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How have the institutional and behavioral factors behind patterns of Home and Foreign Biases impacted investment portfolios and diversification ?

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HOW HAVE THE INSTITUTIONAL AND BEHAVIORAL FACTORS BEHIND PATTERNS OF HOME AND FOREIGN BIASES IMPACTED INVESTMENT PORTFOLIOS AND DIVERSIFICATION ?

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In investing, what is comfortable is rarely profitable.

Robert Arnott

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List of abbreviations

Abbreviation	Full form
CAPM	Capital Asset Pricing Model
ETF	Exchange Traded Funds
EU	European Union
FX	Foreign Exchange
GDP	Gross Domestic Product
HFT	High Frequency Trading
ICAPM	International Capital Asset Pricing Model
IMF	International Monetary Fund
LSDV	Least Squared Dummy Variable
MPT	Modern Portfolio Theory
OLS	Ordinary Least Square
UK	United Kingdom
UN	United Nations
US	United States
VIF	Variance Inflation Factor

Introduction

During my studies in Oslo, Norway, my International Corporate Finance teacher made an intriguing statement: "Decrease in Home Bias allows for a decrease in the cost of capital." Curiosity piqued, I sought clarification on the concept of Home Bias, and my teacher proceeded to offer a concise explanation of its significance. This encounter marked the inception of this thesis, as I decided to explore the phenomenon of Home Bias more in depth.

But what is the Home Bias ? Home Bias, a pervasive phenomenon observed among most investors, frequently remains unnoticed or unacknowledged. It entails the tendency for investors to overweight domestic assets within their portfolios, while neglecting foreign securities, despite their awareness of the evident advantages of diversification (French and Poterba, 1991).

Portfolio diversification is a concept that should be known by every investor consisting in a strategic allocation of investments across different asset classes, industries, and geographic regions to minimize risk and optimize returns. By spreading investments across a variety of assets, such as stocks, bonds, and commodities, diversification aims to reduce the impact of volatility in any single asset or market segment. This approach leverages the principle of non-correlation among assets, where movements in one asset may not directly correspond to movements in another. This axiom was notably spotted in the work of Markowitz (1959).

Eager to shed light on this intriguing aspect of investment behavior, I embarked on a journey to unravel its complexities. This thesis aims to provide a comprehensive analysis of Home Bias, focusing on its evolution over time, disparities among European nations, factors supporting its persistence and those allowing for a decrease, as well as distinctions between optimal allocations and realizations beyond the domestic realm (Foreign Bias).

As I delved into preliminary research, I found myself contemplating a cascade of questions: How long has Home Bias been observed ? Does it stay constant or evolve over time? Is it a universal phenomenon experienced by all investors? What factors influence its manifestation? To gain initial insights, I went aboard on a surface-level exploration of existing literature, seeking at first quick answers to my inquiries.

As my exploration deepened, I arrived at a preliminary and admittedly simplistic hypothesis: "Could Home Biases be diminishing over time due to advancements in information technology and globalization ?" At first glance, such a proposition seemed logical, considering the transformative impact of modern technology on information accessibility, reduced costs, and expanded opportunities for portfolio diversification compared to half a century ago.

Finally, this scientific paper ambitions to provide a comprehensive answer to the following question “How have the institutional and behavioral factors behind patterns of Home and Foreign Bias, influenced by technology and globalization, impacted investment portfolios, and what are the resulting implications for portfolio diversification ?".

Considering Europe's rich attributes such as proximity, cultural similarities, and shared languages in some cases (Grinblatt, 2001), it becomes an ideal region to explore and understand the intricacies of this phenomenon. By conducting a broad analysis, drawing upon theoretical frameworks, examining empirical studies, and assessing various factors influencing Home Bias, this paper intent to deepen our understanding of this particular concept and its implications. Ultimately, it seeks to provide valuable insights for individual investors and policy-makers alike, enabling them to make more informed decisions regarding portfolio construction, risk management, and policy development.

This thesis will be structured as follows. Chapter one endeavors to establish the context of the appearance of this particular concept. Chapter two presents the framework underpinning the Home Bias phenomenon, tracing its historical roots and elucidating the myriad of factors that shape it. Subsequently, an exploration of variables previously investigated by esteemed scholars will follow in chapter three. Moving forward, chapter four will delineate the precise objectives and hypotheses formulated for analysis. Chapter five will be devoted to detailing our sample population, the variables under scrutiny, their respective sources, and inherent limitations. In chapter six, the methodologies utilized to examine the proposed hypotheses, along with the chosen variables, will be elaborated upon. Finally, the discourse will culminate in chapter seven with the presentation and interpretation of the findings gleaned from the quantitative analysis, with a concerted effort to deepen countries' specificities.

THEORETICAL PART

1 Historical Context

To be able to comprehend the emergence, evolution, and long-lasting influence of Home Bias on investment behavior, understanding the historical context is key. This particular concept was spotted in the pioneering work of Harry Markowitz in 1952. Its groundbreaking research introduced for the first time the concept of Modern Portfolio Theory (MPT), which transfigured the finance sector by highlighting the crucial role of diversification in portfolio construction.

MPT is a framework for constructing investment portfolios that aim to maximize expected return for a given level of risk, or equivalently, minimize risk for a given level of expected return. The central premise of MPT is that diversification, or spreading investments across a variety of assets, can reduce the overall risk of a portfolio. It posits that every investment carries a certain level of risk and an expected return. By combining assets with different risk and return profiles, especially those that are not perfectly correlated, investors can create a portfolio that achieves a better balance between risk and return. This means that the overall risk of a diversified portfolio is lower than the weighted average risk of the individual assets within it.

Nonetheless, even within the framework of MPT, many researchers observed that investors exhibited a robust predisposition towards domestic securities, contradictory to the optimal international diversification's principle. During the second half of the century, empirical studies began to shed light on the presence and implications of Home Bias. A very noteworthy research made by French and Poterba (1991) which examined the behavior of American, Japanese and Britain investors, found compelling evidence of a significant Home Bias effect. Despite the demonstrated fact that international diversification could lead to potential benefits as notably demonstrated by Grubel, Sercu and Solnik among others, investors still showed a substantial preference for domestic securities.

Several historical factors contributed to the persistence of Home Bias even as modern portfolio theory gained traction. Prior to the liberalization of financial markets, strict capital controls and regulatory barriers limited the ability of investors to invest abroad. These controls were prevalent in the post-World War II era, reflecting a time when many countries sought to maintain economic stability and control over capital flows.

Furthermore, it should be emphasized that some significant economic and political events, happening during periods studied by scholars, played a major role in shaping investor preferences and behaviors. Financial, political, energy crises led to confidence erosion in global markets which might have provoked a stronger Home Bias as investors were seeking for more stability and familiarity and may have found it within their own domestic markets. This reasoning can be applied to every major crisis such as the ones of 1932, 1956, 1982, 1997, 2008, 2020 and 2022.

Over time, technological progress has also left an indelible mark on Home Bias. The arrival of the internet, its development, the rise of online trading platforms, financial news portals and much more new technologies have disrupted the world as it was. It allowed the democratization of access to market information and reduced transaction costs. These developments might have alleviated the barriers that once constrained international investments and diversified portfolio holdings.

The rise of multinational corporations and the gradual easing of capital controls in the late 20th and early 21st centuries began to change the landscape, allowing for greater international investment opportunities. However, the legacy of Home Bias persisted, influenced by the historical context of restricted capital flows and limited information.

Considering the specific region, Europe in our case, the historical context takes on a unique significance. The creation of the European Union (EU) and its multiple predecessors combined with the euro as a common currency have fostered increased economic integration among member states. Discussion about this integration gave, potential reduction of Home Bias within European equity markets, as a result. A major study in this concern is the work of Pagano and Volpin (2005) which explored the impact of the euro's introduction on Home Bias. It provided valuable insights into its evolution within the European context.

2 Home Bias

2.1 Definition

Home Bias entails the tendency for investors to overweight domestic assets within their portfolios, while neglecting foreign securities, despite their awareness of the evident advantages of diversification. The diversification of investments is recognized today as a fundamental element of sound management of financial assets. The pioneering work of Markowitz (1959) is considered the origin of this important axiom of finance although earlier researchers also contributed to this field. Markowitz's groundbreaking insights revolutionized and disrupted the perception of finance and laid the groundwork for Modern Portfolio Theory.

His theoretical framework introduced the concept of an ideal market portfolio that encompasses all listed assets. Thanks to an efficient portfolio frontier that maximizes the expected returns for a given level of risk, he stated that a clever selection of low-correlated securities can yield a return that is less risky overall than the weighted sum of the variances of each individual asset. Diversification allows for a reduction of unsystemic risk of the assets while only the systematic risk remains in the portfolio and is rewarded by the market. Specifically, according to Goetzmann (2003), the most diversified investor group earns 2.40% higher return than the least diversified investor group on an annual basis. The rationale behind a diversified portfolio lies in its potential to mitigate risk and exposure to specific asset classes or regions, consequently fostering greater stability in long-term returns.

Diversification extends beyond merely investing in diverse types of financial assets; it also involves selecting securities within the same asset class to achieve optimal risk reduction. As the number of assets in a portfolio increases, the more the total risk decreases, everything else remaining equal. This theory has been extended to the international context by notable authors such as Solnik (1974), Harvey (1991), De Santis and Gérard (1997). They showed that international diversification allows for considerable portfolio risk reduction and/or anticipated profitability improvement.

Still, many empirical studies showed that, despite knowledge and the obvious gains from diversification, investors tend to hold too large a share of domestic assets in their portfolios detrimental to foreign securities holdings. This phenomenon is called the “domestic bias” or “Home Bias” (French and Poterba, 1991) by opposition to the Foreign Bias.

In order to deepen our understanding of the definition we need to outline what constitutes an "overweight" allocation of domestic equities in a portfolio. Authors such as Baele et al. (2007) extensively examined this choice, proposing five methods to determine asset weights within a benchmark portfolio. One prominent method, the International Capital Asset Pricing Model (ICAPM), originated from the Capital Asset Pricing Model (CAPM) by Sharpe (1964), which evolved from Markowitz's (1952, 1959) Modern Portfolio Theory. The CAPM introduces the concept of a market portfolio, comprised of all assets weighted by their global market capitalization proportions. The ICAPM, introduced by Solnik (1974a, 1974b, 1974c) and Sercu (1980), extends CAPM by incorporating exchange rate effects and redefining ideal asset weights based on global market capitalization. Those specific weights are the ones serving as reference in the method proposed by Mishra (2015) and based and the ICAPM theory. Other benchmark methods developed by Mishra exist such as mean-variance, minimum variance, Bayes-Stein, and Bayesian methods.

The "Home Bias puzzle", as often called, is significant in financial economics and impacts portfolio performances as it challenges the traditional assumption that investors are rational and seek to maximize their risk-adjusted returns. The following reasons can partially explain its significance :

Inefficiency

The Home Bias puzzle suggests that investors are not fully taking advantage of the benefits of international diversification. By concentrating their investments in domestic equities, they may be missing out on opportunities allowing for risk reduction and potentially higher returns that could have been achieved through a universally diversified portfolio thus resulting in a misallocation of resources.

Economic costs of under-diversification

Investors who hold less diversified portfolios tend to have higher levels of idiosyncratic risk, which is the risk that is specific to individual stocks or sectors. This can lead to higher volatility and worse risk-return trade-offs, which can ultimately result in lower returns over the long term. In addition, under-diversification can lead to higher trading costs, as investors may need to trade more frequently to achieve the desired level of diversification. These costs can add up over time and reduce the overall returns of the portfolio (Goetzmann, 2003).

Understanding the reasons behind the Home Bias can provide insights into the factors that impede international capital flows and hinder the efficient functioning of global financial markets. French & Poterba (1991), Coval & Moskowitz (1999), Lewis (1999), Huberman (2001), Strong & Xu (2003) and many other scholars proposed various explanatory factors to this bias ranging from capital control to information asymmetry. With the ongoing increase in market integration, certain factors previously influential are now exerting diminished impact. The emergence of behavioral finance has shed new light on additional factors that contribute to the persistence of home bias in modern investment decisions.

2.2 Close parent : the Foreign Bias

Foreign Bias, in investment terms, refers to the tendency of investors to allocate a disproportionately bigger portion of their portfolios to foreign assets compared to what might be considered optimal based on diversification principles and CAPM. This bias often manifests as an overweighting of specific countries assets in investment portfolios and is defined as the difference between the weight of destination country in home country's total portfolio and the weight of destination country in the benchmark, here the ICAPM.

Various scholars such as Chen et al (2005), Beugelsdijk and Frijns (2010) have studied Foreign Bias and its implications. These are the same as for Home Bias. Firstly, it can lead to suboptimal portfolio diversification, as investors may be missing out on potential opportunities for risk reduction and return enhancement offered by international markets. Additionally, it may result in country risk concentration, leaving investors vulnerable to market fluctuations and economic downturns.

2.3 Evolution over time

Baele et al (2007) have shown by empirical methods that the Home Bias has come down over the years, especially in EU-member states since the European integration.

Prior to the 1970s, global financial markets were less integrated than nowadays, and investors exhibited a relatively strong preference for investing in domestic assets. One could say that Home Bias was prevalent due to limited international investment opportunities, regulatory barriers, and information asymmetry about foreign markets (French and Poterba, 1991).

A shift appeared in the seventies as countries started to liberalize their financial markets and remove capital controls. It was the beginning of the global internalization (Kose et al, 2006). Investors gradually diversified their portfolios by including international assets, but Home Bias remained high due to the persistent dominance of domestic investments (anchoring effect).

As time passed, the world witnessed a significant acceleration in globalization and financial market liberalization. Advances in technology and communication made it easier for investors to access and trade international assets (Hau & Rey, 2006). Institutional investors, such as pension funds and mutual funds, began diversifying their portfolios globally, contributing to a reduction in Home Bias.

The explosion of dot-com bubble in the early 2000s and the consequent market crash led to a reassessment of investment strategies. Investors acknowledged the benefits of diversifying their portfolios across different industries and countries in order to reduce risk. Cross-border capital flows expanded, enabling investors to access a broader range of investment opportunities and conducted to a better integration of global financial markets (Bekaert & Harvey, 2000).

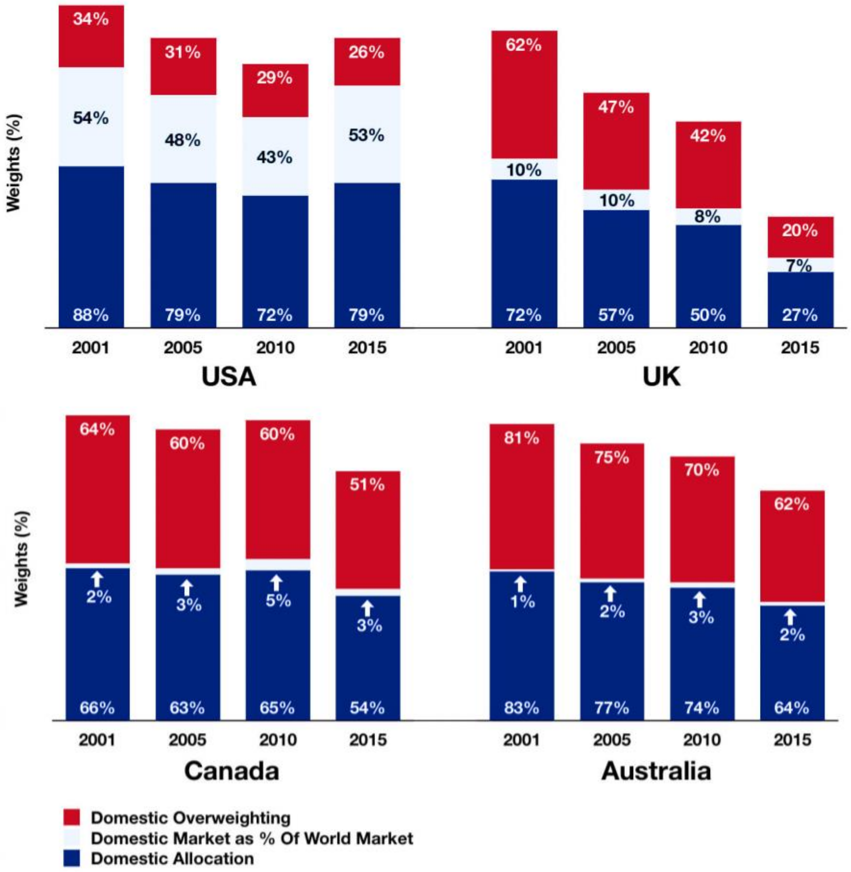
Further globalization and the development of financial instruments that facilitated international investing were observed during the next decades. Exchange-traded funds (ETFs) and index funds made it easier for individual investors to gain exposure to foreign markets with greater diversification and lower costs (Kaniel & Parham, 2017). The increased awareness of diversification profits and the nascent availability of online brokerage platforms contributed to a gradual reduction in domestic bias.

Ongoing advancements in technological and financial innovation continue to advocate towards international assets. Access to a wider range of global investment opportunities, including emerging markets and niche sectors allows for more diversification. The rising recognition of its benefits, coupled with increased financial literacy, has led to a decline in Home Bias among both individual and institutional investors (Forbes & Rigobon, 2002).

However, despite all those tailwinds supposed to boost diversification we observe a persistence of the Home Bias through time. The two subsequent graphs provide insight into domestic equity overexposure, more particularly within four countries: the United States, the United Kingdom, Australia, and Canada. A discernible declining trend but also persistence is evident across these nations over the timeframe under examination in this thesis.

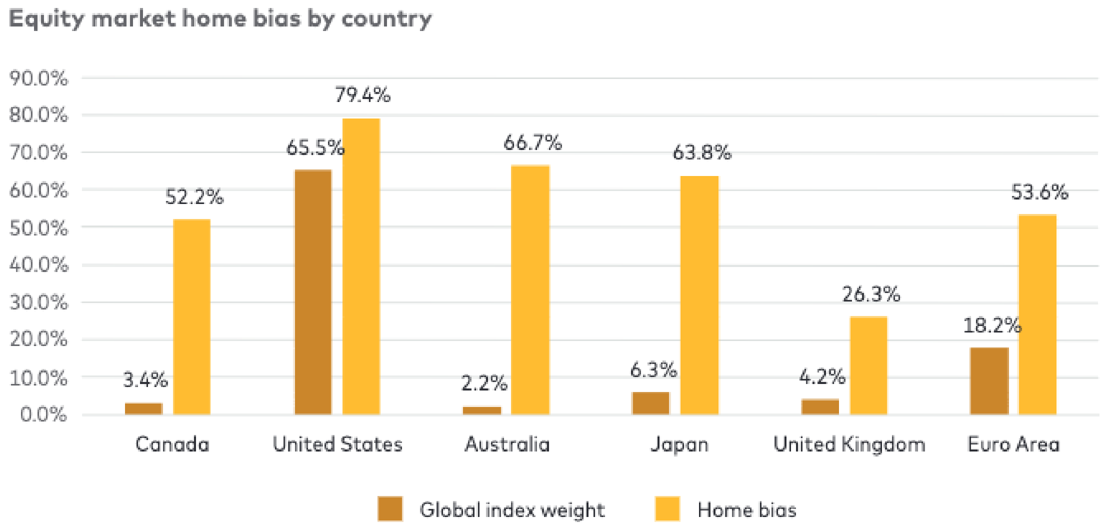
Notably, in 2001, countries such as the United States, already representing 54% of the global market capitalization, displayed a significant deviation, with a 34% divergence from this optimal allocation. Similarly, the United Kingdom exhibited a bias of 62%, deviating considerably from its 10% weight and Australia showed a remarkable deviation of 81%, far from its 1% weight. Over time, observable trends revealed a gradual reduction in bias, albeit persisting. In 2022, these three countries still demonstrated respective deviations of 13.9%, 22.1%, and 64.5%, proving the persistent character of this particular phenomenon. Further emphasis can be placed on the fact that, despite their different economic, geographical, and cultural profiles, all these countries are affected by this investment bias.

Figure 1 : Domestic allocation and overweight : the case of Australia, Canada, USA and UK



Source : Vanguard based on IMF data

Figure 2 : Figure 2 : Overweigh of domestic equity in 2022 : the case of Canada, U.S., Australia, Japan, U.K. and Eurozone



Source : Vanguard based on IMF data

2.4 Technology influenced

In the seventies, some electronic trading systems, such as NASDAQ, were introduced, allowing for computerized transaction and reducing the need for physical open outcry trading. This technology started to disrupt traditional stock exchanges and it facilitated faster and more efficient trading. The main advantages from this were automation and speed, order matching, increased transparency and liquidity, global connectivity (Goldstein et al, 2014).

In the next decade, personal computers began to appear. This widespread adoption empowered retail investors who started to slowly reduce their reliance on brokers or financial institutions. People were still tied up as they needed dial-up services, direct phone orders, fax and mail orders, local trading offices. Before the internet became accessible to each and every one, individuals could only connect from their personal computers to online services via dial-up modems.

The widespread availability of the internet in the 1990s further democratized stock market participation. The internet introduced a revolutionary form of communication that transcended geographic boundaries. It provided a platform for individuals and organizations to connect and communicate with each other instantly and inexpensively, regardless of their physical location (Barber & Odean, 2000). Early communication tools, such as email, instant messaging, and online forums, transformed the way people interacted and shared information. The internet acted as a vast repository of information, making it accessible to a global audience.

Websites emerged as an easy way to publish and share information on various topics globally. Many institutions and organizations began digitalizing their resources in order for users to access a bunch of knowledge online. This accessibility marked a major shift in the way people sought and obtained information. It led to the digitization of financial services itself leading to the opening of online banking platforms allowing individuals to access their accounts, conduct transactions, and manage their finances remotely. This convenience eliminated the need for physical visits to banks and empowered users to take control of their financial activities online.

In the very beginning of the century, High-frequency trading (HFT) became gradually predominant, supported by advanced computer algorithms and high-speed trading systems. Those firms, using sophisticated strategies and technology to execute trades in milliseconds, created liquidity and impacted short-term price movements. HFT has had a transformative effect on market structure (Brogaard & Hendershott, 2014). The way orders were executed, with a shift towards electronic exchanges and alternative trading venues, was a consequence of the rise of HFT.

The upsurge of smartphones and mobile applications in the 2010s brought stock market trading to the fingertips of millions of individuals. Mobile trading apps disrupted the industry by offering commission-free trades, simple interfaces, and gamified experiences, attracting a new generation of retail investors. Mobile trading apps have empowered this generation of investors by providing them with convenient and feature-rich platforms to engage in financial markets (Abuelfald et al, 2016). They have contributed to increased retail participation and changed the dynamics of how individuals manage their investments. Important to note that now retails investor is a powerful player that have to be taken into account and that cannot be ignored anymore (i.e. GameStop case).

ETFs also disrupted the financial world by offering investors easy access to a diversified portfolio of securities, including stocks, bonds, or commodities, representing various markets and geographies while being traded on financial market and still offering liquidity. This ability to invest globally has helped reduce Home Bias. Boermans et al (2021) found, both for Home Bias and for Foreign Bias, that over-weighting is negatively associated with investment via funds and positively associated with direct investment in individual equities. The intensification of ETFs has largely impacted the asset management industry. ETFs, due to their lower costs and tax efficiency, constitute an important competition to traditional mutual fund providers. Consequently, many asset management firms have launched their own ETF offerings or converted their existing mutual funds into ETFs to adapt to changing investor preferences. It has led to benefits for investors such as fee reduction and product innovation. ETFs have also disrupted finance through their flexibility and innovative structures. Beyond traditional ETFs (equity and bond) there are now thematic ETFs, smart-beta ETFs, and leveraged/inverse ETFs, among others (Ben-David et al, 2018).

The increasing use of artificial intelligence (AI) and machine learning algorithms has a profound impact on stock market trading and might be the future of portfolio management. These technologies can analyze vast amounts of data, identify patterns, and make predictions, influencing trading strategies and market dynamics thus helping individuals making more informed decisions (Lopez de Prado, 2020).

2.5 Impact on portfolio performance

A study conducted on defined contribution pension plan in Sweden by Nordén (2010) reveals that individuals exhibiting a pronounced Home Bias tend to experience notably poorer risk-adjusted performance in their portfolios compared to those with a greater allocation to international assets. However, when considering actual portfolio returns without adjusting for risk, Home Bias does not emerge as a significant factor. Consequently, the presence of domestic bias leads to inferior risk-adjusted performance due to insufficient international diversification.

When compared with a strategy focused solely on domestic assets, a portfolio diversified globally is anticipated to yield a superior return over time for equivalent risk or exhibit reduced risk for comparable returns. According to a study conducted by investment managers Gerstein Fisher spanning from 1999 to 2011, a globally diversified portfolio surpassed a portfolio limited to U.S. assets in 96% of consecutive three-year periods, resulting in a cumulative outperformance of 35 percentage points over the 11-year period. Specifically, according to Goetzmann (2003), the most diversified investor group earns 2.40% higher return than the least diversified investor group on an annual basis.

This chapter concludes the discussion on the theoretical foundation of Home Bias, its evolution over time, the role of technology in this phenomenon, and their combined impact on portfolio performance. The subsequent chapter delves into the explanatory factors formulated by scholars, exploring reasons for both the decline and persistence of this particular concept.

3 Literacy review

This section aims to explain the famous Home Bias puzzle as many researchers have already deepen our understanding of this pervasive phenomenon (figure 3). Those reasoning factors are also valid for its close parent, the Foreign Bias, which is less studied in the literature.

3.1 Explanatory factors

They can be classified into two categories: institutional/empirical factors, specific to macroeconomics and microeconomics, and behavioral factors, specific to investors. Empirical factors mostly come from "perfect market" assumptions violation. The breaking of the assumption that investors are rational provokes the behavioral factors. Both influences the asset allocation, directly or indirectly. Note that the following list is not exhaustive and that some factors could be classified into both categories.

3.1.1 Institutional :

Transaction costs and taxation

Transaction costs play a significant role in Home Bias, influencing investors' decisions to allocate their portfolios to domestic assets rather than diversifying globally. The costs associated with buying, selling, and holding foreign assets can impact investment strategies and contribute to the prevalence of Home Bias (French, 2008). Higher transaction costs are associated with stronger home buying preferences, suggesting that the transaction costs of foreign assets act as a barrier to international diversification. Transaction costs include various expenses such as brokerage fees, currency conversion fees, taxes, and regulatory costs. These costs can erode investment returns and create additional hurdles for investors seeking to diversify globally. As a result, investors may opt for domestic assets where transaction costs are typically lower and more familiar. Typically, those costs tend to decrease throughout time as the world becomes more integrated and technology allows for cost optimization. However, authors such as Ahearne et al (2004) concluded that the impact of transaction cost on Home Bias are not a robust explanation.

Mishra and Ratti (2013) studied the Home Bias in the context of cross border taxation. They concluded that dividend imputation is a statistically significant impediment to cross border equity flows and that conversely, a tax credit on those capital gains and dividend tax helps considerably reducing the Home Bias.

Hedging for domestic risks

Using financial instruments or strategies to mitigate the impact of risks specific to a market is known as hedging. The link between hedging for domestic risks like inflation, exchange rate, private assets, and Home Bias lies in the awareness that investing in domestic assets provides a natural hedge against those country-specific risks. Consequently, investors might exhibit a bias towards domestic assets as they think they are more protected against their domestic risks, leading to Home Bias in their investment portfolios (Lynch &Tan, 2011). Many researchers such as Fidora et al (2007) have studied the exchange rate impact on the prevalence of domestic bias suggesting that countries with higher monetary volatility tend to exhibit a higher bias. In the context of this thesis, attention is directed towards the European continent, where the monetary union has contributed to reducing monetary disparities among member states. However, De Santis and Gérard (2006) demonstrate that the European monetary union can introduce a new bias in investors' allocation decisions. Encouraged by the absence of exchange rate risk, investors tend to shift their overweighting of domestic assets towards an exaggerated allocation to European securities, thus creating a "European Bias" (Balli et al., 2010; Othmani et al., 2014; Schoenmaker et al., 2007).

Capital control

Measures imposed by governments to regulate cross-border capital flows are known as capital controls. Those may include limitations on foreign investment or restrictions on capital repatriation. Their presence can influence Home Bias by affecting investors' ability to allocate their portfolios internationally and thus increase their preference for domestic assets. Countries with more severe capital controls tend to exhibit higher levels of domestic bias, as investors face more barriers to diversifying their portfolios abroad (Kose et al, 2006). Errunza and Losq (1985) proved that capital controls can increase Home Bias and result in lower welfare for investors due to reduced risk-sharing opportunities and restricted access to global investment opportunities. It is noteworthy that capital controls mainly occurred in the past, gradually diminishing over decades due to financial liberalization (Coeurdacier & Rey, 2011).

Information asymmetry

It refers to the notion where one party involved in a transaction has access to superior or more information compared to the other party leading to the asymmetry. In the context of Home Bias, this asymmetry play a role in influencing investors' decisions such as the allocation of their portfolios in domestic assets rather than diversifying globally (Ivkovic & Weisbenner, 2005). One aspect of information asymmetry in domestic bias relates to investors' familiarity with domestic markets compared to foreign markets. Investors may have greater access to information, news, and company reports regarding domestic companies, industries, and economic conditions. The lack of information or difficulty in obtaining accurate information about foreign assets can create uncertainty and perceived risk, which may discourage investors from diversifying globally and result in Home Bias (French & Poterba, 1991; Tesar & Werner, 2005).

This informational advantage may stem from various local factors (Coval & Moskowitz, 1999, 2001), such as cultural norms, economic, legal or political context, corporate management practices, or the language of the country. Geographical distance is also playing a role here. Indeed, neighboring countries are inclined to have greater mutual familiarity due to closer media coverage, enhanced commercial and tourist relations, as well as shared cultural similarities and a sense of familiarity among residents (Grinblatt & Keloharju's, 2001 ; Portes & Rey, 2005). In such proximate conditions, investors perceive themselves to possess an informational advantage over financial assets compared to those that are more "distant" geographically, culturally, socially, or economically, leading to an increase in their equity bias. A study conducted by Cooper et al. (2017) suggests that it is indeed the perception of distance, whether geographical, cultural, economic, or social, that deters investors from sufficiently investing in distant countries.

Investor protection

La Porta et al. (2000), has established a correlation between the level of investor protection and the development of financial markets. This relationship implies that investors are generally more hesitant to invest in countries with weaker investor rights. Factors influencing this assessment include the level of legal infrastructure, transparency of information, extent of minority investor safeguards, risks of confiscation or nationalization, and efficiency of the judicial system. Consequently, it is anticipated that countries with less favorable investor-protection mechanisms will experience an increase in informational asymmetries between domestic and foreign investors inducing an increase in Home Bias (Chan et al., 2005).

Corporate/Political governance

According to a study by Dahlquist et al (2003), corporate governance practices impact Home Bias. Strong corporate governance mechanisms, such as transparent financial reporting, effective board oversight, and protection of shareholder rights, can enhance the confidence of investors in a country's domestic market. When investors perceive better corporate governance standards in their home country, they may be more inclined to allocate a higher proportion of their investments domestically, leading to increased their domestic bias. Political stability, the rule of law, and the enforcement of property rights are essential determinants of investor confidence (Forbes, 2002). Variations in corporate governance standards across countries affect foreign investment decisions. Investors tend to exhibit a preference for countries with stronger corporate governance practices when allocating funds internationally. This preference is driven by the belief that companies in countries with better governance will provide more accurate and reliable information, reducing information asymmetry and increasing investor confidence (Giannetti & Simonov, 2006)

Market size

In his research, French (2008) proposed that investors tend to exhibit a Home Bias due to the size of their domestic market relative to global markets. The basic idea is that investors, particularly individual investors, may feel more comfortable and knowledgeable about investing in their home market, especially if it is large and offers a diverse array of investment opportunities. Conversely, they may perceive smaller or less developed markets as riskier or less familiar, leading them to allocate a greater portion of their portfolio to domestic assets. French's research suggests that the size and characteristics of the domestic market play a significant role in shaping investors' asset allocation decisions and contribute to the observed phenomenon. This was notably proven in Mishra’s model (2015).

Economic growth

Investors may feel more confident investing in their home market, believing it to offer better growth opportunities or economic stability compared to foreign markets (Chan et al, 2005). Robust economic growth serves as a significant catalyst for attracting capital inflows (Ritter, 2004). Investors tend to allocate a considerable portion of their portfolios to their home country when it undergoes a period of economic prosperity. Research conducted in emerging economies, as exemplified by the work of Edwards (2005), substantiates the correlation between a nation's growth trajectory and the inflows of capital into its economy.

Recent stock market performance

Earlier research by Froot et al (1992), Bohn and Tesar (1996), highlights that institutional investors engage in positive feedback trading behavior, buying during market upswings and selling during downturns. Conversely, Grinblatt and Keloharju (2001) demonstrate that while foreign investors in Finland follow positive feedback trading patterns, domestic investors in Finland adopt contrarian-trading strategies. Seasholes & Zhu (2010) and Pool et al. (2012), have found no significant association between excess return and Home Bias.

3.1.2 Behavioral

As outlined in the introduction of this chapter, behavioral factors stem from the hypothesis that investors, presumed to act rationally, deviate from rationality in practice. Behavioral finance has emerged as a significant field in recent decades, offering insights into compelling explanatory factors, particularly relevant in the realm of investment decisions (Kahneman & Tversky, 1979).

Familiarity

Investors tend to favor investments they are familiar with, understand by that domestic securities, consequently to the sense of comfort and confidence they feel about it. They believe that they have a better understanding of the domestic market and its companies (Huberman, 2001). Familiarity can arise from various sources, such as personal experiences, local media, shared value, distance. Domestic information canals often offer more details and is more timely effective. Familiarity provides a psychological comfort to investors. They see domestic investments as more predictable and less risky due to their familiar knowledge of local economic conditions, business practices, and regulations. This familiarity-induced sense of control and reduced perceived risk encourages investors to allocate a larger portion of their portfolio to domestic assets. This factor is closely related to information asymmetry.

Culture

This seminal work by Hofstede explores the cultural dimension and its impact on organizational behavior, which can also be extended to decision-making processes, including investment decisions. Culture plays a crucial role in investment decisions and shapes investor behavior and preferences. Different national cultures have different attitudes towards risk, as some countries are more risk-averse/risk-taking than others, leading to different investment behaviors. Trust, group orientation versus individual orientation are other important dimensions to explore. Individualistic cultures show a higher propensity for self-directed investment decisions, while collectivist cultures place a greater emphasis on community-based investing.

An examination of Finland data by Grinblatt and Keloharju in 2000 shows that investors have incentives to invest in countries with similar cultures. Shared history, culture, social and linguistic ties are elements playing an important role in the Foreign Bias.

Religion

According to the findings of the very recent study on religion and equity Home Bias by Lee et al (2023) religiosity positively influences equity Home Bias with countries with higher levels of religiosity tending to exhibit a higher degree of bias. This is attributed to the higher risk aversion and uncertainty avoidance of religious investors, making them more hesitant towards foreign investments and more inclined towards domestic investments.

Conversely, countries with greater religious diversity tend to have lower levels of Home Bias. The integration of various ideas and values from different religious backgrounds fosters a more open attitude towards foreign investments, leading to reduced domestic bias. This result aligns with Niszczota study's results (2013) which states that countries with open minded culture are less prone to experience a high degree of bias.

Educational level

Bose et al (2019) have analyzed the link between financial education and investment decision. The authors suggest that financial education enhances investors' understanding of the benefits of international diversification and reduces their tendency to invest disproportionately in domestic assets thus implying that individuals with higher levels of financial education exhibit lower levels of Home Bias. Another study confirms this by suggesting that higher levels of education in finance or general financial literacy can help mitigate domestic bias by increasing investors' understanding of the benefits and opportunities associated with global diversification (Bekaert & Harvey, 2007).

Psychology

In finance, we observe something called the "Confirmation bias". It refers to the tendency of individuals to seek and interpret information in a way that confirms their pre-existing beliefs or biases, while disregarding or downplaying contradictory evidence. This is a cognitive bias and it can have major implications on decision-making, as it can lead to suboptimal outcomes. For example, investors may seek out information or opinions that align with their existing beliefs about a particular stock, market trend, or investment strategy. They may focus on news articles, research reports, or expert opinions that support their views and disdain or soften information that contradicts their beliefs. Ritter (2003) notes that people tend to give more weight to information that confirms their existing beliefs, leading to resistance in updating beliefs when faced with contradictory evidence. This tendency can result in both under-reaction and overreaction to new information over time.

Daniel and Hirshleifer (2015), in their paper, discuss how confirmation bias can lead to overconfidence among investors and impact their decisions in the foreign exchange market. Overconfidence stands for investors that may become excessively confident in their beliefs and fail to adequately consider alternative perspectives or potential risks, leading to poor investment choices. Anchoring, another cognitive bias elucidated by Kahneman and Tversky (1974), involves individuals relying heavily on initial information when making judgments or estimates. This anchoring effect can lead to significant errors in decision-making if the initial information is flawed or irrelevant.

Optimism, the hopeful anticipation of positive outcomes, is deeply ingrained in human psychology. Montier (2002) suggests that this optimism often arises from cognitive biases, such as the illusion of control and self-attribution bias. These biases skew perceptions, leading individuals to overestimate their abilities and the likelihood of success.

Lastly, mental accounting, as outlined by Thaler (1985), describes how individuals categorize and treat money differently based on its source or intended use. This practice influences financial decision-making and can lead to suboptimal allocation of resources.

Together, these cognitive biases and heuristics shape human decision-making processes, often leading to deviations from rationality and impacting various aspects of life, from financial choices to social interactions.

Jet lag

As said in familiarity, access to “on time” information is crucial. Because we experienced different time of the day throughout the world, investors may feel aggrieved because they cannot access the information at the same time as other investors. Moreover, stock market do not have the same opening and closing hours leading to a psychological barrier for the investors according to Sendi and Belallah (2010).

This chapter wraps up the investigation into explanatory factors associated with the widespread phenomena of Home and Foreign Biases that the literature has sought to clarify and validate. Over time, the diversity and quantity of justifications have grown exponentially, indicating numerous opportunities for further research in the literature and underscoring the importance of the present study. The subsequent chapter outlines the objectives and hypotheses of this research.

EMPIRICAL PART

4 Objectives and research objectives

4.1 Objectives

This thesis seeks to address several inquiries pertaining to the phenomenon of Home Bias in investment decisions. Firstly, our objective is to empirically investigate whether the intuitive and seemingly straightforward decline in domestic bias occurred over the period under scrutiny, paying particular attention to potential disparities across different countries. To achieve this objective, we firstly calculate the Home Bias relative to stocks for our studied sample. Subsequently, should such discrepancies emerge, our aim is to ascertain the extent to which identified factors contributed to this decline and to quantify their respective influences. Thirdly, we endeavor to introduce novel factors or refined measurements of existing factors to elucidate their associations with Home Bias more comprehensively. Furthermore, we will attempt to explore a relatively understudied dimension, that of Foreign Bias, wherein countries show a propensity to invest immoderately in certain foreign countries owing to shared behavioral or empirical characteristics. Through meticulous analysis and examination, we intend to contribute to a deeper understanding of the intricacies underlying Home Bias and Foreign Bias in investment behavior, shedding light on both individual and collective decision-making dynamics within the global financial landscape.

4.2 Evolution by countries and patterns

In the appendix, figures 6 to 10 depict the trajectory of Home Bias across various countries throughout the entire period under investigation. These figures are categorized initially based on geographical distinctions as defined by the United Nations (UN), followed by the level of country economic development, again according to the UN, and finally by the degree of bias observed in last studied period. These distinct categorizations facilitate an easy visual assessment to ascertain if there are overarching factors influencing the persistence or reduction of bias. These will also serve further in our principal component analysis.

Our analysis reveals a global decline in bias (scale of 0 to 1) across the scrutinized countries with the biggest reduction being Latvia with a decline of 0.85 of its bias and Romania being the steadiest one only losing 0.1 over the period. This trend is further supported by the diminishing mean, falling from 0.73 in 2001 to 0.4 in 2022. Specifically, countries in northern and western regions tend to demonstrate lower starting levels of Home Bias, whereas results are more varied for southern and eastern nations. This could potentially be linked to their economic development state. More developed countries tend to exhibit lower levels of bias compared to their counterparts with Greece being the exception. Despite starting from a lower point in 2001, the diverse levels and the spread of fluctuations of bias hinder our ability to discern a unified pattern or trend, except for the overall decrease. While developing countries, limited to just three, could have offered more informative power, conclusion are difficult to draw. Romania and Poland show similar steady curves, whereas Hungary demonstrates a notable reduction of 0.4 in its bias over the timeframe. Still those three countries appear in the five countries with the highest Home Bias in 2022. We can thus conclude that economic development level plays a role in the decrease of this phenomenon through time with more advanced economies often leading.

Furthermore, in figures 14 to 17, we analyze disparities in patterns among countries exhibiting high, medium, and low terminal levels of Home Bias in 2022. Although all countries except The Netherlands display a bias, they have been classified into three categories based on thresholds of 0.35 and 0.75. The first category, with biases exceeding 75%, does not display a uniform pattern. Greece, for example, showed a decreasing trend until the 2011 sovereign crisis abruptly halted its progress, leaving it among the top three most biased countries alongside Poland and Romania. The second group, while initially showing wide variations with a spread up to 0.9, converged to a narrower spread of 0.17 by the end of the analysis. Excluding countries with heavy fluctuations, the remaining four countries (Denmark, France, Sweden, Switzerland) demonstrated a slow decrease in bias ranging from 0.12 to 0.19 over 22 years. France is noteworthy for maintaining the fourth-highest bias level in 2022, at 0.6.

The last category displays a wider dispersion in terminal values due to varying starting points (ranging from 0.38 to 0.87). Notably, this category displays a faster decrease in bias, as indicated by the slope of the category mean in figure 17. Interestingly enough, countries from all four geographical regions are present in the latter two categories, suggesting that factors influencing these patterns are more complex than initially assumed.

Notably, it is observed that overall, some countries seem to have experienced a resurgence of their domestic bias during the periods of crisis in 2008-2009 and 2011-2013, as nations redirected their funds towards their domestic economies. However, some countries such as Czech Republic and Spain, while exhibiting a nearly constant domestic bias between 2001 and 2011 with occasional resurgences, accelerated the reduction of their bias by nearly halving it between 2012 and 2022

I have statistically tested the linear decrease through time to evaluate if our first naïve and intuitive reasoning was right. The results suggests that 56.19% of the variability in the bias is explained by the linear relationship with the years after accounting for individual-specific effects. It not only confirms the significance of the relationship between the years and the bias but also suggests that the observed decrease in bias over time may not be solely attributed to the linear trend in the year variable but may also be influenced by country-specific factors that vary over time.

It is noteworthy that the R^2 values display significant variation across the observed cases. On average, most of the countries exhibit a R^2 superior to 80%. For instance, Italy displays a notably high R^2 of 96.4%, indicative of an almost perfect linear decline in the equity bias over the examined timeframe. In contrast, Portugal shows a much lower R^2 of 25.3%, suggesting that the bias may not have decreased linearly but rather exhibited fluctuations notably during the 2011 financial crisis. Countries' discrepancies could potentially be attributed to a variety of factors such as the following ones.

4.3 Hypothesis to test

After these preliminary observations, we introduce our research hypotheses aiming at providing a more comprehensive understanding of influential factors through quantitative analysis. These hypotheses are derived from our literature review, selecting both well-established factors with new measures or data sources, and novel factors, thus contributing new insights to the study of this phenomenon.

Tax regime

Tax regimes play a significant role in influencing investment decisions within a monetary union context, such as the European Union. In a monetary union, the elimination of foreign exchange (FX) rate risks due to a common currency reduces one major barrier to cross-border investment. Consequently, countries within the EU can invest in each other with greater ease, as the common currency mitigates exchange rate uncertainties (Suriani et al, 2015). Conversely, tax regimes vary significantly across countries, leading to disparities in fiscal attractiveness for investors. Countries with higher tax regimes tend to deter investment flows, as investors may find it less financially rewarding to allocate their capital in jurisdictions with heavier tax burdens. As a result, differences in tax policies can influence the direction of investment flows, diverting capital away from higher tax countries towards those with

more favorable fiscal environments (McDowell et al, 2020). To evaluate the tax regimes of European countries, I focused on key parameters such as tax policies on dividends and capital gains. By creating a nine-grid box ranking based on fiscal attractiveness, countries were assessed in terms of their appeal to investors.
F1 : The lower the tax regime (the higher the fiscal attractiveness), the higher the Home Bias.

The financial knowledge of citizens

The level of financial knowledge among citizens, especially investors, significantly influences the rationality of investment decisions. Individuals with a higher degree of financial literacy are more inclined to question their investment allocations and adhere to the principles of diversification outlined by the CAPM (Sharpe, 1964). Financially literate investors possess a deeper understanding of investment concepts and principles, enabling them to make more informed and rational decisions regarding portfolio allocation. They are less susceptible to behavioral biases and emotional reactions, instead relying on evidence-based strategies to guide their investment decisions (Bose et al, 2015).
F2 : The more financially educated the investors, the less they are prone to be home biased.

Technological influence and mastery

The accessibility of information facilitated by new technologies has contributed to the decline in Home Bias over time, primarily by reducing information asymmetry and lowering access costs (Goldman et al, 2009). Advancements in technology, particularly the internet and digital platforms, have democratized access to financial information. Investors now have unprecedented access to real-time market data, research reports, and investment analysis tools, regardless of their geographical location. This increased transparency helps to level the playing field, empowering investors to make more informed decisions about allocating their capital across borders.

Moreover, technological innovations have significantly reduced the costs associated with accessing and processing information. Traditionally, gathering information about foreign markets and companies was time-consuming and expensive. However, with the advent of digital technologies, investors can access a wealth of information at minimal cost, enabling them to conduct thorough research and analysis before making investment decisions. By providing greater visibility into international markets and investment opportunities, technology has encouraged investors to diversify their portfolios globally, seeking higher returns and better risk-adjusted performance. The mastery of technology further enhances investors' ability to navigate global financial markets effectively and allows them to be less mutual fund dependent. Those who possess technological proficiency can leverage advanced analytical tools, algorithmic trading platforms, and artificial intelligence-driven investment strategies to optimize their investment portfolios and capitalize on market opportunities (Lopez de Prado, 2020).
F3 : Information accessibility and quality of analysis influence negatively the domestic bias.

Economic growth

Investing in a country with a higher growth profile compared to others appears to be a logical choice for investors seeking to maximize returns. The allure of robust economic growth prospects can lead investors to disproportionately allocate their portfolios towards such countries, deviating from the optimal allocation recommended by the CAPM. However, this approach overlooks the principles of portfolio diversification advocated by the CAPM. Overweighting portfolios in high-growth countries exposes investors to elevated levels of country-specific risk, which may not be adequately compensated by the expected returns (Chan et al, 2005).
F4 : The economic growth is positively correlated to the Home Bias.

Stock market return of countries

The past stock market returns of countries play a role in shaping investment preferences. Countries with consistently strong and outperforming stock market performances often become highly appealing to investors. This appeal is further amplified for domestic investors by the familiarity explanation, wherein investors feel more comfortable investing in their home country due to their familiarity with its market dynamics, regulatory environment, and economic conditions (French and Poterba, 1992). Lastly, it assumes the improbable scenario of consistent and perpetual outperformance of the domestic market, ignoring the cyclicality and unpredictability inherent in stock market returns (Froot et al, 1992).

F5 : The better and the most consistent the return of a country's market place is, the higher the Home Bias.

Market capitalization and number of listed companies

Market size may serve as a significant factor influencing investment behavior, with larger market capitalization countries often perceived as representing greater global economic significance. This perception stems from the assumption that countries with larger market capitalization possess a broader diversity of sectors, industries, and investment opportunities, thereby enticing investors to allocate a disproportionate share of their portfolio to this country. It comes from the belief that investing in countries with substantial market capitalization provides investors with inherent diversification benefits (Mishra, 2015). Domestic investors may erroneously assume that by investing in their own country, which could be a major player on the global economic stage, they are effectively diversifying their portfolio across various sectors and industries. However, this overlooks the inherent country-specific risks associated with concentrating investments in a single geographical region. Research conducted by Amadi (2004) highlights the potential pitfalls of this approach, emphasizing the importance of considering country-specific risks in portfolio allocation decisions.

The number of listed companies in a country is another market size estimator, which might influence investment decisions. A large number of listed companies can provide domestic investors with greater sectorial diversification and a broader range of investment opportunities. This can also be perceived as an indicator of the vitality and depth of a country's financial market. Domestic investors may be more inclined to invest in their own country if there are many listed companies, as it gives them easier access to a variety of stocks and industry sectors.

F6 : The market capitalization is positively correlated to the Home Bias.

F7: The higher the number of listed companies the higher the Home Bias.

The average age of investors

The relationship between age and Home Bias is not the clearest and few researches seems to have deepen the subject. However, I thought it was interesting to investigate if the age of the investor has an impact on the bias. Generally, we think of older investors as exhibiting a stronger domestic bias due to factors such as familiarity with their home market, a desire for stability, patriotism. Conversely, younger investors might be more open minded to international diversification, more informed technology-wise and less influenced by home country preferences.

F8 : As the investor gets holder, the bias is increasing.

Propensity to save

Feldstein and Horioka (1980) document high positive correlation between a country's savings and its investment rate, arguing that capital flows to familiar (domestic) investment opportunities, not necessarily to the most profitable. Individuals who have a higher propensity to save may also show a stronger preference for investing in domestic assets rather than international ones. This could be due to factors such as familiarity with domestic markets, perceived lower risk.

F9 : the more people save, the more they are keen on investing home.

These nine proposed hypothesis aim to elucidate the temporal patterns of the Home Bias, either by elucidating its decline or persistence over time. Their function lies in providing explanatory frameworks for this phenomenon as our second and third thesis objective stated. The following table summarize the hypothesis that will be tested in the scope of this thesis.

Table 1 : Hypothesis summary and their analysis type

Name	Explicative Factors	Intuitive relationship with the Home Bias	Analyze type
F1	Tax regime	Negative	Linear regression PCA
F2	The financial knowledge of citizens	Negative	Linear regression PCA
F3	Technological influence and mastery	Negative	Panel regression PCA
F4	Economic growth	Positive	Panel regression PCA
F5	Stock market return of countries	Positive	Panel regression PCA
F6	Market capitalization	Positive	Panel regression PCA
F7	Number of listed companies	Positive	Panel regression PCA
F8	Age of investors	Positive	Panel regression PCA
F9	Propensity to save	Positive	Panel regression PCA

PCA stands for Principal Component Analysis

Source : our construction

4.4 Foreign Bias hypothesis

Conversely, in pursuit of identifying potential excessive investment in certain countries, our last research objective, I have delineated five variables that could lead to immoderate investment without rational explanation. This concept is built upon the research conducted by Bekaert and Wang (2009), which suggests that Foreign Bias manifests as an overexposure to countries perceived as close, potentially in physical proximity, for instance. Note that the nine hypothesis regarding the domestic bias might be reasons of over-exposition to certain countries and will thus serve as independent variables in our quantitative regressions. Here, the five elements should be viewed as linking factors and are as follows:

Cultural similarities

Cultural similarities exert a profound influence on investment decisions, particularly through the lens of familiarity. Investors tend to gravitate towards regions or countries with cultures similar to their own, perceiving a greater sense of understanding and shared values. This perceived familiarity often leads investors to believe they possess an informational advantage over others, thereby biasing their investment choices (Huberman, 2001). Furthermore, cultural affinity fosters a predisposition towards investing in companies and nations that align with one's values and worldview. This inclination stems from the belief that shared cultural norms and perspectives create a foundation for mutual trust and cooperation, thereby reducing perceived risks associated with investment. As a result, investors are more inclined to allocate their capital towards entities that resonate with their cultural identity and beliefs.
L1 : The cultural similarities is positively related to an over-exposition.

Physical distance

The proximity of countries plays a role in shaping investors' comfort levels, with closer distances often fostering a sense of familiarity and confidence in investment decisions. Investors tend to exhibit greater ease and willingness to invest in neighboring countries due to the perceived informational advantage derived from geographical proximity (Choe et al., 1999). The rationale behind this phenomenon lies in the notion that physical proximity facilitates access to information about companies and markets in neighboring countries. Investors feel more connected to these regions, often relying on local media sources and firsthand knowledge to inform their investment choices. Sharing a time zone is also perceived as enhancing this psychological proximity. Moreover, the inner sense of closeness associated with nearby countries instills a greater level of confidence in investors, leading them to perceive reduced risks and enhanced opportunities for investment.
L2 : The closest the country, the higher the tendency to invest excessively.

Spoken languages and spoken languages

The spoken languages factor, extensively studied by Grinblatt and Keloharju, sheds light on the phenomenon of Foreign Bias in investment behavior. Countries that share common languages are predisposed to invest in each other, primarily due to the linguistic familiarity facilitating the comprehension of financial disclosures and information (Grinblatt & Keloharju, 2001). The rationale behind this measure lies in the ease of communication and understanding afforded by shared languages. Investors find it more convenient to analyze and interpret financial data from countries where the spoken language is familiar, thus reducing linguistic barriers to investment. This linguistic affinity fosters a sense of trust and confidence among investors, encouraging cross-border investment within linguistic clusters. Moreover, the linguistic similarity facilitates cultural exchange and collaboration, creating a conducive environment for investment activities. Investors within language-affiliated regions often share similar cultural norms and business practices, further reinforcing the propensity to invest in each other's markets. Chan et al (2005), studied countries sharing a language and concluded that it reduces the Home Bias as investors tend to disproportionately invest in their related counterparties.
L3 : Sharing an official language increase the bias of investing in countries sharing this language.

L4 : Speaking the same language increase the bias of investing in countries sharing this language.

