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THE IMPACT OF SEARCH VOLUME INDEX ON FDI OUTFLOW: THE MODERATING ROLE OF UNCERTAINTY AVOIDANCE

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Abstract. This study examines the relationship between the Search Volume Index (SVI) and FDI outflow levels and tests whether the level of national culture, particularly whether the Uncertainty Avoidance Index (UAI), moderates such a relationship. The authors document that SVI is positively associated with FDI outflow in the sample of 69 countries. When we distinguish between low and high-uncertainty avoidance countries, we find that this positive association is significant at the current value of SVI for countries with low uncertainty avoidance. However, the relationship becomes stronger for countries with high uncertainty avoidance at the one-year time lag of SVI. Moreover, the results remain intact after various robustness checks. These results imply that the level of national culture may cause individuals to hesitate to invest through internet search queries. Our empirical findings should be particularly informative for investors from countries whose governments exhibit high levels of uncertainty avoidance, as they spend more time on investment planning than investors from countries whose governments exhibit low uncertainty avoidance.

Keywords: Search Volume Index, FDI outflow, developing countries, developed countries, Uncertainty Avoidance Index, culture.

JEL Classification: O57, E37, F37.

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1. Introduction

The improvements in information and communication technologies (ICT), alongside the evolution of highly effective supply chains and the forces of globalization, incentivized companies to expand their operations and production in overseas markets or countries. The primary goal of this expansion is to access a larger consumer base and enhance competitiveness and productivity levels. Recognizing the importance of this global reach, governments actively encourage their local businesses to venture abroad by providing a variety of formal and informal incentives. FDI outflow policies mainly serve the interests of the home country. By investing overseas, investors can increase their exports and improve their competitiveness (United Nations Conference on Trade and Development [UNCTAD], 2020). As the volume of foreign direct investment (FDI) outflow policies continues to expand significantly, it is posited that the Search Volume Index (SVI) can have a positive effect, as we explain next.

Several trends indicate that digitalization matters in global investment. First, 70% of the world's population is online and spends 2.3 hours on social media daily (Kemp, 2025). Second,

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the internet penetration rate reached 80% by early 2025 because of the expansion of 5G, fiber, and satellite networks (Marketing4eCommerce, 2025). By considering the significant increase in internet penetration and rapid development of ICT since 2011 has changed the way investors can analyse the global markets and assess the risk. Therefore, the rapid growth of online searches can show real-time signals of interest and volatility of investors. Thus, internalization is no longer a response to only economic signals but is also influenced by digital collective attention and information-seeking behaviour, which can increase or delay cross-country investment decisions.

Technological advancements have made the Search Volume Index (SVI) an increasingly significant data source worldwide (Cebrián & Domenech, 2023). Researchers who have selectively used Google data in measuring the information-seeking behaviour of individuals about public health, economics, and media studies around the world have risen (Dancy & Fariss, 2024). Notably, there has been relatively little cross-national empirical study on the internet search queries that play in investor attention. Investor attention refers to the amount of time investors have available to concentrate on information that may have an impact on their investment choices (Barber & Odean, 2008; Wang et al., 2022). Thus, the effective capturing of investors' attention might be a very important step for the reliable prediction of FDI outflow.

Investor attention is a limited resource, and this limitation also extends to investors. Prior research, such as Barber and Odean (2008), has empirically shown that decisions made by investors are influenced by their limited attention. A significant challenge, however, is the difficulty in directly measuring investor attention. For instance, indirect measures have faced criticism due to their limitations in past studies. Therefore, there is a necessity for a direct measure that can be utilized in analysing Foreign Direct Investment (FDI) outflow across all countries (i.e., including low-income developing nations where data is often scarce) and this can accurately represent investor attention. Since investment decisions by firms or individuals require detailed information about the legal, regulatory, policy, and institutional frameworks of host countries, alongside economic and financial factors, SVI proves to be as a highly effective direct measure of investor attention. It can effectively forecast the scale and intensity of cross-country FDI outflow, which can provide effective nowcasting and a broader analysis.

The article presents a cross-national empirical study using a sample of 69 countries from 2004–2022. Countries were divided into two categories by their level of uncertainty avoidance: high uncertainty avoidance (HUACs) and low uncertainty avoidance countries (LUACs), to capture the time lag in the SVI and FDI outflow association. The results show that SVI is an important determinant of FDI outflow in both categories. For HUACs, however, the association is stronger and statistically significant when the one-year lagged value of SVI is included. In contrast, for LUACs, the relationship is stronger and statistically significant when the current value of SVI is considered. By integrating insights from the "theory of planned behaviour" (Ajzen, 1991) and the national cultural framework (Hofstede & Minkov, 2010), this research sheds light on how culture influences the connection between SVI and FDI outflow.

This study makes several critical contributions to the economic literature. It is the first to empirically examine the association between Search Volume Index (SVI) and Foreign Direct Investment (FDI) outflow. It thereby fills a major gap in the existing literature, as no prior study has explored this linkage. Second, it builds upon the pioneering work of Narita and Yin (2018) and distinguishes itself from prior studies that have focused mainly on FDI inflow determinants. Our analysis emphasizes cultural dimensions as a significant factor influencing FDI outflow, which have been overlooked in previous research. Third, our study contributes to the current discussion by performing a comparative analysis between countries with high uncertainty avoidance (HUACs) and those with low uncertainty avoidance (LUACs). This extension allows us to explore whether the impact of low or high uncertainty avoidance cultural traits influences the Search Volume Index (SVI) for FDI outflow within these two distinct groups. This novel contribution highlights the influence of culture on investors' search behaviour, thus emphasizing the importance of developing context-specific policy responses. Finally, the paper integrates substantial, real-time, and rapidly growing data sets automatically collected by Google Trends into scientific FDI research, thus paving the way for further research opportunities.

