign Ownership* (AW_{ijt}), is an adjusted measure of foreign ownership by the benchmark weight (Bekaert and Wang, 2009; Baltzer, Stolper, and Walter, 2013):

$$AW_{ijt} = \begin{cases} \frac{W_{ijt}-w^*_{jt}}{w^*_{jt}} & \text{when} \quad W_{ijt} \leq w^*_{jt} \\ \frac{W_{ijt}-w^*_{jt}}{1-w_{jt}{}^*} & \text{when} \quad W_{ijt} > w^*_{jt} \end{cases} \tag{2}$$

In this equation, w^*_{jt} is the benchmark weight calculated as:

$$w^*_{jt} = \frac{\text{Market cap}_{jt}}{\sum_{j=1}^{n} \text{Market cap}_{jt}} \tag{3}$$

Thus, the portfolio weight on each foreign country j is adjusted by the benchmark weight of this country in the world economy. The benchmark weight of a given country is its market capitalization to the world market capitalization.[2] With this definition, AW_{ijt} ranges from -1 to 1, where an increase in AW_{ijt} indicates a higher portfolio weight by investors in the home country i on foreign country j in year t. A negative (positive) value of AW_{ijt} indicates under-investment (over-investment) in the foreign country j. A value of zero arises when $W_{ijt} = w^*_{jt}$, and thus, the weight attached to the foreign country in the home investors' portfolio is equal to the benchmark weight of the foreign country in the world.

The key independent variable in our models is *Travel*, defined as the natural logarithm of the number of citizens of the home country i travelling to the foreign country j in year t, as obtained from UNWTO.

In our regression specifications, we include several control variables that have been shown to influence foreign equity investments. First, we account for general country characteristics. We incorporate the foreign market's benchmark weight in the global market

[2]This benchmark weight is widely used in the literature on the home bias puzzle (e.g. Chan, Covrig, and Ng, 2005; Bekaert and Wang, 2009; Choi et al., 2017).

portfolio, which captures any size-related effects. *Market Cap/GDP (H)* and *Market Cap/GDP (F)* are market capitalizations scaled by GDP, which proxy for the equity market development in the home and foreign countries (Bekaert and Wang, 2009).[3] *GDP growth (H)* and *GDP growth (F)* are the GDP growth rates of the home and foreign countries. *CPI (H)* and *CPI (F)* are the annual percentage changes of the Consumer Pricing Indices (CPI) in the home and foreign countries. *Ln(Population)* is the population of the home country. Additionally, we include *Corruption control (F)* to capture the quality of corporate governance in the foreign market (Kaufmann, Kraay, and Mastruzzi, 2009). *Developed dummy (H)* and *Developed dummy (F)* are dummy variables equal to one when the home or foreign countries are developed, and zero otherwise.

We also include several financial market variables. Ret_{t-1}*(H)* ($Ret_{t-6,t-2}$*(H)*) and Ret_{t-1}*(F)* ($Ret_{t-6,t-2}$*(F)*) are the market index returns of the home and foreign countries in the previous year (in the previous t-6 to t-2 years), respectively. Vol_{t-1}*(F)* and $Vol_{t-6,t-2}$*(F)* are the volatilities of market index returns of the foreign countries in the previous year and in the previous t-6 to t-2 years, respectively. *Return covariance* is the return covariance between a home country and a foreign country. *P/E ratio (F)* is the annual average daily price to earnings (P/E) ratio in a foreign country. *Relative P/E ratio* is the relative P/E ratio between a home and a foreign country, measured as *P/E ratio (H) over P/E ratio (F)*. *EPS estimate (F)* is a foreign stock market index's 12-month forward analyst earnings forecast.

We further control for potential links between a home and a foreign country by including *Ln (Distance)*, the distance between home and foreign countries, and an indicator of whether the same official language is used in the two countries. *Overlap trading hours* is the number of overlapping trading hours between a home and a foreign country. *Ln(Trade)* controls country-pair bilateral trade (e.g. Brennan and Cao, 1997; Portes and Rey, 2005; Bekaert and Wang, 2009; Thapa and Poshakwale, 2012).

Additionally, we control transaction costs by including *REER*, the real effective exchange rate. *Amihud illiquidity (F)* measures the liquidity of the stock market of a foreign country (e.g., Lesmond, 2005; Fidora, Fratzscher, and Thimann, 2007; Thapa and Poshakwale, 2012). *Same currency* is an indicator variable equal to one if a home country and a foreign country use the same currency, and zero otherwise. Details on the

[3] H indicates home country, and F indicates foreign country.

construction of all the control variables are provided in Appendix Table 2.A1.

Our baseline regression specification is as follows:

$$Y_{ijt} = \alpha + \beta_1 \cdot Ln(Travel_{ij,t-1}) + \mathbf{X}' \cdot \beta_{\mathbf{A}} + \text{Fixed effects} + \epsilon_{ijt} \tag{4}$$

where Y_{ijt} is either the *Foreign Ownership* of residents of the home country i in foreign country j in year t (W_{ijt}) or *Adjusted Foreign Ownership* (AW_{ijt}). $Ln(Travel_{ij,t-1})$ is our main variable of interest, which captures the number of people from country i travelling to country j. $\mathbf{X}'$ is the vector of control variables, measured in year t-1. We apply various fixed effects. Following Bekaert and Wang (2009), standard errors are clustered by country pair for all our models.

2.2.3 Summary Statistics

Table 2.2 reports the summary statistics, averaged for home countries. Notably, the overall average value of *Adjusted Foreign Ownership* is negative, consistent with the evidence in the home bias literature (e.g., French and Poterba, 1991; Cooper, Sercu, and Vanpée, 2017).

In Appendix Table 2.B1, we present descriptive statistics for *Adjusted Foreign Ownership* for each home country separately. We find that the mean value is negative for all countries, with considerable variation at a given time across countries and at a given country across years. Appendix Table 2.B2 presents averages of key variables at the foreign country level, and Table 2.B3 presents correlations between the variables, respectively.

[Insert Table 2.2 here]

2.3 Main Empirical Results

In this section, we test our main hypothesis. We first present our baseline results using ordinary least squares panel regressions.[4] We then address the possibility that *Travel* is an economically endogenous variable by estimating a two-stage instrumental variables model.

[4] We multiply all coefficients by 100 when the dependent variable is *Foreign Ownership* in this section and all following sections.

2.3.1 Baseline Results

We report the baseline estimation results in Table 2.3. The dependent variable in Panel A is *Foreign Ownership* and in Panel B is *Adjusted Foreign Ownership.* In Columns (2) and (7), we include the full set of controls, along with time fixed effects. In line with the recognition hypothesis, we find that the coefficient on *Travel* is positive and statistically significant in both models. This effect is also economically meaningful. For instance, a one standard deviation increase in *Travel* is associated with a 1.25% ($1.92 \times 0.65/100$) increase in *Foreign Ownership*, which roughly corresponds to \$8.73B (1.25% × \$698.76B).[5] Similarly, a one standard deviation increase in *Travel* is associated with a 13.45% (1.92×0.07) increase in *Adjusted Foreign Ownership*, i.e. bringing the portfolio weight put on foreign countries closer to the theoretically predicted benchmark weight by 13.45%.

In Columns (3) and (8), we augment the model to include *Home* and *Foreign* country fixed effects, which control for any time-invariant country-level attributes, such as the general level of trust exhibited toward outsiders (e.g., Guiso, Sapienza, and Zingales, 2009). In Columns (4) and (9), we include *Home country* × *Time* and *Foreign country* × *Time* fixed effects, which control time-varying country-level attributes, such as economic growth, inflation, risk tolerance, sentiment, among others. Finally, in Columns (5) and (10), we follow Glick and Rose (2002) and include *Country-pair* fixed effects, which control additional factors, such as cultural differences between countries (e.g., Guiso, Sapienza, and Zingales, 2009). The control variables in our specifications vary depending upon the choice of the fixed effect.

As shown in Panels A and B of Table 2.3, the coefficient on *Travel* is positive and statistically significant across all specifications. Examining the estimates of the control variables, we find that the benchmark weight of the foreign country in the global market portfolio has a positive and statistically significant effect. The ratio *Market Cap/GDP* of the foreign country is negative and statistically significant, consistent with the findings of Andrade and Chhaochharia (2010). Moreover, we find that the indicators of common language and same currency both positively affect foreign investment, in line with the findings in Portes and Rey (2005).

[Insert Table 2.3 here]

[5] 1.92 is the standard deviation of $Ln(Travel_{ij,t-1})$. \$698.76B are the mean of total foreign equity holdings.

2.3.2 Instrumental Variables Model

One limitation of outbound tourism data from UNWTO is that it does not ensure that all tourists only travel for recreational purposes. Those tourists who travel for business, or both recreational and business purposes tend to be endogenously related to economic activities, such as searching for investment opportunities. To address these potential endogeneity concerns that our main explanatory variable *Travel* is endogenously related to economic activities and foreign equity investments, we use an instrumental variables (IV) model to identify the causal effect of recreational travel on foreign equity investments. Following the tourism literature, we use two variables that measure how attractive it is to travel to a country for recreational purposes.

The first instrument, *Holiday Climatic Index* (*HCI*), measures the comfortable weather with which tourists can engage in outdoor activities in a specific country. It is designed by Scott et al. (2016) to assess the climatic suitability of destinations for leisure tourism, based on the literature on tourist climatic preferences. According to Scott et al. (2016), the rating and weighting scheme of *HCI* combines tourist climatic literature and a range of surveys across countries over ten years. Then it has been empirically validated in the tourist marketplace, so it is not a subjective scale. *HCI* incorporates four aspects of climate important to leisure tourism activities in tourism literature, and it is calculated using the following formula:

$$HCI = 4 \times T + 2 \times A + 3 \times R + W \tag{5}$$

where T = thermal comfort (°C), A = cloud cover (%), R = daily precipitation (mm), and W = wind speed (km/h). Thermal comfort is also called effective temperature, capturing daily maximum temperature (°C) and mean relative humidity (%). The weighting of each climatic variable is assigned based on the ranking of the relative importance of tourist preferences of these climatic variables from the surveys. Each climatic variable is rated on a scale from 0 to 10, with an overall *HCI* score from 0 (dangerous for tourists) to 100 (ideal for leisure tourists). Table 2.C1 in Appendix C shows the rating scales of each climatic variable in Scott et al. (2016).

We obtain the annual data of average cloud cover and average daily precipitation for each country in our sample from the Climatic Research Unit (CRU), University of

East Anglia. Data of daily maximum temperature, mean relative humidity, and wind speed are obtained from POWER Data Access Viewer, NASA. NASA provides city-level data for relative humidity and wind speed. If the database provides data for a number of cities, we use the average of those values in our calculations.[6] We use the effective temperature table of the U.S. National Oceanic and Atmospheric Administration (NOAA) to identify thermal comfort based on corresponding maximum temperature and mean relative humidity.[7] Finally, we use annual average of each climatic variable to compute the HCI for each country in each year. Taking HCI of U.K. in 2015 as example, the annual average thermal comfort (T) is 12.5°C, annual average cloud cover (A) is 78.7%, annual average daily precipitation (R) is 3.86mm, and annual average wind speed (W) is 20.58km/h. Following the rating scheme, T = 5, A = 4, R = 8, W = 8, then the HCI of U.K. in 2015 is 4 x 5 + 2 x 4 + 3 x 8 + 8 = 60.

The second instrumental variable, *Scenery Index* (*SI*), is the number of sites in a country registered in the World Heritage List, using data from the United Nations Educational, Scientific, and Cultural Organization (UNESCO). World Heritage List includes unique landmark which is geographically and historically identifiable and has special cultural or natural significance across the world. Sites in World Heritage List attract large number of visitors every year (Arezki, Cherif, and Piotrowski, 2009). We calculate the *HCI* and *SI* for all the countries (i.e., both the home and foreign countries) in our sample each year. These two instruments capture two key reasons that underpin recreational travel, enjoying good weather and visiting famous locations. The positive effect of *HCI* and *SI* on international tourism has been previously documented in the tourism literature (Arezki, Cherif, and Piotrowski, 2009; Culiuc, 2014; Saha and Yap, 2014; Scott et al., 2016).

However, there are some limitations to using these two indices directly. First, they are stagnant at the country level so they may be weakly related to the time-varying outbound tourism. Weak identification of instruments could amplify the biased estimation of endogenous variables (Jiang, 2017). Second, a vital issue underpinning the IV estimation is whether these indices meet the exclusion restrictions and the relevance condition. The literature has provided abundant evidence on the significant impact of climate or weather

[6]For some countries in our sample, NASA only has data of the capital cities (i.e., Austria, Czech Republic, Denmark, Egypt, Finland, Indonesia, Israel, Malaysia, Morocco, Netherlands, Norway, Peru, Philippines, Portugal, Singapore, South Korea, Sweden, Thailand, Turkey, and Venezuela).

[7]More detailed explanations of each variable used in the IV analysis are shown in Table 2.C2, Appendix C.

conditions on economic production and investment behaviour (e.g., Burke et al., 2015; Barnett et al., 2020; Krueger et al., 2020, etc.). Violating exclusion restriction makes instruments invalid and leads to biased estimations.

To implement a more effective IV methodology, we use the difference between the index for the foreign and the home country as the relative instruments in our instrumental variable model (*RHCI* and *RSI*) instead of country-specific *HCI* or *SI*. First, the relative instruments have larger variations than country-level indices.[8] Second, we are comparing the difference between climate and scenery for country pairs. The relative instruments are related to recreational travel, i.e. enjoy better weather or more interesting sites, but less likely to contain any country-level (home or foreign) specific economic information that may affect foreign equity investments. We do not see a compelling argument in favour of *RHCI* or *RSI* capturing endogenous economic variables that may affect decisions to invest in foreign equity markets. We expect a positive relation between the instrumental variables and tourism, as tourists are more likely to visit countries with relatively better weather and more interesting locations.

The first stage model for our instrumental variable model is shown below:

$$Ln(Travel_{ij,t-1}) = \alpha + \beta_1 \cdot RHCI_{ij,t-1} + \beta_2 \cdot RSI_{ij,t-1} + \mathbf{X}^{'} \cdot \beta_{\mathbf{A}} + \text{Fixed effects} + u_{ij,t-1} \quad (6)$$

where $RHCI_{ij,t-1}$ is the relative *HCI* between home country i and foreign country j in year t-1. A positive (negative) value of $RHCI_{ij,t-1}$ means a foreign country has better (worse) weather for outdoor leisure activities than the home country. $RSI_{ij,t-1}$ is the relative *SI* between home country i and foreign country j in year t-1. Positive (negative) value of$RSI_{ij,t-1}$ means a foreign country has more (less) famous sites than the home country. The vector of control variables is the same as the baseline model (4).

With the predicted $Ln(\widehat{Travel}_{ij,t-1})$ in the first stage model, our second stage model is:

$$Y_{ijt} = \alpha + \beta_1 \cdot Ln(\widehat{Travel}_{ij,t-1}) + \mathbf{X}^{'} \cdot \beta_{\mathbf{A}} + \text{Fixed effects} + \epsilon_{ijt} \quad (7)$$

We present the estimates from the instrumental variable models in Table 2.4. Panel A reports the coefficients of the instruments from the first stage model. In line with the evi-

[8] Table 2.C3 in Appendix C reports summary statistics of *HCI*, *RHCI*, *SI*, and *RSI* for each country in our sample.

dence of the tourism literature, the coefficients on the instruments are positive and statistically significant, indicating that people tend to travel to foreign countries with relatively better weather and more interesting sites than home countries. The effects of first stage instruments on predicted tourism are economically significant. A one standard deviation increase in $RHCI_{ij,t-1}$ would increase predicted tourism $Ln(\widehat{Travel}_{ij,t-1})$ by $13 \times 0.05 = 0.65$, corresponding to $0.65/11.39 = 5.7\%$ of the average value of $Ln(Travel_{ij,t-1})$.[9] A one standard deviation increase in $RSI_{ij,t-1}$ would increase predicted tourism $Ln(\widehat{Travel}_{ij,t-1})$ by $16 \times 0.20 = 3.2$, corresponding to $3.2/11.39 = 28.1\%$ of the average value of $Ln(Travel_{ij,t-1})$.[10]

Although we use relative instruments instead of country-specific indices, they may still be weakly related to outbound tourism, for example, stagnant for some country pairs. Weak instruments will amplify small biased estimates. To check if they are weakly identified, we report the Kleibergen and Paap (2006) F-statistic (K-P Wald F) at the bottom of the table, which comfortably exceeds the Stock-Yogo (2005) critical value of 19.93. However, Jiang (2017) argue that the K-P Wald F-statistic does not necessarily justify the choice of instrument variables when the first-stage model is estimated with numerous controls and fixed effects. Thus, we also report the R^2 and Shea's partial R^2 on the instruments in the first-stage model, Panel A. The partial R^2 shows the IVs' incremental explanatory power in the first stage model is not minuscule, which indicates that our instruments are less likely to be weak. The p-value from Hansen's (1982) J-test for over-identifying restrictions indicates that the null hypothesis, i.e. instruments are valid and uncorrelated with the error term, cannot be rejected. Overall, the results from these diagnostic tests suggest that our instrumental variables are valid.

Panel B presents the coefficient estimates for the predicted values of *Travel*. In Columns (1) and (2), we find that the coefficient on *Travel* is positive and significant for both *Foreign Ownership* and *Adjusted Foreign Ownership*. We find similar results when including country-pair fixed effects in Columns (3) and (4). Overall, the IV results are consistent with our baseline estimates and suggest that the effect of tourism on foreign equity investment is likely to be causal.[11]

[9] 13 is the standard deviation of $RHCI_{ij,t-1}$. 11.39 is the average value of $Ln(Travel_{ij,t-1})$.

[10] 16 is the standard deviation of $RSI_{ij,t-1}$.

[11] Stock and Yogo (2005) discuss how using multiple instruments can sometimes produce biased results if some instruments are weak. Possible solutions are to estimate the model using the limited information maximum likelihood method (Hansen, Hausman, and Newey, 2008). For robustness, we conduct the IV test using this method and find that our results continue to hold. These results are available in Appendix Table 2.C4.

[Insert Table 2.4 here]

2.4 Robustness Checks

In this section, we conduct additional tests to ensure the robustness of our findings.

2.4.1 Alternative Definition for Tourism

In our first robustness test, we use a different definition of tourism. Specifically, we use $Travel\ ratio_{ij,t-1}$ as our main explanatory variable, which is calculated as the number of outbound visitors from the home country i to foreign country j, scaled by the total number of outbound visitors from the home country i in year t-1.

The results in Table 2.5 show that the coefficient on $Travel\ ratio_{ij,t-1}$ is positive and statistically significant in all the regression specifications. It is also economically significant, since a one standard deviation increase in the *Travel ratio* leads to a 2.12% increase in *Foreign Ownership* (which roughly corresponds to \$1.76B) and to a 5.04% increase in *Adjusted Foreign Ownership*.

[Insert Table 2.5 here]

2.4.2 Are Results Driven by Dominant Countries?

We also examine whether our results are driven by a few economically dominant countries in our sample. To help alleviate this concern, we exclude the largest countries in our sample and re-estimate our baseline models. The estimates in Table 2.6 show that our results continue to hold when we exclude one of the following countries: China, France, Germany, Japan, U.K., and the U.S.. Specifically, the coefficient on *Travel* remains positive and significant in all the regression specifications.

[Insert Table 2.6 here]

2.4.3 Attention, Migration, and Remittance

Our travel variable may capture the attention that the residents of a home country pay towards another foreign country at a given time. To control general public attention effects, we use *Google trends* as an additional control variable in our models. In particular, we use the Search Volume Index (SVI) of Google that corresponds to a specific term for each country, e.g., the SVI for the topic "France" searched by people in Germany for a specific year.[12]

Another possibility is that our results are related to trends in migration between different countries. For example, citizens from certain home countries may exhibit a greater propensity to migrate to another foreign country during specific periods. Although this is a permanent flow of people that are not included in our travel measure, it may be related to subsequent leisure-related travelling as friends or relatives of the migrants may travel to visit them. To control for these migration spillover effects, we augment our baseline model to control for the bilateral migration and bilateral personal remittances for each country pair, obtained from the World Bank. Because we only have data on migration and remittance starting in 2010, the sample used for this test spans from 2010 to 2016.

Consistent with our main findings, the results in Table 2.7 show that the coefficient on *Travel* continues to be positive and statistically significant. *Ln(Migration)* has a positive and *Ln(Remittances)* has a negative effect on foreign investments. The effect of *Google Trends* is statistically insignificant.

[Insert Table 2.7 here]

2.4.4 Reverse Causality

Another potential explanation for our results is that more people may travel to foreign countries in which they hold equities. To address the possibility of reverse causality, we examine whether lagged *Foreign Ownership* or *Adjusted Foreign Ownership* can predict *Travel*. If a relation exists, then reverse causality becomes more plausible.

To conduct this test, we regress *Travel* from the home country i to foreign country j in year t on the lagged *Foreign Ownership* or *Adjusted Foreign Ownership* measures between these countries. We include a vector of control variables as our baseline model and country-pair fixed effects. Table 2.8 reports the regression results. The estimates rule out this alternative reverse causality explanation, as the coefficients on *Foreign Ownership* and *Adjusted Foreign Ownership* are statistically insignificant.

[Insert Table 2.8 here]

[12] For every home country, we obtain the SVI for all foreign countries. Namely, we set the home country as Germany, and then obtain the SVI of all foreign countries in our sample. The SVI includes search results related to all topics about a specific foreign country, in any language. For example, if we set France as the search topic, the SVI will include people in Germany searching for France in English, or in German (i.e., Französisch).

2.5 Additional Findings

In this section, we perform tests to examine if the patterns we document are stronger for specific country pairs. We also directly examine the implications of our findings for home bias.

2.5.1 Splitting by Geographical Distance

Travel induced recognition is likely to be stronger for countries that are geographically farther apart. Therefore, *Travel* should be more predictive of equity investments for country pairs that are more distant. To test this idea, we perform a subsample analysis by splitting our sample based on the median distance (6,650 km) between home and foreign countries.

The results in Table 2.9 are consistent with this hypothesis. When foreign countries are farther apart, tourism positively predicts foreign equity investments. However, the effect is weaker for geographically closer countries.

[Insert Table 2.9 here]

2.5.2 Splitting by Uncertainty Avoidance

Different cultures have different propensities to take risks (e.g., Li et al., 2013). To examine whether the risk-taking propensity of a given home country interacts with *Travel*, we split the countries in our sample according to their Uncertainty Avoidance Index. We use the index proposed by Hofstede (2001), which has been shown to affect financial decision making (e.g., Li et al., 2013; Kanagaretnam, Lim, and Lobo, 2013). The results in Table 2.10 show that *Travel* has a significant effect only if the home country has an above-median value (65) for uncertainty avoidance. International tourism has a more potent effect in countries with relatively more risk-averse cultures.

[Insert Table 2.10 here]

2.5.3 Tourism and Home Bias

It is well known that investors tend to over-weight their home country in their portfolios, a phenomenon known as the home bias (French and Poterba, 1991; Karolyi and Stulz, 2003). In this section, we directly examine whether our finding that travel induces foreign equity investments is also associated with a reduction in the home bias.

To examine this issue, we use two country-level models, with two dependent variables. The first is the weight home investors place on their home country i in their portfolios, Whi_{it}, in year t. The second is the standardized home bias exhibited by these investors following the specification in Chan, Covrig, and Ng (2005) as $HB_{it} = ln(Whi_{it}/w^*_{it})$, where w^*_{it} is the weight that the home country receives in the global portfolio, according to its market capitalization. Our key independent variable is the natural logarithm of the total number of tourists travelling from the home country to all foreign countries, *Total travel*. If tourism is associated with a reduction in the home bias, we expect the coefficient on *Total travel* to be negative and statistically significant in both models.[13]

We control for variables that may capture the sophistication of investors in the home country (all lagged), as well as the financial performance of the equity market in the home country: the size of the home country market in the global market, the ratio between its stock market value and its GDP, the natural logarithm of the population, GDP growth, inflation, and a dummy indicating whether it is classified as a developed or developing country. We also consider financial variables, namely the returns and volatilities in year t-1 and in years t-6 to t-2.

The results in Table 2.11 support our hypothesis. *Total travel* is negatively related to both Whi_{it} and HB_{it}. The economic effect is meaningful, as a one standard deviation increase in *Total travel* is associated with a 9.8% reduction in the home bias HB_{it}. Overall, these findings suggest that outward travel is associated with a reduction in the home bias , which can help investors construct more diversified equity portfolios.

[Insert Table 2.11 here]

2.5.4 Familiarity or Information?

In the last test, we examine the possibility that superior information about the financial markets in a specific country rather than recognition-induced familiarity is the main driver of our empirical findings. In a theoretical study, Van Nieuwerburgh and Veldkamp (2009) suggest that the home bias puzzle could reflect superior information for the local market. Extending this logic, it is possible that investors are able to obtain value-relevant information about the foreign country during their travels. This may help them in constructing superior international portfolios that earn higher returns.

[13] In Table 2.B4, we report summary statistics of these two variables. The home bias is positive for all countries,consistent with the original findings in French and Poterba (1991).

To examine whether tourists extract value-relevant information during their travels, we test whether travel is associated with better returns. Specifically, we calculate the six-month and twelve-month returns of the foreign portfolio held by investors in home country i in year t.[14] We then examine whether *Total travel* can predict the portfolio returns. If travellers obtain value relevant information from their travels, then the coefficient on *Total travel* should be positive and statistically significant. Control variables in these specifications are the same as in Table 2.11, plus the home bias exhibited by the investors in this country.

The results in Table 2.12 suggest that outbound visitors are not extracting value-relevant information from their travels, as the coefficient on *Total travel* is statistically insignificant. These results indicate that the relation between travel and foreign equity investments is unlikely to reflect superior country-level information.

[Insert Table 2.12 here]

2.6 Conclusion

We examine whether recreational travel can stimulate foreign equity investments. Our main conjecture is that tourism generates positive externalities in financial markets. Specifically, when residents of a home country travel to another foreign country for recreational purposes, they are more likely to recognize this country in the future. Consequently, they are more likely to invest in its financial markets.

Consistent with this conjecture, we find that higher levels of outward tourism are associated with higher levels of foreign equity investments. This leads to a reduction in home bias and improved diversification. The impact of tourism is stronger for countries that are farther apart or when the home country has higher Uncertainty Avoidance Index. Using predictors of recreational travel as instruments, we show that the relation between foreign travel and foreign equity investments is causal. We also establish that superior information about the financial markets in a certain country is not the main driver of our findings.

[14] For example, suppose the foreign equity investments of investors in year t-1 in country i are split equally between foreign countries A and B. In that case, for this country, the dependent variable in year t is $0.5 \times \text{Ret}_{A,t} + 0.5 \times \text{Ret}_{B,t}$, where $\text{Ret}_{A,t}$ and $\text{Ret}_{B,t}$ are the market indices returns in foreign country A and foreign country B, respectively.

Table 2.1: Country List

This table provides the list of 37 home countries and 41 foreign countries in our final sample.

Panel A: List of 37 home countries			
Developed Countries (22 countries)		Developing Countries (15 countries)	
Australia	Austria	Argentina	Brazil
Belgium	Canada	Chile	China
Czech Republic	Denmark	Colombia	Egypt
Finland	France	Hungary	Indonesia
Germany	Greece	Malaysia	Philippines
Israel	Italy	Poland	Russia
Japan	Netherlands	South Africa	Thailand
Norway	Portugal	Turkey	
South Korea	Spain		
Sweden	Switzerland		
U.K.	U.S.		

Panel B: List of 41 foreign countries			
Developed Countries (23 countries)		Developing Countries (18 countries)	
Australia	Austria	Brazil	Chile
Belgium	Canada	China	Egypt
Czech Republic	Denmark	India	Indonesia
Finland	France	Malaysia	Mexico
Germany	Greece	Morocco	Peru
Israel	Italy	Philippines	Poland
Japan	Netherlands	Romania	Russia
New Zealand	Portugal	South Africa	Thailand
Singapore	South Korea	Turkey	Venezuela
Spain	Sweden		
Switzerland	U.K.		
U.S.			

Panel C: Countries in sample by continents

Europe: Austria, Belgium, Czech Republic, Denmark, Finland, France, German, Greece, Hungary, Italy, Netherlands, Norway, Poland, Portugal, Romania, Russia, Spain, Sweden, Switzerland, Turkey, and U.K..
Oceania: Australia, and New Zealand.
Asia: China, India, Indonesia, Israel, Japan, Malaysia, Philippines, Singapore, South Korea, and Thailand.
Africa: Egypt, Morocco, and South Africa.
America: Argentina, Brazil, Canada, Chile, Colombia, Mexico, Peru, U.S., and Venezuela.

Table 2.2: Summary Statistics

This table presents summary statistics for variables in the analysis. Definitions of the variables are provided in Appendix Table 2.A1. H = home country. F = foreign country.

Variable	Obs.	Mean	Std. Dev.	Q1 (25%)	Median	Q3 (75%)
W_{ijt} (%)	11,775	3.779	10.195	0.066	0.447	17.514
AW_{ijt}	11,775	-0.444	0.431	-0.878	-0.494	0.004
$Travel_{ij,t-1}$	11,775	554,452	2,045,618	22,773	85,048	323,202
General Country Characteristics						
$w^*_{j,t-1}$	11,775	0.038	0.095	0.003	0.009	0.029
Market Cap/GDP (H)	11,775	0.636	0.450	0.321	0.431	0.864
Market Cap/GDP (F)	11,775	0.630	0.450	0.295	0.539	0.867
Population(H)(million)	11,775	82.629	200.131	10.261	34.301	65.737
GDP growth (H)	11,775	0.057	0.114	-0.012	0.050	0.129
CPI (H)	11,775	0.090	0.109	0.037	0.085	0.109
GDP growth (F)	11,775	0.066	0.115	-0.002	0.057	0.140
CPI (F)	11,775	0.035	0.071	0.009	0.021	0.036
Corruption control (F)	11,775	0.878	1.072	-0.140	1.090	1.900
Developed dummy (H)	11,775	0.728	0.445	0	1	1
Developed dummy (F)	11,775	0.624	0.484	0	1	1
Financial Variables						
Ret_{t-1} (H)	11,775	0.081	0.222	-0.080	0.088	0.224
Ret_{t-1} (F)	11,775	0.101	0.281	-0.057	0.087	0.228
$Ret_{t-6,t-2}$ (H)	11,775	0.108	0.125	0.030	0.091	0.169
$Ret_{t-6,t-2}$ (F)	11,775	0.123	0.162	0.036	0.096	0.174
Return covariance	11,775	0.002	0.002	0.001	0.001	0.002
Vol_{t-1} (F)	11,775	0.052	0.029	0.033	0.045	0.063
$Vol_{t-6,t-2}$ (F)	11,775	0.063	0.027	0.046	0.057	0.073
P/E ratio (F)	11,775	15.934	6.582	12.200	15.600	18.500
Relative P/E ratio	11,775	1.120	0.706	0.758	0.993	1.287
EPS estimate (F)	11,775	1.115	1.331	0.181	0.632	1.544
Links between the Two Countries						
Distance(km)	11,775	6,679	4,901	1,932	6,650	9,803
Common language	11,775	0.117	0.322	0	0	0
Overlap trading hours	11,775	4.179	3.394	1	3.5	8
Trade (million)	11,775	7.456	20.201	0.527	1.785	5.785
Transaction Costs						
REER	11,775	1.014	0.200	0.930	1.000	1.079
Amihud illiquidity (F)	11,775	0.017	0.230	0.001	0.007	0.051
Same currency	11,775	0.089	0.285	0	0	0

Table 2.3: Travel and Foreign Equity Holdings

This table presents our baseline results. The dependent variables are *Foreign Ownership* and *Adjusted Foreign Ownership* from home country i in foreign country j in year t (W_{ijt} and AW_{ijt}, respectively). The main explanatory variable is the natural logarithm of outbound visitors from home country i to foreign country j in year t-1 (*Ln(Travel)*). Control variables are lagged by one year. Definitions of the variables are provided in Appendix Table 2.A1. H = home country, and F = foreign country. Standard errors shown in parentheses are clustered by country pair. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Panel A: W_{ijt}					**Panel B:** AW_{ijt}				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Ln(Travel_{ij,t-1})$	1.40***	0.65***	0.39**	0.41**	0.99***	0.12***	0.07***	0.04***	0.05***	0.06***
	(0.15)	(0.15)	(0.20)	(0.21)	(0.32)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
General Country Characteristics										
$w^{*}_{j,t-1}$		73.39***	99.70***		62.82***		0.39*	1.28**		0.01
		(8.96)	(24.44)		(9.40)		(0.20)	(0.56)		(0.20)
Market Cap/GDP (H)		-0.15	-0.73		-0.22		0.05**	0.01		0.08***
		(0.36)	(0.45)		(0.35)		(0.02)	(0.02)		(0.02)
Market Cap/GDP (F)		-1.30***	-3.12***		-1.35***		-0.16***	-0.08***		-0.07***
		(0.42)	(0.97)		(0.48)		(0.02)	(0.03)		(0.02)
Ln(Population)(H)		-0.37*	-3.03		-1.06**		-0.01	-0.08		0.02
		(0.21)	(4.18)		(0.45)		(0.01)	(0.18)		(0.02)
GDP growth (H)		-0.34	-1.37		0.90		-0.01	-0.09**		0.01
		(1.25)	(0.87)		(0.94)		(0.06)	(0.04)		(0.04)
CPI(H)		-0.55	1.01		-0.11		-0.09	0.02		0.05
		(1.42)	(1.39)		(1.32)		(0.08)	(0.05)		(0.05)
GDP growth (F)		-2.36***	-0.83		-2.05***		-0.10**	-0.07*		-0.14***
		(0.76)	(0.59)		(0.65)		(0.05)	(0.04)		(0.04)
CPI(F)		2.68**	-1.03		-0.19		0.70***	-0.19***		-0.17***
		(1.36)	(0.77)		(1.01)		(0.11)	(0.06)		(0.06)
Corruption control (F)		1.19***	-1.29*		2.42***		0.11***	0.01		0.06***
		(0.21)	(0.67)		(0.75)		(0.02)	(0.02)		(0.02)
Developed dummy(H)		-2.13***					0.02			
		(0.78)					(0.03)			
Developed dummy(F)		-1.04**					0.02			
		(0.43)					(0.03)			
Financial Variables										
Ret_{t-1}(H)		0.69	0.81**		0.08		0.08**	0.07***		0.04**
		(0.79)	(0.40)		(0.53)		(0.03)	(0.02)		(0.02)
Ret_{t-1}(F)		0.78***	0.75***		0.29		-0.10***	-0.04***		-0.05***
		(0.24)	(0.20)		(0.25)		(0.02)	(0.02)		(0.02)
$Ret_{t-6,t-2}$(H)		1.86	1.92		1.10		-0.07	0.06		-0.06
		(1.75)	(1.39)		(1.35)		(0.07)	(0.04)		(0.05)
$Ret_{t-6,t-2}$(F)		2.25***	1.78***		0.78		-0.01	-0.08*		-0.03
		(0.59)	(0.52)		(0.74)		(0.05)	(0.04)		(0.05)
Return covariance		125.47	-12.58	48.38	119.42*		22.26***	2.79	29.13***	-1.68
		(126.31)	(64.46)	(158.23)	(66.31)		(5.40)	(3.62)	(8.81)	(3.17)
Vol_{t-1}(F)		-11.99***	3.15		-7.73		-1.39***	0.11		-0.14
		(4.14)	(2.87)		(6.18)		(0.30)	(0.25)		(0.24)
$Vol_{t-6,t-2}$(F)		-9.50**	-6.29**		-5.28		0.34	-0.59***		-0.49*
		(4.24)	(3.19)		(5.48)		(0.32)	(0.23)		(0.26)
P/E ratio (F)		-0.15***	-0.01		-0.06***		-0.04***	-0.01		-0.04***
		(0.03)	(0.02)		(0.02)		(0.01)	(0.01)		(0.01)
Relative P/E ratio		-0.02	0.12	0.18	-0.30		-0.04***	0.01	0.03	-0.02***
		(0.29)	(0.17)	(0.45)	(0.20)		(0.01)	(0.01)	(0.02)	(0.01)
EPS estimate(F)		0.07	0.19		0.21		0.01	0.01		0.01
		(0.13)	(0.12)		(0.20)		(0.01)	(0.01)		(0.01)
Links between the Two Countries										
Ln (Distance)		-0.22	-0.06	0.02			-0.07***	0.01	0.01	
		(0.49)	(0.72)	(0.72)			(0.02)	(0.02)	(0.02)	
Common language		2.49**	2.04**	1.76**			0.07*	0.10***	0.09**	
		(1.03)	(0.93)	(0.88)			(0.04)	(0.04)	(0.04)	
Overlap trading hours		0.17	0.08	0.01			0.01*	0.02***	0.02***	
		(0.14)	(0.17)	(0.16)			(0.01)	(0.01)	(0.01)	
Ln(Trade)		0.29	0.87***	1.17***	-1.64***		0.01	0.06***	0.06***	0.01
		(0.20)	(0.29)	(0.30)	(0.47)		(0.01)	(0.01)	(0.01)	(0.02)
Transaction Costs										
REER		-2.09	2.56***	12.73**	-2.38**		0.05	0.11***	0.35	-0.05
		(1.32)	(0.87)	(6.39)	(1.04)		(0.05)	(0.03)	(0.26)	(0.04)
Amihud illiquidity (F)		2.00	-3.40***		0.96		0.87***	-0.14		-0.02
		(1.64)	(1.09)		(1.24)		(0.21)	(0.14)		(0.14)
Same currency		3.11***	3.74***	3.50***			0.16***	0.28***	0.27***	
		(0.58)	(0.80)	(0.78)			(0.03)	(0.03)	(0.03)	
Home Country FE	No	No	Yes	No	No	No	No	Yes	No	No
Foreign Country FE	No	No	Yes	No	No	No	No	Yes	No	No
Home-Time FE	No	No	No	Yes	No	No	No	No	Yes	No
Foreign -Time FE	No	No	No	Yes	No	No	No	No	Yes	No
Country Pair FE	No	No	No	No	Yes	No	No	No	No	Yes
Time FE	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes
Observations	11,775	11,775	11,775	11,775	11,775	11,775	11,775	11,775	11,775	11,775
R^2	0.07	0.58	0.63	0.24	0.78	0.27	0.46	0.62	0.32	0.75

Table 2.4: Travel and Foreign Equity Holdings (IV)

This table presents results from the instrumental variable model. In Panel A, we present results from the first-stage model, where the dependent variable is the natural logarithm of outbound visitors from home country i to foreign country j in year t-1 (*Ln(Travel)*). Control variables are the same as in Table 2.3 and are lagged by one year. The instruments are the differences in the climatic and scenery indices between foreign country j and home country i in year t-1 (*RHCI* and *RSI*, respectively). Panel B presents results from the second stage model, where the dependent variables are *Foreign Ownership* and *Adjusted Foreign Ownership* from home country i in foreign country j in year t (W_{ijt} and AW_{ijt}, respectively). The control variables in the second stage model are the same as in the first stage model. Definitions of the variables are provided in Appendix Table 2.A1. Standard errors shown in parentheses are clustered by country pair. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We also report the Kleibergen and Paap (2006) F-statistic (K-P Wald F), and p-value from Hansen's J-test.