Religion

Nations characterized by greater religiosity tend to demonstrate a heightened inclination towards equity Home Bias. This trend is attributed to the elevated levels of risk aversion and aversion to uncertainty among religious investors, which leads them to display a reluctance towards foreign investments while favoring domestic ones. More religious countries tend to share similar beliefs thus favoring cross country investments in those countries (Lee et al, 2023).

L5 : Tendency of countries sharing a religion to invest in each other due to similar beliefs.

Table 2 : Linking factors for Foreign Bias

Name	Potential clusters links	Criteria
L1	Cultural similarities	4th quartile of the cultural similarity score
L2	Physical distance	1st decile of the distance between countries
L3+L4	Official languages and spoken languages	Countries sharing a language (official or spoken)
L5	Religion	Countries having the same dominant religion

Source : own construction

The table sums up the identified factors and outlines the criteria that will be used to quantify their influence. This concludes our chapter on hypothesis formulation, paving the way for data delineation.

5 Data

In this chapter, we delineate the variables employed to evaluate the hypothesis and factors outlined earlier and to conduct quantitative analysis to validate the proposed hypothesis. We will elucidate the rationale behind their selection, their origins, and any necessary modifications made to ensure their suitability for analysis. The variables chosen for examination encompass a range of economic, financial, and socio-cultural indicators that provide insights into investors' preferences, market dynamics, and risk factors.

5.1 Sample chosen : Panel, individuals and time period

The sample selected for analysis consist of twenty-three European countries, chosen based on specific criteria to ensure the robustness of the study. The dataset encompasses longitudinal (study of the same individual through time) and cross-sectional (study of different individual at a particular point of time) perspectives, spanning twenty-two years from 2001 to 2022, providing rich insights into the evolution of investment behavior over time. Except for two "one-time" measurement variables, these cross-sectional data are defined as "panel data." This sample structure enables gathering more information about a phenomenon and thus providing better estimates. It also allows for studying trends and testing various hypotheses regarding individual evolution or the unobservable sources of individual heterogeneity. Our panel is structured cylindrically as each individual is observed every year. Consequently, variables have a maximum of 506 observations.

The decision to focus exclusively on European countries was motivated by several factors. Firstly, the European region has been relatively understudied compared to the United States, which have a significantly higher weight in the global stock market. Additionally, the proximity, cultural similarities, shared values, and potential membership in the European Union among the selected countries offer a rich context for studying investment behaviors and particularly the Foreign Bias. This allows for an exploration of both commonalities and differences, including political, linguistic, and economic factors, contributing to a comprehensive understanding of investment dynamics within the European continent.

Furthermore, the availability of data served as a crucial criterion in the selection process. Only countries with reliable and consistent data throughout the chosen period were included in the analysis. Major financial hubs, such as Ireland and Luxembourg, were excluded to prevent skewing the analysis due to their unique characteristics and influence in global finance.

The chosen countries encompass a diverse range of economic, political, and cultural backgrounds, enhancing the representativeness and generalizability of the findings. These countries include Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Latvia, The Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, Sweden, Switzerland, and the United Kingdom.

The analyzed period started in 2001, coinciding with the introduction of the Euro as a common currency. It extends from 2001 to the latest available data in 2022.

In summary, the selection of twenty-three European countries based on specific criteria, spanning a twenty-two-year period, ensures a rigorous and comprehensive analysis of the factors influencing investment behavior and Home Bias within the European context.

5.2 Variables

This section will outline the selected variables intended to represent our explanatory hypotheses. Their sources, construction methods, and possible limitations will also be described.

5.2.1 Dependent variable : Sources, construction and limitations

5.2.1.1 Home Bias

Following Baele et al work (2007), making a distinction between a "model-based" approach and "data-based" approach to measure the Home Bias, I decided to keep it consistent by using the model-based one, being the most used in practice.

In this methodology, we utilize the optimal portfolio weights obtained from an international asset-pricing model as benchmark weights for comparing them with the actual portfolio holdings. Mishra (2015) recognized the ease of utilization of the ICAPM despite being based on strong assumptions. The world CAPM is indeed based on several assumptions, including the notion that all investors exhibit mean-variance preferences and hold the same beliefs regarding the distribution of real asset returns. Additionally, all participants face identical investment opportunities, and there are no transaction costs, taxes, or exchange rate risks. Furthermore, inflation is either independent of asset returns or non-existent. These assumptions result in the well-known relationship:

$$E(r_j) - r = \beta_j * [E(r_w) - r] \text{ (1)}$$

where $E(r_j)$ and $E(r_w)$ denote the expected returns on any asset and on the world portfolio respectively, r is the risk-free rate, and $\beta_j = cov(r_{w,}r_j)/var(r_{w,})$.

According to the CAPM, all investors hold the world market portfolio, which consists of assets weighted proportionally to their share in the global market capitalization. However, Sercu's international asset pricing model, introduced in 1980, incorporates exchange rates. In this case, equation (1) is modified to include the term:

$$E(r_j) - r = \beta_j * [E(r_w) - r] + \sum_{i=1}^{N-1} \delta_{j,s_t} [E(s_i + r_i) - r] \text{ (2)}$$

where N is the number of countries worldwide, s denotes the exchange rate change and r is now the risk-free rate of reference country N. Sercu's model allows for perfect hedging of currency risk through the investors' own risk-free asset, leading to the same conclusion as the world CAPM: all investors hold the world market portfolio of risky assets. In practice, the empirical validity of the CAPM is very weak and its assumption of perfectly integrated markets is untenable (Ferson & Harvey, 1994). This is particularly evident when evaluating the prediction that all investors should hold the same portfolio. In either model, the Home Bias measure is equal to the difference between the optimal CAPM domestic country weight in the portfolio and observed holdings of domestic equities:

$$HB_{\text{CAPM}} = domestic\ holdings\ \% - \frac{home\ capitalization}{\text{world capitalization}} \text{ (3)}$$

Which can also be written still conducting the same message :

$$HB_{\text{CAPM}} = 1 - \frac{share\ of\ foreign\ equity\ in\ portfolio}{share\ of\ foreign\ equity\ in\ golbal\ investable\ portfiolio} \text{ (4)}$$

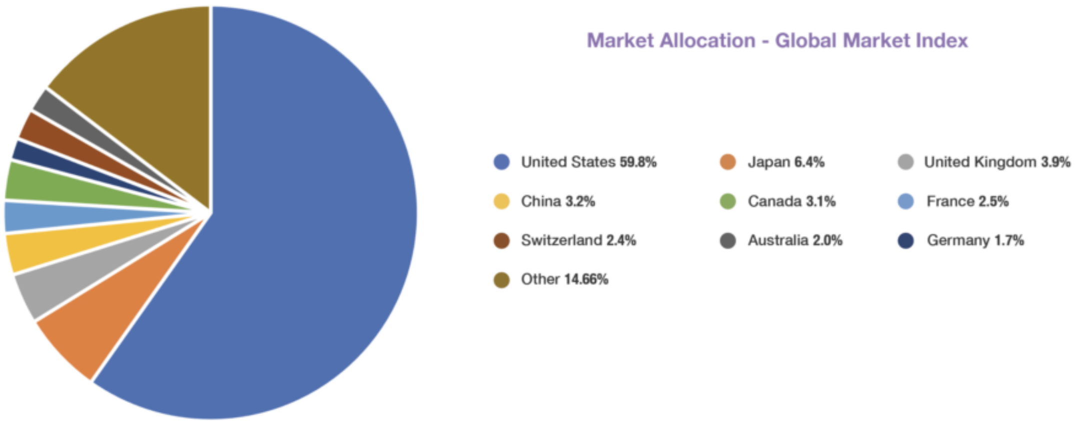
And refined as :

$$HB_{\text{CAPM}} = 1 - \frac{\frac{Foreign\ equity\ capitalization\ hold\ by\ home\ country\ (a)}{Total\ home\ equity\ portfolio\ capitalization\ (b)}}{\frac{Global\ market\ capitalization\ except\ home\ country\ (c)}{Global\ market\ capitalization\ (d)}} \quad (5)$$

Where :
(a) The market capitalization of all foreign stocks held by the home country in year t.
(b) The market capitalization of the total portfolio of stocks of the home country (the aggregation of portfolios of all investors in the home country).
This is equal, for year t, to:
+ (b1) the market capitalization of domestic stocks of home country.
- (b2) the market capitalization of domestic stocks held by foreign countries.
+ (b3) the market capitalization of foreign stocks held by home country.
(c) The market capitalization of the global stock market minus the market capitalization of domestic stocks of the home country.
(d) The market capitalization of the global stock market.

If the country perfectly owns the same amount of foreign equity as it should according to the benchmark or more, the second term of the equation 5 is at least equal to one implying a zero or less Home Bias measure. In any other case, the country will exhibit a domestic bias. Figure 4 presents the weights countries should follow in 2022 to be allocated as recommended by the CAPM.

Figure 4 : Countries weight in world index



Source : As of 31 July 2022, based on the Morningstar Global Market Index

Critics, such as Dahlquist et al (2003), argue that the definition of the equity Home Bias as the difference between the proportional domestic equity investments and the proportional market capitalization – the benchmark portfolio of the model-based approach – is incorrect. The total market capitalization of stocks, which also contains assets that are not freely tradable due to, for example, controlling shareholders who are reluctant to sell their shares. As a result, regular investors are unable to hold the world market portfolio accurately. To address this limitation, it is recommended to use the world float portfolio, which represents the market capitalization-weighted portfolio consisting of freely floated shares, as proposed by La Porta, Lopez-de-Silanes, and Shleifer (1999). This alternative benchmark portfolio should be employed when comparing it with actual portfolio holdings.

By adopting the world float portfolio as the benchmark, Dahlquist et al. have demonstrated that the Home Bias, although reduced, persists. This suggests that even when accounting for the freely tradable shares, there remains a tendency for investors to display a preference for domestic holdings in their equity portfolios.

The selected dataset for this computation (b2 and b3) is the "Coordinated Portfolio Investment Survey (CPIS)" database from the International Monetary Fund (IMF), which is widely used in the literature due to its extensive coverage over time and across geographical regions. However, there are several limitations associated with this dataset. Firstly, participation in the survey is voluntary, leading to incomplete data availability. Secondly, some member countries refrain from disclosing the value of their foreign holdings due to concerns about anonymity loss, which conducted to some missing data. Additionally, in cases where the value in dollars is equal to or less than $500,000 USD, a zero is indicated. The table 11 of the dataset is the one I focused on and the monetary unit used is the dollar.

The data for the benchmark (a, b1, c and d) are from a combination of the World Bank database and from Refinitiv when missing. This second source of data has been verified to be concordant with the World Bank.

5.2.1.2 Foreign Bias

As previously mentioned, the last objective of this thesis is to identify deviations from optimal CAPM allocation other than to the home country. Those deviations represent investment biases and the thesis aims at finding a theoretical ground for those deviations. The methodology employed to identify these deviations involves calculating the Foreign Bias using a slightly modified version of one of the two general formulas for the Home Bias (equation 3).

$$FB = country_j's\ country_i\ holdings\ \%\ (a/b) - \frac{country_i\ capitalization\ (c)}{world\ capitalization\ (\mathrm{d})}\ (6)$$

(a) The market capitalization of $country_i$ stocks held by $country_j$ in year t.

(b) The market capitalization of the total portfolio of stocks of $country_j$ (the aggregation of portfolios of all investors in $country_j$).
This is equal, for year t, to:
+ (b1) the market capitalization of $country_j's$ stocks of $country_j$.
- (b2) the market capitalization of $country_j$'s stocks held by foreign countries.
+ (b3) the market capitalization of foreign stocks held by $country_j$.

(c) The market capitalization of the global stock market minus the market capitalization of $country_i's$ stocks.

(d) The market capitalization of the global stock market.

5.2.2 Independent variables : Sources, construction and limitations

This section introduces the independent variables utilized to measure our hypotheses in our quantitative models. We discuss their sources, construction methods, and eventual limitations. Tables 3 and 4 summarize the section, providing an overview of the variables and their characteristics.

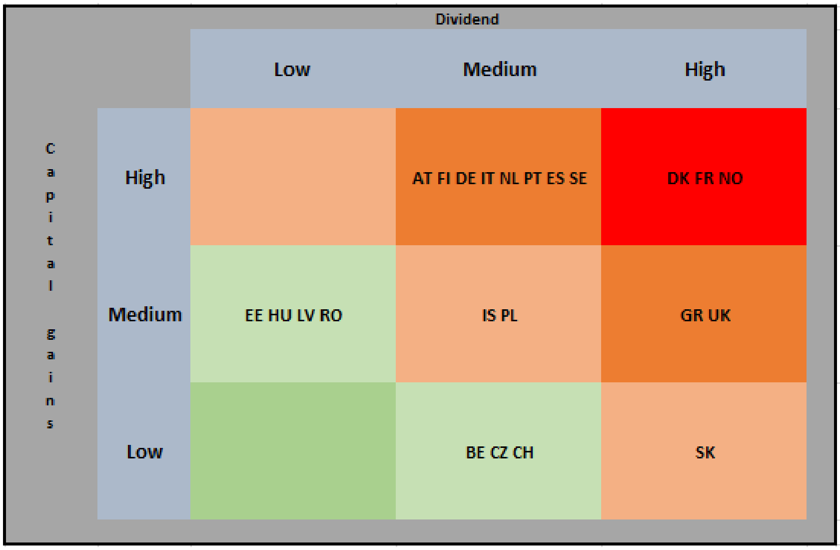
5.2.2.1 Home Bias

Tax regime

Both capital gain and dividend taxation data were sourced from the Tax Foundation Europe, which compiles extensive tax-related information about European countries. To facilitate analysis, I harmonized the data into a nine-grid classification system. Dividend regimes were differentiated using thresholds of 15% and 30%, while capital gains were categorized based on thresholds of 0% and 25%. Once classified in the 9-grid box, I allocated a tax score from 1 to 5 representing the weight tax has on

investors. 1 is allocated to the dark green case corresponding to tax heaven, 2 to the light green cases, 3 to the diagonal cases (light orange), 4 to the dark orange case while the 5 is attributed to the red case representing the highest tax heavy countries. The major limitation of this data source is the one time measurement character of the variable, which impede a true analyze through time. Using a 5-scale system for ranging values also result in loss of precision.
The hypothesis one suggests that as tax regimes become more favorable, a propensity for Home Bias in investment is predicted to increase.

Figure 5 : Tax Burden by country



		Dividend		
		Low	Medium	High
Capital gains	High		AT FI DE IT NL PT ES SE	DK FR NO
	Medium	EE HU LV RO	IS PL	GR UK
	Low		BE CZ CH	SK

Source : own construction based on Tax Foundation Europe data

The financial knowledge

The data originates from the Flash Eurobarometer FL525, which tracks the level of financial literacy within the EU. While this source is comprehensive for EU countries, it lacks information for European countries outside the EU. For countries with incomplete information, I opted to assign them a score equivalent to that of a nation I deem comparable. For instance, assigning the same score to Norway as to Sweden results in both countries being treated equally, potentially overlooking nuanced differences between them. An important limitation is the static information character as this study was realized in 2023.
Overall, the hypothesis two proposes that as financial literacy increases, the tendency for Home Bias is anticipated to decrease.

Technological influence and mastery

This variable is using the percentage of citizens using the internet every year since 1990 as a measure of technological advancement of countries. The information is collected on the International Telecommunication Union Datahub which is the world's richest source of information and communication technologies (ICT) statistics and regulatory information. The limitation of this variable lies in the ability of internet usage to capture the technological influence and asymmetry information relation with the studied phenomenon.
The hypothesis three states that as the usage percentage increase, the Home Bias is expected to decrease.

Economic growth

The data regarding economic growth are measure through the gross domestic product (GDP) and are extracted from the World Bank, which systematically collects the GDP of each country for every year. This suggests that economic prosperity and growth could play a significant role in shaping investment preferences and biases.

The hypothesis four posits that countries experiencing higher GDP growth rates are more likely to attract significant inflows of capital, potentially leading to an increase in Home Bias as citizen investors do not have any reason not to invest disproportionally in their country.

Stock market return

In a similar vein to GDP growth, the focus shifts to the performance of countries' stock markets, with data sourced from the World Bank. While there may be correlations between GDP growth and stock market performance, numerous factors can cause them to vary independently or even move in opposite directions.

The hypothesis five suggests that countries with higher recent stock market returns are likely to attract greater inflows of capital, potentially leading to an increase in Home Bias.

The market capitalization

The size of a country's stock market, as an indicator of investment opportunities and capital flow, is derived from data obtained from the World Bank and completed with Refinitiv data when missing. Although not exactly the same, their correlation has been verified by multiples countries validating the dataset.

The hypothesis six suggests that countries with larger stock markets are more likely to be judged as sufficient diversifier by citizens resulting in an increase in Home Bias.

The number of listed companies

The World Bank has a dataset on the number of listed companies per 1.000.000 citizens. This indicator, in essence similar to market capitalization, serves our purpose as it shows the size of domestic investment universe available to citizens. This dataset although very useful has a consequent number of missing data. To solve the issue I copied the previously known value for each data that was missing. Doing this suppose the number of listed companies has moved proportionally to the population.

The hypothesis seven suggests that the larger the domestic investment universe, the higher the Home Bias.

The age of investors

The dataset is coming from Eurostat, which compile the average age of citizens. I made the important assumption that the average age of investors is the same as the one of citizens in order to test the potential correlation between the age and the bias.

This hypothesis suggests that the older the investor gets, the more biased he is.

The propensity to save

The propensity to save, derived from World Bank data, represents the gross savings of a country as a percentage of its GDP. This metric serves as both a risk and economic indicator. A high savings percentage may reflect a country's wealth, as well as the population's inclination to preserve financial resources rather than engage in spending. Consequently, such nations may harbor citizens who exhibit risk-averse investment behaviors, seeking familiarity and security in their investment choices.

The hypothesis nine posits that the higher the propensity to save, the higher the Home Bias.

Those nine variables will be tested out in our quantitative models to find their potential contribution to the Home Bias, explaining either its decrease or persistence.

The following table summarizes the information delineated in this chapter segment.

Table 3 : Independent variables : Sources, construction and limitations

Name	Explicative Factors	Intuitive relationship with the Home Bias	Approximation – Independent variables	Source	Name
F1	Tax regime	Negative	Own construction	Tax foundation - Europe	Tax
F2	The financial knowledge of citizens	Negative	Financial literacy score	European Union Dataset	Literacy
F3	Technological influence and mastery	Negative	Internet usage rate	ITU Datahub	Internet
F4	Economic growth	Positive	GDP growth	World Bank (The global economy)	GDP
F5	Stock market return of countries	Positive	Stock return	The World Bank	Return
F6	Market capitalization	Positive	Country capitalization	The World Bank + Refinitiv	Cap
F7	Listed companies	Positive	Number of listed companies by inhabitants	The World Bank	Listed companies
F8	Age of investors	Positive	Mean age of inhabitants	Eurostat	Age
F9	Propensity to save	Positive	Savings as a % of GDP	The World Bank	Savings

Source : our construction

5.2.2.2 Foreign bias

After computing the Foreign Bias, I am endeavoring to establish an approach grounded in theoretical frameworks, employing a top-down methodology. This approach starts by identifying potential factors that may contribute to deviations, such as cultural affinities, geographical proximity, religiosity, or linguistic commonalities. These linking factors will assist us in creating groups for regression analysis, enabling us to identify correlations among countries.

Cultural similarities

The Cultural Similarity Index is a quantitative metric designed to assess the degree of cultural likeness between different groups of people through pairwise comparisons established by the Institute for Sociology at the Free University Berlin. It was developed within the framework of research on transnationalization and aims to elucidate the breadth and depth of transnational connections. Grounded in the concept of culture as "relatively stable interpretive frameworks and values shared by a collective and utilized in understanding the world" (Gerhards, 2000), the index draws upon questions derived from the European Social Survey that pertain to the value dimensions proposed by Shalom Schwartz. Ranging from 0 to 1, with 1 indicating maximum similarity and 0 indicating minimum similarity (or maximum dissimilarity), this index facilitates the identification and explanation of biases within clusters.

The first linking factor posits that nations sharing a comparable culture are more inclined to exhibit an investment bias toward each other.

Physical distance

This dataset records the distances in kilometers between European capital cities. It was compiled by Kristian Skrede Gleditsch, the Regius Professor of Political Science in the Department of Government at the University of Essex.

The linking factor two suggests that countries physically closer are more prone to exhibit bias toward each other.

Official languages and spoken languages

Europe, comprising approximately 50 countries, boasts a rich linguistic landscape where each nation typically possesses its own distinct national language. In certain instances, countries may even have multiple official languages. Along the borders of countries, languages often overlap, leading to linguistic interchangeability among residents of neighboring regions. This linguistic affinity may foster a sense of cultural similarity and shared identity, thereby influencing attitudes and perceptions towards other nations. Those variables were constructed by attributing a number to each official and spoken language to further develop the results of this linking factor according to data from the "One World Nation Online" website.

Official
1 : French
2 : German
3 : Hungarian
4 : Italian
5 : Swedish

Spoken
1 : Danish
2 : English
3 : Finnish
4 : German
5 : Hungarian
6 : Norwegian
7 : Swedish

Linking factors three and four suggest that countries sharing a common language, either official or just spoken, are more likely to exhibit bias toward each other.

Religion

The 2019 Eurobarometer survey enables the classification of countries based on their dominant religion, despite certain nations displaying a low level of religiosity. To undertake this distinction, I categorized combinations of countries into four distinct groups. It is plausible to hypothesize that, even if the populace is less religious compared to previous eras, remnants of religious precepts and beliefs persist, exerting influence.

- 0: Differing dominant religions
- 1: Both countries have Christianity as their dominant religion
- 2: Both countries have Protestantism as their dominant religion
- 3: Both countries have Orthodoxy as their dominant religion

This last linking factor posits that countries sharing a common dominant religion may be inclined to invest more in each other than in nations with differing religious beliefs.

Table 4 : Linking factors for Foreign Bias : Source, construction and limitations

Name	Potential clusters links	Intuitive relation with the deviation	Source	Abbreviation
L1	Cultural similarities	Positive	Institute of Sociology – Free University Berlin	CULT
L2	Physical distance	Positive	Kristian Skrede Gleditsch (Regius professor – University of Essex)	DIST
L3+L4	Official languages and spoken languages	Positive	One World Nations Online	OFFL (official languages) SPOL (Spoken languages)
L5	Religion	Positive	Eurobarometer	REL

Source : our construction

This chapter concludes the presentation of both independent variables and grouping factors. In the following chapter, we will describe the construction of quantitative models using the outlined data, facilitating the verification of our theoretical hypotheses.

6 Empirical models

This chapter is dedicated to outlining the models employed to achieve our research objectives and the methodology utilized to construct them. We will begin by providing descriptive statistics to elucidate the characteristics of each variable under consideration. Subsequently, based on the nature of the variables, we will perform either linear regression or panel regression. The resulting analyses will then be scrutinized to address the hypotheses formulated earlier, thereby advancing our research objectives. Lastly, multiples principal component analysis will be conducted to boost the results related statistical inference.

6.1 Descriptive statistics

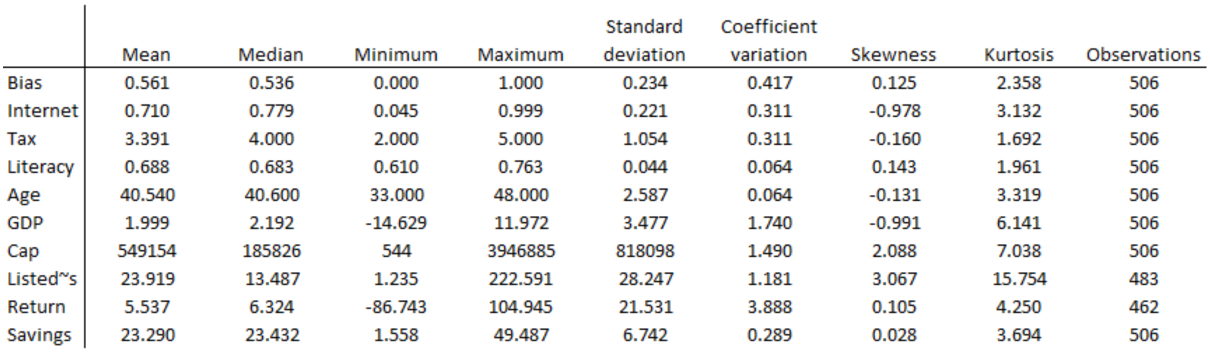
6.1.1 Home Bias

Firstly, it is pertinent to highlight that both methodologies employed for computing the Home Bias, as delineated in Section 5.2.1.1, yield nearly identical outcomes. Consequently, using either will results in the same conclusions. I have opted to proceed with the findings derived from the second approach.

The "Bias" variable, representing the Home Bias, ranges from 0 to 1 as exhibited in the summarizing table 5, with a mean of approximately 0.56 implying a consequent deviation from optimal allocation. Notably, it exhibits a considerable spread around the average, as evidenced by a standard deviation of 0.234, indicating the extent of variability in values. The slightly positive asymmetry (skewness) of 0.13 suggests a tendency towards higher bias values, while the kurtosis (2.36) indicates a distribution that deviates from normality, likely due to the bounded nature of the variable. These descriptive statistics underscore the diverse and nuanced nature of domestic bias within the dataset.

Table 5 : Descriptive statistics

Sample composed of 23 European countries from 2001 to 2022.



	Mean	Median	Minimum	Maximum	Standard deviation	Coefficient variation	Skewness	Kurtosis	Observations
Bias	0.561	0.536	0.000	1.000	0.234	0.417	0.125	2.358	506
Internet	0.710	0.779	0.045	0.999	0.221	0.311	-0.978	3.132	506
Tax	3.391	4.000	2.000	5.000	1.054	0.311	-0.160	1.692	506
Literacy	0.688	0.683	0.610	0.763	0.044	0.064	0.143	1.961	506
Age	40.540	40.600	33.000	48.000	2.587	0.064	-0.131	3.319	506
GDP	1.999	2.192	-14.629	11.972	3.477	1.740	-0.991	6.141	506
Cap	549154	185826	544	3946885	818098	1.490	2.088	7.038	506
Listed~s	23.919	13.487	1.235	222.591	28.247	1.181	3.067	15.754	483
Return	5.537	6.324	-86.743	104.945	21.531	3.888	0.105	4.250	462
Savings	23.290	23.432	1.558	49.487	6.742	0.289	0.028	3.694	506

Source : Stata based on our database

Analyzing the trends, it becomes evident that several major economies have witnessed notable changes in their Home Bias levels. For instance, the United Kingdom and Italy experienced substantial decreases over the analyzed period, with the UK's home bias declining from 0.7 to 0.27. Similarly, Italy underwent a similar reduction in its Home Bias. Conversely, countries like France have also seen decreases in their Home Bias, albeit to a much lesser extent, with France maintaining a bias of nearly 0.6 in 2022, from 0.78 at the beginning.

In contrast to these trends, the Netherlands emerges as an interesting case, demonstrating minimal bias in its investment portfolios over the last five years. Despite fluctuations in global markets and economic conditions, the Netherlands appears to have consistently maintained a balanced allocation strategy in its investment decisions till the point of respecting its CAPM allocated weight.

Furthermore, upon examining the graphical representation provided in figure 14, it becomes apparent that certain countries, including Romania, Greece, and Poland, show persistently high levels of bias throughout the analyzed period. Despite different economic dynamics, these countries appear to consistently favor domestic assets in their investment portfolios.

Acknowledging the longitudinal nature of the dataset encompassing 23 countries over a span of 22 years, the analysis reveals variable economic trends and market behaviors.

Delving into the "Internet” variable which represent internet usage reveals a broad spectrum of values, spanning from as low as 4.5% in 2001 to as high as 99.9% in 2022, with an average of approximately 71%. However, despite this overall increasing average through time, there exists significant variability across different countries, as indicated by a standard deviation of 22.

One noteworthy observation is the stark contrast in internet usage trends among various nations. For instance, Romania experienced a remarkable surge in internet usage, starting the analysis period at a mere 4.5% and concluding with a substantial 85.5%. This remarkable leap positions Romania above countries like Italy, Portugal, and Greece in terms of internet penetration in 2022.

Interestingly enough, while analyzing the relationship between Home Bias levels and internet usage rates, it becomes apparent that countries with elevated levels of Home Bias tend to fall within the category of nations with less than 90% internet usage in 2022 (9 out of 23). This correlation suggests that a higher inclination towards domestic assets may be associated with lower levels of internet adoption.

Conversely, "Tax" as only measured once, remain quite static across the dataset, with values primarily clustering between 2 to 5, and a mean of 3.39. The same analyze can be applied to “Literacy”, which demonstrate the lowest standard deviation of all variables and fit into the range 0.61 – 0.763.

Among the countries studied, the mean age stands at approximately 40.54 years. Notably, there is a considerable range in ages, with the youngest recorded age being 33 years old and the oldest reaching 48 years old. This wide span of 15 years highlights the diversity in age distributions across the dataset's countries but more importantly the aging population through the years. Analyzing individual countries' data sheds additional light on age distributions. For instance, Iceland exhibits the youngest population, with a mean age of 35 years, while Italy has the oldest population, with a maximum age of 48 years. This disparity in mean ages among countries underscores the demographic diversity captured within the dataset. Again, countries experiencing higher bias tend to have an individual mean lower than the overall one.

Analyzing the "GDP" variable across different countries reveals that the mean across all countries is approximately 2% corresponding to the inflation target in Europe. The minimum recorded GDP is -14.63%, was experienced in Estonia in 2009, while the maximum of 12% was reached by Latvia in 2006. We find that the standard deviation is approximately 3.5, suggesting considerable variability in economic output across countries. The coefficient of variation, which measures the relative variability of GDP, is about 1.7, indicating that the dispersion of GDP values around the mean is moderate.

Furthermore, looking at individual countries, we observe notable differences. For instance, Austria has a mean GDP of 1.43, while Czech Republic has a mean GDP of 2.52, indicating differences in economic performance between these two countries. Similarly, Greece has a relatively high coefficient of

variation for GDP at 14.58, suggesting higher variability in economic output compared to other countries in the dataset notably due to the 2011 crisis.
Considerable disparities in market capitalization among different countries are readily apparent when examining contrasting market environments. The United Kingdom stands out as the largest economy in this regard, while Latvia represents the smallest stock market. To gain deeper insights into the market size potential available to citizens, it may be more illuminating to consider the variable "Listed companies," which is normalized by each country's population.

Interestingly, Iceland emerges as the leader in this measure, whereas Czech Republic finds itself at the lower end of the spectrum. Despite the average number of listed companies per 1 million inhabitants being 24, the median is notably lower at 13.5, suggesting a skew towards higher values, notably exemplified by Iceland, which exhibits an outlier at 222.

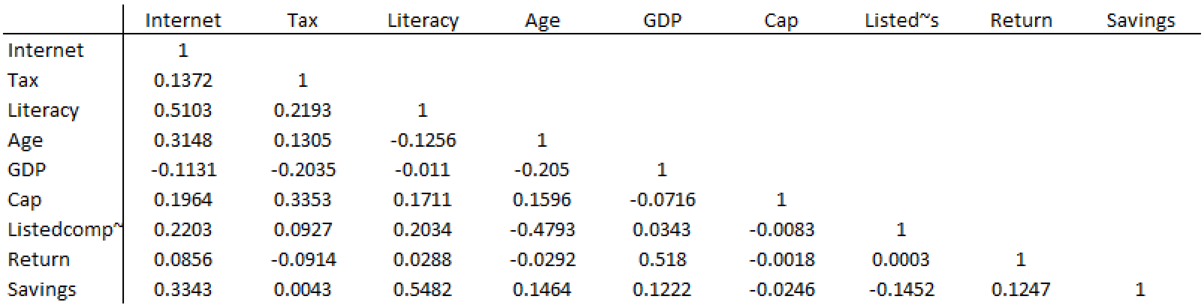
Iceland once again emerges as an outlier in the analysis of the "Return" variable, notably due to its staggering -86% return in 2009, coinciding with the country's bankruptcy. Conversely, Slovakia witnessed a remarkable surge of 105% in 2005, a phenomenon potentially linked to 2004’s adhesion to the European Union.

The average annual stock market return across the examined period stands at 5.5%, aligning closely with expectations for the European continent in terms of average return. However, the variable exhibits a high kurtosis, indicating heightened volatility. This variability stems from the diverse range of years under scrutiny, characterized by starkly contrasting market conditions. Some periods witnessed exuberantly positive returns amidst economic booms or bubbles, while others were marred by crises such as the financial crisis, sovereign debt crises, and the COVID-19 pandemic, thereby contributing to the observed volatility in the variable.

When examining the “Savings” variable, it is notable that both the mean and median values are closely aligned, standing at 23.3% of savings to GDP. This proximity suggests a relatively stable distribution of savings across the dataset. The coefficient of variation, calculated at 0.29, further supports this observation, indicating minimal variation in savings percentages.

However, it is important to recognize that the variability within the dataset is influenced by outliers, particularly evident in countries with notably high savings percentages such as Norway and Switzerland, where savings can reach up to 49.5% of GDP. Conversely, Iceland's data point in 2008 presents a stark contrast, with a mere 1.6% of savings to GDP, contributing to the overall variability observed.

Table 7 : Correlation matrix (Pearson) without the Home Bias variable



	Internet	Tax	Literacy	Age	GDP	Cap	Listed~s	Return	Savings
Internet	1								
Tax	0.1372	1							
Literacy	0.5103	0.2193	1						
Age	0.3148	0.1305	-0.1256	1					
GDP	-0.1131	-0.2035	-0.011	-0.205	1				
Cap	0.1964	0.3353	0.1711	0.1596	-0.0716	1			
Listedcomp~	0.2203	0.0927	0.2034	-0.4793	0.0343	-0.0083	1		
Return	0.0856	-0.0914	0.0288	-0.0292	0.518	-0.0018	0.0003	1	
Savings	0.3343	0.0043	0.5482	0.1464	0.1222	-0.0246	-0.1452	0.1247	1

Source : Stata based on our database

Table 7 presents the Pearson correlation coefficients between the independent variables to be utilized in our quantitative analyses. These coefficients gauge the degree of linear relationship, commonly referred to as the degree of co-movement, existing between two variables. They range from -1 to 1, where both extremes signify a perfect correlation or decorrelation respectively between two variables. They fluctuate precisely in the same proportions and either in the same direction if the coefficient is 1, or in opposite directions if the coefficient is -1.

In the table provided, two correlations stand out as particularly noteworthy, aligning with the observations highlighted by Cooper et al. (2012). Specifically, a positive correlation is observed between the financial literacy and internet usage variables, suggesting that individuals with greater mastery of technology are more financially educated. Additionally, a similar positive correlation is observed between GDP and stock market returns, indicating that periods of higher GDP growth coincide with higher returns in the stock market. Both of these relationships offer reasonable explanations based on economic principles and empirical evidences. However, it is important to note that correlation does not imply causation, and further analysis is necessary to confirm these relationships and explore potential underlying mechanisms.

This correlation matrix is also crucial for the principal component analyses we conduct. Indeed, this type of analysis relies on the correlation matrix. If all correlation coefficients were close to zero, the analysis would lack significance.

6.1.2 Foreign Bias

Initially, our exploration delves into the Foreign Bias, an indicator of divergence from optimal allocation prescribed by the CAPM. The distribution unveils a median deviation hovering around -0.001, signifying a balanced distribution on a median basis. This also suggests that on a median basis, countries respect ideal allocation in our selected dataset. With a mean deviation of approximately -0.0037 and a standard deviation of 0.0145, the dataset manifests a relatively constrained dispersion. Nevertheless, positive skewness of 1.229 hints at a skewed distribution towards higher deviation values, while a kurtosis of 26.09 accentuates the presence of heavy-tailed outliers. The dataset spans from a minimum of -0.080 to a maximum of 0.228, underscored by noteworthy overweight and underweight deviations among certain countries.

Certain countries exhibit persistent overweight towards specific counterparts throughout the study period. Notable relations (the first country overweighting the second) are Austria-Germany; Belgium-France, Czech Republic-Austria; Czech Republic-Belgium; Estonia-Finland; Finland-Sweden; Portugal-Spain; Slovakia-Austria. These represent eight out of 506 relations demonstrating an average positive deviation of at least three percent, rendering them the most biased relations. Interestingly, only 92 out of 506 relations exhibit a positive bias, suggesting that, on average, a country overweight one-fifth of its investments. The five previously identified linking factors aim to elucidate potential reasons underpinning deviations from optimal allocation.

Additionally, an intriguing observation emerges regarding the underweight of the United Kingdom in many countries' portfolios. Despite boasting the largest capitalization in our sample with 3.9% of the world portfolio in 2022, the UK is consistently underweighted, with an average negative deviation of 3.27%. Norway and The Netherlands emerge as the sole countries overweighting the UK.

Transitioning to the "CULT" variable, which gauges societal norm and value similarities among countries, its median stands at 0.628 (index ranging from 0 to 1), indicative of a moderately similar cultural landscape. The data portrays a slight negative skewness (-0.127) and a kurtosis of 2.421, suggesting a distribution slightly skewed towards lower cultural similarities with sporadic outliers.

Noteworthy relations include Iceland-Italy, showcasing the lowest cultural correlation (0.364), and Belgium-Spain (0.863), emerging as the most culturally related.

Furthermore, the "DIST" variable delineates geographical separation between countries' capitals. With a median distance of 1288 km, the dataset spans from a minimum of 62 to a maximum of 4138km. Positive skewness of 0.681 indicates a distribution skewed towards shorter distances, while a kurtosis of 3.032 hints at heavy-tailed outliers, amplifying dataset variance. This skewness underscores the geographical proximity of European countries.

"OFFL" and "SPOL" variables serve as categorical variables with different number each representing a language. Notable observations include German being the most shared language in Europe, with four countries listing it as an official language and eight recognizing it as a spoken language. Nordic languages and Hungarian exhibit similar spoken trends, while French is official in three countries.

Lastly, the "REL" variable, scaling between zero and three, reveals thirteen countries sharing Christianity as their dominant religion, while eight out of twenty-three studied countries adhere to Protestantism. Greece and Romania emerge as the sole representatives of Orthodox Christianity.

6.2 Panel regression

In this section, we lay down the theoretical foundations of panel data regressions, outlining the potential estimation models applicable to this data type. Subsequently, we delve into the construction of our panel regressions, encompassing linear equations, assumptions, and statistical tests for selecting the estimation model that fits best.

Panel regression, also known as longitudinal data analysis or panel data analysis, is a statistical method used to analyze data that contains both cross-sectional and time-series dimensions. It is particularly useful in our case as we have data collected over multiple time periods for multiple countries. Panel regression methods account for the panel structure of the data by considering the correlation of observations within the same entity over time. This helps to improve efficiency and address issues such as serial correlation and heteroscedasticity that may arise in cross-sectional or time-series data analysis alone.

6.2.1 Panel econometrics principles

The generalized panel regression equation, as formulated by seminal scholars such as Wooldridge (2010), serves as a fundamental framework in econometrics.

$$y_{it} = \beta_0 + \beta_1 x_{1,it} + \beta_2 x_{2,it} + \cdots + \beta_k x_{k,it} + \mathcal{E}_{it} \text{ (7)}$$

It studies the links between the dependent variable y and a matrix of k independent variables x_1 ,..., x_k. Within this equation, the residual term $\mathcal{E}_{it}$ amalgamates both individual-specific errors a_i and random errors e_{it} , elucidating the interplay between observable and unobservable variables.

$$\mathcal{E}_{it} = a_i + e_{it}$$

6.2.1.1 Ordinary Least Squares

Ordinary Least Squares (OLS) is a statistical method used to estimate the parameters of a linear regression model by minimizing the sum of the squared differences between the observed and predicted values of the dependent variable. It is widely employed in econometrics and other fields for modeling relationships between variables. In the context of panel data analysis, this method overlooks temporal and individual dimensions and conducts a straightforward analysis. This means that the data from each entity are aggregated together without considering the temporal or individual structure. This model relies on numerous assumptions, including the absence of correlation between the individual-specific effects of unobservable variables (represented by the term a_i for each individual i) and the independent variables. This prerequisite, called exogeneity is articulated as follows, for any individual i, any year t, and all independent variables (x_1 ,..., x_k):

$$Cov\ (x_{it}, a_i) = 0$$

The assumptions for this model are the same as for the simple regression model as described by Greene (2012). There are six of them:

- The model is linear: $y_i = \beta_0 + \beta_1 \mathrm{x}_{1,i} + \beta_2 \mathrm{x}_{2,i} + \cdots + \beta_k \mathrm{x}_{k,i} + \mathcal{E}_i$
- There is no perfect collinearity: $rank\ (X) = rank\ (X'\ X) = K$,

where X is the factor matrix with K columns and $N = nt$ rows.

- Exogeneity: $E\ (\mathcal{E}_{it}|X)$ = 0 ; $Cor\ (\mathcal{E}_{it}, X) = 0$,
- Homoscedasticity: $Var\ (\mathcal{E}_{it}|X) = E\ ({\mathcal{E}^2}_{it}|X) = \sigma^2$,
- No cross section or time series correlation: $Cov\left(\mathcal{E}_{it}, \mathcal{E}_{js}|X\right) = E\left(\mathcal{E}_{it}\mathcal{E}_{js}|X\right) = 0 \qquad i \neq j; t \neq s$,
- Normal distribution of the disturbances $\mathcal{E}_{it}$.

While the method is simple and easy to implement, it overlooks critical features of panel data, leading to biased and inefficient estimates. Thus, I chose to focus on other panel regression techniques, such as fixed effects or random effects models, which are preferred as they account for individual and time effects, handle correlation within units, and provide more efficient estimation. Both are based on indigeneity.

$$Cov\ (x_{it}, a_i)\ \neq 0$$

for any individual i, any year t, and all independent variables (x_1 ,..., x_k).

6.2.1.2 Hausman test

The Hausman Test, also known as the Hausman specification test, serves to identify endogenous regressors within a regression model. Endogenous variables are those whose values are influenced by other variables within the system. The presence of endogenous regressors can undermine the validity of OLS estimators, as one of the assumptions of OLS is the absence of correlation between predictor variables and the error term. In such cases, instrumental variables estimators may offer an alternative solution. However, before determining the most appropriate regression method, it is crucial to ascertain whether predictor variables are indeed endogenous, a task for which the Hausman test is designed.

The Hausman test helps choosing between fixed effects and random effects models. The null hypothesis posits that the exogeneity hypothesis is respected and, by default, the preferred model is the random effects model, while the alternative hypothesis if the null hypothesis is rejected suggests the fixed effects model. Essentially, the test examines whether there exists a correlation between the unique errors and the regressors in the model, with the null hypothesis assuming no such correlation.

Interpreting the results of a Hausman test is relatively straightforward: a small p-value (less than 0.05) leads to the rejection of the null hypothesis. However, it is important to note that there exist various versions of the test, each with different hypotheses and potential conclusions.

6.2.1.3 Fixed effects model

The fixed effects method accounts for unobserved heterogeneity among entities that are constant over time. This method is particularly useful when there are time-invariant characteristics of entities that may affect the dependent variable. In fixed effects, the equation is expressed as follows:

$$y_{it} = a_i + \beta_1 x_{1,it} + \beta_2 x_{2,it} + \cdots + \beta_k x_{k,it} + \mathcal{E}_{it} \text{ (8)}$$

Where compared to the OLS equation, there is no more constant term. Instead of the β_0 term, this model present an individual-specific component capturing their specific characteristics or behaviors that influence the dependent variable. However, it is important to note that the slopes (parameters) remain the same for all individuals, indicating that the effects of the independent variables on the dependent variable are constant across individuals. Fixed effects estimation is particularly useful when there is concern about omitted variables that vary across entities but are constant over time. By including entity-specific fixed effects, this method controls for such unobserved heterogeneity.

When our software, Stata, performs panel regression using fixed effects, it uses the "within" method, also known as the fixed differences method. This method eliminates unobservable individual effects by subtracting individual means of each variable for each individual, effectively taking the difference between each observation and the individual mean for each individual (Balgati, 2005).

The "within" method is generally preferred over the alternative method which is the Least Squares Dummy Variable (LSDV) approach. This is because the "within" method eliminates individual effects, which can lead to more efficient estimates and allows for controlling for time-invariant variables without relying on additional dummy variables, as in the LSDV approach. However, there is debate over the choice as some prefer the LSDV method, which maintains the estimation of the constant and provides correct R^2 and standard errors, unlike the “within” estimator where these values are biased.

Despite its advantage, fixed effects estimation also has limitations. It requires a large number of periods to effectively control for entity-specific effects, and it cannot estimate the effects of time-invariant independent variables. Additionally, fixed effects models assume that the entity-specific effects are uncorrelated with the independent variables, which may not always hold true (Wooldridge, 2010).

6.2.1.4 Random effects model

The last method, the random effects method allows for unobserved heterogeneity among entities while assuming that entity-specific effects are random variables with specific distributional assumptions. This method is useful when there are unobserved entity-specific characteristics that may be correlated with the independent variables. The individual-specific component a_i is not treated as a fixed parameter and it is not estimated separately. Instead, it is considered as a random variable with mean μ and variance σ_α^2. The random effects model can thus be written as:

$$y_{it} = \mu + \beta_1 x_{1,it} + \beta_2 x_{2,it} + \cdots + \beta_k x_{k,it} + (\alpha_i - \mu) + \varepsilon_{it} \text{ (9)}$$

where μ is the average individual effect.

Let $\mu_{it} = (a_i - \mu) + \mathcal{E}_{it}$ and (9) can be rewritten as:

$$y_{it} = \mu + \beta_1 x_{1,it} + \beta_2 x_{2,it} + \cdots + \beta_k x_{k,it} + u_{it}$$

The random effects model allows for unobserved entity-specific effects that are correlated with the independent variables. Random effects estimation is particularly useful when there are time-invariant unobserved characteristics of entities that may affect the dependent variable and are correlated with the independent variables. By including random effects, this method accounts for such unobserved heterogeneity. This model can be viewed as a combination of the OLS and fixed effects models. At each period, one of these two models is chosen based on the autocorrelation of the error term a_i.

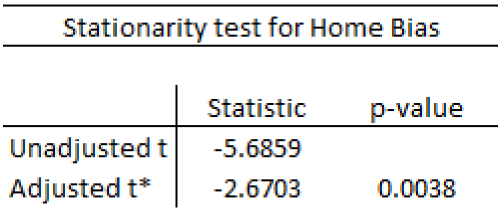
However, random effects estimation also has limitations. It assumes that entity-specific effects are uncorrelated with the independent variables, which may not always hold true. Additionally, random effects models do not provide estimates of the effects of time-invariant independent variables (Baltagi, 2005).

6.2.1.5 Stationarity

Testing stationarity in panel regression is crucial to ensure the validity of the obtained results. Stationarity implies that the statistical characteristics of the time series, such as mean and variance, remain constant over time. If data is non-stationary, it can compromise the efficiency of estimations and lead to biased results. In panel regression, where data is collected over multiple time periods for several individual units, stationarity is essential as it ensures the stability of relationships between variables over time. Testing stationarity also helps identify trends or temporal patterns that could affect analysis outcomes. By ensuring data stationarity, one ensures reliable coefficient estimations and interpretable regression results.

Table 8 : Stationarity test : Levin-Lin-Chu test for Home Bias

H0: Panels contain unit roots <> Ha: Panels are stationary



Stationarity test for Home Bias

	Statistic	p-value
Unadjusted t	-5.6859	
Adjusted t*	-2.6703	0.0038

Source : Stata based on our database

The unadjusted t-statistic is -5.69, indicating significant evidence against the null hypothesis of unit roots. The adjusted t-statistic is -2.67 with a p-value of 0.0038, which also suggests the rejection of the null hypothesis. This provides further evidence that the panels are stationary.

6.2.2 Models

6.2.2.1 Home bias model

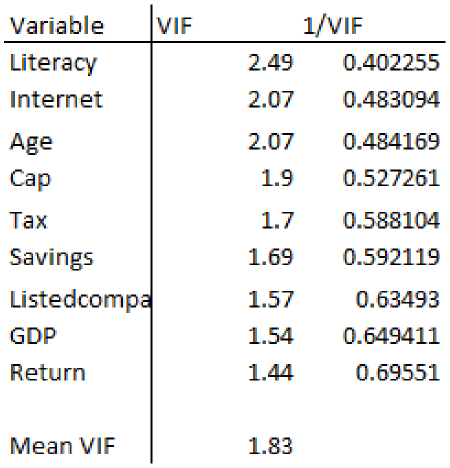
The employed model will seek to ascertain the prospective utility of identified explanatory factors across the studied timeframe. Our objective is to scrutinize the interplay among Home Bias, tax burden, financial literacy, internet usage, economic growth of nations, stock market size (2 measures), their associated returns, investor age and their saving tendency. The equation is expressed as follows:

$$HB_{it} = c + \beta_1 TAX_{it} + \beta_2 FIN_{it} + \beta_3 TECH_{it} + \beta_4 GDP_{it} + \beta_5 RTRN_{it} + \beta_6 CAP_{it} + \beta_7 COMP_{it} \\ + \beta_8 AGE_{it} + + \cancel{\beta_9 SAVE_{it}} + u_{it}$$

To conduct a robust regression analysis, three variables required normalization. I opted to apply natural logarithm transformations to the variables "Cap," "Comp," and "Age" to achieve normal distributions. However, subsequent regression analyses using both fixed and random effects revealed that certain variables were not statistically significant in one or both methods, as evidenced by p-values exceeding our chosen 0.05 significance level. Notably, the variable "Cap" showed insignificance in both methods. Despite this, recognizing the theoretical significance of studying market size, I chose to retain the variable in my regression model. Moreover, removing the variable could overlook potential indirect effects or interactions it may have with other variables in the model. Thus, retaining "Cap" ensures a more comprehensive and nuanced understanding of the relationships between variables and the Home Bias phenomenon.

To bolster the robustness of my choices, I concurrently looked at the correlation matrix (table 7) and conducted the following variance inflation factor test (VIF - table 9) to assess the extent of multicollinearity in the regression analysis. This additional examination aimed to ensure the integrity of the regression model by identifying and addressing any issues stemming from multicollinearity among the predictor variables. Scholars commonly use specific thresholds to identify multicollinearity. A VIF value less than 5 is generally considered acceptable, indicating that multicollinearity is not a concern. Values between 5 and 10 suggest moderate multicollinearity while value greater than 10 indicates high multicollinearity, suggesting that the predictor variables are highly correlated and typically requiring corrective action, such as removing or combining variables. In our case, the test confirms tolerable levels reinforcing my choice of keeping the “Cap” variable.

Table 9 : Variance inflation factor



Variable	VIF	1/VIF
Literacy	2.49	0.402255
Internet	2.07	0.483094
Age	2.07	0.484169
Cap	1.9	0.527261
Tax	1.7	0.588104
Savings	1.69	0.592119
Listedcompa	1.57	0.63493
GDP	1.54	0.649411
Return	1.44	0.69551
Mean VIF	1.83	

Source : Stata based on our database

Regrettably, owing to the no statistical relevance and minimal explanatory power observed in the variable "SAVE" I made the decision to omit it from further analysis. Consequently, I opted not to evaluate the ninth hypothesis, which posited that the inclination to save could serve as a determinant influencing Home Bias.

6.2.2.1.1 Ordinary Least Squares

This method is based on the six assumptions outlined in the point 6.2.1.1. The first condition pertains to the linearity of the model, which can be assessed through scatter plots depicting the relationship between Home Bias and each independent variable (figures 18 to 26). These figures are very instructive about the allure of the link between both variables and helps us easily seeing correlation sign.

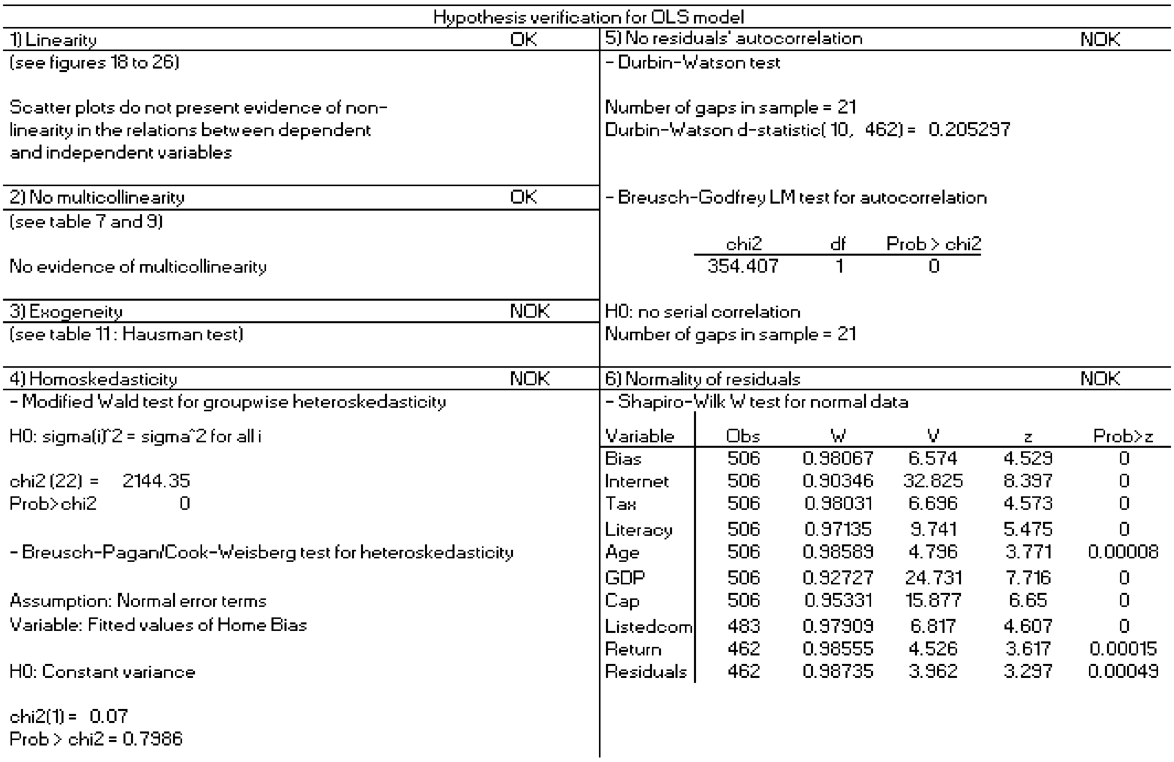
The second condition concerns the absence of multicollinearity among independent variables and can be evaluated using correlation matrices or variance inflation factors, which were just detailed. The third condition concerns exogeneity, as discussed in the theoretical section on panel regressions. It will be tested later using the Hausman test.