In essence, our research reveals that the rise in digital information-seeking behaviour within these cultures helps to reduce information asymmetries and speeds up investment choices, thereby enhancing the agility of international capital flows. These findings provide practical insights for policymakers and investors looking to utilize online search patterns to optimize their cross-border investment strategies in such cultural settings.

The next section presents the research background. Section 3 provides hypothesis development. Section 4 covers research design. Section 5 reports the empirical results from the analysis. Section 6 concludes, suggesting implications and setting limitations.

2. Research background

Incorporating *SVI* can provide new insights and previously unexplored relationships that were overlooked by traditional methods and offer a valuable approach for forecasting various economic and financial activities (Da et al., 2011; Narita & Yin, 2018; Choi & Varian, 2012; Perlin et al., 2017). One notable paper by Narita and Yin (2018) stands out for exploring Google Trends' data in predicting short-term capital flows. Their empirical research reveals that incorporating search frequency into models enhances the accuracy of predicting outcomes beyond the observed data. Moreover, several research works have employed the Search Volume Index (SVI) to anticipate tourist flows and demand. A higher SVI value correlates with increased tourist numbers or hotel occupancy rates (Havranek & Zeynalov, 2021; Li et al., 2020; He et al., 2020). Additionally, investor sentiment and fear can be effectively gauged through Google searches. For instance, data retrieved from web searches demonstrate a statistically significant association with stock prices and returns while improving the predictive power of existing models for assessing the risk and volatility of financial derivatives (Fan et al., 2021; Salisu et al., 2021; Lyócsa et al., 2020; Subramaniam & Chakraborty, 2021). Given that people often disclose information through online search behaviour, GSVI is also used to analyse economic phenomena such as the unemployment rate and consumption level. Forecasts based on Google Trends provide very accurate predictions of the youth unemployment rate and consumption growth and allow a faster adjustment of dynamics compared to other traditional approaches, which support the claim that people gather information before taking action (Simionescu & Cifuentes-Faura, 2022; Bleher & Dimpfl, 2022). Lastly, the web search data on Google Trends was effectively used and played a vital role in the early detection of infectious events, especially COVID-19 infections, which was crucial for allocating health resources and increasing the preparedness of healthcare systems (Mavragani & Gkillas, 2020; Venkatesh & Gandhi, 2020).

However, a small body of the literature investigates the influence of the Search Volume Index (SVI) on FDI outflow levels and tests whether the level of national culture, particularly whether the Uncertainty Avoidance Index (UAI), moderates such a relationship. Our study aims to make a significant contribute to and further develop this existing body of literature.

3. Hypotheses development

3.1. Search Volume Index (SVI) and FDI outflow

Da et al. (2011) conducted the first original study on the direct measure of investor attention using the value of Google search data in the literature. Since data from social media activities such as Wikipedia (Moat et al., 2013; Focke et al., 2020), Twitter (Bollen et al., 2011; Li et al., 2016), and news articles (Tetlock, 2007) is used as an indirect proxy, Da et al. (2011) argue that it is difficult to measure investor attention with these indirect measures as the main premise of these proxies is that attention-grabbing events should have drawn the attention of investors. As a result, they recommend utilizing the Search Volume Index (SVI) as a direct proxy because these proxies reflect the interests of actively engaged investors and hence lessen the intrinsic limitations the indirect measures face. To examine how individuals' beliefs about trustworthiness affect intentions and actual behaviours in online investing, the Theory of Planned Behaviour (TPB), which was developed by Ajzen (1991), can be utilized. The theory posits that when individuals share the same intention to engage in a behaviour, the individual with a stronger belief in his or her abilities is more likely to achieve success compared to one who has uncertainties. TPB provides a strong foundation for examining whether attitudes toward Internet investing correlate with the intention for foreign direct investment, which, in turn, is linked to actual investing behaviour.

Investors often face and make decisions under conditions of information asymmetry, where the business, legal, political, and economic environment of the host countries is not perfectly observable (Akerlof, 1970; Stiglitz & Weiss, 1981). The SVI from Google search data serves as a behavioral trace of the information-seeking process of investors to reduce the uncertainty in the FDI decision-making process. Thus, the increase in SVI levels signals increased investor engagement in information acquisition and optimal allocation of the limited attention of agents to the most informative signals, which is theoretically grounded in rational inattention theory (Sims, 2003). Viewed through these theoretical justifications, SVI is not only a proxy variable for attention as suggested by Da et al. (2011), but also an information source for reducing information asymmetry, especially for countries with low transparency and weak institutional quality.

Thus, we formulate our first hypothesis as:

H1. There is an association between SVI and FDI outflow.