Panel A: First-stage results	(1) $Ln(Travel_{ij,t-1})$	(2) $Ln(Travel_{ij,t-1})$	(3) $Ln(Travel_{ij,t-1})$	(4) $Ln(Travel_{ij,t-1})$
RHCI	0.10***	0.10***	0.05**	0.05**
	(0.02)	(0.02)	(0.03)	(0.03)
RSI	0.21***	0.21***	0.20***	0.20***
	(0.02)	(0.02)	(0.03)	(0.03)
Control Variables	Yes	Yes	Yes	Yes
Country Pair FE	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	11,775	11,775	11,775	11,775
R^2	0.78	0.78	0.93	0.93
Shea's Partial R^2	0.13	0.13	0.18	0.18
Panel B: Second-stage results	(1) W_{ijt}	(2) AW_{ijt}	(3) W_{ijt}	(4) AW_{ijt}
$Ln(Travel_{ij,t-1})$	2.01***	0.14***	3.48***	0.20***
	(0.55)	(0.03)	(0.82)	(0.03)
Control Variables	Yes	Yes	Yes	Yes
Country Pair FE	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	11,775	11,775	11,775	11,775
R^2	0.56	0.43	0.77	0.72
K-P Wald F	63.25	63.25	38.38	38.38
Hansen J	0.25	0.44	0.28	0.37

Table 2.5: Alternative Travel Specification

This table presents results with an alternative definition for tourism. The dependent variables are *Foreign Ownership* and *Adjusted Foreign Ownership* from home country i in foreign country j in year t (W_{ijt} and AW_{ijt}, respectively). The main explanatory variable is the number of outbound visitors from home country i to foreign country j divided by the total number of outbound travellers from home country i in year t-1. Control variables are the same as in Table 2.3 and are lagged by one year. Definitions of the variables are provided in Appendix Table 2.A1. Standard errors shown in parentheses are clustered by country pair. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Panel A: W_{ijt}					**Panel B:** AW_{ijt}				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Travel\ ratio_{ij,t-1}$	49.47***	26.44***	27.54***	25.73***	41.40***	1.73***	0.63***	0.46***	0.40***	1.06***
	(9.90)	(6.61)	(7.12)	(6.74)	(10.78)	(0.16)	(0.17)	(0.16)	(0.13)	(0.22)
Control Variables	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Home Country FE	No	No	Yes	No	No	No	No	Yes	No	No
Foreign Country FE	No	No	Yes	No	No	No	No	Yes	No	No
Home-Time FE	No	No	No	Yes	No	No	No	No	Yes	No
Foreign -Time FE	No	No	No	Yes	No	No	No	No	Yes	No
Country Pair FE	No	No	No	No	Yes	No	No	No	No	Yes
Time FE	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes
Observations	11,775	11,775	11,775	11,775	11,775	11,775	11,775	11,775	11,775	11,775
R^2	0.16	0.61	0.66	0.29	0.79	0.11	0.45	0.62	0.32	0.74

Table 2.6: Country Exclusion

This table presents results when we exclude economically dominant countries from our sample. The dependent variable is *Adjusted Foreign Ownership* from home country i in foreign country j in year t (AW_{ijt}). The main explanatory variable is the natural logarithm of outbound visitors from home country i to foreign country j in year t-1 (*Ln(Travel)*). In each Column from (1) to (6), we exclude one economically dominant country and re-estimate the model. Control variables are the same as in Table 2.3 and are lagged by one year. Definitions of the variables are provided in Appendix Table 2.A1. Standard errors shown in parentheses are clustered by country pair. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Excluding:	(1) China	(2) France	(3) Germany	(4) Japan	(5) U.K.	(6) U.S.
$Ln(Travel_{ij,t-1})$	0.07***	0.05***	0.05***	0.03**	0.06***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Country Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,145	10,980	10,905	10,845	10,890	10,800
R^2	0.73	0.72	0.73	0.74	0.73	0.74

Table 2.7: Google Trends, Migration, and Remittance

This table presents results when we control additional variables in our models. The dependent variables are *Foreign Ownership* and *Adjusted Foreign Ownership* from home country *i* in foreign country *j* in year *t* (W_{ijt} and AW_{ijt}, respectively). The main explanatory variable is the natural logarithm of outbound visitors from home country *i* to foreign country *j* in year *t*-1 (*Ln(Travel)*). We add three new control variables in these models, which are *Google trends*, *Ln(Migration)* and *Ln(Remittance)* between each country pair, all lagged by one year. Other control variables are the same as in Table 2.3 and are lagged by one year. Definitions of the variables are provided in Appendix Table 2.A1. Standard errors shown in parentheses are clustered by country pair. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) W_{ijt}	(2) AW_{ijt}	(3) W_{ijt}	(4) AW_{ijt}
$Ln(Travel_{ij,t-1})$	0.74***	0.06***	1.41***	0.08***
	(0.19)	(0.01)	(0.48)	(0.02)
Google trends	2.64	-0.26	5.50	-0.01
	(5.20)	(0.17)	(5.71)	(0.20)
Ln(Migration)	1.95	1.33***	9.96	0.32
	(5.97)	(0.31)	(7.00)	(0.29)
Ln(Remittance)	-26.48**	-0.53	-11.03	-0.34
	(11.99)	(0.54)	(13.97)	(0.50)
Other Control Variables	Yes	Yes	Yes	Yes
Country Pair FE	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	4,666	4,666	4,666	4,666
R^2	0.57	0.51	0.78	0.80

Table 2.8: Reverse Causality

This table tests for reverse causality. The dependent variable is the natural logarithm of outbound visitors from home country *i* to foreign country *j* in year *t* (*Ln(Travel)*). The explanatory variables are *Foreign Ownership* and *Adjusted Foreign Ownership* from home country *i* in foreign country *j* in year *t-1* ($W_{ijt\text{-}1}$ and $AW_{ijt\text{-}1}$, respectively). Control variables are the same as in Table 2.3 and are lagged by one year. Definitions of the variables are provided in Appendix Table 2.A1. Standard errors shown in parentheses are clustered by country pair. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$Ln(Travel_{ijt})$			
	(1)	(2)	(3)	(4)
$W_{ij,t-1}$	0.33		-1.16	
	(0.58)		(0.84)	
$AW_{ij,t-1}$		0.12		-0.01
		(0.13)		(0.14)
Control Variables	Yes	Yes	Yes	Yes
Country Pair FE	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	11,775	11,775	11,775	11,775
R^2	0.29	0.29	0.67	0.67

Table 2.9: Subsample Test by Distance

This table presents sub-sample results when we split our sample into two groups based on the geographical distance between the capitals of two countries (cutting at the median distance 6,650 km). The dependent variables are *Foreign Ownership* and *Adjusted Foreign Ownership* from home country i in foreign country j in year t (W_{ijt} and AW_{ijt}, respectively). The main explanatory variable is the natural logarithm of outbound visitors from home country i to foreign country j in year t-1 (*Ln(Travel)*). Control variables are the same as in Table 2.3 and are lagged by one year. Definitions of the variables are provided in Appendix Table 2.A1. Standard errors shown in parentheses are clustered by country pair. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Small Distance		Large Distance	
	(1) W_{ijt}	(2) AW_{ijt}	(3) W_{ijt}	(4) AW_{ijt}
$Ln(Travel_{ij,t-1})$	-0.30	0.01	2.39***	0.10***
	(0.39)	(0.01)	(0.61)	(0.02)
Control Variables	Yes	Yes	Yes	Yes
Country Pair FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster by Country Pair	Yes	Yes	Yes	Yes
Observations	6,075	6,075	5,700	5,700
R^2	0.78	0.70	0.78	0.68

Table 2.10: Subsample Test by Culture

This table presents sub-sample results when we split our sample into two groups based on the Uncertainty Avoidance Index (UAI) of the home country from Hofstede (2001) (cutting at the median UAI 65). The dependent variables are *Foreign Ownership* and *Adjusted Foreign Ownership* from home country i in foreign country j in year t (W_{ijt} and AW_{ijt}, respectively). The main explanatory variable is the natural logarithm of outbound visitors from home country i to foreign country j in year t-1 (*Ln(Travel)*). Control variables are the same as in Table 2.3 and are lagged by one year. Definitions of the variables are provided in Appendix Table 2.A1. Standard errors shown in parentheses are clustered by country pair. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Low UAI		High UAI	
	(1) W_{ijt}	(2) AW_{ijt}	(3) W_{ijt}	(4) AW_{ijt}
$Ln(Travel_{ij,t-1})$	0.39	-0.01	1.03***	0.06***
	(0.58)	(0.02)	(0.30)	(0.02)
Control Variables	Yes	Yes	Yes	Yes
Country Pair FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster by Country Pair	Yes	Yes	Yes	Yes
Observations	5,865	5,865	5,910	5,910
R^2	0.90	0.79	0.81	0.77

Table 2.11: Travel and Home Bias

In this table, we examine whether travel affects the home bias. The dependent variables are: i) the weight that the residents of home country i place on equities in their own country (Whi_{it}), and ii) the standardized home bias exhibited by the residents of home country i, calculated as $ln(Whi_{it}/w^*_{it})$, where w^*_{it} is the benchmark weight of home country i in the global portfolio according to its market capitalization. The main explanatory variable is the natural logarithm of total outbound visitors from home country i in year t-1. *Market Cap/GDP* is market capitalization over GDP at year t-1. *Ln(Population)* is the natural logarithm of the population of country i in year t-1. *GDP growth* is the annual GDP growth rate at year t-1. *CPI* is the consumer price index at year t-1. *Developed dummy* is an indicator equal to one if the home country is a developed country, and zero otherwise. Ret_{t-1} is the market index return at year t-1. $Ret_{t-6,t-2}$ is the average market index return from year t-2 to year t-6. Vol_{t-1} is the volatility of market index return in year t-1. $Vol_{t-6,t-2}$ is the volatility of market index return from year t-6 to year t-2. Standard errors shown in parentheses are clustered at the home country level. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) Whi_{it}	(2) HB_{it}
$Ln(Total\ travel_{i,t-1})$	-0.05**	-0.31***
	(0.02)	(0.06)
$w^*_{i,t-1}$	0.24	-1.82*
	(0.24)	(1.00)
Market Cap/GDP	0.09*	-1.37****
	(0.05)	(0.36)
Ln(Population)	0.06*	-0.62***
	(0.03)	(0.10)
GDP growth	0.10*	-0.35
	(0.06)	(0.33)
CPI	0.10	-1.11***
	(0.07)	(0.35)
Developed dummy	-0.20**	-1.56***
	(0.08)	(0.18)
Ret_{t-1}	0.06	-0.29
	(0.04)	(0.21)
$Ret_{t-6,t-2}$	0.10	-0.56
	(0.06)	(0.42)
Vol_{t-1}	-0.74	2.36
	(0.49)	(1.78)
$Vol_{t-6,t-2}$	0.94	3.37
	(0.66)	(2.15)
Time FE	Yes	Yes
Observations	555	555
R^2	0.68	0.88

Table 2.12: Travel and Portfolio Returns

In this table, we examine whether tourism can predict stock returns. The dependent variables are the six-month (from January to June, $Ret_{Jan-Jun,t}$) and twelve-month returns (from January to December, $Ret_{Jan-Dec,t}$) of the foreign portfolio held by investors in home country i in year t. To calculate the foreign portfolio return of investors in home country i, we use the past year weight of each foreign country j and the current year daily market index returns of each foreign country j to calculate an overall portfolio annual return in year t. The main explanatory variable is the natural logarithm of total outbound visitors from home country i in year t-1. *Home Bias* is the standardized home bias exhibited by the residents of home country i in year t-1, calculated as $ln(Whi_{i,t-1}/w^*_{i,t-1})$. Other control variables are the same as in Table 2.11 and are lagged by one year. Standard errors shown in parentheses are clustered at the home country level. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) $Ret_{Jan-Jun,t}$	(2) $Ret_{Jan-Dec,t}$
$Ln\,(Total\ travel_{i,t-1})$	0.03	0.05
	(0.09)	(0.12)
Home Bias	0.17	0.15
	(0.13)	(0.22)
Other Control Variables	Yes	Yes
Time FE	Yes	Yes
Observations	555	555
R^2	0.86	0.96

Appendix A: Variable Definitions

Table 2.A1: Description and Data Source of Variables

All data are employed at the annual frequency.

Variables (Indicator)	**Description and Data Source**
Foreign equity holdings (FEH)	Holdings of dollar valued foreign equity in a foreign market by home country investors. *Source:* CPIS, IMF
Foreign Ownership (W_{ijt})	The dollar value of the equity holdings in a foreign country j by investors of the home country i in year t, scaled by the total foreign equity holdings by investors of home country i in year t: $W_{ijt} = \frac{FEH_{ijt}}{\sum_{j=1}^{n} FEH_{ijt}}$. *Source:* CPIS, IMF
Adjusted Foreign Ownership (AW_{ijt})	Adjusted foreign ownership in a foreign country j by investors of the home country i in year t: $$AW_{ijt} = \begin{cases} \frac{W_{ijt} - w^*_{jt}}{w^*_{jt}} & \text{when} \quad W_{ijt} \leq w^*_{jt} \\ \frac{W_{ijt} - w^*_{jt}}{1 - w_{jt}^*} & \text{when} \quad W_{ijt} > w^*_{jt} \end{cases}$$. *Source:* CPIS, IMF
w^*_{jt}	The capitalization-based benchmark weight that foreign country j receives in the global market portfolio, calculated as: $w^*_{jt} = \frac{\text{Market cap}_{jt}}{\sum_{j=1}^{n} \text{Market cap}_{jt}}$. *Source:* CPIS, IMF
$Ln(Travel_{ij,t-1})$	The natural logarithm of the number of outbound visitors from home country i to foreign country j in year t-1. *Source:* UNWTO
$Travel\ ratio_{ij,t-1}$	The number of outbound visitors from home country i to foreign country j divided by the total number of outbound travellers from home country i in year t-1. *Source:* UNWTO
Market Capitalization/GDP	Market capitalization of the individual market divided by its real gross domestic product. *Source:* DataStream (MV) and World Bank (GDP)
Ln(Population)	The natural logarithm of the population of the home country. *Source:* World Bank
GDP growth	Annual percentage change of GDP. *Source:* World Bank

Table 2.A1: Description and Data Source of Variables (Cont.)

Variables (Indicator)	**Description and Data Source**
CPI	Annual percentage change of Consumer Price Index. *Source:* World Bank
Corruption control	Control of Corruption Index. *Source:* World Bank
Developed dummy	Dummy variables equal to one if the home or foreign countries are classified as developed, and zero otherwise. *Source:* IMF and World Bank
Ret_{t-1}	Stock market index return in the previous year. *Source:* DataStream (RI)
$Ret_{t-2,t-6}$	The average annual market index return from year t-6 to t-2. *Source:* DataStream (RI)
Return covariance	Covariance of daily market index returns between a country pair. *Source:* DataStream (RI)
Vol_{t-1}	Volatility of daily market index returns in year t-1. *Source:* DataStream (RI)
$Vol_{t-6,t-2}$	Volatility of daily market index returns from year t-6 to t-2. *Source:* DataStream (RI)
P/E ratio	Average daily price to earnings ratio of the market index. *Source:* DataStream (PE)
Relative P/E ratio	Average daily price to earnings ratio of the foreign market index divided by the Average daily price to earnings ratio of the home market index. *Source:* DataStream (PE)
EPS estimate	12-month earnings per share forecast. *Source:* DataStream (DIEP)
Ln(Distance)	The natural logarithm of the geographical distance between capitals of two countries. *Source:* http://www. freemaptools.com.
Common language	A dummy variable taking the value of one if the country pair have the same official language, and zero otherwise. *Source:* http://www.nber.org/~wei/.
Overlap trading hours	The number of overlapping trading hours of the stock exchanges in a country pair. *Source:* https://www.stockmarketclock.com/
Ln(Trade)	The natural logarithm of total bilateral trade (Imports + Exports) between a country pair. *Source:* World Integrated Trade Solution

Table 2.A1: Description and Data Source of Variables (Cont.)

Variables (Indicator)	**Description and Data Source**
REER	The real effective exchange rate, calculated as the geometric weighted average of a basket of bilateral exchange rates adjusted by relative consumer prices levels. We use foreign country REER divided by home country REER to measure the relative exchange rate. *Source:* World Bank
Amihud illiquidity	The annual average of daily market return divided by dollar trading volume following Amihud (2002). *Source:* DataStream (RI and VA)
Same currency	A dummy variable taking the value of one if the country pair has the same official currency, and zero otherwise. *Source:* Wikipedia
Google trends	Search Volume Index (SVI), which measures the internet searching intensity for foreign country-related topics by people in a home country. *Source:* Google Trends
Ln(Migration)	The natural logarithm of the total number of international migrants from home country to foreign country. *Source:* World Bank
Ln(Remittance)	The natural logarithm of the sum of money sent back to a home country by migrants in a foreign country. *Source:* World Bank
Whi_{it}	The weight put on home equities in a country portfolio. *Source:* CPIS, IMF
HB_{it}	The standardized home bias in the home country, calculated as $ln(Whi_{it}/w^*_{it})$, where w^*_{it} is the benchmark weight of home country i in the global portfolio according to its market capitalization. *Source:* CPIS, IMF
$Ret_{Jan-Jun,t}$	Home country portfolio return of foreign equities from January to June in year t. *Source:* DataStream (RI)
$Ret_{Jan-Dec,t}$	Home country portfolio return of foreign equities from January to December in year t. *Source:* DataStream (RI)

Appendix B: Supplementary Tables

Table 2.B1: Summary Statistics of Key Variables by Home Countries

This table shows the mean and standard deviation of total foreign equity holdings in each year, W_{ijt}, total outbound visitors, and AW_{ijt} by home countries during our sample period. The Number of observations for all variables is 11,775.

	Foreign Equity Holdings (billion)		W_{ijt} **(%)**		**Outbound Visitors (million)**		AW_{ijt}	
Countries	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**
Argentina	17.64	4.12	3.33	16.65	3.93	1.78	-0.85	0.41
Australia	267.07	127.33	6.25	14.67	5.77	1.49	-0.34	0.31
Austria	226.30	54.00	2.56	5.29	12.29	1.19	-0.42	0.42
Belgium	421.32	98.23	2.63	5.35	11.89	1.70	-0.55	0.45
Brazil	9.29	7.06	5.56	15.32	3.45	1.78	-0.53	0.47
Canada	653.54	308.00	2.50	9.51	24.91	5.27	-0.44	0.32
Chile	41.27	28.03	4.00	15.52	1.18	0.49	-0.68	0.44
China	259.62	67.90	4.55	7.99	13.46	10.47	-0.39	0.41
Colombia	9.76	6.66	16.67	35.80	0.75	0.36	-0.50	0.68
Czech Republic	14.19	5.13	4.35	5.80	12.34	2.59	-0.42	0.46
Denmark	222.90	82.83	2.56	5.54	5.99	1.01	-0.30	0.34
Egypt	1.46	1.86	25.00	28.00	0.10	0.03	-0.15	0.44
Finland	165.53	57.14	5.56	5.66	3.26	0.44	-0.26	0.41
France	1,802.74	525.32	2.56	4.47	36.09	4.79	-0.48	0.41
Germany	1,555.52	488.01	2.63	4.48	104.61	6.09	-0.40	0.41
Greece	49.79	23.82	4.35	10.96	2.35	0.20	-0.41	0.46
Hungary	3.50	2.01	3.70	6.67	4.03	0.68	-0.44	0.43
Indonesia	2.26	1.92	14.29	17.96	4.27	1.45	-0.37	0.50
Israel	39.52	25.69	8.33	23.06	1.34	0.28	-0.49	0.47
Italy	556.00	94.87	2.56	5.40	22.07	1.86	-0.47	0.42
Japan	1,942.90	570.84	2.56	7.86	19.90	1.38	-0.44	0.39
South Korea	82.17	63.10	3.23	10.44	11.64	3.67	-0.46	0.38
Malaysia	22.40	22.01	5.88	10.61	5.83	2.04	-0.43	0.46
Netherland	1,139.81	308.59	2.56	5.54	26.52	1.34	-0.36	0.36
Norway	546.08	303.48	2.86	5.21	6.80	1.55	-0.29	0.36
Philippines	3.91	1.63	9.09	20.52	1.96	0.67	-0.38	0.49
Poland	5.77	3.25	9.09	10.64	3.67	1.06	-0.33	0.45
Portugal	92.10	27.30	2.86	5.28	4.36	0.63	-0.56	0.46
Russian	6.16	3.03	4.35	14.91	11.47	4.67	-0.71	0.46
South Africa	66.63	30.57	4.17	14.99	0.95	0.09	-0.79	0.39
Spain	323.24	90.74	6.67	7.64	11.77	2.65	-0.28	0.41
Sweden	290.62	88.90	2.63	6.02	8.19	1.25	-0.45	0.39
Switzerland	600.40	172.18	2.56	5.32	24.71	4.33	-0.40	0.40
Thailand	10.91	7.92	3.70	10.23	3.48	0.81	-0.56	0.45
Turkey	1.01	0.59	7.14	14.85	1.08	0.41	-0.54	0.48
U.K.	2,166.46	621.20	2.63	5.84	49.57	3.32	-0.22	0.30
U.S.	4,680.58	1666.55	2.50	4.11	76.83	6.98	-0.23	0.28

Table 2.B2: Summary Statistics of Key Variables by Foreign Countries

This table shows the mean and standard deviation of total inbound visitors in each year, W_{ijt} market capitalization, and GDP by foreign countries during our sample period. The Number of observations for all variables is 11,775.

	Inbound Visitors (million)		W_{ijt} **(%)**		**Market Cap (Billion $)**		**GDP (Trillion $)**	
Countries	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**
Australia	3.64	0.54	2.28	4.12	0.86	0.33	0.99	0.40
Austria	19.81	1.99	2.97	4.88	0.10	0.05	0.36	0.08
Belgium	6.54	0.41	1.58	2.57	0.26	0.09	0.43	0.09
Brazil	3.92	0.52	1.28	1.90	0.65	0.40	1.55	0.74
Canada	30.53	7.32	1.45	2.22	1.25	0.46	1.39	0.36
Chile	1.84	0.76	0.13	0.30	0.15	0.08	0.18	0.07
China	15.04	3.27	0.93	3.15	3.08	2.48	5.58	3.56
Czech Republic	4.07	0.50	0.39	1.00	0.03	0.02	0.17	0.05
Denmark	6.95	2.08	1.84	2.65	0.18	0.08	0.29	0.06
Egypt	5.63	1.95	0.03	0.05	0.04	0.03	0.19	0.09
Finland	2.02	0.20	0.89	1.37	0.19	0.05	0.23	0.05
France	54.94	2.53	10.47	6.07	1.67	0.44	2.40	0.46
Germany	21.78	4.49	11.47	7.39	1.33	0.38	3.19	0.58
Greece	10.70	1.03	0.99	1.39	0.09	0.05	0.25	0.06
India	3.05	1.01	0.50	0.76	0.71	0.45	1.33	0.59
Indonesia	2.98	0.73	1.16	4.33	0.16	0.11	0.58	0.28
Israel	2.22	0.60	0.21	0.90	0.11	0.04	0.21	0.07
Italy	61.64	5.05	4.36	5.68	0.65	0.18	1.93	0.34
Japan	6.39	3.48	3.06	3.89	3.58	0.78	4.95	0.61
South Korea	7.00	2.95	1.95	6.51	0.59	0.29	1.03	0.28
Malaysia	6.74	2.17	0.53	1.20	0.23	0.12	0.22	0.08
Mexico	20.87	3.43	1.46	0.79	0.29	0.13	1.00	0.19
Morocco	2.64	0.29	0.01	0.02	0.04	0.02	0.08	0.02
Netherlands	9.86	1.67	10.64	11.58	0.54	0.12	0.75	0.15
New Zealand	2.13	0.33	0.18	0.37	0.04	0.01	0.14	0.04
Peru	3.08	1.41	0.08	0.25	0.05	0.03	0.13	0.06
Philippines	2.59	0.96	0.18	0.28	0.09	0.07	0.18	0.08
Poland	45.62	5.21	1.05	2.22	0.10	0.05	0.40	0.13
Portugal	4.96	1.14	0.74	1.08	0.07	0.02	0.21	0.04
Romania	3.23	0.48	0.15	0.44	0.03	0.02	0.14	0.06
Russia	5.59	0.86	0.68	1.25	0.45	0.33	1.28	0.65
Singapore	8.90	2.53	2.80	7.71	0.32	0.17	0.20	0.08
South Africa	2.67	0.40	0.39	1.12	0.30	0.14	0.29	0.09
Spain	53.03	5.43	4.27	5.02	0.63	0.19	1.24	0.28
Sweden	3.86	0.43	2.73	3.97	0.41	0.14	0.45	0.10
Switzerland	7.21	0.63	1.78	2.00	1.04	0.30	0.53	0.15
Thailand	11.56	4.83	0.28	0.51	0.15	0.09	0.29	0.11
Turkey	15.18	4.07	0.42	1.15	0.08	0.33	0.65	0.24
U.K.	23.24	2.52	13.90	15.25	2.88	0.05	2.53	0.40
U.S.	38.64	8.07	37.96	26.79	14.70	0.09	14.60	2.39
Venezuela	0.55	0.14	0.09	0.14	0.03	0.40	0.28	0.13

Table 2.B3: Correlation Coefficients

This table provides Pearson correlations between pairs of all variables. Definitions of the variables are provided in Appendix Table 2.A1.

	W_{ijt}	AW_{ijt}	$w^*_{j,t-1}$	Travel	M/G(H)	M/G(F)	Pop	GDPg(H)	GDPg(F)	CPI(H)	CPI(F)	Corrupt	Dev(H)	Dev(F)	Ret(H)	Ret(F)
W_{ijt}	1.00															
AW_{ijt}	0.45	1.00														
$w^*_{j,t-1}$	0.30	0.52	1.00													
$Ln(Travel_{ij,t-1})$	0.70	0.07	0.16	1.00												
M/G(H)	-0.04	0.06	0.11	-0.04	1.00											
M/G(F)	0.15	-0.06	0.00	0.22	0.02	1.00										
Population	0.02	-0.01	0.29	0.02	-0.04	0.03	1.00									
GDPg(H)	0.02	-0.05	-0.08	0.02	-0.03	0.00	0.05	1.00								
CPI(H)	0.02	-0.01	0.00	0.03	-0.02	-0.02	0.00	-0.06	1.00							
GDPg(F)	-0.07	-0.11	-0.07	-0.06	0.00	-0.04	0.00	0.54	-0.07	1.00						
CPI(F)	-0.07	-0.06	-0.13	-0.07	0.02	-0.20	0.01	0.02	-0.01	0.08	1.00					
Corrupt	0.18	0.23	0.03	0.13	-0.04	0.49	-0.01	0.03	-0.02	-0.13	-0.39	1.00				
Dev(H)	-0.11	0.17	0.21	-0.11	0.17	-0.08	-0.32	-0.18	-0.02	0.00	0.01	-0.04	1.00			
Dev(F)	0.22	0.29	0.15	0.18	-0.03	0.25	-0.04	0.01	-0.01	-0.19	-0.33	0.75	-0.05	1.00		
Ret(H)	0.02	-0.04	-0.03	0.02	-0.02	0.03	0.03	0.27	-0.03	0.23	0.01	-0.01	-0.13	0.00	1.00	
Ret(F)	-0.06	-0.08	-0.08	-0.06	0.02	-0.11	0.01	0.14	-0.04	0.23	0.52	-0.21	0.01	-0.21	0.44	1.00
Ret(mH)	0.04	-0.04	-0.10	0.03	0.07	0.07	0.00	0.15	0.09	-0.06	-0.01	0.03	-0.23	0.02	-0.27	-0.24
Ret(mF)	-0.09	-0.10	-0.11	-0.09	0.06	0.00	0.01	-0.06	0.03	0.18	0.42	-0.25	0.01	-0.28	-0.21	0.04
Cov	0.05	0.13	0.12	-0.01	-0.12	-0.05	-0.07	-0.11	0.08	-0.12	-0.05	0.05	0.06	0.10	-0.38	-0.31
V(F)	-0.07	-0.02	-0.03	-0.08	0.03	-0.19	-0.02	-0.12	0.11	-0.07	0.40	-0.29	0.02	-0.17	-0.32	0.02
V(mF)	-0.12	-0.03	-0.06	-0.12	-0.05	-0.29	-0.02	0.07	0.05	0.14	0.20	-0.35	0.03	-0.24	-0.01	0.07
PE	0.08	-0.08	0.01	0.22	0.05	0.20	0.00	0.13	0.03	0.10	-0.18	0.16	-0.02	0.11	0.15	0.03
RPE	0.08	-0.11	-0.04	0.16	-0.17	0.10	-0.04	-0.01	-0.01	-0.03	-0.13	0.11	-0.10	0.08	-0.02	-0.07
Forecast	0.18	0.14	0.11	0.17	-0.01	0.21	-0.02	-0.03	-0.04	-0.11	-0.11	0.24	-0.04	0.41	0.00	-0.06
Distance	-0.11	-0.50	-0.51	0.13	0.07	0.06	0.23	0.03	-0.02	0.06	0.09	-0.12	-0.16	-0.20	0.03	0.05
Language	0.15	0.10	0.17	0.07	0.16	0.13	0.09	0.02	-0.03	0.00	-0.02	0.10	-0.07	0.05	0.02	0.00
Overlap	0.07	0.43	0.38	-0.18	-0.07	-0.07	-0.25	-0.01	0.03	-0.05	-0.04	0.05	0.07	0.11	-0.02	-0.04
Trade	0.35	0.40	0.78	0.29	0.07	0.11	0.38	-0.04	-0.02	-0.06	-0.12	0.11	0.08	0.17	0.01	-0.06
REER	-0.18	-0.02	-0.01	-0.16	0.10	-0.15	-0.01	0.07	-0.02	0.04	0.12	-0.22	0.22	-0.23	-0.10	0.10
Amihud	-0.03	-0.01	-0.08	-0.04	-0.01	-0.11	0.01	-0.01	-0.03	0.04	0.45	-0.18	0.00	-0.13	-0.01	0.47
Currency	0.11	0.36	0.27	-0.09	-0.12	-0.11	-0.09	-0.05	-0.01	-0.07	-0.07	0.10	0.18	0.22	-0.06	-0.07

	Ret(mH)	Ret(mF)	Cov	V(F)	V(mF)	P/E	RP/E	Forecast	Distance	Language	Overlap	Trade	REER	Amihud	Currency
Ret(mH)	1.00														
Ret(mF)	0.26	1.00													
Cov	0.31	0.24	1.00												
V(F)	0.23	0.42	0.47	1.00											
V(mF)	-0.10	0.26	0.12	0.32	1.00										
P/E	0.03	0.02	-0.17	-0.12	-0.08	1.00									
RP/E	-0.02	0.01	0.01	-0.05	-0.06	0.54	1.00								
Forecast	0.00	-0.06	0.07	-0.09	-0.14	-0.02	0.01	1.00							
Distance	0.03	0.05	-0.19	-0.05	-0.06	0.05	0.03	-0.20	1.00						
language	0.00	-0.03	-0.09	-0.09	-0.13	-0.01	-0.02	0.01	0.02	1.00					
Overlap	0.01	0.00	0.20	0.06	0.06	-0.15	-0.04	0.07	-0.81	-0.09	1.00				
Trade	-0.10	-0.12	0.10	-0.05	-0.06	0.08	-0.01	0.26	-0.37	0.10	0.22	1.00			
REER	-0.06	0.02	-0.03	0.07	0.02	-0.13	-0.14	-0.19	0.08	-0.03	-0.05	-0.06	1.00		
Amihud	-0.04	0.07	-0.04	0.30	0.05	-0.11	-0.07	-0.03	0.02	-0.01	-0.02	-0.07	0.09	1.00	
Currency	-0.07	-0.08	0.17	0.03	0.03	-0.02	0.00	0.11	-0.39	-0.06	0.40	0.19	-0.03	-0.03	1.00

Table 2.B4: Summary Statistics of Home Bias by Home Countries

This table shows the mean and standard deviation of the weights put on home equities in home country portfolio (Whi_{it}), and the standardized home bias in home country (HB_{it}). HB_{it} is calculated as $ln(Whi_{it}/w^*_{it})$, where w^*_{it} is the benchmark weight of home country i in the global portfolio according to its market capitalization. The Number of observations for all variables is 555.