The forth condition involves homoscedasticity of residuals, indicating a constant variance of error terms. This condition is assessed using The Wald test for groupwise heteroscedasticity that tests the null hypothesis, stating that the variance of the error term is the same across all groups (in this case, countries) in the panel data model. In our output, the chi-square test statistic is 2144.35 and the p-value associated with the chi-square test statistic is 0.0000. It indicates strong evidence against the null hypothesis. We reject the null hypothesis of homoscedasticity in favor of the alternative hypothesis of groupwise heteroscedasticity (unequal error variances across groups). This suggests that the error variances differ significantly across the different countries. Concurrently, Breusch-Pagan test associated with a high p-value, far superior to significance level, imply that we fail to reject the null hypothesis suggesting that there is no evidence of heteroscedasticity this time in the error terms.

The fifth condition pertains to the absence of residual autocorrelation, which is evaluated using the Durbin-Watson and Breusch-Godfrey tests. Both result in evidence of autocorrelation within the residuals. The last condition stipulates that the errors terms are assumed to follow a normal distribution. Based on the Shapiro-Wilk test results for normality, it appears that none of the variables nor the residuals have p-values greater than 0.05, indicating that they do not follow a normal distribution. This suggests that the assumption of normality of the variables do not hold.

Table 10 summarizes these assumptions, their tests, and their outcomes. It can be asserted that the assumptions of homoscedasticity and absence of residual autocorrelation are not met. Consequently, the method of estimating OLS is biased. Indeed, it was highly likely that this method would not be suitable for our model as it fails to consider the diversity of the studied individuals or the temporal dimension, and it overlooks any unobserved individual effects that may exist (unobserved heterogeneity).

Table 10 : Hypothesis verification for the OLS model



Hypothesis verification for OLS model

1) Linearity OK

(see figures 18 to 26)

Scatter plots do not present evidence of non-linearity in the relations between dependent and independent variables

2) No multicollinearity OK

(see table 7 and 9)

No evidence of multicollinearity

3) Exogeneity NOK

(see table 11 : Hausman test)

4) Homoskedasticity NOK

- Modified Wald test for groupwise heteroskedasticity

H0: sigma(i)^2 = sigma^2 for all i

chi2 (22) = 2144.35
Prob>chi2 0

- Breusch-Pagan/Cook-Weisberg test for heteroskedasticity

Assumption: Normal error terms
Variable: Fitted values of Home Bias

H0: Constant variance

chi2(1) = 0.07
Prob > chi2 = 0.7986

5) No residuals' autocorrelation NOK

- Durbin-Watson test

Number of gaps in sample = 21
Durbin-Watson d-statistic(10, 462) = 0.205297

- Breusch-Godfrey LM test for autocorrelation

chi2	df	Prob > chi2
354.407	1	0

H0: no serial correlation
Number of gaps in sample = 21

6) Normality of residuals NOK

- Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
Bias	506	0.98067	6.574	4.529	0
Internet	506	0.90346	32.825	8.397	0
Tax	506	0.98031	6.696	4.573	0
Literacy	506	0.97135	9.741	5.475	0
Age	506	0.98589	4.796	3.771	0.00008
GDP	506	0.92727	24.731	7.716	0
Cap	506	0.95331	15.877	6.65	0
Listedcom	483	0.97909	6.817	4.607	0
Return	462	0.98555	4.526	3.617	0.00015
Residuals	462	0.98735	3.962	3.297	0.00049

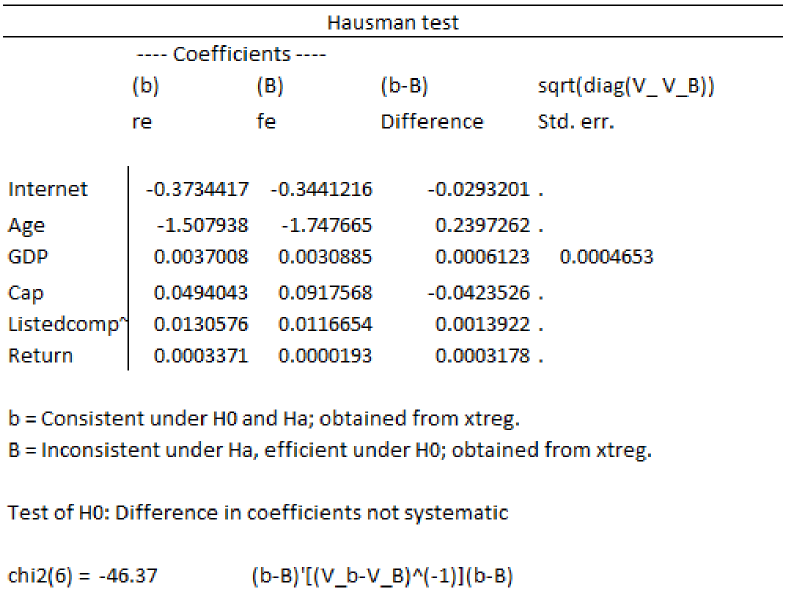
Source : Stata based on our database

6.2.2.1.2 Fixed effects

Coming back to our Hausman test, the following table sumps up our findings. Since the p-value is less than the conventional significance level of 0.05, we reject the null hypothesis that the difference in coefficients between the fixed effects and random effects models is not systematic. This suggests that the coefficients differ between the two models, indicating that the random effects model may be biased. Therefore, based on the Hausman test results, the fixed effects model appears to be more appropriate than the random effects model.

It is noteworthy that we adjust the standard errors of estimates using the White estimator, which is robust to heteroscedasticity and error term autocorrelation. Specifically, the White tool has been tailored to the panel data context by Arellano (1987), who applied it to a fixed effects model.

Table 11 : Hausman test for the Home Bias



Hausman test

	---- Coefficients ----			
	(b)	(B)	(b-B)	sqrt(diag(V_ V_B))
	re	fe	Difference	Std. err.
Internet	-0.3734417	-0.3441216	-0.0293201	.
Age	-1.507938	-1.747665	0.2397262	.
GDP	0.0037008	0.0030885	0.0006123	0.0004653
Cap	0.0494043	0.0917568	-0.0423526	.
Listedcomp~	0.0130576	0.0116654	0.0013922	.
Return	0.0003371	0.0000193	0.0003178	.

b = Consistent under H0 and Ha; obtained from xtreg.
B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

chi2(6) = -46.37 (b-B)'[(V_b-V_B)^(-1)](b-B)

Source : State based on our database

Results of this model will be delineated in the next chapter allowing us to verify our hypothesis.

6.2.3 Foreign Bias model

This model employs identical assumptions and independent variables as the Home Bias model, but it is executed based on theoretical groupings delineated by the five identified linking factors.

$$FB_{it} = c + \beta_1 TAX_{it} + \beta_2 FIN_{it} + \beta_3 TECH_{it} + \beta_4 GDP_{it} + \beta_5 RTRN_{it} + \beta_6 CAP_{it} + \beta_7 COMP_{it} + \beta_8 AGE_{it} + u_{it}$$

The grouping selection criteria are the following :

DIST : Countries in the first decile of values
CULT : Countries in the last quartile of values
OFFL : Countries having an official language in common
SPOL : Countries having a spoken language in common
REL : Countries having the same dominant religion

I will further decompose the results of this regression to verify if our linking factors hypothesis were right. This model is once again based on fixed effect regression as the reasons were outline in the previous chapter' sub-section. The variables pertaining to the distance and the culture cannot be decomposed any more but the other three will be segregated and decomposed as follow :

- Official language (OFFL)
  - French : Belgium, France and Switzerland
  - German : Austria, Belgium, Germany and Switzerland
  - Hungarian : Austria and Hungary
  - Italian : Italy and Switzerland
  - Swedish : Finland and Sweden
- Spoken language (SPOL)
  - Danish : Denmark and Iceland
  - English : Iceland and The United Kingdom
  - Finnish : Estonia, Finland, Iceland, Norway and Sweden
  - German : Austria, Belgium, Denmark, Germany, Hungary, Iceland, Romania and Switzerland
  - Hungarian : Austria, Hungary, Romania and Slovak Republic
  - Norwegian : Iceland and Norway
  - Swedish : Finland, Iceland and Sweden
- Religion (REL)
  - Christianity : Austria, Belgium, Czech Republic, France, Germany, Hungary, Italy, Latvia, The Netherlands, Poland, Portugal, Slovak Republic and Spain
  - Protestantism : Denmark, Estonia, Finland, Iceland, Norway, Sweden, Switzerland and The United Kingdom
  - Orthodoxy : Greece and Romania

6.3 Principal component analysis

Our second set of quantitative studies comprises multiple principal component analyses of our sample. These analyses serve two main purposes: firstly, to supplement the statistical inference of the regressions conducted to verify hypotheses, and secondly, to examine disparities related to domestic bias across geographical areas, levels of economic development, and the ultimate level of bias.

PCA is a fundamental statistical technique widely employed for dimensionality reduction and data exploration across various fields. Initially introduced by Pearson in 1901, PCA aims to condense the information contained in a high-dimensional data set into a smaller set of orthogonal variables called principal components (Jolliffe, 1986).

The utility of PCA lies in its ability to transform a complex data set into a lower-dimensional space while retaining as much of the original variability as possible. This transformation is achieved by projecting the data onto a new set of axes defined by the principal components, where the first principal component captures the maximum variance in the data, followed by subsequent components in descending order of variance (Hotelling, 1933). In essence, one can envision that the software performing principal component analysis will identify a line through the eight-dimensional graph that best corresponds to the cluster of data points. This line is the one that maximizes the variance of the points' projections onto itself, thereby retaining as much information as possible from the data, including their variance.

The methodology of PCA involves several key steps. First, the data is standardized to have a mean of zero and a standard deviation of one to ensure that all variables contribute equally to the analysis. Then, the covariance matrix of the standardized data is computed to quantify the relationships between variables. The eigenvalue decomposition of the covariance matrix yields the eigenvalues and corresponding eigenvectors, which represent the variance and direction of the principal components, respectively (Jolliffe, 1986).

Selection of principal components is based on the magnitude of the eigenvalues, with larger eigenvalues indicating greater variability in the data. Typically, only the first few principal components, accounting for a significant proportion of the total variance, are retained for analysis, while the rest are discarded. This allows for dimensionality reduction without substantial loss of information (Abdi and Williams, 2010).

Despite its widespread application, PCA has certain limitations that must be considered. Firstly, PCA assumes linear relationships between variables, which may not hold true in all cases. Secondly, the interpretability of principal components may be challenging, particularly when dealing with a large number of variables. Additionally, PCA is sensitive to outliers, which can disproportionately influence the resulting principal components (Jolliffe, 1986).

This chapter marks the conclusion of detailing our research objectives, sample characteristics, hypotheses, and their quantitative analyses methods. We have thoroughly explored the theoretical foundations and their practical implications within our sample, ensuring that our analytical results reflect reality and are relevant to our research context. In the next chapter, we will now present the findings and delve into their interpretations.

7 Empirical results

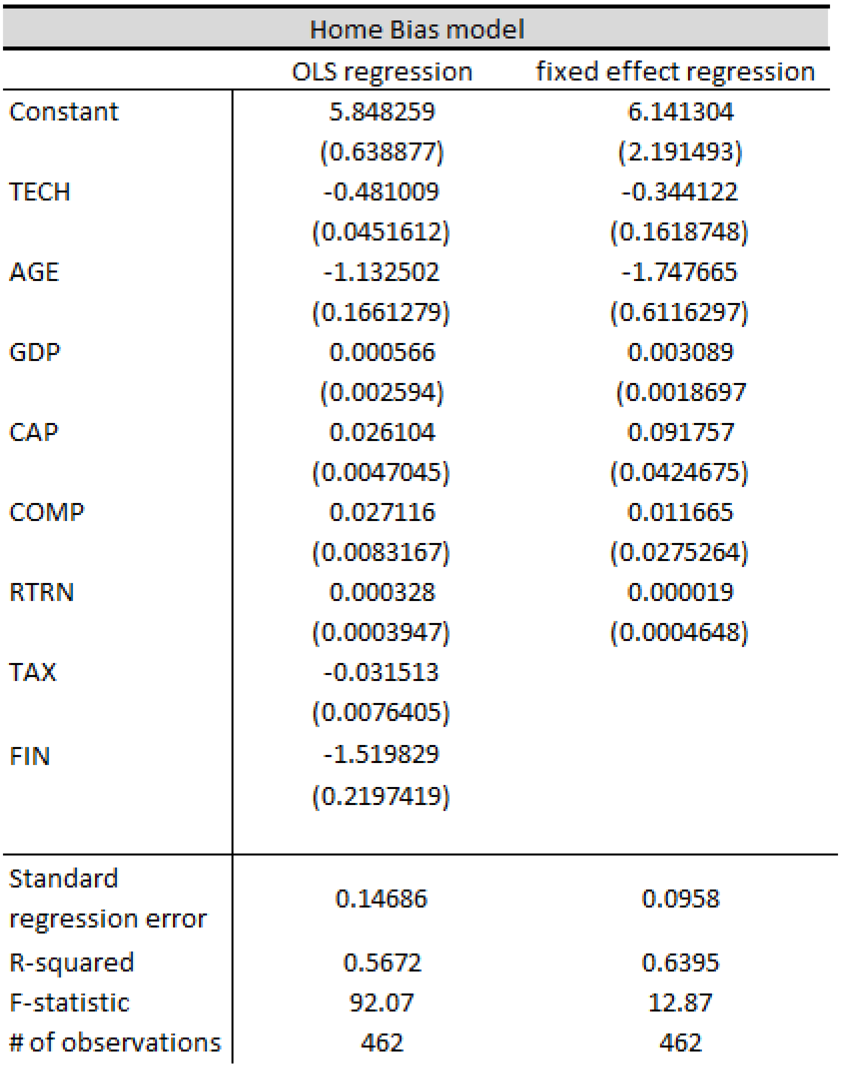
This chapter presents the results of our regression models for Home and Foreign Biases, offering insights into the validation of our hypotheses and the potential linking variables. Following this, we will present the results of the principal component analysis, which will provide additional insights and enhance the statistical inference of our regressions.

7.1 Models validity

7.1.1 Home Bias model

The table below displays the outcomes of the panel regression employing fixed effects, juxtaposed with a comparison against OLS results, thereby elucidating the enhancement derived from our model selection. It is worth noting that both the literacy and tax ("FIN" and "TAX") variables cannot be assessed from the fixed effect model, as they remain constant over time.

Table 9 : Home Bias panel regression model results



	Home Bias model	
	OLS regression	fixed effect regression
Constant	5.848259	6.141304
	(0.638877)	(2.191493)
TECH	-0.481009	-0.344122
	(0.0451612)	(0.1618748)
AGE	-1.132502	-1.747665
	(0.1661279)	(0.6116297)
GDP	0.000566	0.003089
	(0.002594)	(0.0018697
CAP	0.026104	0.091757
	(0.0047045)	(0.0424675)
COMP	0.027116	0.011665
	(0.0083167)	(0.0275264)
RTRN	0.000328	0.000019
	(0.0003947)	(0.0004648)
TAX	-0.031513	
	(0.0076405)	
FIN	-1.519829	
	(0.2197419)	
Standard regression error	0.14686	0.0958
R-squared	0.5672	0.6395
F-statistic	92.07	12.87
# of observations	462	462

Source : Stata based on our database

The fixed-effects regression model demonstrates an R^2 value of approximately 64%, indicating that it explains a substantial portion of the variability in the dependent variable. This suggests a moderately strong association between the independent variables and the Home Bias phenomenon. Conversely, the R^2 value for the ordinary least squares regression model is slightly lower at 56.8%, indicating a somewhat weaker relationship between the variables, despite incorporating two additional explanatory variables. Both models exhibit statistical significance, as evidenced by high F-statistics and low p-values (<0.000), indicating that the models effectively account for the variance in the dependent variable even at a significance level of 1%. However, a less stringent significance threshold of 5% is applied to assess the statistical significance of individual coefficients in each regression.

The superior R^2 value and lower standard regression error of the fixed-effects model suggest a better fit compared to the OLS model. The standard error of the regression with fixed effect estimation is 9.6%, notably lower than the 14.7% observed with OLS. While this level of error is not exceptionally low, it is typical for macroeconomic analyses. Consequently, we consider our fixed-effects model sufficiently precise and will proceed with our analysis based on its outcomes.

7.1.2 Foreign Bias Model

The tables 13 – 16 summarize information for the Foreign Bias model across various regressions, all of which (for table 13 only) exhibit p-values below the significance threshold, indicating their statistical significance.

Starting with the OLS model on the table 13 for comparison, the R^2 value stands at 0.0421, indicating that approximately 4.21% of the variability in the deviation of investment allocation is accounted for by the independent variables. Meanwhile, the F-statistic yields a significant result indicating that the overall regression model is statistically significant.

Transitioning to the fixed effects model on the whole sample, the R^2 value doubles to 0.0856. This indicates that incorporating country-specific effects enhances the model's explanatory power, accounting for approximately 8.56% of the deviation in investment allocation. Additionally, the significant F-statistic for the fixed effects model reinforces its statistical significance.

Comparing standard errors between the two models reveals a notably lower standard error of the regression in the fixed effects model compared to the OLS model. This suggests a better fit of the fixed effects model to the data and higher precision in predicting the dependent variable.

Further analysis involves comparing results from the fixed effects model on the whole sample to results obtained by selecting only countries' combinations meeting specific criteria. The number of observations varies widely depending on the selected criteria, ranging from a minimum of 528 to a maximum of 6108. Interestingly, all regressions on the selected values yield higher R^2 values than the whole sample, except for the spoken cluster, which returns a lower R^2. With this exception, all other regressions show higher explanatory power while maintaining a relatively low standard error, with a maximum of 1.21%.

The criteria pertaining to languages and religions were run on the total number of individuals meeting these criteria across all sub-sections without distinction. Subsequently, these criteria will be disaggregated to conduct regressions on their respective sub-criteria as specified in section 6.2.3.

Table 13 : Foreign Bias regression model results

White-Arellano standard errors clustered by country are in brakets.

Foreign Bias model							
	OLS regression	Fixed effects regression					
	Whole sample	Whole Sample	Distance	Culture	Official	Spoken	Religion
Constant	-0.040328	-0.065571	-0.113275	-0.149361	-0.027040	0.093716	-0.022557
	(0.0130419)	(0.0380187)	(0.3268357)	(0.0621752)	(0.2247012)	(0.1646693)	(0.0804542)
TECH	0.010549	0.008077	0.017764	0.007711	0.021591	0.020705	0.014586
	(0.0009372)	(0.0023799)	(0.0148428)	(0.0042373)	(0.0134179)	(0.0093571)	(0.004844)
AGE	0.004748	0.019818	0.050740	0.044744	0.016462	-0.017408	0.012426
	(0.0033108)	(0.010009)	(0.0850386)	(0.0172562)	(0.0676565)	(0.0444124)	(0.0206593)
GDP	-0.000096	-0.000006	0.000047	0.000017	-0.000010	-0.000108	-0.000052
	(0.0000475)	(0.0000224)	(0.0001137)	(0.0000492)	0.000100	(0.0000746)	(0.0000456)
CAP	-0.000309	-0.001430	-0.006490	-0.002030	-0.003357	-0.003562	-0.002873
	(0.0000851)	(0.0004258	(0.0022424)	(0.0008264)	(0.0032445)	(0.0012258)	(0.0009962)
COMP	-0.000947	-0.000149	-0.001797	-0.000222	0.000213	-0.000844	-0.000135
	(0.0001608)	(0.000209)	(0.0017471)	(0.0002863)	(0.0005316)	(0.0009692)	(0.0004554)
RTRN	-0.000015	-0.000018	0.000028	-0.000020	-0.000023	-0.000026	-0.000021
	(0.00000965)	(0.00000752)	(0.000036)	(0.0000114)	(0.2247012)	(0.000324)	(0.0000151)
TAX	0.000911						
	(0.0001478)						
FIN	0.021260						
	(0.0040986)						
Standard regression error	0.1421	0.0070	0.0121	0.0074	0.0081	0.0105	0.0090
R-squared	0.0421	0.0856	0.1175	0.1488	0.141	0.0759	0.0895
F-statistic	58.89	21.29	5.62	9.59	2.7	3.68	11.87
# of observations	10586	10586	1103	2582	528	1809	4478

Source : Stata based on our database

Table 14 : Foreign Bias – Official Language regression model results

White-Arellano standard errors clustered by country are in brakets.

Foreign Bias model					
Fixed effects regression - Official language					
	French	German	Hungarian	Italian	Swedish
Constant	-0.145714	-0.258528	0.842255	0.001432	2.231453
	(0.2928112)	(0.3031175)	(0.2377666)	(0.2780868)	(1.210736)
TECH	0.002761	0.013018	0.087116	0.014717	0.130027
	(0.0152753)	(0.0188374)	(0.0021265)	(0.0126423)	(0.0733498)
AGE	0.016942	0.094105	-0.207544	-0.030248	-0.611349
	(0.0861401)	(0.0997816)	(0.0625254)	(0.0600944)	(0.3118796)
GDP	0.000061	-0.000353	0.000106	0.000145	0.000021
	(0.0000982)	(0.0001575)	(0.0002527)	(0.0000736)	(0.0001461)
CAP	0.005892	-0.007254	-0.011296	0.006674	-0.002858
	(0.0027344)	(0.0066094)	(0.0004456)	(0.0043223)	(0.0090506)
COMP	0.000622	0.000050	0.002229	-0.000601	-0.000227
	(0.0007606	(0.0008247)	(0.000638)	(0.0008663)	(0.0003872)
RTRN	-0.000055	-0.000020	0.000066	-0.000073	-0.000094
	(0.0000196)	(0.0000424)	(0.0000249)	(0.000461)	(0.000907)
Standard regression error	0.0057	0.0090	0.0056	0.0028	0.0088
R-squared	0.1671	0.1734	0.7266	0.4669	0.4061
F-statistic	-	1.95	-	-	-
# of observations	132	264	44	44	44

Source : Stata based on our database

Table 15 : Foreign Bias – Spoken Language regression model results

White-Arellano standard errors clustered by country are in brakets.

Foreign Bias model							
Fixed effects regression - Spoken language							
	Danish	English	Finnish	German	Hungarian	Norwegian	Swedish
Constant	0.708180	1.128035	0.465748	0.020581	0.042305	0.987730	1.068581
	(0.06612145)	(0.1781287)	(0.28462201)	(0.0858656)	(0.5289151)	(0.3693105)	(0.4078324)
TECH	0.045324	0.053095	0.057112	0.017458	0.013000	0.060846	0.070590
	(0.0378531)	(0.0047185)	(0.0180789	(0.0073735)	(0.0312272)	(0.0192751)	(0.0301638)
AGE	-0.207628	-0.325498	-0.131399	-0.002210	-0.005899	-0.284893	-0.310392
	(0.1915018)	('0.063498)	(0.0812395)	(0.0244544)	(0.1455677)	(0.1206065)	(0.1180861)
GDP	-0.000443	-0.000469	0.000198	-0.000005	-0.000117	-0.001500	0.000041
	(0.000206)	(0.0017505)	(0.0001397)	(0.0000601)	(0.000788)	(0.000013)	(0.0001438)
CAP	0.000803	-0.012331	-0.002127	-0.002280	-0.001342	0.000977	0.001663
	(0.000344)	(0.0049494)	(0.0017474)	('0.0008573)	(0.001981)	(0.0048579)	(0.0018287)
COMP	0.000308	-0.000385	0.000497	-0.000006	-0.004229	-0.002553	0.000169
	(0.0003992)	(0.0017629)	(0.0003565)	(0.0002293)	(0.0047561)	(0.0000167)	(0.0003389)
RTRN	-0.000177	-0.000643	-0.000104	-0.000027	0.000719	-0.000318	-0.000155
	('0.0000769)	(0.0001109)	(0.0000476)	('0.0000167)	(0.0000304)	(0.0003148	(0.0000805)
Standard regression error	0.0059	0.0185	0.0091	0.0062	0.0187	0.0119	0.0074
R-squared	0.5673	0.6809	0.1805	0.1568	0.0458	0.5579	0.3215
F-statistic	-	-	1.79	2.62	1.44	-	-
# of observations	42	40	422	1217	264	42	126

Source : Stata based on our database

Table 16 : Foreign Bias – Religion regression model results

White-Arellano standard errors clustered by country are in brakets.

Foreign Bias model				
Fixed effects regression - Religion				
	No common	Christianity	Protestantism	Orthodoxy
Constant	-0.096248	-0.058829	0.074341	0.025727
	(0.030033)	(0.0939219)	(0.1838203)	(0.0744574)
TECH	0.003606	0.011288	0.029454	0.003938
	(0.0020384)	(0.0056493)	(0.0102085)	(0.0027539)
AGE	0.026262	0.020583	-0.016723	-0.009291
	(0.0080999)	(0.0238811)	(0.052539)	(0.0222056)
GDP	0.000013	-0.000016	-0.000054	-0.000180
	(0.0000216)	(0.0000529)	(0.00000752)	(0.0001653)
CAP	-0.000781	-0.002203	-0.003060	0.000547
	(0.0003804)	(0.0010586)	(0.0017419)	(0.0008505)
COMP	-0.000122	-0.000067	0.000062	0.000597
	(0.0001376)	(0.0006030)	(0.0002243)	(0.0009578)
RTRN	-0.000013	0.000004	-0.000098	-0.000037
	(0.00000577)	(0.0000145)	(0.0000362)	(0.00000804)
Standard regression error	0.0049	0.0089	0.0092	0.0018
R-squared	0.1076	0.0856	0.1543	0.4093
F-statistic	11.04	9.8	2.99	-
# of observations	6108	3244	1190	44

Source : Stata based on our database

7.2 Hypothesis verification – Home Bias

F1 – TAX : Our initial hypothesis posits that nations burdened with high taxes, measured through a composite of dividend and capital gains taxes, prompt investors to seek more lucrative investment opportunities elsewhere. Conversely, tax havens are expected to attract capital inflows, encouraging domestic investors to retain their investments locally and limiting portfolio diversification. It is important to note that the variable for this hypothesis features only a single measurement, at best allowing for a linear regression measurement through OLS regression. As anticipated, the coefficient is negative, aligning with our predictions that high tax burdens deter investments, and the associated p-value underscores the significance of the relationship. Nevertheless, the relatively low R^2 value suggests that merely 2.1% of the variance in Home Bias can be attributed to the TAX hypothesis.

F2 – FIN : The financial literacy of investors is anticipated to exert a direct influence on Home Bias, with higher levels of financial knowledge, such as the basic diversification principle of Markowitz, serving as a diversifier and thereby reducing this bias. It is expected that countries with lower levels of financial literacy will exhibit higher levels of bias. Despite financial literacy being a one-time measurement such as the TAX hypothesis, the linear regression (OLS) yields a significantly higher R^2 value, with literacy explaining nearly 19% of the observed bias. As anticipated, the coefficient is negative, signifying a reduction in bias with increasing literacy, and the relationship is statistically significant even if this model is not the best to account for individual-specific elements and do not present the best fit.

F3 – TECH : The third variable is investing the impact of financial information asymmetry as impacting the bias. It posits that the higher the internet usage and mastery, which induce reduced asymmetry, the lower the bias. The fixed-effects regression analysis reveals a statistically highly significant negative association between internet usage and bias. Overall, the regression model accounts for approximately 38.10% of the variability in bias. These findings underscore the substantial influence of internet usage on Home Bias reduction and emphasize its importance in shaping investment decisions across diverse geographical contexts. Enhancements in information technology play a pivotal role in mitigating information asymmetry, thereby contributing significantly to reducing bias.

F4 – GDP : In this investigation, we assert that the economic growth of a country will serve as catalyst for investment flows. A citizen in those countries would thus see less interest in investing elsewhere. The findings reveal a statistically significant positive association between GDP and Home Bias even if the coefficient value is low. It allows us to validate the hypothesis stating that the economic growth encourage Home Bias even if it is on a very limited scope ($R^2 = 4.6\%$).

F5 – RTRN : This hypothesis parallels the theory of economic growth, positing that nations exhibiting recent or persistent higher stock market returns will attract greater capital inflows, thereby dissuading domestic investors from diversifying away from their home country, particularly when returns are elevated. Despite the R^2 metrics indicating mere explanatory power, the analysis reveals a positive coefficient and a statistically significant relationship when examined on an individual basis, thus validating our hypothesis.

F6 – CAP : As anticipated in our initial expectations, the coefficient exhibits a positive sign, indicating a positive relationship between the size of the stock market and Home Bias. It is noteworthy that although the coefficient is positive, its magnitude is exceedingly small and approaches zero. Similarly, the R-squared value is also minimal, suggesting limited explanatory power of the model. However, despite these modest metrics, the relationship is deemed statistically significant, with a p-value inferior to the 5% significance threshold. While having mere explanatory power, the result allows to validate the hypothesis confirming a positive relation between market size and Home Bias.

F7 – COMP : The use of the number of listed companies per 1.000.000 inhabitants on each stock market serves as an alternative metric for market size and operates under the same rationale as market capitalization. The premise is that domestic investors, with a plethora of investment opportunities within their own country, are less inclined to seek investments elsewhere. This metric analysis also reveals a statistically significant relationship with a positive coefficient as anticipated. However, it is important to note that the overall R-squared remains very low, indicating minimal impact on Home Bias from this metric alone which is consistent with our findings regarding market size.

F8 – AGE : Contrary to prior expectations, the age variable demonstrates a negative and statistically significant coefficient under both models, implying a negative association between investors' age and Home Bias. This outcome aligns with another notion that can be considered as intuitive which states that individuals tend to become more financially literate and rational as they age, leading to a reduction in bias. Additionally, the model exhibits a noteworthy R-squared value of 13%, indicating a significant explanatory power regarding Home Bias. These results underscore the importance of considering investors' age as a determinant in understanding and addressing biases in investment decision-making. While being the less studied explanation, results are quite outstanding proving a real link between the age of investors and the domestic bias.

The eight regressions yielded diverse results but confirmed at least eight out of our nine stated hypotheses. However, due to the lack of statistical significance, the propensity to save variable was excluded, preventing us from drawing inferences or validating our hypothesis. In summary, four of the eight variables are inversely related to Home Bias, indicating a reduction in Home Bias with an increase in tax burden, financial literacy, technology mastery, and investor age. Conversely, economic growth, stock market returns, size, and investment opportunities act as boosters of the bias, hindering its further decline. An interesting point to highlight is that the three specific regressions with the highest explanatory power were all associated with factors targeting the reduction of Home Bias over time, which is consistent with the declining trend. These factors include addressing information asymmetry, enhancing financial literacy, and considering investor age.

7.3 Linking factors verification – Foreign Bias

L1 – DIST : Narrowing down our sample to 1103 individuals, following the first decile rule on the distance criteria, leads to a notable enhancement in the explanatory capacity of our regression model compared to the whole sample regression. Specifically, the R² increases from 8.56% to 11.75%. Though modest, it underscores the significance of our hypothesis, suggesting that physical proximity plays a role in incentivizing overweighting. The results are in accordance with what is found in the literature.

L2 – CULT : After initially evaluating the last decile as a criterion to keep consistency with the DIST variable, I subsequently tested the last quartile and found that it resulted in a higher R², indicating greater explanatory power and improved model fit. Continuing to expand the sample size in order to identify the inflection point where the R² begins to decrease, my analysis revealed that utilizing the last quartile as the criterion provides the optimal outcome. This heightened R² serves further validating our hypothesis that greater cultural similarities contribute to deviations from optimal allocation.

L3 – OFFL : When considering a combination of countries sharing a common language (Table 13), the results once again demonstrate an improvement in the R², increasing the explanatory power to 0.141. Notably, this regression comprises the lowest number of observations, with only 528 individuals included. This outcome reinforces our initial hypothesis that the shared language among countries introduces bias in investors' behavior.

An intriguing question arises: "Is the effect consistent across different languages?" Table 14 presents the results after segregating the official language into five categories: French, German, Hungarian, Italian, and Swedish. The number of observations varies from 44 (representing two countries) to 264 (representing four countries). The variability in explanatory power is substantial, with the French language, consisting of three countries, exhibiting the lowest R^2 of 0.1671, while the Hungarian language boasts a significantly higher R^2 of 0.7266, suggesting a strong correlation between Austria and Hungary.

However, the absence of reported F-statistics and p-values hinders our ability to determine the overall statistical significance of these regressions. Consequently, we cannot ascertain the significance of the relationship between the independent variables and the dependent variable in these analyses. Furthermore, the frequent changes in coefficient signs across regressions make it challenging to determine the correct signs for the independent variables with certainty. These observations also apply to the sub-regressions for the variables "SPOL" and "REL".

L4 – SPOL : While the regression analysis of the overall official language variable led to an increase in the R^2, the spoken language did not behave alike, experiencing a decrease to 7.59% from the whole sample R^2. At first glance, this discrepancy appears to hinder our ability to validate our hypothesis. However, the wide variability in spoken languages impedes us from drawing definitive conclusions. Therefore, it might be more informative to examine the results of sub-regressions focusing on seven specific languages: Danish, English, Finnish, German, Hungarian, Norwegian, and Swedish.

Once again, the number of observations varies widely, ranging from 40 (representing two countries) for English to 1217 (representing eight countries) for German. The explanatory power of these seven regressions also varies significantly, ranging from 4.58% to 68%. Interestingly, Hungarian, this time, has the lowest R^2, suggesting that while Austria and Hungary may exhibit a propensity to invest disproportionately in each other, the inclusion of Romania and the Slovak Republic in the mix indicates that speaking Hungarian alone is not sufficient to provoke allocation overweighting.

Conversely, English, Danish, and Norwegian suggest the higher correlations between the countries within their respective compositions. Another noteworthy observation concerns the German language. Thanks to a sufficient number of observations for the regression to yield an F-statistic and p-value, it confirms that the relationship between German-speaking countries is statistically significant, with an R^2 of 15.68%. It thus certifies us that sharing a language such as German makes overweighting in those sharing-language countries possible and definitively validate our initial hypothesis.

L5 – REL : While examining the impact of sharing a dominant religion does not significantly enhance the explanatory power at the aggregate level (considering all religions indiscriminately), a closer investigation through sub-regressions reveals more nuanced findings.

Sharing Christianity as a dominant religion does not contribute to increased explanatory power compared to the regression conducted on the entire sample. Despite Christianity being the most prevalent religion in our dataset, with thirteen out of the twenty-three countries adhering to it, the regression yields an identical R^2 of 0.0856. This suggests that factors such as the wide dispersion of countries within this sub-criteria or variations in religiosity levels within the dominant religion may account for this lack of association.

Conversely, Protestantism and Orthodoxy exhibit higher R^2 values of 0.1543 and 0.4093, respectively. These findings lend support to the hypothesis that religion may indeed influence the deviation from the CAPM rule in investment allocation. Although the statistical significance of Orthodoxy cannot be conclusively established, Protestantism is confirmed with a p-value below the 5% threshold, indicating its potential impact. This underscores the importance of considering specific religious denominations in understanding investment behavior and allocation decisions.

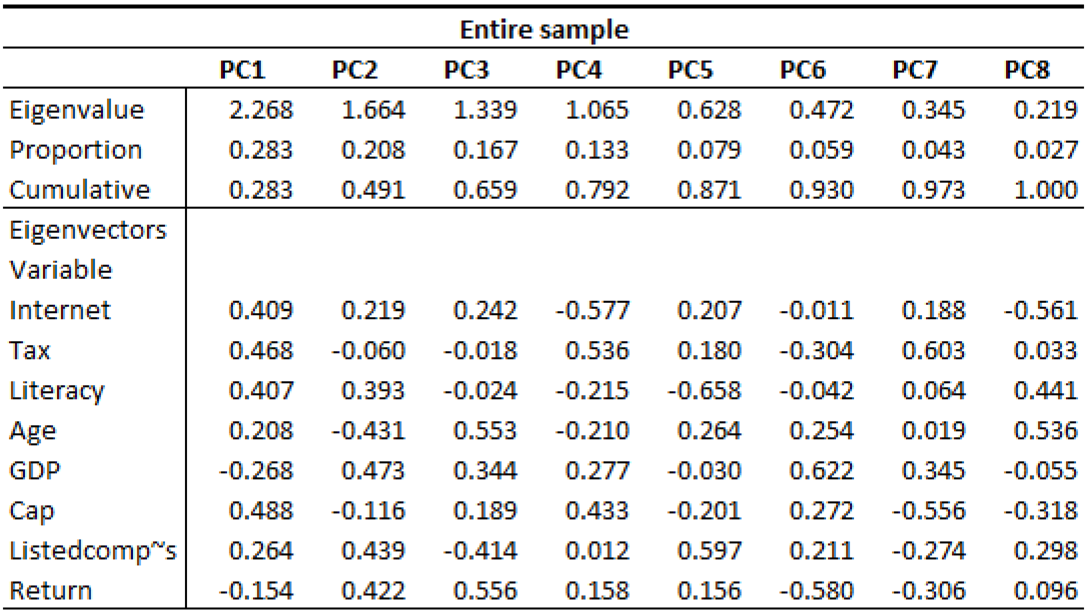
7.4 *Principal component analysis*

Entire sample analysis

In our PCA, we focus only on the principal components that present an eigenvalue superior to 1 according to Kaiser criteria. In our case, four of them present a superior eigenvalue as evidenced in table 17. Combined together, those components explain 79% of the total inertia (inertia is the right term to describe variance in a PCA). The second criteria to be met is the Coude criteria : it means that on the figure 27 we need to consider only component before the eigenvalues form an “elbow” on the scree plot. The change in slope observed on the scree plot is commonly referred to as the "elbow point." This is the point where the plot starts to flatten out after a steep decline, indicating a diminishing return in explaining variance with each additional component. This allows us to validate our first assumption that we need to focus on the first four principal components.

Table 17 : Entire sample’s principal component analysis

The analysis was conducted with all independent variables for the 23 countries on 22 years.



	Entire sample							
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	2.268	1.664	1.339	1.065	0.628	0.472	0.345	0.219
Proportion	0.283	0.208	0.167	0.133	0.079	0.059	0.043	0.027
Cumulative	0.283	0.491	0.659	0.792	0.871	0.930	0.973	1.000
Eigenvectors								
Variable								
Internet	0.409	0.219	0.242	-0.577	0.207	-0.011	0.188	-0.561
Tax	0.468	-0.060	-0.018	0.536	0.180	-0.304	0.603	0.033
Literacy	0.407	0.393	-0.024	-0.215	-0.658	-0.042	0.064	0.441
Age	0.208	-0.431	0.553	-0.210	0.264	0.254	0.019	0.536
GDP	-0.268	0.473	0.344	0.277	-0.030	0.622	0.345	-0.055
Cap	0.488	-0.116	0.189	0.433	-0.201	0.272	-0.556	-0.318
Listedcomp~s	0.264	0.439	-0.414	0.012	0.597	0.211	-0.274	0.298
Return	-0.154	0.422	0.556	0.158	0.156	-0.580	-0.306	0.096

Source : Stata based on our database

The first principal component is mostly positively influenced by market size measured as the market capitalization, tax burden, internet usage and literacy level. This means that these variables account for a larger portion of the variability observed in the eight-dimensional scatter plot compared to the remaining variables. As we move along the axis of principal components, these specific variables contribute more significantly to the overall inertia observed in the dataset, capturing essential aspects of the data's structure.

Analyzing the distribution of data points across different geographical regions on a score plot (figure 30) sheds further light on the relationships between variables. Notably, northern countries align closely with the aforementioned influential variables, albeit with some exceptions such as Latvia and Estonia, which exhibit behaviors more akin to eastern countries. Despite this deviation, we maintain consistency in categorization as dictated by the United Nations while acknowledging these outliers. Western countries exhibit similar trends, although with lesser intensity, and show potential for leveraging factors like age and market capitalization.

In contrast, southern countries lack distinct patterns while Eastern countries, conversely, demonstrate a divergence from the influential variables driving the first component, suggesting unique economic dynamics and a negative contribution. Additionally, a plausible positive correlation with economic growth emerges, aligning positively with the second component. Eastern countries tend to exhibit faster growth rate compared to other regions. Economic development measured notably by market size, technology mastery and higher financial literacy serves as a significant factor in the bias reduction. The more advanced the economy, the less biased the country tends to be in a general case (e.g., France).

Inside the second component, economic growth, financial literacy, stock market return and the number of listed companies have a positive and heavy weight while investor age exert a negative influence. It accounts for nearly 21% of the inertia. Northern countries once again are positively related to those while on the contrary southern countries are negatively influenced by the age variable.

Further decomposition of components reveals additional insights, with the third component positively influenced by investor age and stock market return, while the fourth component shows negative associations with internet usage and positive correlations with the tax burden. Together these component account for 30% of the total inertia.

In summary, our PCA analysis confirms the importance of literacy and technology mastery, signs of economic development, in addressing information asymmetry, providing valuable insights into the factors shaping investment behaviors across different regions.

Geographical decomposition

To deepen our understanding, we partitioned our dataset into four distinct geographical regions to examine any disparities or consistencies across them. Figures 33 to 48 display the outcomes of these analyses. We utilized consistent criteria, retaining only components with eigenvalues exceeding 1 and scrutinizing the scree plot for alterations in slopes. The number of components ranged from three to four, while the percentage of explained variance ranged from 77% to 90%, contingent upon the region.

In the Northern region, the contribution plot closely resembled that of the entire sample. The primary component was again positively influenced by literacy, tax, internet usage, and market size. Examination of the second component revealed significant weights on two variables, albeit in opposing directions: the number of listed companies positively influenced the component, while age had a negative impact. The emergence of GDP and market return in the third component brings attention back to these variables, which were previously overlooked but were found to have a positive contribution to Home Bias in our regression analyses. Removing Estonia and Latvia, which exhibited behaviors akin to Eastern countries, revealed a distinct group aligning precisely with the four crucial elements of the first component. Additionally, Iceland appeared as the most out of line, notably influenced by its number of listed companies per million inhabitants. This allows us to further validate our hypothesis regarding the importance of financial literacy, information asymmetry, tax burden and market size in shaping the bias at least for northern countries.

Western Europe's analysis was underpinned by four components, accounting for 27%, 24%, 19%, and 12% of the total inertia, respectively. The score plot demonstrated interesting shape, each country forming a horizontal line. This pattern suggests that the differences in those countries only stem from the influence of the number of listed companies, which have positive influence on the second component while tax have contrarian influence. This is exemplified by Switzerland and France, respectively representing these opposing trends.

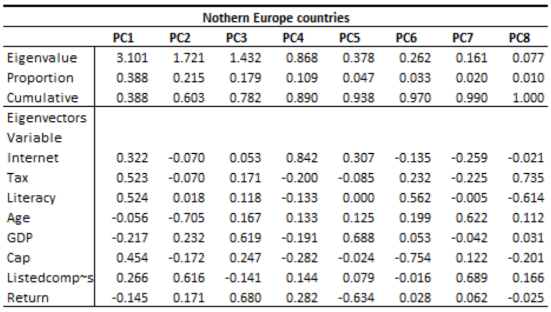
In Southern countries, the analysis explained 90% of the inertia across four components. However, the score plot, depicting four countries, failed to reveal distinct patterns for individual countries or the region as a whole, rendering conclusions elusive for this particular region. Italy stands out as the sole country demonstrating a tangible positive correlation with the first principal component, driven primarily by its aging population, as evidenced by the significant weight of the age variable in this component. This further support our novel hypothesis suggesting negative correlation between investor age and Home Bias. Indeed, Italy shows the oldest population of the dataset and a shrinking bias measure. In contrast, Spain contributes positively to the second principal component, while Portugal is negatively impacted due to its lower internet usage and aging population.

The analysis of Eastern countries revealed a distinct pattern on the biplot, characterized by a vertical line. This suggests a uniform influence of the second component across these countries. Specifically, market return and GDP displayed opposing directions to age and internet usage, indicating established negative relationships with Home Bias compared to the first two variables.

Furthermore, the other variables influenced by the first component highlight differences between countries. Notably, Poland stands out from the rest due to its significantly larger market size. As the sole representative of a positive influence of the first component, Poland's profile validates the hypothesis that a higher market size hinders domestic investors from investing elsewhere for this particular region.

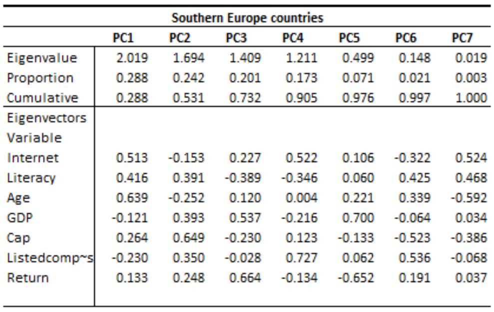
Table 18 : Principal component analysis by geographical zone

The analyses are conducted for the period 2001-2022. The northern countries comprise Denmark, Estonia, Finland, Iceland, Latvia, Norway, Sweden and United Kingdom. The western countries are composed of Austria, Belgium, France, Germany, The Netherlands and Switzerland. The south of Europe is represented by Greece, Italy, Portugal and Spain while the eastern countries comprise Czechia, Hungary, Poland, Romania and Slovak Republic.



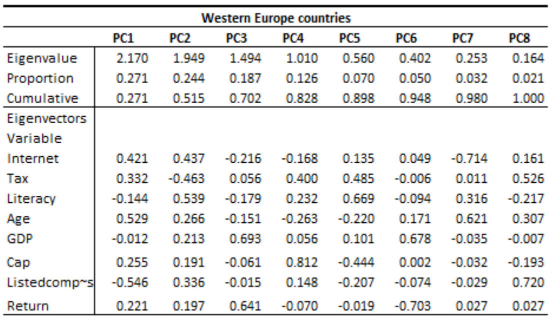
Nothern Europe countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	3.101	1.721	1.432	0.868	0.378	0.262	0.161	0.077
Proportion	0.388	0.215	0.179	0.109	0.047	0.033	0.020	0.010
Cumulative	0.388	0.603	0.782	0.890	0.938	0.970	0.990	1.000
Eigenvectors								
Variable								
Internet	0.322	-0.070	0.053	0.842	0.307	-0.135	-0.259	-0.021
Tax	0.523	-0.070	0.171	-0.200	-0.085	0.232	-0.225	0.735
Literacy	0.524	0.018	0.118	-0.133	0.000	0.562	-0.005	-0.614
Age	-0.056	-0.705	0.167	0.133	0.125	0.199	0.622	0.112
GDP	-0.217	0.232	0.619	-0.191	0.688	0.053	-0.042	0.031
Cap	0.454	-0.172	0.247	-0.282	-0.024	-0.754	0.122	-0.201
Listedcomp~s	0.266	0.616	-0.141	0.144	0.079	-0.016	0.689	0.166
Return	-0.145	0.171	0.680	0.282	-0.634	0.028	0.062	-0.025



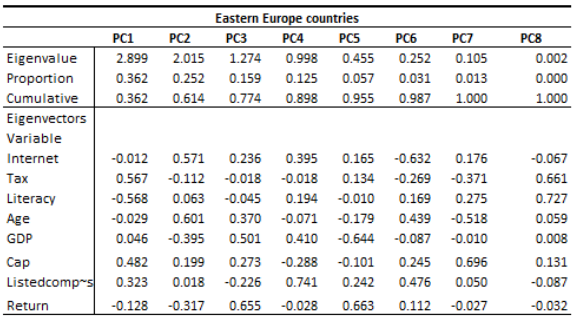
Southern Europe countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Eigenvalue	2.019	1.694	1.409	1.211	0.499	0.148	0.019
Proportion	0.288	0.242	0.201	0.173	0.071	0.021	0.003
Cumulative	0.288	0.531	0.732	0.905	0.976	0.997	1.000
Eigenvectors							
Variable							
Internet	0.513	-0.153	0.227	0.522	0.106	-0.322	0.524
Literacy	0.416	0.391	-0.389	-0.346	0.060	0.425	0.468
Age	0.639	-0.252	0.120	0.004	0.221	0.339	-0.592
GDP	-0.121	0.393	0.537	-0.216	0.700	-0.064	0.034
Cap	0.264	0.649	-0.230	0.123	-0.133	-0.523	-0.386
Listedcomp~s	-0.230	0.350	-0.028	0.727	0.062	0.536	-0.068
Return	0.133	0.248	0.664	-0.134	-0.652	0.191	0.037



Western Europe countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	2.170	1.949	1.494	1.010	0.560	0.402	0.253	0.164
Proportion	0.271	0.244	0.187	0.126	0.070	0.050	0.032	0.021
Cumulative	0.271	0.515	0.702	0.828	0.898	0.948	0.980	1.000
Eigenvectors								
Variable								
Internet	0.421	0.437	-0.216	-0.168	0.135	0.049	-0.714	0.161
Tax	0.332	-0.463	0.056	0.400	0.485	-0.006	0.011	0.526
Literacy	-0.144	0.539	-0.179	0.232	0.669	-0.094	0.316	-0.217
Age	0.529	0.266	-0.151	-0.263	-0.220	0.171	0.621	0.307
GDP	-0.012	0.213	0.693	0.056	0.101	0.678	-0.035	-0.007
Cap	0.255	0.191	-0.061	0.812	-0.444	0.002	-0.032	-0.193
Listedcomp~s	-0.546	0.336	-0.015	0.148	-0.207	-0.074	-0.029	0.720
Return	0.221	0.197	0.641	-0.070	-0.019	-0.703	0.027	0.027



Eastern Europe countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	2.899	2.015	1.274	0.998	0.455	0.252	0.105	0.002
Proportion	0.362	0.252	0.159	0.125	0.057	0.031	0.013	0.000
Cumulative	0.362	0.614	0.774	0.898	0.955	0.987	1.000	1.000
Eigenvectors								
Variable								
Internet	-0.012	0.571	0.236	0.395	0.165	-0.632	0.176	-0.067
Tax	0.567	-0.112	-0.018	-0.018	0.134	-0.269	-0.371	0.661
Literacy	-0.568	0.063	-0.045	0.194	-0.010	0.169	0.275	0.727
Age	-0.029	0.601	0.370	-0.071	-0.179	0.439	-0.518	0.059
GDP	0.046	-0.395	0.501	0.410	-0.644	-0.087	-0.010	0.008
Cap	0.482	0.199	0.273	-0.288	-0.101	0.245	0.696	0.131
Listedcomp~s	0.323	0.018	-0.226	0.741	0.242	0.476	0.050	-0.087
Return	-0.128	-0.317	0.655	-0.028	0.663	0.112	-0.027	-0.032

Source : Stata based on our database

Economic level and terminal Home Bias value decomposition

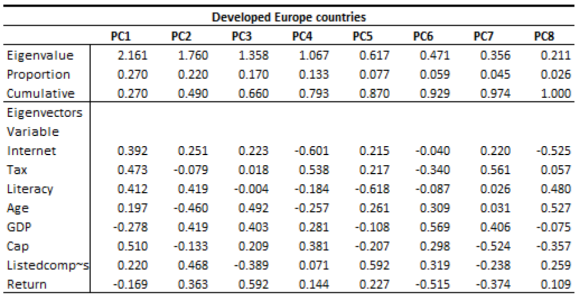
The level of economic development, while influential, is difficult to analyze in our context due to the high diversity of developed countries in our sample and the lack of precise development level measurement. However, it offers insights into the behavior of developing nations which present more unified findings. These countries exhibit patterns resembling those of eastern countries, indicative of their regional affiliations. Moreover, the first component in developing countries accounts nearly for half of the variance. Very high loadings are put on tax and literacy oppositely which differentiate Poland from Hungary. This once again validate our hypothesis regarding these factors but this time for developing countries. The one time measurement character of those two variables induce the linear shape while influential variables in the second component such as age and internet level make observations vary as they both grew through the period analyzed. Though studying the economic development was a good idea, lack of refinement prevent us from drawing real conclusion.

Moreover, examining the terminal Home Bias level provides more valuable insights, with highly biased countries displaying characteristics reminiscent of a blend of eastern and southern countries. This suggests that nations with elevated Home Bias tend to be located in those regions and to exhibit lower literacy levels and technological advancement, validating our hypotheses regarding the significance of literacy and technology in mitigating bias. Poland once again serves as a validation point for our hypothesis regarding the negative impact of literacy on bias. Conversely, Greece emerges as an outlier, displaying patterns contrary to major assumptions.

When examining countries that successfully reduced their bias, one key variable stand out as positively correlated with both first two principal components: financial literacy. Importantly, it exhibits a negative relationship with Home Bias, further confirming the validity of our hypothesis. Countries leaning towards this upper end of bias reduction include Norway, Finland, the UK, and the Netherlands.