3.2. The moderating role of uncertainty avoidance on the association between Search Volume Index (SVI) and FDI outflow

It should be noted that diverse economies have also witnessed varying cultural preferences because of globalization. Gravity models are often used to study bilateral foreign direct investment (FDI) because they effectively capture the impact of economic size and geographic distance on investment choices (Anderson et al., 2017; Schneider & Wacker, 2022). According to Fiorini et al. (2017), incorporating cultural factors enhances the explanatory power of these models. Therefore, an important factor in the success of FDI outflow may also be national culture. National culture is the identity that distinguishes one group of people from another (Hofstede, 2011). We will use the uncertainty avoidance index as a cultural dimension to demonstrate how foreign direct investment moves from source countries. According to Hofstede (2011), uncertainty avoidance is "the extent to which the members of a culture feel threatened by uncertain or unknown situations." Moreover, the orientation of cultural distance matters when there is a discrepancy in uncertainty avoidance between host and home countries (Tang, 2012). If there are larger discrepancies in uncertainty avoidance between the countries, then it increases perceived risks and reduces FDI flow. This cultural dimension, particularly uncertainty avoidance, mediates how Search Volume Index (SVI) data is interpreted by investors, helping to explain variations in FDI outflow beyond economic and geographic factors. Notably, culture influences how a person lives and thinks, which is especially significant in this scenario as it also affects how they use the Internet (Michopoulou & Moisa, 2016). In the realm of investment activities, individuals may face significant uncertainty. When conducting research online, investors from cultures with a strong aversion to uncertainty tend to seek more information. They rely heavily on search engines to gather information because countries with high uncertainty avoidance have a low tolerance for uncertainty and ambiguity (Amaro & Duarte, 2017). Cultures that have low uncertainty avoidance tend to be satisfied with gathering minimal information when searching online (Jordan et al., 2013). Hence, it is important to have a delay between when intentions are assessed and when behaviours are assessed (Ajzen, 1991; George, 2004). Thus, we also formulate our second hypothesis as:

H2. The time lag should be greater (smaller) for SVI when Foreign Direct Investment flows from a source country with high uncertainty avoidance (low uncertainty avoidance).

4. Research design

4.1. Sample

The final sample includes 69 countries, with 36 classified under high uncertainty avoidance (HUACs) and 33 under low uncertainty avoidance countries (LUACs), covering 2004 to 2022. The period is driven by SVI's availability, which has only been computed since 2004. The period does not go beyond 2022, as the World Bank does not have the *FDI outflow* statistics available for 2023.

4.2. Variable measurement

4.2.1. FDI outflow

In all model specifications, the dependent variable is *FDI outflow*, the amount of outward Foreign Direct Investment (FDI) measured in billions of US dollars. *FDI outflow* includes the movement of equity capital, reinvested earnings, and other capital from the origin country to the rest of the world and is derived from the Balance of Payments database of the IMF, which is supplemented by data from the United Nations Conference on Trade and Development and official national sources (World Bank, n.d.). FDI indicates the cross-border investments of a resident in another economy with at least 10 percent ownership of ordinary shares of voting stock, which signifies the control or influence. FDI also includes greenfield investments, joint ventures, and mergers or acquisitions to establish long-term control.

4.2.2. Search Volume Index (SVI)

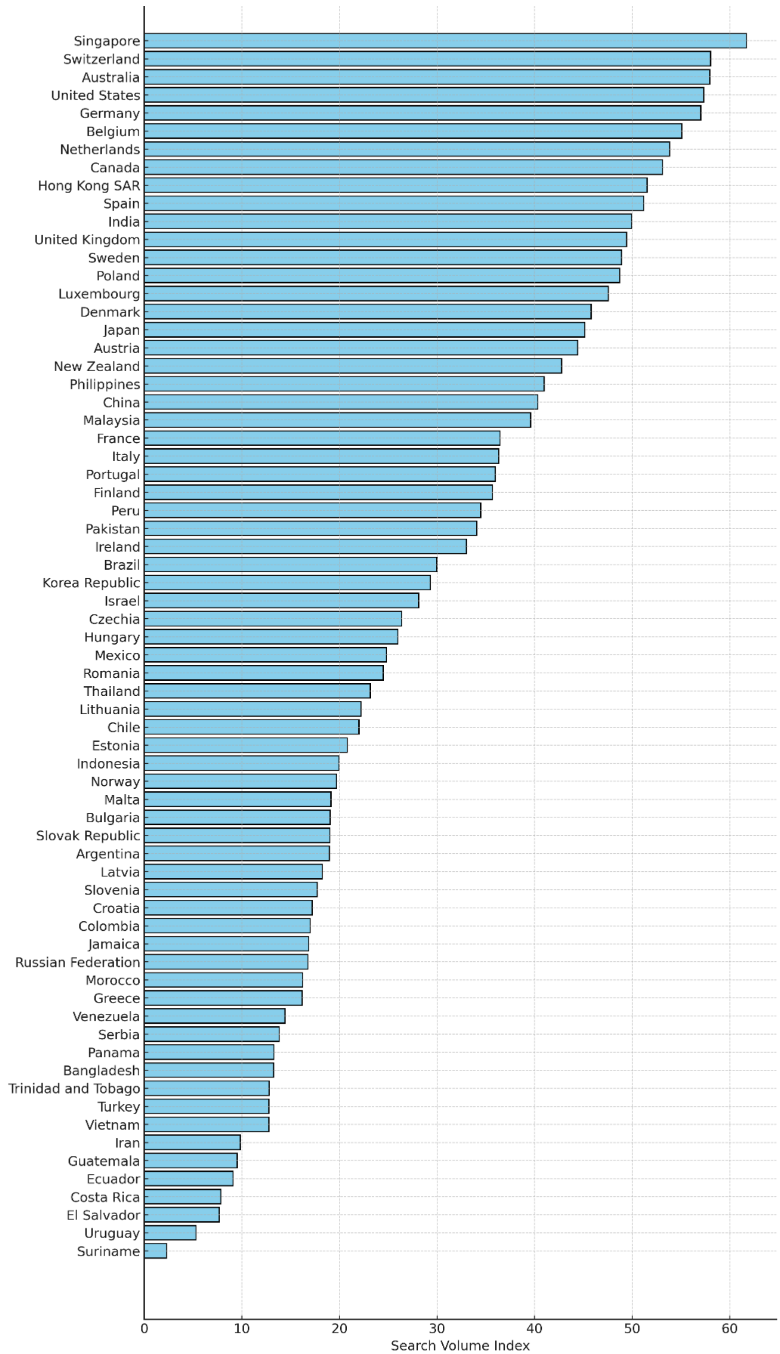
The Search Volume Index (*SVI*) for the term "investment" is the independent variable across all models. Although the SVI index from different search topics, such as "Business & Industrial", "Finance", "Law & Government", and others, can be used in the empirical investigation, this study used the "investment" keyword to obtain the index for several reasons. Firstly, unlike topic-specific terms, the "investment" keyword on the search is an umbrella term that includes various types of investment, including FDI, portfolio investment, and venture capital, allowing for capturing the investor's attention. This minimizes the risk of omitting the key search interest of investors. Secondly, the search term "investment" is commonly used and easily understandable in the English-speaking world and beyond. Thus, this recognition makes it a strong tool for capturing investor intention, regardless of geographic and cultural differences. Thirdly, previous studies have shown a statistically significant relationship between SVI for investment-related terms and real investor behaviour, such as stock market returns, the trading volume of stocks, and foreign capital flows (Ayala et al., 2024; Swamy et al., 2019). Overall, the aforementioned scholarly papers support the idea that "investment" as a keyword in Search Volume Index often provides more stable and higher search volumes than more narrowly defined terms such as "FDI" or "Foreign direct investment".