	$Whi_{i,t}(\%)$		$HB_{i,t}$	
Countries	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**
Argentina	62.16	8.72	6.63	0.17
Australia	76.56	4.47	3.55	0.24
Austria	28.37	7.95	4.75	0.30
Belgium	37.11	7.44	3.99	0.20
Brazil	98.51	0.93	4.24	0.57
Canada	65.93	5.92	3.01	0.20
Chile	80.77	8.66	5.41	0.46
China	84.15	13.47	2.84	0.90
Colombia	86.98	5.89	6.46	1.14
Czech Republic	68.67	6.62	6.71	0.39
Denmark	44.16	5.88	4.56	0.20
Egypt	96.01	3.32	6.99	0.71
Finland	52.63	10.10	4.60	0.16
France	47.35	5.15	2.36	0.19
Germany	45.50	5.59	2.55	0.12
Greece	60.42	13.94	5.66	0.45
Hungary	86.47	7.18	7.29	0.38
Indonesia	98.49	0.75	5.77	0.75
Israel	74.11	7.56	5.64	0.32
Italy	52.64	5.84	3.39	0.28
Japan	64.38	5.34	1.88	0.13
South Korea	88.95	4.86	4.15	0.44
Malaysia	92.96	4.93	5.12	0.35
Netherland	31.56	8.22	3.06	0.18
Norway	27.13	7.36	4.06	0.45
Philippines	93.36	4.80	6.25	0.64
Poland	93.61	2.96	6.01	0.41
Portugal	42.65	6.84	5.41	0.28
Russia	97.60	2.20	4.85	1.02
South Africa	81.33	3.74	4.70	0.35
Spain	65.19	7.08	3.66	0.28
Sweden	57.49	6.11	3.98	0.12
Switzerland	62.74	3.65	3.11	0.93
Thailand	93.22	4.35	5.66	0.59
Turkey	97.90	2.41	6.36	0.54
U.K.	56.69	5.70	1.97	0.12
U.S.	75.44	5.16	0.63	0.11

Appendix C: Instrumental Variables

Table 2.C1: Holiday Climate Index Rating Systems

This table shows the rating systems of Holiday Climate Index (*HCI*). *HCI* incorporates four climatic factors: thermal comfort (T), cloud cover (A), daily precipitation (R), and wind speed (W). The rating of each factor ranges from 0 to 10.

T (°C)	**A (%)**	**R (mm)**	**W (km/h)**	**Rating**
23–25	11–20	0	1–9	10
26	1–10	<3.00	10–19	9
20–22	21–30			
27–28	0	3.00–5.99	0	8
	31–40		20–29	
29–30	41–50			7
18–19				
31–32	51–60		30–39	6
15–17				
33–34	61–70	6.00–8.99		5
11–14				
35–36	71–80			4
7–10				
0–6	81–90		40–49	3
37–39	90–99	9.00–12.00		2
-1– -5				
≤-6	100			1
≥39		>12.00	50–70	0

Table 2.C2: Description and Data Source of Instrumental Variables

Variables	Description and Data Source
Holiday Climatic Index (HCI)	HCI = 4 × T + 2 × A + 3 × R + W. We first compute yearly HCI for both home country and foreign country. Then, we use the relative HCI (RHCI) which is the difference between foreign country HCI and home country HCI as the first instrument.
T = Thermal comfort	The effective temperature based on daily maximum temperature (°C) and mean daily relative humidity (%). *Source*: Effective temperature table of U.S. National Oceanic and Atmospheric Administration (NOAA)
Daily maximum temperature (°C)	The daily maximum air temperature (°C). *Source:* POWER Data Access Viewer, The National Aeronautics and Space Administration (NASA)
Mean daily relative humidity (%)	The average ratio of the partial pressure of water vapour to the equilibrium vapor pressure of water at a given temperature. *Source:* POWER Data Access Viewer, The National Aeronautics and Space Administration (NASA)
A = Cloud cover (%)	The annual average of cloud cover percentage refers to the fraction of the sky obscured by clouds. *Source:* Climatic Research Unit (CRU), University of East Anglia
R = Daily precipitation (mm)	The annual average of any product of atmospheric water vapour that falls under gravity daily, including drizzle, rain, snow, graupel and hail measured in millimetres. *Source:* Climatic Research Unit (CRU), University of East Anglia
W = Wind speed (km/h)	The annual average wind speed (km/h). *Source:* POWER Data Access Viewer, The National Aeronautics and Space Administration (NASA)
Scenery index (SI)	The number of world historical heritage sites in the World Heritage List. We use the relative Scenery Index (RSI), which is the difference between foreign country SI and home country SI, as the second instrument. *Source:* UNESCO

Table 2.C3: Summary Statistics of Instrumental Variables by Countries

This table shows the mean and standard deviation of instruments Holiday Climatic Index (HCI), relative Holiday Climatic Index (RHCI), Scenery Index (SI), and relative Scenery Index (RSI) during our sample period by countries. The Number of observations for all variables is 11,775.

	HCI		**RHCI**		**SI**		**RSI**	
Countries	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**
Argentina	86.38	1.05	-14.82	9.77	8	1	6	11
Australia	81.25	1.99	-15.59	7.10	17	2	2	11
Austria	63.50	2.37	6.77	9.68	9	1	-7	11
Belgium	67.63	2.67	2.67	9.91	10	2	-5	12
Brazil	67.50	2.07	4.59	10.10	18	1	3	11
Canada	58.00	0.00	12.59	9.29	14	1	0	11
Chile	46.35	3.16	0.80	10.02	5	2	-13	12
China	68.00	0.00	1.01	9.65	37	7	23	12
Colombia	61.69	4.41	6.35	7.34	6	1	13	13
Czech Republic	64.88	0.99	3.70	8.98	12	0	-5	11
Denmark	65.31	0.98	4.91	9.53	5	1	-15	13
Egypt	81.75	0.98	-16.89	4.46	7	1	-8	11
Finland	59.63	2.26	8.54	8.50	7	0	-9	12
France	70.38	0.78	-0.28	9.56	34	4	18	12
Germany	64.63	0.93	5.88	9.49	34	4	18	12
Greece	86.13	0.48	-17.39	8.67	17	1	1	11
Hungary	71.13	0.99	-1.50	9.38	8	0	9	12
India	77.00	1.62	-8.66	8.87	27	3	12	12
Indonesia	60.19	3.28	6.73	9.47	7	1	-7	11
Israel	88.25	1.72	-21.53	6.71	5	2	-10	11
Italy	76.31	1.93	-6.37	9.60	45	5	32	10
Japan	67.75	0.66	2.41	9.57	13	1	-2	12
South Korea	69.75	0.97	0.33	9.83	9	2	-6	11
Malaysia	59.88	4.37	6.80	8.26	3	1	-13	12
Mexico	77.63	1.39	-13.56	6.35	28	4	11	5
Morocco	89.94	0.24	-21.81	7.65	8	1	-8	11
Netherlands	64.13	1.22	3.43	9.86	9	1	-8	11
New Zealand	65.81	1.74	-0.83	57.09	3	0	-12	12
Norway	56.50	1.46	12.74	9.36	6	1	9	12
Peru	81.13	1.87	-13.90	7.86	12	1	-4	11
Philippines	62.88	0.49	4.82	9.90	5	0	-11	12
Poland	66.00	0.71	0.20	7.36	13	1	-3	10
Portugal	83.19	1.38	-12.71	9.49	13	1	-4	12
Romania	69.50	2.06	-5.53	43.03	8	0	-8	11
Russian	58.00	0.00	14.92	9.88	23	3	8	11
Singapore	58.75	3.33	9.54	9.16	0	0	-14	11
South Africa	89.50	1.94	-20.20	9.53	6	1	-9	11
Spain	81.25	4.36	-15.15	7.46	42	3	27	10
Sweden	61.25	1.56	8.56	9.09	14	1	-3	12
Switzerland	60.63	1.83	9.72	9.53	9	3	-6	11
Thailand	68.88	1.17	1.29	10.08	5	0	-11	12
Turkey	75.00	1.74	-9.19	7.87	10	2	-6	11
U.K.	60.94	0.97	9.54	9.55	27	2	13	11
U.S.	70.13	1.32	0.16	9.58	21	1	7	11
Venezuela	68.56	3.30	-1.29	8.35	3	0	-14	11

Table 2.C4: Travel and Foreign Equity Holdings (LIML)

This table presents results from the instrumental variable model, estimated with the limited information maximum likelihood method (LIML). In Panel A, we present results from the first-stage model, where the dependent variable is the natural logarithm of outbound visitors from home country i to foreign country j in year t-1 (*Ln(Travel)*). Control variables are the same as in Table **??** and are lagged by one year. The instruments are the differences in the climatic and scenery indices between foreign country j and home country i in year t-1 (*RHCI* and *RSI*, respectively). Panel B presents results from the second stage model, where the dependent variables are *Foreign Ownership* and *Adjusted Foreign Ownership* from home country i in foreign country j in year t (W_{ijt} and AW_{ijt}, respectively). The control variables in the second stage model are the same as in the first stage model. Definitions of the variables are provided in Appendix Table 2.A1. Standard errors shown in parentheses are clustered by country pair. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We also report the Kleibergen and Paap (2006) F-statistic (K-P Wald F), and p-value from Hansen's J-test.

Panel A: First-stage results	(1) $Ln(Travel_{ij,t-1})$	(2) $Ln(Travel_{ij,t-1})$	(3) $Ln(Travel_{ij,t-1})$	(4) $Ln(Travel_{ij,t-1})$
RHCI	0.10***	0.10***	0.05**	0.05**
	(0.02)	(0.02)	(0.03)	(0.03)
RSI	0.21***	0.21***	0.20***	0.20***
	(0.02)	(0.02)	(0.03)	(0.03)
Control Variables	Yes	Yes	Yes	Yes
Country Pair FE	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	11,775	11,775	11,775	11,775
R^2	0.78	0.78	0.93	0.93
Shea's Partial R^2	0.13	0.13	0.18	0.18
Panel B: Second-stage results	(1) W_{ijt}	(2) AW_{ijt}	(3) W_{ijt}	(4) AW_{ijt}
$Ln(Travel_{ij,t-1})$	2.05***	0.14***	3.54***	0.20***
	(0.57)	(0.03)	(0.84)	(0.03)
Control Variables	Yes	Yes	Yes	Yes
Country Pair FE	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	11,775	11,775	11,775	11,775
R^2	0.56	0.43	0.45	0.72
K-P Wald F	63.25	63.25	36.65	36.65
Hansen J	0.25	0.44	0.28	0.37

Chapter 3

Air Travel, Analyst Coverage, and Forecast Accuracy

3.1 Introduction

Sell-side analysts are specialized financial information providers to other market participants. They acquire, process, and deliver financial information between public companies and investors. Besides firm-specific information and abnormal stock returns, analyst coverage and forecasts are documented to influence security issuance (Chang, Dasgupta, and Hilary, 2006), earnings management (Yu, 2008), stock return synchronicity (Crawford, Roulstone, and So, 2012), and innovation (He and Tian, 2013). However, because little is known about the "black box" that how analysts acquired information, analyst forecasts can be biased (Ramnath, Rock, and Shane, 2008). Analysts may be optimistic or subjective about specific firms and make biased forecasts (e.g. Easterwood and Nutt, 1999; Walther and Wills, 2013).

Recent behavioural finance literature explains determinants of analyst coverage and forecast accuracy dependent on proximity and information between analysts and firms, e.g. geographical distance (Malloy, 2005), political contribution (Jiang, Kumar, and Law, 2016), culture proximity (Du, Yu, and Yu, 2017), and gender and alumni connections (Fang and Huang, 2017). This paper extends this growing literature by examining the implications of air travel for analyst coverage and processing of financial information.

Air travel dramatically reduces the time required to travel long distances. Air travel reduces the difficulty of acquiring information from a far space and improve knowledge dispersion (Hovhannisyan and Keller, 2015). During air travel, visitors have gained first-hand knowledge about the destination's customs, culture, living standards, local products, services, and attitudes of its citizens. As a result, the visitor's overall knowledge about the destination will increase (Le, 2008; Andersen and Dalgaard, 2011). After travel, visitors are likely to share their experiences with others, further stimulating information dispersion. In this way, air travellers are able to improve the information environment. Domestic air travel strengthens national awareness and the sense of belonging, contributes to new ideas and acculturation, reduces social barriers, and spreads economic development (Jafari, 1987).

With air travel improving the information environment, recent studies have documented the important implications of air travel on financial outcomes through two channels. On the one hand, air travel improves information transfer and reduce information asymmetry. For example, Giroud (2013) finds that air travel facilitates internal monitoring within firms and improves their performance. On the other hand, air travel leads to a strong sense of recognition, familiarity and biased overreaction to the information. It is because of *recognition heuristic* (Goldstein and Gigerenzer, 2002), whereby people, when having to rank objects in a set according to their attractiveness, tend to assign a higher value to those objects that are more familiar and recognized. For example, Da et al. (2021) document that air travellers across the U.S. make investors more familiar with firms in destination states and increase portfolio investments in those firms, but there is no better portfolio performance.

Motivated by these findings, the first hypothesis is that air travel from analyst location to firm location attracts analyst attention to firms in the distance and stimulates analyst coverage. Sell-side analysts are specialized financial market participants. They are likely to exploit the richer information environment brought by air travel.

To further identify which channel has a dominant influence, this paper then examines how air travel impacts analyst forecast errors. As specialized participants of financial markets to produce and disseminate firm-specific information, their forecast accuracy regarding the earnings of firm inevitably influences investors' investment decisions and portfolio performance. However, *ex-ante*, whether and how air travel affects the accuracy of analysts' information processing can be ambiguous.

Through the first channel, *information advantage*, highly skilled financial analysts likely have several attributes that alleviate information asymmetry of firms in the distance. Air travel breaks the obstruct of geographical distance and improves the information environment between analysts and companies, allowing analysts to access firm-specific information quickly. Well-educated analysts may possess specialized knowledge and channels to access insider information, then give more accurate forecasts. Therefore, air travel can improve information dispersion and reduce information asymmetry. In this case, air travel is expected to be negatively associated with analyst forecast errors.

Through the second channel, *recognition heuristic*, air travel makes firms in destination more familiar and recognized to local analysts. People are more likely to bet on their own judgement if they consider themselves are more knowledgeable about the underlying topic (e.g., Heath and Tversky, 1991). Tetlock (2005) documents that experts are more inclined to be overconfident with their predictions, as a result, their predictions of political and economic trends have no better than non-experts. Even though air travel improves the information environment, analysts may overreact to the richer information environment. In this way, air travel may lead to more optimistic and overconfident bias in expectations, and degrade forecast accuracy.

To explore the effect of air travel on analyst earnings forecasts, I firstly obtain data of quarterly analyst earnings forecasts for U.S. public firms traded on NYSE, AMEX, or NASDAQ from Thomson Reuters' Institutional Brokers Estimate System (IBES). Following Jiang, Kumar, and Law (2016), because the earnings forecast announcement dates before 1993 are unreliable, I focus on the earnings forecast data from 1994 to 2018. Analyst coverage is based on the availability of quarterly earnings per share (EPS) estimations provided by analysts. In this paper, I use two measurements of analyst coverage. The first one is the number of analysts following a given firm. The second one is the number of forecasts produced for a given firm.

Following Da et al. (2021), the U.S. Department of Transportation (DOT) provides monthly data on origin airport, destination airport, and the number of passengers starting from January 1990. I obtain the location of airports, including cities, states, and zip codes, and the number of passengers on each flight from the DOT T-100 Domestic Segment Database. I then calculate the total number of air travellers between every two cities in each quarter.

Travellers get first-hand information and knowledge about distant places during travel, and they are likely to share their experiences with others after coming back (Kim and Stepchenkova, 2015; Prayag et al., 2017). Individuals, even economic agents, are easier to follow information obtained through word-of-mouth communication (Ellison and Fudenberg, 1995). With more people travelling, there are better information transfer and a richer information environment between two distant places than fewer people travelling. Therefore, the number of air travellers from the analyst location city to firm headquarter city is applied to proxy the information environment of analysts with target companies, instead of the number of flights. Even though I do not have the data of analysts' travel, I can stand by the information environment strengthened by air travellers and examine its implications for analyst forecasts.

To match the earnings forecast and air travel data, I need to identify the location of analysts and the location of firms. I firstly match IBES data with CRSP and Compustat datasets. CRSP provides monthly stock prices, returns, and shares outstanding. Compustat provides firm size, leverage, location of each company's headquarter, and other accounting variables. I then obtain the data of analysts' branch office location following Jiang, Kumar, and Law (2016) and Cuculiza et al. (2021), based on IBES analyst and broker translation files, Thomson Reuters, and the BrokerCheck website by FINRA.[1] Analysts and firms located outside the U.S. are excluded. In the final sample, there are 5,324 analysts giving earnings forecasts for 4,264 firms.

The first finding is that air travel is positively and significantly correlated with analyst coverage at the firm to analyst city level. The dependent variable in the OLS regressions is the number of analyst coverage of a firm by analysts from each analyst location city. The main explanatory factor is the number of air travellers from analyst location city to firm headquarter city. By controlling the year-quarter fixed effect, firm fixed effect, and firm-analyst city pair fixed effect, I can address the concern that firms and analysts are located in cities that have a large number of air travellers. In economic terms, I find a one standard deviation increase in air travel from analyst location city to firm headquarter city is associated with about a 2% increase in analyst coverage. This finding suggests that air travel is associated with a positive externality, in that it makes firms attract more attention from analysts.

To address the endogeneity concern that air travel is capturing the effect of omitted economic variables, and to identify a causal effect of air travel on analyst coverage, two instrumental variables regarding exogenous shocks on air travel are applied following

[1] https://brokercheck.finra.org/. The website provides a time series of firms and locations where an analyst registers.

Giroud (2013) and Cuculiza et al. (2021). The first instrument variable is the new air route operation between the analyst location city and the firm headquarter city. The opening of a new air route brings more air travellers between two places. With more air travellers, the new air routes further improve the information environment.

I do not see a compelling argument favouring new air routes directly stimulating analyst coverage. However, the new air routes can be potentially in response to some economic activities such as new investment opportunities, which may drive analysts attention to firms in destinations. The endogenous instrument will lead to biased estimates of air travel. To further address this concern, terrorist attacks and mass shootings near firm headquarters are employed as the second instrumental variable. People become more pessimistic in their risk assessments when they are exposed to extreme negative events such as terrorist attacks (Lerner and Keltner, 2001). Unlike Cuculiza et al. (2021), who focus on the terrorist attacks and mass shootings occurred near analyst location, I investigate these negative exogenous shocks that occurred near firm headquarter. Terrorist attacks and mass shootings make air travellers feel more pessimistic and riskier about the firm headquarter city, which lowers their expectations on travel. The literature has documented the effect of terrorist attacks on analyst pessimism forecasts (e.g. Cuculiza et al. (2021)), but I do not see a compelling argument in favour of extreme negative shocks directly reducing analyst coverage. Therefore, terrorist attacks and mass shoots are expected to negatively impact the number of air travellers but exogenous to analyst coverage.

The first-stage results in the 2SLS regressions show a positive influence of new air route opening on air travel, while a negative influence of terrorist attacks and mass shootings on air travel. The second-stage results confirm the findings in baseline results that air travel has positive predictability on analyst coverage. The two instruments pass the K-P *LM* test for under-identification and the K-P Wald *F* test for weak-identification, indicating that they are valid. The 2SLS tests document a causal effect of air travel on analyst coverage.

The literature thus far has shown that recognition and information are cultivated by locality (Grinblatt and Keloharju, 2001; Malloy, 2005; Mian, 2006). To ensure that my tests are not only picking up this effect, I split the sample of analyst-firm pairs into two groups based on geographical distance (high vs. low cutting at the median), and perform the analysis separately for each group. I find that air travel is positively related to analyst coverage stronger for firms that are far from analysts, which suggest that the influence of air travel outperform the influence of geographical distance.

Another subsample test examines whether air travel has a stronger effect in the poor economic condition states. There is less initial attention put into poor states, so the increase in air travellers is expected to have a larger improvement of the information environment in the poor states. I split the sample by the median personal income in the firm headquarter states, finding that the effect of travel on analyst coverage is concentrated in the subsample of less personal income states.

I then explore the influence of air travel on analyst coverage within different degrees of firm information asymmetry. I adopt capital-market-based and financial-statement-based information environment proxies following Du, Yu, and Yu (2017), which are institutional ownership and earnings management. Analysts are easier to process the information if the information transparency of a firm is high, but are more likely to depend on their own recognition if the information transparency is low. The results present that air travel has a stronger effect in the more opaque information environment sample, which suggests high dependency on improved information environment and recognition by air travel.

Another two additional tests are conducted to check results robustness. The first one is a subsample test with the time period post-Reg FD, which is 2001-2018. Reg FD implemented by the U.S. Securities and Exchange Commission (SEC) in Aug 2000 eliminated the channel and benefit of private access to management and firm-specific information (Koch, Lefanowicz, and Robinson, 2013). Air travel tends to become less helpful for information dispersion in the post-Reg FD period. In this case, the positive and significant coefficients of air travel on analyst coverage provide evidence of the recognition channel during the post-Reg FD period.

The second robustness check of air travel and analyst coverage is based on the firm aggregate analyst coverage. I examine the influence of total air travel inward firm headquarter city on the firm's total analyst coverage. Both OLS results and 2SLS results show that the aggregate inward air travel has positive predictability on total analyst coverage of a given firm, which confirms the hypothesis.

To examine the second hypothesis that air travel breeds information advantage or recognition heuristic, I test the air travel and analyst forecast errors at the analyst-firm level. In this test, the main explanatory variable is still the air travellers from analyst location city to firm headquarter city. The dependent variables are three measures of analysts forecast errors. I firstly measure analyst forecast errors with the absolute forecast error, which is the absolute value of the difference between forecasted and actual earnings then scaled by the average share price in the previous quarter. I then compute the de-mean and proportional median analyst forecast error to compare the forecast error of a given analyst with other analysts' forecasts following the same firm in the same quarter.

I find positive and significant correlations between air travel and all three measures of analyst forecast errors. Economically, a one standard deviation increase in air travel is associated with a 4% increase in absolute forecast error, a 1.95% increase in de-mean analyst forecast error, and a 3.25% increase in proportional median analyst forecast error, respectively. These findings support the hypothesis that air travel reflects the recognition heuristic and leads to more biased expectations, rather than information advantage. I also conduct the above additional tests with analyst forecast errors, and I find similar results in line with analyst coverage. Air travel has a stronger influence on analyst forecast errors when firms are located distantly or in poor states, when firms have a less transparent information environment, and during the post-Reg FD period.

Since the analyst forecast errors only reflect the level of forecast bias, they do not present the overestimate or underestimate. The next test in this paper examines air travel and analyst optimism. Using OLS, Logit, and Probit model, respectively, I find air travel is positively and significantly correlated with analyst optimistic forecast, consistent with the literature that recognition heuristic is associated with optimism and overconfidence (e.g. Tetlock, 2005).

Then, this paper examines how the financial market reacts to the influence of air travel on analyst forecasts. Air travel drives analyst coverage and forecasts. Shared analyst coverage connects firms and promotes their return comovement (Muslu, Rebello, and Xu, 2014). Due to limited attention, analysts sometimes make forecasts for a target firm just based on information and commonalities of similar firms instead of a thorough investigation. When investors follow these sluggish forecasts, there are return comovement (Muslu, Rebello, and Xu, 2014) and momentum spillover effect (Ali and Hirshlerfer, 2020) between stocks with shared analyst coverage. If air travel drives analyst attention and coverage, it also likely leads to stock comovement and momentum spillover effect of firms with shared analyst coverage.

To test this conjecture, I first directly examine air travel and daily return correlation between stocks that share analyst coverage, following Muslu, Rebello, and Xu (2014). Higher air travels lead to optimistic forecasts. Investors' reactions to these biased forecasts drive the stock correlation of firms with more air travel. I find that the average air travel from shared analysts' locations to headquarter locations of two firms can predict the return correlation of these two firms.

Second, I test the momentum spillover effect between stocks with shared analyst coverage following Ali and Hirshlerfer (2020), which is the return predictability of connected firms on a given firm dependent on analyst coverage and air travel. Air travel drives analyst attention to firms in the distance. Using air travel from analyst location to firm headquarter location as the weight to proxy the attention put on each firm, I calculate the weighted average analyst portfolio returns (*AP RET*) and the weighted average connected-firm returns (*CF RET*) for each stock. *AP RET* is the weighted average portfolio return of all other stocks in each analyst's portfolio covering the given stock. *CF RET* is the weighted average portfolio return of all stocks having analyst coverage connection with the given stock. I find both *AP RET* and *CF RET* report positive predictability on the given stock's return.

Finally, I make a trading strategy, where I rank stocks into quintiles based on the *CF RET* and calculate the equal-weighted and value-weighted return of each quintile portfolio. The positive alphas in the high rank quintiles verify that past *CF RET* forecasts future abnormal returns. Overall, these findings indicate an interaction effect of air travel and shared analyst coverage on return comovement and predictability.

This research firstly sheds new light on the "black box" of analyst information acquisition and processing underlying analysts' behaviour. The examination of air travel influencing analyst forecasts is related to the extensive literature on analyst information acquisition (Fischer and Stocken, 2010), analyst attention (Gibbons, Iliev, and Kalodimos, 2021), contribution to market efficiency (Chen, Cheng, and Lo, 2010), earnings forecast accuracy (Clement, 1999), analyst recommendations (Bradshaw, 2004), and forecasts informativeness (Lys and Sohn, 1990). The results in this study show that with a better information environment, air travel is correlated with more analysts' coverage but biased optimism forecasts.

This work also contributes to the recent literature on the economic implications of air travel for financial outcomes. Giroud (2013) finds that air travel facilitates internal monitoring within firms and improves their performance. Bernstein, Giroud, and Townsend (2016) document that air travel benefits the allocation of venture capitalists and enhances performance. Chemmanur, Hull, and Krishnan (2015) show that open-sky agreements improve the performance of private equity investments in foreign countries. Da et al. (2021) find that air travel within the U.S. increases cross-state investments by institutional investors, lowers the cost of equity for small businesses, and facilitates corporate acquisitions. This study shows that air travel also influences the behaviour of financial analysts by attracting analyst attention and explaining analyst biased earnings forecasts.

This study finally complements the behavioural literature of recognition and familiarity affecting financial market participants, including institutional investors (Coval and Moskowitz, 1999), individual investors (Huberman, 2001), mutual fund managers (Chan, Covrig, and Ng, 2005), household portfolios (Dimmock et al., 2016), economics exchange (Guiso, Sapienza, and Zingales, 2009), and international bank loans (Giannetti and Yafeh, 2012). This paper extends this literature by focusing on sell-side financial analysts, showing that recognition and familiarity cultivated by air travel also influence analysts' coverage and earnings forecast accuracy. A few previous studies are close to this paper, but in these studies, recognition and familiarity are typically captured with "fixed" variables at the analyst-firm level, such as geographical proximity (Malloy, 2005) or cultural distance (Du, Yu, and Yu, 2017). With controlling the fixed analyst and firm characteristics, models in this study focus on the effect of variations in air travel. This work highlights a more dynamic effect of recognition and familiarity.

The rest of the paper is organized as follows: Section 2 describes the data and methodology, Section 3 presents the results of analyst coverage, Section 4 discusses air travel and analyst forecast accuracy, Section 5 contains market reactions, and Section 6 concludes.

3.2 Data and Methodology

This section describes my sample data collection methods and the baseline model. I design the research around U.S. analyst forecasts, with air travellers from the cities where analysts' branch offices are located to the cities where public firms are headquartered. I focus on a sample of sell-side analysts who are located in the U.S. and give annual earnings forecasts for firms headquartered in the U.S.

3.2.1 Data

I collect quarterly analyst earnings forecasts for U.S. public firms traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or NASDAQ from Thomson Reuters' Institutional Brokers Estimate System (IBES). According to Jiang, Kumar, and Law (2016), the earnings forecasts before 1993 are unreliable as there are significant lags based on the arrival time of the monthly forecasts in batches. Therefore, the sample period in this paper starts from 1994 to 2018, including 27,216 analysts who gave annual forecasts for 19,558 firms.

The air travel data are obtained from the U.S. Department of Transportation (DOT) T-100 Domestic Segment Database. It provides monthly data of each airline starting from 1990, including origin airport, origin city, origin state, destination airport, destination city, destination state, the distance between two airports, and the number of passengers carried by each flight. I require that the distance between two airports must be longer than 100 miles, and the total number of passengers between two airports must be more than 1,000 in a month.

To merge analyst earnings forecasts and air travel data, I need first to identify analysts' location and firms' location. I follow Jiang, Kumar, and Law (2016) and Cuculiza et al. (2021) to identify the location of each analyst by the city each analyst's branch office is located in, using IBES analyst and broker translation files, sell-side analyst reports from Thomson Reuters, and the BrokerCheck website by FINRA. Analysts who are located outside the U.S. are dropped from my sample. The location of each firm is identified by the firm headquarter city, which is obtained from Compustat. I restrict the sample to common stocks (share codes 10 or 11) that are traded on NYSE, AMEX, or NASDAQ, following Jiang, Kumar, and Law (2016). Firms headquartered outside the U.S. are dropped. I also collect data on monthly stock prices, returns, and shares outstanding from CRSP. After matching analyst location, firm location and air travel data, there are 5,324 analysts covering 4,264 firms in the final sample.[2]

[2] I drop analyst-firm pairs if there are no air travel connections.

3.2.2 Model

The following baseline model examines the effect of air travel from analyst location city to firm headquarter city on analyst coverage of a specific firm, at the firm i to analyst location city j level.

$$Y_{ij,t+1} = \alpha + \beta_1 \cdot \textit{Air travel}_{ijt} + \mathbf{X}^{'} \cdot \beta_{\mathbf{A}} + \text{Fixed effects} + \epsilon_{ijt} \tag{1}$$

where where i indicates firm, j indicates analyst location city and t indicates quarter. $Y_{ij,t+1}$ is the analyst coverage, which includes two different measures, $Coverage_{ij,t+1}$ and $Forecasts_{ij,t+1}$. $Coverage_{ij,t+1}$ is the natural logarithm of one plus the number of analysts from location city j covering firm i in a given quarter $t+1$. $Forecasts_{ij,t+1}$ is the natural logarithm of one plus the number of earnings forecasts given by all analysts in location city j for firm i in a given quarter $t+1$. $\textit{Air travel}_{ijt}$ is the nature logarithm of air travel passengers from analyst location city j to the city where firm i headquartered in quarter t. $\mathbf{X}^{'}$ contains several control variables regarding analyst level characteristics, firm-level characteristics, economic conditions, and geographical distance following (Du, Yu, and Yu, 2017; Cuculiza et al., 2021).[3] All independent variables are lagged by one quarter. Fixed effects include time fixed effect, industry fixed effect, firm fixed effect, and firm to analyst location city fixed effect in different specifications. Standard errors are double clustered by firm and quarter.

The analyst level characteristics include forecast horizon, followed companies, analyst experience, number of revisions, broker size, and All-star analysts. *Forecast horizon* is the natural logarithm of one plus the number of days between an analyst issuing an earnings forecast and the corporate earnings announcement date. *Companies* is the natural logarithm of one plus the number of companies an analyst follows during a specific quarter. *Firm experience* is the natural logarithm of one plus the number of months an analyst has covered a specific firm. *Total experience* is the natural logarithm of one plus the number of months since this analyst's first forecast in the IBES. *Revisions* is the natural logarithm of one plus the number of forecast revisions made by an analyst regarding the same firm in the same forecasting quarter prior to the current forecast. *Broker size* is the natural logarithm of one plus the number of analysts employed by the brokerage of an analyst

[3] Definitions of the variables are provided in Appendix A.

covering firm i. Data of the above analyst characteristics come from IBES. *All-star* is a dummy equal to one if an analyst following the firm i is defined as *All-star* analysts by *Institutional Investor* magazine in a given quarter. Because model (1) is set at the firm i to analyst city j level, all analyst level control variables are taken from the average of all analysts from location city j covering firm i.

Company characteristics include firm leverage, firm value size, and the absolute value of the change in earnings. *Firm leverage* is the total liabilities divided by total assets. *Firm size* is the natural logarithm of total assets. *Earnings change* is the absolute value of the change in earnings over the previous quarter, scaled by the previous quarter's earnings. Data are obtained from Compustat.

Several control variables are used to capture economic conditions and geographical distance. *PI (A)* is the natural logarithm of one plus the personal income in analyst location j state. *PI (F)* is the natural logarithm of one plus the personal income in firm i headquarter state. The personal income data come from the U.S. Bureau of Economic Analysis (BEA). *Distance* is the natural logarithm of the geographical distance between the analyst location city j and the firm headquarter city i.

3.2.3 Summary Statistics

Panel A of Table 3.1 provides the distribution of the final sample across years, including the number of firm headquarter cities, analyst location cities, firm city and analyst city pairs, total number of earnings forecasts, average quarterly air travel passengers from each analyst location city to firm headquarter city pair, and average geographical distance (miles) between firm city and analyst city pairs in each year. There is an increasing trend of air travel passengers and an increasing trend of the average distance from 1994 to 2018. Air travel connects more distant city pairs, so the distance incline. These results also indicate that analysts tend to put more attention on firms in the distance. The number of forecasts shows an uptrend before the 2008 global financial crisis, whereas a downtrend after that. Panel B of Table 3.1 reports the summary statistics of variables in the sample of model (1). On average, analysts in the final sample have more than 13 years of experience and cover 20 firms. Companies are covered by two analysts and given three earnings forecasts from each analyst location city on average. All-star analysts consist of 10% of the final sample.