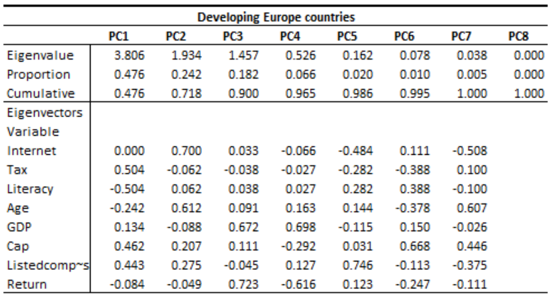
Table 19 : Principal component analysis by economic development

The analyses are conducted on a period spanning from 2001 to 2022. Developed countries are composed of Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Italy, The Netherlands, Norway, Portugal, Slovak Republic, Spain, Sweden, Switzerland and the United Kingdom while the developing countries represent Hungary, Poland and Romania



Developed Europe countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	2.161	1.760	1.358	1.067	0.617	0.471	0.356	0.211
Proportion	0.270	0.220	0.170	0.133	0.077	0.059	0.045	0.026
Cumulative	0.270	0.490	0.660	0.793	0.870	0.929	0.974	1.000
Eigenvectors								
Variable								
Internet	0.392	0.251	0.223	-0.601	0.215	-0.040	0.220	-0.525
Tax	0.473	-0.079	0.018	0.538	0.217	-0.340	0.561	0.057
Literacy	0.412	0.419	-0.004	-0.184	-0.618	-0.087	0.026	0.480
Age	0.197	-0.460	0.492	-0.257	0.261	0.309	0.031	0.527
GDP	-0.278	0.419	0.403	0.281	-0.108	0.569	0.406	-0.075
Cap	0.510	-0.133	0.209	0.381	-0.207	0.298	-0.524	-0.357
Listedcomp~s	0.220	0.468	-0.389	0.071	0.592	0.319	-0.238	0.259
Return	-0.169	0.363	0.592	0.144	0.227	-0.515	-0.374	0.109



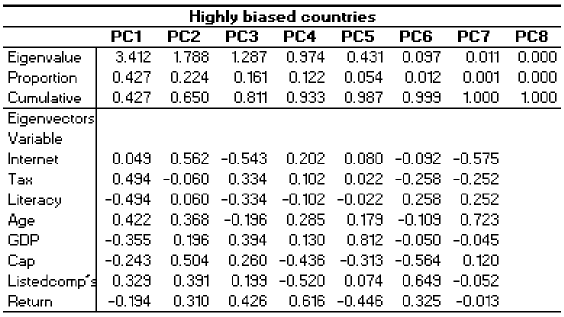
Developing Europe countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	3.806	1.934	1.457	0.526	0.162	0.078	0.038	0.000
Proportion	0.476	0.242	0.182	0.066	0.020	0.010	0.005	0.000
Cumulative	0.476	0.718	0.900	0.965	0.986	0.995	1.000	1.000
Eigenvectors								
Variable								
Internet	0.000	0.700	0.033	-0.066	-0.484	0.111	-0.508	
Tax	0.504	-0.062	-0.038	-0.027	-0.282	-0.388	0.100	
Literacy	-0.504	0.062	0.038	0.027	0.282	0.388	-0.100	
Age	-0.242	0.612	0.091	0.163	0.144	-0.378	0.607	
GDP	0.134	-0.088	0.672	0.698	-0.115	0.150	-0.026	
Cap	0.462	0.207	0.111	-0.292	0.031	0.668	0.446	
Listedcomp~s	0.443	0.275	-0.045	0.127	0.746	-0.113	-0.375	
Return	-0.084	-0.049	0.723	-0.616	0.123	-0.247	-0.111	

Source : Stata based on our database

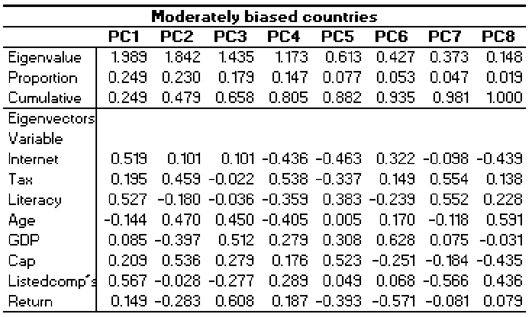
Table 20 : Principal component analysis by terminal level of 2022 Home Bias

The analyses are conducted on a period spanning from 2001 to 2022. Highly biased countries represent Greece, Poland and Romania. Moderately biased countries are composed of Czechia, Denmark, France, Hungary, Iceland, Portugal, Spain, Sweden and Switzerland. Lowly biased countries comprise Austria, Belgium, Estonia, Finland, Germany, Italy, Latvia, The Netherlands, Norway, Slovak Republic and the United Kingdom.



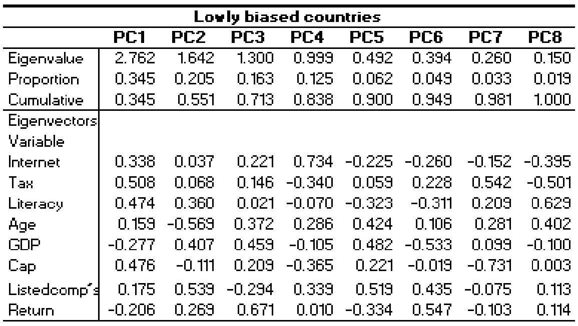
Highly biased countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	3.412	1.788	1.287	0.974	0.431	0.097	0.011	0.000
Proportion	0.427	0.224	0.161	0.122	0.054	0.012	0.001	0.000
Cumulative	0.427	0.650	0.811	0.933	0.987	0.999	1.000	1.000
Eigenvectors								
Variable								
Internet	0.049	0.562	-0.543	0.202	0.080	-0.092	-0.575	
Tax	0.494	-0.060	0.334	0.102	0.022	-0.258	-0.252	
Literacy	-0.494	0.060	-0.334	-0.102	-0.022	0.258	0.252	
Age	0.422	0.368	-0.196	0.285	0.179	-0.109	0.723	
GDP	-0.355	0.196	0.394	0.130	0.812	-0.050	-0.045	
Cap	-0.243	0.504	0.260	-0.436	-0.313	-0.564	0.120	
Listedcomp´s	0.329	0.391	0.199	-0.520	0.074	0.649	-0.052	
Return	-0.194	0.310	0.426	0.616	-0.446	0.325	-0.013	



Moderately biased countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	1.989	1.842	1.435	1.173	0.613	0.427	0.373	0.148
Proportion	0.249	0.230	0.179	0.147	0.077	0.053	0.047	0.019
Cumulative	0.249	0.479	0.658	0.805	0.882	0.935	0.981	1.000
Eigenvectors								
Variable								
Internet	0.519	0.101	0.101	-0.436	-0.463	0.322	-0.098	-0.439
Tax	0.195	0.459	-0.022	0.538	-0.337	0.149	0.554	0.138
Literacy	0.527	-0.180	-0.036	-0.359	0.383	-0.239	0.552	0.228
Age	-0.144	0.470	0.450	-0.405	0.005	0.170	-0.118	0.591
GDP	0.085	-0.397	0.512	0.279	0.308	0.628	0.075	-0.031
Cap	0.209	0.536	0.279	0.176	0.523	-0.251	-0.184	-0.435
Listedcomp´s	0.567	-0.028	-0.277	0.289	0.049	0.068	-0.566	0.436
Return	0.149	-0.283	0.608	0.187	-0.393	-0.571	-0.081	0.079



Lowly biased countries								
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	2.762	1.642	1.300	0.999	0.492	0.394	0.260	0.150
Proportion	0.345	0.205	0.163	0.125	0.062	0.049	0.033	0.019
Cumulative	0.345	0.551	0.713	0.838	0.900	0.949	0.981	1.000
Eigenvectors								
Variable								
Internet	0.338	0.037	0.221	0.734	-0.225	-0.260	-0.152	-0.395
Tax	0.508	0.068	0.146	-0.340	0.059	0.228	0.542	-0.501
Literacy	0.474	0.360	0.021	-0.070	-0.323	-0.311	0.209	0.629
Age	0.159	-0.569	0.372	0.286	0.424	0.106	0.281	0.402
GDP	-0.277	0.407	0.459	-0.105	0.482	-0.533	0.099	-0.100
Cap	0.476	-0.111	0.209	-0.365	0.221	-0.019	-0.731	0.003
Listedcomp´s	0.175	0.539	-0.294	0.339	0.519	0.435	-0.075	0.113
Return	-0.206	0.269	0.671	0.010	-0.334	0.547	-0.103	0.114

Source : Stata based on our database

7.5 Results conclusion

In this concluding segment, we can positively summarize the results for both Home Bias and Foreign Bias.

For Home Bias, the statistical significance of our tested hypotheses enabled us to validate seven out of eight (F1 to F7) through panel regression analysis. Although the hypothesis regarding investor age (F8) was initially stated on a contrarian sign impeding us to confirm our hypothesis, further reflection make complete sense on the sign direction. The propensity to save as a factor influencing domestic bias was not tested in our analysis due to its lack of statistical significance. To ascertain its relevance, further investigation into past literature discussing this factor is necessary.

Notably, four of the eight tested variables demonstrated an inverse relationship with Home Bias, indicating a reduction in bias with an increase in tax burden, financial literacy, technology mastery (lower information asymmetry), and investor age. Conversely, economic growth, stock market returns, market size, and investment opportunities acted as enhancers of domestic bias, impeding its decline. Interestingly enough, the regressions with the highest explanatory power targeted factors aimed at reducing Home Bias over time, such as addressing information asymmetry, enhancing financial literacy, and considering investor age. This helps partially explaining the declining observed trend.

Linear relationships analysis revealed and confirmed significant linear decreasing relations for investor age, information asymmetry, and propensity to save (contrarian to what was hypothesized), while economic growth exhibited a strong positive correlation with Home Bias.

PCA provided further insights into the fixed effects regression, enhancing our understanding of the underlying dynamics. The analysis reveals distinct patterns across geographical regions regarding factors influencing investment bias. Northern countries align closely with variables such as literacy, tax, internet usage, and market size, validating their importance in the bias and our hypothesis. Western countries exhibit similar trends, with differences primarily stemming from the influence of the number of listed companies confirming its powerful character. Southern countries lack clear patterns, while Eastern countries demonstrate a divergence from influential variables, suggesting unique economic dynamics. Notably, Poland's large market size validates the hypothesis that it hinders domestic investors from investing elsewhere which had little explanatory power in our regression. The lack of refinement in measuring the state of economic development limits our ability to draw conclusive findings regarding the distinction between developed and developing countries. Highly biased countries exhibit characteristics resembling a blend of Eastern and Southern countries, indicating lower literacy levels and technological advancement. Overall, the analysis underscores the significance of financial literacy and technology mastery in mitigating investment bias across different regions. These factors, which are measures of economic development, represent major points of divergence between countries.

The results for Foreign Bias are somewhat more varied, yet overall satisfactory. In our sample of 23 countries implying 506 countries’ relations, the initial assessment revealed a relatively favorable scenario, with only one-fifth of investments showing a bias. While this proportion is lower than anticipated based on observations of Home Bias deviation, it still represents a noteworthy deviation. Moreover, the examination of five linking factors as explanatory variables yielded positive outcomes. All five factors contributed to enhancing the explanatory power of their respective regressions, thus validating their influence on Foreign Bias.

Analyses across various criteria related to geographical, cultural, linguistic, and religious factors provided valuable insights into the complexities shaping investment behavior and allocation decisions, leading to overweight in countries perceived as "closer" either physically or psychologically. Narrowing down the sample based on distance and cultural similarity yielded significant enhancements in explanatory power, confirming hypotheses regarding the influence of physical proximity and cultural affinity on investment biases. Similarly, exploring shared language and dominant religion shed light on how linguistic and religious factors contribute to deviations from optimal allocation.

Considering countries with a common language led to an improvement in explanatory power, reinforcing the hypothesis that shared language introduces bias in investor behavior. Yet, variations across different languages necessitate further investigation. Sub-regressions focusing on specific languages revealed varied results, with some languages exhibiting much stronger correlations in investment behavior than others.

Regarding religion, while sharing a dominant religion did not significantly enhance explanatory power at the aggregate level, nuanced findings emerged in sub-regressions. Protestantism and Orthodoxy exhibited higher explanatory power, suggesting that specific religious denominations may influence investment allocation decisions.

Conclusion

Home and Foreign Biases are pervasive phenomena with complex underlying mechanisms. Despite extensive literature and research by eminent scholars, a comprehensive understanding of these biases remains elusive. While recent decades have brought significant advancements in our knowledge, gaps persist in our understanding. My investigation into this subject suggests that behavioral finance has had a profound impact, deepening our understanding of these biases. However, behavioral finance is inherently linked to human nature, which evolves continuously, presenting challenges in fully encapsulating human behavior within a structured framework.

In our research on Home Bias, we corroborated the findings of numerous previous studies: investors exhibit a pronounced bias, disproportionately favoring investments in their home country. Among the twenty-three countries examined, all persistently demonstrated a bias towards their domestic market, with the notable exception of the Netherlands over the last five years. The extent of this bias varies significantly across the countries studied, and in order to explain it, we combined previously tested and novel hypotheses to account for this phenomenon over time. Our regression analysis predominantly utilized empirical factors such as tax burden, economic growth, stock market returns, information asymmetry, and market size, alongside behavioral factors including financial literacy and investor age. The results revealed significant explanatory power for financial literacy, information asymmetry, and investor age, all of them having a negative relation with the domestic bias. This perfectly aligns with the trend observed in both this thesis and previous research, indicating that this bias is decreasing over time. However, economic growth emerged as a major impediment to reducing Home Bias in our analysis, whereas other factors did not show significant influence, thus hampering our ability to draw conclusive findings on their impact over time. PCA analysis revealed that economic development, notably measured by financial literacy and technology mastery, could serves as a nice refinement but we lack conclusive evidence in this thesis. It also revealed that market size plays a role in those less economically advanced countries. It further confirmed some of our hypotheses and highlighted differences in behavior across geographical regions.

Subsequently, we examined the Foreign Bias, a closely related concept to Home Bias, focusing on explaining where the rest of investments goes when excluding the home country. Surprisingly enough, only one fifth of the investments analyzed show a positive deviation from an optimal allocation point of view. This is notably due to the presence of Home Bias, which takes a significant part of the investment portfolio and the restricting nature of our sample. While employing similar independent variables as for Home Bias to examine those deviations, our analysis placed greater emphasis on behavioral characteristics such as distance, culture, language, and religion. The results are promising, indicating that each linking factor has a notable impact on enhancing the explanatory power of our variables on Foreign Bias deviation. The variability inherent in human behavior, coupled with its complex nature, poses challenges to achieving categorical certainty in our findings. Nevertheless, empirical evidence suggests that certain proximities, whether physical or psychological, exhibit a propensity to influence investment decisions, thereby inducing deviations. While the impact of factors such as language, religion, culture, or geographical proximity may not be universal, empirical observations indicate that positive deviations frequently manifest in the presence of these interconnecting elements. Further research in the field is needed to obtain a more comprehensive understanding of these findings.

Our research contributes new insights to existing literature, particularly in highlighting the significance of investor age in explaining Home Bias. Our database facilitated precise analysis, allowing for the identification of specific sub-groups within Foreign Bias. Moving forward, there is scope to enhance the methods of analyzing explanatory factors of Foreign Bias, with qualitative analyses potentially offering deeper insights into investors' psychological reasoning. Furthermore, efforts in the domain of behavioral finance could yield valuable insights into both Home and Foreign Bias, with opportunities for expanding research to less studied regions or conducting global worldwide spectrum analyses if data availability permits. Further research into states of level of economic development could be fascinating in order to deepen our findings.

In conclusion, the study of Home Bias illuminates the intricate interplay between human psychology, socio-cultural factors, and investment behavior. As our research corroborates, investors often exhibit a propensity to favor their domestic market and some other markets, albeit with varying degrees of bias across different contexts. While not devoid of complexities, this bias underscores the enduring influence of familiarity and proximity in investment decision-making processes.

As Nobel laureate Daniel Kahneman famously remarked, "The illusion that we understand the past fosters overconfidence in our ability to predict the future." In the realm of Home Bias, this quote resonates profoundly, reminding us of the limitations inherent in our understanding of human behavior and the complexities of financial markets.

Moving forward, our findings underscore the importance of continued research into the underlying mechanisms driving Home Bias and its implications for portfolio diversification and global market integration. By deepening our understanding of these dynamics, we can strive towards more informed investment strategies and foster greater international cooperation in the realm of finance.

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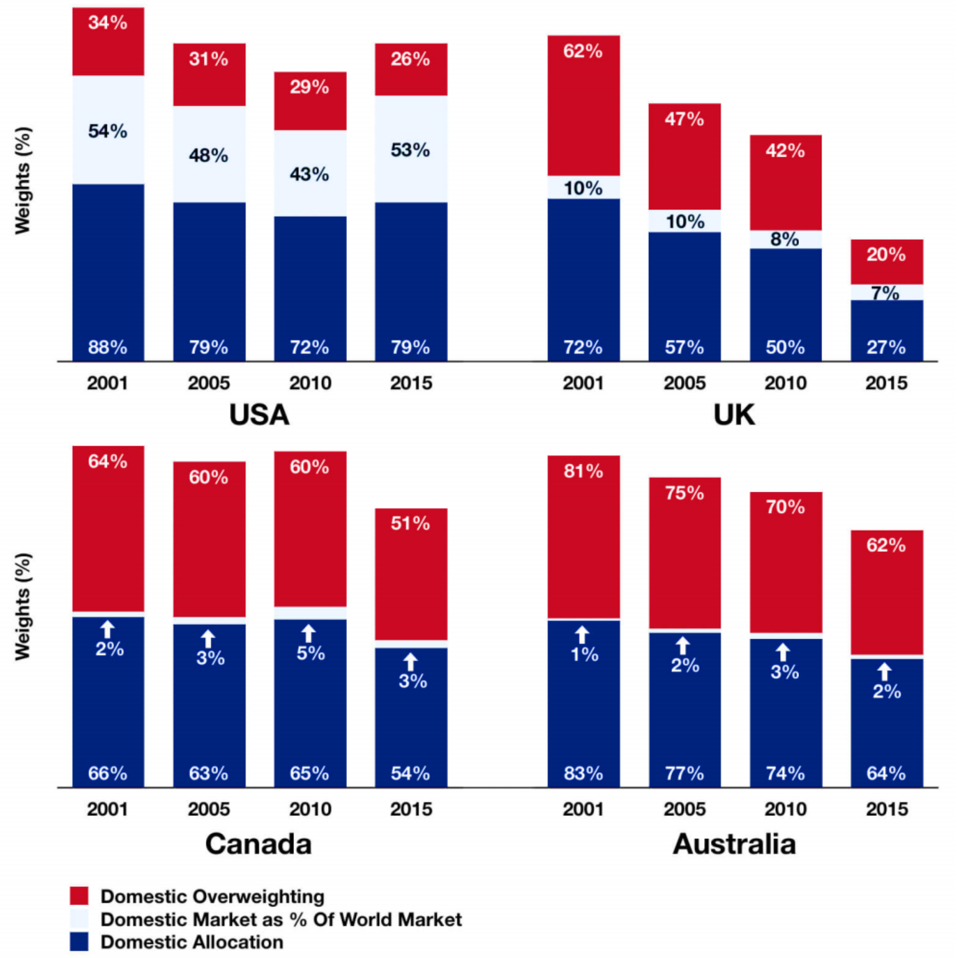
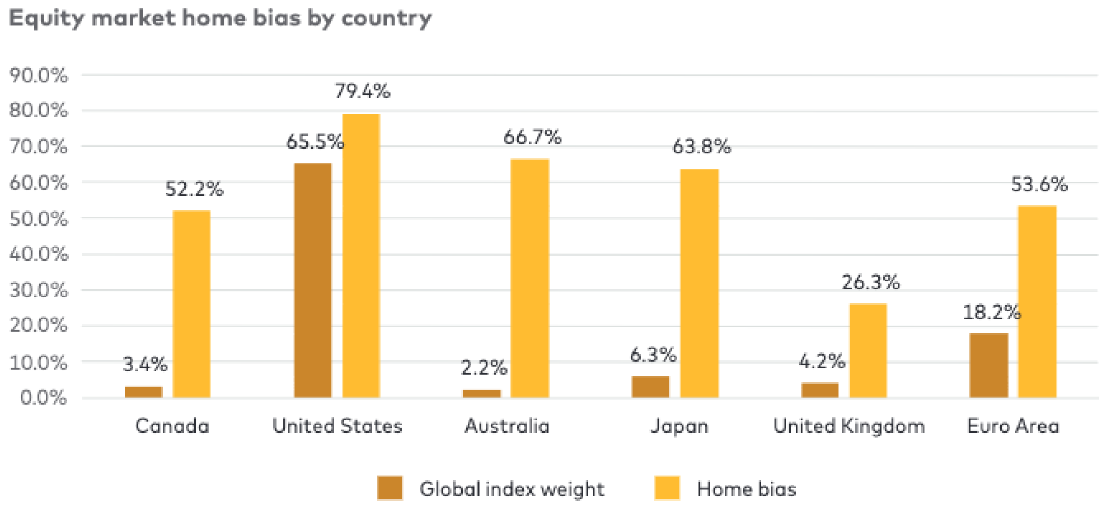
Figure 1 : Domestic allocation and overweight : the case of Australia, Canada, USA and UK



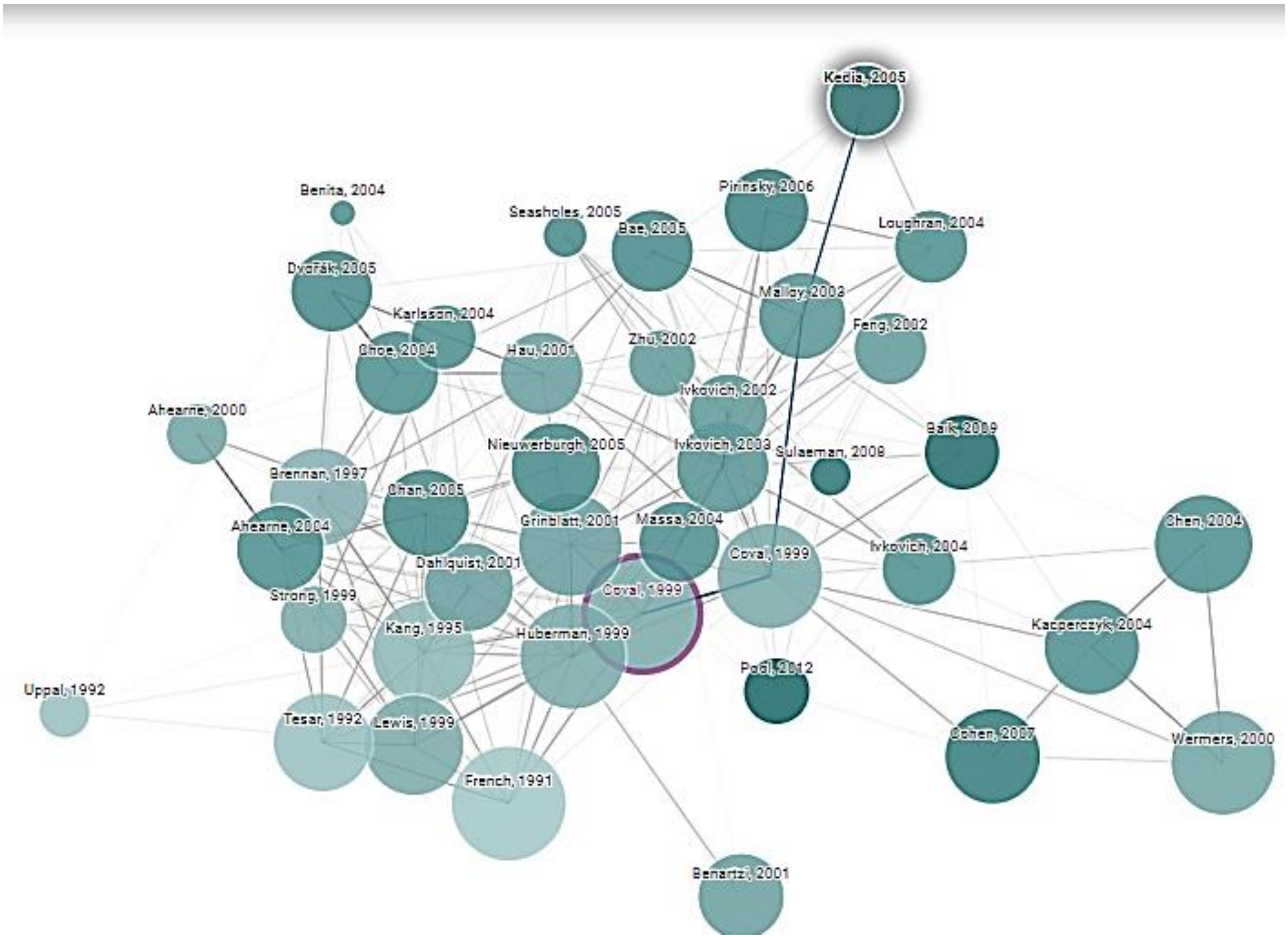
Source : Vanguard based on IMF data

Figure 2 : Overweigh of domestic equity in 2022 : the case of Canada, U.S., Australia, Japan, U.K. and Eurozone



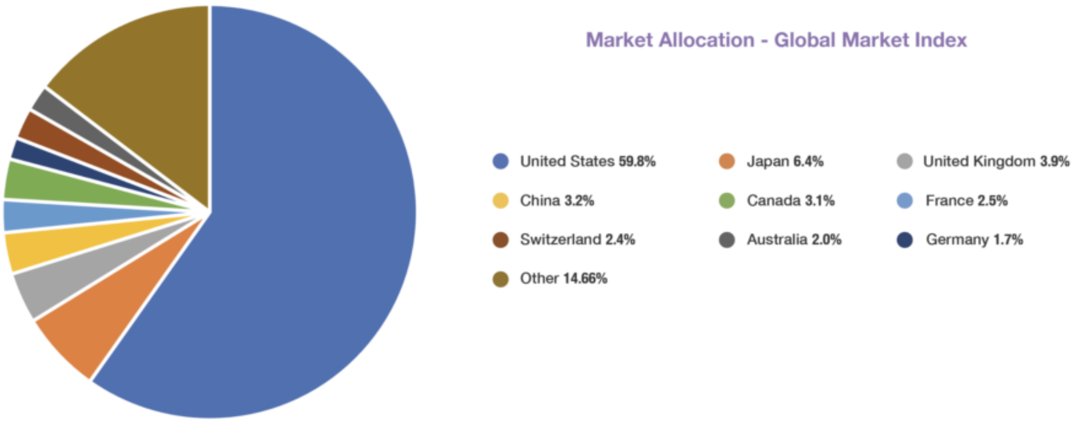
Source : Vanguard based on IMF data (2022)

Figure 3 : Scheme of most significant Home Bias research over time



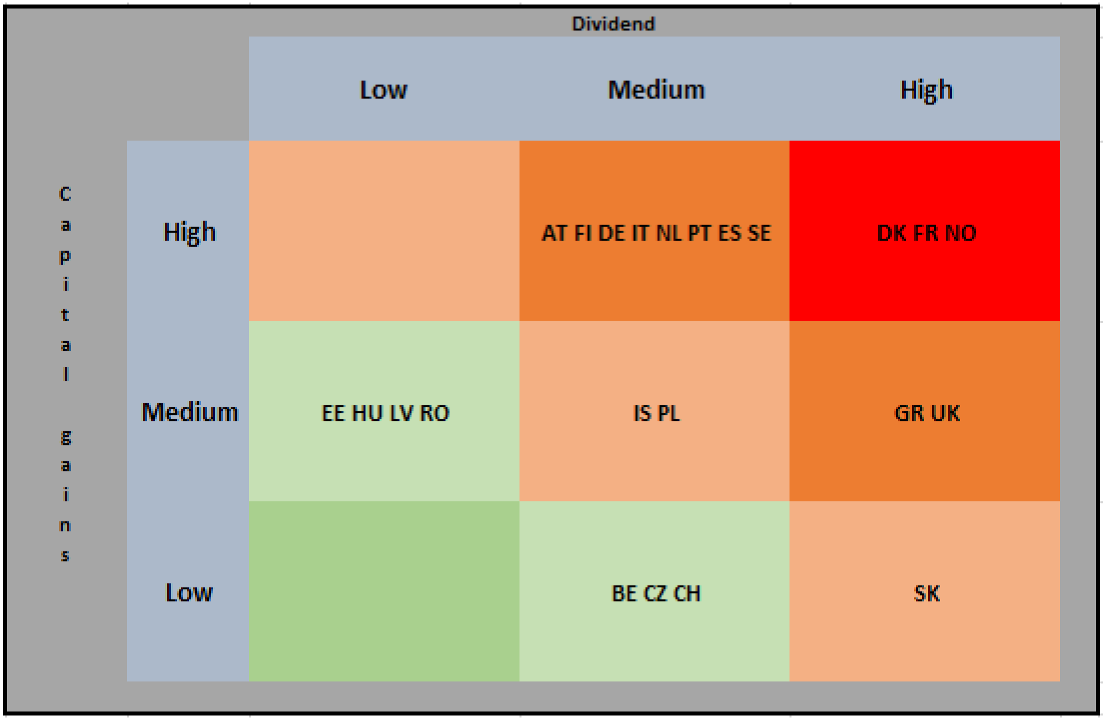
Source : Connected Paper

Figure 4 : Countries' weight in world index



Source : As of 31 July 2022, based on the Morningstar Global Market Index

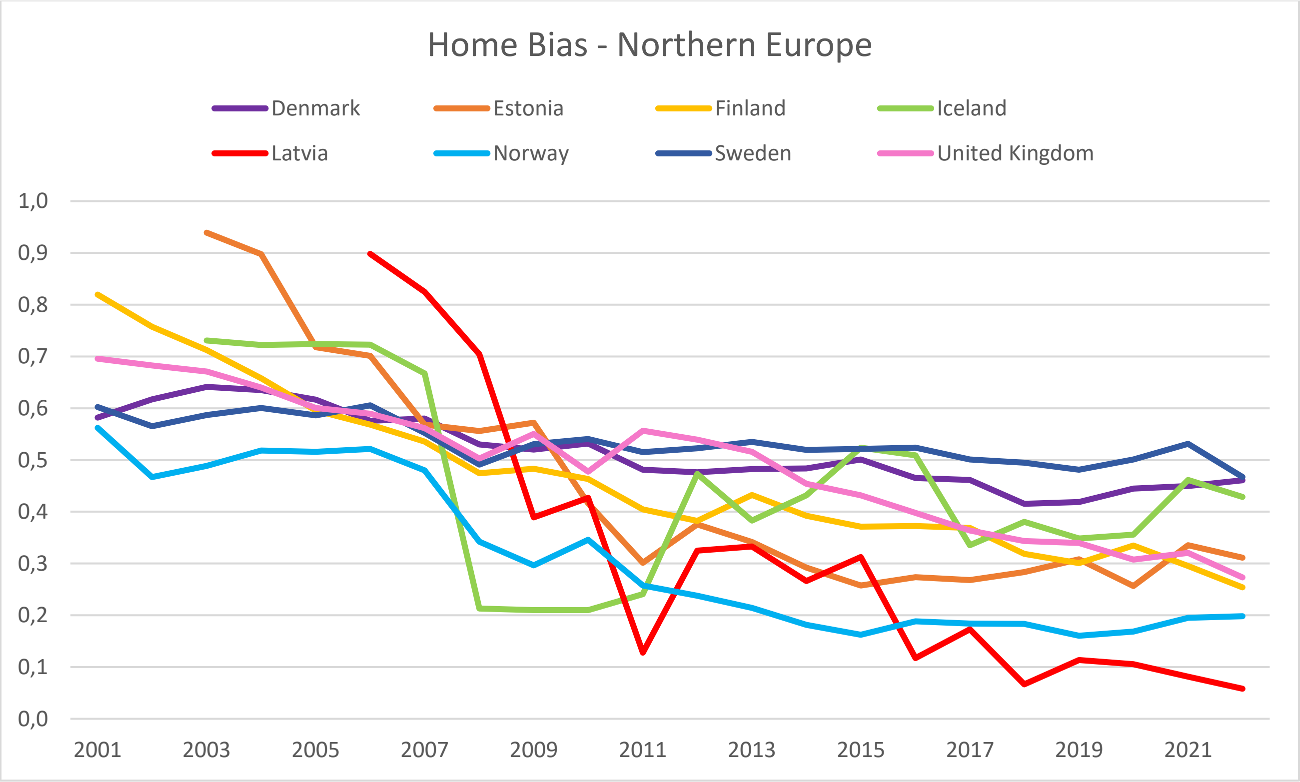
Figure 5 : Tax Burden by country



		Dividend		
		Low	Medium	High
Capital gains	High		AT FI DE IT NL PT ES SE	DK FR NO
	Medium	EE HU LV RO	IS PL	GR UK
	Low		BE CZ CH	SK

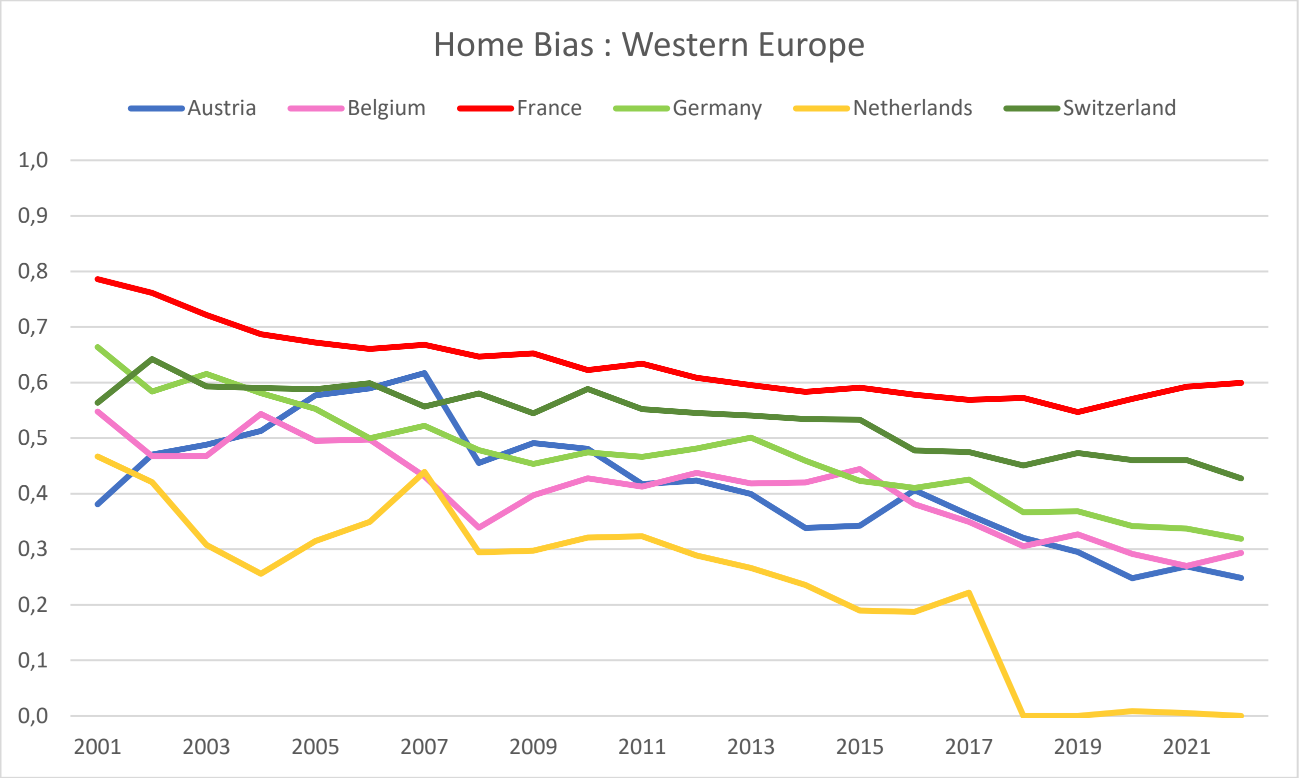
Source : own construction based on Tax Foundation Europe data

Figure 6 : Home Bias in Northern Europe between 2001 and 2022



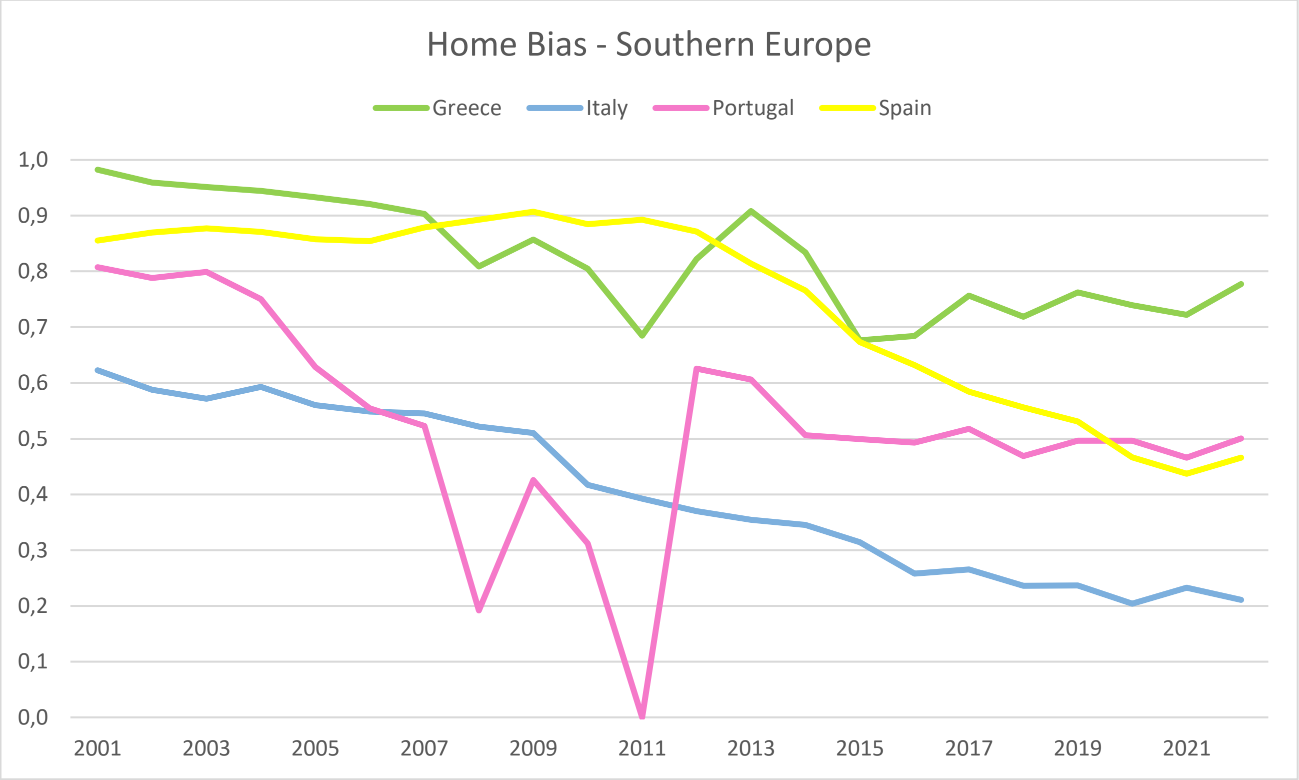
Source : Own calculation, IMF, World Bank, Refinitiv

Figure 7 : Home Bias in Western Europe between 2001 and 2022



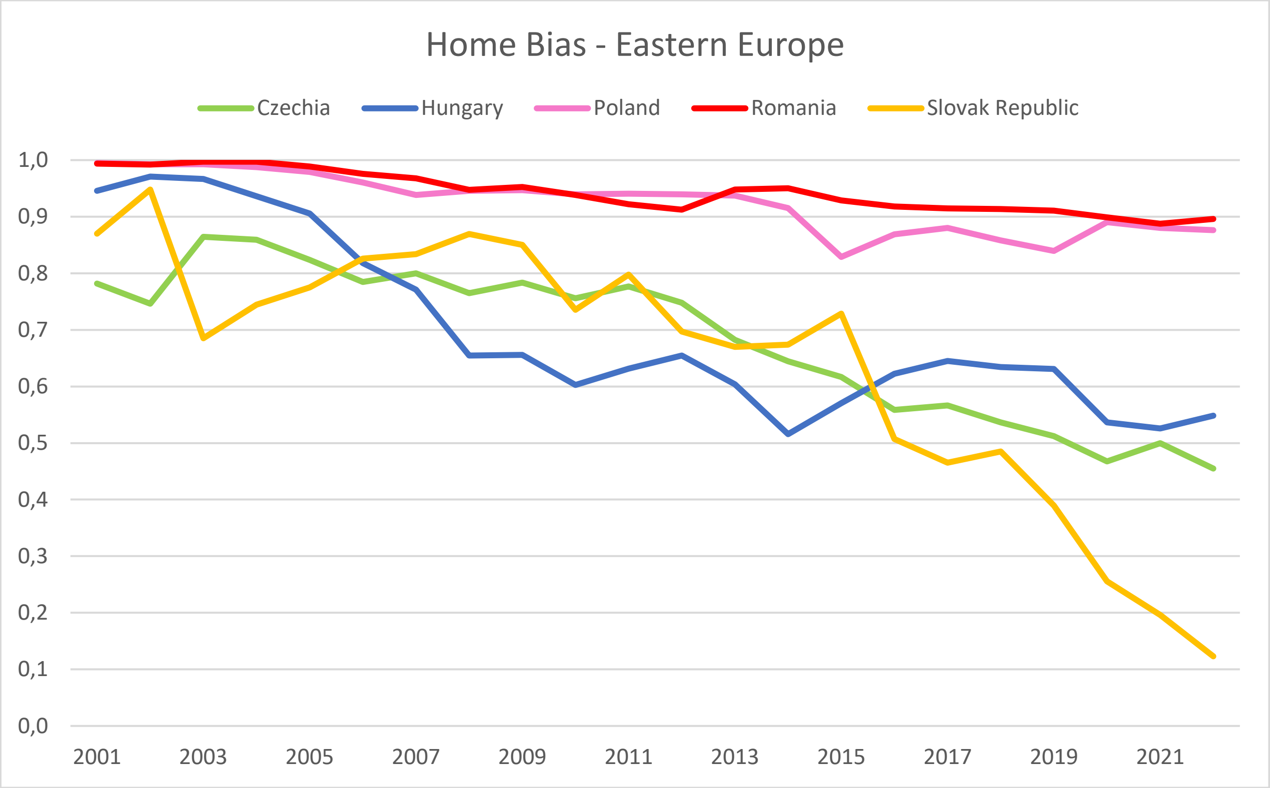
Source : Own calculation, IMF, World Bank, Refinitiv

Figure 8 : Home Bias in Southern Europe between 2001 and 2022



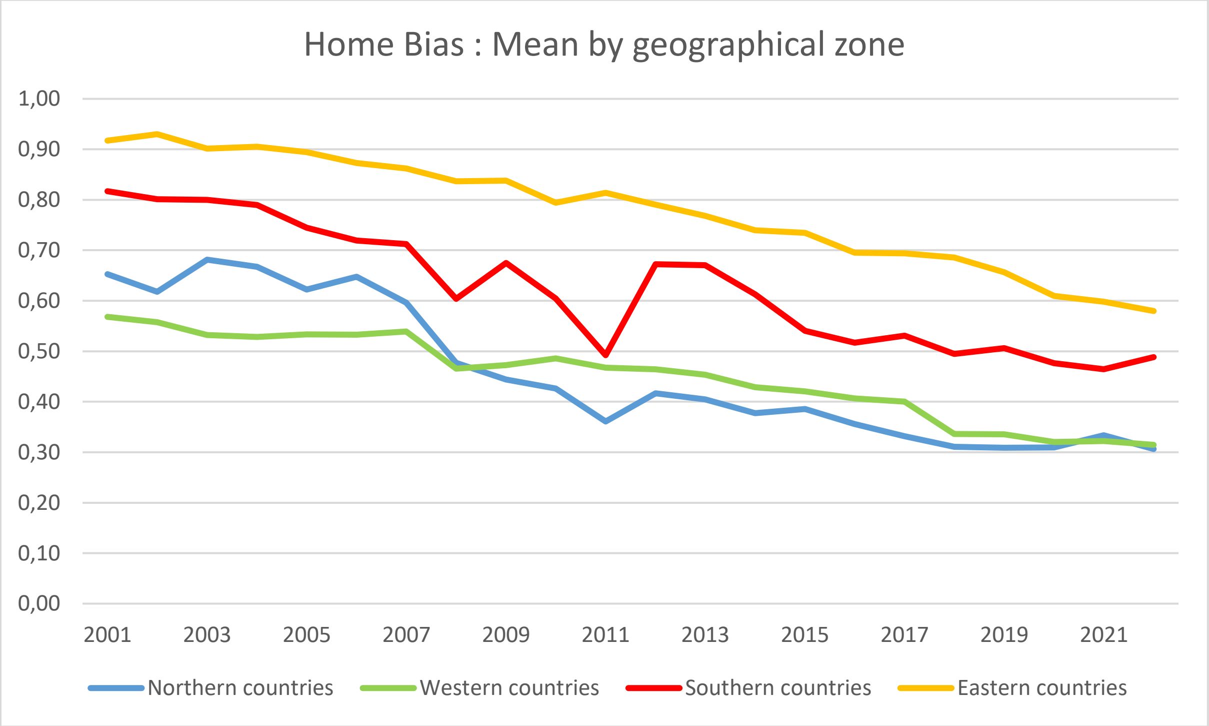
Source : Own calculation, IMF, World Bank, Refinitiv

Figure 9 : Home Bias in Eastern Europe between 2001 and 2022



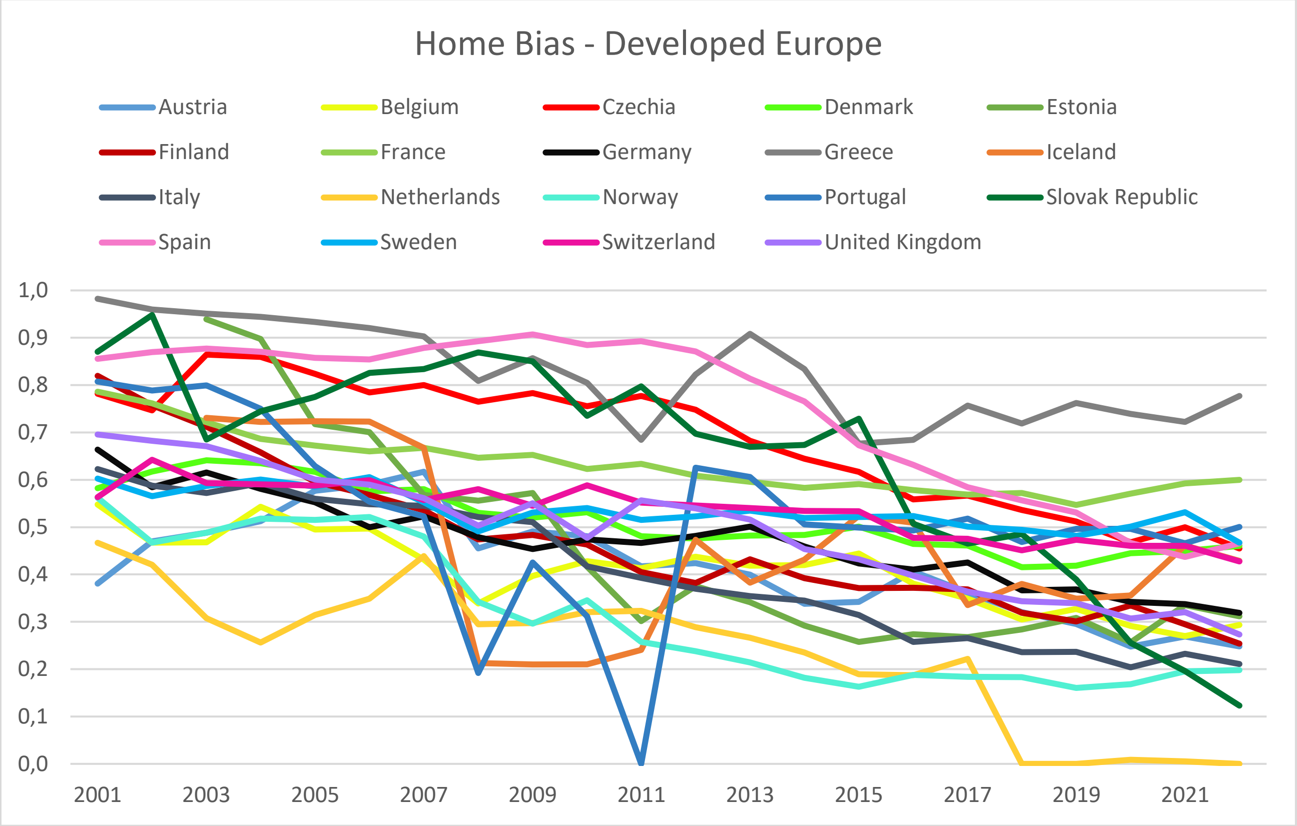
Source : Own calculation, IMF, World Bank, Refinitiv

Figure 10 : Home Bias mean by geographical zone between 2001 and 2022



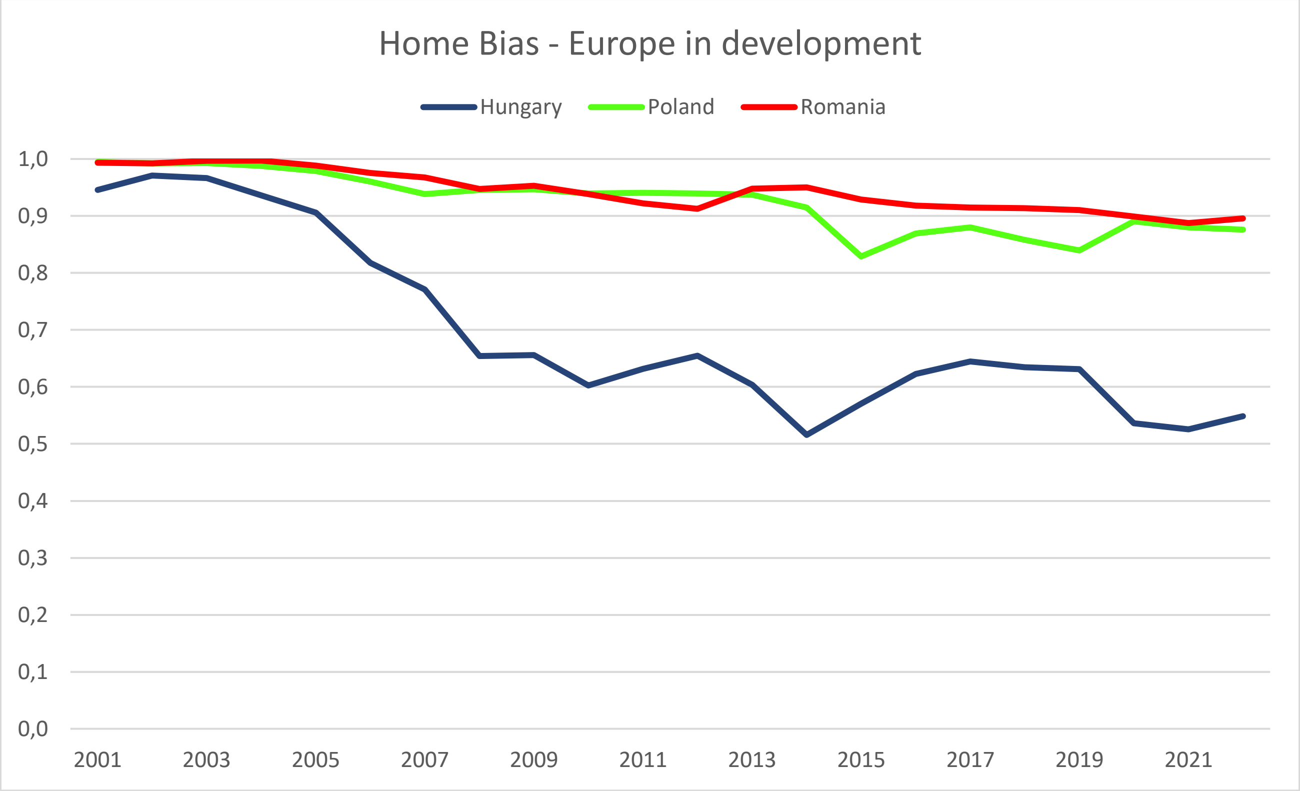
Source : Own calculation, IMF, World Bank, Refinitiv