Additionally, Figure 1 shows the average SVI scores for each country in the sample over the observation period. Singapore has the highest average score (exceeding 60 units). The lowest average score is calculated for Suriname (below 10 units). This observation, however, does not indicate a consistent geographical pattern, as European countries like Estonia and Hungary have lower scores compared to countries such as Malaysia and Brazil. This again helped that selecting countries based on their maximum and minimum internet penetration provides more meaningful comparisons than grouping them by geographical region. As we compare the mean and variance of three different keywords, the selection of countries for comparison should be based on factors they have in common, such as the internet penetration rate.

Google Trends developed the Search Volume Index (*SVI*) to show public interest and sentiment through Internet search queries related to specific terms, topics, or countries. The Search Volume Index (SVI) on Google is calculated by dividing the number of searches on a specific keyword or query q by the total number of searches that were submitted in time *t* at location *i*. The value of SVI is normalized by setting the maximum value of it to 100. The value for periods is determined relatively by considering that the value of the index was set to zero at the beginning of 2004. Furthermore, the SVI is constructed based on a random sample from all searches, as it is difficult to process all searched data quickly. The provided sample is generally considered to be representative of all Google searches and provides a direct measure of investors' attention. However, this feature can lead to a problem if not addressed in the research, as each sample can produce different outcomes. One simple way to overcome this problem is to gather many samples from Google Trends and average every period, providing a more reliable time series. Therefore, to overcome this issue, we closely followed the methodology of Medeiros and Pires (2021) and collected the same data nine times, which gave nine different samples of SVI. Finally, the yearly averages of each sample were calculated, and the average of nine samples was used to determine the final SVI value used in this study.

4.2.3. The moderating variable: uncertainty avoidance

The *Uncertainty Avoidance Index* (*UAI*) data, Hofstede's cultural dimension, have been obtained from https://www.hofstede-insights.com. This index ranges from 0 to 100, and higher scores correspond to a higher influence of the cultural dimension in a country.



Note: The figure represents an overview of average SVI for all 68 countries in the sample for the observation period 2004–2022.

Figure 1. The Search Volume Index (SVI) per country

4.2.4. Control variables

The control variables in the model are selected based on past studies. Real *GDP* per capita, *Inflation*, *Trade Openness Index*, *Government Effectiveness Index*, and *Tertiary Education* are included to ensure the reliability of the coefficients of the model (Bhasin & Jain, 2013; Zhang & Daly, 2011; Holtbrügge & Kreppel, 2012; Perea & Stephenson, 2017; Buitrago & Barbosa Camargo, 2020; Al-Kasasbeh et al., 2022).

The GDP per capita variable was collected from the World Bank (2023), which was converted by purchasing power parity (PPP) conversion factor. Higher GDP per capita indicates greater economic development and capital accumulation, enabling domestic firms to seek investment opportunities abroad. As a measure of capital abundance, GDP per capita is expected to generate positive FDI outflow for source countries, supported by empirical findings of previously conducted studies (Imran & Rashid, 2023).

Inflation – a percentage change in the prices of a basket of goods and services measured by the Consumer Price Index (CPI) and calculated with 2015 as a base year – is included as one of the determinants of FDI outflow in this study. Intuitively, higher volatility in the price level which can be well proxied by the inflation rate is a sign of a higher degree of uncertainty that perverts investor insights into the profitability of investment. Although conventional economic theories expect the positive impact of inflation on FDI outflow, the sign of association is highly dependent on the magnitude of inflation which is highly diverse between developing and developed country groups (Hysa et al., 2022).

The trade openness index, which was collected from the World Bank (2023), is a measure that shows the magnitude of a country's engagement in international trade relative to the size of its economy. It is included as one of the conventional determinants of FDI outflow. Open trade policies facilitate easier access to foreign markets and allow local firms to identify and pursue opportunities that may not be readily available domestically (Stoian, 2013; Saini & Singhania, 2018).