[Insert Table 3.1 here]

3.3 Analyst Coverage and Air Travel

This section reports the results from regressions examining the effect of air travel on analyst coverage.[4] I first report the baseline results of model (1). To address the endogenous concern, I then apply two instrumental variables and 2SLS regressions. I also explore the influence of air travel in subsample tests within different conditions. Finally, the impact of air travel is examined at the firm level.

3.3.1 Baseline Results

Table 3.2 reports the baseline results of model (1). The dependent variable is analyst coverage of firm i by analysts in location j, and the key explanatory variable is the nature logarithm of air travel passengers from analyst location city j into the city in which firm i is headquartered. The results of $Coverage_{ij,t+1}$ are shown in Columns (1), (3) and (5), while the results of $Forecasts_{ij,t+1}$ are shown in Columns (2), (4) and (6). Columns (1) and (2) control year-quarter fixed effect and industry fixed effect. Columns (3) and (4) control year-quarter fixed effect and firm fixed effect. Firm fixed effect and year-quarter fixed effect address the endogenous concern that many firms are headquartered in large cities such as New York, LA, or Chicago, and these cities initially have a large number of inward air travellers. Columns (5) and (6) control year-quarter fixed effect and firm to analyst location city fixed effect. The firm to analyst location city fixed effect captures the time-invariant economic conditions of each firm location and analyst location pair, e.g. the firm has a branch office in the analyst location city. Results show that air travellers have a positive and significant coefficient ranging from 0.3 to 0.8. Economically, a one standard deviation increase in $Air\ travel_{ijt}$ is associated with a 1.0% to 2.3% increase in analyst coverage. Consistent with my hypothesis, analysts tend to put more attention on the firms headquartered in a city with better information environment, i.e. more air travellers.

In terms of control variables, analyst forecast horizon, experience, number of revisions, and economic state of analyst location are positively correlated with analyst coverage. Attentions of experienced analysts on firms in the distance are concentrated. Broker size also shows a positive coefficient, which means analysts from large brokerage have a correlated concentration in specific firms. Firms with more analyst coverage also attract more All-star analysts. Consistent with the literature, geographical distance has a

[4] All coefficients are multiplied by 100 in this section.

negative influence as analysts prefer to focus on local firms. Finally, firms that have large size, low leverage and are located in wealthy states attract more analysts.

[Insert Table 3.2 here]

3.3.2 Instrumental Variable Results (2SLS)

Even though I use fixed effects to control firms located in large cities that attract many air travellers, another endogeneity concern is that air travel is capturing the effect of omitted economic variables that drive analyst forecasts. To address this endogeneity concern and to identify a causal effect of air travel on analyst coverage, I employ two instrumental variables, which are two exogenous shocks on air travel following Giroud (2013) and Cuculiza et al. (2021).

The first exogenous shock on air travel is the new air route operation between the analyst location city and firm headquarter city. Following Giroud (2013) and Da et al. (2021), a new air route between two places reduces travel time, brings more air travellers, and simplifies acquiring information, especially if there is no direct flight between these two places before. To fully capture the effect of air routes changing, I consider both opening and cancellation of air routes. Furthermore, I require that the initiation of a new air route must transport at least 1,000 passengers in the first three quarters. If an air route is cancelled, the route must have transported at least 1,000 passengers in the previous three quarters.

The variable $Route_{ijt}$ captures the initiation and cancellation of air routes between firm headquarter city and analyst location city in a given quarter. It is an indicator equal to 1 in the following two quarters after a new airline route is initiated between firm headquarter city and analyst location city, equal to -1 in the following two quarters after an airline route is cancelled, and 0 otherwise. Then I take the sum of this indicator in each quarter. If a new air route opens, people will have a new choice of going to the firm headquarter city. More people are able to get first-hand knowledge about firms in the destination, and more information can transfer between the two places.

Even though I do not see any convincing research arguing that air routes directly drive analyst coverage, one potential limitation of new air routes is that they may be in response to local economic activities at the firm headquarter city and so endogenously related to analyst coverage. The endogeneity of instrumental variable biases the estimates of air travel on analyst coverage. To avoid this potential concern, I introduce the second exogenous shock on air travel, which is the terrorist attacks and mass shootings near firm headquarter city. Psychology literature finds that people become more pessimistic in their risk assessments when exposed to extreme negative events such as terrorist attacks (Lerner and Keltner, 2001). Cuculiza et al. (2021) find that if terrorist attacks or mass shootings occur near the analyst location, analysts tend to give more pessimistic forecasts. Different from them, I focus on the terrorist attacks and mass shootings around firm headquarter city, conjecturing that the air travel from analyst location city to firm headquarter city decreases if a terrorist attack or mass shooting occurs near the firm headquarter city. Terrorist attacks and mass shootings make air travellers feel more pessimistic about the firm headquarter city, which lowers their desires to travel.

Following Cuculiza et al. (2021), I obtained terrorist attacks data from Global Terrorism Database (GTD) and mass shootings data from Mother Jones. The variable $Attack_{it}$ captures the terrorist attacks and mass shootings close to firm headquarter, which is a dummy equal to one in the quarter if a terrorist attack or mass shooting occurs within a 100-mile radius of firm headquarter leading to at least one human casualty, and zero otherwise. Table 3.B1 in Appendix B shows the terrorist attacks and mass shootings in my sample.

Table 3.3 reports the 2SLS results. $Route_{ijt}$ is the instrumental variable in Columns (1) to (3), while $Attack_{it}$ is the instrumental variable in Columns (4) to (6). Column (1) presents the first-stage result of new air routes opening. Column (4) presents the first-stage result of terrorist attacks and mass shootings. As expected, $Route_{ijt}$ has a positive influence on air travel while $Attack_{it}$ shows a negative influence. Other columns show the second-stage results. Air travel still reports positive and significant coefficients on analyst coverage, both for $Coverage_{ij,t+1}$ and $Forecasts_{ij,t+1}$. However, the coefficients of $Air\ travel_{ijt}$ in Columns (5) and (6) of Table 3.3 are only significant at the 10% level and much larger than the corresponding coefficients in OLS regressions reported in Columns (5) and (6) of Table 3.2. The reason would be that $Attack_{it}$ is a firm-level instrumental variable, not a firm-analyst cross-sectional. To check the validity of these two instrumental variables, I report the K-P LM statistics of under-identification and K-P Wald F statistics of the weak-identification test at the end of second-stage columns. The p-value of K-P LM statistics is close to 0, which means I can reject the null hypothesis that the model is under-identified. The K-P Wald F statistics is larger than 10, rejecting the null hypothesis that instrumental variables are weak. However, according to Jiang (2017), K-P Wald F statistics may not justify the weak instruments when the first-stage model has control variables and fixed effects. Thus, I also report the R^2 and Shea's partial R^2 of the first-stage model, indicating that these two instruments are not obviously weak.

[Insert Table 3.3 here]

3.3.3 Geographical Distance and Personal Income

In the literature, the locality is thought to be cultivated by the physical proximity of some agent with a "special" entity of interest. For instance, people prefer to invest in local companies (Coval and Moskowitz, 1999). To examine whether air travel is also captured by the locality or beyond the locality, I split the sample into two groups by the median geographical distance (826 miles) between analyst location city and firm headquarter city. I then estimate the baseline model of analyst coverage in each group separately.

Results are reported in Panel A of Table 3.4. Air travel is positively and significantly correlated with analyst coverage in the long-distance group only. This finding suggests that air travel improves the information environment of a far destination to the local people, attracting large attention of local analysts on firms in the distance. The result also suggests that air travel has a stronger effect beyond geographical proximity, as more air travel is associated with more coverage even though the firm headquarter is far from the analyst location.

It is interesting to observe the findings dependent on the economic state of destination places. Wealthy states initially have a large number of inward air travellers and attract the large attention of analysts, so the increase in air travellers is associated with a smaller improvement of information transfer. However, there are fewer air travellers into poor states initially, so the increase in air travellers is expected to have a larger improvement of the information environment. To examine the effect of air travel in different economic states of destinations, I split the sample into two groups based on the median personal income (486,527 million dollars) in the firm headquarter state, and perform the baseline model separately.

Panel B of Table 3.4 presents the results. The coefficients of air travel are significant only in the low personal income group. Consistent with the hypothesis, air travel tends to have a stronger effect in the sample of low personal income states, rather than in the sample of high personal income states.

[Insert Table 3.4 here]

3.3.4 Firm Information Environment

I then explore the impact of air travel on analyst coverage in different degrees of initial information asymmetry. Specifically, I examine how the effect of air travel varies among firms with different information environments. Information of more transparent firms is easier to spread, and analysts tend to depend less on personal information channels. However, it is hard to obtain insider information from less transparent firms, and analysts are more likely to cover these firms based on personal knowledge. As air travel improves the information environment, I expect that the effect of air travel should be more prominent for less transparent firms. Following Du, Yu and Yu (2017), I employ two proxies to assess a firm's information environment.

The first proxy is the institutional ownership which reflects the capital-market-based information environment. According to Amihud and Li (2006), the presence of institutional investors contributes to a more transparent information environment. I collect the institutional holdings data from Factset and compute a firm's quarterly institutional ownership as the market value of shares held by institutional investors scaled by the total market value of shares outstanding. Following Du, Yu, and Yu (2017), a firm is classified as having high (low) institutional ownership if its average institutional ownership over the previous three years (i.e. 12 quarters) is above (below) the sample median average institutional ownership in each quarter.[5] I report the results in Panel A of Table 3.5, where I estimate the baseline model in the high and low institutional ownership samples, respectively. Air travel has significant results in both groups but is stronger in the low institutional holding sample with larger coefficients.

The second proxy is the earnings management which reflects the financial-statement-based information transparency. I proxy earnings management with the firm's prior 3-year moving sum of the absolute value of discretionary accruals following Yu (2008) and Hutton, Marcus, and Tehranian (2009).[6] Dechow, Sloan, and Sweeney (1996) document that firms are more likely to be managing earnings if they have consistently large absolute values of

[5]The value of the observation is treated as missing if no available institutional ownership information.
[6]The estimation of discretionary accruals follows Yu (2008). See Appendix in Yu (2008) for more details.

discretionary accruals, which indicates the opacity of a firm's financial reports. I classify a firm as having a less (more) opaque information environment if its discretionary accruals are lower (more) than the sample median in each quarter. The results are presented in Panel B of Table 3.5. As expected, the coefficient of air travel is positive and significant only in the more earnings management sample.

Overall, results in Table 3.5 suggest that air travel has a more substantial effect in the sample of a more opaque and less transparent initial firm information environment. With the improved information environment by air travel, analysts are more likely to provide forecasts based on their personal information or recognition channel for the firms with large information asymmetry.

[Insert Table 3.5 here]

3.3.5 Superior Access to Firm-specific Information

To check whether an analyst's superior access to firm-specific information accounts for my findings, I restrict the sample to the period after the implementation of Reg FD (2001-2018). The Reg FD implemented by the U.S. Securities and Exchange Commission (SEC) in Aug 2000 claims that all publicly traded firms must disclose information to all investors simultaneously. Reg FD aims to wipe out selective disclosure where some market professionals could receive market information before others. Cohen, Frazzini, and Malloy (2010) document that Reg FD significantly reduces an analyst's private channel to firm-specific information. During the post-Reg FD period, the channel of analysts to obtain private information through air travel is largely stamped out. Results are shown in Table 3.6. The results of air travel still hold with positive and significant coefficients. After cutting down the channel of private information, air travel still provides the recognition channel which attracts analysts' interest.

[Insert Table 3.6 here]

3.3.6 Analyst Coverage and Aggregate Inward Air Travel

The number of analyst coverage at the firm to analyst location city level is only three on average. To further identify the impact of air travel on analyst coverage, I estimate model (1) at the firm level and examine how the aggregate air travel into firm location stimulates the total analyst coverage.[7] OLS results are shown in Table 3.7. The dependent variable is the nature logarithm of total analyst coverage of firm i in quarter $t+1$, including the total number of analysts who give forecasts for firm i ($Total\ coverage_{i,t+1}$) and the total number of analyst forecasts given for firm i ($Total\ forecasts_{i,t+1}$). The key explanatory variable $Total\ air\ travel_{it}$ is the nature logarithm of aggregate air travel passengers inward the city firm i headquartered. Analyst level control variables are taken from the average value of all analysts who cover the given firm i. Personal income in firm location and the firm fixed effect are used to capture economic conditions. Results show that aggregate inward air travellers have positive and significant coefficients ranging from 0.5 to 0.8 in Table 3.7. Economically, a one standard deviation increase in $Total\ air\ travel_{it}$ is associated with a 1.6% to 2.5% increase in analyst coverage.

[Insert Table 3.7 here]

2SLS results of analyst coverage and aggregate inward air travel are shown in 3.8. The first instrumental variable $Route_{it}$ is equal to 1 if the number of new air routes is more than the number of cancelled air routes, -1 if the number of cancelled air routes is more than the number of new air routes, and 0 otherwise, when the firm headquarter city is the destination of air routes in quarter t. The second instrumental variable is still $Attack_{it}$ capturing the terrorist attacks and mass shootings close to firm headquarter in quarter t. The first-stage results are shown in Columns (1) and (4), indicating that new air route opening is positively related to air travel, whereas the terrorist attacks and mass shootings are negatively related to air travel. In Columns (2), (3), (5) and (6), the positive externality of air travel on analyst coverage still holds in second-stage results.

[Insert Table 3.8 here]

3.4 Analyst Forecast Accuracy and Air Travel

This section aims to identify how air travel impacts analyst forecast accuracy. First, I examine the links between analyst forecast errors and air travel passengers. Second, I examine the correlation between analyst forecast optimism and air travel passengers.

[7] Panel A of Table 3.B2 in Appendix B presents the descriptive statistics of variables in the aggregate firm-level specifications. The average analyst coverage and forecasts are 7 and 11, respectively.

3.4.1 Analyst Forecast Errors

Ex-ante, the influence of air travel on analyst forecast errors is ambiguous. According to Hovhannisyan and Keller (2015), air travel helps information dispersion and alleviates the difficulty of information acquirement. Air travellers gain knowledge and information during travel and spread them after travel. In this way, air travel combines with an information advantage. Highly skilled financial analysts are likely to access firm-specific information quickly. They are able to possess specialized knowledge and channels to access insider information. Therefore, if air travel reduces information asymmetry, analysts are expected to produce fewer forecast errors.

Otherwise, air travel could be related to the recognition heuristic, where people tend to bet on subjective value and have a biased expectation of familiar objects. Goldstein and Gigerenzer (2002) conduct an experimental research finding that more familiar objects in a set are ranked as more attractive to subjects. Kilka and Weber (2000) show that American subjects had higher expectations about the future performance of American companies, whereas German subjects were more optimistic about German companies than American companies. This finding suggests that there may be a positive bias in expectations about a specific topic induced by familiarity, which implies that familiar firms are expected more favourably. Several finance studies document evidence that the recognition heuristic exists among financial market participants. Dimmock et al. (2016) find that households are more likely to participate in stock markets if they proclaim to be more knowledgeable about the financial markets. Households would like to allocate a large part of their retirement savings in their employers' stocks (Benartzi, 2001). Air traffic increases the familiarity of institutional investors with firms in the distance but without better portfolio returns, meaning that air traffic does not confer enough informational advantage (Da et al., 2021). Therefore, if air travel leads to a recognition heuristic and only makes analysts more optimistic or overconfident, analysts are expected to produce more forecast errors.

Thus, the second hypothesis is that air travel impacts analyst forecast errors, but the relationship is ambiguous *ex-ante*. The following model is employed to examine the air travel on analyst forecast errors, at the analyst forecast level,

$$\textit{Forecast Errors}_{ia,t+1} = \alpha + \beta_1 \cdot \textit{Air travel}_{iat} + \mathbf{X}^{'} \cdot \beta_{\mathbf{A}} + \text{Fixed effects} + \epsilon_{iat} \qquad (2)$$

where i indicates firm, a indicates analyst and t indicates quarter. The dependent variable is analyst forecast errors $Forecast\ Errors_{ia,t+1}$. The key explanatory variable $Air\ travel_{iat}$ is the nature logarithm of air travel passengers from analyst a location city to firm i headquarter city in quarter t. Control variables are similar to model (1) with the additional control of analyst coverage, which is the total number of analysts covering firm i.[8]

I use three different analyst forecast errors $Forecast\ Error_{ia,t+1}$ following Du, Yu, and Yu (2017), Gibbons, Iliev, and Kalodimos (2021), and Cuculiza et al. (2021). The first one is the absolute analyst forecast error $AFE_{ia,t+1}$, which is the analyst a forecast error of firm i, calculated as the absolute value of the difference between forecasted and actual earnings scaled by the average share price in the previous quarter, $\frac{|\text{Forecast}_{ia,t+1}-\text{Actural}_{i,t+1}|}{\text{Share Price}_{it}}$. The second measure is $DAFE_{ia,t+1}$, which is the de-mean absolute forecast error, calculated as the difference between analyst a absolute forecast error $AFE_{ia,t+1}$ and the average $AFE_{ia,t+1}$ of other analysts following the same firm i during the same quarter, scaled by the average $AFE_{i,t+1}$ of other analysts following the same firm i during the same quarter, $\frac{\text{AFE}_{ia,t+1}-\overline{\text{AFE}_{i,t+1}}}{\overline{\text{AFE}_{i,t+1}}}$. The third measure is $PMAFE_{ia,t+1}$, which is the proportional median absolute error, calculated as the difference between analyst a absolute forecast error $AFE_{ia,t+1}$ and the median $AFE_{i,t+1}$ of other analysts following the same firm i during the same quarter, scaled by the median $AFE_{i,t+1}$ of other analysts following the same firm i during the same quarter, $\frac{\text{AFE}_{ia,t+1}-\widehat{\text{AFE}_{i,t+1}}}{\widehat{\text{AFE}_{i,t+1}}}$.

Since $AFE_{ia,t+1}$ is the absolute difference between analyst forecast earnings and the actual earnings, it does not reflect the relative forecast bias compared with other analysts. However, $DAFE_{ia,t+1}$ and $PMAFE_{ia,t+1}$ reflect the analyst forecast errors referring to other analysts who follow the same firm. According to Clement (1999), the advantage of using $DAFE_{ia,t+1}$ and $PMAFE_{ia,t+1}$ is that they account for average forecast errors at firm and time levels. A negative value of $DAFE_{ia,t+1}$ or $PMAFE_{ia,t+1}$ suggests that an analyst has a better than average (or median) performance. In contrast, a positive value suggests that an analyst has a worse than average (or median) performance.

Results are shown in Table 3.9. Firm fixed effect and year-quarter fixed effect are controlled in all columns to address the concern of large city effect. Analyst fixed effect is controlled in Columns (2), (4) and (6) to address the concern that there are more outward air travels if an analyst is located in a large city. Standard errors are double clustered by

[8]Panel B of Table 3.B2 in Appendix B reports the descriptive statistics of variables in the analyst forecast level specifications. The analyst level factors do not need to take average in this section.

firm and year-quarter. Absolute analyst forecast error $AFE_{ia,t+1}$ is the dependent variable in Columns (1) and (2). The positive and significant coefficients of $Air\ travel_{iat}$ reflect the positive correlation between air travel and analyst forecast errors. More air travel is associated with more biased analyst forecasts. Economically, a one standard deviation increase in air travel is associated with a 6% increase in the absolute analyst forecast errors.

$DAFE_{ia,t+1}$ is the dependent variable in Columns (3) and (4), while $PMAFE_{ia,t+1}$ is the dependent variable in Columns (5) and (6). The results indicate that air travel is positively correlated with $DAFE_{ia,t+1}$ and $PMAFE_{ia,t+1}$, which suggest that air travel is related to more biased forecasts compared with the mean or median forecast errors of other analysts following the same firm. In economic terms, a one standard deviation increase in air travel is associated with a 1.8% increase in $DAFE_{ia,t+1}$ and a 3.9% increase in $PMAFE_{ia,t+1}$. Overall, the results in Table 3.9 indicate that air travel leads to more biased forecasts, which confirms the hypothesis that air travel reflects the use of recognition heuristic rather than information advantage. Analysts tend to give biased forecasts for their familiar firms.[9]

[Insert Table 3.9 here]

3.4.2 Analyst Optimism

Results above show that air travel is positively related to analyst forecast errors. However, the measure of analyst forecast errors is the absolute difference between analyst forecast value and the firm's actual earnings. It only reflects the level of absolute forecast bias ($AFE_{ia,t+1}$) or the level of absolute forecast bias compared with other analysts ($DAFE_{ia,t+1}$ and $PMAFE_{ia,t+1}$), not the tendency to overestimate or underestimate. If air travel strengthens the recognition heuristic, analysts are expected to have optimistic and overconfident estimations of company earnings. To test this hypothesis, I define a dummy variable $Optimism_{ia,t+1}$ equal to one if the earnings forecast of analyst a is higher than the average earnings forecasts of other analysts who cover the same firm i within the same quarter t+1, and zero otherwise, following Cuculiza et al. (2021).

Table 3.10 reports the results of analyst optimism and air travel. The dependent variable is $Optimism_{ia,t+1}$ in all models. The key explanatory variable is $Air\ travel_{iat}$. In

[9] Subsample test results are reported in Tables 3.B3, 3.B4 and 3.B5 in Appendix B. Generally, the findings are similar to analyst coverage tests. Air travel has a dominant influence in the sample of firms in the distance, firms in low personal income states, and less transparent firms. Air travel still significantly impacts analyst forecast errors after the implementation of Reg FD.

Columns (1) to (4), OLS regressions are adopted with different specifications of fixed effects. Logit model result is shown in Column (5), and Column (6) presents the Probit model result. Air travel still has positive and significant results in all specifications, which indicates that air travel stimulates optimistic analyst forecasts.

[Insert Table 3.10 here]

3.5 Market Reactions

Analysts tend to give biased forecasts for firms located in cities with more inbound air travel passengers. What is the market reaction to these air travel bred analyst forecasts? Analysts convey coverage-specific information to investors, emphasising commonalities and linkages among stocks in their coverage even though stocks are from multiple industries. As analyst forecasts are an essential information source for investors, investors will raise expectations about shared economic exposure among stocks covered by shared analysts, which will result in higher comovement between stock returns. The past literature has documented the significant impact of shared analyst coverage on stocks comovement and return predictability, compared with industry, geographic, and supply-chain linkage.[10] Air travel passengers drive both analyst coverage and optimism forecasts. Shared analyst coverage then breeds stock comovement. The optimistic forecasts may raise investors' expectations of stocks. Therefore, I conjecture that air travel passengers from analyst location to firm headquarter cities are positively associated with market reactions of stock comovement and return predictability. This section first describes three tests to identify this link, and then provides a trading strategy.

3.5.1 Stock Comovement and Return Predictability

The first test directly examines air travel and return comovement between stocks with shared analyst coverage. According to Muslu, Rebello, and Xu (2014), shared analyst coverage should increase the volume of research that ties the two stocks together and promote their return comovement. Analysts may produce sluggish forecasts for a firm based on their research of another similar firm in their coverage. Investors' reactions to sluggish analyst forecasts further raise the short-term stock comovement. As air travel

[10]For more details about shared analyst coverage and stock comovement, please see Muslu, Rebello, and Xu (2014), Israelsen (2016), and Ali and Hirshleifer (2020).

drives analysts' attention and the volume of research on firms, I expect that air travel from analyst location city to each firm's headquarter city should increase the return comovement between firm pairs with shared analyst coverage.

I define the return comovement between two stocks as the correlation of their daily stock returns in a given quarter, following Muslu, Rebello, and Xu (2014). The main explanatory variable *Mean air travel* is the mean of air travel passengers from analyst location city to each firm's headquarter city for all analysts who cover both firms in lagged one quarter. To be precise, I firstly compute the average air travel passengers from each analyst location to headquarter cities of both firms in a pair, then take the mean of the average air travellers of all analysts covering the given firm pair.[11] For example, firm A and firm B have shared analysts X, Y, Z. I firstly compute the average air travel passengers (J) of X to A and X to B, the average air travel passengers (K) of Y to A and Y to B, and the average air travel passengers (L) of Z to A and Z to B. Then, I compute the mean of J, K and L. Finally, I take the natural logarithm of this mean of air travellers as the main explanatory factor.

Results are reported in Columns (1) and (2) of Table 3.11. Control variables in Column (1) are the natural logarithm of geographical distance between the firm pair and a dummy that whether they are in a similar industry, i.e. the same two-digit SIC code. Then I add another six controls in Column (2), including the similar firm size, similar leverage, similar earnings change, similar stock price, similar personal income in the state of firm headquarter, and similar total analyst coverage.[12] Fixed effects include each firm's fixed effect and year-quarter fixed effect. All independent variables are lagged by one quarter. Accordingly, air travel reports positive and significant coefficients at 0.121 and 0.116. A one standard deviation increase in average air travellers is associated with a 2% increase in stock return correlation. More air travel breeds higher return correlation. Meanwhile, the negative coefficient of distance confirms the argument of geographic comovement in the literature. Finally, the positive coefficients of similar firm-level factors indicate that similar firms tend to have higher return correlation.

[11] I only keep the firm pairs with shared analysts and require that there must be non-zero air travellers from analyst location to headquarter location city of both firms in a pair.

[12] These similar factors are the absolute difference between corresponding factors of two firms in a pair, then taken natural logarithm if necessary. For example, the similar firm size is the natural logarithm of one plus absolute difference between firm A total assets and firm B total assets. Finally, all of these similar factors are multiplied by -1 so that a higher value means more similar. The coefficients of all explanatory variables are multiplied by 100. More detailed definitions of variables are provided in Appendix A.

Next, I explore the return predictability of connected firms based on analyst coverage and air travel. If analyst coverage conveys specific information about commonalities and comovement, the analyst portfolio returns can predict stock returns (Liu, 2011; Muslu, Rebello, and Xu, 2014). The stock comovement associated with sluggish analyst forecasts further breeds stock return predictability. Following them, I first examine whether the weighted average returns of analyst portfolio (*AP RET*) can predict stock returns in Columns (3) and (4) of Table 3.11.

The dependent variable is the quarterly return of each given stock. The main explanatory variable *AP RET* is the one-quarter lagged weighted average portfolio return of all other firms in each analyst's portfolio that covers the given stock. As air travel attracts analyst coverage and attention, the weight of each stock in the analyst portfolio is the air travel passengers from the analyst location city to the given firm headquarter city. Controls include analyst level factors, firm level factors and geographical distance as same as the model (2), but results are not reported for brevity.[13] Fama-French four factors, including market portfolio return, SMB, HML, and UMD, are included in Column (4).[14] Standard errors are taken the Newey-West standard errors with 3-lags. The coefficient of *AP RET* is positive and significant at the 1% level in both columns. A one standard deviation increase in past *AP RET* predicts an increase of 19 basis points in future stock returns in Column (4). With the air travel as weight, the analyst portfolio reports positive predictability on stock returns.

A portfolio of firms connected by shared analyst coverage can be identified as a momentum factor and generate positive alpha (Ali and Hirshleifer, 2020). Following Ali and Hirshleifer (2020), I then examine whether stock returns can be predicted by the past return of connected-firm portfolio (*CF RET*). *CF RET* is the one-quarter lagged weighted average portfolio return of all firms having analyst coverage connection with the given firm. Using air travel to proxy the attention analysts put on each firm, the weight of a connected firm in the given firm's portfolio is the mean of air travel passengers from analyst location city to headquarter cities of both given and connected firm for all shared analysts, i.e. *Mean air travel* in the tests in Columns (1) and (2) of Table 3.11. Taking

[13]Firm level factors include *Firm leverage, Firm size, Earnings change, Total coverage,* and *PI(F)*. Analyst level factors include *Forecast horizon*, *Companies, Firm experience*, *Total experience*, *Revisions, Broker size*, *All-star*, and *PI(A)*. I also control the *Distance* between analyst location city and firm headquarter city.

[14]Fama-French four factors are obtained from Ken French's library website. Quarterly factors are compounded by monthly factors.

the earlier example that firm A is connected to firm B with shared analysts X, Y, Z, the weight of firm B in the connected-firm portfolio of firm A is the mean of average air travel passengers J, K and L.

Results are shown in Columns (5) and (6) of Table 3.11. The dependent variable is the quarterly return of each given stock, and the main explanatory variable is the one-quarter lagged *CF RET*. Controls are the firm-level factors, but results are not reported. Fama-French four factors are included in Column (6). Standard errors are taken the Newey-West standard errors with 3-lags. The coefficient of *CF RET* is positive and significant at the 1% level. A one standard deviation increase in one-quarter lagged *CF RET* predicts an increase of 65 basis points in future stock returns in Column (6). Connected firms report a momentum effect with air travel as the weight. Air travel promotes the connection of firms within the analyst portfolio by driving analysts' attention to firms with more air travel. Sell-side analysts then incorporate news about these air travel linked firms sluggishly, making the stock return predictable by connected-firms.[15]

[Insert Table 3.11 here]

3.5.2 Trading Strategy

I finally examine the relation between past *CF RET* and future stock return with a trading strategy following Ali and Hirshleifer (2020). I first rank stocks, which have both shared analyst coverage and air travel data, into quintiles based on the *CF RET* at the end of each quarter from lowest (quintile 1) to highest (quintile 5). Then I calculate equal-weighted and value-weighted returns of these quintile portfolios in the next three months. The Weight of each stock in quintile portfolios is its market value at the end of last quarter. Table 3.12 reports the excess returns, four-factor alphas, and factor loadings of these portfolios. The four-factor model includes market, size (SMB), value (HML), and momentum (UMD) factors.

Table 3.12 shows a monotonic relation between quintile rank and alphas, especially for the equal-weighted portfolios. The long-short portfolio, which is quintile 5-1 in Table 3.12, is to long top-quintile stocks and short bottom-quintile stocks. It reports a significantly positive alpha within the equal-weighted portfolio but insignificant alpha within the value-weighted portfolio, consistent with the hypothesis that small stocks are more likely

[15]In unreported tests, I use Fama-MacBeth two-step procedure instead of OLS regressions for tests in Columns (3) to (6) of Table 3.11, and I find results still hold.

mispricing due to less available information. The positive alphas in the high rank quintiles show that past *CF RET* forecasts future abnormal returns. As *CF RET* is weighed by air travel and shared analysts, this trading strategy further identifies the interaction influence of analyst coverage and air travel on market reactions.

[Insert Table 3.12 here]

3.6 Conclusion

This paper examines how air travel affects sell-side analyst coverage and forecast accuracy. The number of air travellers from analyst location city to firm headquarter city is employed to proxy the information environment of analysts on firms. This study proves that air travel has an important implication for analyst forecasts, not just investors documented in previous literature.

I first find evidence that air travel improves analyst coverage. After controlling firm-specific characteristics and firm to analyst location city fixed effect, I find air travellers from analyst location city to firm headquarter city have positive predictability on analyst coverage. Firms headquartered in the cities with more inward air travel tend to be covered by more analysts. The causal effect is identified with exogenous shocks on air travel, which are new air route openings, terrorist attacks, and mass shootings. Furthermore, the effect of air travel on analyst coverage is stronger with firms located far from analyst locations, firms headquartered in poorer states, and firms with a more opaque information environment. The results still hold in the post-Reg FD period sample. At the analyst forecast level, this study documents that air travel stimulates analyst forecast errors. Analysts tend to give larger and optimistic biased forecasts for firms headquartered in cities with more inward air travel from the analyst location city. Finally, I find strong market reactions of stock return comovement and predictability under the interaction effect of air travel and shared analyst coverage.

Overall, this study highlights the positive externalities of air travel on financial market participants, especially sell-side analysts, in both driving analyst coverage and stimulating biased forecasts.

Table 3.1: Summary Statistics

Panel A of this table presents the distribution of the sample across years, including the number of firm headquarter cities, analyst location cities, firm and analyst city pairs, the total number of earnings forecasts, average quarterly air travel passengers from analyst location city to firm headquarter city, and average distance (in miles) between firm and analyst city pairs in each year. Panel B of this table presents descriptive statistics of variables in the model (1). Definitions of the variables are provided in Appendix A.