Figure 11 : Home Bias in Developed Europe between 2001 and 2022



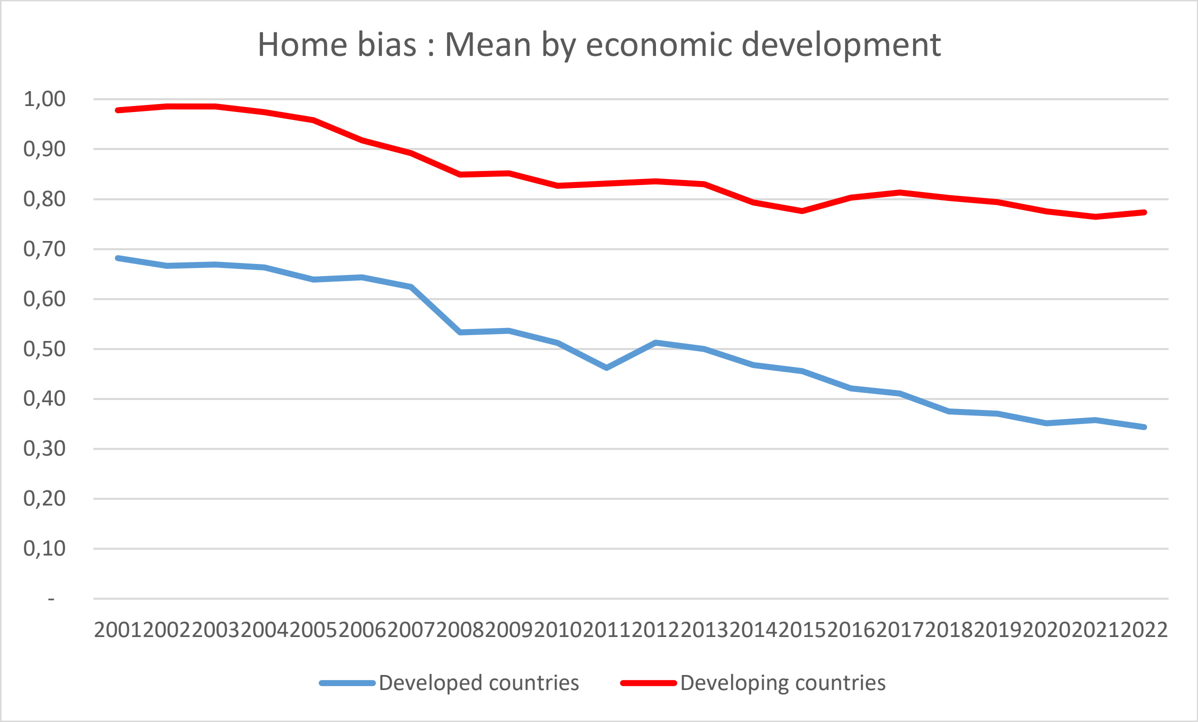
Source : Own calculation, IMF, World Bank, Refinitiv

Figure 12 : Home Bias in Developing Europe between 2001 and 2022



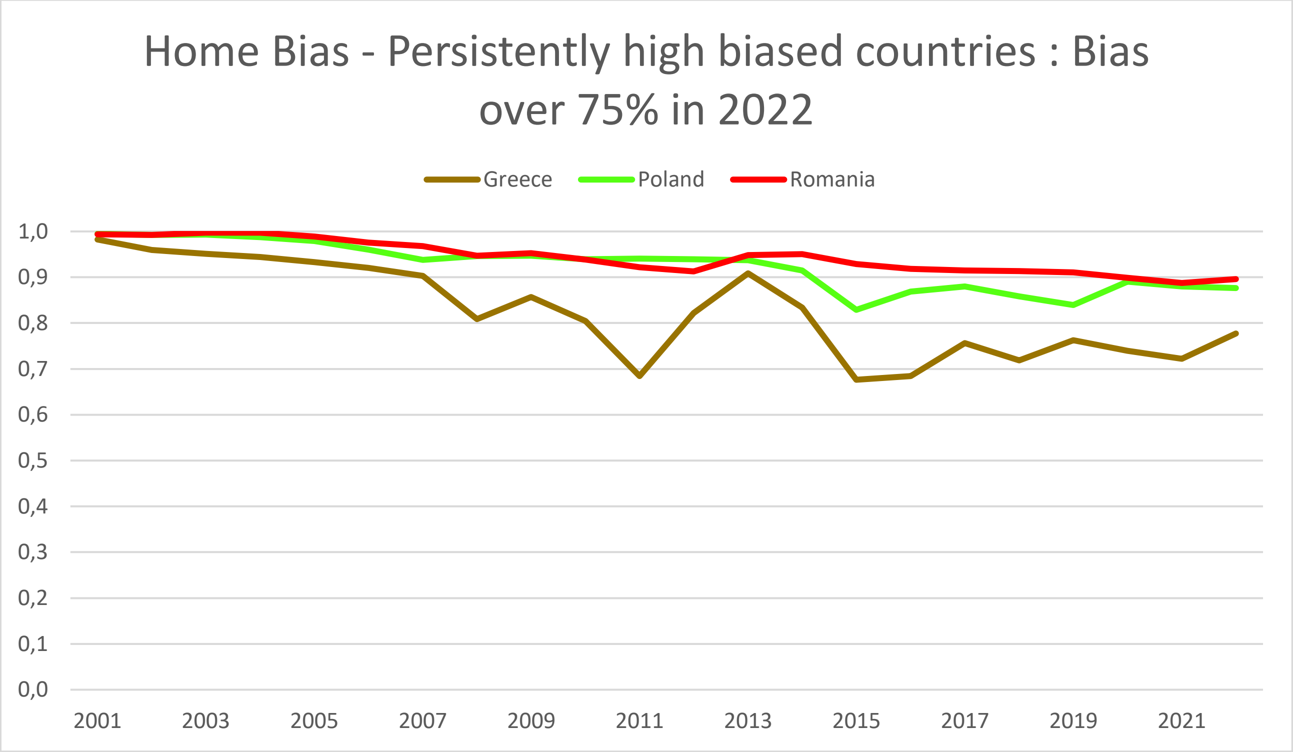
Source : Own calculation, IMF, World Bank, Refinitiv

Figure 13 : Home Bias mean by economic development between 2001 and 2022



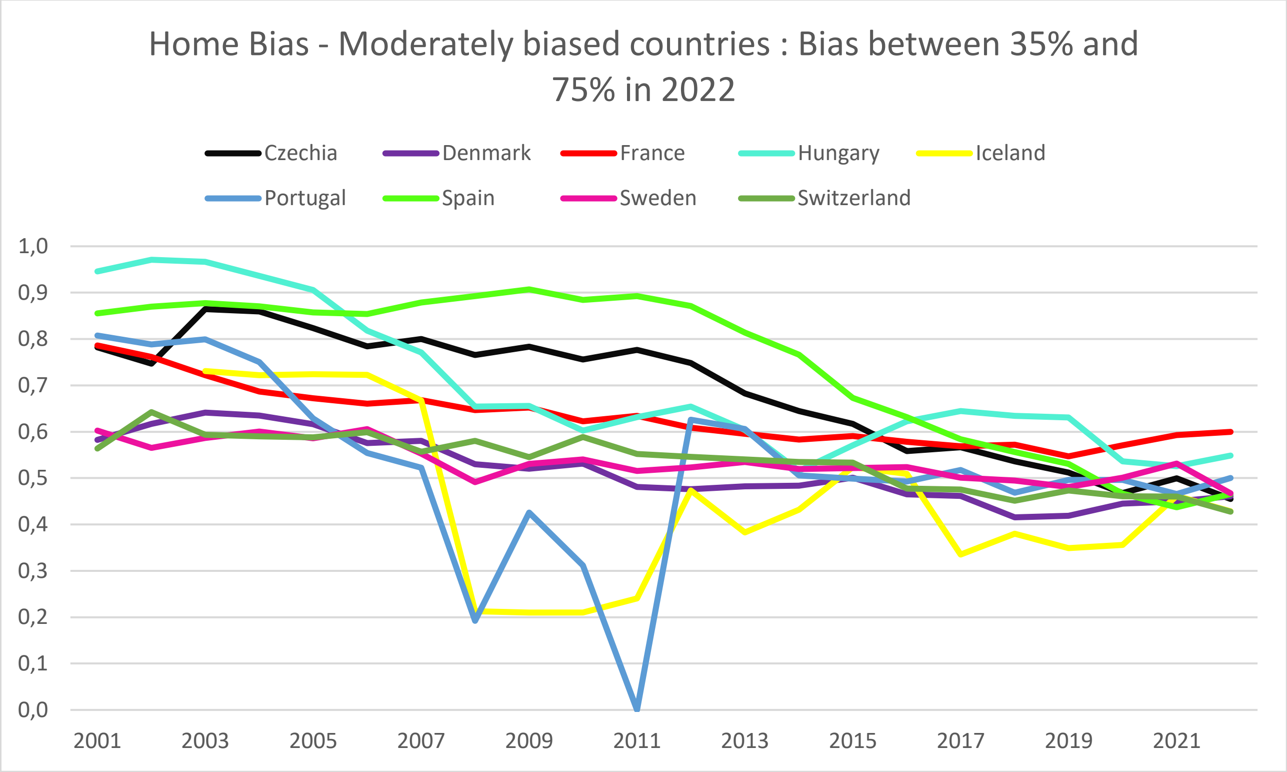
Source : Own calculation, IMF, World Bank, Refinitiv

Figure 14 : High terminal level of Home Bias countries between 2001 and 2022 (bias over 75% in 2022)



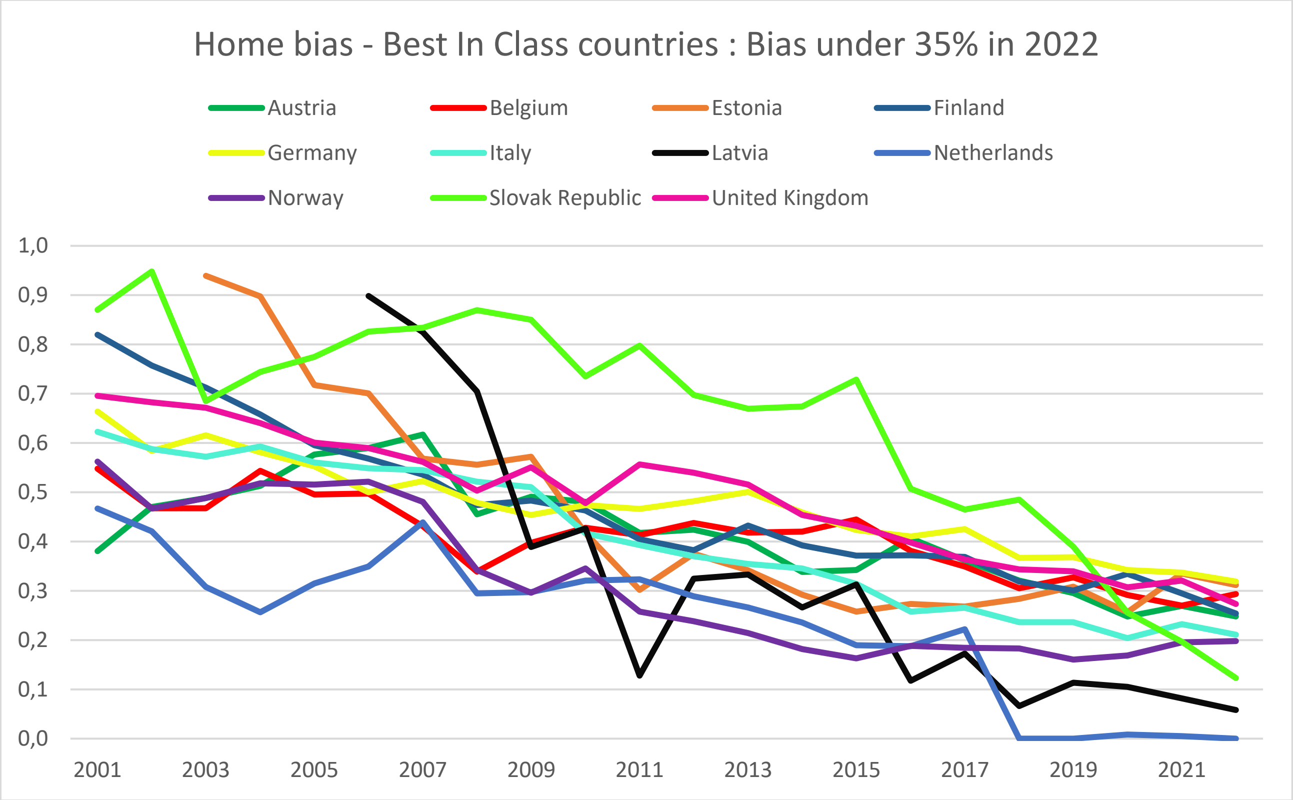
Source : Own calculation, IMF, World Bank, Refinitiv

Figure 15 : Medium terminal level of Home Bias countries between 2001 and 2022 (bias between 35%-75% in 2022)



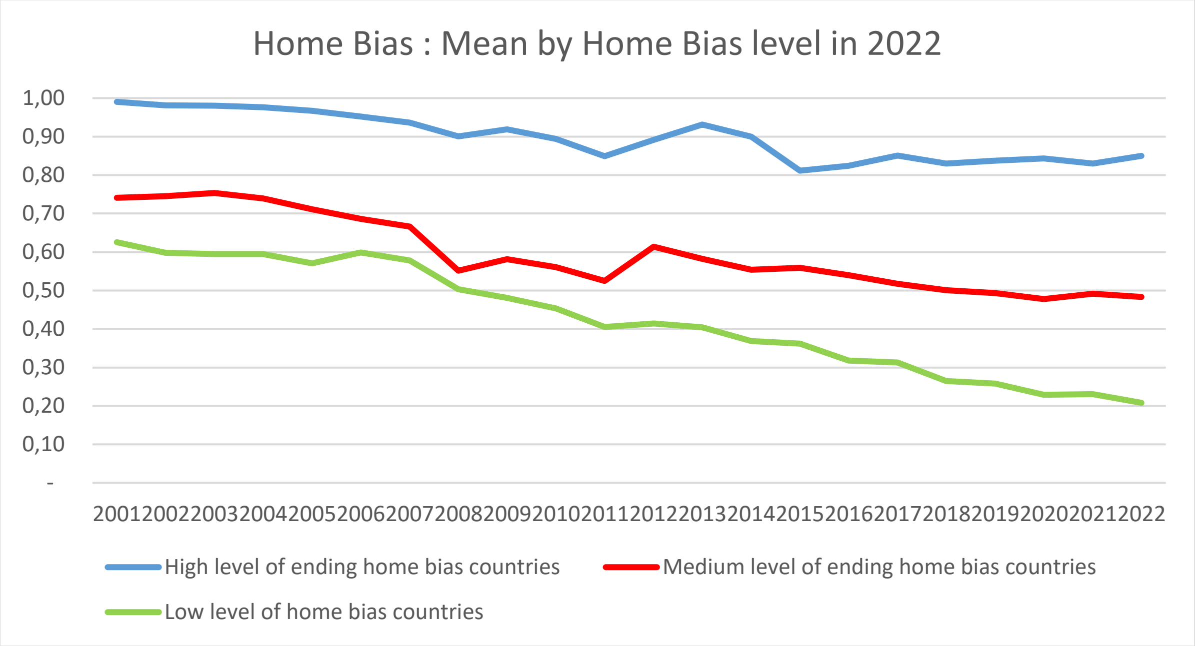
Source : Own calculation, IMF, World Bank, Refinitiv

Figure 16 : Low terminal level of Home Bias countries between 2001 and 2022 (bias under 35% in 2022)



Source : Own calculation, IMF, World Bank, Refinitiv

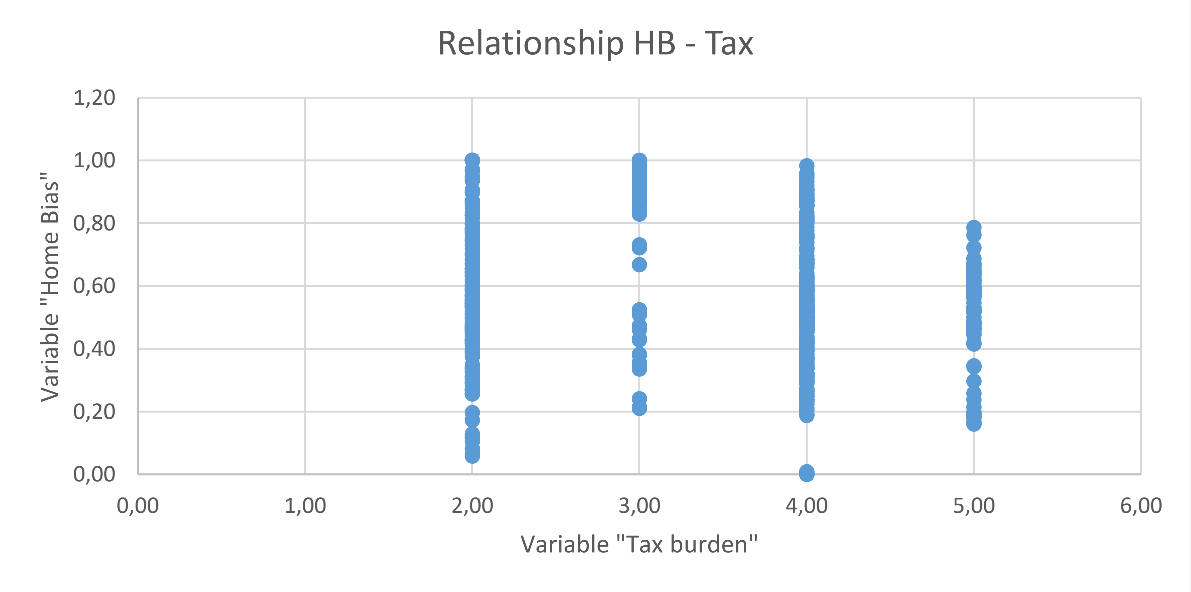
Figure 17 : Home Bias mean between 2001 and 2022 by terminal level of home bias in 2022



Source : Own calculation, IMF, World Bank, Refinitiv

Figure 18 : Scatter plot – Relation between variables HB and TAX

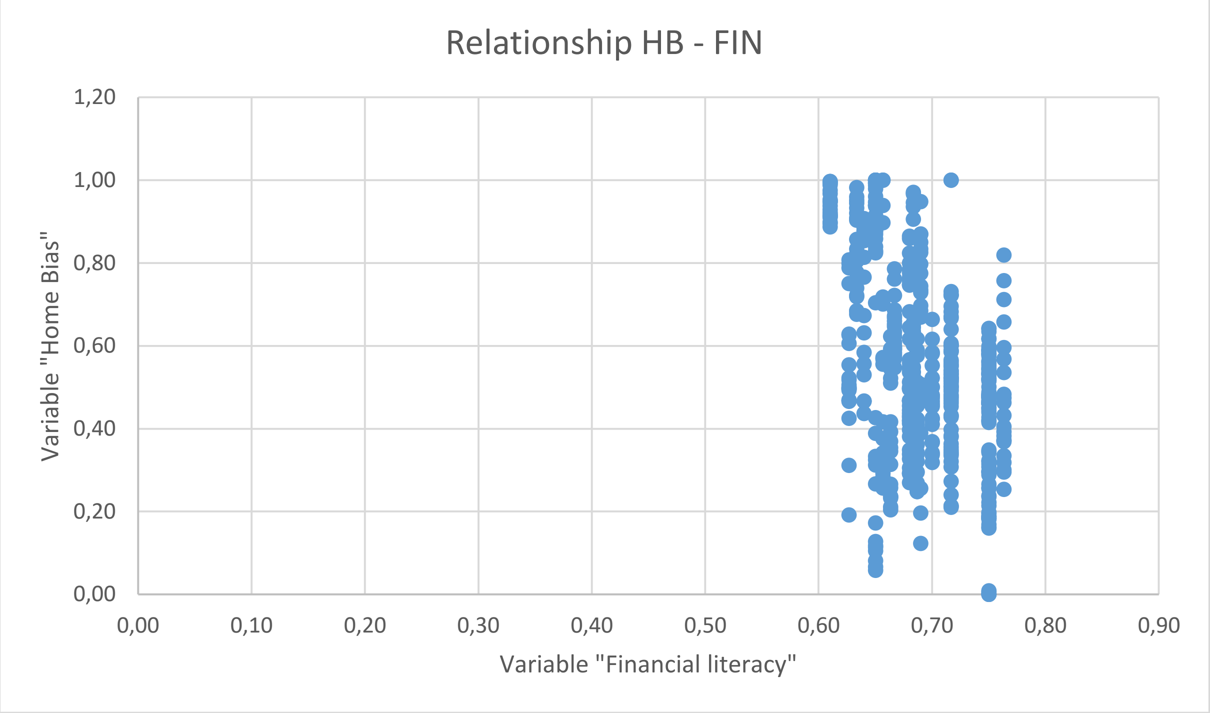
This graph is not very representative because the variable TAX is a one time measurement thus varying only with individuals but not through time. This results in a “Bar” chart.



Source : Own construction with our database

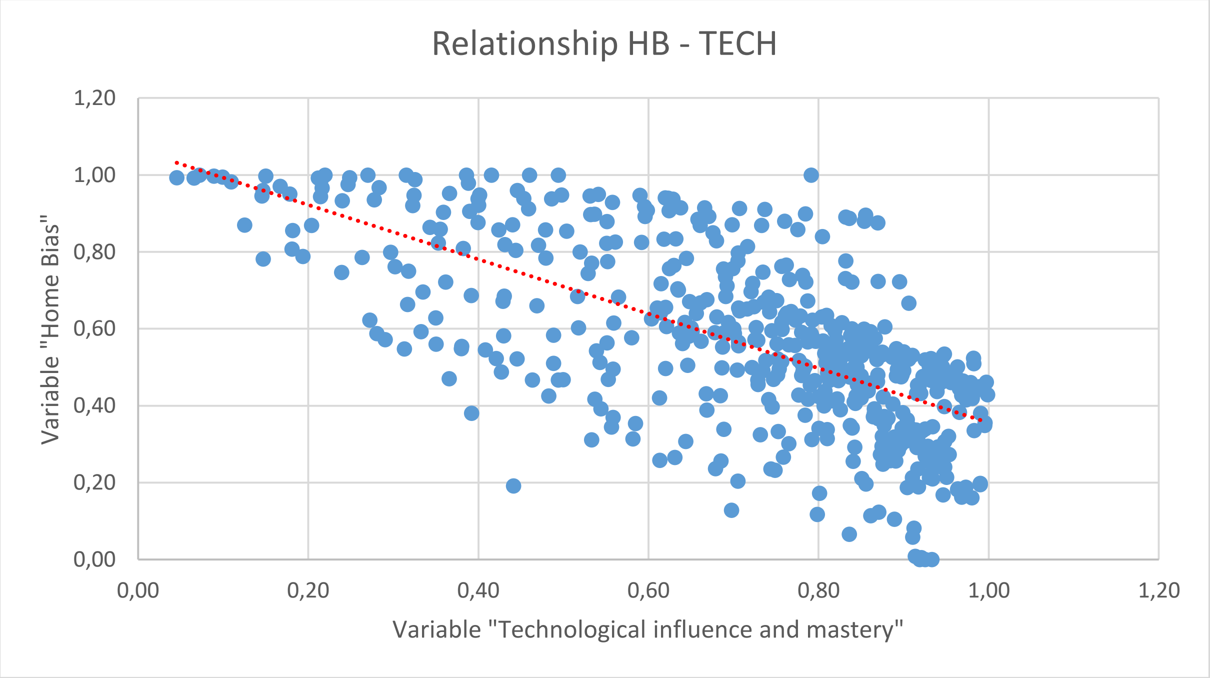
Figure 19 : Scatter plot – Relation between variables HB and FIN

This graph is not very representative because the variable FIN is a one time measurement thus varying only with individuals but not through time. This results in a "Bar" chart.



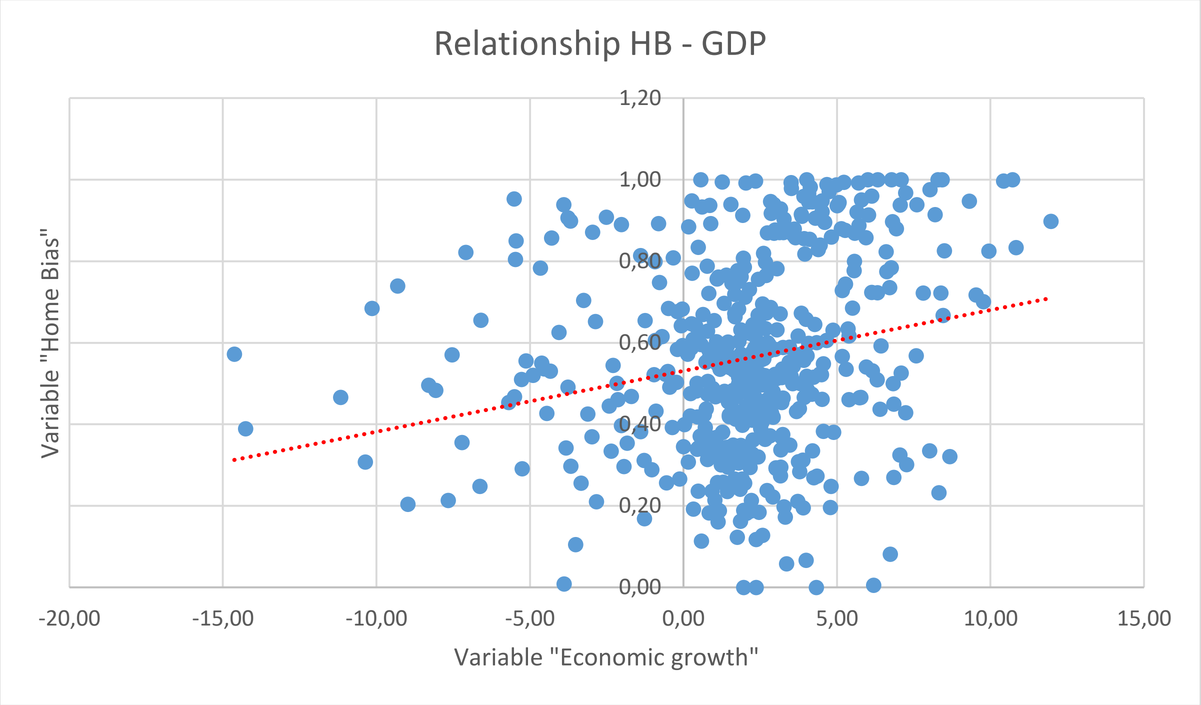
Source : Own construction with our database

Figure 20 : Scatter plot – Relation between variables HB and TECH



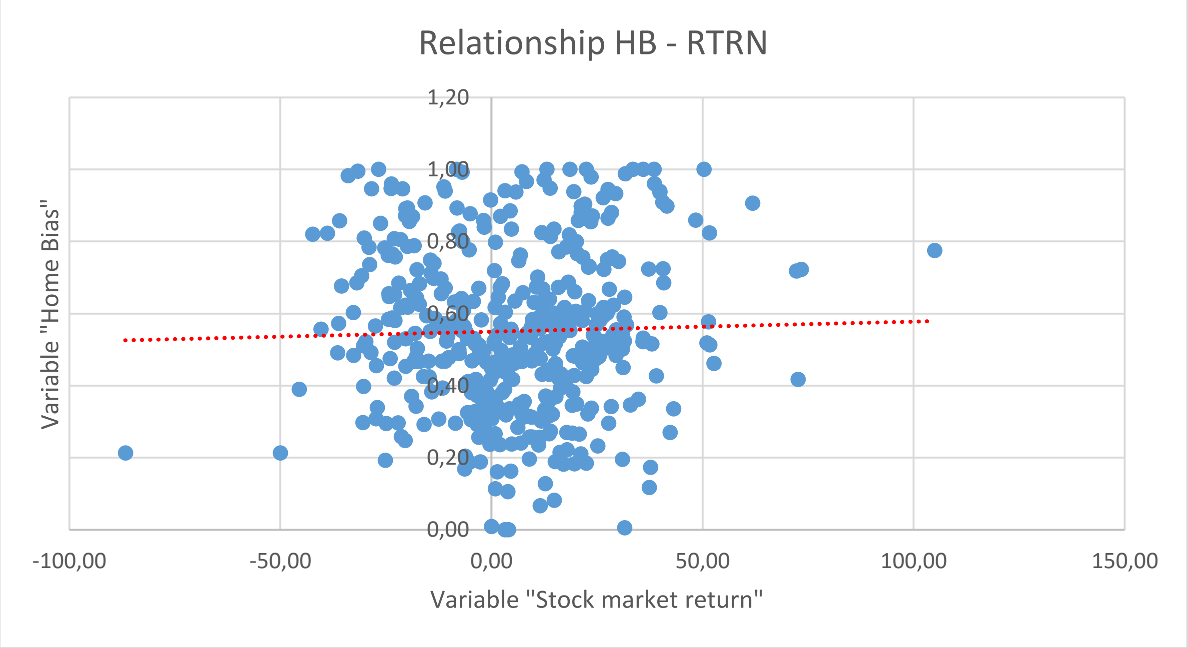
Source : Own construction with our database

Figure 21 : Scatter plot – Relation between variables HB and GDP



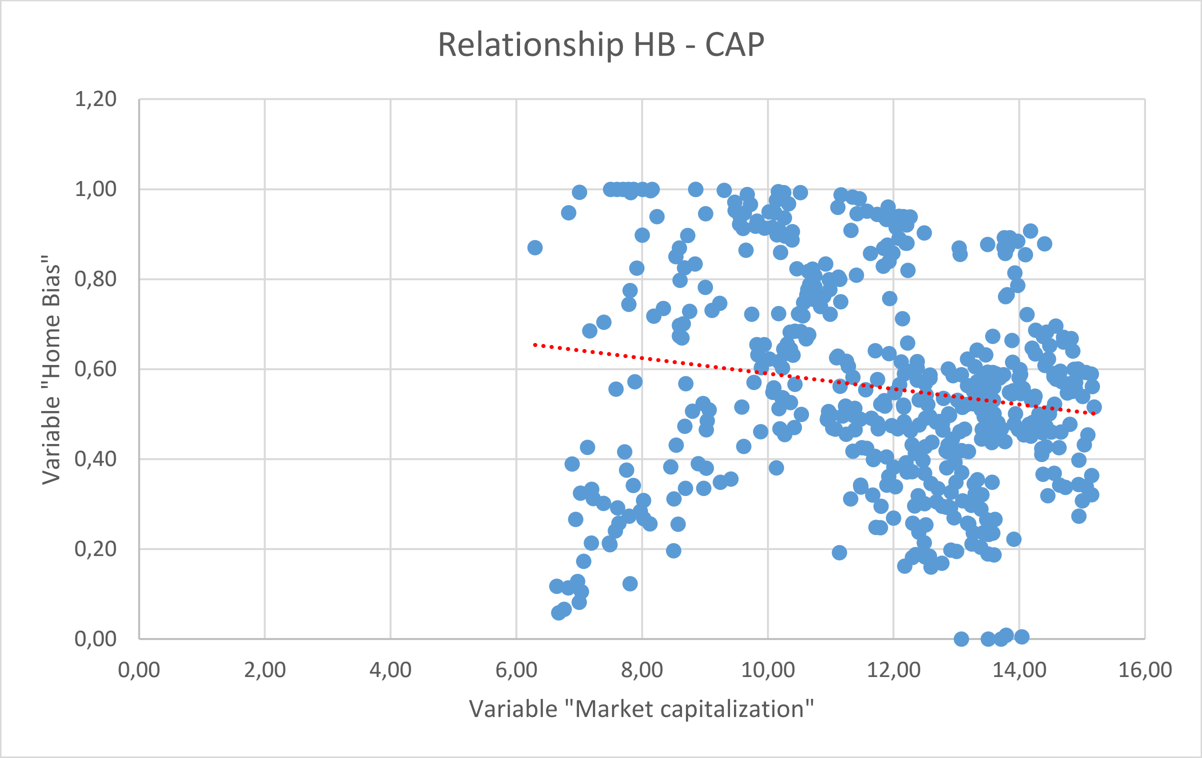
Source : Own construction with our database

Figure 22 : Scatter plot – Relation between variables HB and RTRN



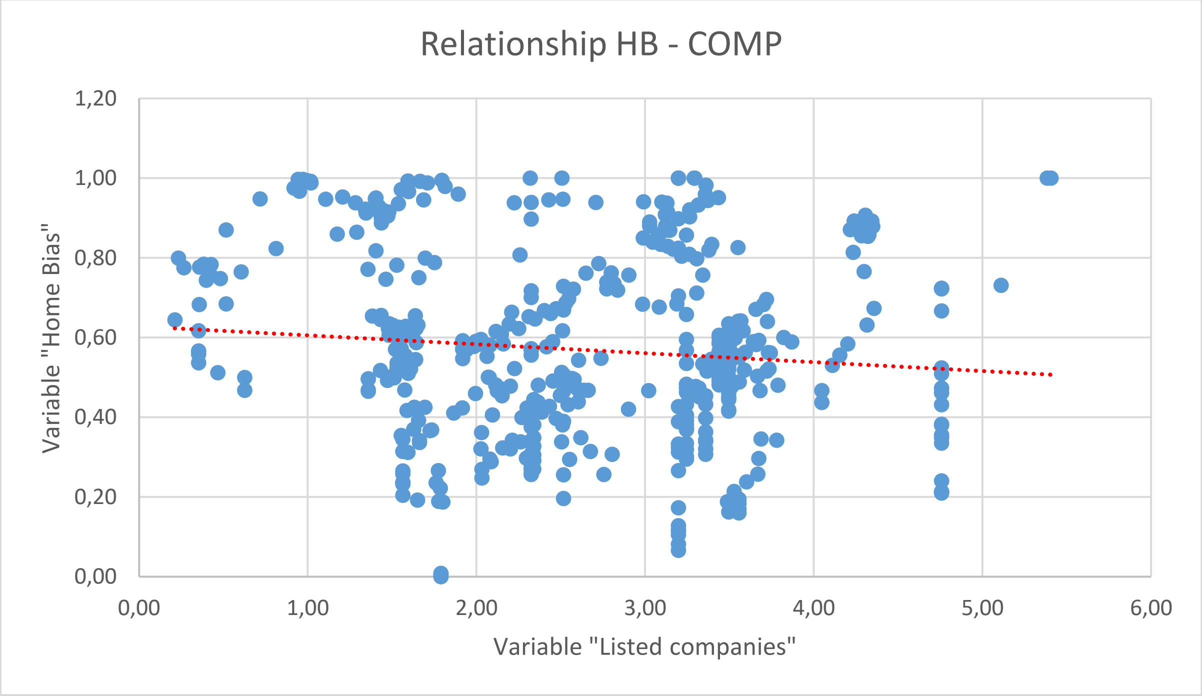
Source : Own construction with our database

Figure 23 : Scatter plot – Relation between variables HB and CAP



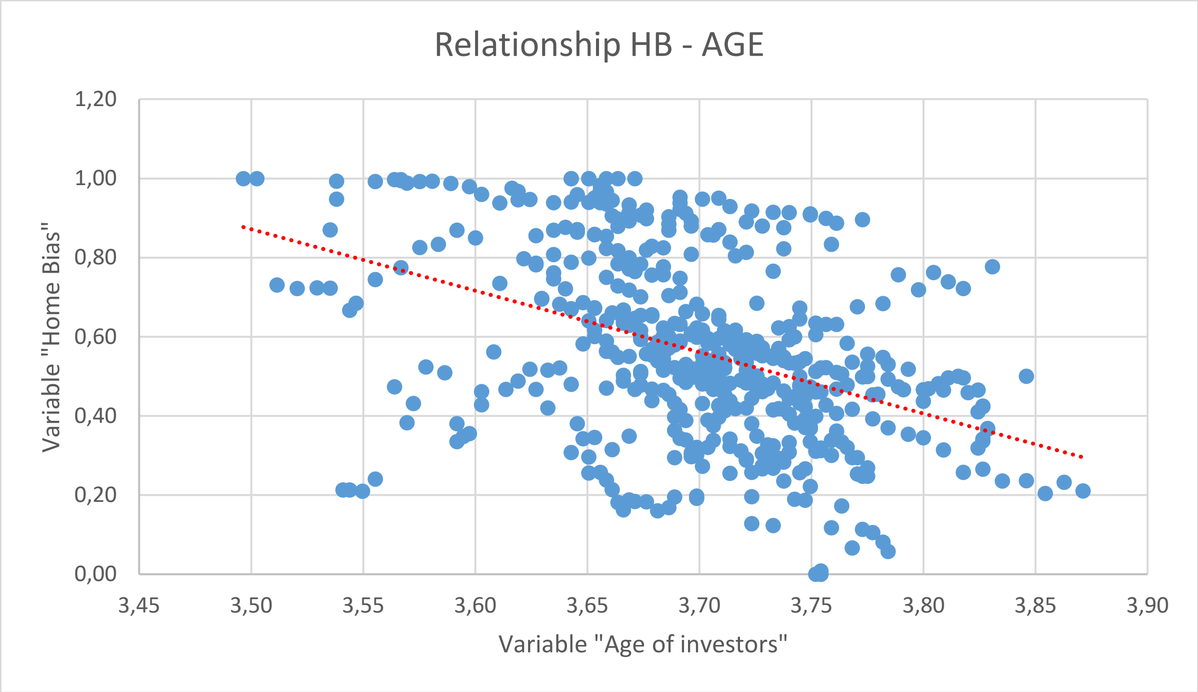
Source : Own construction with our database

Figure 24 : Scatter plot – Relation between variables HB and COMP



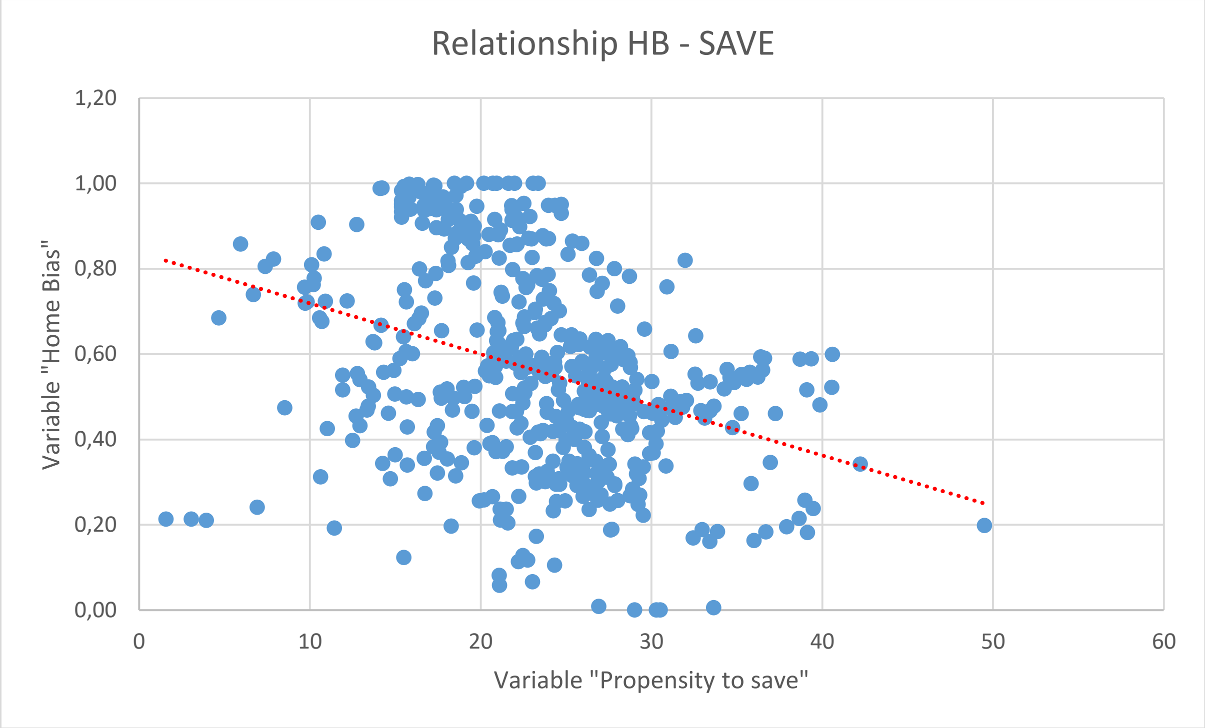
Source : Own construction with our database

Figure 25 : Scatter plot – Relation between variables HB and AGE



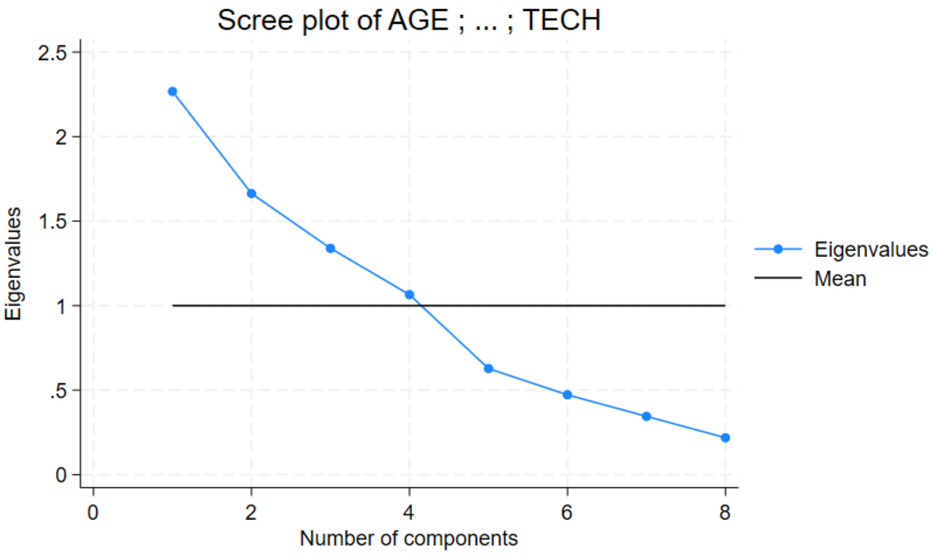
Source : Own construction with our database

Figure 26 : Scatter plot – Relation between variables HB and SAVE



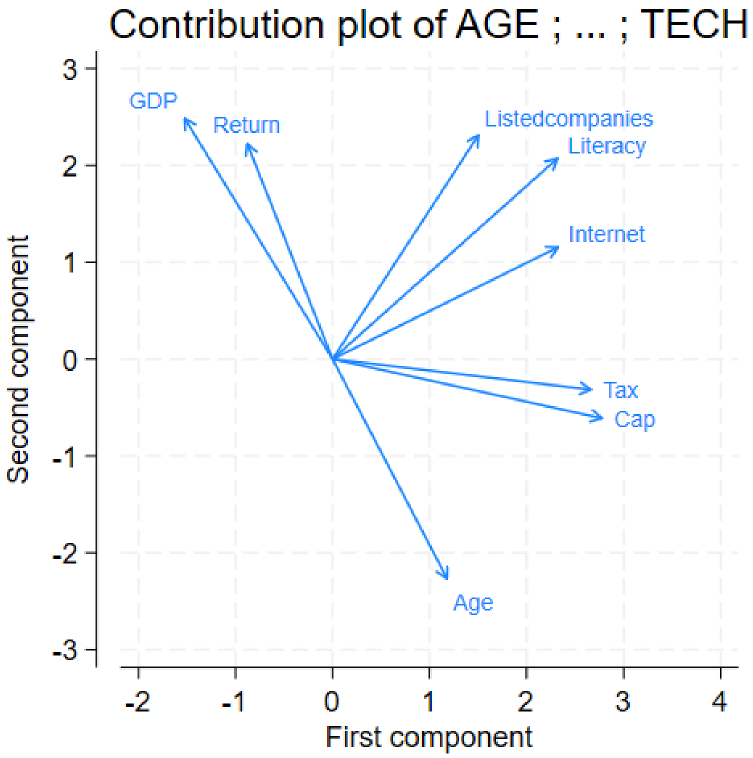
Source : Own construction with our database

Figure 27 : Principal Component Analysis scree plot for the entire sample



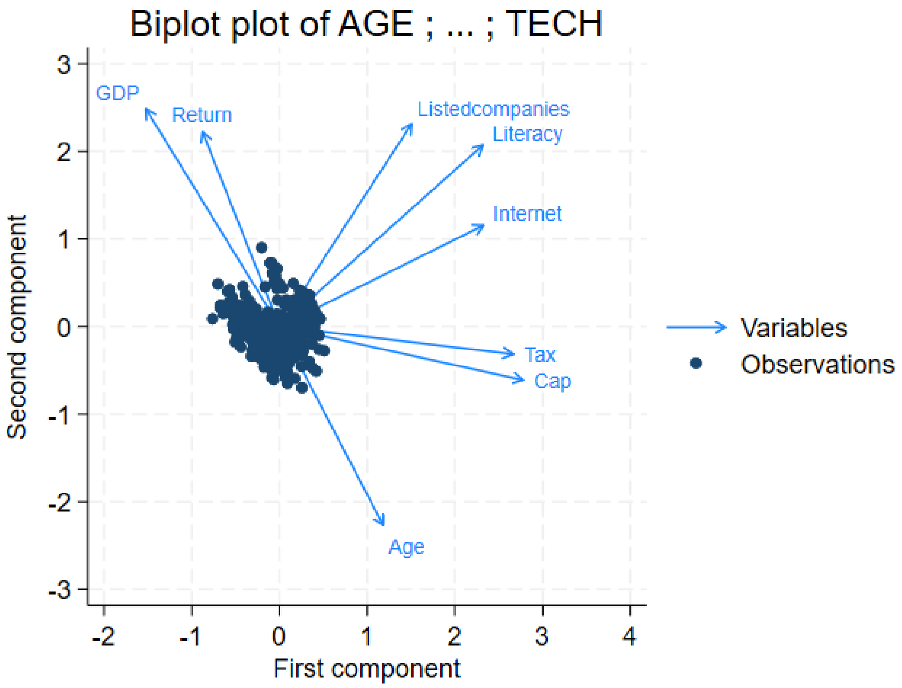
Source : Stata with our database

Figure 28 : Principal Component Analysis contribution plot for the entire sample



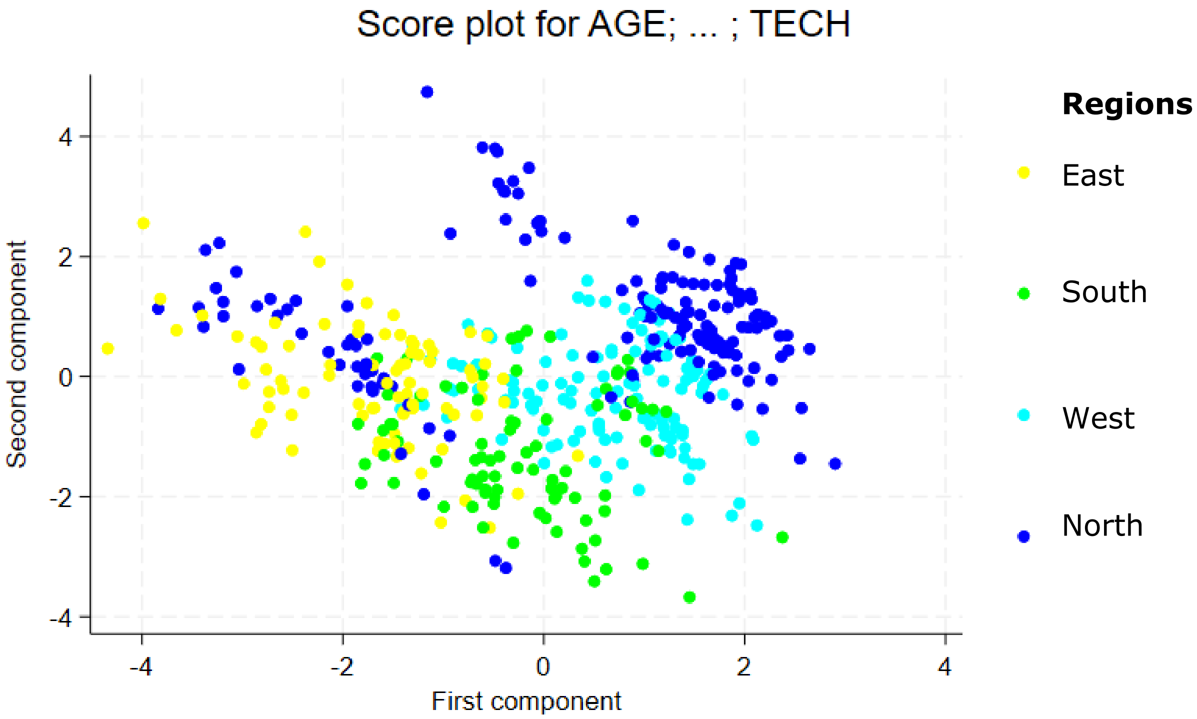
Source : Stata with our database

Figure 29 : Principal Component Analysis biplot for the entire sample



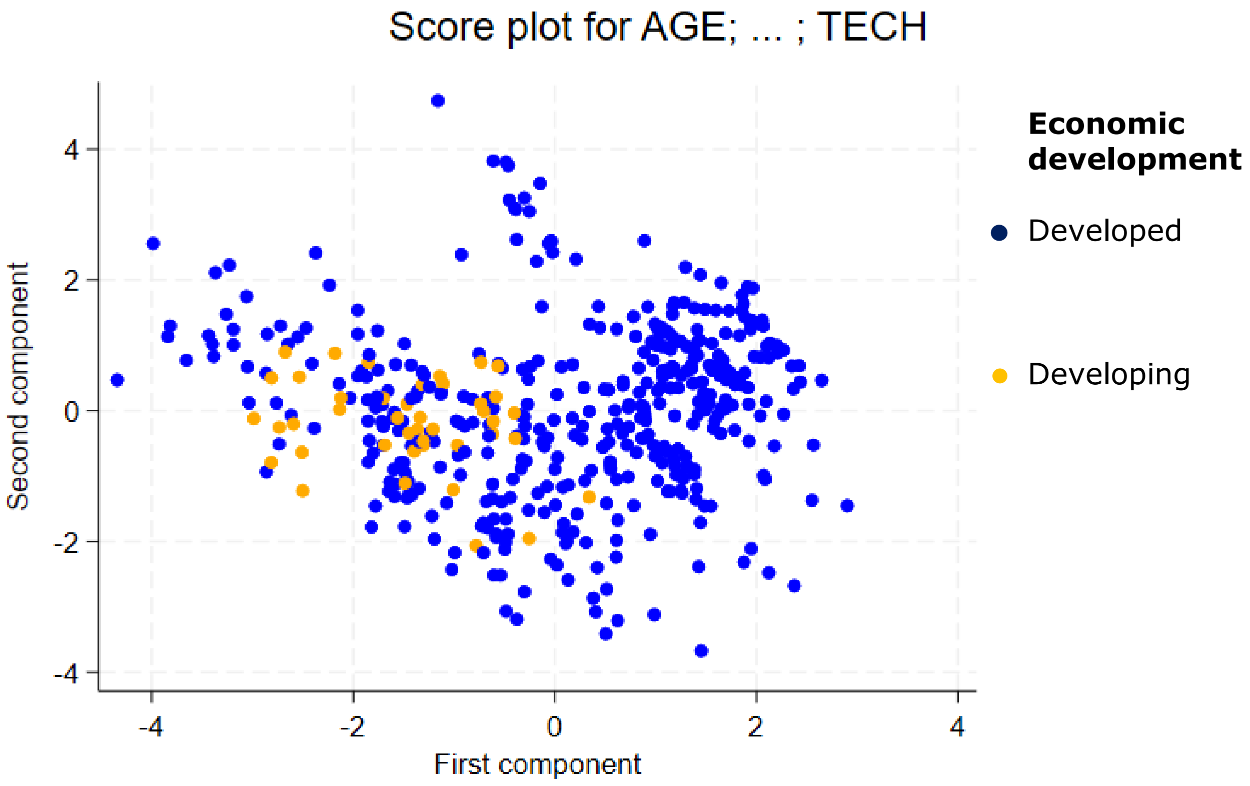
Source : Stata with our database

Figure 30 : Principal Component Analysis score plot for the entire sample by geographical region



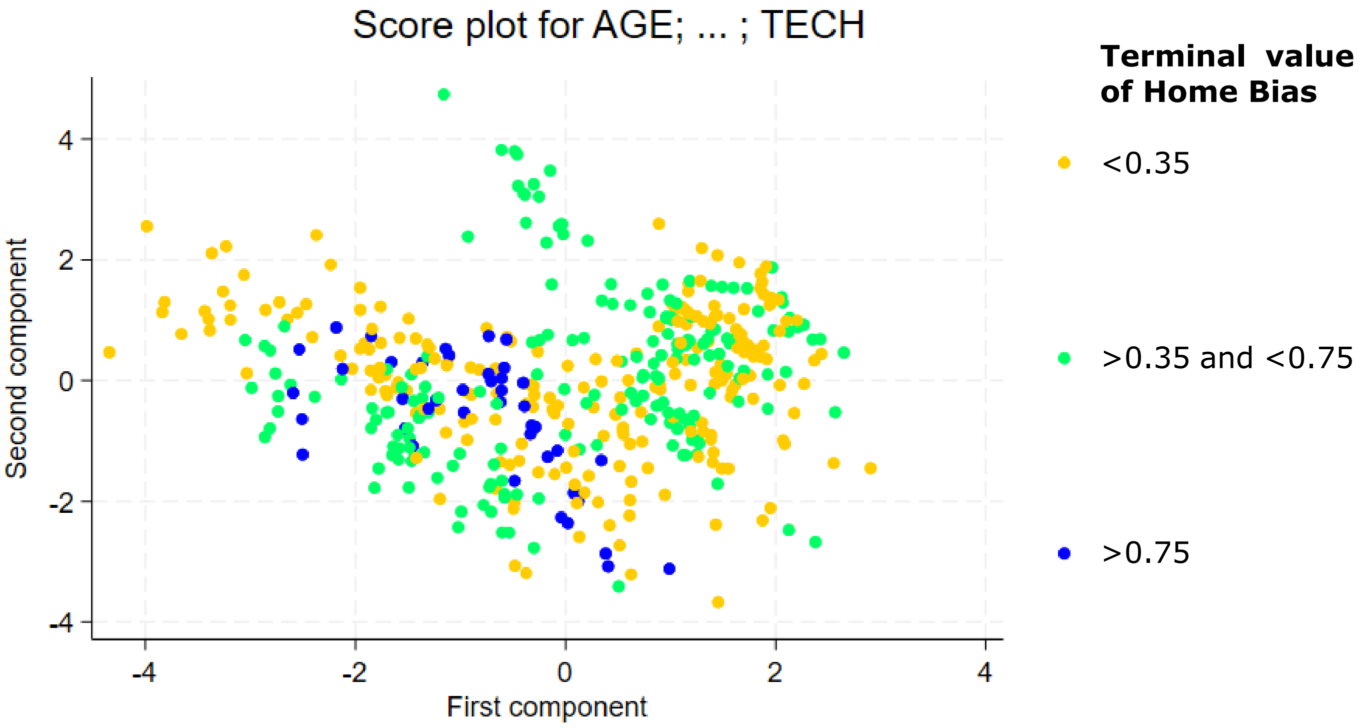
Source : Stata with our database

Figure 31 : Principal Component Analysis scree plot for the entire sample by economic development level