The government effectiveness index was included as a control variable and used to rank state capacity to assess the quality of public services, the formulation and implementation of policy, and the credibility of government commitment (Kaufmann & Kraay, 2024). The governments with higher effectiveness and strong institutional frameworks facilitate international investment and support firms' international expansion (Sabir et al., 2019; Kayalvizhi & Thenmozhi, 2018).

Tertiary education refers to the proportion of the population with formal post-secondary education, which is also included as a determinant of FDI outflow. Higher tertiary education leads to stronger technical and managerial abilities to carry out international operations and more involvement in foreign ventures (Buitrago & Barbosa Camargo, 2020)

4.3. Model specification

To test the empirical validity of the hypothesis formulated above, the baseline model for this study is as follows:

$$FDI\ outflow_{it} = \beta_0 + \beta_1 \times FDI\,outflow_{it-1} + \beta_2 \times SVI_{it} + \beta_3 \times SVI_{it-1} + \beta_4 \times X_{it} + \gamma_{it} + \varepsilon_{it}, \quad (1)$$

where *i* and *t* indicate countries and years, *FDI outflow* is the net Outflow of investment from the reporting economy to the rest of the world, *SVI* is the main regressor of interest, *X* is the vector of the control variables, γ refers to time-specific effects, and ε is the error term.

Traditional panel data models, such as fixed effect, random effect, or pooled OLS, are no longer useful for finding causality between web searches and *FDI outflow* as the regression will produce biased and inconsistent parameter estimates, which were rooted in the discussed cross-sectional dependency, heteroscedasticity, and serial correlation of error terms problems (Albaladejo et al., 2016). Therefore, dynamic panel estimators can be used as a baseline model by using the lagged value of dependent variables as instruments to address the endogeneity issue and to get consistent and unbiased estimates. Nevertheless, Arellano-Bond, or the first difference GMM estimator, can be used to remove the country-specific unobserved effects, it suffers from the removal of cross-sectional information reflected in differences between countries (Roodman, 2009). Therefore, a two-step system GMM estimation is used instead, which considers time-invariant regressors and accounts for potential endogeneity (Roodman, 2009; Nadirov & Dehning, 2020). It retains the variation by including a levels equation which allows a better estimation of the coefficients of highly persistent variables. The two-step system GMM has several advantages over other dynamic panel models, such as Arellano-Bond and first difference GMM estimators. Firstly, the results are improved by using residuals from two-step GMM to get a more accurate weighting matrix that better accounts for heteroscedasticity and irregularities in the data (Windmeijer, 2005). Secondly, it adjusts for serial correlation, making model coefficients more robust than other dynamic panel models (Blundell & Bond, 2000). Thirdly, two-step GMM is asymptotically more normal for large samples (Windmeijer, 2005). Fourthly, including both levels and first difference equations allows the system GMM to deal more effectively with omitted variable bias, especially in unobserved heterogeneity. These facts make the two-step GMM the preferred choice when data exhibits cross-sectional dependency, heteroscedasticity, and serial correlation.

5. Empirical results and analysis

5.1. Descriptive statistics

Table 1 provides the summary statistics for all countries in the sample and is broken down by the level of uncertainty. Low and high uncertainty avoidance groups are determined using the median value of Hofstede's Uncertainty Avoidance Index.

5.2. Univariate analysis

Before using the dynamic panel model estimation, it is essential to gain initial insights into the relationship between the variables in the model. The correlation analysis in Table 2 highlights a modest positive correlation between $FDIO_t$ and SVI_{t-1} for HUACs (0.329) which is slightly stronger than the correlation with the current SVI_t (0.298), suggesting more reliance on past market information when making investment decisions due to more anxiety about the future and risk-averse characteristics of this group of countries. They are more cautious and deliberate in investment decision-making and more heavily rely on historical data rather than immediate trends. In contrast, LUACs exhibit a stronger correlation between $FDIO_t$ and SVI_t (0.415) compared to SVI_{t-1} (0.400), indicating a quick processing and immediate impact of gathered information from web searches on investment decisions.

Table 1. Summary statistics

Variable	Definition	Source	All countries (N = 69)	HUACs (N = 36)	LUACs (N = 33)
FDIO	Foreign Direct Investment Outflow (bn. dollars)	WB (2023)	26.1 (67.6)	15.1 (36.1)	38.6 (89.5)
SVI	Search Volume Index	GT (2023)	29.7 (20.2)	25.3 (17.7)	34.7 (21.6)
UAI	Uncertainty Avoidance Index	Hofstede Insights	67.7 (23.5)	86.6 (9.5)	47.3 (15.9)
RGDP	Real Gross Domestic Product per capita	WB (2023)	29834.7 (21141.3)	26685.3 (18333.7)	23392.6 (1916.7)
INF	Inflation	WB (2023)	4.8 (10.3)	5.8 (13.5)	3.7 (4.7)
TOI	Trade Openness Index	WB (2023)	97.7 (75.6)	89.4 (66.9)	106.8 (83.2)
GEI	Government Effectiveness Index	WB (2023)	0.5 (0.9)	0.6 (0.9)	0.3 (0.9)
TED	Tertiary Education	WB (2023)	58.43 (24.74)	60.4 (24.4)	56.2 (24.9)

Notes: Values are given as a mean (standard deviation).