Panel A: Distribution of the sample across years

Year	Firm Cities	Analyst Cities	City pairs	Forecasts	Air travel	Distance
1994	116	31	637	9,927	64,993	957
1995	131	32	806	15,260	63,467	935
1996	144	35	899	17,672	66,016	936
1997	140	37	980	20,308	66,141	923
1998	136	38	983	23,442	67,738	915
1999	130	37	970	24,991	70,001	973
2000	132	38	958	25,170	73,672	987
2001	131	37	920	25,888	70,612	970
2002	128	37	861	23,946	62,983	976
2003	139	38	942	26,873	63,147	951
2004	147	35	1,053	31,384	64,302	983
2005	150	32	1,096	33,684	66,149	997
2006	151	34	1,042	33,079	65,874	977
2007	159	34	1,038	33,723	66,544	982
2008	143	32	1,019	36,093	64,267	973
2009	137	31	962	33,006	64,205	981
2010	143	32	958	31,593	64,969	973
2011	141	31	927	31,759	65,536	988
2012	135	30	883	30,768	70,795	1,011
2013	128	31	843	28,221	73,714	1,011
2014	133	28	852	27,185	76,774	1,019
2015	132	29	830	27,830	84,099	994
2016	132	28	804	25,846	86,807	1,008
2017	134	30	789	24,349	85,441	1,000
2018	139	30	765	23,807	87,986	1,006

Panel B: Variable descriptive statistics

VARIABLES	Obs.	Mean	Std. Dev	Q1	Median	Q3
Coverage	206,318	1.935	2.086	1	1	2
Forecasts	206,318	2.918	3.882	1	2	3
Air travel	206,318	89,095	106,751	9,549	47,037	132,578
Forecast horizon	206,318	209.427	98.900	118	199	285
Companies	206,318	19.908	8.823	15	19	24
Firm experience	206,318	50.062	50.610	13	34	73
Total experience	206,318	166.432	93.948	97	156	227
Revision	206,318	1.245	2.372	1	1	2
Broker size	206,318	57.294	50.112	21	42	81
All-star	206,318	0.096	0.241	0	0	0
Firm size	206,318	19,760	108,355	483	1,835	7,492
Firm leverage	206,318	0.568	0.262	0.381	0.562	0.748
Earnings change	206,318	0.326	3.733	0.024	0.189	0.585
PI (F) (millions)	206,318	654,228	529,434	238,357	486,527	937,760
PI (A) (millions)	206,318	685,820	492,579	279,647	571,643	955,431
Distance (miles)	206,318	1,039	788	393	826	1532

Table 3.2: Analyst Coverage and Air Travel

This table presents the baseline results from panel regressions examining the effect of air travel passengers from analyst location city to firm headquarter city on analyst coverage of firms. The first dependent variable *Coverage* is the natural logarithm of one plus the number of analysts from each analyst location covering a given firm in a given quarter. The second dependent variable *Forecasts* is the natural logarithm of one plus the number of analysts' forecasts for a given firm from each analyst location in a given quarter. The main explanatory variable *Air travel* is the nature logarithm of air travel passengers from analyst location city to firm headquarter city in a given quarter. Definitions of the variables are provided in Appendix A. *Forecast horizon*, *Companies*, *Firm experience*, *Total experience*, *Revision, Broker size*, and *All-star* are taken from the average value of analysts covering the same firm in a given analyst location city. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	(1) Coverage	(2) Forecasts	(3) Coverage	(4) Forecasts	(5) Coverage	(6) Forecasts
Air travel	0.516***	0.533***	0.816***	0.843***	0.334***	0.349***
	(0.025)	(0.026)	(0.033)	(0.035)	(0.057)	(0.060)
Forecast horizon	1.005***	0.970***	1.008***	0.987***	0.448***	0.422***
	(0.129)	(0.133)	(0.121)	(0.124)	(0.081)	(0.084)
Companies	-0.721***	-0.811***	1.233***	1.239***	-0.013	-0.039
	(0.190)	(0.197)	(0.210)	(0.217)	(0.288)	(0.299)
Firm experience	3.168***	3.292***	2.984***	3.089***	0.651***	0.653***
	(0.056)	(0.058)	(0.063)	(0.065)	(0.083)	(0.086)
Total experience	2.764***	2.875***	2.976***	3.091***	4.343***	4.500***
	(0.083)	(0.087)	(0.094)	(0.098)	(0.237)	(0.246)
Revision	26.454***	130.081***	23.514***	126.692***	7.457***	109.618***
	(0.343)	(0.364)	(0.344)	(0.363)	(0.199)	(0.214)
Broker size	10.409***	10.784***	11.432***	11.873***	6.335***	6.629***
	(0.087)	(0.090)	(0.100)	(0.105)	(0.175)	(0.181)
All-star	47.865***	49.468***	51.062***	52.819***	7.616***	7.919***
	(0.764)	(0.792)	(0.795)	(0.825)	(0.711)	(0.737)
Firm leverage	-4.331***	-4.552***	-3.816***	-4.008***	-3.736***	-3.892***
	(0.339)	(0.350)	(0.479)	(0.492)	(0.485)	(0.502)
Firm size	3.719***	3.814***	3.048***	3.108***	4.347***	4.529***
	(0.048)	(0.049)	(0.158)	(0.164)	(0.203)	(0.212)
Earnings change	-0.001**	-0.001**	-0.001*	-0.001**	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
PI (F)	0.814***	0.815***	5.607***	5.424***	10.673***	10.778***
	(0.086)	(0.089)	(1.579)	(1.610)	(2.295)	(2.389)
PI (A)	10.951***	11.222***	11.358***	11.629***	15.841***	16.345***
	(0.086)	(0.090)	(0.100)	(0.104)	(0.708)	(0.740)
Distance	-1.974***	-2.037***	-3.836***	-3.964***		
	(0.084)	(0.087)	(0.108)	(0.112)		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	No	No
Firm FE	No	No	Yes	Yes	No	No
Firm-Analyst City FE	No	No	No	No	Yes	Yes
Observations	206,318	206,318	206,038	206,038	196,754	196,754
R^2	0.318	0.557	0.394	0.606	0.859	0.910

Table 3.3: Analyst Coverage and Air Travel (IV)

This table presents 2SLS results from the instrumental variable regressions examining the effect of air travel passengers from analyst location city to firm headquarter city on analyst coverage of firms. The first dependent variable *Coverage* is the natural logarithm of one plus the number of analysts from each analyst location covering a given firm in a given quarter. The second dependent variable *Forecasts* is the natural logarithm of one plus the number of analysts' forecasts for a given firm from each analyst location in a given quarter. The main explanatory variable *Air travel* is the nature logarithm of air travel passengers from analyst location city to firm headquarter city in a given quarter. Column (1) and Column (4) show the first-stage results. Instrumental variables are *Route* and *Attack*. Control variables are the same as Table 3.2, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. I also report the Kleibergen and Paap (2006) *LM*-statistics (K-P *LM*) and *F*-statistic (K-P Wald *F*).

VARIABLES	(1) Air travel	(2) Coverage	(3) Forecasts	(4) Air travel	(5) Coverage	(6) Forecasts
Route	0.105***					
	(0.007)					
Attack				-0.043***		
				(0.012)		
Air travel		1.360***	1.374**		1.519*	1.671*
		(0.526)	(0.551)		(0.808)	(0.992)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Analyst City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196,754	196,754	196,754	196,754	196,754	196,754
R^2	0.889	0.252	0.612	0.881	0.148	0.596
Shea's Partial R^2	0.187			0.103		
K-P *LM*		0.000	0.000		0.000	0.000
K-P Wald *F*		22.90	22.90		13.34	13.34

Table 3.4: Geographical Distance and Personal Income

This table presents subsample test results from regressions examining the effect of air travel passengers from analyst location city to firm headquarter city on analyst coverage of firms. In Panel A, the sample is split by the median geographical distance (826 miles) between the firm headquarter city and analyst location city pairs. In panel B, the sample is split by the median personal income in the firm headquarter state (486,527 million dollars). The first dependent variable *Coverage* is the natural logarithm of one plus the number of analysts from each analyst location covering a given firm in a given quarter. The second dependent variable *Forecasts* is the natural logarithm of one plus the number of analysts' forecasts for a given firm from each analyst location in a given quarter. The main explanatory variable *Air travel* is the nature logarithm of air travel passengers from analyst location city to firm headquarter city in a given quarter. Control variables are the same as Table 3.2, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	(1) Coverage	(2) Coverage	(3) Forecasts	(4) Forecasts
Panel A: By geographical distance				
	High	Low	High	Low
Air travel	0.705***	0.093	0.735***	0.099
	(0.084)	(0.062)	(0.087)	(0.064)
Control Variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Firm-Analyst City FE	Yes	Yes	Yes	Yes
Observations	98,096	98,308	98,096	98,308
R^2	0.871	0.870	0.916	0.919
Panel B: By personal income				
	High	Low	High	Low
Air travel	0.124	0.454***	0.138	0.471***
	(0.094)	(0.067)	(0.099)	(0.069)
Control Variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Firm-Analyst City FE	Yes	Yes	Yes	Yes
Observations	98,150	97,775	98,150	97,775
R^2	0.870	0.856	0.918	0.906

Table 3.5: Firm Information Environment

This table presents subsample test results from regressions examining the effect of air travel passengers from analyst location city to firm headquarter city on analyst coverage of firms by information environment. In Panel A, the sample is split by the median institutional ownership. A firm is classified as having high (low) institutional ownership if its average institutional ownership over the previous three years (i.e. 12 quarters) is above (below) the sample median average institutional ownership. In Panel B, the sample is split by the median earnings management measured by discretionary accruals. A firm is classified as having a less (more) opaque information environment if its discretionary accruals are lower (more) than the sample median. The first dependent variable *Coverage* is the natural logarithm of one plus the number of analysts from each analyst location covering a given firm in a given quarter. The second dependent variable *Forecasts* is the natural logarithm of one plus the number of analysts' forecasts for a given firm from each analyst location in a given quarter. The main explanatory variable *Air travel* is the nature logarithm of air travel passengers from analyst location city to firm headquarter city in a given quarter. Control variables are the same as Table 3.2, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	(1) Coverage	(2) Coverage	(3) Forecasts	(4) Forecasts
Panel A: Institutional ownership				
	High	Low	High	Low
Air travel	0.213***	0.325***	0.223***	0.329***
	(0.082)	(0.091)	(0.086)	(0.096)
Control Variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Firm-Analyst City FE	Yes	Yes	Yes	Yes
Observations	80,540	78,142	80,540	78,142
R^2	0.883	0.868	0.925	0.917
Panel B: Earnings management				
	High	Low	High	Low
Air travel	0.284***	0.148	0.294***	0.154
	(0.100)	(0.090)	(0.105)	(0.095)
Control Variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Firm-Analyst City FE	Yes	Yes	Yes	Yes
Observations	76,770	76,087	76,770	76,087
R^2	0.868	0.873	0.916	0.920

Table 3.6: Superior Access to Firm-specific Information

This table presents results from regressions examining the effect of air travel passengers from analyst location city to firm headquarter city on analyst coverage of firms during the post-Reg FD period (2001-2018). The first dependent variable *Coverage* is the natural logarithm of one plus the number of analysts from each analyst location covering a given firm in a given quarter. The second dependent variable *Forecasts* is the natural logarithm of one plus the number of analysts' forecasts for a given firm from each analyst location in a given quarter. The main explanatory variable *Air travel* is the nature logarithm of air travel passengers from analyst location city to firm headquarter city in a given quarter. Control variables are the same as Table 3.2, but results are not reported for brevity. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	(1) Coverage	(2) Forecasts	(3) Coverage	(4) Forecasts	(5) Coverage	(6) Forecasts
Air travel	0.737***	0.763***	1.159***	1.194***	0.221***	0.229***
	(0.027)	(0.029)	(0.036)	(0.038)	(0.058)	(0.061)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	No	No
Firm FE	No	No	Yes	Yes	No	No
Firm-Analyst City FE	No	No	No	No	Yes	Yes
Observations	163,721	163,721	163,504	163,504	157,279	157,279
R^2	0.316	0.562	0.395	0.612	0.870	0.918

Table 3.7: Analyst Coverage and Aggregate Inward Air Travel

This table presents results from regressions examining the effect of aggregate air travel passengers into firm headquarter city on analyst coverage of firms. The first dependent variable *Total coverage* is the natural logarithm of one plus the total number of analysts covering a given firm in a given quarter. The second dependent variable *Total forecasts* is the natural logarithm of one plus the total number of analysts' forecasts for a given firm in a given quarter. The main explanatory variable *Total air travel* is the nature logarithm of total air travel passengers into firm headquarter city in a given quarter. Definitions of the variables are provided in Appendix A. *Forecast horizon, Companies, Firm experience, Total experience, Revision, Broker size,* and *All-star* are taken from the average value of all analysts covering the same firm. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	(1) Total coverage	(2) Total forecasts	(3) Total coverage	(4) Total forecasts
Total air travel	0.545***	0.587***	0.628***	0.777***
	(0.045)	(0.047)	(0.199)	(0.214)
Forecast horizon	1.658***	1.622***	1.499***	1.630***
	(0.295)	(0.310)	(0.230)	(0.246)
Companies	-0.522	-0.706	-0.123	-0.318
	(0.476)	(0.500)	(0.474)	(0.504)
Firm experience	4.164***	3.874***	2.427***	2.187***
	(0.158)	(0.168)	(0.166)	(0.177)
Total experience	1.809***	2.152***	4.032***	4.447***
	(0.313)	(0.329)	(0.301)	(0.319)
Revision	56.901***	155.436***	35.823***	131.024***
	(0.800)	(0.878)	(0.612)	(0.695)
Broker size	16.596***	16.905***	8.375***	8.398***
	(0.235)	(0.249)	(0.246)	(0.265)
All-star	-6.443***	-6.732***	-8.325***	-8.376***
	(1.360)	(1.425)	(1.187)	(1.266)
Firm leverage	-0.350	-0.356	-0.859	-0.862
	(0.477)	(0.484)	(0.606)	(0.608)
Firm size	19.899***	20.549***	25.959***	26.924***
	(0.111)	(0.116)	(0.339)	(0.359)
Earnings change	-0.007***	-0.007***	0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
PI (F)	2.767***	2.763***	10.108***	8.960***
	(0.162)	(0.171)	(2.653)	(2.983)
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Observations	89,748	89,748	89,441	89,441
R^2	0.574	0.669	0.806	0.842

Table 3.8: Analyst Coverage and Aggregate Inward Air Travel (IV)

This table presents 2SLS results from the instrumental variable regressions examining the effect of aggregate air travel passengers into firm headquarter city on analyst coverage of firms. The first dependent variable *Total coverage* is the natural logarithm of one plus the total number of analysts covering a given firm in a given quarter. The second dependent variable *Total forecasts* is the natural logarithm of one plus the total number of analysts' forecasts for a given firm in a given quarter. The main explanatory variable *Total* a*ir travel* is the nature logarithm of total air travel passengers into firm headquarter city in a given quarter. Column (1) and Column (4) show the first-stage results. Instrumental variables are *Route* and *Attack*. Control variables are the same as Table 3.7, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. I also report the Kleibergen and Paap (2006) *LM*-statistics (K-P *LM*) and *F*-statistic (K-P Wald *F*).

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Total air travel	Total coverage	Total forecasts	Total air travel	Total coverage	Total forecasts
Route	0.136***					
	(0.008)					
Attack				-0.024***		
				(0.006)		
Total air travel		1.114***	1.519***		2.585**	2.852**
		(0.411)	(0.389)		(1.245)	(1.257)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	89,441	89,441	89,441	89,441	89,441	89,441
R^2	0.979	0.123	0.362	0.977	0.102	0.240
Shea's Partial R^2	0.145			0.117		
K-P *LM*		0.000	0.000		0.000	0.000
K-P Wald *F*		27.46	27.46		14.09	14.09

Table 3.9: Analyst Forecast Errors and Air Travel

This table presents results from regressions examining the effect of air travel passengers from analyst location city to firm headquarter city on analyst forecast errors. The dependent variables are three measures of analyst forecast errors. *AFE* is the absolute analyst forecast error, calculated as the absolute value of the difference between forecasted and actual earnings, scaled by the average share price in the previous quarter. *DAFE* is the de-mean absolute forecast error, calculated as the difference between *AFE* and the average *AFE* of other analysts following the same firm during the same quarter, scaled by the average *AFE* of other analysts following the same firm during the same quarter. *PMAFE* is the proportional median absolute error, calculated as the difference between *AFE* and the median *AFE* of other analysts following the same firm during the same quarter, scaled by the median *AFE* of other analysts following the same firm during the same quarter. The main explanatory variable *Air travel* is the nature logarithm of air travel passengers from analyst location city to firm headquarter city in a given quarter. Definitions of the variables are provided in Appendix A. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	(1) AFE	(2) AFE	(3) DAFE	(4) DAFE	(5) PMAFE	(6) PMAFE
Air travel	0.018**	0.029**	0.005***	0.006***	0.010***	0.013***
	(0.009)	(0.015)	(0.002)	(0.002)	(0.002)	(0.003)
Forecast horizon	0.485***	0.459***	0.156***	0.156***	0.140***	0.136***
	(0.036)	(0.037)	(0.007)	(0.007)	(0.008)	(0.008)
Companies	0.077	-0.013	0.026***	0.003	0.040***	0.004
	(0.049)	(0.081)	(0.010)	(0.019)	(0.011)	(0.019)
Firm experience	0.119***	0.151***	0.002	0.007*	0.006	0.013***
	(0.019)	(0.022)	(0.004)	(0.004)	(0.005)	(0.005)
Total experience	-0.108***	-0.121***	-0.005	0.022*	-0.012*	0.033**
	(0.025)	(0.040)	(0.005)	(0.012)	(0.006)	(0.015)
Revision	-0.120***	-0.154***	-0.110***	-0.114***	-0.194***	-0.202***
	(0.041)	(0.045)	(0.006)	(0.006)	(0.012)	(0.013)
Broker size	0.000	0.000	0.000*	0.000*	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
All-star	-0.003	0.016	-0.020**	-0.006	-0.020	-0.006
	(0.038)	(0.061)	(0.010)	(0.016)	(0.014)	(0.021)
Firm leverage	4.546***	4.725***	0.012	0.018	0.014	0.028
	(0.579)	(0.627)	(0.024)	(0.025)	(0.046)	(0.049)
Firm size	0.306***	0.306***	0.033***	0.036***	0.061***	0.060***
	(0.088)	(0.090)	(0.008)	(0.009)	(0.015)	(0.016)
Earnings change	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Total coverage	-1.202***	-1.319***	-0.149***	-0.150***	-0.110***	-0.106***
	(0.136)	(0.145)	(0.015)	(0.016)	(0.024)	(0.025)
PI (F)	2.089*	2.671**	0.083	0.020	0.329***	0.338***
	(1.163)	(1.306)	(0.052)	(0.064)	(0.098)	(0.109)
PI (A)	-0.015	-0.147**	0.011**	-0.039***	0.021***	-0.029
	(0.031)	(0.063)	(0.005)	(0.014)	(0.007)	(0.023)
Distance	-0.001	0.016	-0.002	0.002	-0.003	0.002
	(0.027)	(0.052)	(0.003)	(0.005)	(0.004)	(0.007)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	No	Yes
Observations	597,123	596,928	597,123	596,928	597,123	596,928
R^2	0.290	0.302	0.029	0.052	0.031	0.056

Table 3.10: Analyst Optimism and Air Travel

This table presents results from regression examining the effect of air travel passengers from analyst location city to firm headquarter city on analyst optimism. The dependent variable *Optimism* is a dummy equal to one if the earnings forecast of an analyst is higher than the average earnings forecast of other analysts who cover the same firm within the same quarter, and zero otherwise. OLS results are reported in Columns (1) to (4) with different fixed effects. Logit and Probit model results are shown in Columns (5) and (6), respectively. The main explanatory variable *Air travel* is the nature logarithm of air travel passengers from analyst location city to firm headquarter city in a given quarter. Definitions of the variables are provided in Appendix A. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: *Optimism*					
	(1)	(2)	(3)	(4)	Logit	Probit
Air travel	0.003***	0.003***	0.003***	0.002***	0.007***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Forecast horizon	0.093***	0.093***	0.109***	0.108***	0.394***	0.244***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.004)
Companies	0.012***	0.006**	0.013***	0.010***	0.017***	0.011***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.006)	(0.004)
Firm experience	0.006***	0.007***	0.006***	0.008***	0.027***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Total experience	-0.004***	0.003	-0.004***	0.003	-0.010***	-0.006***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
Revision	-0.060***	-0.064***	-0.063***	-0.068***	-0.225***	-0.140***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.006)	(0.004)
Broker size	-0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
All-star	-0.004*	0.006**	-0.004*	0.005	-0.022***	-0.014***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.008)	(0.005)
Firm leverage	0.014**	0.018***	0.011**	0.015***	-0.056***	-0.034***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.013)	(0.008)
Firm size	0.003*	0.003*	0.003*	0.003*	0.022***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Earnings change	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total coverage	-0.074***	-0.075***	-0.076***	-0.077***	-0.276***	-0.172***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.004)
PI (F)	0.033***	0.040***	0.055***	0.066***	-0.048***	-0.030***
	(0.005)	(0.007)	(0.014)	(0.016)	(0.003)	(0.002)
PI (A)	0.002**	-0.007*	0.002**	-0.007*	-0.059***	-0.037***
	(0.001)	(0.004)	(0.001)	(0.004)	(0.003)	(0.002)
Distance	-0.003***	-0.002**	-0.003***	-0.002*	-0.015***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Time FE	Yes	Yes	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes	No	No
Analyst FE	No	Yes	No	Yes	No	No
Observations	597,303	597,108	597,123	596,928	597,303	597,303
R^2	0.058	0.073	0.063	0.078	0.034	0.035

Table 3.11: Comovement and Return Predictability

This table presents regression results of comovement and return predictability. In Columns (1) and (2), the dependent variable is the correlation between two paired firms covered by at least one same analyst in a given quarter. The main explanatory variable *Mean air travel* is the mean of air travel passengers from analyst location city to each firm's headquarter city for all analysts who cover both firms. Control variables are pair-wise between each firm pair. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). In Columns (3) to (6), the dependent variable is the quarterly stock return of the given firm. In Columns (3) and (4), the main explanatory variable *AP RET* is the one-quarter lagged weighted average portfolio return of all other firms in each analyst's portfolio that covers the given firm. Other controls are the same as Table 3.9, but results are not reported for brevity. In Columns (5) and (6), the main explanatory variable *CF RET* is the one-quarter lagged weighted average portfolio return of all firms having analyst coverage connection with the given firm. Other controls include firm-level factors, but results are not reported for brevity. Fama-French four factors are controlled in Columns (4) and (6). Definitions of the variables are provided in Appendix A. Newey-West standard errors with three lags are reported in parentheses in Columns (3) to (6). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	(1) Correlation	(2) Correlation	(3) Return	(4) Return	(5) Return	(6) Return
Mean air travel	0.120***	0.116***				
	(0.035)	(0.035)				
AP RET			0.017***	0.010***		
			(0.003)	(0.002)		
CF RET					0.038***	0.038***
					(0.008)	(0.007)
Firm distance	-0.273***	-0.266***				
	(0.027)	(0.062)				
Similar industry	6.465***	6.415***				
	(0.231)	(0.220)				
Similar firm size		0.917***				
		(0.045)				
Similar leverage		3.336***				
		(0.325)				
Similar earnings change		0.002**				
		(0.001)				
Similar price		0.496***				
		(0.048)				
Similar PI(F)		0.141***				
		(0.036)				
Similar coverage		0.235***				
		(0.010)				
Market portfolio				1.021***		1.008***
				(0.006)		(0.013)
SMB				0.512***		0.672***
				(0.010)		(0.021)
HML				0.247***		0.267***
				(0.008)		(0.018)
UMD				-0.151***		-0.163***
				(0.007)		(0.017)
Other Controls	No	No	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No	No	No
Connected Firm FE	Yes	Yes	No	No	No	No
Time FE	Yes	Yes	No	No	No	No
Observations	1,210,977	934,140	342,699	342,699	88,986	88,986
R^2	0.582	0.600	0.017	0.203	0.012	0.167

Table 3.12: Quintile Portfolio Returns and Alphas

This table presents the excess returns, four-factor alphas, and factor loadings of quintile portfolios. The sample includes common stocks listed on NYSE, AMEX or NASDAQ that are covered by analysts with data of air travel passengers from analyst location city to firm headquarter city. In each quarter, stocks are ranked into quintile portfolios based on *CF RET* from lowest (quintile 1) to highest (quintile 5). Then equal-weighted and value-weighted return in the next three months of each portfolio are calculated. Market, size (SMB), value (HML), and momentum (UMD) factor returns are obtained from Ken French's website. Newey-West standard errors with three lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Quintile	(1) Excess ret	(2) 4-factor alpha	(3) Mkt-Rf	(4) SMB	(5) HML	(6) UMD
Panel A: Equal weighted						
1	0.004	-0.002	1.165***	0.566***	-0.092	-0.467***
	(0.004)	(0.002)	(0.052)	(0.122)	(0.115)	(0.080)
2	0.009**	0.002*	1.042***	0.445***	0.324***	-0.277***
	(0.003)	(0.001)	(0.037)	(0.091)	(0.060)	(0.032)
3	0.010***	0.003**	0.973***	0.371***	0.432***	-0.143***
	(0.003)	(0.001)	(0.040)	(0.094)	(0.072)	(0.037)
4	0.011***	0.004***	1.016***	0.470***	0.472***	-0.065
	(0.003)	(0.001)	(0.031)	(0.066)	(0.059)	(0.044)
5	0.013***	0.005***	1.022***	0.788***	0.239**	0.005
	(0.004)	(0.002)	(0.039)	(0.056)	(0.111)	(0.083)
5-1	0.009***	0.007**	-0.143*	0.222	0.331	0.472***
	(0.003)	(0.003)	(0.079)	(0.152)	(0.216)	(0.157)
Panel B: Value weighted						
1	0.013***	0.006***	1.084***	-0.032	-0.087	-0.302***
	(0.004)	(0.002)	(0.078)	(0.084)	(0.110)	(0.070)
2	0.014***	0.007***	1.005***	-0.124**	0.152**	-0.190***
	(0.003)	(0.002)	(0.050)	(0.053)	(0.064)	(0.042)
3	0.011***	0.004***	0.931***	-0.153***	0.244***	-0.016
	(0.003)	(0.001)	(0.036)	(0.059)	(0.058)	(0.032)
4	0.013***	0.005***	1.059***	-0.018	0.308***	0.163***
	(0.003)	(0.001)	(0.031)	(0.039)	(0.061)	(0.037)
5	0.016***	0.008***	1.000***	0.209***	0.095	0.202***
	(0.003)	(0.002)	(0.057)	(0.071)	(0.118)	(0.070)
5-1	0.003	0.002	-0.084	0.241**	0.182	0.504***
	(0.003)	(0.004)	(0.109)	(0.110)	(0.186)	(0.083)

Appendix A: Variable Definitions

Baseline Regressions:

Coverage: The natural logarithm of one plus the number of analysts from each analyst location city covering a given firm in a given quarter. *Source:* IBES.

Forecasts: The natural logarithm of one plus the number of analyst forecasts for a given firm from each analyst location city in a given quarter. *Source:* IBES.

Air travel: The nature logarithm of air travel passengers from analyst location city to firm headquarter city in each quarter. *Source:* T-100 Domestic Segment Database, U.S. Department of Transportation (DOT).

Forecast horizon: The natural logarithm of one plus the number of days between an analyst issuing an earnings forecast and the corporate earnings announcement date. *Source:* IBES.

Companies: The natural logarithm of one plus the number of companies an analyst follows during a specific quarter. *Source:* IBES.

Firm experience: The natural logarithm of one plus the number of months an analyst has covered a specific firm. *Source:* IBES.

Total experience: The natural logarithm of one plus the number of months since an analyst issued a forecast for a company first available in the IBES database. *Source:* IBES.

Revision: The natural logarithm of one plus the number of forecast revisions made by an analyst regarding the same firm in the same forecasting quarter prior to the current forecast. *Source:* IBES.

Broker size: The natural logarithm of one plus the number of analysts employed by an analyst's brokerage firm in the quarter. *Source:* IBES.

All-star: A dummy equal to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in a given quarter, and zero otherwise. *Source:* Institutional Investor.

Firm leverage: Total liabilities divided by total assets. *Source:* Compustat.

Firm size: The natural logarithm of total assets. *Source:* Compustat.

Earnings change: The absolute value of the change in earnings over the previous quarter, scaled by the previous quarter's earnings. *Source:* Compustat.

PI (F): The natural logarithm of one plus the personal income in the firm headquarter state. *Source*: The U.S. Bureau of Economic Analysis (BEA).

PI (A): The natural logarithm of one plus the personal income in the analyst location state. *Source*: The U.S. Bureau of Economic Analysis (BEA).

Distance: The natural logarithm of the geographical distance between the analyst location city and the firm headquarter city. *Source:* Simplemaps.com.

Instrumental Variables:

Route: An indicator equal to 1 in the next two quarters after a new airline route is initiated between firm headquarter city and analyst location city, equal to -1 in the next two quarters after an airline route is cancelled, and 0 otherwise. Then I take the sum of this indicator in each quarter. *Source:* T-100 Domestic Segment Database, U.S. Department of Transportation (DOT).

Attack: A dummy equal to one in the quarter if a terrorist attack or mass shooting occurs within a 100-mile radius of firm headquarter leading to at least one human casualty, and zero otherwise. *Source:* Global Terrorism Database (GTD) and Mother Jones.

Aggregate Firm-level Regressions:

Total coverage: The natural logarithm of one plus the total number of analysts covering a given firm in a given quarter. *Source:* IBES.

Total forecasts: The natural logarithm of one plus the total number of analyst forecasts for a given firm in a given quarter. *Source:* IBES.

Total air travel: The nature logarithm of total air travel passengers into firm headquarter city in a given quarter. *Source:* T-100 Domestic Segment Database, U.S. Department of Transportation (DOT).

Analyst Forecast Errors Regressions:

AFE: The absolute analyst forecast error, calculated as the absolute value of the difference between forecasted and actual earnings, scaled by the average share price in the previous quarter. *Source:* IBES, CRSP.

DAFE: The de-mean absolute forecast error, calculated as the difference between AFE and the average AFE of other analysts following the same firm during the same quarter, scaled by the average AFE of other analysts following the same firm during the same quarter. *Source:* IBES, CRSP.

PMAFE: The proportional median absolute error, calculated as the difference between AFE and the median AFE of other analysts following the same firm during the same quarter, scaled by the median AFE of other analysts following the same firm during the same quarter. *Source:* IBES, CRSP.

Optimism: A dummy equal to one if the earnings forecast of an analyst is higher than the average earnings forecast of other analysts who cover the same firm within the same quarter, and zero otherwise. *Source:* IBES.

Market Reactions:

Correlation: Daily return correlation between two paired firms which covered by at least one same analyst in a given quarter. *Source:* CRSP.

Return: The quarterly return of a given stock. *Source:* CRSP.

Mean air travel: The nature logarithm of the mean of air travel passengers from analyst location city to each firm's headquarter city for all analysts who cover both firms. *Source:* T-100 Domestic Segment Database, U.S. Department of Transportation (DOT).

AP RET: Weighted average portfolio return of all other firms in each analyst's portfolio that covers the given stock. Weight of each stock in the analyst portfolio is the air travel passengers from analyst location city to firm headquarter city. *Source:* DOT, CRSP.

CF RET: Weighted average portfolio return of all firms having analyst coverage connection with the given firm. Weight of each connected-firm in the portfolio is the mean of air travel passengers from analyst location city to headquarter city of each connected firm for all shared analysts. *Source:* DOT, CRSP.

Firm distance: The natural logarithm of the geographical distance between the firm pair. *Source:* Compustat, Simplemaps.com.

Similar industry: A dummy equal to one if the two-digit SIC code of a firm pair is the same, and zero otherwise. *Source:* Compustat.

Similar firm size: The natural logarithm of one plus the absolute difference between the firm size of a firm pair. Then multiply by -1. *Source:* Compustat.

Similar leverage: The absolute difference between the firm leverage ratio of a firm pair.

Then multiply by -1. *Source:* Compustat.

Similar earnings change: The absolute difference between the earnings change ratio of a firm pair. Then multiply by -1. *Source:* Compustat.

Similar price: The natural logarithm of one plus the absolute difference between the quarterly end stock price of a firm pair. Then multiply by -1. *Source:* Compustat.

Similar PI(F): The natural logarithm of one plus the absolute difference between the state-level personal income of a firm pair. Then multiply by -1. *Source:* The U.S. Bureau of Economic Analysis (BEA).

Similar coverage: The natural logarithm of one plus the absolute difference between the total number of analyst coverage of a firm pair. Then multiply by -1. *Source:* IBES.

Appendix B: Supplementary Tables

Table 3.B1: Terrorist Attacks and Mass Shootings in the Sample

This table presents the terrorist attacks and mass shootings in the sample. I only consider events that resulted in at least one human casualty and have firms located within a 100-mile radius.

Date	State	City	Type	Date	State	City	Type
3/1/1994	NY	New York City	Terrorist	3/13/2013	NY	Herkimer County	Shooting
3/9/1994	FL	Miami	Terrorist	4/15/2013	MA	Boston	Terrorist
5/29/1994	NY	New York City	Terrorist	4/17/2013	TX	West	Terrorist
7/29/1994	FL	Pensacola	Terrorist	4/18/2013	MA	Cambridge	Terrorist
9/12/1994	DC	Washington	Terrorist	4/19/2013	MA	Watertown	Terrorist
12/10/1994	NJ	Caldwell	Terrorist	7/26/2013	FL	Hialeah	Shooting
12/30/1994	MA	Brookline	Terrorist	9/16/2013	DC	Washington	Shooting
4/3/1995	TX	Corpus Christi	Shooting	4/3/2014	TX	Fort Hood	Shooting
4/19/1995	OK	Oklahoma City	Terrorist	4/13/2014	KS	Overland Park	Terrorist
4/24/1995	CA	Sacramento	Terrorist	6/6/2014	GA	Cumming	Terrorist
12/8/1995	NY	New York City	Terrorist	6/25/2014	NJ	West Orange	Terrorist
1/23/1996	FL	Miami	Terrorist	9/12/2014	PA	Blooming Grove	Terrorist
2/9/1996	FL	Fort Lauderdale	Shooting	10/23/2014	NY	New York City	Terrorist
7/27/1996	GA	Atlanta	Terrorist	11/28/2014	TX	Austin	Terrorist
2/23/1997	NY	New York City	Terrorist	12/18/2014	NC	Morganton	Terrorist
9/15/1997	SC	Aiken	Shooting	12/20/2014	NY	New York City	Terrorist
12/30/1997	IL	Oakwood	Terrorist	2/10/2015	NC	Chapel Hill	Terrorist
1/29/1998	AL	Birmingham	Terrorist	3/20/2015	LA	New Orleans	Terrorist
3/6/1998	CT	Newington	Shooting	5/3/2015	TX	Garland	Terrorist
3/24/1998	AR	Jonesboro	Shooting	6/11/2015	WI	Menasha	Shooting
5/21/1998	OR	Springfield	Shooting	6/17/2015	SC	Charleston	Terrorist
7/24/1998	DC	Washington	Terrorist	7/16/2015	TN	Chattanooga	Terrorist
10/23/1998	NY	Amherst	Terrorist	7/23/2015	LA	Lafayette	Terrorist
7/2/1999	IL	Skokie	Terrorist	2/11/2016	OH	Columbus	Terrorist
7/4/1999	IN	Bloomington	Terrorist	2/20/2016	MI	Kalamazoo County	Shooting
7/29/1999	GA	Atlanta	Shooting	2/25/2016	KS	Hesston	Shooting
9/15/1999	TX	Fort Worth	Shooting	6/12/2016	FL	Orlando	Terrorist
12/30/1999	FL	Tampa	Shooting	7/7/2016	TN	Bristol	Terrorist
12/26/2000	MA	Wakefield	Shooting	7/7/2016	TX	Dallas	Terrorist
2/5/2001	IL	Melrose Park	Shooting	7/17/2016	LA	Baton Rouge	Terrorist
9/11/2001	NY	New York City	Terrorist	8/13/2016	NY	New York City	Terrorist
9/11/2001	PA	Shanksville	Terrorist	9/16/2016	PA	Philadelphia	Terrorist
9/11/2001	VA	Arlington	Terrorist	9/17/2016	MN	St. Cloud	Terrorist
10/2/2001	FL	Boca Raton	Terrorist	11/28/2016	OH	Columbus	Terrorist
10/9/2001	DC	Washington	Terrorist	1/6/2017	FL	Fort Lauderdale	Terrorist
10/15/2001	DC	Washington	Terrorist	2/22/2017	KS	Olathe	Terrorist
10/29/2001	NY	New York City	Terrorist	3/20/2017	NY	New York City	Terrorist
11/14/2001	CT	Oxford	Terrorist	4/13/2017	CA	Fresno	Terrorist
7/8/2003	MS	Meridian	Shooting	5/12/2017	OH	Kirkersville	Shooting
12/8/2004	OH	Columbus	Shooting	5/19/2017	FL	Tampa	Terrorist
3/12/2005	WI	Brookfield	Shooting	5/20/2017	MD	College Park	Terrorist
10/2/2006	PA	Lancaster County	Shooting	6/5/2017	FL	Orlando	Shooting
4/16/2007	VA	Blacksburg	Shooting	6/7/2017	PA	Tunkhannock	Shooting
12/5/2007	NE	Omaha	Shooting	6/14/2017	VA	Alexandria	Terrorist
2/7/2008	MO	Kirkwood	Shooting	7/5/2017	NY	Bronx	Terrorist
2/14/2008	IL	DeKalb	Shooting	8/12/2017	VA	Charlottesville	Terrorist
6/25/2008	KY	Henderson	Shooting	9/12/2017	LA	Baton Rouge	Terrorist
7/27/2008	TN	Knoxville	Terrorist	9/14/2017	LA	Baton Rouge	Terrorist
3/29/2009	NC	Carthage	Shooting	9/24/2017	TN	Antioch	Terrorist
4/3/2009	NY	Binghamton	Shooting	10/18/2017	MD	Edgewood	Shooting
5/31/2009	KS	Wichita	Terrorist	10/31/2017	NY	New York City	Terrorist
6/1/2009	AK	Little Rock	Terrorist	11/5/2017	TX	Sutherland Springs	Shooting
6/10/2009	DC	Washington	Terrorist	12/22/2017	PA	Harrisburg	Terrorist
11/5/2009	TX	Killeen	Terrorist	1/28/2018	PA	Melcroft	Shooting
2/18/2010	TX	Austin	Terrorist	2/14/2018	FL	Parkland	Shooting
3/4/2010	VA	Arlington	Terrorist	4/22/2018	TN	Nashville	Shooting
8/3/2010	CT	Manchester	Shooting	5/18/2018	TX	Santa Fe	Terrorist
9/1/2010	MD	Silver Spring	Terrorist	6/28/2018	MD	Annapolis	Terrorist
2/21/2012	GA	Norcross	Shooting	9/6/2018	OH	Cincinnati	Terrorist
9/27/2012	MN	Minneapolis	Shooting	9/20/2018	MD	Perryman	Shooting
12/14/2012	CT	Newtown	Shooting				

Table 3.B2: Variable Descriptive Statistics

Panel A of this table presents descriptive statistics of variables in the aggregate firm-level specifications. Panel B of this table presents descriptive statistics of variables in the analyst forecast level specifications. Definitions of the variables are provided in Appendix A.