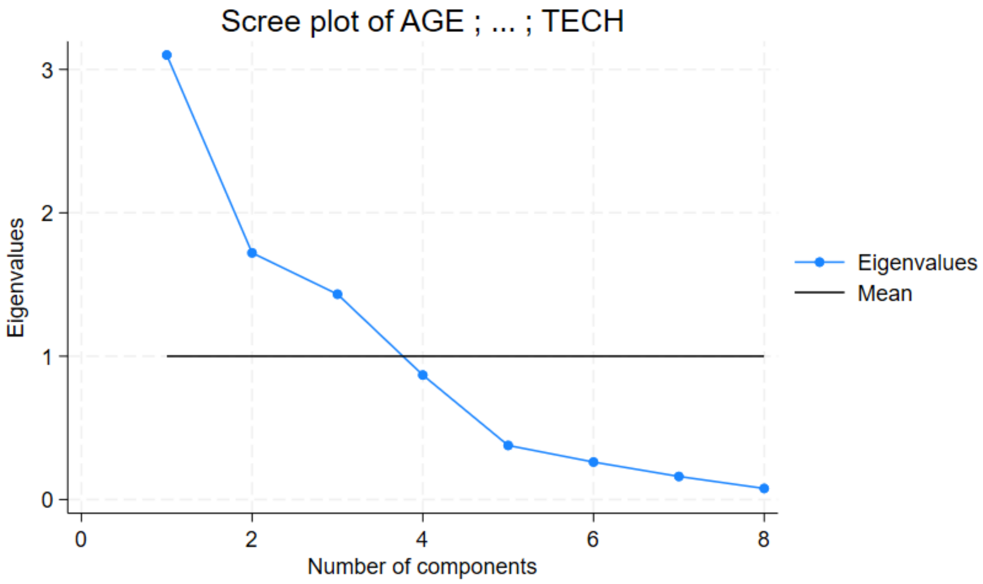
Source : Stata with our database

Figure 32 : Principal Component Analysis scree plot for the entire sample by terminal Home Bias level



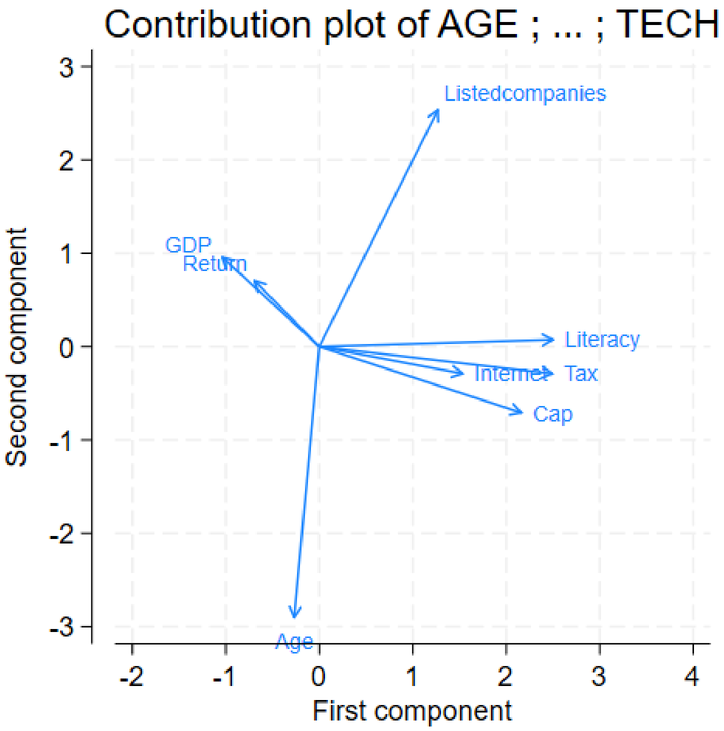
Source : Stata with our database

Figure 33 : Principal Component Analysis scree plot for northern countries



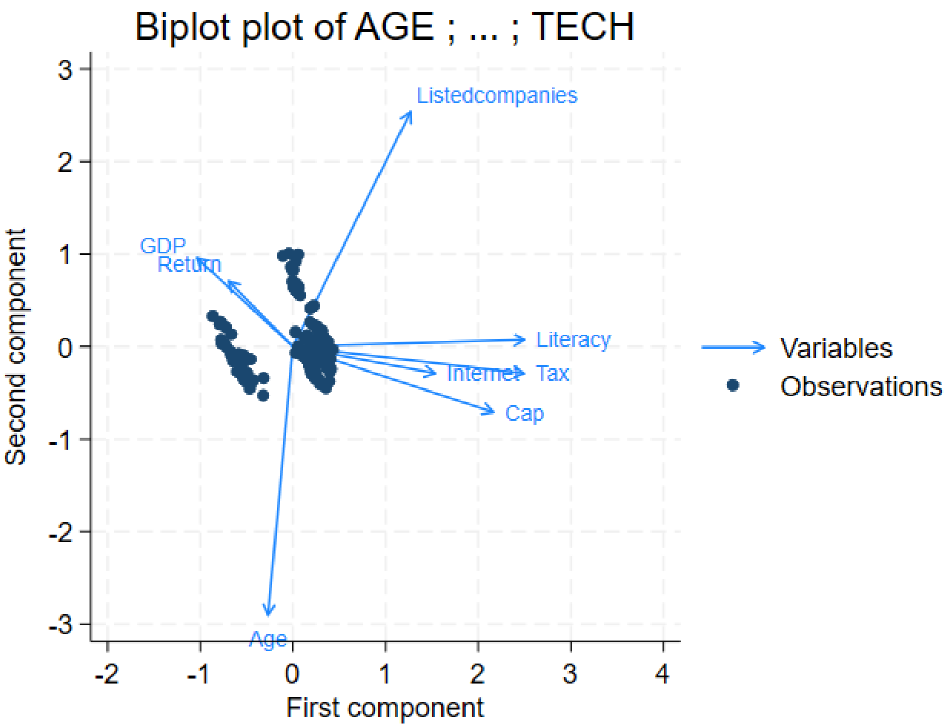
Source : Stata with our database

Figure 34 : Principal Component Analysis contribution plot for northern countries



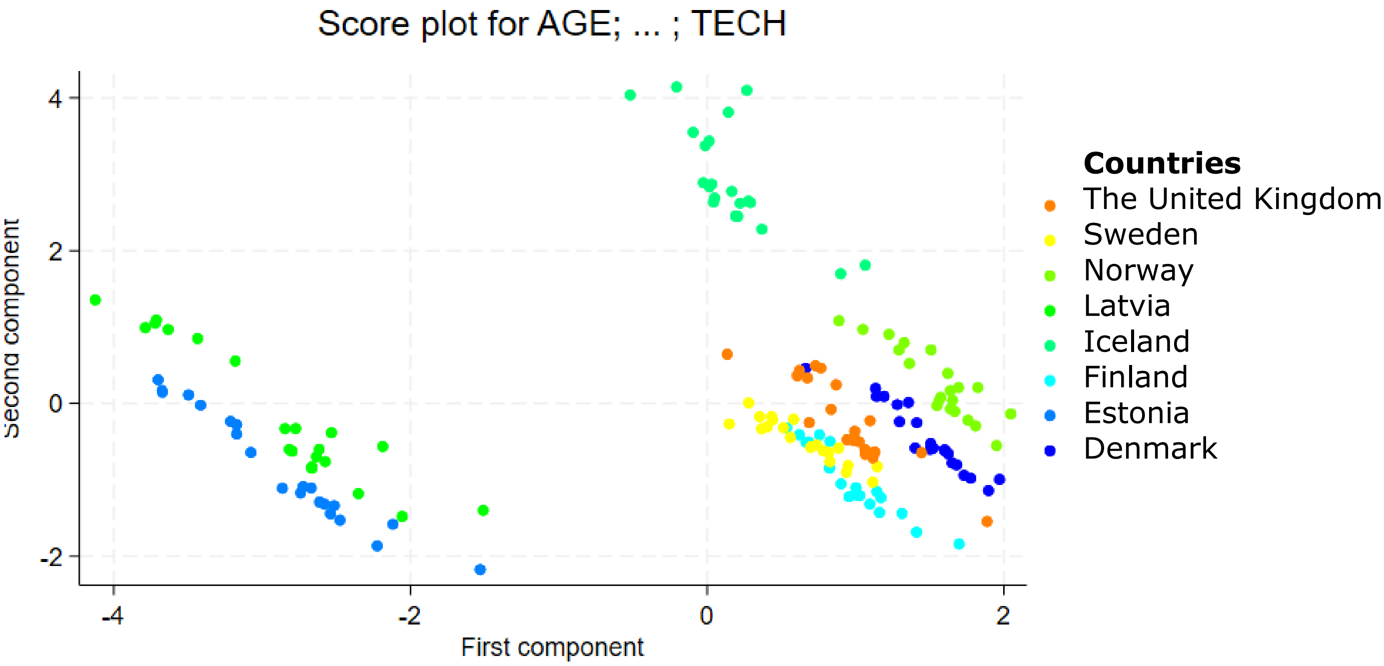
Source : Stata with our database

Figure 35 : Principal Component Analysis biplot for northern countries



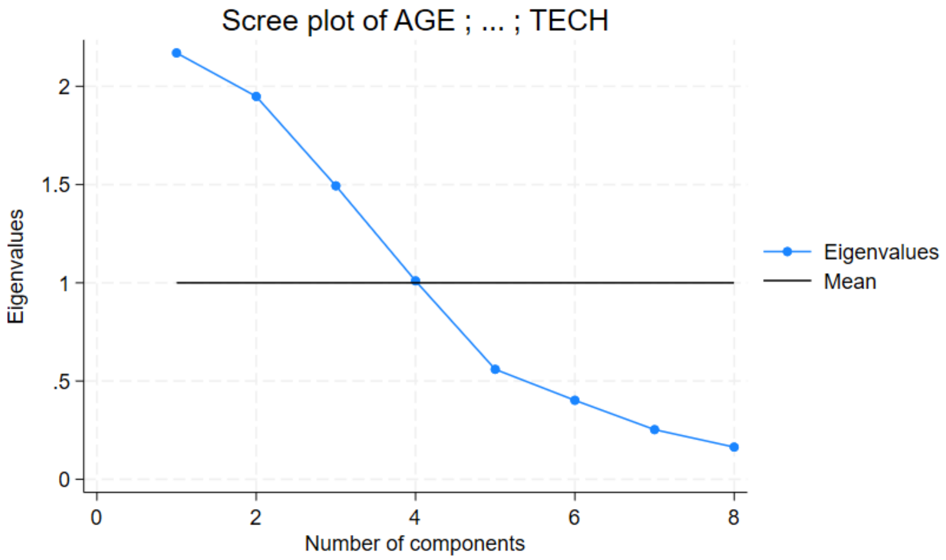
Source : Stata with our database

Figure 36 : Principal Component Analysis score plot for northern countries



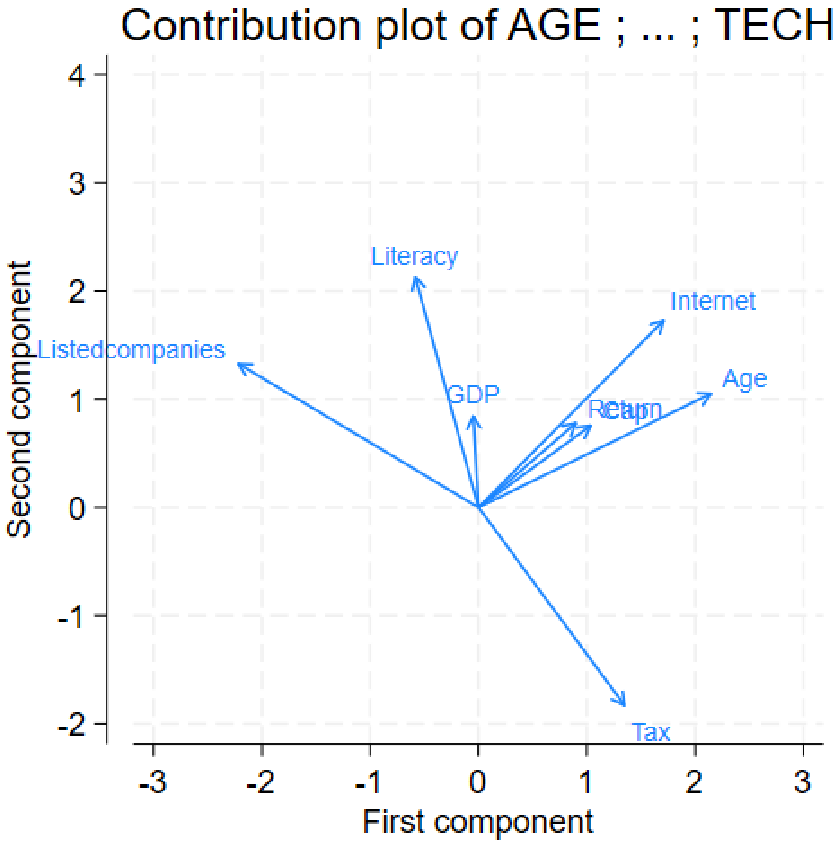
Source : Stata with our database

Figure 37 : Principal Component Analysis scree plot for western countries



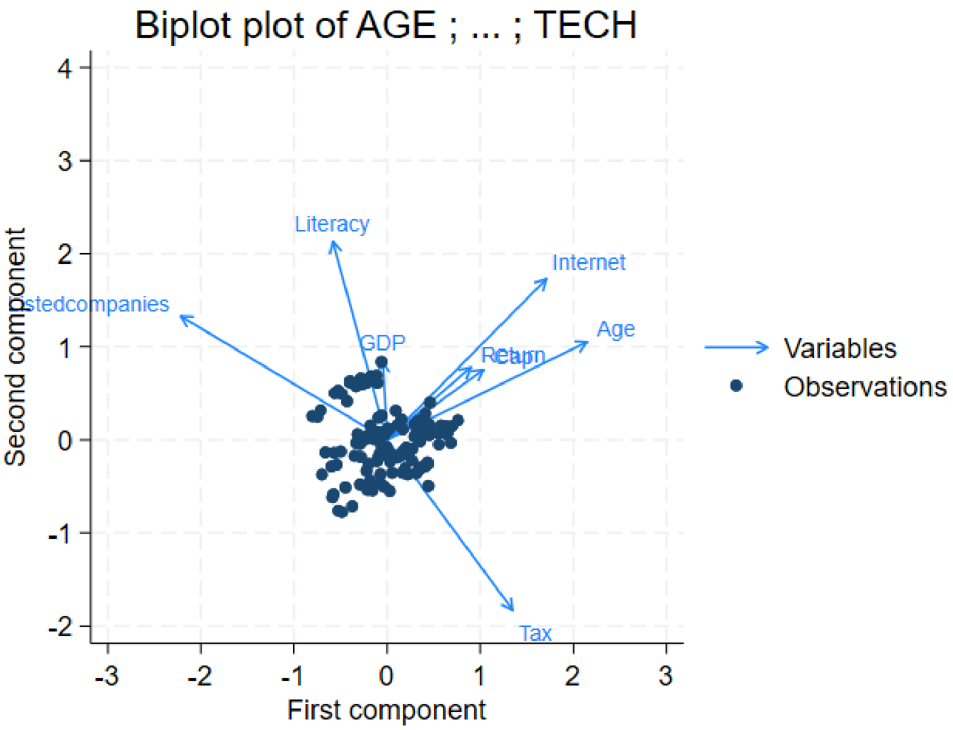
Source : Stata with our database

Figure 38 : Principal Component Analysis contribution plot for western countries



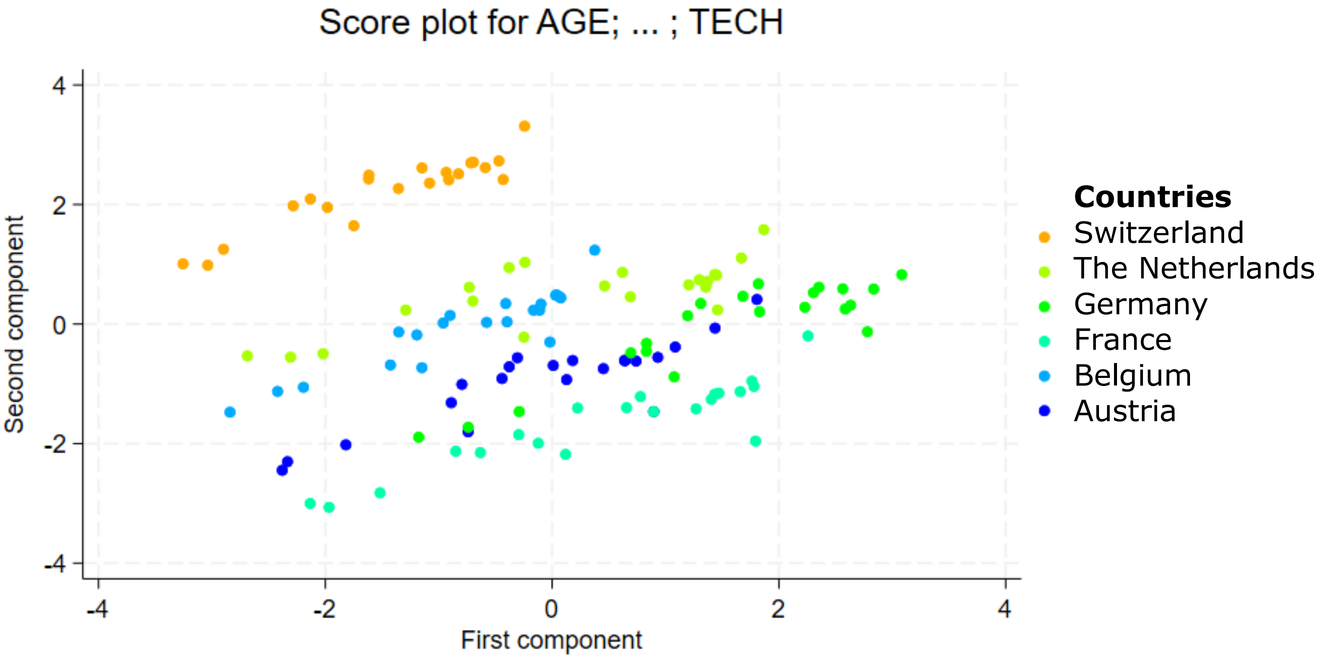
Source : Stata with our database

Figure 39 : Principal Component Analysis biplot for western countries



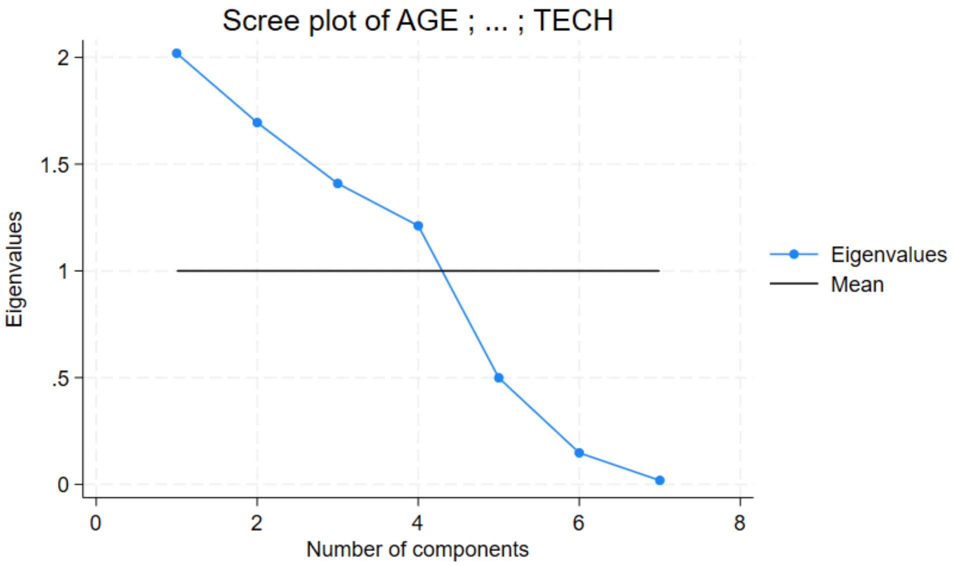
Source : Stata with our database

Figure 40 : Principal Component Analysis score plot for western countries



Source : Stata with our database

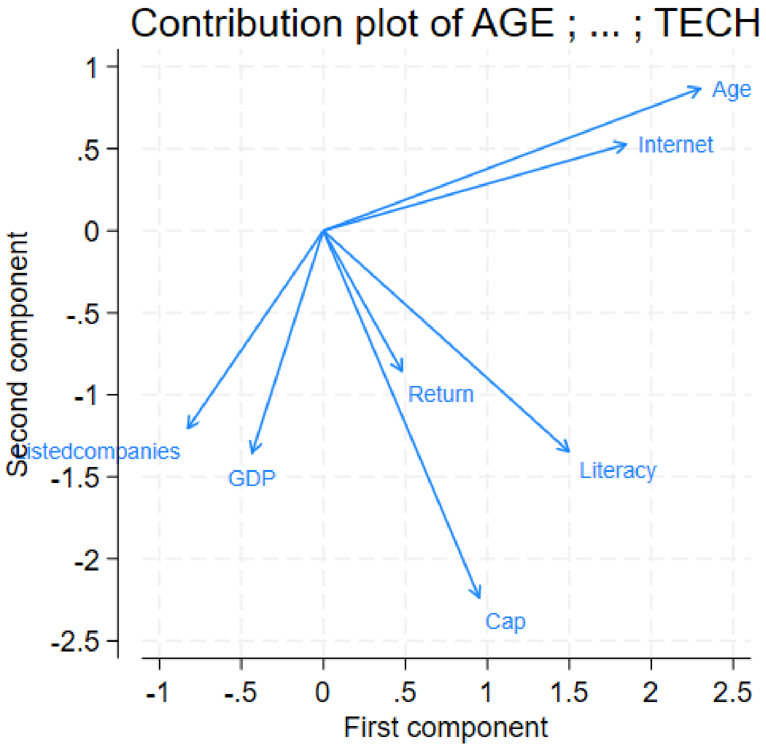
Figure 41 : Principal Component Analysis scree plot for southern countries



Source : Stata with our database

Figure 42 : Principal Component Analysis contribution plot for southern countries

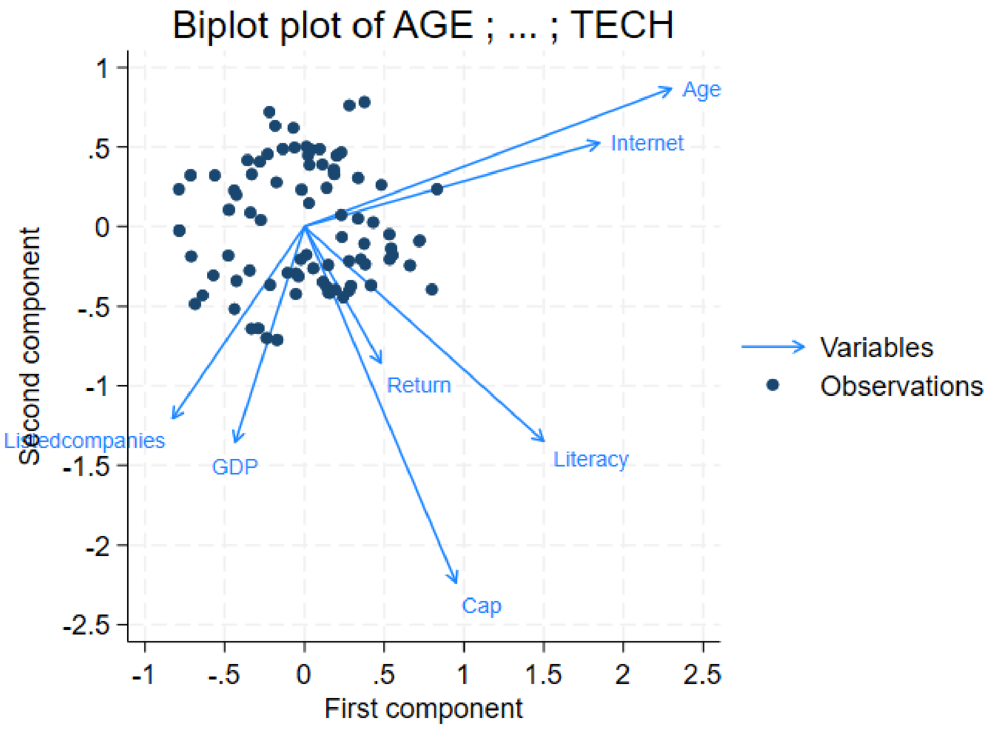
TAX dropped due to zero variance



Source : Stata with our database

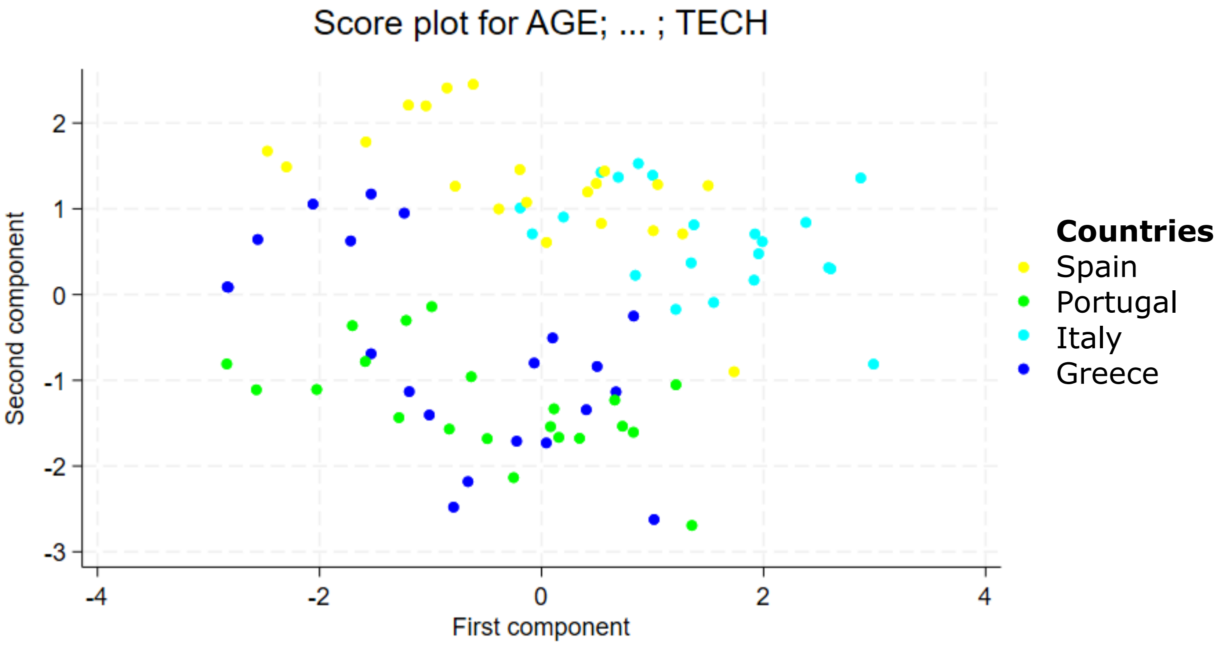
Figure 43 : Principal Component Analysis biplot for southern countries

TAX dropped due to zero variance



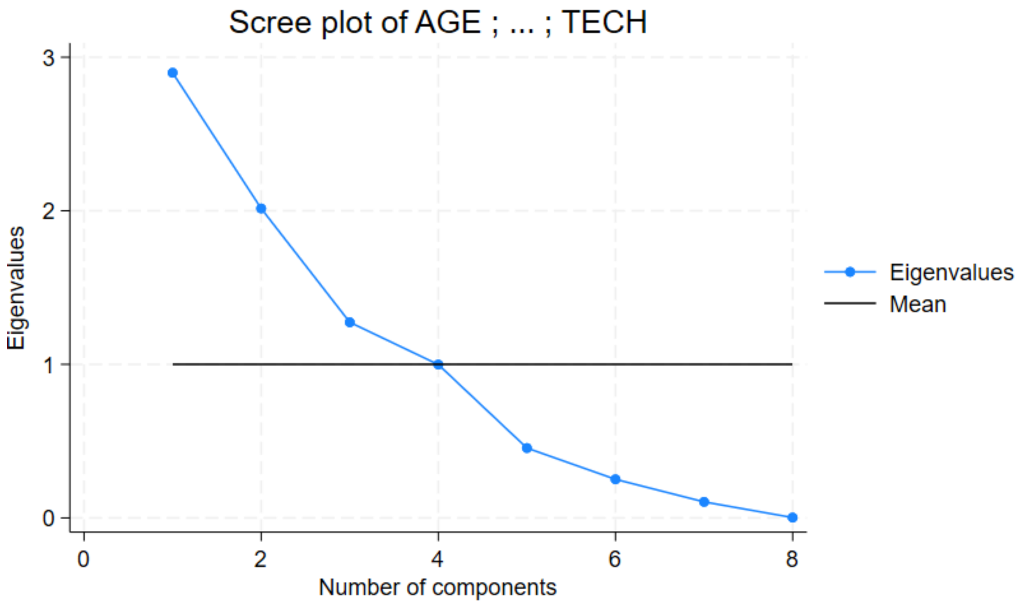
Source : Stata with our database

Figure 44 : Principal Component Analysis score plot for southern countries



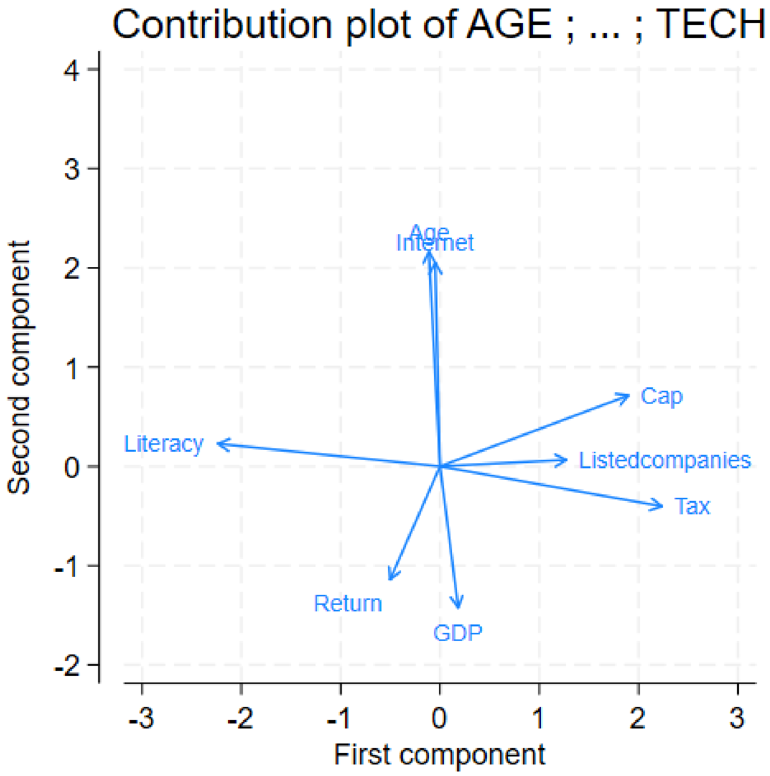
Source : Stata with our database

Figure 45 : Principal Component Analysis scree plot for eastern countries



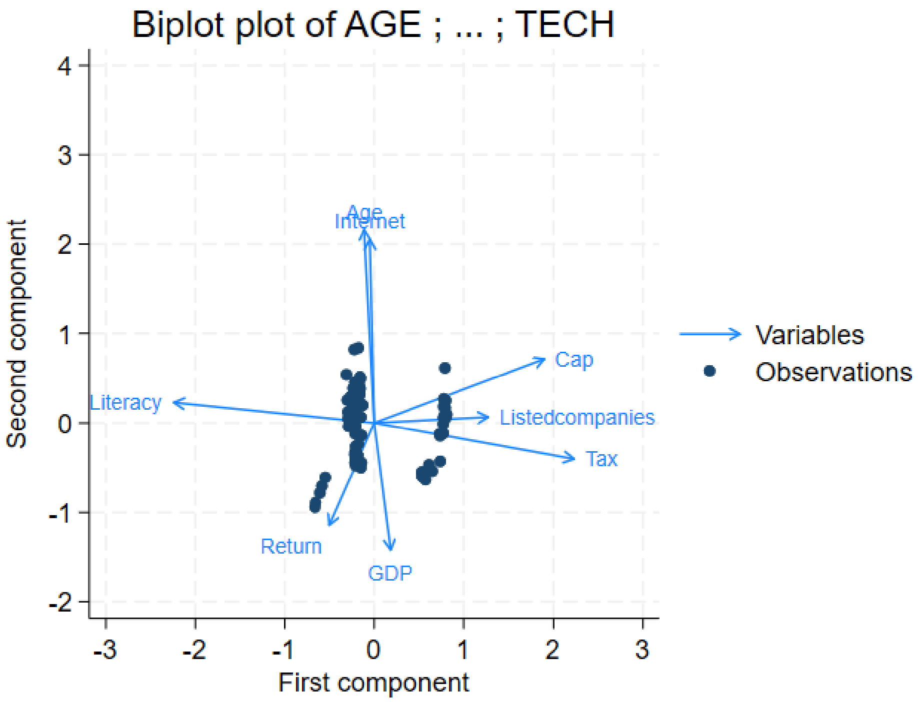
Source : Stata with our database

Figure 46 : Principal Component Analysis contribution plot for eastern countries



Source : Stata with our database

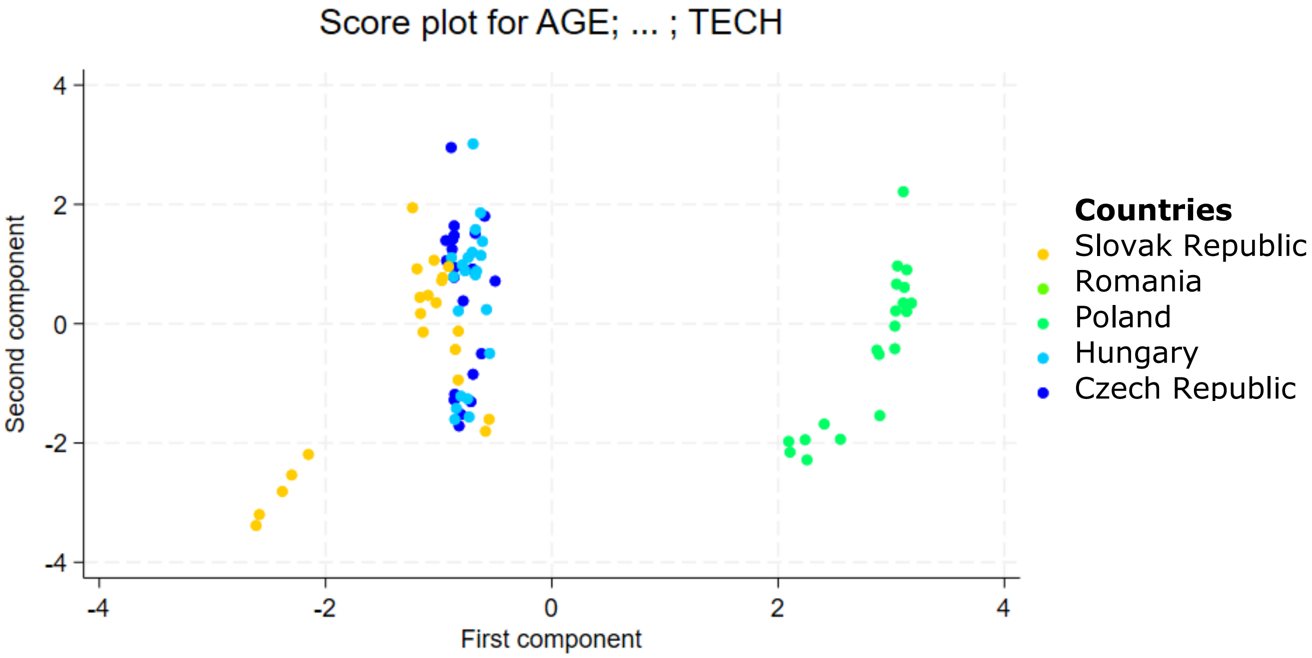
Figure 47 : Principal Component Analysis biplot for eastern countries



Source : Stata with our database

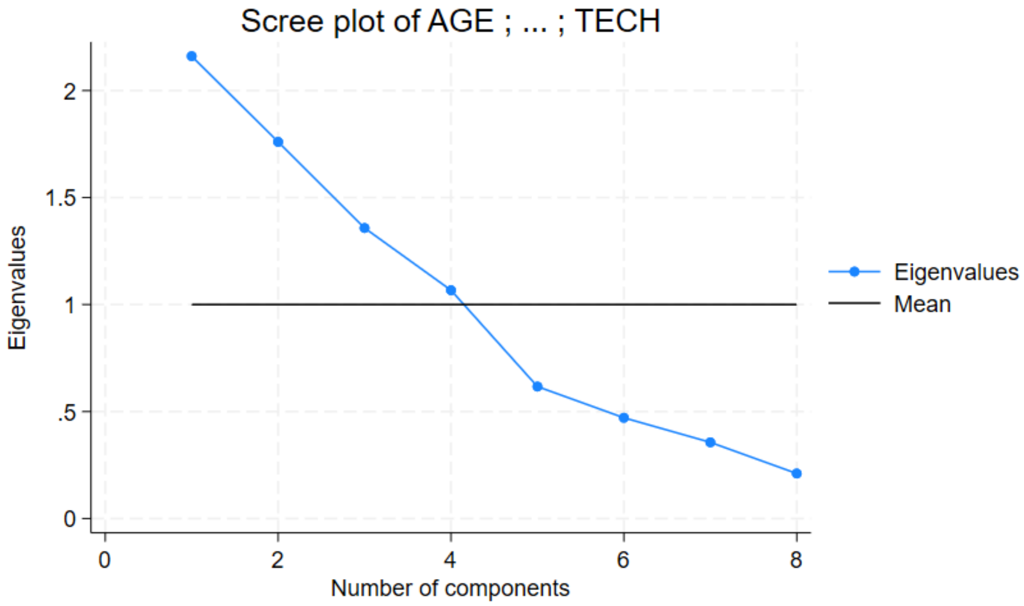
Figure 48 : Principal Component Analysis score plot for eastern countries

Romania is missing from the plot as it exhibits some missing values



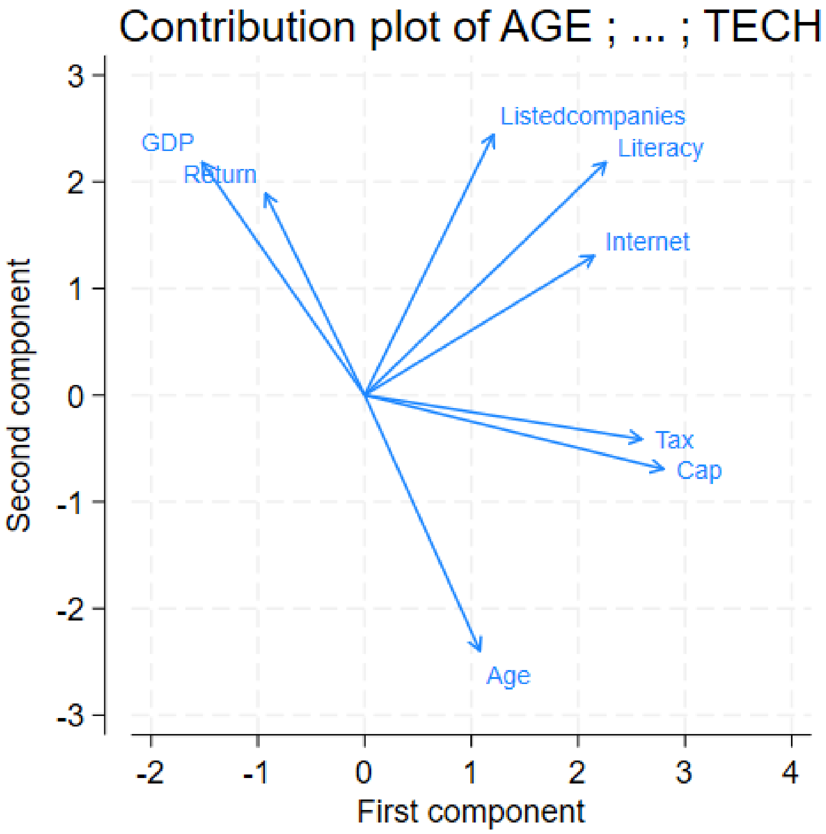
Source : Stata with our database

Figure 49 : Principal Component Analysis scree plot for developed countries



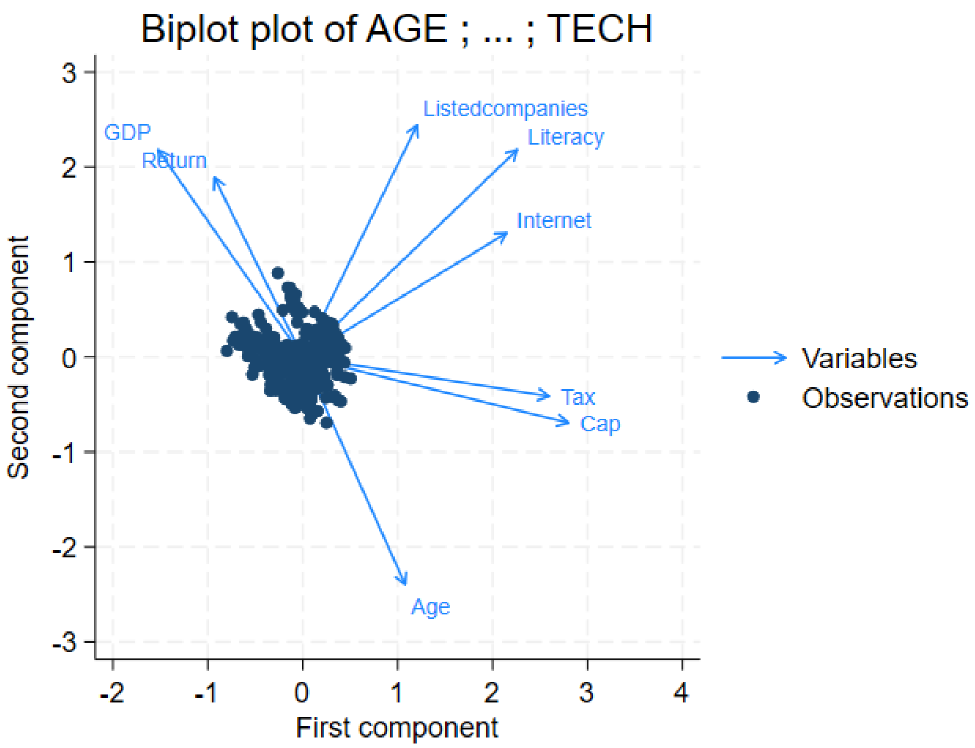
Source : Stata with our database

Figure 50 : Principal Component Analysis contribution plot for developed countries



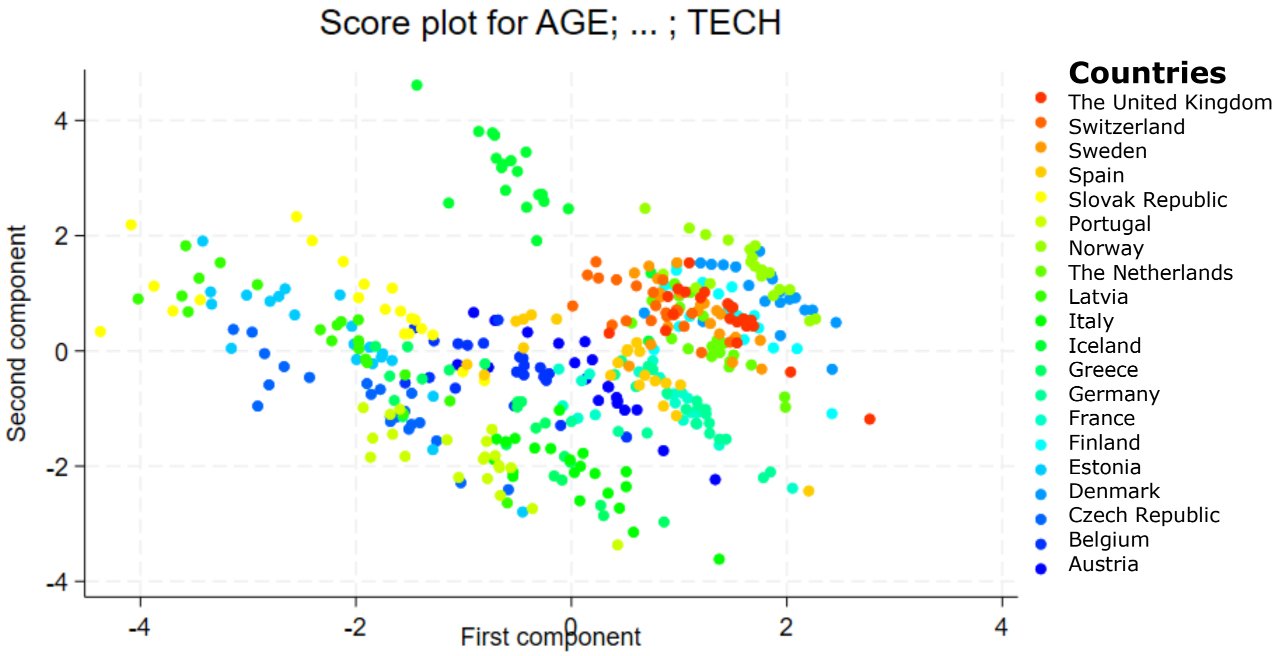
Source : Stata with our database

Figure 51 : Principal Component Analysis biplot for developed countries



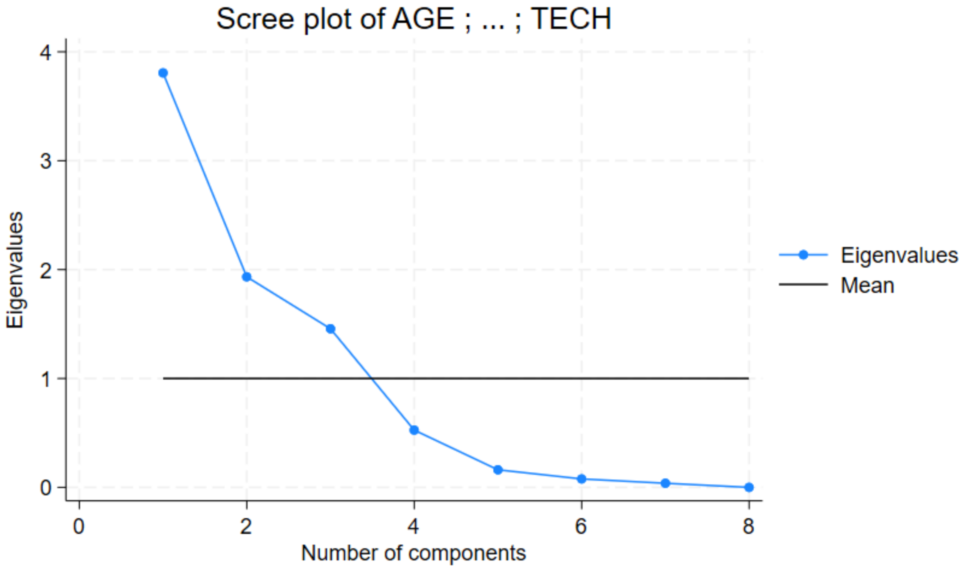
Source : Stata with our database

Figure 52 : Principal Component Analysis score plot for developed countries



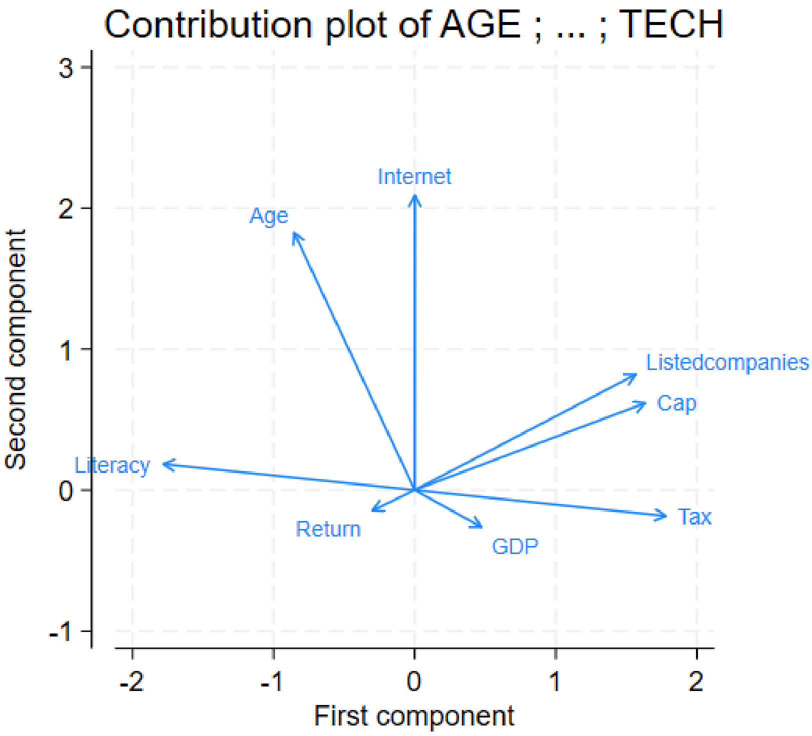
Source : Stata with our database

Figure 53 : Principal Component Analysis scree plot for developing countries



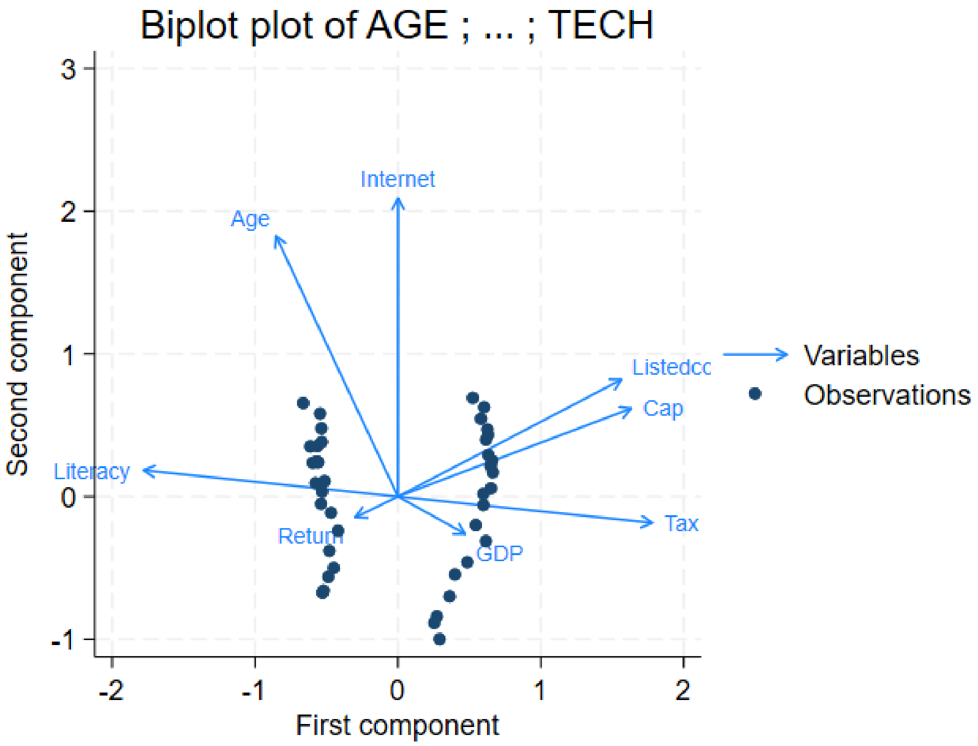
Source : Stata with our database

Figure 54 : Principal Component Analysis contribution plot for developing countries



Source : Stata with our database

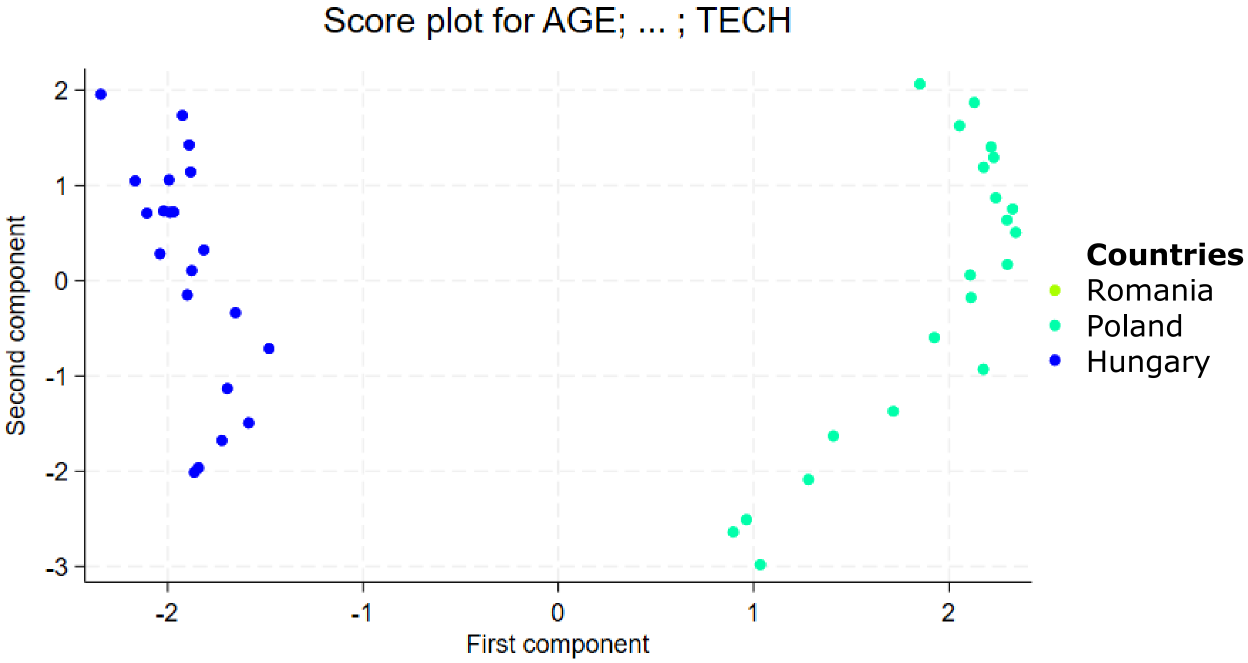
Figure 55 : Principal Component Analysis biplot for developing countries