Table 2. Pairwise correlations between FDI outflow and SVI variables

Variables	All countries			HUACs			LUACs		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
(1) $FDIO_t$	1.000			1.000			1.000		
(2) SVI_t	0.395*	1.000		0.298*	1.000		0.415*	1.000	
(3) SVI_{t-1}	0.394*	0.960*	1.000	0.329*	0.943*	1.000	0.400*	0.969*	1.000

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%; $FDIO_t$ = Foreign Direct Investment outflow at period *t*; SVI_t = Search Volume Index at period *t*; SVI_{t-1} = Search Volume Index at period $t-1$.

5.3. Diagnostic results

Before conducting a regression on a panel dataset, several preliminary tests are essential to ensure the model's appropriateness and its results' reliability (see Table 3). The Im-Pesaran-Shin and Fisher-type tests indicate that we can reject the null hypothesis of a unit root, confirming that the panel is stationary (Im et al., 2003; Maddala & Wu, 1999). Given the potential size distortions of the Breusch-Pagan LM test when (N) is large and (T) is finite, the Pesaran CD statistic is used to assess cross-sectional dependency in our panel data (De Hoyos & Sarafidis, 2006). Since (N > T) in the dataset, we opt for a fixed effect model to evaluate this dependency. The Pesaran test statistics reveal strong cross-sectional dependency, as we reject the null hypothesis of weak dependency at a 1% significance level, suggesting that our estimates from traditional panel data models, such as fixed effect and random effect models, will be inconsistent and not efficient. Additionally, we check for groupwise heteroscedasticity using the Modified Wald test, as tests like the Breusch-Pagan or White tests are not suitable for the panel datasets with a large number of groups and fail to distinguish between within-group and between-group heteroscedasticity. The test results confirm the presence of heteroscedasticity in the fixed effect model (Baum, 2001). Lastly, the Wooldridge test is used to test serial correlation as it is more suitable for panel data, particularly in fixed effect models (Born & Breitung, 2016). The rejection of the null hypothesis of no first-order autocorrelations indicates the existence of serial correlation of idiosyncratic error terms.

Table 3. Diagnostic results (source: author's elaboration)

Test	Result
Im-Pesaran-Shin	−1.3415* (0.089)
Fisher-type	4.6736*** (0.000)
Pesaran CD	8.672*** (0.000)
Modified Wald	2.699*** (0.000)
Wooldridge	23.539*** (0.000)

5.4. Dynamic panel system GMM baseline model results

Table 4 shows the results of the two-step system GMM estimation for *Search Volume Index* (*SVI*) and *FDI outflow*, where lagged *FDI outflow* is treated as endogenous due to potential two-way causality between them and *FDI outflow* (the dependent variable). The inclusion of past realisations of FDI outflow is especially problematic in the short-run panels, as it causes the Nickell bias. Lagged *FDI outflow* is positively significant in all specifications, which supports the persistence in *FDI outflow*. The relatively larger coefficient of the lagged dependent variable in the HUACs specification demonstrates that the persistence gets even stronger in countries with high uncertainty avoidance. This supports our selection of the two-step system GMM estimator as the *FDI outflow* depends on its own past realisations. We also control for other potential exogenous determinants of *FDI outflow*, including real *GDP* per capita, *Inflation*, *Trade Openness Index*, *Government Effectiveness Index*, and *Tertiary Education*, which were included as exogenous variables in the GMM estimation given in Table 4. It should be noted that it is important to show some statistical tests before interpreting a two-step system GMM estimation. In this case, the Arellano-Bond tests show that there is no serial correlation in the error terms (p-value ranging from 0.07 to 0.23), the number of instruments does not exceed the number of countries in all model specifications (i.e., 26 < 62), and the Hansen J-test is not significant (p-value ranging from 0.14 to 0.39), which shows that the employed instruments can be treated as exogenous. This implies that the results remain valid when steps are taken to address the potential endogeneity.

Furthermore, the estimation results indicate a statistically significant relationship between *SVI* and *FDI outflow*. The base model (Column 1 of Table 4) shows that the coefficient of *SVI* is positive and statistically significant at a 5% level in the case of the static model of all sub-samples. Its positive and significant coefficient signifies the usefulness of web searches in predicting economic and financial variables. Although the coefficient of *SVI* is still positive, it is not statistically significant in the second specification when the one-year lagged value of *SVI* is included in the first sub-sample of all countries in the study.

Then, the analysis focuses on the impact of *SVI* in different sub-samples, such as high uncertainty avoidance (HUACs) and low uncertainty avoidance countries (LUACs). For HUACs, the impact of *SVI* on *FDI outflow* in the static model is positive and highly significant ($p = 0.008$), but with a relatively smaller coefficient of 0.242 compared to another group of countries. However, the current web search is no longer a significant determinant after adding a one-year lagged value of *SVI* ($p = 0.587$). As expected by the literature, the HUACs are not good negotiators and are characterized by more anxiety about the future, which makes them fear failure and risk risk-averse. Therefore, any information collected from web searches that are quantified with *SVI* does not lead to a significant change in investment activities, as can be seen from the insignificant coefficient of the current value of SVI in the specifications of the HUACs sub-sample (columns 3 and 4). It implies that it takes them longer to make an investment decision. This fact is supported by the positive and statistically significant coefficient of the one-year lagged value of *SVI* ($p = 0.03$). In contrast, the current value of *SVI* (columns 5 and 6) is a significant determinant of *FDI outflow* for LUACs. The lagged value of *SVI* is not statistically significant for this group, which is in line with our hypothesis. In countries with a lower uncertainty avoidance index, investment decisions can be made quickly, as those countries are not risk-averse, and any information gathered immediately affects their investment choices.