	Obs.	**Mean**	**Std. Dev**	**Q1**	**Median**	**Q3**
Panel A: Aggregate firm-level						
Total coverage	89,748	6.737	6.214	3	5	10
Total forecasts	89,748	10.901	12.054	3	7	14
Total air travel	89,748	2,825,844	2,865,242	352,862	1,791,944	4,792,043
Forecast horizon	89,748	208.955	94.220	119	202	283
Companies	89,748	20.223	8.605	15	19	23
Firm experience	89,748	47.677	41.443	16	37	69
Total experience	89,748	166.751	75.986	115	158	213
Revision	89,748	1.259	0.314	1	1	1
Broker size	89,748	59.750	39.066	31	54	81
All-star	89,748	0.106	0.187	0	0	0
Firm size	89,748	13,814	91,606	310	1,223	4,731
Firm leverage	89,748	0.586	1.552	0.386	0.579	0.776
Earnings change	89,748	0.325	3.473	0	0.181	0.600
PI (F) (millions)	89,748	594.420	523,072	204,349	412,594	873,365
Panel B: Analyst forecast level						
AFE	597,303	1.723	15.582	0.108	0.350	1.080
DAFE	597,303	0.140	2.587	-0.446	-0.037	0.316
PMAFE	597,303	0.390	3.323	-0.367	0.000	0.420
Optimism	597,303	0.473	0.499	0	0	1
Air travel	597,303	97,631	110,977	12,139	57,635	144,497
Forecast horizon	597,303	204.762	108.361	110	197	288
Companies	597,303	19.959	9.963	14	18	24
Firm experience	597,303	57.689	62.581	12	36	83
Total experience	597,303	170.118	101.443	90	160	240
Revision	597,303	1.368	2.763	0	1	2
Broker size	597,303	74.348	68.470	23	53	112
All-star	597,303	0.173	0.378	0	0	0
Firm size	597,303	38,412	177,220	937	3,623	16,184
Firm leverage	597,303	0.584	0.251	0.414	0.581	0.756
Earnings change	597,303	0.471	2.344	0.037	0.209	0.600
Total coverage	597,303	13.877	8.468	7	13	19
PI (F) (millions)	597,303	653,026	514,317	245,210	509,751	931,790
PI (A) (millions)	597,303	783,673	412,072	508,259	757,870	1,035,573
Distance	597,303	1,096	816	418	922	1,557

Table 3.B3: Geographical Distance and Personal Income (Forecast Errors)

This table presents subsample test results from regressions examining the effect of air travel passengers from analyst location city to firm headquarter city on analyst forecast errors. In Panel A, the sample is split by the median geographical distance (922 miles) between firm headquarter city and analyst location city pairs. In Panel B, the sample is split by the median personal income in the firm headquarter state (509,751 million dollars). The dependent variables are three measures of analyst forecast errors. *AFE* is the absolute analyst forecast error, calculated as the absolute value of the difference between forecasted and actual earnings, scaled by the average share price in the previous quarter. *DAFE* is the de-mean absolute forecast error, calculated as the difference between *AFE* and the average *AFE* of other analysts following the same firm during the same quarter, scaled by the average *AFE* of other analysts following the same firm during the same quarter. *PMAFE* is the proportional median absolute error, calculated as the difference between *AFE* and the median *AFE* of other analysts following the same firm during the same quarter, scaled by the median *AFE* of other analysts following the same firm during the same quarter. The main explanatory variable *Air travel* is the nature logarithm of air travel passengers from analyst location city to firm headquarter city in a given quarter. Control variables are the same as Table 3.9, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	(1) AFE	(2) AFE	(3) DAFE	(4) DAFE	(5) PMAFE	(6) PMAFE
Panel A: By geographical distance						
	High	Low	High	Low	High	Low
Air travel	0.059***	0.029*	0.008*	0.003	0.008*	0.001
	(0.022)	(0.015)	(0.005)	(0.003)	(0.005)	(0.006)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	298,326	298,181	298,326	298,181	298,326	298,181
R^2	0.291	0.396	0.070	0.093	0.072	0.106
Panel B: By personal income						
	High	Low	High	Low	High	Low
Air travel	0.010	0.043*	0.005	0.012***	0.008**	0.019***
	(0.012)	(0.024)	(0.003)	(0.004)	(0.004)	(0.005)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	297,883	298,744	297,883	298,744	297,883	298,744
R^2	0.327	0.312	0.067	0.057	0.076	0.064

Table 3.B4: Firm Information Environment (Forecast Errors)

This table presents subsample test results from regressions examining the effect of air travel passengers from analyst location city to firm headquarter city on analyst forecast errors by information environment. In Panel A, the sample is split by the median institutional ownership. A firm is classified as having high (low) institutional ownership if its average institutional ownership over the previous three years (i.e. 12 quarters) is above (below) the sample median average institutional ownership. In Panel B, the sample is split by the median earnings management measured by discretionary accruals. A firm is classified as having a less (more) opaque information environment if its discretionary accruals are lower (more) than the sample median. The dependent variables are three measures of analyst forecast errors. *AFE* is the absolute analyst forecast error, calculated as the absolute value of the difference between forecasted and actual earnings, scaled by the average share price in the previous quarter. *DAFE* is the de-mean absolute forecast error, calculated as the difference between *AFE* and the average *AFE* of other analysts following the same firm during the same quarter, scaled by the average *AFE* of other analysts following the same firm during the same quarter. *PMAFE* is the proportional median absolute error, calculated as the difference between *AFE* and the median *AFE* of other analysts following the same firm during the same quarter, scaled by the median *AFE* of other analysts following the same firm during the same quarter. The main explanatory variable *Air travel* is the nature logarithm of air travel passengers from analyst location city to firm headquarter city in a given quarter. Control variables are the same as Table 3.9, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	(1) AFE	(2) AFE	(3) DAFE	(4) DAFE	(5) PMAFE	(6) PMAFE
Panel A: Institutional ownership						
	High	Low	High	Low	High	Low
Air travel	0.004	0.052**	0.001	0.004*	0.005	0.009**
	(0.006)	(0.026)	(0.003)	(0.002)	(0.005)	(0.004)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	249,814	249,701	249,814	249,701	249,814	249,701
R^2	0.335	0.407	0.064	0.075	0.077	0.078
Panel B: Earnings management						
	High	Low	High	Low	High	Low
Air travel	0.021*	0.005	0.006**	0.005	0.009*	0.004
	(0.013)	(0.012)	(0.002)	(0.005)	(0.005)	(0.004)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	244,010	243,643	244,010	243,643	244,010	243,643
R^2	0.373	0.507	0.084	0.081	0.082	0.079

Table 3.B5: Superior Access to Firm-specific Information (Forecast Errors)

This table presents results from regressions examining the effect of air travel passengers from analyst location city to firm headquarter city on analyst forecast errors during the post-Reg FD period (2001-2018). The dependent variables are three measures of analyst forecast errors. *AFE* is the absolute analyst forecast error, calculated as the absolute value of the difference between forecasted and actual earnings, scaled by the average share price in the previous quarter. *DAFE* is the de-mean absolute forecast error, calculated as the difference between *AFE* and the average *AFE* of other analysts following the same firm during the same quarter, scaled by the average *AFE* of other analysts following the same firm during the same quarter. *PMAFE* is the proportional median absolute error, calculated as the difference between *AFE* and the median *AFE* of other analysts following the same firm during the same quarter, scaled by the median *AFE* of other analysts following the same firm during the same quarter. The main explanatory variable *Air travel* is the nature logarithm of air travel passengers from analyst location city to firm headquarter city in a given quarter. Control variables are the same as Table 3.9, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. All independent variables are lagged by one quarter. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	(1) AFE	(2) AFE	(3) DAFE	(4) DAFE	(5) PMAFE	(6) PMAFE
Air travel	0.017***	0.023**	0.004***	0.002	0.008***	0.007**
	(0.007)	(0.010)	(0.001)	(0.002)	(0.003)	(0.003)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes	No	Yes
Observations	454,642	454,465	454,642	454,465	454,642	454,465
R^2	0.319	0.330	0.025	0.055	0.027	0.058

Chapter 4

It Takes Two to Tango: Cross-Cultural Marriages and Corporate Risk-taking

4.1 Introduction

When President Harry S. Truman left office, he asked the American people to recognize the critical role of the first lady and urged them to "assess the many burdens she has to bear and the contributions she makes."[1] President Truman's remarks shed light on the important influence that his spouse, Bess Truman, had on his career and political decision-making. Several studies in political science systematically analyse the role of first ladies, and conclude that they indirectly influence political decisions in the United States (U.S.).[2] Some scholars even suggest that first ladies are, in fact, critical players in presidents' inner circles, and thus their opinions and preferences significantly influence political decisions (O'Connor, Nye, and Van Assendelft, 1996).

A natural question that follows from these findings and is relevant to financial markets is whether the preferences of CEOs' spouses affect corporate decisions. It is not apparent whether the spouses' preferences should play a role in this setting. On the one hand, CEOs are the sole decision-makers in the firm, hired for their specific skills, knowledge and preferences. Thus, the preferences of their spouses should not affect

[1] Marianne Means, The Woman in the White House (New York: Signet Press, 1963), p. 210.
[2] For instance, see O'Connor, Nye, and Van Assendelft (1996).

corporate decisions, as there is no reason to expect that they add value to the firm. On the other hand, evidence suggests that individuals' personal traits such as risk preferences can become more similar over time in closely related groups such as marriages.[3] Such convergence in preferences between CEOs and their spouses may lead spouses to influence corporate decisions *indirectly*, much like first ladies have been shown to affect political strategy. In this paper, we explore this question. Our hypothesis is that CEOs married to spouses who are relatively more risk-averse will take on less corporate risk.

The risk preferences of CEOs and their spouses are not directly observed. Thus, to empirically test our hypothesis, we examine whether culturally related differences in the propensity to take risks between CEOs and their spouses affect corporate decisions. The choice to measure risk preferences through a cultural lens is motivated by evidence that risk preferences are, to some extent, shaped by cultural heritage (Falk et al., 2018). Like biologically predisposed behaviours, cultural values are deeply rooted and slowly moving (e.g. Glazer and Moynihan, 1963). Culturally transmitted preferences are determined early in life and persistent over several subsequent generations among descendants of immigrants (Guiso, Sapienza, and Zingales, 2006; Giavazzi, Petkov, and Schiantarelli, 2019). Some studies also argue that culture is specific social transmitted information. An individual can acquire cultural information not just from her parents or other elder members of her clan (vertical transmission), also from her peers (horizontal transmission) (Boyd and Richerson, 1985; Robalino and Robson, 2013).

We follow this literature by conjecturing that CEO's culture-related risk attitude is inherited from parents and impacted by her/his spouse. If a CEO is married to a spouse from a relatively more risk-averse culture, then the firm managed by this CEO is expected to have less corporate risk-taking. Various studies in finance show that the culture of the CEO matters for corporate risks (e.g., Ahern, Daminelli, and Fracassi, 2015; Pan, Siegel, and Wang, 2017; Nguyen, Hagendorff, and Eshraghi, 2018). However, no study examines whether differences in risk-related culture norms between CEOs and their spouses affect corporate risk-taking.

To construct our variable, we first manually collect data on the cultural origins of CEOs of S&P500 firms and their spouses, measuring their risk attitude using the Hofstede Uncertainty Avoidance Index (UAI) for their countries of origin. To assign a country of

[3]For examples of peer effects on personality traits , including risk attitude, see Ahern, Duchin, and Shumway (2014), Rammstedt and Schupp (2008) and Serra-Garcia (2021).

origin to each CEO and spouse, we follow Nguyen, Hagendorff, and Eshraghi (2018) and Pan, Siegel, and Wang (2017), using their names, as well as other biographical data. Our variable of interest, $\Delta UAI = (UAI_{Spouse} - UAI_{CEO})/UAI_{CEO}$, measures the proportional difference in the UAI between spouse and CEO. A higher value of ΔUAI indicates that a spouse is relatively more risk-averse compared to the CEO and, to some extent, would thus indirectly discourage corporate risk.

One concern is that if risk preferences are influenced by current marriage, why risk preferences of CEOs have not changed in response to cross-cultural marriages of their parents. First, the literature argues that cross-cultural marriages were not common in the early and mid 20 century. There are quite slow rates of cultural convergence and assimilation among immigrants in the U.S. (Pagnini and Morgan 1990; Borjas, 1995). Family socialization and intense searching for homogamous mates enhance the intergenerational transmission of culture, ethnic and religious traits (Bisin and Verdier 2000). However, with the increasing number of immigrants into the U.S. and increasing descendants of immigrants, there are fewer restrictions on heterogamous marriages and dramatic increases in the number of inter-culture marriages from the 1980s. In our sample, we also find that the proportion of intra-cultural marriages among CEOs and spouses with directly observed cultural origins decreases from 74% in the 1950s to 18% in the 2000s. There is no contradiction between this paper and the cultural literature findings that view culturally-transmitted preferences as time-invariant.

To measure corporate risk-taking, we follow the literature and use the industry-adjusted volatility of return on assets, $\sigma(ROA)$ (e.g., John, Litov, and Yeung, 2008; Laeven and Levine, 2009; Faccio, Marchica, and Mura, 2011, 2016; Li et al., 2013). An increase in $\sigma(ROA)$ reflects higher volatility in the returns to capital, which is a mark of riskier corporate policies. Compared with market-based volatility which is largely driven by market factors (e.g. standard deviation of stock return), the benefit of $\sigma(ROA)$ is that it reflects firm's operation risk which is mostly determined by CEOs. We expect a negative and statistically significant relationship between $\sigma(ROA)$ and ΔUAI, which would indicate that firms with higher ΔUAI have a lower industry-adjusted ROA volatility.

To ensure that our results are not driven by factors known to influence corporate decisions, we include several CEO and firm-level controls in our models. Moreover, in our models, we include a CEO-origin fixed effect, which controls for the cultural origins of the CEO, as well as an industry-year fixed effect, to control for time-varying industry dynamics.

Consistent with our conjecture, we find that ΔUAI has a negative and statistically significant effect on a firm's operation risk. This finding suggests that, in the cross-section of CEO-spouse pairs, firms that are headed by a CEO whose spouse comes from a relatively more risk-averse culture adopt relatively safer corporate policies. This effect is economically meaningful, as a one standard deviation increase in risk-related cultural distance ΔUAI is associated with a reduction of about 0.17% in corporate risk-taking $\sigma(ROA)$, relative to 8.18% of the unconditional average $\sigma(ROA)$ in our sample.

An important concern that pertains to our analysis is endogeneity, obviously, since the choice of spouse is not random. CEOs with lower risk-taking preferences may choose spouses with lower risk preferences. These CEOs personally also pursue low-risk strategies. Suppose CEOs tend to marry spouses with similar risk preferences, ΔUAI could be capturing the effect of the CEOs' own risk preferences rather than any intra-marriage spillover in risk attitudes. Even though our baseline models include CEO-origin fixed effects, thus estimating the coefficient of interest using variation in spouses UAI within each CEO cultural origin group, it is possible that non-cultural aspects of CEOs' risk attitude are affecting our results. It is hard to observe the counterfactual results and establish causality. However, even if our results somehow capture the risk-attitude of CEOs, it is still interesting to see that this risk attitude (as measured by choice of spouses) affects corporate risk-taking. So, we are not trying to deny the impact of CEOs' personal risk preferences. However, we are trying to reveal the intra-marriage spillover effect of CEOs' spouses after controlling CEOs' personal risk preferences.

To identify the spillover effect of CEOs' spouses, we conduct two additional tests. First, we conduct a placebo test where we randomly match a CEO to a different spouse in our sample. If our findings are merely capturing the effect of CEOs' own risk preferences, we should continue to find that ΔUAI is negative and significant since it does not matter whom we pair a CEO with. We conduct 1,000 random matchings and compare the placebo coefficients on ΔUAI with the actual coefficient estimated in the baseline model. As shown in Figure 4.1, the actual estimate is quite visibly an extreme outlier in the distribution of placebo coefficients, which is centred around zero. This finding also suggests that our findings are not merely capturing the effect of CEOs' own risk attitudes. Second, we estimate a model with CEO fixed effects, which absorb CEO-level personal characteristics, including their risk attitudes. In this model, where we restrict our sample only to include CEOs who have experienced more than one marriage, our results continue to hold, which suggests that our findings are not driven by CEOs' personal characteristics. The variation of ΔUAI comes from the CEO changing spouses in this specification. The result indicates that different spouses have different spillover influences on corporate risk-taking with the same CEO.

Another alternative explanation for our findings is that firms headed by CEOs married to spouses from different cultures differ in key characteristics. These differences could be driving our results. To address this concern, we perform a propensity score matching exercise. Precisely, we match firms headed by CEOs married to someone from a different culture to firms headed by CEOs married to someone from the same culture, based on several firm-level attributes (industry, size, market-to-book ratio, Tobin's Q, and performance). This match allows us to compare similar firms whose only difference comes from whether their CEOs share a similar cultural background with their spouses. We find that ΔUAI continues to be negative and statistically significant in this model. In another robustness check, we restrict our sample to firms that experienced a change in CEO during our sample period and estimate the model with firm fixed effects. Our results continue to hold.

We also show that our results still hold when we only use the sample of CEOs and corresponding spouses both have directly observed ancestry origin. We then find ΔUAI cannot be predicted from lagged $\sigma(ROA)$, which suggests that there is no evidence of reverse causality (i.e., firms hiring CEOs with particular ΔUAI according to their risk profiles). Our findings are also robust to a Heckman (1979) two-step selection model that corrects for selection biases in the CEOs or spouses who end up in our final sample.

For our next test, we test the hypothesis using two different measures of corporate risk-taking. First, we use firms' expenditure on research and development (R&D), as these are risky investments (Bargeron, lehn, and Zutter, 2010; Li et al., 2013; Pan, Siegel, and Wang, 2017). The second measure is the number of litigation suits against the firm, which is an indicator of potential corporate risk (Hutton, Jiang, and Kumar, 2015). We find that the relationship between ΔUAI and R&D expenditures or litigation risk is negative and statistically significant, in line with our hypothesis. The effects are also economically meaningful, as a one standard deviation increase in ΔUAI reduces R&D and litigation cases by 4.91% and 13.18%, respectively, relative to their unconditional average.

We then investigate if CEOs who come from countries with lower Hofstede individualistic scores (IDV) are more affected by their spouses. Individualism reflects the degree to which people in a specific society are integrated into groups, with a higher individualism value indicating a society where people tend to act more in isolation in pursuit of their own interests. Some studies also suggest that greater individualism implies more overconfidence (e.g., Chui, Titman, and Wei, 2010). Therefore, it is possible that CEOs whose countries of origin have higher IDV values could be less influenced by their spouses. The results confirm this prediction, as we find that the effect of ΔUAI on corporate risk-taking is stronger in the subsample of CEOs whose country of origin has a lower individualistic score.

For our final test, we examine whether our findings are stronger for CEOs who are low generation immigrants to the U.S. Contrary to the literature that cultural values are time-invariant, some studies argue that immigrants tend to be gradually assimilated by native culture after many generations (Strauss, 1997). The influence of cultural origin may dissipate over generations. Nguyen, Hagendorff, and Eshraghi (2018) show that the influence of cultural heritage of CEOs become weaker for those who are fourth or higher generation immigrants. Consistent with their findings, we find that cultural distance has a significant influence in the subsample of CEOs classed as first-, second- or third-generation immigrants, but is insignificant in the subsample of CEOs who are classed as fourth or higher generation immigrants.

Our study contributes to various lines of research. First, we contribute to the literature that examines how peer effects affect financial decisions. For instance, Ahern, Duchin, and Shumway (2014) show that peers studying for an MBA degree become more similar in their attitudes towards risk. Within the context of marital relationships, Addoum, Kung, and Morales (2016) find that changes in relative income in a household between spouses lead to changes in portfolio choices. Further, Addoum (2017) indicates that couples reallocate their stock investments when they transition to retirement. Serra-Garcia (2021) uses survey data to show that spouses' attitudes towards risk converge after spending much time together. To our knowledge, our study is the first to show that cultural differences in risk attitudes between CEOs and their spouses influence corporate decisions.

Our work also complements the literature examining how culture affects corporate decisions. Ahern, Daminelli, and Fracassi (2015) show that the volume of cross-border mergers is lower when countries are more culturally distant. Nguyen, Hagendorff, and Eshraghi (2018) show that a CEO's cultural heritage affects firm performance and this effect depends on the industry's competitive pressure. Giannetti and Zhao (2019) show that cultural diversity in firms' boards is associated with more innovation. Pan, Siegel, and Wang (2020) show that CEOs from cultures with typically higher uncertainty avoidance are less likely to engage in corporate acquisitions.[4] Our work extends this literature by showing that cultural differences in the risk-taking propensity of CEOs and their spouses affect corporate risk-taking.

Finally, we advance the literature that examines whether a CEO's family environment affects corporate outcomes. Cronqvist and Yu (2017) show that when a CEO has a daughter, the corporate social responsibility rating of the company increases. Similarly, Calder-Wang and Gompers (2021) find that the CEOs of venture capital firms are more likely to hire female partners if they parent more daughters. In a related study, Roussanov and Savor (2014) suggest that single CEOs seem to take more risks than married CEOs. Nicolosi and Yore (2015) indicate that marriages and divorces affect CEOs' risk tolerance levels. Different to these studies, we show that the cultural composition of a CEO's household affects corporate decisions and corporate risk-taking.

The rest of the paper is organized as follows: Section 2 describes the data and the methodology, Section 3 presents the main results, Section 4 presents the results from additional tests, and Section 5 concludes.

4.2 Data and Methodology

In this section, we describe our sample data collection methods and the model.

4.2.1 Sample Description

Our sample consists of Standard & Poor's (S&P) 500 firms from 2000 to 2015. Specifically, we use the Compustat – Capital IQ and S&P ExecuComp databases to identify the constituent firms. We focus on S&P500 since it includes the largest and most recognizable firms, and therefore, it is more likely that information about the cultural heritage of the

[4] Other work showing the effects of culture on asset pricing includes stock market participants (Guiso, Sapienza, and Zingales, 2006), trading volume (Chui, Titman, and Wei, 2010), and bank loans (Giannetti and Yafeh, 2012).

CEOs and their spouses can be obtained. Following the literature (e.g., Chen, Goldstein, and Jiang, 2007; Cronqvist and Yu, 2017), we exclude utility (Standard Industrial Classification (SIC) codes 4900-4999) and financial (SIC codes 6000-6999) firms.

4.2.2 Biographical Information of CEOs and their Spouses

To identify the cultural heritage of S&P500 CEOs and their spouses, we collect various demographic characteristics. These include the name of the CEO, name of her/his spouse,[5] year of their marriage, number of their children, their birthplaces, and their divorce date (if any). We also obtain the names and birthplaces of CEOs' parents and their spouses' parents. We use the above information to identify the cultural heritage of CEOs and spouses.

To collect these data, we start by obtaining the names of the CEOs from ExecuComp, which results in 1,465 CEO names. We then enter their names in the complete *Marquis Who's Who Biographies Online* resource through LexisNexis, which is a comprehensive source of personal biographical information. We acquire the necessary biographical information from this database for about 40% of the CEOs and spouses in our sample. For the remaining CEOs, we search for their names in the Notable Names Database,[6] Wikipedia, Ancestry.com, YouTube, and Google. After completing these steps, we are able to obtain the biographical information for 1,036 S&P500 CEOs and 1,128 spouses.[7]

4.2.3 Cultural Heritage of CEOs and their Spouses

We follow Nguyen, Hagendorff, and Eshraghi (2018) to assign a cultural origin to CEOs and spouses, which is a four-step procedure. First, we search for direct information on the birthplaces of CEOs and their spouses from the following media sources: *Marquis Who's Who,* Notable Names Database, Ancestry.com, as well as various news sources and interviews (accessed through Google or YouTube). At this step, we are able to assign countries of origin to 115 CEOs and 136 spouses who are born outside the U.S. We classify these CEOs and spouses as first-generation immigrants.

Second, to assign a cultural heritage to the remaining pool of U.S.-born CEOs and spouses, we use the birth country of their fathers, as in Liu (2016).[8] For those CEOs

[5] If a female CEO or spouse has changed surname after marriage, we use her maiden name in the analysis.
[6] https://www.nndb.com/
[7] There is a greater number of spouses than CEOs since some CEOs have been married more than once.
[8] It is more difficult to identify the maiden names of CEOs' or their spouses' mothers, and therefore, we

and spouses who are born prior to 1940, we start by locating the birth country of their fathers from the U.S. Census Bureau records, accessed through Ancestry.com.[9] Using this information, we assign the foreign country where a CEO's or a spouse's father was born as their cultural origin. If the father was also born in the U.S., then we continue searching for her/his grandfather or earlier ancestors in Ancestry.com until we find the country her/his ancestors emigrated from. Using this procedure, we identify 118 CEOs and 85 spouses.

In the third step, for U.S. born CEOs and spouses that were born after 1940, we firstly obtain their fathers' names from *Marquis Who's Who,* Notable Names Database, Family tree in Ancestry.com, Obituary, and Google searches. Then we search for their birth country in the U.S. Census Bureau records. If a CEO's or a spouse's father is also born in the U.S., we continue our cultural heritage search using the names of their grandfathers or earlier ancestors. Using this procedure, we identify an additional 266 CEOs and 219 spouses. After the second and third steps, we find that 74 CEOs and 58 spouses are second-generation immigrants (i.e., parents are foreign-born), 69 CEOs and 49 spouses are third-generation immigrants (i.e., grandparents are foreign-born), 241 CEOs and 197 spouses are fourth or higher generation immigrants.

Fourth, if we cannot find the paternal ancestry of a CEO or a spouse, we search for families with the same surname as the CEO or spouse using the U.S. Census Bureau records through Ancestry.com. We require the families with the same surname lived in the same or adjacent county where and when the CEO or spouse was born. If we find more than one family that meet these criteria, and if all these families emigrated from the same country, then we assign this country as the cultural origin of the CEO or the spouse. This step identifies an additional 93 CEOs and 51 spouses.

For the remaining 385 CEOs and 575 spouses, for whom we are unable to identify their cultural origin through the above four-step procedure, we follow Pan, Siegel, and Wang (2017) and estimate the likelihood that their ancestors emigrated from a specific country. Specifically, we use their surnames and the passenger lists of immigrants arriving in New York City between 1820 and 1957. The passenger lists are also available on Ancestry.com and provide passengers' names, ages, ethnicities, birthplaces, and other demographic

rely on paternal ancestry, similar to Liu (2016). Fortunately, cross-cultural marriages were not common in the U.S. in the early 20th century (Pagnini and Morgan 1990).

[9] Every ten years, the Census Bureau counts the total number of residents in the country and records various demographic characteristics of the household members (e.g., birth years, birthplaces, income, etc.). To protect the identity of individuals, the data is only made publicly available after 72 years. Therefore, the most recently available census records are before 1940.

characteristics. We search for a CEO's or a spouse's surname and use the source countries of passengers with the same surname to calculate the frequency distribution across possible countries of origin. For example, among passengers with the last name Fritzky, 80% have German origin and 20% have Hungarian origin.[10]

After completing all these steps, we are able to collect the ancestry information of 1,066 couples (i.e., 977 CEOs and 1,066 spouses).[11] Table 4.1 shows descriptive statistics of the sample, including CEOs' and spouses' basic information and immigrant generations.[12]

[Insert Table 4.1 here]

4.2.4 Culture and Preference Towards Risk

The six country-level cultural dimensions of Hofstede (1980, 2001), and Hofstede, Hofstede, and Minkov (2010) have been widely used across the social sciences.[13] Several studies in finance have used this data to study the effects of culture on financial outcomes (e.g., Aggarwal, Kearney, and Lucey, 2012; Li et al., 2013; Karolyi, 2016; Pan, Siegel, and Wang, 2017, 2020; Nguyen, Hagendorff, and Eshraghi, 2018). We use the Uncertainty Avoidance Index (UAI), which "*expresses the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity*".[14] Hofstede (1980) constructed this index using surveys of IBM employees in 50 countries, and the survey has since then been conducted with non-IBM participants in 34 additional countries.[15]

Our primary explanatory variable, $\Delta UAI = (UAI_{Spouse} - UAI_{CEO})/UAI_{CEO}$, measures the cultural distance between CEOs and their spouses regarding their attitudes towards uncertainty, using the UAI of their respective cultural origin countries.[16] For those whose cultural origins are a distribution, under the procedure of Pan, Siegel, and Wang (2017), their UAI is a weighted average of the UAI of individual countries, with weights

[10] In 175 cases, we are unable to identify the parents' names or the maiden names of some female spouses. To assign a cultural heritage to these cases, we search for their first names in the passenger lists. If their first names have origins in less than three countries, we use this distribution to calculate their cultural heritage. Otherwise, we exclude them from our sample, a filter that resulted in 62 of these cases being dropped.

[11] In Table 4.B1 in the Appendix B, we report the countries of origin of the CEOs and spouses in our sample.

[12] Some cultural origins use historical names or individual regions in the Census Records and passenger lists. We assign them to their modern Counterparts (i.e., German, Pomerania, and Prussian to Germany; English, Scottish, and Welsh to Great Britain, etc.).

[13] Information on these indices can be found at https://hi.hofstede-insights.com/national-culture.

[14] Hofstede Insights: https://hi.hofstede-insights.com/national-culture.

[15] The Hofstede indices aggregate some groups of countries like East Africa, West Africa, and Arab countries. Since we do not have individual indices for these countries, we also group them together in the analysis. Such groupings affect less than 3% of the observations in our sample.

[16] UAI_{Spouse} is the spouse's UAI, and UAI_{CEO} is the CEO's UAI.

reflecting the likelihood that the person comes from these countries.[17] Increases in ΔUAI indicate that a spouse comes from a relatively more risk-averse culture compared to the CEO. Thus, under our hypothesis, there would be less corporate risk-taking in such cases.

4.2.5 Corporate Risk-taking

To measure corporate risk-taking, we follow the literature and use the industry-adjusted volatility of the firm's ROA, *σ(ROA)*, (e.g., John, Litov, and Yeung, 2008; Laeven and Levine, 2009; Faccio, Marchica, and Mura, 2011, 2016; Li et al., 2013). Compared with market measures of risk (e.g. return volatility) which are more likely under the influence of stock market exogenous shocks and investors' trading strategies, *σ(ROA)* reflects the degree of risk-taking in firms' operations by the volatility of corporate earnings. The firm's operations are more likely under the CEO's control, whose riskier corporate decisions lead to more volatile earnings. Precisely, we first compute each firm's ROA (EBITDA scaled by one-quarter lagged total assets) in each quarter. Second, we compute the industry average ROA (two-digit SIC code) in each quarter. Then we compute the difference between each firm's ROA and the industry average ROA in each quarter. We finally calculate the standard deviation of this difference for each firm over five years (20 quarters) using overlapping leading windows, which is *σ(ROA)*.

4.2.6 Empirical Methodology

To examine whether the cultural differences between CEOs and their spouses affect corporate risk-taking, we estimate the following model:

$$\sigma(ROA)_{it} = \alpha + \beta_1 \cdot \Delta UAI_{i,t-1} + \mathbf{X}' \cdot \beta_{\mathbf{A}} + \text{Fixed Effects} + \epsilon_{it}, \tag{1}$$

where i indicates firm and t indicates quarter. The dependent variable is *σ(ROA)*, which proxies for corporate risk-taking in investment decisions and operations. The main explanatory variable is ΔUAI, which measures the differences in attitudes towards uncertainty avoidance between the CEO-spouse couples. We include several control variables $\mathbf{X}'$ in our models, which have been shown to influence corporate risk-taking, capturing both CEO and firm characteristics.

[17] For example, the UAI of CEO with the surname "Fritzky" is equal to 80% times German UAI plus 20% times Hungarian UAI.

In terms of the former, we include the following controls. Risk-taking propensity varies over the life cycle, and the age of the CEO has been shown to influence the firm's crash risk (Andreou, Louca, and Petrou, 2017). To account for such effects, we control for the CEOs' age (*ln(1+AGE)*). Moreover, it has been shown that female CEOs take on less risk (Faccio, Marchica, and Mura, 2016), thus we include a dummy to capture a CEOs gender (*FEMALE*). Educational levels of CEOs have been shown to influence firm performance (King, Srivastav, and Williams 2016), thus we control for the education level of the CEO (*EDUCATION*). CEO's tenure may reflect their ability or bargaining power within the firm, thus we control for it in the models (*ln(1+TENURE)*). Finally, the decision to marry someone from a different culture may indicate a higher tolerance toward risk. Thus, we include a dummy that flags CEOs' who have a different cultural heritage from their spouses (*DIFF_CULTURE)* in our models.