Source : Stata with our database

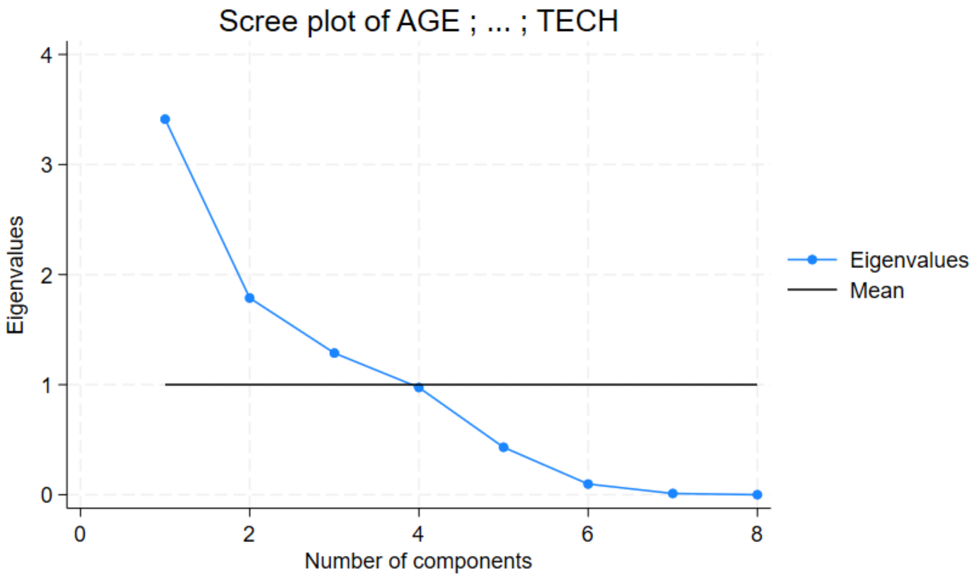
Figure 56 : Principal Component Analysis score plot for developing countries

Romania is missing from the plot as it exhibits some missing values



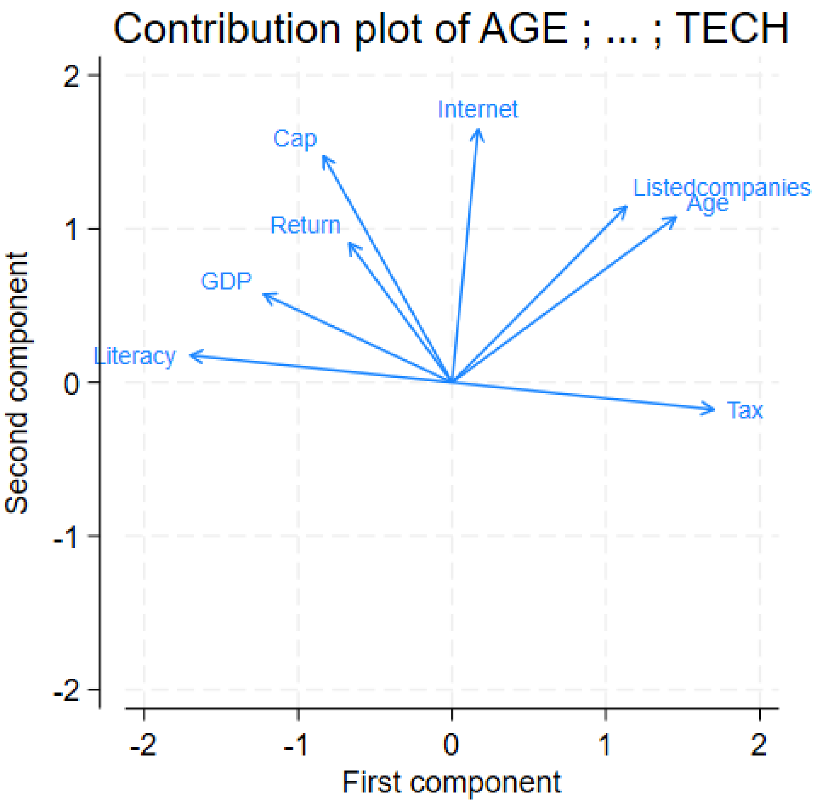
Source : Stata with our database

Figure 57 : Principal Component Analysis scree plot for high terminal Home Bias level countries



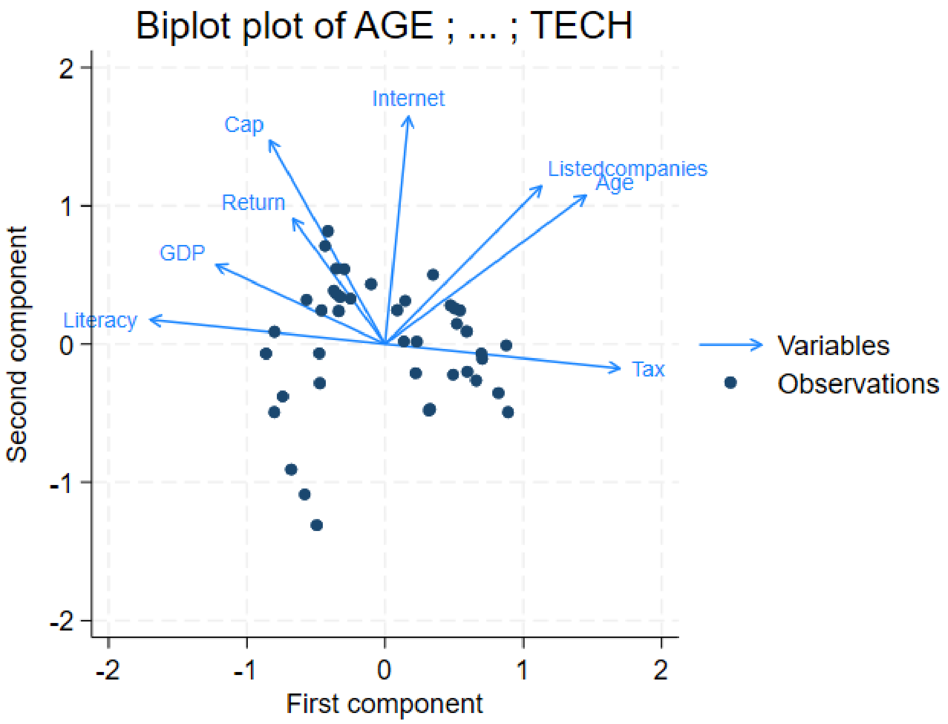
Source : Stata with our database

Figure 58 : Principal Component Analysis contribution plot for high terminal Home Bias level countries



Source : Stata with our database

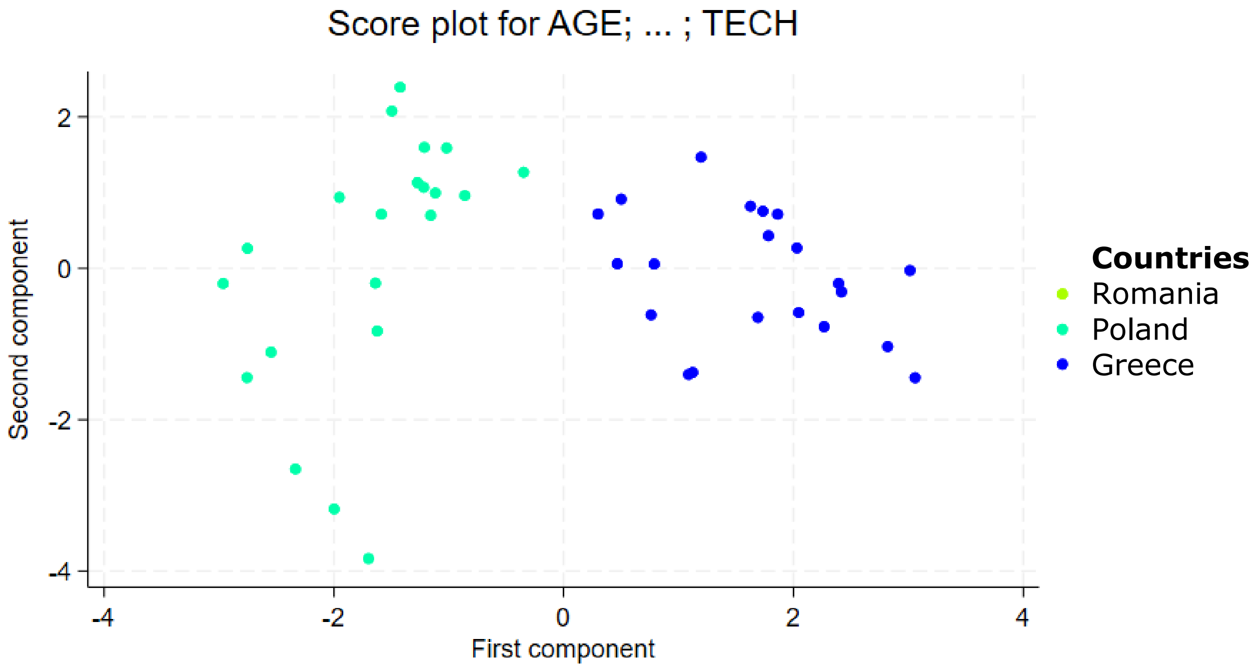
Figure 59 : Principal Component Analysis biplot for high terminal Home Bias level countries



Source : Stata with our database

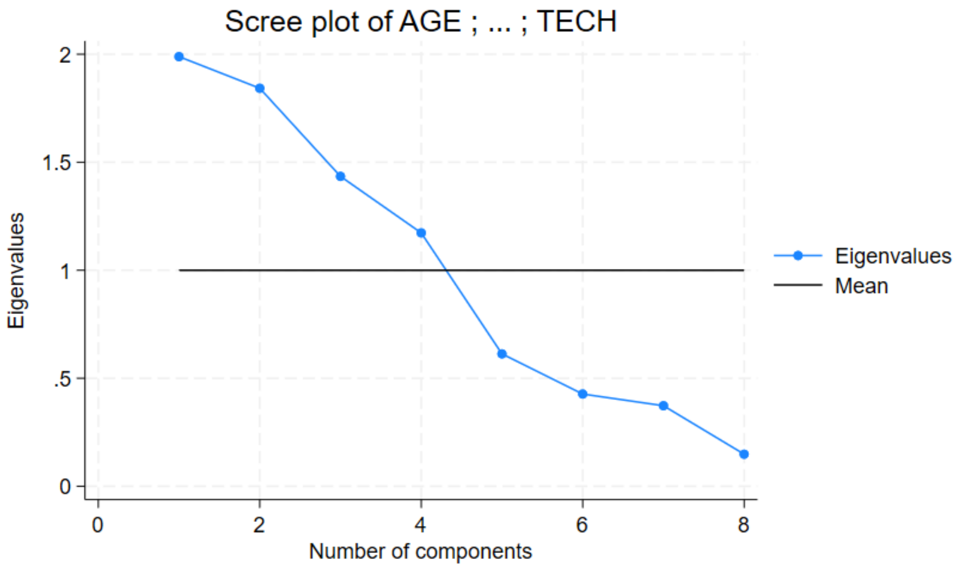
Figure 60 : Principal Component Analysis score plot for high terminal Home Bias level countries

Romania is missing from the plot as it exhibits some missing values



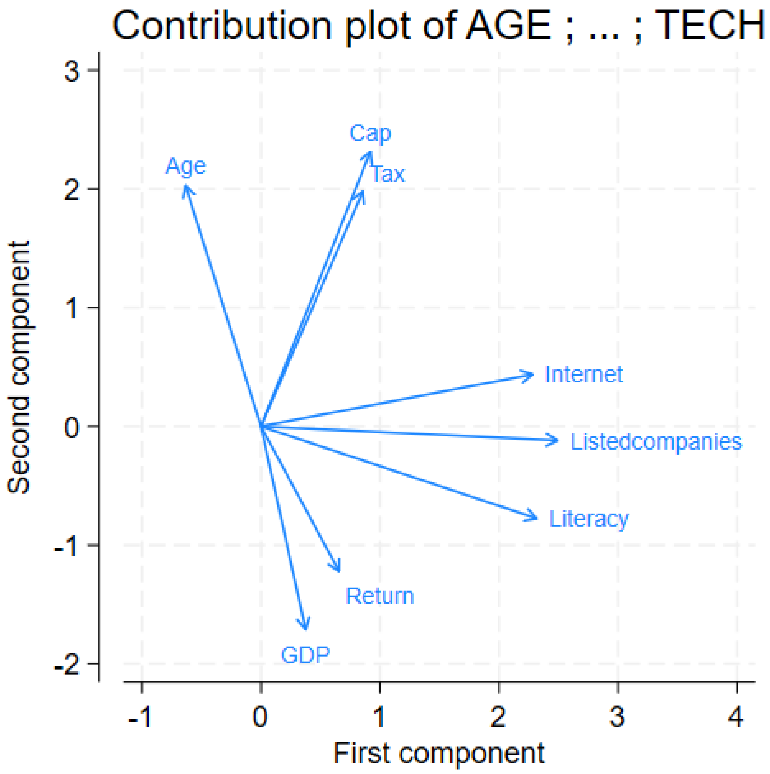
Source : Stata with our database

Figure 61 : Principal Component Analysis scree plot for medium terminal Home Bias level countries



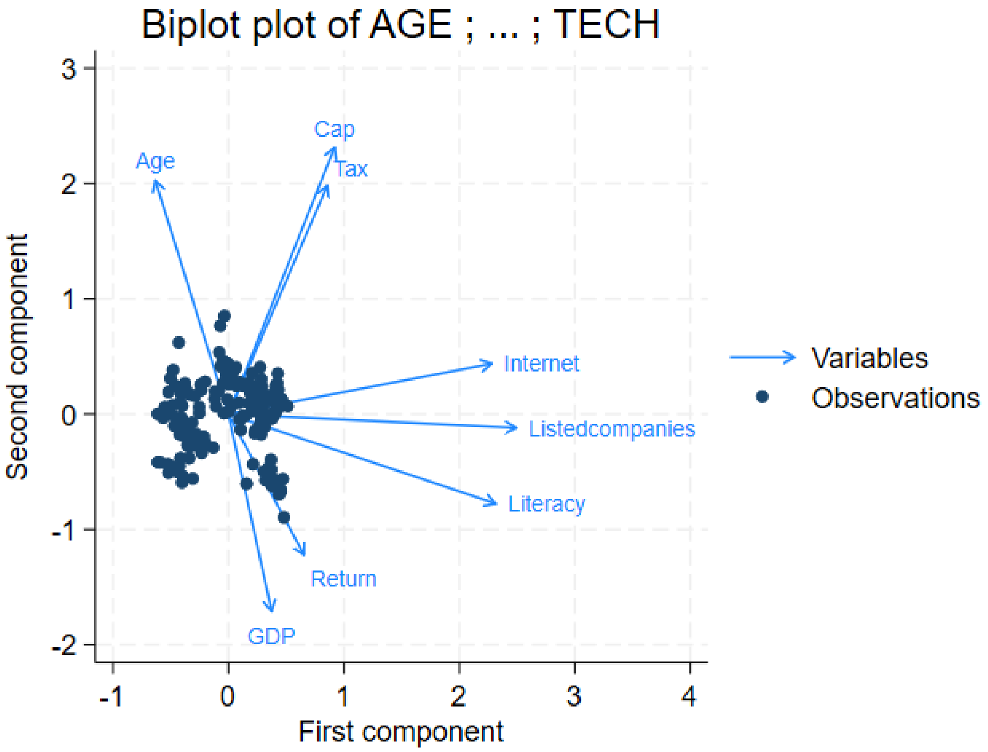
Source : Stata with our database

Figure 62 : Principal Component Analysis contribution plot for medium terminal Home Bias level countries



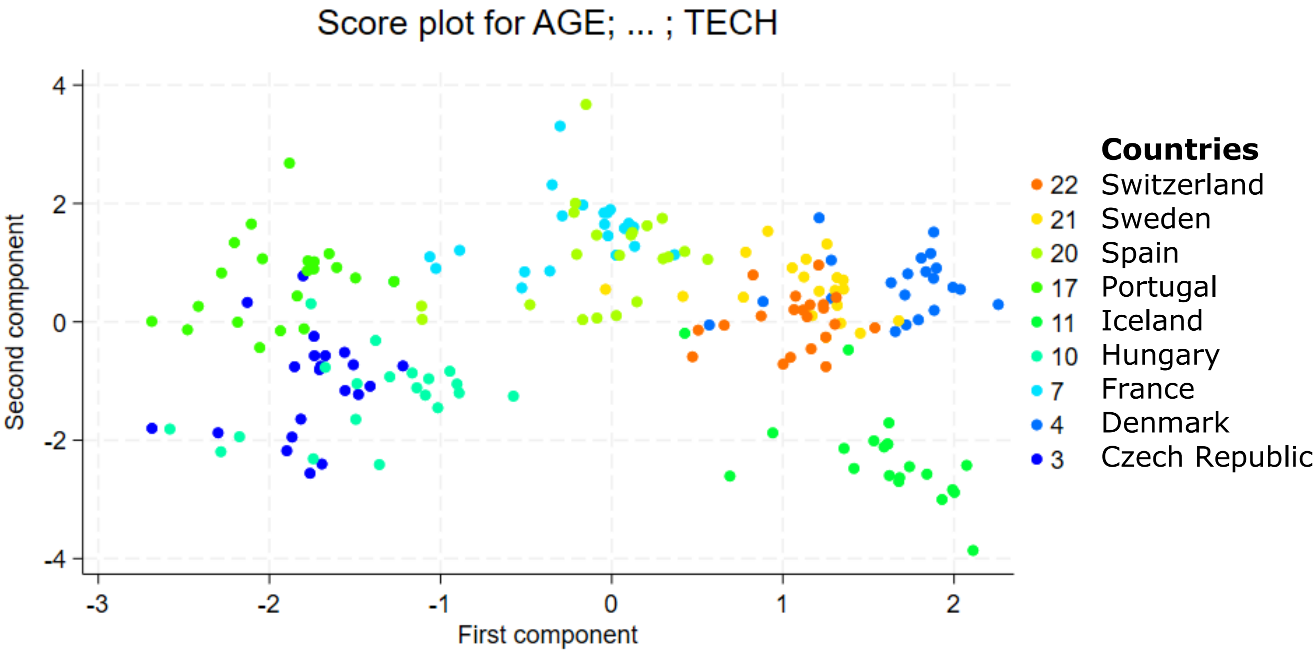
Source : Stata with our database

Figure 63 : Principal Component Analysis biplot for medium terminal Home Bias level countries



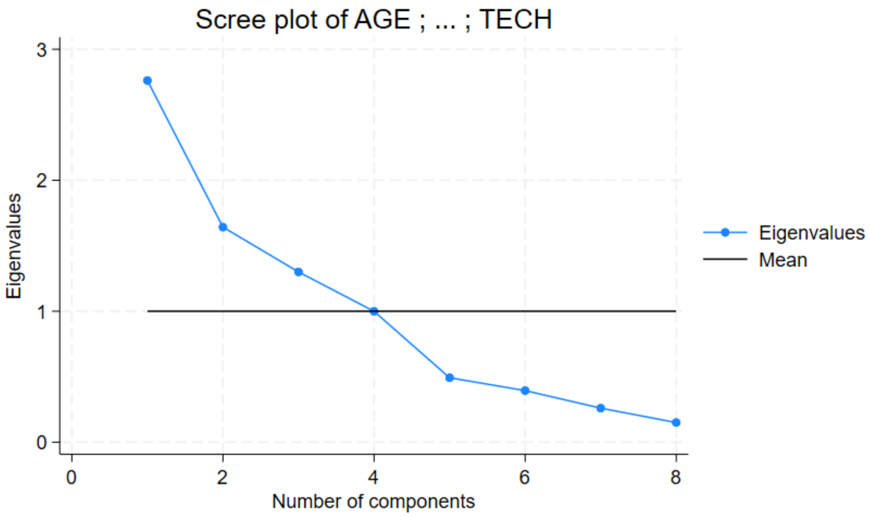
Source : Stata with our database

Figure 64 : Principal Component Analysis score plot for medium terminal Home Bias level countries



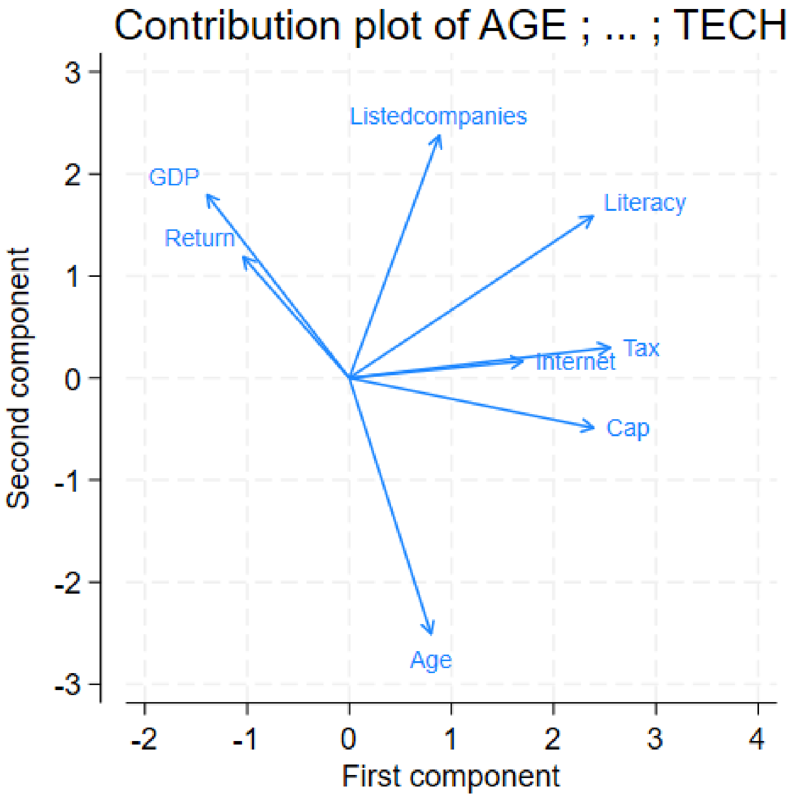
Source : Stata with our database

Figure 65 : Principal Component Analysis scree plot for low terminal Home Bias level countries



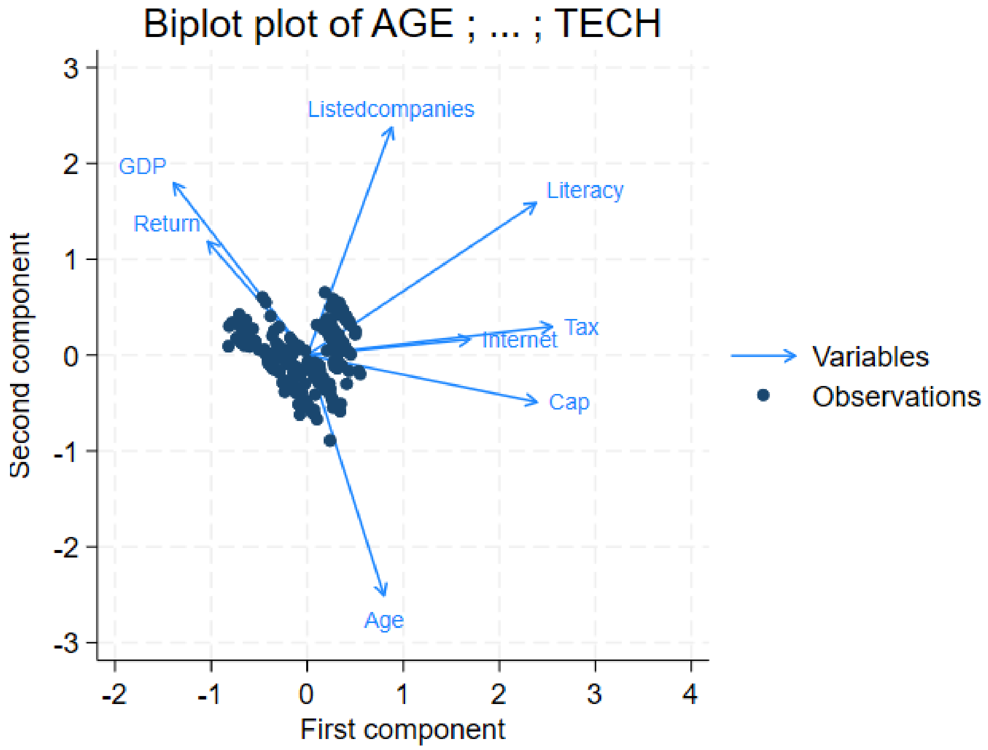
Source : Stata with our database

Figure 66 : Principal Component Analysis contribution plot for low terminal Home Bias level countries



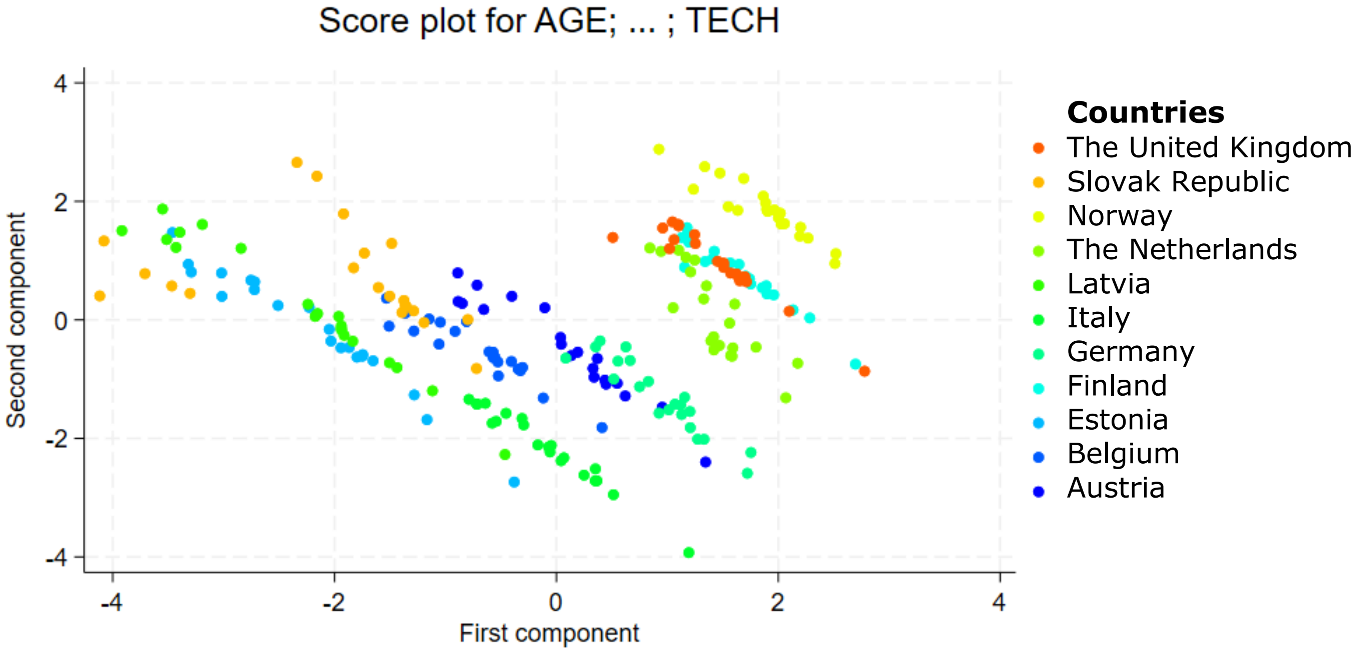
Source : Stata with our database

Figure 67 : Principal Component Analysis biplot for low terminal Home Bias level countries



Source : Stata with our database

Figure 68 : Principal Component Analysis score plot for low terminal Home Bias level countries



Source : Stata with our database

Appendices – Tables

Table 1 : Hypothesis summary and their analysis type

Name	Explicative Factors	Intuitive relationship with the Home Bias	Analyze type
F1	Tax regime	Negative	Linear regression PCA
F2	The financial knowledge of citizens	Negative	Linear regression PCA
F3	Technological influence and mastery	Negative	Panel regression PCA
F4	Economic growth – GDP	Positive	Panel regression PCA
F5	Stock market return of countries	Positive	Panel regression PCA
F6	Market capitalization	Positive	Panel regression PCA
F7	Number of listed companies	Positive	Panel regression PCA
F8	Age of investors	Positive	Panel regression PCA
F9	Propensity to save	Positive	Panel regression PCA

"PCA" means "Principal component analysis"

Source : our construction

Table 2 : Linking factor for Foreign Bias

Name	Potential clusters links	Criteria
L1	Cultural similarities	4th quartile of the cultural similarity score
L2	Physical distance	1st decile of the distance between countries
L3+L4	Official languages and spoken languages	Countries sharing a language (official or spoken)
L5	Religion	Countries having the same dominant religion

Source : our construction

Table 3 : Independent variables : Sources, construction and limitations

Name	Explicative Factors	Intuitive relationship with the Home Bias	Approximation – Independent variables	Source	Name
F1	Tax regime	Negative	Own construction	Tax foundation - Europe	Tax
F2	The financial knowledge of citizens	Negative	Financial literacy score	European Union Dataset	Literacy
F3	Technological influence and mastery	Negative	Internet usage rate	ITU Datahub	Internet
F4	Economic growth	Positive	GDP growth	World Bank (The global economy)	GDP
F5	Stock market return of countries	Positive	Stock return	The World Bank	Return
F6	Market capitalization	Positive	Country capitalization	The World Bank + Refinitiv	Cap
F7	Listed companies	Positive	Number of listed companies by inhabitants	The World Bank	Listed companies
F8	Age of investors	Positive	Mean age of inhabitants	Eurostat	Age
F9	Propensity to save	Positive	Savings as a % of GDP	The World Bank	Savings

Source : our construction

Table 4 : Linking factors for Foreign Bias : Source, construction and limitations

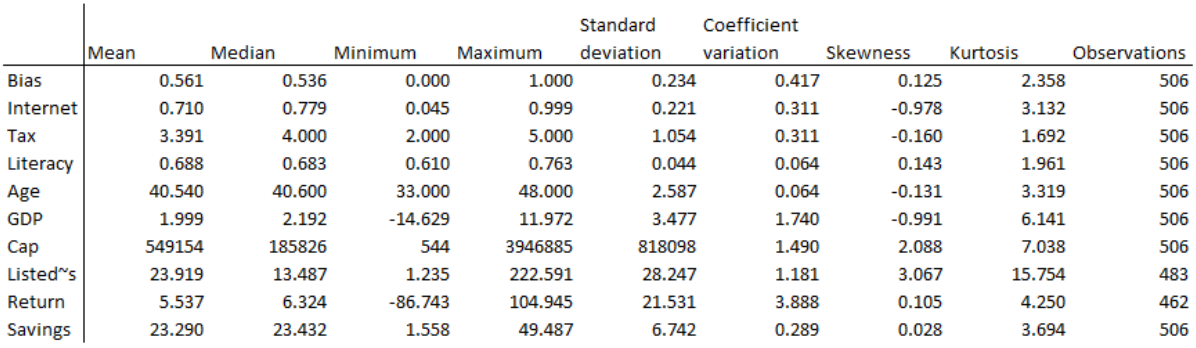
Name	Potential clusters links	Intuitive relation with the deviation	Source	Abbreviation
L1	Cultural similarities	Positive	Index on Cultural Similarity (European social survey)	CULT
L2	Physical distance	Positive	Kristian Skrede Gleditsch (Regius professor – University of Essex)	DIST

L3+L4	Official languages and spoken languages	Positive	Database of One World Nations Online	OFFL (official languages) SPOL (Spoken languages)
L5	Religion	Positive	Eurobarometer	REL

Source : our construction

Table 5 : Descriptive statistics

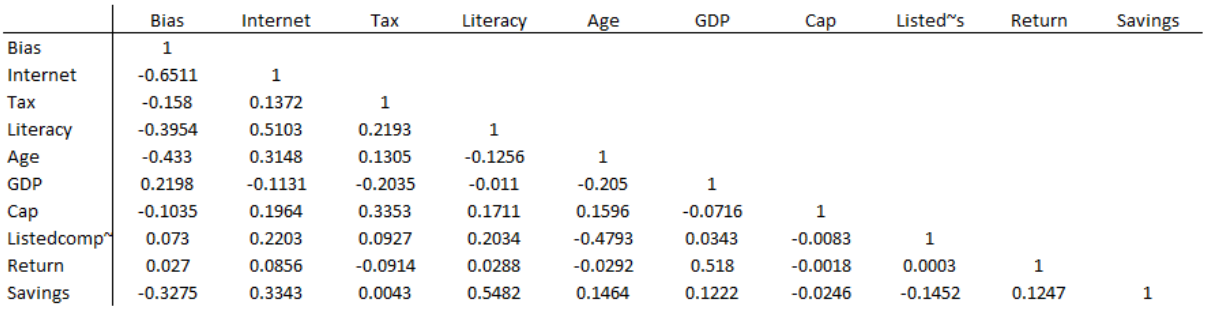
Sample's characteristics composed of 23 European countries from 2001 to 2022.



	Mean	Median	Minimum	Maximum	Standard deviation	Coefficient variation	Skewness	Kurtosis	Observations
Bias	0.561	0.536	0.000	1.000	0.234	0.417	0.125	2.358	506
Internet	0.710	0.779	0.045	0.999	0.221	0.311	-0.978	3.132	506
Tax	3.391	4.000	2.000	5.000	1.054	0.311	-0.160	1.692	506
Literacy	0.688	0.683	0.610	0.763	0.044	0.064	0.143	1.961	506
Age	40.540	40.600	33.000	48.000	2.587	0.064	-0.131	3.319	506
GDP	1.999	2.192	-14.629	11.972	3.477	1.740	-0.991	6.141	506
Cap	549154	185826	544	3946885	818098	1.490	2.088	7.038	506
Listed~s	23.919	13.487	1.235	222.591	28.247	1.181	3.067	15.754	483
Return	5.537	6.324	-86.743	104.945	21.531	3.888	0.105	4.250	462
Savings	23.290	23.432	1.558	49.487	6.742	0.289	0.028	3.694	506

Source : Stata based on our database

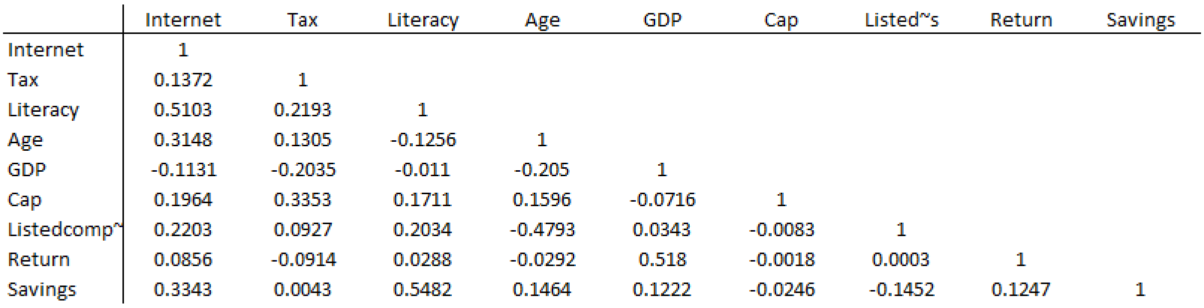
Table 6 : Correlation Matrix (Pearson) with the Home Bias variable



	Bias	Internet	Tax	Literacy	Age	GDP	Cap	Listed~s	Return	Savings
Bias	1									
Internet	-0.6511	1								
Tax	-0.158	0.1372	1							
Literacy	-0.3954	0.5103	0.2193	1						
Age	-0.433	0.3148	0.1305	-0.1256	1					
GDP	0.2198	-0.1131	-0.2035	-0.011	-0.205	1				
Cap	-0.1035	0.1964	0.3353	0.1711	0.1596	-0.0716	1			
Listedcomp~	0.073	0.2203	0.0927	0.2034	-0.4793	0.0343	-0.0083	1		
Return	0.027	0.0856	-0.0914	0.0288	-0.0292	0.518	-0.0018	0.0003	1	
Savings	-0.3275	0.3343	0.0043	0.5482	0.1464	0.1222	-0.0246	-0.1452	0.1247	1

Source : Stata based on our database

Table 7 : Correlation Matrix (Pearson) without the Home Bias variable

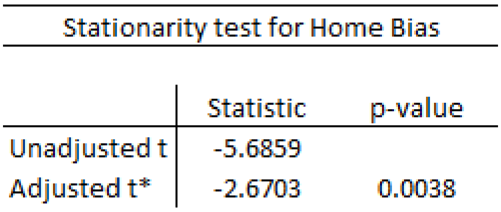


	Internet	Tax	Literacy	Age	GDP	Cap	Listed~s	Return	Savings
Internet	1								
Tax	0.1372	1							
Literacy	0.5103	0.2193	1						
Age	0.3148	0.1305	-0.1256	1					
GDP	-0.1131	-0.2035	-0.011	-0.205	1				
Cap	0.1964	0.3353	0.1711	0.1596	-0.0716	1			
Listedcomp~	0.2203	0.0927	0.2034	-0.4793	0.0343	-0.0083	1		
Return	0.0856	-0.0914	0.0288	-0.0292	0.518	-0.0018	0.0003	1	
Savings	0.3343	0.0043	0.5482	0.1464	0.1222	-0.0246	-0.1452	0.1247	1

Source : Stata based on our database

Table 8 : Stationarity test : Levin-Lin-Chu test for Home Bias

H0: Panels contain unit roots <> Ha: Panels are stationary

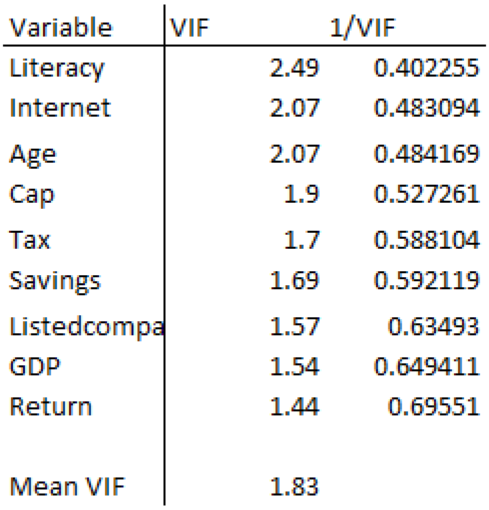


Stationarity test for Home Bias

	Statistic	p-value
Unadjusted t	-5.6859	
Adjusted t*	-2.6703	0.0038

Source : Stata based on our database

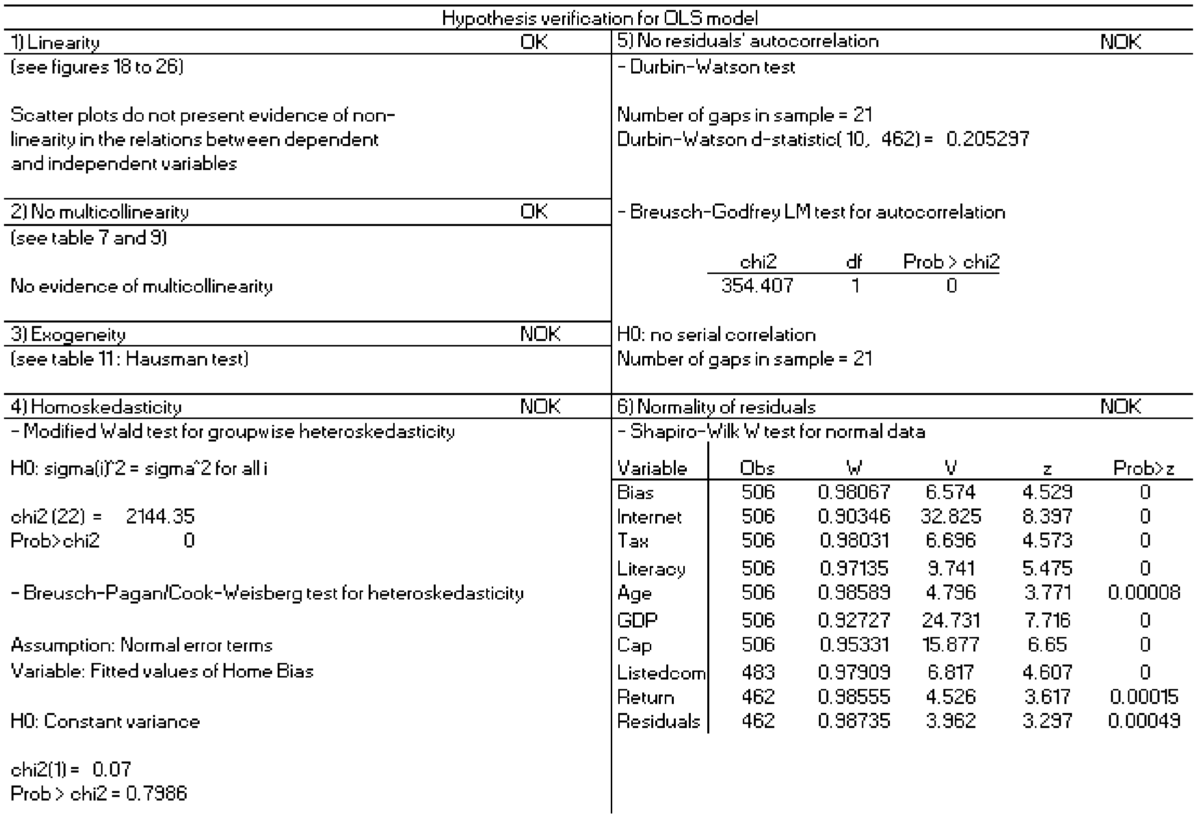
Table 9 : Variance inflation factor



Variable	VIF	1/VIF
Literacy	2.49	0.402255
Internet	2.07	0.483094
Age	2.07	0.484169
Cap	1.9	0.527261
Tax	1.7	0.588104
Savings	1.69	0.592119
Listedcompa	1.57	0.63493
GDP	1.54	0.649411
Return	1.44	0.69551
Mean VIF	1.83	

Source : Stata based on our database

Table 10 : Hypothesis verification for the OLS model



Hypothesis verification for OLS model

1) Linearity OK

(see figures 18 to 26)

Scatter plots do not present evidence of non-linearity in the relations between dependent and independent variables

2) No multicollinearity OK

(see table 7 and 9)

No evidence of multicollinearity

3) Exogeneity NOK

(see table 11 : Hausman test)

4) Homoskedasticity NOK

- Modified Wald test for groupwise heteroskedasticity

H0: sigma(i)^2 = sigma^2 for all i

chi2 (22) = 2144.35
Prob>chi2 0

- Breusch-Pagan/Cook-Weisberg test for heteroskedasticity

Assumption: Normal error terms
Variable: Fitted values of Home Bias

H0: Constant variance

chi2(1) = 0.07
Prob > chi2 = 0.7986

5) No residuals' autocorrelation NOK

- Durbin-Watson test

Number of gaps in sample = 21
Durbin-Watson d-statistic(10, 462) = 0.205297

- Breusch-Godfrey LM test for autocorrelation

chi2	df	Prob > chi2
354.407	1	0

H0: no serial correlation
Number of gaps in sample = 21

6) Normality of residuals NOK

- Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
Bias	506	0.98067	6.574	4.529	0
Internet	506	0.90346	32.825	8.397	0
Tax	506	0.98031	6.696	4.573	0
Literacy	506	0.97135	9.741	5.475	0
Age	506	0.98589	4.796	3.771	0.00008
GDP	506	0.92727	24.731	7.716	0
Cap	506	0.95331	15.877	6.65	0
Listedcom	483	0.97909	6.817	4.607	0
Return	462	0.98555	4.526	3.617	0.00015
Residuals	462	0.98735	3.962	3.297	0.00049

Source : Stata based on our database

Table 11 : Hausman test for the Home Bias

Hausman test

	---- Coefficients ----			
	(b)	(B)	(b-B)	sqrt(diag(V_ V_B))
	re	fe	Difference	Std. err.
Internet	-0.3734417	-0.3441216	-0.0293201	.
Age	-1.507938	-1.747665	0.2397262	.
GDP	0.0037008	0.0030885	0.0006123	0.0004653
Cap	0.0494043	0.0917568	-0.0423526	.
Listedcomp~	0.0130576	0.0116654	0.0013922	.
Return	0.0003371	0.0000193	0.0003178	.

b = Consistent under H0 and Ha; obtained from xtreg.
B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

chi2(6) = -46.37 (b-B)'[(V_b-V_B)^(-1)](b-B)

Source : State based on our database

Table 12 : Home Bias panel regression model results

	OLS	Fixed effects
Constant	5.84800	6.14130
	(0.638877)	(0.918209)
Internet	-0.48101	-0.34412
	(0.045161)	(0.063683)
Age	-1.13250	-1.74767
	(0.166128)	(0.254371)
GDP	0.00566	0.00309
	(0.002594)	(0.001636)
Cap	0.02610	0.09176
	(0.004705)	(0.011599)
Listedcompanies	0.02711	0.01167
	(0.008317)	(0.015706)
Return	0.00033	0.00002
	(0.000395)	(0.000277)
Literacy	-1.51983	-
	(0.219742)	
Tax	-0.03151	-
	(0.007641)	
R^2 within	0.567	0.640
R^2 Between		0.003
R^2 Overall		0.127
F stat	92.07	128.32
Observation	462	462

Source : Stata based on our database

Table 13 : Foreign Bias regression model results

White-Arellano standard errors clustered by country are in parentheses.

Foreign Bias model							
	OLS regression	Fixed effects regression					
	Whole sample	Whole Sample	Distance	Culture	Official	Spoken	Religion
Constant	-0.040328	-0.065571	-0.113275	-0.149361	-0.027040	0.093716	-0.022557
	(0.0130419)	(0.0380187)	(0.3268357)	(0.0621752)	(0.2247012)	(0.1646693)	(0.0804542)
TECH	0.010549	0.008077	0.017764	0.007711	0.021591	0.020705	0.014586
	(0.0009372)	(0.0023799	(0.0148428)	(0.0042373)	(0.0134179)	(0.0093571)	(0.004844)
AGE	0.004748	0.019818	0.050740	0.044744	0.016462	-0.017408	0.012426
	(0.0033108)	(0.010009)	(0.0850386)	(0.0172562)	(0.0676565)	(0.0444124)	(0.0206593)
GDP	-0.000096	-0.000006	0.000047	0.000017	-0.000010	-0.000108	-0.000052
	(0.0000475)	(0.0000224)	(0.0001137)	(0.0000492)	0.000100	(0.0000746)	(0.0000456)
CAP	-0.000309	-0.001430	-0.006490	-0.002030	-0.003357	-0.003562	-0.002873
	(0.0000851)	(0.0004258	(0.0022424)	(0.0008264)	(0.0032445)	(0.0012258)	(0.0009962)
COMP	-0.000947	-0.000149	-0.001797	-0.000222	0.000213	-0.000844	-0.000135
	(0.0001608)	(0.000209)	(0.0017471)	(0.0002863)	(0.0005316)	(0.0009692)	(0.0004554)
RTRN	-0.000015	-0.000018	0.000028	-0.000020	-0.000023	-0.000026	-0.000021
	(0.00000965)	(0.00000752)	(0.000036)	(0.0000114)	(0.2247012)	(0.000324)	(0.0000151)
TAX	0.000911						
	(0.0001478)						
FIN	0.021260						
	(0.0040986)						
Standard regression error	0.1421	0.0070	0.0121	0.0074	0.0081	0.0105	0.0090
R-squared	0.0421	0.0856	0.1175	0.1488	0.141	0.0759	0.0895
F-statistic	58.89	21.29	5.62	9.59	2.7	3.68	11.87
# of observations	10586	10586	1103	2582	528	1809	4478

Source : Stata based on our database

Table 14 : Foreign Bias – Official Language regression model results

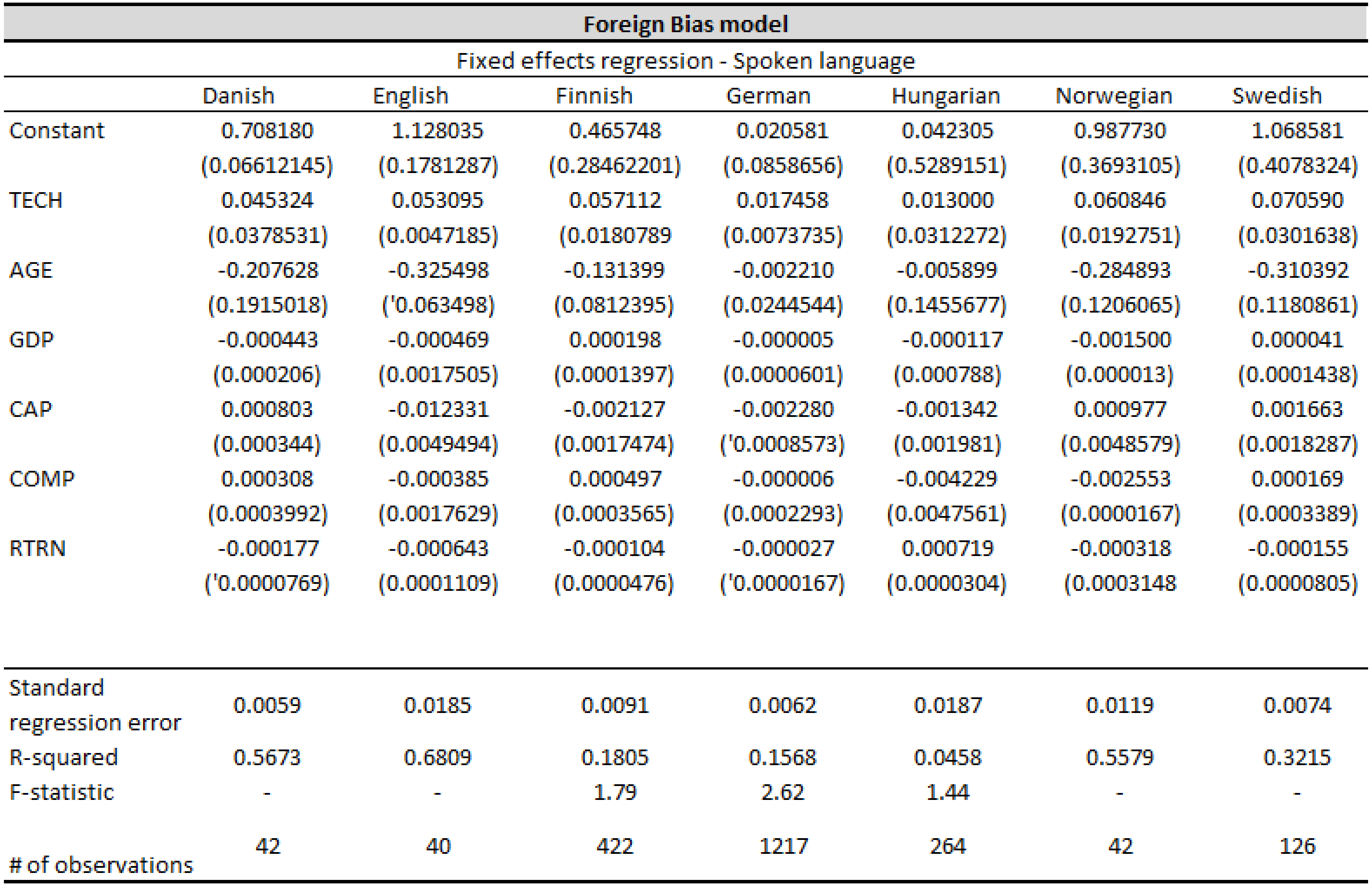
White-Arellano standard errors clustered by country are in parentheses.

Foreign Bias model					
Fixed effects regression - Official language					
	French	German	Hungarian	Italian	Swedish
Constant	-0.145714	-0.258528	0.842255	0.001432	2.231453
	(0.2928112)	(0.3031175)	(0.2377666)	(0.2780868)	(1.210736)
TECH	0.002761	0.013018	0.087116	0.014717	0.130027
	(0.0152753)	(0.0188374)	(0.0021265)	(0.0126423)	(0.0733498)
AGE	0.016942	0.094105	-0.207544	-0.030248	-0.611349
	(0.0861401)	(0.0997816)	(0.0625254)	(0.0600944)	(0.3118796)
GDP	0.000061	-0.000353	0.000106	0.000145	0.000021
	(0.0000982)	(0.0001575)	(0.0002527)	(0.0000736)	(0.0001461)
CAP	0.005892	-0.007254	-0.011296	0.006674	-0.002858
	(0.0027344)	(0.0066094)	(0.0004456)	(0.0043223)	(0.0090506)
COMP	0.000622	0.000050	0.002229	-0.000601	-0.000227
	(0.0007606	(0.0008247)	(0.000638)	(0.0008663)	(0.0003872)
RTRN	-0.000055	-0.000020	0.000066	-0.000073	-0.000094
	(0.0000196)	(0.0000424)	(0.0000249)	(0.000461)	(0.000907)
Standard regression error	0.0057	0.0090	0.0056	0.0028	0.0088
R-squared	0.1671	0.1734	0.7266	0.4669	0.4061
F-statistic	-	1.95	-	-	-
# of observations	132	264	44	44	44

Source : Stata based on our database

Table 15 : Foreign Bias – Spoken Language regression model results

White-Arellano standard errors clustered by country are in parentheses.