Table 4. Two-step System Generalized Method of Moments (GMM) estimates

	All countries		HUACs		LUACs	
Endogenous variables $FDIO_{t-1}$	0.466*** (0.084)	0.466*** (0.084)	0.425*** (0.078)	0.417*** (0.077)	0.447*** (0.105)	0.454*** (0.104)
Exogenous variables SVI_t	0.388*** (0.105)	0.302 (0.214)	0.242*** (0.078)	–0.159 (0.159)	0.697*** (0.186)	1.253** (0.469)
SVI_{t-1}		0.086 (0.156)		0.398** (0.165)		–0.549 (0.383)
$\ln(RGDPG)_t$	12.893*** (4.728)	12.529*** (4.543)	17.332** (7.015)	19.159** (7.167)	18.747** (8.377)	19.057** (8.694)
INF_t	–0.005 (0.121)	–0.008 (0.121)	–0.147 (0.133)	–0.159 (0.144)	0.141 (0.280)	0.272 (0.262)
TOI_t	–0.046 (0.038)	–0.044 (0.037)	–0.109** (0.049)	–0.121** (0.052)	–0.060 (0.064)	–0.053 (0.063)
GEI_t	–0.122 (1.679)	–0.301 (1.723)	0.523 (1.770)	0.722 (2.009)	–5.667 (6.150)	–6.031 (6.608)
TED_t	–0.159* (0.083)	–0.152* (0.079)	–0.194* (0.098)	–0.219** (0.105)	–0.265 (0.237)	–0.291 (0.225)
Obs.	907	907	477	477	430	430
Number of Countries	62	62	33	33	29	29
Number of Instruments	25	26	24	25	25	26
Wald $\chi 2$	312.92***	318.02***	77.91***	77.70***	188.92***	188.35***

End of Table 4

	All countries		HUACs		LUACs	
$AR(1)\ (p - value)$	0.04	0.04	0.04	0.04	0.10	0.10
$AR(2)\ (p - value)$	0.07	0.07	0.10	0.10	0.23	0.23
Hansen J-test	18.04	18.61	17.65	21.41	17.67	23.20
$Hansen(p - value)$	0.39	0.35	0.34	0.16	0.41	0.14

Notes: The dependent variable is Foreign Direct Investment (FDI) outflow. The one-year lagged value of FDI outflow is endogenous. The Wald test statistics for the model hold in all specifications. The p-value of the Arellano-Bond test for AR(2) in all specifications, which has a range from 0.14 to 0.39, suggests that the model does not suffer from serial correlation. The model does not reject the Null hypothesis, which indicates that instruments are valid and uncorrelated with the error term according to the Hansen J-test of overidentification of GMM instruments (p-values ranging from 0.07 to 0.23). The number of instruments does not exceed the number of countries in each specification. All specifications include a constant term and are estimated using STATA 13. Windmeijer-corrected standard errors in parentheses. *, **, and *** indicate that the model variable is significant at 10, 5, and 1%, respectively.

Furthermore, in Table 4, we control for other effects to confirm our main findings. Notably, we added a natural logarithmic transformation of real GDP per capita, inflation rate, trade openness index, government effectiveness index, and tertiary education. Among the control variables in Table 4, the real GDP growth (RGDP) is positive and statistically significant in all model specifications, including both HUACs and LUACs, which aligns with existing economic theories and literature (Imran & Rashid, 2023). Higher real GDP growth reflects the overall economic strength of the home country and indicates the economy's ability to generate surplus resources that can be used for outward investment. In contrast, the inflation rate as a control variable does not have a robust and significant effect on FDI outflow across all specifications. We also observe that dissimilarities exist between the effects of inflation on FDI, particularly in the presence of differences in the level of uncertainty avoidance index between HUACs and LUACs. The sign of inflation is negative in the HUACs group, which seems counterintuitive given their risk-averse nature. Our findings in this direction remain different from earlier studies (Hysa et al., 2022; Agudze & Ibhagui, 2021). Nevertheless, this ambiguous sign of impact can be since HUACs societies are characterized by a lower tolerance for ambiguity and uncertainty, which can prevent or negatively influence their investment decisions abroad (Hofstede, 2011). Furthermore, across different sub-panels, we find that the estimated coefficients of the trade openness index are negative. It significantly differs from zero in the HUACs group, suggesting that the trade openness index (p = 0.020) has a robust and significant effect on the current FDI outflow. The economic intuition behind this behaviour may be hinged on the possibility that trade openness can act as a substitute rather than a complement to FDI for HUACs, as FDI involves higher risk than trade (Albahouth & Tahir, 2024). In contrast, it is not an important determinant of outward FDI for lower uncertainty countries. We also find out that the government effectiveness index does not appear to have a robust and positive impact on FDI outflow. Instead, it seems to have decreased FDI outflow in all countries and the LUACs group. Lastly, the impact of tertiary education is not statistically significant at a 5% significance level in all model specifications, except the HUACs group (p = 0.037). Surprisingly, the sign of the estimated impact is also negative in this sub-sample, which can be explained by the economic intuition that a well-educated workforce with higher innovation and productivity capabilities reduces the need for firms to seek foreign markets to access special talents and advanced skills (Al-Sadiq, 2013).