In terms of firm variables, we control for a firm's size (*ln(ASSETS)*), market-to-book ratio (*MB*), Tobin's Q (*Q*), and whether the firm reported losses in the previous quarter (*LOSS*).[18] The effect of these variables on corporate decisions and risks has been shown in various studies, such as Lee (1997), Lewellen (1999), and Bhagat, Bolton, and Lu (2015). Moreover, motivated by the extant literature showing that corporate governance influences firms' operations and risks (e.g., John, Litov, and Yeung, 2008; Andreou et al., 2016), we control for several governance related variables, namely board size (*BOARD_SIZE*), the fraction of independent directors on the board (*BOARD_INDEPENDENCE*), and the number of shares held by board members scaled by the number of shares outstanding (*BOARD_OWNERSHIP*). All variable definitions are available in Appendix A. We provide descriptive statistics for the variables used in our empirical analysis in Table 4.2.[19] The positive mean of ΔUAI indicates that spouses come from relatively more risk-averse cultures than CEOS in general.

Our regression specifications include CEO culture origin, industry, time (i.e., year-quarter), or industry × time fixed effects. The CEO cultural origin fixed effect captures the CEOs' own culture-related risk-taking propensity.[20] The industry × time fixed effect,

[18] *MB*, *ln(ASSETS)* and *Q* are winsorized at the 1st and 99th percentile.

[19] Table 4.B2 in Appendix B reports the correlation coefficients of these variables. We do not see very obvious multicollinearity between explanatory variables.

[20] For CEOs whose cultural origins reflect multiple countries under the procedure of Pan, Siegel, and Wang (2017), the CEO origin fixed effect captures the combination of these countries with the order of their likelihood. For example, in our earlier example, the likelihood that a CEO whose surname is "Fritzky" to come from Germany (A) is 80%, and 20% from Hungary (B). So, in this case, this CEO is placed in group AB, and all the CEOs that belong in this group receive the fixed effect AB. If another CEO with a

which we include in our baseline models, captures time-varying factors that may affect firms' behaviour in a given industry at a specific quarter, such as shocks to product demand or production costs, etc. Standard errors in all our models are double clustered by firm and time (year-quarter).

[Insert Table 4.2 here]

4.3 Empirical Results

In this section, we report our main empirical results. We also implement several additional tests to address potential endogeneity concerns.

4.3.1 Baseline Results

We report our baseline results in Table 4.3. Consistent with our hypothesis, we find that the coefficient on ΔUAI is negative and statistically significant. Specifically, in Column (3), where we include industry $\times$ time fixed effects, the coefficient on ΔUAI is -0.314 and statistically significant at the 1% level. In economic terms, a one standard deviation increase in ΔUAI, which means the spouse comes from a relatively more risk-averse culture than the CEO by 55% of UAI_{CEO}, is associated with a 0.17% (= 0.314 $\times$ 0.55/100) decrease in $\sigma(ROA)$, relative to 8.18% (= 0.314 $\times$ 0.55/2.11) of the unconditional average $\sigma(ROA)$ in our sample. The baseline results confirm our hypotheses that if CEOs marry with spouses from relatively more risk-averse cultures, they will take less corporate risk-taking.

In terms of other control variables, we first find that CEOs with longer tenures take less risks. Further, larger firms are associated with less volatility in ROA, consistent with Cain and Mckeon (2016). Firms with higher Tobin's Q or companies that experienced a loss are associated with higher future volatility.

[Insert Table 4.3 here]

4.3.2 Endogeneity

Since the choice of spouse is not random, there is an endogeneity concern as it is possible that our results reflect the effect of CEOs' own risk attitudes on corporate policies rather than the (indirect) influence of their spouses' risk attitudes. We cannot ignore the influence

different surname is more likely to come from B rather than A, then this CEO would belong in group BA. We group CEOs in such a manner to ensure that we have enough CEOs in each group so that the model can be estimated.

of CEOs' personal risk preferences, even CEOs married before becoming CEO in most cases. However, even though our results to some extent capture the risk attitudes of CEOs, it is still interesting to see that choice of spouse affects corporate risk-taking. In this section, we aim to identify the intra-marriage spillover effect of CEOs' spouses after controlling CEO personal risk preferences. To some extent address this concern, we conduct the following tests.

First, we perform a placebo test, whereby we randomly match CEOs and spouses. If the effect is driven by CEOs' own UAI, then we expect that the coefficient on ΔUAI will continue to be statistically significant even under random matching since it does not matter whom we match a CEO with.[21] However, if the effect is driven by a spouse's influence on a CEO's attitude towards uncertainty via ΔUAI, then we should no longer find a statistically significant effect after we randomize the corresponding spouses. We perform 1,000 such random matchings, estimate the baseline model for each of them and record the coefficient on ΔUAI. In Table 4.4, Column (1), we report the average of the distribution of placebo coefficients and its standard error. As seen, the null hypothesis that the average is zero cannot be rejected. In Figure 4.1, we plot the distribution of placebo coefficients and superimpose in this histogram the actual estimate (the continuous red line). As is evident from the histogram, the actual estimate is an extreme outlier in this distribution.

[Insert Figure 4.1 here]

As a second test to identify the spillover effect of CEOs' spouses, we estimate a model with CEO fixed effects, which will absorb any CEO-level time-invariant personal characteristic, including risk attitudes. Importantly, risk attitude in this model is controlled more holistically, since the CEO fixed effect will account for both cultural and non-cultural dimensions of CEOs' risk attitude. For this estimation, we restrict our sample to firms with CEOs married more than once in our sample period, thus achieving within CEO variation in ΔUAI for the same firm.[22] We also note that the act of getting a divorce could itself be a mark of a CEOs' own risk attitude. However, in this sample, identification comes from variation in ΔUAI across all CEOs who have experienced a divorce. The estimate in Table

[21] Even though our models include a CEO origins fixed effect, the estimation of this fixed effect entails some groupings of CEOs (see footnote 20), which may be biasing our estimates. For example, a CEO who is 80% to come from A and 20% to come from B will receive the same fixed effect as one who is 90% to come from A and 10% to come from B, so it is possible that the effect of the individual UAI of these CEOs on corporate risk is not fully captured by the fixed effect.

[22] The sample does not entail cases where the CEO of one S&P500 company goes to another S&P500 company, thus the variation in ΔUAI due to more than one marriage is within firms.

4.4 Column (2) shows that the coefficient on ΔUAI continues to be negative and highly statistically significant. Although CEOs' risk preferences may change due to previous marriage, this result indicates that different spouses have a different intra-marriage spillover impact on corporate risk-taking within the same CEO.

[Insert Table 4.4 here]

We further provide a balance test shown in Table 4.5 to show whether the subsample of CEOs who marry spouses with the same cultural origin manage similar firms (before separation) than the subsample of those who marry spouses with different cultural origins in the CEO fixed effect specification. The balance tests in Table 4.5 reports the mean, standard errors, t-test of difference in mean, standard deviation, and F-test of variance comparison of firm-level variables, which are *σ(ROA)*, *MB*, *ln(ASSETS)*, *Q*, and *LOSS*, between the two subsamples. We find the corporate risk-taking *σ(ROA)* and firm size *ln(ASSETS)* are slightly higher in the sample of CEOs with spouses from the same cultural origin with a significance level at 10% but without significant different variance. There is no significant different *MB*, *Q* and *LOSS* between the two groups. These results suggest that the cultural distance in risk preferences in the specification of CEO fixed effect are not driven by observable differences in firm characteristics.

[Insert Table 4.5 here]

Overall, the findings from the tests in this section support the claim that the effect of ΔUAI on corporate risk reflects the indirect spillover influence of the CEOs' spouses on their risk attitudes.

4.3.3 Firm-Level Characteristics

It is possible that firm characteristics that are correlated with ΔUAI are affecting our results. To examine this possibility, we first perform a test whereby we create matched control group of firms using propensity score matching for each firm. In this model, our treatment group consists of firms that are headed by CEOs who are married to someone from a different culture. The control group is comprised of firms that are headed by CEOs who are married to someone from the same culture. We match control firms to treated firms based on time, industry, firm size, market-to-book ratio, Tobin's Q, and reported losses using the nearest neighbour matching strategy. We utilize both the five best matches and the single best match. Additionally, we perform these two matching approaches with and without the replacement of control firms. In these models, we include a fixed effect for each treated-control matched group, so essentially are controlling for the effect of these matching dimensions on corporate risk-taking, whilst isolating the effect of cultural differences between CEOs and their spouses.

The results are reported in Table 4.6. In Columns (1) and (2), we present the findings of the five closest matches, and in Columns (3) and (4), we present the results of the single closest match. In Column (1), where we match with replacement, the coefficient on ΔUAI is -0.273, which is statistically significant at the 5% level. Column (2) shows that the results are robust to matching without replacement, as the coefficient on ΔUAI remains negative and statistically significant. Similar results are shown in Columns (3) and (4), where we match our treated firms to the single closest match both with and without replacement, respectively. We also conduct balance tests to compare firm characteristics between treatment and control groups in the matched sample. For example, Table 4.B3 in Appendix B shows the balance test of five closest matches with replacement, i.e. Column (1) in Table 4.6. We find there is no significant difference in firm characteristics between the two groups.

To further control for the effect of any omitted firm-level characteristics that may be influencing our results, we estimate a model with firm fixed effects. For this test, we restrict our sample to only include firms with one or more CEO turnover during our sample period, therefore we are able to examine how variations in ΔUAI within firms are associated with changes in corporate risk-taking.[23] In Table 4.6, Column (5) shows that the results are robust to including firm-level fixed effects in our regression specification. Specifically, the coefficient on ΔUAI is negative and statistically significant, -0.334 (p-value $< 1\%$). Overall, the results in this section do not lend support to the view that differences in firm characteristics that correlate with ΔUAI are driving our results.

[Insert Table 4.6 here]

4.3.4 Robustness Checks

We conduct three additional tests to ensure the robustness of our findings. The first robustness check examines whether our results still hold for CEO-spouse couples whose

[23] We do not include CEOs who have changed spouses in this sample, and thus the variation in ΔUAI here only comes from CEO turnover in the same firm. For this test, we do not include a CEO-origin fixed, as the firm fixed effect captures the average level of risk of each firm across all the years, using within-firm variation via CEO turnover to estimate the coefficient on ΔUAI.

cultural origins are both directly observed. In our sample, the cultural origins of CEOs and spouses are not all directly observed. Through the data collection procedure in Section 4.2.3, we are able to identify the ancestry records of 499 CEOs and 440 spouses, for whom we have their exact ancestry origin. Among them, ancestry records of 319 CEO-spouse couples are both directly identified. For the remaining 478 CEOs and 626 spouses, we estimate their cultural heritage with passenger lists of immigrants and ancestry records of families with the same surname. To check the robustness of our results, we restrict our sample to the 319 couples whom we can directly observe ancestry records of both. Column (1) of Table 4.7 reports the result. The observations of this test are 2,725, which is about 22.10% of the full sample. The result of ΔUAI is still significant at the 1% level.

As an additional check to examine whether reverse causality affects our findings (i.e., firms hire CEOs with certain ΔUAI that align with firms' risk profiles), we follow the analysis in Cronqvist and Yu (2017) and Nguyen, Hagendorff, and Eshraghi (2018) to examine if lagged $\sigma(ROA)$ in the prior 20 quarters can predict the incoming CEO's ΔUAI when the firm experience a CEO turnover. Under endogenous matching, we expect to find a significant coefficient on lagged $\sigma(ROA)$. However, inconsistent with this view, the estimate in Table 4.7 Column (2) shows that the coefficient on lagged $\sigma(ROA)$ is statistically insignificant.

Another concern is that our sampling procedure, which is heavily based on the names of CEOs and their spouses, could give rise to a selection bias. For example, it is possible that CEOs or spouses with more common or shorter surnames are more difficult to be uniquely identified with demographic records and cultural heritage. Thus, such CEOs and spouses are more likely to be excluded from our sample, leading to a biased selection.

To assess whether such a bias is affecting our findings, we follow Nguyen, Hagendorff, and Eshraghi (2018) and use a Heckman (1979) two-step selection model. In the first stage of the estimation, we use the length of surnames of CEOs and their spouses as instruments. We include all CEOs and spouses in this sample, even those that were not included in our baseline analysis (as we could not obtain information of their cultural heritage). In the second stage, the model includes our standard controls and an additional variable (λ) that corrects for the probability that a CEO (or spouse) enters our sample (from the first stage). The result, which is shown in Table 4.7 Column (3), indicates a negative and statistically significant association between ΔUAI and corporate risk-taking, even after controlling for the probability that a CEO or a spouse is included in our sample.

[Insert Table 4.7 here]

4.4 Additional Tests

In this section, we first test our hypothesis with different measures of corporate risk-taking. Then, we examine whether our findings differ in the cross-section of CEO-spouse pairs.

4.4.1 Alternative Corporate Risk-taking Measures

This additional test uses two different measures of corporate risk-taking to test our hypothesis. The first measure is expenditure on research and development (*R&D*), defined as the natural logarithm of a firm's quarterly R&D expense, as in Knott (2008). This choice of dependent variable is motivated by the corporate finance literature, which suggests that R&D expenditures are riskier investments with a high degree of uncertainty (e.g., Bargeron, Lehn, and Zutter, 2010; Li et al., 2013; Pan, Siegel, and Wang, 2017). Similar to our baseline specification, we expect to find a negative association between ΔUAI and *R&D*.

The estimates are reported in Panel A of Table 4.8. We find that when we regress *R&D* on ΔUAI, along with a vector of control variables, the coefficient on our main variable of interest is negative and statistically significant at the 5% level in all specifications. The estimates range from -0.149 to -0.158. This effect is economically significant. For instance, a one standard deviation increase in ΔUAI leads to approximately a 4.91% decrease in R&D expenditures, relative to its unconditional average in our sample.

The second alternative corporate risk measure we use is the number of litigation suits against a specific firm in a given quarter, calculated as in Hutton, Jiang, and Kumar (2015). Being involved in such lawsuits is also a form of corporate risk, as it is likely to indicate potentially unlawful behaviour on the part of the firm. The measure, *LITIGATION*, is defined as the natural logarithm of one plus the lawsuits against a particular firm in a given quarter, which we expect to be negatively related to ΔUAI. The results, reported in Panel B of Table 4.8, show that indeed the coefficient on ΔUAI is negative and statistically significant, in line with our hypothesis. The effect is economically meaningful, as a one standard deviation increase in ΔUAI reduces litigation cases by 13.18%, relative to its unconditional average in our sample.

Overall, in this section, we find that our baseline results continue to hold for different aspects of corporate risk-taking.

[Insert Table 4.8 here]

4.4.2 Individualism vs. Collectivism Index

The Individualism vs. Collectivism Index (IDV) is another cultural dimension proposed by Hofstede's (2001) framework, reflecting the degree to which people in a society are integrated into groups. A higher IDV value suggests that people in a society are expected to take more care of themselves and pursue their own interests. Some studies suggest that greater individualism implies more overconfidence (e.g., Chui, Titman, and Wei, 2010). Therefore, it is possible that CEOs whose countries of origin have higher IDV values could be less influenced by their spouses as they are more individualistic. To test this conjecture, we divide our sample into two subgroups, cutting at the average IDV of CEOs (IDV= 70).

The results are presented in Table 4.9. The coefficient on ΔUAI is negative and statistically significant in each subsample, but more so for the sample where CEOs come from low IDV countries. This finding suggests that spillover effects are less likely when CEOs come from more individualistic countries, and therefore, are less prone to be influenced by their spouse.

[Insert Table 4.9 here]

4.4.3 Immigrant Generation

The influence of cultural origins on risk attitudes is likely to dissipate over generations of immigrants because of the risk of cultural assimilation documented in Strauss (1997). Along these lines, Nguyen, Hagendorff, and Eshraghi (2018) show that in their tests, the cultural heritage of the CEO has a stronger effect for the first three generations of immigrants, becoming weaker for the fourth or higher generations of immigrants. Motivated by their finding, we examine whether our findings are driven by the immigrant generation of CEOs.

In Column (1) of Table 4.10, we do a subsample test focusing on CEOs who are first-, second- or third-generation immigrants. In Column (2), we create another subsample with CEOs who are the fourth or higher generation of immigrants.[24] We find ΔUAI has a significant influence on $\sigma(ROA)$ in Column (1) but insignificant in Column (2). This

[24] The sample size in this test is smaller than the sample of our baseline model because we drop those CEOs who we do not know their immigrant generation.

finding suggests that the effects of cultural origins on risk-taking dissipate over long periods, consistent with the findings in Nguyen, Hagendorff, and Eshraghi (2018).

[Insert Table 4.10 here]

4.5 Conclusion

This paper examines whether the risk preferences of a CEO's spouse has an intra-marriage spillover influence on corporate policies. Our main conjecture is that, as a consequence of the transmission of cultural norms between married couples, a CEO's personal risk preference will be influenced by her/his spouse's risk preference, leading CEOs who are married to spouses from more risk-averse cultures to take on less corporate risk. To operationalize our empirical analysis, we identify the cultural origins of CEOs and spouses, and use the Hofstede (2001) Uncertainty Avoidance Index for their countries of origin to measure their risk attitudes. We then take the difference between these Hofstede values for spouses and CEOs, expecting that, in the cross-section of companies, a higher difference (indicating a more risk-averse spouse relative to the CEO) lower the corporate risk-taking.

Our findings support this prediction. This effect is economically meaningful, as a one standard deviation increase in the difference in Uncertainty Avoidance Index between spouse and CEO is associated with a reduction of about 8% in corporate risk-taking, relative to the unconditional average in our sample. To address endogeneity concerns, we first randomly match spouses to CEOs, finding results not hold in the randomly matched sample. Then we estimate our model with CEO fixed effects, using CEOs who have been married more than once during our sample period and find that our results continue to hold. We use other econometric specifications to control for the possibility that cultural differences correlate with firm-specific variables, and we continue to find a negative association between our variable of interest and corporate risk-taking. Overall, our work supports the view that the cultural composition of a CEO's household affects corporate decisions.

Figure 4.1: Placebo Test

This figure presents results from the placebo test. We randomly match CEOs and spouses, and calculate a new ΔUAI using the CEOs' UAI and the UAI of the random spouses. Following each match, we re-estimate model (1) and retain the coefficient on ΔUAI, repeating this procedure 1,000 times. The coefficients on ΔUAI are plotted in the histogram below. The x-axis reports the range of coefficient estimates in bins with a width of 0.05. The y-axis reports the percentage of observations in each bin. The vertical line is the coefficient on ΔUAI from the actual sample, which is Column (3) in Table 4.3.

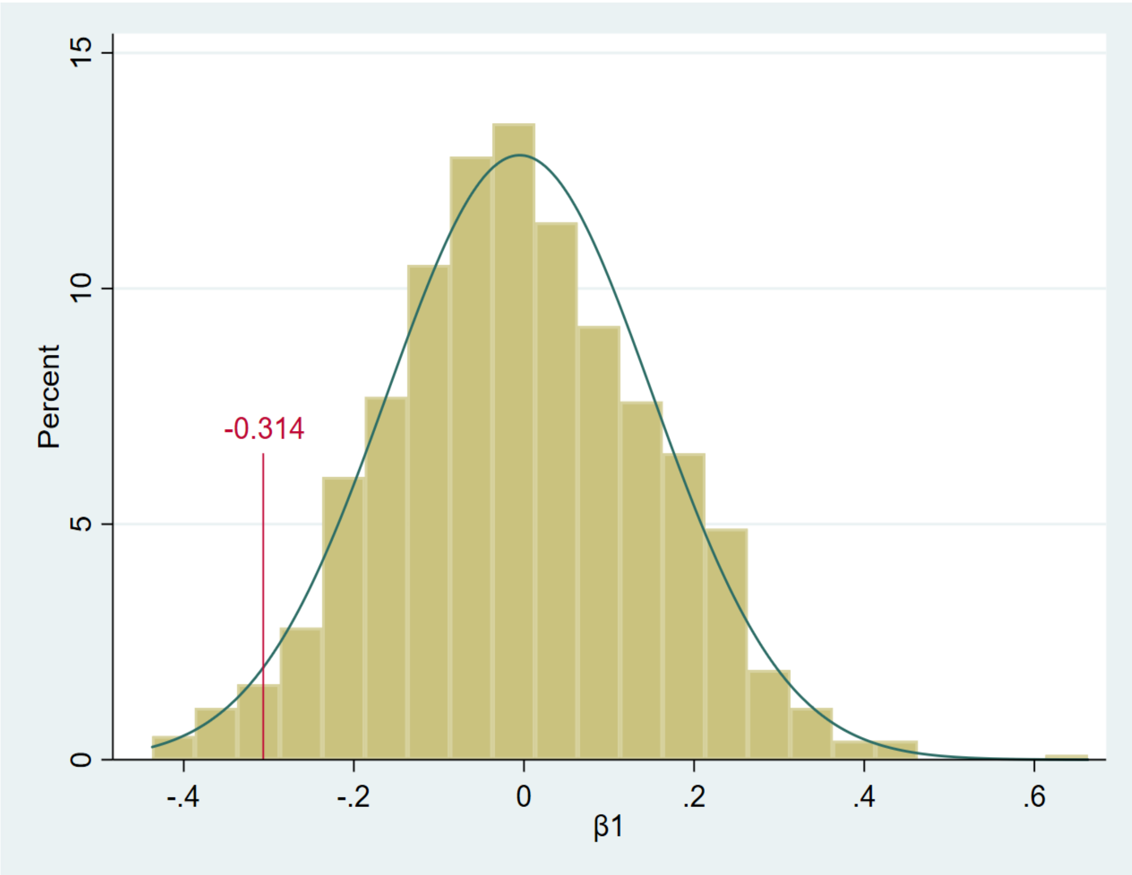

Table 4.1: Descriptive Statistics on Cultural Origins

This table presents descriptive statistics on the cultural origins of CEOs and their spouses. Panel A reports the ancestry information of CEOs and their spouses. Panel B classifies CEOs and their spouses as *Gen 1* (foreign-born CEOs or spouses), *Gen 2* (second-generation immigrants whose parents are foreign-born), *Gen 3* (third-generation immigrants whose grandparents are foreign-born), *Gen 4+* (fourth- or higher generation immigrants), and *Others* (without immigrant generation information).

Panel A: CEOs' and CEO spouses' basic information

	No.	Share of Total Couples
CEOs with more than one marriage	72	6.75%
Female CEOs	40	3.75%
CEOs with exact ancestry origin	499	46.81%
Spouses with exact ancestry origin	440	41.28%
Couples with exact ancestry origin	319	29.92%
Couples with the same ancestry origin	147	13.79%
Couples with ancestry information	1,066	100%

Panel B: CEOs' and CEO spouses' immigrant generation

	No. of CEO	Share of Total CEOs	No. of CEO spouses	Share of Total CEO spouses
Gen 1	115	11.77%	136	12.76%
Gen 2	74	7.57%	58	5.44%
Gen 3	69	7.06%	49	4.60%
Gen 4+	241	24.67%	197	18.48%
Others	478	48.93%	626	58.72%
Total	977	100%	1,066	100%

Table 4.2: Summary Statistics

This table presents summary statistics for the variables used in the paper. Panel A provides descriptive statistics for CEO characteristics, Panel B reports descriptive statistics for firm-level variables, and Panel C provides descriptive statistics for the corporate governance variables. Definitions of the variables are provided in Appendix A.

	Obs.	**Mean**	**Std. Dev**	**Q1 (25%)**	**Median**	**Q3 (75%)**
Panel A: CEO characteristics						
UAI_CEO	12,330	54.79	20.94	35	49	75
UAI_SPOUSE	12,330	52.51	20.39	35	43.51	68.60
ΔUAI	12,330	0.08	0.55	-0.29	0.00	0.21
EDUCATION	12,330	1.66	0.73	1	2	2
FEMALE	12,330	0.03	0.17	0	0	0
MARRIAGE YEAR	12,330	27.95	9.09	22	29	35
AGE	12,330	56.64	7.08	52	57	61
DIFF_CULTURE	12,330	0.87	0.34	1	1	1
TENURE	12,330	7.14	7.15	2	5	9
IDV_CEO	12,330	70.40	15.96	63	74.50	82.73
Panel B: Firm characteristics						
σ(ROA) × 100	12,330	2.11	2.44	0.97	1.56	2.59
R&D	12,330	124.62	431.39	0.00	0.00	46.03
LITIGATION	12,330	0.05	0.59	0	0	0
MB	12,330	4.01	5.36	1.86	2.90	4.58
ASSETS	12,330	22,044.02	40,244.17	3,673.60	8,232.65	22,289.88
Q	12,330	2.16	1.25	1.36	1.78	2.50
LOSS	12,330	0.11	0.32	0	0	0
Panel C: Corporate governance						
BOARD_SIZE	12,330	10.48	2.13	9	10	12
BOARD_OWNERSHIP	12,330	0.05	0.15	0.01	0.01	0.04
BOARD_INDEPENDENCE	12,330	0.76	0.14	0.70	0.80	0.89

Table 4.3: Cultural Distance and Corporate Risk-taking

This table reports the baseline results from panel regressions examining the effect of the cultural distance between a CEO and her/his spouse on corporate risk-taking. The dependent variable is the volatility of a firm's operating return on assets ($\sigma(ROA) \times 100$). The main explanatory variable is the UAI distance between a CEO and her/his spouse (ΔUAI). Definitions of the variables are provided in Appendix A. Industry is based on two-digit SIC codes. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
ΔUAI	-0.383**	-0.329**	-0.314***
	(0.161)	(0.152)	(0.114)
CEO Characteristics			
EDUCATION	0.243**	0.214**	0.120
	(0.100)	(0.095)	(0.075)
FEMALE	-0.214	-0.117	0.010
	(0.451)	(0.355)	(0.304)
ln(1+ MARRIAGE_YEAR)	-0.049	-0.029	0.074
	(0.117)	(0.114)	(0.118)
ln(1+AGE)	-1.375**	-0.824	-0.624
	(0.677)	(0.659)	(0.545)
DIFF_CULTURE	0.164	0.154	0.122
	(0.207)	(0.198)	(0.176)
ln(1+TENURE)	-0.258***	-0.161**	-0.108*
	(0.080)	(0.073)	(0.060)
Firm Characteristics			
MB	-0.005	-0.002	-0.007
	(0.006)	(0.004)	(0.004)
ln(ASSETS)	-0.279***	-0.126*	-0.126**
	(0.075)	(0.066)	(0.057)
Q	0.065	0.080	0.143*
	(0.080)	(0.073)	(0.082)
LOSS	0.530***	0.562***	0.748***
	(0.142)	(0.140)	(0.124)
Corporate Governance			
BOARD_SIZE	-0.006	-0.031	-0.020
	(0.034)	(0.032)	(0.024)
BOARD_OWNERSHIP	0.816*	0.713*	0.587
	(0.459)	(0.401)	(0.394)
BOARD_INDEPENDENCE	-0.071	1.381**	0.528
	(0.423)	(0.572)	(0.395)
CEO origin FE	Yes	Yes	Yes
Industry FE	Yes	Yes	No
Year-Quarter FE	No	Yes	No
Industry-quarter FE	No	No	Yes
Observations	12,330	12,330	11,613
R^2	0.400	0.463	0.831

Table 4.4: Endogenous Spouse Selection

This table presents estimates from models that address the potential endogeneity in the choice of spouse and corporate risk-taking. In Column (1), we present the results from a placebo test. In this test, we randomly match CEOs with spouses and calculate a new ΔUAI using the CEOs' UAI and the UAI of the random spouses. For each match, we re-estimate model (1) and retain the coefficient on ΔUAI, repeating this procedure 1,000 times. In Column (1), we report the average coefficient on ΔUAI and its standard error. In Column (2), we use a model with a CEO fixed effect in a sample that only includes firms headed by CEOs with more than one marriage in our sample period. The dependent variable is the volatility of a firm's operating return on assets ($\sigma(ROA) \times 100$). ΔUAI is the UAI distance between a CEO and her/his spouse. Control variables are the same as Table 4.3, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. Industry is based on two-digit SIC codes. In Column (2), the standard error shown in parentheses is double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) Placebo Test	(2)
ΔUAI	0.005	-3.771***
	(0.005)	(1.366)
Control Variables	Yes	Yes
CEO origin FE	Yes	No
Industry-quarter FE	Yes	Yes
CEO FE	No	Yes
Observations	1,000	3,690
R^2		0.952

Table 4.5: Balance Tests of Firm Characteristics

This table presents the balance tests of firm characteristics in the specification of CEO fixed effect model. We compare the mean, standard errors, t-test of difference in mean, standard deviation, and F-test of variance comparison, for firm-level variables which are *σ(ROA)*, *MB*, *ln(ASSETS)*, *Q*, and *LOSS*, between the sample of CEOs with spouses from same cultural origin and the sample of CEOs with spouses from different cultural origins. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variable		**Obs.**	**Mean**	**Std. Err.**	**Difference (same - diff)**	**Std. Dev.**	**Std(same) / Std(diff)**
$\sigma(ROA)$	same culture origin	923	2.137	(0.049)	0.115*	2.551	1.037
	different cultrue origin	2767	2.021	(0.047)	p-value = 0.088	2.505	p-value = 0.492
MB	same culture origin	923	4.418	(0.096)	0.132	6.008	1.277***
	different cultrue origin	2767	4.286	(0.082)	p-value = 0.293	5.316	p-value = 0.000
ln(ASSETS)	same culture origin	923	9.422	(0.020)	0.055*	1.273	0.947
	different cultrue origin	2767	9.367	(0.020)	p-value = 0.085	1.308	p-value = 0.318
Q	same culture origin	923	2.281	(0.021)	0.033	1.335	1.244***
	different cultrue origin	2767	2.247	(0.018)	p-value = 0.242	1.197	p-value = 0.000
LOSS	same culture origin	923	0.102	(0.005)	-0.001	0.302	0.995
	different cultrue origin	2767	0.103	(0.005)	p-value = 0.938	0.303	p-value = 0.934

Table 4.6: Controls for Firm Characteristics

This table presents results from tests that control for the effect of firm characteristics on our baseline findings. In Columns (1)-(4), we conduct a propensity score matching exercise. The treated group consists of couples with different cultural backgrounds, and the control group consists of couples with the same cultural backgrounds. We match each treated firm to a firm(s) from the control group based on time, industry, size, market-to-book ratio, Tobin's Q, and reported losses. In Columns (1) and (2), we match each treated firm to the five closest control firms. In Columns (3) and (4), we use the single closest match. We match with replacement in Columns (1) and (3), and without replacement in Columns (2) and (4). In Column (5), we include a firm fixed effect in our baseline model in a reduced sample that only includes firms that experienced a change in their CEO without CEOs changing spouse during our sample period. In all columns, the dependent variable is the volatility of a firm's operating return on assets ($\sigma(ROA) \times 100$). ΔUAI is the UAI distance between a CEO and her/his spouse. Control variables are the same as Table 4.3, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. Industry is based on two-digit SIC codes. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
ΔUAI	-0.273**	-0.655**	-0.280**	-0.753***	-0.334***
	(0.121)	(0.325)	(0.122)	(0.241)	(0.138)
Control Variables	Yes	Yes	Yes	Yes	Yes
CEO origin FE	Yes	Yes	Yes	Yes	No
Industry-quarter FE	Yes	Yes	Yes	Yes	Yes
Matched FE	Yes	Yes	Yes	Yes	N/A
Firm FE	No	No	No	No	Yes
Observations	8,143	2,164	8,430	2,277	7,413
R^2	0.816	0.915	0.815	0.907	0.852

Table 4.7: Additional Robustness Checks

This table presents the results from additional robustness tests. In Column (1), we restrict our sample to CEO-spouse couples whose origins of culture are both directly observed. In Column (2), we check the reverse causality, where the dependent variable is ΔUAI of incoming CEO and the primary explanatory variable of interest is $\sigma(ROA) \times 100$ in the prior 20 quarters. In Column (3), we use a Heckman two-stage test to adjust for a potential selection bias by including the inverse Mills ratio from a first-stage Probit regression (since the likelihood that a CEO-spouse couple is in our sample may depend on the nature of their names). The dependent variable in Columns (1) and (3) is the volatility of a firm's operating return on assets ($\sigma(ROA) \times 100$). ΔUAI is the UAI distance between a CEO and her/his spouse. Control variables are the same as Table 4.3, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. Industry is based on two-digit SIC codes. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent Var.	(1) σ(ROA)	(2) ΔUAI	(3) σ(ROA)
ΔUAI	-0.742***		-0.179**
	(0.169)		(0.080)
σ(ROA) in prior 20 quarters		-1.526	
		(9.419)	
Lambda			-0.129*
			(0.075)
First-stage results of Heckman two-stage test			
CEO surname length			-0.070
			(0.049)
CEO spouse surname length			0.555***
			(0.032)
Control Variables	Yes	Yes	Yes
CEO origin FE	Yes	No	Yes
Industry-quarter FE	Yes	Yes	Yes
Observations	2,725	202	11,613
R^2	0.800	0.032	

Table 4.8: Alternative Measures of Corporate Risk-taking

This table presents results when testing the hypothesis using alternative measures of corporate risk-taking. In Columns (1) to (3), the dependent variable is the natural logarithm of R&D expenditure (*ln(1+R&D)*). In Columns (4) to (6), the dependent variable is litigation (*ln(1+LITIGATION)* $\times$ 100). ΔUAI is the UAI distance between a CEO and her/his spouse. Control variables are the same as Table 4.3, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. Industry is based on two-digit SIC codes. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Panel A: R&D			**Panel B: Litigation**		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔUAI	-0.149**	-0.151**	-0.158**	-0.831**	-0.766*	-0.688*
	(0.065)	(0.065)	(0.065)	(0.390)	(0.392)	(0.386)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
CEO origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	Yes	Yes	No
Year-Quarter FE	No	Yes	No	No	Yes	No
Industry-quarter FE	No	No	Yes	No	No	Yes
Observations	12,330	12,330	11,613	12,330	12,330	11,613
R^2	0.682	0.714	0.723	0.065	0.073	0.160

Table 4.9: Sub-sample Tests based on Individualism

This table presents results when estimating the baseline model in sub-samples formed on the basis of the Hofstede Individualism vs. Collectivism Index for the country of origin of the CEO, cutting at the average value (70). The dependent variable is the volatility of a firm's operating return on assets ($\sigma(ROA) \times 100$). ΔUAI is the UAI distance between a CEO and her/his spouse. Control variables are the same as Table 4.3, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. Industry is based on two-digit SIC codes. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) Low	(2) High
ΔUAI	-0.979***	-0.271**
	(0.242)	(0.128)
Control Variables	Yes	Yes
CEO origin FE	Yes	Yes
Industry-quarter FE	Yes	Yes
Observations	4,363	6,217
R^2	0.760	0.820

Table 4.10: Sub-sample Tests based on Immigrant Generation of CEOs

This table presents results when estimating the baseline model in sub-samples formed based on the immigrant generation of CEOs. Column (1) reports the subsample test of CEOs who are first-, second-, or third-generation immigrants (*Gen 1-3*), and Column (2) reports the subsample test of CEOs who are fourth (or higher) generation immigrants (*Gen 4+*). The dependent variable is the volatility of a firm's operating return on assets ($\sigma(ROA) \times 100$). ΔUAI is the UAI distance between a CEO and her/his spouse. Control variables are the same as Table 4.3, but results are not reported for brevity. Definitions of the variables are provided in Appendix A. Industry is based on two-digit SIC codes. Standard errors shown in parentheses are double-clustered by firm and time (year-quarter). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) Gen 1-3	(2) Gen 4+
ΔUAI	-0.972***	-0.146
	(0.318)	(0.247)
Control Variables	Yes	Yes
CEO origin fixed effect	Yes	Yes
Industry-quarter fixed effect	Yes	Yes
Observations	2,324	2,305
R^2	0.693	0.932

Appendix A: Variable Definitions

CEO and CEO Spouse Characteristics:

UAI_CEO: Uncertainty Avoidance Index for the CEO. *Source:* Marquis Who's Who, Notable Names Database, Wikipedia, interviews or news about CEO couples through Google search and YouTube, and Ancestry.com. Hofstede, Hofstede, and Minkov (2010).