	Foreign Bias model						
	Fixed effects regression - Spoken language						
	Danish	English	Finnish	German	Hungarian	Norwegian	Swedish
Constant	0.708180	1.128035	0.465748	0.020581	0.042305	0.987730	1.068581
	(0.06612145)	(0.1781287)	(0.28462201)	(0.0858656)	(0.5289151)	(0.3693105)	(0.4078324)
TECH	0.045324	0.053095	0.057112	0.017458	0.013000	0.060846	0.070590
	(0.0378531)	(0.0047185)	(0.0180789	(0.0073735)	(0.0312272)	(0.0192751)	(0.0301638)
AGE	-0.207628	-0.325498	-0.131399	-0.002210	-0.005899	-0.284893	-0.310392
	(0.1915018)	('0.063498)	(0.0812395)	(0.0244544)	(0.1455677)	(0.1206065)	(0.1180861)
GDP	-0.000443	-0.000469	0.000198	-0.000005	-0.000117	-0.001500	0.000041
	(0.000206)	(0.0017505)	(0.0001397)	(0.0000601)	(0.000788)	(0.000013)	(0.0001438)
CAP	0.000803	-0.012331	-0.002127	-0.002280	-0.001342	0.000977	0.001663
	(0.000344)	(0.0049494)	(0.0017474)	('0.0008573)	(0.001981)	(0.0048579)	(0.0018287)
COMP	0.000308	-0.000385	0.000497	-0.000006	-0.004229	-0.002553	0.000169
	(0.0003992)	(0.0017629)	(0.0003565)	(0.0002293)	(0.0047561)	(0.0000167)	(0.0003389)
RTRN	-0.000177	-0.000643	-0.000104	-0.000027	0.000719	-0.000318	-0.000155
	('0.0000769)	(0.0001109)	(0.0000476)	('0.0000167)	(0.0000304)	(0.0003148	(0.0000805)
Standard regression error	0.0059	0.0185	0.0091	0.0062	0.0187	0.0119	0.0074
R-squared	0.5673	0.6809	0.1805	0.1568	0.0458	0.5579	0.3215
F-statistic	-	-	1.79	2.62	1.44	-	-
# of observations	42	40	422	1217	264	42	126

Source : Stata based on our database

Table 16 : Foreign Bias – Religion regression model results

White-Arellano standard errors clustered by country are in parentheses.

	Foreign Bias model			
	Fixed effects regression - Religion			
	No common	Christianity	Protestantism	Orthodoxy
Constant	-0.096248	-0.058829	0.074341	0.025727
	(0.030033)	(0.0939219)	(0.1838203)	(0.0744574)
TECH	0.003606	0.011288	0.029454	0.003938
	(0.0020384)	(0.0056493)	(0.0102085)	(0.0027539)
AGE	0.026262	0.020583	-0.016723	-0.009291
	(0.0080999)	(0.0238811)	(0.052539)	(0.0222056)
GDP	0.000013	-0.000016	-0.000054	-0.000180
	(0.0000216)	(0.0000529)	(0.00000752)	(0.0001653)
CAP	-0.000781	-0.002203	-0.003060	0.000547
	(0.0003804)	(0.0010586)	(0.0017419)	(0.0008505)
COMP	-0.000122	-0.000067	0.000062	0.000597
	(0.0001376)	(0.0006030)	(0.0002243)	(0.0009578)
RTRN	-0.000013	0.000004	-0.000098	-0.000037
	(0.00000577)	(0.0000145)	(0.0000362)	(0.00000804)
Standard regression error	0.0049	0.0089	0.0092	0.0018
R-squared	0.1076	0.0856	0.1543	0.4093
F-statistic	11.04	9.8	2.99	-
# of observations	6108	3244	1190	44

Source : Stata based on our database

Table 17 : Entire sample's principal component analysis

The analysis was conducted with all independent variables for the 23 countries on 22 years.

Entire sample								
	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**
Eigenvalue	2.268	1.664	1.339	1.065	0.628	0.472	0.345	0.219
Proportion	0.283	0.208	0.167	0.133	0.079	0.059	0.043	0.027
Cumulative	0.283	0.491	0.659	0.792	0.871	0.930	0.973	1.000
Eigenvectors								
Variable								
Internet	0.409	0.219	0.242	-0.577	0.207	-0.011	0.188	-0.561
Tax	0.468	-0.060	-0.018	0.536	0.180	-0.304	0.603	0.033
Literacy	0.407	0.393	-0.024	-0.215	-0.658	-0.042	0.064	0.441
Age	0.208	-0.431	0.553	-0.210	0.264	0.254	0.019	0.536
GDP	-0.268	0.473	0.344	0.277	-0.030	0.622	0.345	-0.055
Cap	0.488	-0.116	0.189	0.433	-0.201	0.272	-0.556	-0.318
Listedcomp~s	0.264	0.439	-0.414	0.012	0.597	0.211	-0.274	0.298
Return	-0.154	0.422	0.556	0.158	0.156	-0.580	-0.306	0.096

Source : Stata based on our database

Table 18 : Principal component analysis by geographical zone

The analyses are conducted for the period 2001-2022. The northern countries comprise Denmark, Estonia, Finland, Iceland, Latvia, Norway, Sweden and United Kingdom. The western countries are composed of Austria, Belgium, France, Germany, The Netherlands and Switzerland. The south of Europe is represented by Greece, Italy, Portugal and Spain while the eastern countries comprise Czechia, Hungary, Poland, Romania and Slovak Republic.

Nothern Europe countries								
	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**
Eigenvalue	3.101	1.721	1.432	0.868	0.378	0.262	0.161	0.077
Proportion	0.388	0.215	0.179	0.109	0.047	0.033	0.020	0.010
Cumulative	0.388	0.603	0.782	0.890	0.938	0.970	0.990	1.000
Eigenvectors								
Variable								
Internet	0.322	-0.070	0.053	0.842	0.307	-0.135	-0.259	-0.021
Tax	0.523	-0.070	0.171	-0.200	-0.085	0.232	-0.225	0.735
Literacy	0.524	0.018	0.118	-0.133	0.000	0.562	-0.005	-0.614
Age	-0.056	-0.705	0.167	0.133	0.125	0.199	0.622	0.112
GDP	-0.217	0.232	0.619	-0.191	0.688	0.053	-0.042	0.031
Cap	0.454	-0.172	0.247	-0.282	-0.024	-0.754	0.122	-0.201
Listedcomp~s	0.266	0.616	-0.141	0.144	0.079	-0.016	0.689	0.166
Return	-0.145	0.171	0.680	0.282	-0.634	0.028	0.062	-0.025

Southern Europe countries							
	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**
Eigenvalue	2.019	1.694	1.409	1.211	0.499	0.148	0.019
Proportion	0.288	0.242	0.201	0.173	0.071	0.021	0.003
Cumulative	0.288	0.531	0.732	0.905	0.976	0.997	1.000
Eigenvectors							
Variable							
Internet	0.513	-0.153	0.227	0.522	0.106	-0.322	0.524
Literacy	0.416	0.391	-0.389	-0.346	0.060	0.425	0.468
Age	0.639	-0.252	0.120	0.004	0.221	0.339	-0.592
GDP	-0.121	0.393	0.537	-0.216	0.700	-0.064	0.034
Cap	0.264	0.649	-0.230	0.123	-0.133	-0.523	-0.386
Listedcomp~s	-0.230	0.350	-0.028	0.727	0.062	0.536	-0.068
Return	0.133	0.248	0.664	-0.134	-0.652	0.191	0.037

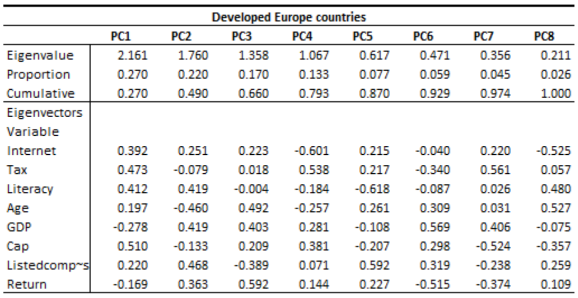
Western Europe countries								
	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**
Eigenvalue	2.170	1.949	1.494	1.010	0.560	0.402	0.253	0.164
Proportion	0.271	0.244	0.187	0.126	0.070	0.050	0.032	0.021
Cumulative	0.271	0.515	0.702	0.828	0.898	0.948	0.980	1.000
Eigenvectors								
Variable								
Internet	0.421	0.437	-0.216	-0.168	0.135	0.049	-0.714	0.161
Tax	0.332	-0.463	0.056	0.400	0.485	-0.006	0.011	0.526
Literacy	-0.144	0.539	-0.179	0.232	0.669	-0.094	0.316	-0.217
Age	0.529	0.266	-0.151	-0.263	-0.220	0.171	0.621	0.307
GDP	-0.012	0.213	0.693	0.056	0.101	0.678	-0.035	-0.007
Cap	0.255	0.191	-0.061	0.812	-0.444	0.002	-0.032	-0.193
Listedcomp~s	-0.546	0.336	-0.015	0.148	-0.207	-0.074	-0.029	0.720
Return	0.221	0.197	0.641	-0.070	-0.019	-0.703	0.027	0.027

Eastern Europe countries								
	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**
Eigenvalue	2.899	2.015	1.274	0.998	0.455	0.252	0.105	0.002
Proportion	0.362	0.252	0.159	0.125	0.057	0.031	0.013	0.000
Cumulative	0.362	0.614	0.774	0.898	0.955	0.987	1.000	1.000
Eigenvectors								
Variable								
Internet	-0.012	0.571	0.236	0.395	0.165	-0.632	0.176	-0.067
Tax	0.567	-0.112	-0.018	-0.018	0.134	-0.269	-0.371	0.661
Literacy	-0.568	0.063	-0.045	0.194	-0.010	0.169	0.275	0.727
Age	-0.029	0.601	0.370	-0.071	-0.179	0.439	-0.518	0.059
GDP	0.046	-0.395	0.501	0.410	-0.644	-0.087	-0.010	0.008
Cap	0.482	0.199	0.273	-0.288	-0.101	0.245	0.696	0.131
Listedcomp~s	0.323	0.018	-0.226	0.741	0.242	0.476	0.050	-0.087
Return	-0.128	-0.317	0.655	-0.028	0.663	0.112	-0.027	-0.032

Source : Stata based on our database

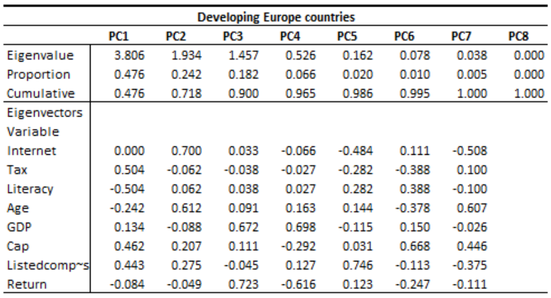
Table 19 : Principal component analysis by economic development

The analyses are conducted on a period spanning from 2001 to 2022. Developed countries are composed of Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Italy, The Netherlands, Norway, Portugal, Slovak Republic, Spain, Sweden, Switzerland and the United Kingdom while the developing countries represent Hungary, Poland and Romania



Developed Europe countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	2.161	1.760	1.358	1.067	0.617	0.471	0.356	0.211
Proportion	0.270	0.220	0.170	0.133	0.077	0.059	0.045	0.026
Cumulative	0.270	0.490	0.660	0.793	0.870	0.929	0.974	1.000
Eigenvectors								
Variable								
Internet	0.392	0.251	0.223	-0.601	0.215	-0.040	0.220	-0.525
Tax	0.473	-0.079	0.018	0.538	0.217	-0.340	0.561	0.057
Literacy	0.412	0.419	-0.004	-0.184	-0.618	-0.087	0.026	0.480
Age	0.197	-0.460	0.492	-0.257	0.261	0.309	0.031	0.527
GDP	-0.278	0.419	0.403	0.281	-0.108	0.569	0.406	-0.075
Cap	0.510	-0.133	0.209	0.381	-0.207	0.298	-0.524	-0.357
Listedcomp~s	0.220	0.468	-0.389	0.071	0.592	0.319	-0.238	0.259
Return	-0.169	0.363	0.592	0.144	0.227	-0.515	-0.374	0.109



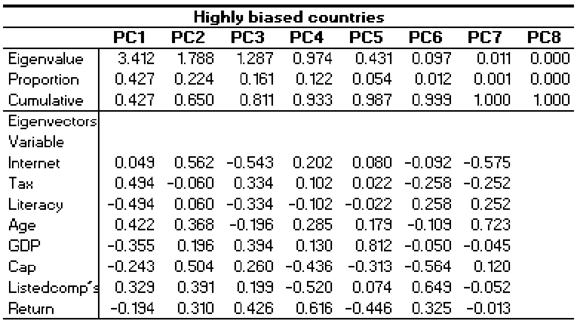
Developing Europe countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	3.806	1.934	1.457	0.526	0.162	0.078	0.038	0.000
Proportion	0.476	0.242	0.182	0.066	0.020	0.010	0.005	0.000
Cumulative	0.476	0.718	0.900	0.965	0.986	0.995	1.000	1.000
Eigenvectors								
Variable								
Internet	0.000	0.700	0.033	-0.066	-0.484	0.111	-0.508	
Tax	0.504	-0.062	-0.038	-0.027	-0.282	-0.388	0.100	
Literacy	-0.504	0.062	0.038	0.027	0.282	0.388	-0.100	
Age	-0.242	0.612	0.091	0.163	0.144	-0.378	0.607	
GDP	0.134	-0.088	0.672	0.698	-0.115	0.150	-0.026	
Cap	0.462	0.207	0.111	-0.292	0.031	0.668	0.446	
Listedcomp~s	0.443	0.275	-0.045	0.127	0.746	-0.113	-0.375	
Return	-0.084	-0.049	0.723	-0.616	0.123	-0.247	-0.111	

Source : Stata based on our database

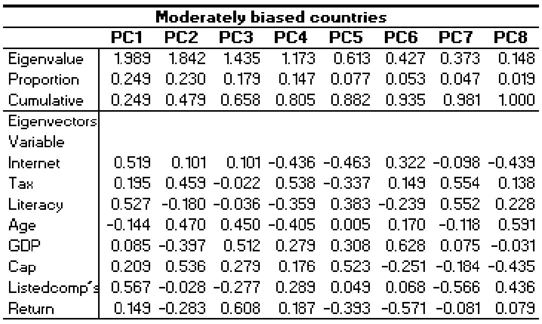
Table 20 : Principal component analysis by terminal level of 2022 Home Bias

The analyses are conducted on a period spanning from 2001 to 2022. Highly biased countries represent Greece, Poland and Romania. Moderately biased countries are composed of Czechia, Denmark, France, Hungary, Iceland, Portugal, Spain, Sweden and Switzerland. Lowly biased countries comprise Austria, Belgium, Estonia, Finland, Germany, Italy, Latvia, The Netherlands, Norway, Slovak Republic and the United Kingdom.



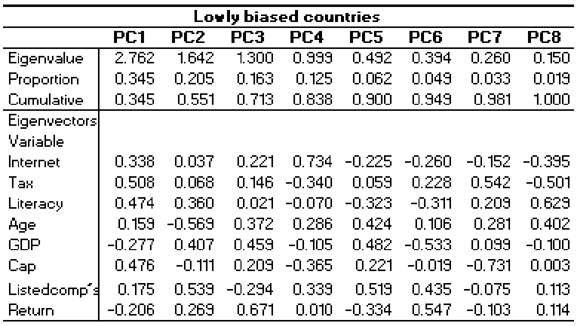
Highly biased countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	3.412	1.788	1.287	0.974	0.431	0.097	0.011	0.000
Proportion	0.427	0.224	0.161	0.122	0.054	0.012	0.001	0.000
Cumulative	0.427	0.650	0.811	0.933	0.987	0.999	1.000	1.000
Eigenvectors								
Variable								
Internet	0.049	0.562	-0.543	0.202	0.080	-0.092	-0.575	
Tax	0.494	-0.060	0.334	0.102	0.022	-0.258	-0.252	
Literacy	-0.494	0.060	-0.334	-0.102	-0.022	0.258	0.252	
Age	0.422	0.368	-0.196	0.285	0.179	-0.109	0.723	
GDP	-0.355	0.196	0.394	0.130	0.812	-0.050	-0.045	
Cap	-0.243	0.504	0.260	-0.436	-0.313	-0.564	0.120	
Listedcomp´s	0.329	0.391	0.199	-0.520	0.074	0.649	-0.052	
Return	-0.194	0.310	0.426	0.616	-0.446	0.325	-0.013	



Moderately biased countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	1.989	1.842	1.435	1.173	0.613	0.427	0.373	0.148
Proportion	0.249	0.230	0.179	0.147	0.077	0.053	0.047	0.019
Cumulative	0.249	0.479	0.658	0.805	0.882	0.935	0.981	1.000
Eigenvectors								
Variable								
Internet	0.519	0.101	0.101	-0.436	-0.463	0.322	-0.098	-0.439
Tax	0.195	0.459	-0.022	0.538	-0.337	0.149	0.554	0.138
Literacy	0.527	-0.180	-0.036	-0.359	0.383	-0.239	0.552	0.228
Age	-0.144	0.470	0.450	-0.405	0.005	0.170	-0.118	0.591
GDP	0.085	-0.397	0.512	0.279	0.308	0.628	0.075	-0.031
Cap	0.209	0.536	0.279	0.176	0.523	-0.251	-0.184	-0.435
Listedcomp´s	0.567	-0.028	-0.277	0.289	0.049	0.068	-0.566	0.436
Return	0.149	-0.283	0.608	0.187	-0.393	-0.571	-0.081	0.079



Lowly biased countries

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	2.762	1.642	1.300	0.999	0.492	0.394	0.260	0.150
Proportion	0.345	0.205	0.163	0.125	0.062	0.049	0.033	0.019
Cumulative	0.345	0.551	0.713	0.838	0.900	0.949	0.981	1.000
Eigenvectors								
Variable								
Internet	0.338	0.037	0.221	0.734	-0.225	-0.260	-0.152	-0.395
Tax	0.508	0.068	0.146	-0.340	0.059	0.228	0.542	-0.501
Literacy	0.474	0.360	0.021	-0.070	-0.323	-0.311	0.209	0.629
Age	0.159	-0.569	0.372	0.286	0.424	0.106	0.281	0.402
GDP	-0.277	0.407	0.459	-0.105	0.482	-0.533	0.099	-0.100
Cap	0.476	-0.111	0.209	-0.365	0.221	-0.019	-0.731	0.003
Listedcomp´s	0.175	0.539	-0.294	0.339	0.519	0.435	-0.075	0.113
Return	-0.206	0.269	0.671	0.010	-0.334	0.547	-0.103	0.114

Source : Stata based on our database

Bibliography and references

Aabo, T., Pantzalis, C., & Sørensen, M. S. (2013). Game hoarding in Europe : Stock-price consequences of local bias? *The European Journal of Finance*, *19*(4), 318-335. https://doi.org/10.1080/1351847X.2012.689775

Abdi, H., & Williams, L. J. (2010). Principal component analysis. *Wiley Interdisciplinary Reviews. Computational Statistics*, *2*(4), 433–459. https://doi.org/10.1002/wics.101

Abreu, M., Mendes, V., & Santos, J. A. C. (2011). Home country bias : Does domestic experience help investors enter foreign markets? *Journal of Banking & Finance*, *35*(9), 2330-2340. https://doi.org/10.1016/j.jbankfin.2011.01.032

Abuelfadl, M., Choi, S., & Abbey, B. (2016). Mobile Stock Trading Platforms and Individual Investors' Financial Performance. *Annals of Management Science*, *5*(1), 1-17. https://doi.org/10.24048/ams5.no1.2016-1

Ahearne, A. G., Griever, W. L., & Warnock, F. E. (2004). Information costs and home bias: an analysis of US holdings of foreign equities. *Journal of International Economics,* 62(2), 313–336. https://doi.org/10.1016/s0022-1996(03)00015-1

Amadi, A. (2004). Equity Home Bias: A Disappearing Phenomenon? *SSRN Electronic Journal*, 1–37. https://doi.org/10.2139/ssrn.540662

Anderson, C. W., Fedenia, M., Hirschey, M., & Skiba, H. (2011). Cultural influences on home bias and international diversification by institutional investors. *Journal of Banking & Finance*, *35*(4), 916-934. https://doi.org/10.1016/j.jbankfin.2010.09.006

Anderson, T., & Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data. *Journal of Econometrics*, 18(1), 47–82. https://doi.org/10.1016/03044076(82)90095-1

Antoniou, A., Olusi, O., & Paudyal, K. (2010). Equity Home-Bias: A Suboptimal Choice for UK investors? *European Financial Management : the Journal of the European Financial Management Association*, *16*(3), 449–479. https://doi.org/10.1111/j.1468-036X.2008.00462.x

Arellano, M. (1987). Computing Robust Standard Errors for Within-groups Estimators. *Oxford Bulletin of Economics and Statistics*, 49(4), 431–434. https://doi.org/10.1111/j.1468-0084.1987.mp49004006.x

Arouri, M. E. H. (s. d.). *Le Biais Domestique : Concept, Mesure et Explications*. Consulté 16 novembre 2023, à l'adresse https://shs.hal.science/halshs-00204103

Bae, K.-H., Stulz, R. M., & Tan, H. (2008). Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts. *Journal of Financial Economics*, 88(3), 581–606. https://doi.org/10.1016/j.jfineco.2007.02.004

Baele, L., Pungulescu, C., & Ter Horst, J. (2007). Model uncertainty, financial market integration and the home bias puzzle. *Journal of International Money and Finance*, *26*(4), 606–630. https://doi.org/10.1016/j.jimonfin.2007.03.007

Balli, F., Basher, S. A., & Ozer-Balli, H. (2010). From home bias to Euro bias: Disentangling the effects of monetary union on the European financial markets. *Journal of Economics and Business, 62*(5), 347–366. https://doi.org/10.1016/j.jeconbus.2010.04.004

Baltagi, B. H. (2005). Econometric Analysis of Panel Data (3rd ed.). https://himayatullah.weebly.com/uploads/5/3/4/0/53400977/baltagi-econometricanalysis-of-panel-data_himmy.pdf

Baltzer, M., Stolper, O., & Walter, A. (2015). Home-field advantage or a matter of ambiguity aversion? Local bias among German individual investors. *The European Journal of Finance*, *21*(9), 734-754. https://doi.org/10.1080/1351847X.2013.877514

Barber, B. M., & Odean, T. (2001). Boys will be Boys: Gender, Overconfidence, and Common Stock Investment. *The Quarterly Journal of Economics*, *116*(1), 261–292. https://doi.org/10.1162/003355301556400

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. Handbook of the Economics of Finance, 1(Part B), 1053–1128. https://doi.org/10.1016/s15740102(03)01027-6

Barron, J. M., & Ni, J. (2008). Endogenous asymmetric information and international equity home bias: The effects of portfolio size and information costs. *Journal of International Money and Finance*, 27(4), 617–635. https://doi.org/10.1016/j.jimonfin.2008.02.003

Bekaert, G., & Harvey, C. R. (1995). Time-Varying World Market Integration. *The Journal of Finance (New York),* 50(2), 403–444. https://doi.org/10.1111/j.1540-6261.1995.tb04790.x

Bekaert, G., & Harvey, C. R. (2000). Foreign Speculators and Emerging Equity Markets. *The Journal of Finance*, *55*(2), 565-613. https://doi.org/10.1111/0022-1082.00220

Ben-David, I., Franzoni, F., & Moussawi, R. (2017). Exchange-Traded Funds. *Annual Review of Financial Economics*, *9*(1), 169–189. https://doi.org/10.1146/annurev-financial-110716-032538

Beugelsdijk, S., & Frijns, B. (2010). A cultural explanation of the foreign bias in international asset allocation. *Journal of Banking & Finance*, *34*(9), 2121-2131. https://doi.org/10.1016/j.jbankfin.2010.01.020

Boermans, M. A. (2022). A literature review of securities holdings statistics research and a practitioner's guide. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4304056

Boermans, M., Cooper, I., Sercu, P., & Rosanne VanpÃ©e. (2022). Foreign bias in equity portfolios: Informational advantage or familiarity bias? *IDEAS Working Paper Series from RePEc.*

Bohn, H., & Tesar, L. L. (1996). U.S. Equity Investment in Foreign Markets: Portfolio Rebalancing or Return Chasing? *The American Economic Review*, 86(2), 77–81.

Bose, U., MacDonald, R., & Tsoukas, S. (2015). Education and the local equity bias around the world. *Journal of International Financial Markets, Institutions and Money*, *39*, 65-88. https://doi.org/10.1016/j.intfin.2015.06.002

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-Frequency Trading and Price Discovery. *Review of Financial Studies*, *27*(8), 2267-2306. https://doi.org/10.1093/rfs/hhu032

Burnside, C., Han, B., Hirshleifer, D., & Wang, T. Y. (2011). Investor Overconfidence and the Forward Premium Puzzle. *The Review of Economic Studies*, *78*(2), 523-558. https://doi.org/10.1093/restud/rdq013

Carvalho, D. (2022). The portfolio holdings of euro area investors : Looking through investment funds. *Journal of International Money and Finance*, *120*, 102519. https://doi.org/10.1016/j.jimonfin.2021.102519

Chan, K., Covrig, V., & Ng, L. (2005). What Determines the Domestic Bias and Foreign Bias? Evidence from Mutual Fund Equity Allocations Worldwide. *The Journal of Finance*, *60*(3), 1495-1534. https://doi.org/10.1111/j.1540-6261.2005.768_1.x

Choe, H., Kho, B.-C., & Stulz, R. M. (1999). Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial Economics*, 54(2), 227–264. https://doi.org/10.1016/S0304-405X(99)00037-9

Chniguir, M. C., Kefi, M. K., & Henchiri, J. H. (2017). The Determinants of Home Bias in Stock Portfolio: An Emerging and Developed Markets Study. *International Journal of Economics and Financial Issues,* 7(6), 182–191. Retrieved from http://www.econjournals.com/index.php/ijefi/article/view/2406

Coeurdacier, N., & Guibaud, S. (2011). International portfolio diversification is better than you think. *Journal of International Money and Finance*, *30*(2), 289-308. https://doi.org/10.1016/j.jimonfin.2010.10.003

Connected Papers. (2023, April 2). *Find and explore academic papers*. https://www.connectedpapers.com/main/2f37e287578fa20b5bd4298c0f71a5c88d813412/Home-Bias-at-Home%3A-Local-Equity-Preference-in-Domestic-Portfolios/graph

Cooper, I., & Kaplanis, E. (1994). Home Bias in Equity Portfolios, Inflation Hedging, and International Capital Market Equilibrium. *Review of Financial Studies*, 7(1), 45–60. https://doi.org/10.1093/rfs/7.1.45

Cooper, I., Sercu, P., & Vanpée, R. (2012). The Equity Home Bias Puzzle: A Survey. *Foundations and Trends® in Finance*, 7(4), 289–416. https://doi.org/10.1561/0500000039

Cooper, I., Sercu, P., & Vanpée, R. (2017). A Measure of Pure Home Bias. *Review of Finance,* 22(4), 1469–1514. https://doi.org/10.1093/rof/rfx005

Coval, J. D., & Moskowitz, T. J. (1999). Home Bias at Home : Local Equity Preference in Domestic Portfolios. *The Journal of Finance*, *54*(6), 2045-2073. https://doi.org/10.1111/0022-1082.00181

Coval, J. D., & Moskowitz, T. J. (2001). The Geography of Investment: Informed Trading and Asset Prices. *The Journal of Political Economy*, 109(4), 811–841. https://doi.org/10.1086/322088

Cultural Similarity. (2023, November 23). *Index on Cultural Similarity*. https://userpage.fu-berlin.de/~jroose/index_en/main_indexvalues.htm

Dahlquist, M., Pinkowitz, L., Stulz, R. M., & Williamson, R. (2003). Corporate Governance and the Home Bias. *Journal of Financial and Quantitative Analysis*, 38(1), 87–110. https://doi.org/10.2307/4126765

Daniel, K., & Hirshleifer, D. (2015). Overconfident Investors, Predictable Returns, and Excessive Trading. *Journal of Economic Perspectives*, *29*(4), 61-88. https://doi.org/10.1257/jep.29.4.61

Data Europa EU. (2023, December 1). Flash Eurobarometer FL525 : Monitoring the level of financial literacy in the EU https://data.europa.eu/data/datasets/s2953_fl525_eng?locale=en

De BONDT, W. F. M., & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance (New York),* 40(3), 793–805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

De Marco, F., Macchiavelli, M., & Valchev, R. (2022). Beyond Home Bias : International Portfolio Holdings and Information Heterogeneity. *The Review of Financial Studies*, *35*(9), 4387-4422. https://doi.org/10.1093/rfs/hhab135

De Santis, G., & Gerard, B. (1997). International Asset Pricing and Portfolio Diversification with Time-Varying Risk. *The Journal of Finance (New York)*, *52*(5), 1881–1912. https://doi.org/10.1111/j.1540-6261.1997.tb02745.x

EBI. (2023, September 23). *Home Bias vs Global Diversification. Evidence Based Investing.* https://ebi.co.uk/market-commentary-blogs/home-bias-vs-global-diversification/

Edwards, S. (2007). Capital Controls, Capital Flow Contractions, and Macroeconomic Vulnerability. *NBER Working Paper Series,* 12852. https://doi.org/10.3386/w12852

Edwards, S. (2005). Capital Controls, Sudden Stops and Current Account Reversals. *NBER Working Paper Series*, 11170. https://doi.org/10.3386/w11170

Edwards, W. (1982). Conservatism in human information processing. Judgment under Uncertainty, 359–369. https://doi.org/10.1017/cbo9780511809477.026

Errunza, V., & Losq, E. (1989). Capital Flow Controls, International Asset Pricing, and Investors' Welfare: A Multi-Country Framework. *The Journal of Finance (New York),* 44(4), 1025. https://doi.org/10.2307/2328622

Eun, C. S., & Resnick, B. G. (1995). International Diversification of Investment Portfolios : U.S. and Japanese Perspectives. *Financial Services Review*, *4*(1), 67. https://doi.org/10.1016/1057-0810(95)90037-3

Eurobarometer survey. (2023, November 21). *Monitoring the level of financial literacy in the EU – juillet 2023* https://europa.eu/eurobarometer/surveys/detail/2953

European Commission. Directorate General for Financial Stability, Financial Services and Capital Markets Union. & Bruegel. (2016). *Analysis of developments in EU capital flows in the global context : Third annual report.* Publications Office. https://data.europa.eu/doi/10.2874/553086

Farrell, M., Green, T. C., Jame, R., & Markov, S. (2022). The democratization of investment research and the informativeness of retail investor trading. *Journal of Financial Economics*, *145*(2), 616-641. https://doi.org/10.1016/j.jfineco.2021.07.018

Feldstein, M., & Horioka, C. (1980). Domestic Saving and International Capital Flows. *The Economic Journal*, *90*(358), 314. https://doi.org/10.2307/2231790

Fellner-Röhling, G., & Maciejovsky, B. (2003, March). The Equity Home Bias: Contrasting an Institutional with a Behavioral Explanation (3). *Max Planck Institute for Research 74 into Economic Systems, Papers on Strategic Interaction.* https://doi.org/10.2139/ssrn.390100

Ferson, W. E., & Harvey, C. R. (1991). The Variation of Economic Risk Premiums. *The Journal of Political Economy,* 99(2), 385–415. https://doi.org/10.1086/261755

Ferson, W. E., & Harvey, C. R. (1994). Sources of risk and expected returns in global equity markets. *Journal of Banking & Finance,* 18(4), 775–803. https://doi.org/10.1016/0378-4266(93)00020-P

Fidora, M., Fratzscher, M., & 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*(4), 631-655. https://doi.org/10.1016/j.jimonfin.2007.03.002

Forbes, K. J., & Rigobon, R. (2002). No Contagion, Only Interdependence : Measuring Stock Market Comovements. *The Journal of Finance*, *57*(5), 2223-2261. https://doi.org/10.1111/0022-1082.00494

French, K. R. (2008). Presidential Address: The Cost of Active Investing. *The Journal of Finance (New York),* 63(4), 1537–1573. https://doi.org/10.1111/j.1540-6261.2008.01368.x

French, K., & Poterba, J. (1991). Investor Diversification and International Equity Markets (w3609; p. w3609). *National Bureau of Economic Research*. https://doi.org/10.3386/w3609

Froot, K. A., Scharfstein, D. S., & Stein, J. C. (1992). Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation. *The Journal of Finance (New York),* 47(4), 1461. https://doi.org/10.2307/2328947

Gaar, E., Scherer, D., & Schiereck, D. (2022). The home bias and the local bias : A survey. *Management Review Quarterly*, *72*(1), 21-57. https://doi.org/10.1007/s11301-020-00203-8

Gerhards, J., (2000). Literatur. In: Kulturelle Unterschiede in der Europäischen Union. VS Verlag für Sozialwissenschaften. https://doi-org.ezproxy.library.bi.no/10.1007/978-3-531-90069-8_8

Giannetti, M., & Simonov, A. (2006). Which Investors Fear Expropriation? Evidence from Investors' Portfolio Choices. *The Journal of Finance, 61(3),* 1507–1547. https://doi.org/10.1111/j.1540-6261.2006.00879.x

Goldman, E., Rocholl, J., & So, J. (2009). Do Politically Connected Boards Affect Firm Value? *The Review of Financial Studies*, *22*(6), 2331–2360. https://doi.org/10.1093/rfs/hhn088

Goldstein, M. A., Kumar, P., & Graves, F. C. (2014). Computerized and High-Frequency Trading. *The Financial Review (Buffalo, N.Y.)*, *49*(2), 177–202. https://doi.org/10.1111/fire.12031

Goetzmann, W., Li, L., & Rouwenhorst, K. Geer. (2005). Long-Term Global Market Correlations. The Journal of Business (Chicago, Ill.), 78(1), 1–38. https://doi.org/10.1086/426518

Goetzmann, W. N., & Kumar, A., Diversification Decisions of Individual Investors and Asset Prices (2003). *Yale ICF Working Paper* No. 03-31, Available at SSRN: https://ssrn.com/abstract=469441

Greene, W. H. (2003). Econometric Analysis. Pearson Education. ISBN: 0-13-066189-9

Grinblatt, M., & Keloharju, M. (2001). How Distance, Language, and Culture Influence Stockholdings and Trades. *The Journal of Finance*, *56*(3), 1053-1073. https://doi.org/10.1111/0022-1082.00355

Grubel, H. G. (1968). Internationally Diversified Portfolios : Welfare Gains and Capital Flows. *The American Economic Review*, *Vol. 58 (5)*, 1299-1314.

Harvey, C. R. (1991). The World Price of Covariance Risk. *The Journal of Finance (New York),* 46(1), 111–157. https://doi.org/10.1111/j.1540-6261.1991.tb03747.x

Hau, H., & Rey, H. (2006). Exchange Rates, Equity Prices, and Capital Flows. *Review of Financial Studies*, *19*(1), 273-317. https://doi.org/10.1093/rfs/hhj008

Hotelling, H. (1933). Analysis of a complex of statistical variables into principal components*. Journal of Educational Psychology,* 24(6), 417–441. https://doi.org/10.1037/h0071325

Huberman, G. (2001). Familiarity Breeds Investment. *The Review of Financial Studies*, *14*(3), 659-680. https://doi.org/10.1093/rfs/14.3.659

IMF Data. (2023, May 15). *Table 11 : Geographic Breakdown of Total Portfolio Investment Assets* https://data.imf.org/regular.aspx?key=60587815

International Monetary Fund, Bank for International Settlements, & European Central Bank. (2015). *Handbook on Securities Statistics*. International Monetary Fund.

ITU DataHub. (2023, December 8). *Individuals using the Internet : Individuals using the Internet* https://datahub.itu.int/data/?i=11624&e=5&d=Location

Ivković, Z., & Weisbenner, S. (2005). Local Does as Local Is: Information Content of the Geography of Individual Investors' Common Stock Investments. *The Journal of Finance (New York)*, *60*(1), 267–306. https://doi.org/10.1111/j.1540-6261.2005.00730.x

Jamar de Bolsée, M. (2021). Evolution du biais domestique en Europe et chocs financiers. (Unpublished master's thesis). Université de Liège, Liège, Belgique. Retrieved from https://matheo.uliege.be/handle/2268.2/11525

Joliet, R., & Hübner, G. (2008). Corporate international diversification and the cost of equity : European evidence. *Journal of International Money and Finance*, *27*(1), 102-123. https://doi.org/10.1016/j.jimonfin.2007.04.008

Jolliffe, I. T. (2002). Principal Component Analysis (Second). *Springer New York.* https://doi.org/10.1007/b98835

Jorion, P. (1985). International Portfolio Diversification with Estimation Risk. *The Journal of Business*, *58*(3), 259. https://doi.org/10.1086/296296

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. Econometrica, 47(2), 263–291. https://doi.org/10.2307/1914185

Kang, J.-K., & Stulz, R. (1997). Why is there a home bias? An analysis of foreign portfolio equity ownership in Japan. *Journal of Financial Economics*, *46*(1), 3–28. https://doi.org/10.1016/S0304-405X(97)00023-8

Kaniel, R., & Parham, R. (2017). WSJ Category Kings – The impact of media attention on consumer and mutual fund investment decisions. *Journal of Financial Economics*, *123*(2), 337–356. https://doi.org/10.1016/j.jfineco.2016.11.003

Karlsson, A., & Nordén, L. (2007). Home sweet home: Home bias and international diversification among individual investors. *Journal of Banking & Finance,* 31(2), 317–333. https://doi.org/10.1016/j.jbankfin.2006.04.005 76

Karolyi, G. A., & Stulz, R. M. (2003). Chapter 16 Are financial assets priced locally or globally? In *Handbook of the Economics of Finance* (Vol. 1, p. 975-1020). Elsevier. https://doi.org/10.1016/S1574-0102(03)01025-2

Kho, B. C., Stulz, R. M., & Warnock, F. E. (2009). Financial Globalization, Governance, and the Evolution of the Home Bias. *Journal of Accounting Research,* 47(2), 597–635. https://doi.org/10.1111/j.1475-679x.2009.00323.x

Kilka, M., & Weber, M. (2000). Home Bias in International Stock Return Expectations*. Journal of Psychology and Financial Markets,* 1(3–4), 176–192. https://doi.org/10.1207/s15327760jpfm0134_3

Kose, M. A., Prasad, E. S., & Terrones, M. E. (2006). How do trade and financial integration affect the relationship between growth and volatility? *Journal of International Economics*, *69*(1), 176-202. https://doi.org/10.1016/j.jinteco.2005.05.009

Kristian Skrede Gleditsch // Data, etc. (2023, November 26) Distance Between Capital Cities http://ksgleditsch.com/data-5.html

La Porta, R., Lopez-De-Silanes, F., & Shleifer, A. (1999). Corporate Ownership Around the World. *The Journal of Finance (New York)*, *54*(2), 471–517. https://doi.org/10.1111/0022-1082.00115

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. (2000). Investor protection and corporate governance. *Journal of Financial Economics*, 58(1), 3–27. https://doi.org/10.1016/S0304-405X(00)00065-9

Lau, S. T., Ng, L., & Zhang, B. (2010). The world price of home bias. *Journal of Financial Economics*, 97(2), 191–217. https://doi.org/10.1016/j.jfineco.2010.04.002

Lee, J., Lee, K., & Oh, F. D. (2023). Religion and Equity Home Bias. *Open Economies Review*, 34(5), 1015–1038. https://doi.org/10.1007/s11079-022-09709-y

Levy, H., & Levy, M. (2014). The home bias is here to stay. *Journal of Banking & Finance*, *47*, 29-40. https://doi.org/10.1016/j.jbankfin.2014.06.020

Lewis, K. K. (1999). Trying to Explain Home Bias in Equities and Consumption. *Journal of Economic Literature*, *37*(2), 571-608. https://doi.org/10.1257/jel.37.2.571

Lindblom, T. (2017). Proximity Bias in Investors' Portfolio Choice (*1st ed. 2017.). Springer International Publishing*. https://doi.org/10.1007/978-3-319-54762-6

Longin, F., & Solnik, B. (2001). Extreme Correlation of International Equity Markets. *The Journal of Finance*, *56*(2), 649-676. https://doi.org/10.1111/0022-1082.00340

López De Prado, M. M. (2020). Machine Learning for Asset Managers (1re éd.). *Cambridge University Press.* https://doi.org/10.1017/9781108883658

Lundtofte, F. (2009). Endogenous Acquisition of Information and the Equity Home Bias. *Economica*, *76*(304), 741-759. https://doi.org/10.1111/j.1468-0335.2008.00728.x

Lütje, T., & Menkhoff, L. (2007). What drives home bias? Evidence from fund managers' views. *International Journal of Finance and Economics,* 12(1), 21–35. https://doi.org/10.1002/ijfe.309

Lynch, A. W., & Tan, S. (2011). Explaining the Magnitude of Liquidity Premia : The Roles of Return Predictability, Wealth Shocks, and State-Dependent Transaction Costs. *The Journal of Finance*, *66*(4), 1329-1368. https://doi.org/10.1111/j.1540-6261.2011.01662.x

Mann, C. L., & Meade, E. E. (2002). Home bias, transactions costs, and prospects for the Euro : A more detailed analysis. *London School of Economics and Political Science. Centre for Economic Performance.* http://eprints.lse.ac.uk/20076/

Markowitz, H. M. (1952). Portfolio Selection. *The Journal of Finance*, 7(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Markowitz, H. M. (1959). Portfolio Selection: Efficient Diversification of Investments. Retrieved from https://www.jstor.org/stable/j.ctt1bh4c8h

Massa, M., & Simonov, A. (2006). Hedging, Familiarity and Portfolio Choice. *Review of Financial Studies*, *19*(2), 633-685. https://doi.org/10.1093/rfs/hhj013

McDowell, S., Lee, J. B., & Marsden, A. (2020). The potential effect of taxes on the equity home bias in New Zealand PIEs. *Pacific-Basin Finance Journal*, 62, 101375. https://doi.org/10.1016/j.pacfin.2020.101375

Millo, G. (2017). Robust Standard Error Estimators for Panel Models : A Unifying Approach. *Journal of Statistical Software*, *82*(3). https://doi.org/10.18637/jss.v082.i03

Mishra, A. V. (2015). Measures of equity home bias puzzle. *Journal of Empirical Finance*, 34, 293–312. https://doi.org/10.1016/j.jempfin.2015.08.001

Mishra, A. V., & Ratti, R. A. (2013). Home bias and cross border taxation*. Journal of International Money and Finance*, 32(1), 169–193. https://doi.org/10.1016/j.jimonfin.2012.04.004

Molestina Vivar, L., Lambert, C., Wedow, M., & Giuzio, M. (2020). Is the home bias biased? New evidence from the investment fund sector. https://www.ecb.europa.eu/pub/fie/article/html/ecb.fieart202003_03~9efb363a78.en.html

Montier, J. (2002). Behavioural Finance: Insights into Irrational Minds and Markets. ISBN: 978-0-470-84487-8

Morningstar, Inc. (2023, May 7). *Investors Have Fewer Reasons Than Ever for Home Bias*. https://www.morningstar.com/etfs/investors-have-fewer-reasons-than-ever-home-bias

Morningstar, Inc. (2023, November 12). *You Probably Own Too Much Domestic Equity*. https://www.morningstar.com/portfolios/you-probably-own-too-much-domestic-equity

Nations Online Project. (2023, November 24) *European Languages by Countries : Official and national Languages of Europe* https://www.nationsonline.org/oneworld/european_languages.htm

Niszczota, P. (2014). Cross-country differences in personality and the foreign bias in international equity portfolios. *The European Journal of Finance*, *20*(10), 934-956. https://doi.org/10.1080/1351847X.2013.856332

Nkukpornu, E., Gyimah, P., & Sakyiwaa, L. (2020). Behavioural Finance and Investment Decisions : Does Behavioral Bias Matter? *International Business Research*, *13*(11), 65. https://doi.org/10.5539/ibr.v13n11p65

Nordén, L. (2010). Individual home bias, portfolio churning and performance. *The European Journal of Finance*, *16*(4), 329-351. https://doi.org/10.1080/13518470903037813

OpenAI. (2023). ChatGPT (GPT3.5 version) [Large language model]. https://chat.openai.com/chat

Othmani, S., Ben Saanoun, I., Garali, W., & Ben Arab, M. (2014). Determinants of Home Bias Puzzle in European Countries. *International Review of Management and Business Research*, 3(1), 182–198. Retrieved from https://www.irmbrjournal.com/papers/1389636947.pdf 79

Otten, R., & Bams, D. (2007). The Performance of Local versus Foreign Mutual Fund Managers. *European Financial Management*, *13*(4), 702-720. https://doi.org/10.1111/j.1468-036X.2007.00379.x

Pagano, M. and Volpin, P.F. (2005), Managers, Workers, and Corporate Control. *The Journal of Finance, 60*: 841-868. https://doi-org.ezproxy.library.bi.no/10.1111/j.1540-6261.2005.00748.x

Park, Hun Myoung. 2011. Practical Guides To Panel Data Modeling: A Step-by-step Analysis Using Stata. Tutorial Working Paper. Graduate School of International Relations, International University of Japan.

Pearson, K. (1901). On lines and planes of closest fit to systems of points in space. *Philosophical Magazine*, 6(2), 559-572.

Pool, V. K., Stoffman, N., & Yonker, S. E. (2012). No Place Like Home : Familiarity in Mutual Fund Manager Portfolio Choice. *The Review of Financial Studies*, *25*(8), 2563-2599. https://doi.org/10.1093/rfs/hhs075

Portes, R., & Rey, H. (2005). The determinants of cross-border equity flows. *Journal of International Economics,* 65(2), 269–296. https://doi.org/10.1016/j.jinteco.2004.05.002

Pungulescu, C. (2015). Real effects of financial market integration : Does lower home bias lead to welfare benefits? *The European Journal of Finance*, *21*(10-11), 893-911. https://doi.org/10.1080/1351847X.2012.744762

Ritter, J. R. (2003). Behavioral finance. *Pacific-Basin Finance Journal*, 11(4), 429–437. https://doi.org/10.1016/s0927-538x(03)00048-9

Ritter, J. R. (2005). Economic growth and equity returns. *Pacific-Basin Finance Journal*, *13*(5), 489-503. https://doi.org/10.1016/j.pacfin.2005.07.001

Rousová, L. F., & Caloca, A. R. (s. d.). The use of Securities Holdings Statistics (SHS) for designing new euro area financial integration indicators. *IFC Bulletins chapters Bank for International Settlements (ed.),39.*

Santamaría, M., Ventura, J., & Yeşilbayraktar, U. (2023). Exploring European regional trade. *Journal of International Economics*, 103747-. https://doi.org/10.1016/j.jinteco.2023.103747

Schnabel, J. A. (2012). Consumption hedging and home-country bias in a model of international capital market equilibrium. *Studies in Economics and Finance*, *29*(1), 4-10. https://doi.org/10.1108/10867371211203819

Schneider, J. (2013). *European Business Cycle Convergence : Portfolio Similarity and a Declining Home Bias of Private Investors* (1re éd., Vol. 69). Peter Lang International Academic Publishing Group. https://doi.org/10.3726/978-3-653-01915-5

Schoenmaker, D., & Bosch, T. (2007). Is the Home Bias in Equities and Bonds Declining in Europe? *Investment Management and Financial Innovations*, 5, 90–102. Retrieved from https://ssrn.com/abstract=996914

Seasholes, M. S., & Zhu, N. (2010). Individual Investors and Local Bias. *The Journal of Finance*, *65*(5), 1987-2010. https://doi.org/10.1111/j.1540-6261.2010.01600.x

Sendi, I., & Bellalah, M. (2010). The Equity Home Bias : Explanations and Financial Anomalies. *International Journal of Economics and Finance*, *2*(2), p78. https://doi.org/10.5539/ijef.v2n2p78

Sercu, P. M. F. A., & Vanpee, R. (2007). Home Bias in International Equity Portfolios : A Review. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1025806

Sharpe, W. F. (1964). Capital Asset Prices : A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance (New York)*, *Vol. 19 (3)*, 425–442. https://doi.org/10.1111/j.15406261.1964.tb02865.x

Socaciu, E.-M., Nagy, B.-Z., & Benedek, B. (2023). No place like home : Home bias and flight-to-quality in Group of Seven countries. *Economic Modelling*, *129*, 106549-. https://doi.org/10.1016/j.econmod.2023.106549

Solnik, B. H. (1974). An equilibrium model of the international capital market. *Journal of Economic Theory*, *8*(4), 500-524. https://doi.org/10.1016/0022-0531(74)90024-6

Solnik, B. H. (1995). Why Not Diversify Internationally Rather than Domestically? *Financial Analysts Journal,* 51(1), 89–94. https://doi.org/10.2469/faj.v51.n1.1864

Sørensen, B. E., Wu, Y.-T., Yosha, O., & Zhu, Y. (2007). Home bias and international risk sharing : Twin puzzles separated at birth. *Journal of International Money and Finance*, *26*(4), 587-605. https://doi.org/10.1016/j.jimonfin.2007.03.005

Statistics How To. (2024, April 2). Hausman Test for Endogeneity (Hausman Specification Test) https://www.statisticshowto.com/hausman-test/

Streissler, E. W. (2004). ERICH W. STREISSLER. In I. Barens, V. Caspari, & B. Schefold (Éds.), *Political Events and Economic Ideas*. Edward Elgar Publishing. https://doi.org/10.4337/9781845421526.00038

Strong, N. C., & Xu, X. X. (2003). Understanding the Equity Home Bias: Evidence from Survey Data. *The Review of Economics and Statistics,* 85(2), 307–312. https://doi.org/10.1162/003465303765299837

Stulz, R. M. (1981). On the Effects of Barriers to International Investment. *The Journal of Finance,* 36(4), 923–934. https://doi.org/10.1111/j.1540-6261.1981.tb04893.x

Suriani, S., Kumar, M. D., Jamil, F., & Muneer, S. (2015). Impact of Exchange Rate on Stock Market. *International Journal of Economics and Financial Issues*, 5(1S).

Tax Foundation. (2023, April 28). *2023 Capital Gains Tax Rates in Europe*. https://taxfoundation.org/data/all/eu/capital-gains-tax-rates-in-europe-2023/

Tax Foundation. (2023, April 28). Dividend Tax Rates in Europe. https://taxfoundation.org/data/all/eu/dividend-tax-rates-europe-2022/

Tesar, L. L., & Werner, I. M. (1995). Home bias and high turnover. *Journal of International Money and Finance*, *14*(4), 467-492. https://doi.org/10.1016/0261-5606(95)00023-8

Tilley, T. (2019). Trends in ownership of investment funds. *The European Fund and Asset Management Association*. Retrieved from https://www.efama.org/sites/default/files/files/EFAMA_Ownership_Investment_Funds_0.pdf

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science (American Association for the Advancement of Science),* 185(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Wang, X. (2009). Globalization, Home Bias and Asset Prices. *ProQuest Dissertations Publishing COLUMBIA UNIVERSTIY*.

Wikidocs. (2024, April 27). Principal Component Analysis (PCA). Retrieved from https://wikidocs.net/214094

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data (2nd ed., pp. XXVII, 1064). MIT Press.

World Bank Data. (2023, December 3). *Market capitalization of listed domestic companies (current US$)* https://data.worldbank.org/indicator/CM.MKT.LCAP.CD

World Bank Data. (2024, March 15) *Gross savings (% of GDP)* https://data.worldbank.org/indicator/NY.GNS.ICTR.ZS

You, L., & Daigler, R. T. (2010). Is international diversification really beneficial? *Journal of Banking & Finance*, *34*(1), 163-173. https://doi.org/10.1016/j.jbankfin.2009.07.016

Zhu, Z., Qi, Z., & Jin, Y. (2023). Familiarity bias and economic decisions : Evidence from a survey experiment. Economics Letters, 229, 111197-. https://doi.org/10.1016/j.econlet.2023.111197

Executive Summary

The Home Bias Puzzle, as it is often called, has intrigued researchers for decades, prompting a quest for explanations. In this thesis, we investigate the preference for domestic stocks and other deviations from the optimal allocation among European investors between 2001 and 2022. Utilizing several regression analyses and principal component analyses, we examine the relevance of literature-based justifications for these biases over time. Our findings demonstrate that financial literacy, tax burden, investor age, information asymmetry, economic growth, recent stock market returns, and market size are consistent explanations for Home Bias across the studied period. We also explore how changes in these factors over time have contributed to the observed variations in Home Bias among different countries. Furthermore, we delve into the factors contributing to disproportionate investment in Foreign Bias. Our research confirms that distance, culture, shared languages, and religion serve as key proximity measures—both physical and psychological—that influence investment behavior. This thesis not only corroborates existing theories but also introduces new insights into the dynamic interplay of factors shaping investment preferences. By identifying and validating these determinants, we contribute to a deeper understanding of the persistent nature of Home and Foreign Bias in investment decisions.

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