IDV_CEO: Individualism vs. Collectivism Index for the CEO. *Source:* Marquis Who's Who, Notable Names Database, Wikipedia, interviews or news about CEO couples through Google search and YouTube, and Ancestry.com. Hofstede, Hofstede, and Minkov (2010).

ΔUAI: The difference between the CEO spouse's UAI and CEO's UAI scaled by CEO's UAI.

EDUCATION: The level of the CEO's education. It is equal to three if the CEO holds a doctorate degree, equal to two if the CEO's highest degree is a master's degree, and equal to one if the CEO's highest degree is undergraduate, and zero otherwise. *Source:* Marquis Who's Who, Notable Names Database, Wikipedia.

FEMALE: An indicator equals to one if the CEO is female, and zero otherwise. *Source:* Execucomp item GENDER.

ln(1+MARRIAGE_YEAR): Nature logarithm of one plus years since the CEO-spouse couple's wedding, updated annually. *Source:* Marquis Who's Who, Notable Names Database, Wikipedia, interviews or news about CEO couples through Google search and YouTube, and Ancestry.com. If we cannot find the accurate marriage date of a couple through these ways, we estimate the year of their marriage by using the current year minus the age of their eldest child and one.

ln(1+AGE): Nature logarithm of one plus CEO's age, updated annually. *Source:* Execucomp item AGE.

DIFF_CULTURE: An indicator equals to one if the CEO has a different cultural heritage from her/his spouse, and zero otherwise.

ln(1+TENURE): Nature logarithm of one plus years of service as CEO at a given firm, updated annually. *Source:* Execucomp item YEAR minus BECAMECEO.

CEO surname length: The number of letters in the CEO's surname.

CEO spouse surname length: The number of letters in the spouse's surname.

Firm Characteristics:

σ(ROA): The standard deviation of a firm's demeaned return on assets by the industry average return on assets for 20 quarters (John, Litov, and Yeung, 2008). We require firms to have available earnings and total assets data for at least five years (20 quarters). *Source:* $ROA_t=(NIQ_t+DPQ_t+TXTQ_t+XINTQ_t)/ ATQ_{t-1}$ in Compustat.

R&D: Nature logarithm of R&D expenditure. We replace the quarterly R&D expenditure with zero if it is missing. *Source:* XRDQ in Compustat.

LITIGATION: Nature logarithm of one plus number of lawsuits for a firm in a given quarter. *Source:* Data compiled as in Hutton, Jiang, and Kumar (2015).

MB: Market to Book ratio. *Source:* (PRCC_Q × CSHOQ)/SEQQ in Compustat.

ln(ASSETS): Nature logarithm of total assets. *Source:* ATQ in Compustat.

Q: Tobin's Q. *Source:* [ATQ – SEQQ + (PRCC_Q × CSHOQ)]/ATQ in Compustat.

LOSS: An indicator variable equals to one if a firm has a negative net income in a given quarter, and zero otherwise. *Source:* NIQ in Compustat.

Corporate Governance:

BOARD_SIZE: The number of directors sitting on the board. *Source:* BoardEx.

BOARD_OWNERSHIP: The number of shares held by board members scaled by outstanding shares. NUM_OF_SHARE/CSHO. *Source:* Institutional Shareholder Services (ISS) item NUM_OF_SHARE and Compustat item CSHO.

BOARD_INDEPENDENCE: The fraction of independent directors on the board. *Source:* Institutional Shareholder Services (ISS) item CLASSIFICATION.

Appendix B: Supplementary Tables

Table 4.B1: Cultural Backgrounds of CEOs' and their Spouses'

This table presents the number of CEOs and spouses from each country. The number outside the parentheses is the number of CEOs or spouses with exact information from each country. The number in the parentheses is the number of CEOs or spouses whose ancestry distribution includes the given country.

Countries	N of CEOs	N of Spouses	Countries	N of CEOs	N of Spouses
Arab	4	4	Latvia	0	1(1)
Argentina	0	2(1)	Lebanon	2	1(2)
Armenia	(1)	0	Lithuania	2(1)	1
Australia	12(3)	9(1)	Macedonia	(1)	0
Austria	5(14)	6(14)	Malaysia	2	0
Bangladesh	1	1	Mexico	3	5(2)
Belgium	4(2)	4(4)	Monaco	1	1
Bosnia	0	1	Native American	1	3
Brazil	3(2)	5(2)	Netherlands	21(49)	9(25)
Bulgaria	(2)	0	Norway	11(12)	5(28)
Canada	22(19)	23(43)	Pakistan	1(1)	1
Chile	1	1	Philippines	0	2
China	4	8(1)	Poland	15(14)	11(14)
Colombia	(1)	1	Portugal	1(4)	4(1)
Costa Rica	1	0	Puerto Rico	1	1(2)
Croatia	4(2)	(1)	Romania	3(6)	0.5(2)
Cuba	4(10)	1(6)	Russia	10(48)	5(5)
Czech Republic	8(2)	6(2)	Serbia	2	0
Denmark	4(10)	5(17)	Singapore	0	1
Dominica	(1)	0	Slovak Republic	(7)	1(2)
Egypt	2	1	Slovenia	(3)	2(1)
Estonia	0	(1)	South Africa	3	1
Finland	2(1)	2(10)	Spain	18(14)	12(14)
France	18(43)	26(52)	Sri Lanka	1	0
Germany	80(129)	56(186)	Sweden	17(34)	15(41)
Greece	12(7)	6(7)	Switzerland	6(20)	3(30)
Hungary	6(24)	3(11)	Syria	1(1)	1
India	28	14	Taiwan	6	4
Iran	4	1	Turkey	4(3)	2
Ireland	43(117)	26(254)	U.K.	100 (298)	182(358)
Israel	5	3(1)	Ukraine	2	0
Italy	47(15)	41(54)	U.S.	11	11
Japan	3	2	Yugoslavia	0	1
Jewish	63(14)	44(14)	Zambia	0	1

Table 4.B2: Correlation Coefficients

This table presents the Pearson correlation between pairs of variables. Definitions of the variables are provided in Appendix A.

	σ(ROA)	R&D	LITI-GATION	ΔUAI	EDU	FEMALE	MARRIAGE YEAR	AGE
σ(ROA)	1.00							
R&D	0.05	1.00						
LITIGATION	0.03	0.05	1.00					
ΔUAI	-0.04	-0.03	-0.01	1.00				
EDU	0.08	0.12	0.01	-0.02	1.00			
FEMALE	-0.07	0.09	0.01	0.00	-0.05	1.00		
MARRIAGE YEAR	-0.06	-0.02	0.00	-0.01	0.07	0.01	1.00	
AGE	-0.07	-0.07	-0.02	-0.06	0.03	-0.04	0.31	1.00
DIFF_CULTURE	0.02	-0.04	0.01	0.06	-0.03	-0.05	0.01	-0.01
TENURE	-0.04	-0.06	-0.05	-0.02	-0.01	-0.11	0.04	0.39
MB	0.00	0.10	-0.01	-0.03	0.00	0.04	-0.03	-0.04
ASSET	-0.11	0.15	0.07	-0.02	0.03	0.10	0.10	0.17
Q	0.06	0.22	0.00	-0.02	0.04	0.01	-0.10	-0.10
LOSS	0.16	0.06	0.08	0.00	0.06	-0.02	-0.02	-0.08
BOARD_SIZE	-0.08	-0.02	0.03	0.02	-0.06	0.04	0.12	0.12
OWNERSHIP	0.01	-0.10	0.03	0.02	-0.04	-0.02	-0.03	0.01
INDEPENDENCE	-0.04	0.17	0.00	0.06	0.00	0.06	0.11	0.03
	DIFF_ CULTURE	TENURE	MB	ASSET	Q	LOSS	BOARD_ SIZE	OWNER-SHIP
DIFF_CULTURE	1.00							
TENURE	0.01	1.00						
MB	0.03	0.02	1.00					
ASSET	-0.11	-0.05	-0.09	1.00				
Q	0.02	0.07	0.51	-0.25	1.00			
LOSS	0.01	-0.06	-0.04	-0.06	-0.08	1.00		
BOARD_SIZE	-0.06	-0.08	-0.01	0.45	-0.13	-0.08	1.00	
OWNERSHIP	-0.03	0.04	0.05	-0.12	0.05	0.04	0.02	1.00
INDEPENDENCE	0.03	-0.07	0.02	0.21	-0.07	0.01	0.06	-0.24

Table 4.B3: Balance Tests for Propensity Score Match

This table presents the balance tests of firm characteristics for propensity score matched sample. We compare the mean, standard errors, t-test of difference in mean, standard deviation, and F-test of variance comparison, for firm-level variables which are $\sigma(ROA)$, *MB*, *ln(ASSETS)*, *Q*, and *LOSS*, between the treatment group and control group in Column (1) Table 4.6. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variable		**Obs.**	**Mean**	**Std. Err.**	**Difference (treat - control)**	**Std. Dev.**	**Std(treat) / Std(control)**
$\sigma(ROA)$	treatment group	7130	2.186	(0.045)	-0.117*	2.991	1.093
	control group	1013	2.303	(0.025)	p-value = 0.051	2.735	p-value = 0.968
MB	treatment group	7130	3.891	(0.095)	0.218	4.451	0.847***
	control group	1013	4.036	(0.043)	p-value = 0.293	5.257	p-value = 0.000
ln(ASSETS)	treatment group	7130	9.222	(0.028)	-0.055*	1.303	0.971
	control group	1013	9.257	(0.011)	p-value = 0.067	1.341	p-value = 0.526
Q	treatment group	7130	2.273	(0.021)	-0.008	1.419	1.417***
	control group	1013	2.281	(0.012)	p-value = 0.258	1.001	p-value = 0.000
LOSS	treatment group	7130	0.126	(0.007)	-0.005	0.338	1.002
	control group	1013	0.131	(0.003)	p-value = 0.714	0.337	p-value = 0.974

Chapter 5

Conclusion

This thesis covers three projects in the area of behavioural finance. These studies shed some new light on the societal implications of travel and culture on financial outcomes. The first and second projects document the positive externality of air travel on foreign equity holdings and analyst forecasts, respectively. The third project highlights the implications of the cultural composition of a CEO's household on corporate decisions.

The first project examines whether international tourism, especially recreational travel, can stimulate foreign equity holdings. When residents of a home country travel to another foreign country, they will be more likely to recognize this country and potentially invest in its equities. We find evidence that outward tourism between countries positively predicts foreign equity investments. These investments lead to a reduction in home bias and improved diversification. Moreover, we identify the causal effect with an instrumental variable model, where we use instrumental variables that affect recreational travel. We find that the effects are more potent for farther apart countries or when the country has a high Uncertainty Avoidance Index. However, we do not find superior information and better portfolio performance. Overall, our findings highlight a positive externality of tourism for a specific country in attracting foreign capital to local equities. It would be helpful to examine the long-term effects of tourism-induced foreign investments in future work. Once investors become more aware of a specific country through recreational travel, they may identify undervalued markets and may specialize in those markets.

Continuing with the study of air travel, the second paper examines whether air travel affects sell-side analyst coverage and forecast errors. With the conjecture that air travel improves information dispersion and makes residents become more recognized with another place, the number of air travellers from analyst location city to firm headquarter city is applied to proxy the information environment of analysts with target companies. I firstly find evidence that air travellers from analyst location city to firm headquarter city can positively predict analyst coverage. The causal effect is identified with an instrumental variable model, where two instrumental variables are exogenous shocks on air travel. The first instrument is new air route openings. The second instrument is terrorist attacks and mass shootings. This study then documents that air travel is positively associated with analyst forecast errors at the analyst forecast level. These findings indicate that air travel and familiarity reflect recognition heuristic rather than information advantage. However, I find that the interaction effect of air travel and shared analyst coverage has positive externalities on market reactions: stock return comovement and predictability. In future work, it would be interesting to investigate how travel affects the behaviour of other market participants, such as corporate executives.

The third project examines whether the risk preferences of a CEO's spouse have a spillover influence on corporate risk-taking, especially when CEO and her/his spouse come from a large different cultural background. Risk preferences are shaped by cultural heritage to some extent. We manually collect cultural origin data of CEOs and spouses, and use the Hofstede (2001) Uncertainty Avoidance Index (UAI) to measure their risk attitude. Our findings support the prediction that, as a consequence of the transmission of cultural norms between married couples, a CEO's risk preference will be influenced by their spouse's risk preference, leading CEOs to take on less corporate risk if they are married with spouses from more risk-averse cultures. We use various econometric techniques to address potential endogeneity concerns. First, we randomly match CEOs to a different spouse and find that the pseudo-spouse does not influence a CEO's behaviour. Second, we absorb CEO-level personal characteristics using CEO-level fixed effects. Third, we perform a matching exercise to control several firm-level attributes that could be biasing our estimates. The results show that the effect is driven by firms that are headed by CEOs who have a different country of origin compared to their spouses. It would be interesting to examine whether the spouse's preferences affect other corporate policies in future research. It would also be helpful to examine whether additional market participants, such as institutional and retail investors, are also influenced by their spouses' cultural norms.

Bibliography

Addoum, J.M., Kung, H. and Morales, G., 2016. Limited marital commitment and household portfolios. *Working paper.*

Addoum, J.M., 2017. Household portfolio choice and retirement. *Review of Economics and Statistics*, 99, 870-883.

Aggarwal, R., Kearney, C. and Lucey, B., 2012. Gravity and culture in foreign portfolio investment. *Journal of Banking and Finance*, 36, 525-538.

Ahearne, A. G., Griever, W. L. and Warnock, F. E., 2004. Information costs and home bias: An analysis of US holdings of foreign equities. *Journal of International Economics*, 62, 313-336.

Ahern, K.R., Daminelli, D. and Fracassi, C., 2015. Lost in translation? The effect of cultural values on mergers around the world. *Journal of Financial Economics*, 117, 165-189.

Ahern, K.R., Duchin, R. and Shumway, T., 2014. Peer effects in risk aversion and trust. *Review of Financial Studies*, 27, 3213-3240.

Ali, U. and Hirshleifer, D., 2020. Shared analyst coverage: Unifying momentum spillover effects. *Journal of Financial Economics*, 136, 649-675.

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5, 31-56.

Amihud, Y. and K. Li., 2006. The declining information content of dividend announcements and the effects of institutional holdings. *Journal of Financial and Quantitative Analysis*, 41, 637–660.

Ammer, J., Holland, S.B., Smith, D.C. and Warnock, F.E., 2012. U.S. international equity investment. *Journal of Accounting Research*, 50, 1109-1139.

Andersen, T.B. and Dalgaard, C.J., 2011. Flows of people, flows of ideas, and the inequality of nations. *Journal of Economic Growth*, 16, 1-32.

Andrade, S.C. and Chhaochharia, V., 2010. Information immobility and foreign portfolio investment. *Review of Financial Studies*, 23, 2429-2463.

Andreou, P.C., Antoniou, C., Horton, J. and Louca, C., 2016. Corporate governance and firm-specific stock price crashes. *European Financial Management*, 22, 916-956.

Andreou, P.C., Louca, C. and Petrou, A.P., 2017. CEO age and stock price crash risk. *Review of Finance*, 21, 1287-1325.

Arezki, M.R., Cherif, R. and Piotrowski, J.M., 2009. *Tourism specialization and economic development: Evidence from the UNESCO World Heritage List.* International Monetary Fund.

Baltzer, M., Stolper, O. and Walter, A., 2013. Is local bias a cross-border phenomenon? Evidence from individual investors' international asset allocation. *Journal of Banking and Finance*, 37, 2823-2835.

Bargeron, L.L., Lehn, K.M. and Zutter, C.J., 2010. Sarbanes-Oxley and corporate risk-taking. *Journal of Accounting and Economics*, 49, 34-52.

Barnett, M., Brock, W. and Hansen, L.P., 2020. Pricing uncertainty induced by climate change. *Review of Financial Studies*, 33, 1024-1066.

Bekaert, G. and Wang, X.S. 2009. Home bias revisited. *Working Paper*, Columbia Business School.

Benartzi, S., 2001. Excessive extrapolation and the allocation to 401(k) accounts to company stock. *Journal of Finance*, 56, 1747-1764.

Bernstein, S., Giroud, X. and Townsend, R.R., 2016. The impact of venture capital monitoring. *Journal of Finance*, 71, 1591-1622.

Beugelsdijk, S. and Frijns, B., 2010. A cultural explanation of the foreign bias in international asset allocation. *Journal of Banking and Finance*, 34, 2121-2131.

Bhagat, S., Bolton, B. and Lu, J., 2015. Size, leverage, and risk-taking of financial institutions. *Journal of Banking and Finance*, 59, 520-537.

Bisin, A., and Verdier., T., 2000. Beyond the melting pot: Cultural transmission, marriage, and the evolution of ethnic and religious traits. *Quarterly Journal of Economics*, 115, 955–88.

Borjas, G., 1995. Ethnicity, neighborhoods, and human capital externality. *American Economic Review*, 85, 365–390.

Boyd R. and Richerson P.J., 1985. *Culture and the evolutionary process.* University of

Chicago Press, Chicago.

Bradshaw, M.T., 2004. How do analysts use their earnings forecasts in generating stock recommendations?. *Accounting Review*, 79, 25-50.

Brennan, M.J. and Cao, H.H., 1997. International portfolio investment flows. *Journal of Finance*, 52, 1851-1880.

Burke, M., Hsiang, S.M. and Miguel, E., 2015. Global non-linear effect of temperature on economic production. *Nature*, 527, 235-239.

Cain, M.D. and McKeon, S.B., 2016. CEO personal risk-taking and corporate policies. *Journal of Financial and Quantitative Analysis*, 51, 139-164.

Calder-Wang, S. and Gompers, P.A., 2021. And the children shall lead: Gender diversity and performance in venture capital. *Journal of Financial Economics*, 142, 1-22.

Chan, K., Covrig, V., and Ng, L., 2005. What determines the domestic bias and foreign bias? Evidence from mutual fund equity allocations worldwide. *Journal of Finance*, 60, 1495–1534.

Chang, X., Dasgupta, S. and Hilary, G., 2006. Analyst coverage and financing decisions. *Journal of Finance*, 61, 3009-3048.

Chemmanur, T. J., Hull, T. and Krishnan, K., 2014. Expertise or proximity in international private equity? Evidence from a natural experiment. *Working Paper*, Boston College

Chen, X., Cheng, Q. and Lo, K., 2010. On the relationship between analyst reports and corporate disclosures: Exploring the roles of information discovery and interpretation. *Journal of Accounting and Economics*, 49, 206-226.

Chen, Q., Goldstein, I. and Jiang, W., 2007. Price informativeness and investment sensitivity to stock price. *Review of Financial Studies*, 20, 619-650.

Choi, N., Fedenia, M., Skiba, H. and Sokolyk, T., 2017. Portfolio concentration and performance of institutional investors worldwide. *Journal of Financial Economics*, 123, 189-208.

Chui, A.C., Titman, S. and Wei, K.J., 2010. Individualism and momentum around the world. *Journal of Finance*, 65, 361-392.

Clement, M.B., 1999. Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics*, 27, 285-303.

Cohen, L., Frazzini, A. and Malloy, C.J., 2010. Sell-Side school ties. *Journal of Finance*, 65, 1409-1437.

Cooper, I.A., Sercu, P. and Vanpée, R., 2017. A measure of pure home bias. *Review of Finance*, 22, 1469-1514.

Coval, J.D. and Moskowitz, T.J., 1999. Home bias at home: Local equity preference in domestic portfolios. *Journal of Finance*, 54, 2045-2073.

Crawford, S.S., Roulstone, D.T. and So, E.C., 2012. Analyst initiations of coverage and stock return synchronicity. *Accounting Review*, 87, 1527-1553.

Cronqvist, H. and Yu, F., 2017. Shaped by their daughters: Executives, female socialization, and corporate social responsibility. *Journal of Financial Economics*, 126, 543-562.

Cuculiza, C., Antoniou, C., Kumar, A. and Maligkris, A., 2021. Terrorist attacks, analyst sentiment, and earnings forecasts. *Management science*, 67, 2579-2608.

Culiuc, A., 2014. *Determinants of international tourism.* International Monetary Fund.

Da, Z., Gurun, U.G., Li, B. and Warachka, M., 2021. Investment in a smaller world: The implications of air travel for investors and firms. *Management Science*, 67, 417-435.

Dahlquist, M., Pinkowitz, L., Stulz, R.M. and Williamson, R., 2003. Corporate governance and the home bias. *Journal of Financial and Quantitative Analysis*, 38, 87-110.

Dechow, P.M., Sloan, R.G. and Sweeney, A.P., 1996. Causes and consequences of earnings manipulation: An analysis of firms subject to enforcement actions by the SEC. *Contemporary Accounting Research*, 13, 1-36.

Dimmock S.G., Kouwenberg, R., Mitchell O.S. and Peijnenburg, K., 2016. Ambiguity aversion and household portfolio choice puzzles: Empirical evidence. *Journal of Financial Economics*, 119, 559-577.

Du, Q., Yu, F. and Yu, X., 2017. Cultural proximity and the processing of financial information. *Journal of Financial and Quantitative Analysis*, 52, 2703-2726.

Dumas, B., Lewis, K.K. and Osambela, E., 2017. Differences of opinion and international equity markets. *Review of Financial Studies*, 30, 750-800.

Easterwood, J.C. and Nutt, S.R., 1999. Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism? *Journal of Finance*, 54, 1777-1797.

Ellison, G. and Fudenberg, D., 1995. Word-of-mouth communication and social learning. *Quarterly Journal of Economics*, 110, 93-125.

Faccio, M., Marchica, M.T. and Mura, R., 2011. Large shareholder diversification and corporate risk-taking. *Review of Financial Studies*, 24, 3601-3641.

Faccio, M., Marchica, M.T. and Mura, R., 2016. CEO gender, corporate risk-taking, and the efficiency of capital allocation. *Journal of Corporate Finance*, 39, 193-209.

Falicov, C.J., 1995. Cross-cultural marriages. *Clinical Handbook of Couple Therapy,* 231-246.

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D. and Sunde, U., 2018. Global evidence on economic preferences. *Quarterly Journal of Economics*, 133, 1645-1692.

Fang, L.H. and Huang, S., 2017. Gender and connections among Wall Street analysts. *Review of Financial Studies*, 30, 3305-3335.

Fidora, M., Fratzscher, M. and Thimann, C., 2007. Home bias in global bond and equity markets: The role of real exchange rate volatility. *Journal of International Money and Finance*, 26, 631–655.

Fischer, P.E. and Stocken, P.C., 2010. Analyst information acquisition and communication. *Accounting Review*, 85, 1985-2009.

French, K.R. and Poterba, J.M., 1991. Investor diversification and international equity markets. *American Economic Review*, 81, 222-226.

Giannetti, M. and Yafeh, Y., 2012. Do cultural differences between contracting parties matter? Evidence from syndicated bank loans. *Management Science*, 58, 365-383.

Giannetti, M. and Zhao, M., 2019. Board ancestral diversity and firm-performance volatility. *Journal of Financial and Quantitative Analysis*, 54, 1117-1155.

Giavazzi, F., Petkov, I. and Schiantarelli, F., 2019. Culture: Persistence and evolution. *Journal of Economic Growth*, 24, 117-154.

Gibbons, B., Iliev, P. and Kalodimos, J., 2021. Analyst information acquisition via EDGAR. *Management Science*, 67, 769-793.

Giroud, X., 2013. Proximity and investment: Evidence from plant-level data. *Quarterly Journal of Economics*, 128, 861-915.

Glassman, D.A. and Riddick, L.A., 2001. What causes home asset bias and how should it be measured? *Journal of Empirical Finance*, 8, 35-54.

Glazer, N. and Moynihan, D.P., 1963. *Beyond the melting pot: the Negroes, Puerto Ricans, Jews, Italians, and Irish of New York City.* Cambridge, MA: MIT Press.

Glick, R. and Rose, A.K., 2002. Does a currency union affect trade? The time-series evidence. *European Economic Review*, 46, 1125-1151.

Goldstein, D.G. and Gigerenzer, G., 2002. Models of ecological rationality: The recognition heuristic. *Psychological Review*, 109, 75-90.

Grinblatt, M. and Keloharju, M., 2001. How distance, language, and culture influence stockholdings and trades. *Journal of Finance*, 56, 1053-1073.

Guiso, L., Sapienza, P. and Zingales, L., 2006. Does culture affect economic outcomes?. *Journal of Economic Perspectives*, 20, 23-48.

Guiso, L., Sapienza, P. and Zingales, L., 2009. Cultural biases in economic exchange?. *Quarterly Journal of Economics*, 124, 1095-1131.

Hansen, L.P., 1982. Large sample properties of generalized method of moments estimators. *Econometrica*, 50, 1029-1054.

Hansen, C., Hausman, J. and Newey, W., 2008. Estimation with many instrumental variables. *Journal of Business and Economic Statistics*, 26, 398-422.

He, J.J. and Tian, X., 2013. The dark side of analyst coverage: The case of innovation. *Journal of Financial Economics*, 109, 856-878.

Heath, C. and Tversky, A., 1991. Preference and belief: Ambiguity and competence in choice under uncertainty. *Journal of Risk and Uncertainty*, 4, 5-28.

Heckman, J.J., 1979. Sample selection bias as a specification error. *Econometrica*, 47, 153-161.

Hofstede, G., 1980. Motivation, leadership, and organization: Do American theories apply abroad?. *Organizational Dynamics*, 9, 42-63.

Hofstede, G., 2001. *Culture's consequences: Comparing values, behaviors, institutions and organizations across nations.* Sage publications.

Hofstede, G., Hofstede, G.J. and Minkov, M., 2010. *Cultures and organizations: Software of the mind. 3rd ed.* New York, NY: McGraw-Hill.

Hovhannisyan, N. and Keller, W., 2015. International business travel: an engine of innovation?. *Journal of Economic Growth*, 20, 75-104.

Huberman, G. 2001. Familiarity breeds investment. *Review of Financial Studies*, 3, 659-680.

Hutton, I., Jiang, D. and Kumar, A., 2015. Political values, culture, and corporate litigation. *Management Science*, 61, 2905-2925.

Hutton, A.P., Marcus, A.J. and Tehranian, H., 2009. Opaque financial reports, R2, and crash risk. *Journal of Financial Economics*, 94, 67-86.

Israelsen, R.D., 2016. Does common analyst coverage explain excess comovement?. *Journal of Financial and Quantitative Analysis*, 51, 1193-1229.

Jafari, J., 1987. On domestic tourism. *Journal of Travel Research*, 25, 36-38.

Jiang, W., 2017. Have instrumental variables brought us closer to the truth. *Review of Corporate Finance Studies*, 6, 127-140.

Jiang, D., Kumar, A. and Law, K.K., 2016. Political contributions and analyst behavior. *Review of Accounting Studies*, 21, 37-88.

John, K., Litov, L. and Yeung, B., 2008. Corporate governance and risk-taking. *Journal of Finance*, 63, 1679-1728.

Kanagaretnam, K., Lim, C.Y. and Lobo, G.J., 2014. Influence of national culture on accounting conservatism and risk-taking in the banking industry. *Accounting Review*, 89, 1115-1149.

Karolyi, G.A. and Stulz, R.M., 2003. Are financial assets priced locally or globally?. *Handbook of the Economics of Finance*, 1, 975-1020.

Kaufmann, D., Kraay, A. and Mastruzzi, M., 2009. *Governance matters VIII: Aggregate and individual governance indicators 1996-2008*. The World Bank.

Kilka, M. and Weber, M., 2000. Home bias in international stock return expectations. *Journal of Psychology and Financial Markets*, 1, 176-192.

Kim, H. and Stepchenkova, S., 2015. Effect of tourist photographs on attitudes towards destination: Manifest and latent content. *Tourism Management*, 49, 29-41.

King, T., Srivastav, A. and Williams, J., 2016. What's in an education? Implications of CEO education for bank performance. *Journal of Corporate Finance*, 37, 287-308.

Kleibergen, F. and Paap, R., 2006. Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, 133, 97-126.

Knott, A.M., 2008. R&D/returns causality: Absorptive capacity or organizational IQ. *Management Science*, 54, 2054-2067.

Koch, A.S., Lefanowicz, C.E. and Robinson, J.R., 2013. Regulation FD: A review and synthesis of the academic literature. *Accounting Horizons*, 27, 619-646.

Krueger, P., Sautner, Z. and Starks, L.T., 2020. The importance of climate risks for institutional investors. *Review of Financial Studies*, 33, 1067-1111.

Laeven, L. and Levine, R., 2009. Bank governance, regulation and risk taking. *Journal of Financial Economics*, 93, 259-275.

Le, T., 2008. 'Brain Drain' or 'Brain Circulation:' Evidence from OECD's international migration and R&D spillovers. *Scottish Journal of Political Economy*, 55, 618-636.

Lee, D.Y., 1997. The impact of poor performance on risk-taking attitudes: a longitudinal study with a PLS causal modeling approach. *Decision Sciences*, 28, 59-80.

Lerner, J.S. and Keltner, D., 2001. Fear, anger, and risk. *Journal of Personality and Social Psychology*, 81, 146-159.

Lesmond, D., 2005. Liquidity of emerging markets. *Journal of Financial Economics*, 77, 411-452.

Lewellen, J., 1999. The time-series relations among expected return, risk, and book-to-market. *Journal of Financial Economics*, 54, 5-43.

Li, K., Griffin, D., Yue, H. and Zhao, L., 2013. How does culture influence corporate risk-taking?. *Journal of Corporate Finance*, 23, 1-22.

Liu, M.H., 2011. Analysts' incentives to produce industry-level versus firm-specific information. *Journal of Financial and Quantitative Analysis*, 46, 757-784.

Liu, X., 2016. Corruption culture and corporate misconduct. *Journal of Financial Economics*, 122, 307-327.

Lys, T. and Sohn, S., 1990. The association between revisions of financial analysts' earnings forecasts and security-price changes. *Journal of Accounting and Economics*, 13, 341-363.

Malloy, C.J., 2005. The geography of equity analysis. *Journal of Finance*, 60, 719-755.

Means, M., 1963. *The woman in the White House: The lives, times and influence of twelve notable first ladies.* NY: Signet Press.

McFadden, J., 2001. Intercultural marriage and family: Beyond the racial divide. *Family Journal*, 9, 39-42.

Mian, A., 2006. Distance constraints: The limits of foreign lending in poor economies. *Journal of Finance*, 61, 1465-1505.

Muslu, V., Rebello, M. and Xu, Y., 2014. Sell-side analyst research and stock comovement. *Journal of Accounting Research*, 52, 911-954.

Nguyen, D.D., Hagendorff, J. and Eshraghi, A., 2018. Does a CEO's cultural heritage affect performance under competitive pressure?. *Review of Financial Studies*, 31, 97-141.

Nicolosi, G. and Yore, A.S., 2015. "I do": does marital status affect how much CEOs "do"?. *Financial Review*, 50, 57-88.

O'Connor, K., Nye, B. and Van Assendelft, L., 1996. Wives in the White House: The political influence of first ladies. *Presidential Studies Quarterly*, 26, 835-853.

Pagnini, D.L. and Morgan, S.P., 1990. Intermarriage and social distance among US immigrants at the turn of the century. *American journal of sociology*, 96, 405-432.

Pan, Y., Siegel, S. and Wang, T.Y., 2017. Corporate risk culture. *Journal of Financial and Quantitative Analysis*, 52, 2327-2367.

Pan, Y., Siegel, S. and Wang, T.Y., 2020. The cultural origin of CEOs' attitudes toward uncertainty: Evidence from corporate acquisitions. *Review of Financial Studies*, 33, 2977-3030.

Portes, R. and Rey, H., 2005. The determinants of cross-border equity flows. *Journal of International Economics*, 65, 269-296.

Prayag, G., Hosany, S., Muskat, B. and Del Chiappa, G., 2017. Understanding the relationships between tourists' emotional experiences, perceived overall image, satisfaction, and intention to recommend. *Journal of Travel Research*, 56, 41-54.

Rammstedt, B. and Schupp, J., 2008. Only the congruent survive–personality similarities in couples. *Personality and Individual Differences*, 45, 533-535.

Ramnath, S., Rock, S. and Shane, P., 2008. The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting*, 24, 34-75.

Robalino N. and Robson A,J., 2013. Genes, culture, and preferences. *Biological Theory*, 8, 151-157.

Roussanov, N. and Savor, P., 2014. Marriage and managers' attitudes to risk. *Management Science*, 60, 2496-2508.

Saha, S. and Yap, G., 2014. The moderation effects of political instability and terrorism on tourism development: A cross-country panel analysis. *Journal of Travel Research*, 53, 509-521.

Serra-Garcia, M., 2021. Risk Attitudes and Conflict in the Household. *Economic Journal, forthcoming.*

Scott, D., Rutty, M., Amelung, B. and Tang, M., 2016. An inter-comparison of the holiday climate index (HCI) and the tourism climate index (TCI) in Europe. *Atmosphere*, 7, 80-97.

Stock J.H. and Yogo M., 2005. Testing for Weak Instruments in Linear IV Regressions. *In Identification and Inference for Econometric Models*, ed. Andrews D.W.K. and Stock

J.H., 80–108. Cambridge: Cambridge University Press.

Strauss, L., 1997. Voglio Diversita, Non Razzismo. *Corriere della Sera.*

Tetlock, P.E., 2005. *Expert Political Judgment: How Good Is It? How Can We Know?* Princeton, NJ: Princeton University Press.

Thapa, C. and Poshakwale, S.S., 2012. Country-specific equity market characteristics and foreign equity portfolio allocation. *Journal of International Money and Finance*, 31, 189-211.

Van Nieuwerburgh, S. and Veldkamp, L., 2009. Information immobility and the home bias puzzle. *Journal of Finance*, 64, 1187-1215.

Walther, B.R. and Willis, R.H., 2013. Do investor expectations affect sell-side analysts' forecast bias and forecast accuracy?. *Review of Accounting Studies*, 18, 207-227.

Yu, F.F., 2008. Analyst coverage and earnings management. *Journal of Financial Economics*, 88, 245-271.