5.5. Robustness tests

As the unobserved variables in the error term that influence the SVI might also be related to the FDI outflow, and the changes in the SVI may be influenced by the magnitude of FDI outflow, the issue of potential endogeneity of this variable needs to be considered. SVI, as a direct measure of attention, is likely influenced by economic developments, including FDI flows, which leads to reverse causality. For instance, a sudden increase in FDI outflow from a country could cause news coverage and public interest, which in turn increases SVI searches related to capital outflow. Thus, FDI may also influence the SVI. Even the lagged value of SVI might be correlated with past shocks to FDI or increasing public interest in capital outflow. Therefore, both SVI and the one-year lagged value of it are considered as endogenous in the empirical model, which is given in Table 5.

The estimation results in Table 5 indicate a strongly positive impact of *SVI* on the dependent variable in the specification of all countries, as the increase in attention leads to 0.49 billion dollars more *FDI outflow* (p = 0.000). However, the one-year lagged value of *SVI* does not lead to a significant change as it is consistent with previous estimation results in Table 4 (p = 0.92). For HUACs, the impact of *SVI* on *FDI outflow* is positive and statistically significant at 1% significance level (p = 0.005). One unit increase in the current *SVI* leads to 0.24 billion dollars more *FDI outflow* from the country, which is relatively smaller compared to the sample of all countries. However, the current value of web search is no longer significant after adding a one-year lagged value of *SVI* to the model, which is in line with the hypothesis that it takes time for the investors of this group of countries to process the risk signals and act later. Thus, the one-year lagged value of *SVI* turns out to have a significant and positive change on *FDI outflow* (p = 0.028). In contrast, *SVI* causes an immediate change in FDI outflow for the sample of LUACs. This fact is supported by a positive and statistically significant coefficient of the current value of *SVI* (p = 0.005). This group of countries is not risk-averse and acts more quickly on attention signals. Therefore, the one-year lagged value of *SVI* is not statistically significant, no clear delayed effect (p = 0.291). All in all, the empirical results in the model with current and one-year lagged value of *SVI* as the endogenous variable are the same as the results from the previous model, which supports the robustness and consistency of our findings.

Table 5. Two-step System Generalized Method of Moments (GMM) estimates

	All countries		HUACs		LUACs	
Endogenous variables $FDIO_{t-1}$	0.453*** (0.079)	0.454*** (0.079)	0.419*** (0.074)	0.407*** (0.072)	0.438*** (0.091)	0.438*** (0.091)
SVI_t	0.487*** (0.121)	0.506* (0.279)	0.239*** (0.079)	–0.143 (0.168)	0.709*** (0.232)	1.098** (0.519)
SVI_{t-1}		–0.022 (0.203)		0.389** (0.168)		–0.414 (0.384)
Exogenous variables $\ln(RGDPG)_t$	15.643*** (5.467)	15.395*** (5.330)	17.476** (6.963)	17.909** (7.418)	20.246 (12.074)	21.651** (9.704)
INF_t	–0.063 (0.135)	–0.068 (0.133)	–0.215 (0.189)	–0.197 (0.137)	0.121 (0.335)	0.234 (0.361)

End of Table 5

	All countries		HUACs		LUACs	
TOI_t	–0.073 (0.052)	–0.071 (0.049)	–0.119** (0.055)	–0.114* (0.057)	–0.060 (0.071)	–0.059 (0.072)
GEI_t	–1.497 (2.499)	–1.625 (2.486)	–0.241 (1.753)	0.585 (1.544)	–6.186 (6.466)	–1.382 (9.776)
TED_t	–0.188 (0.085)	–0.187** (0.085)	–0.169* (0.093)	–0.179* (0.097)	–0.350 (0.304)	–0.374 (0.288)
Obs.	907	907	477	477	430	430
Number of Countries	62	62	33	33	29	29
Number of Instruments	44	44	43	43	44	44
Wald $\chi 2$	361.14***	361.14***	117.48***	113.36***	209.60***	208.54***
AR(1) $(p-value)$	0.04	0.04	0.04	0.04	0.09	0.09
AR(2) $(p-value)$	0.07	0.07	0.10	0.10	0.22	0.22
Hansen J-test	43.84	43.51	27.27	26.74	24.14	24.18
$Hansen(p-value)$	0.17	0.15	0.82	0.81	0.93	0.92

Notes: The dependent variable is Foreign Direct Investment (FDI) outflow. One-year lagged value of FDI outflow, and both the current and one-year lagged value of SVI are endogenous. The Wald test statistics for the model hold in all specifications. The p-value of the Arellano-Bond test for AR (2) in all specifications, which has a range from 0.07 to 0.22, suggests that the model does not suffer from serial correlation. The model does not reject the Null hypothesis, which indicates that instruments are valid and uncorrelated with the error term according to the Hansen J-test of overidentification of GMM instruments (p-values ranging from 0.15 to 0.93). The number of instruments does not exceed the number of countries in the specification of all countries (44 < 62). All specifications include a constant term and are estimated using STATA 13. Windmeijer-corrected standard errors in parentheses. *, **, and *** indicate that the model variable is significant at 10, 5, and 1%, respectively.

Beyond statistical significance, the estimated coefficients of SVI also suggest important economic implications. For instance, a one-unit increase in the SVI is associated with an average of a 0.49 billion dollar increase in FDI outflow in the sample of all countries. This change represents nearly 1.9% of average annual FDI outflow, which stresses the economic significance of web searches. The magnitude of the change in FDI outflow is even greater for the LUACs sample. The one unit increase in SVI leads to an increase of 0.709 to 1.09 billion dollars, which reflects the greater responsiveness of investment decisions to current information signals. In contrast, although the immediate impact of SVI is smaller for HUACs sample, with a 0.24 billion dollar increase per unit increase in the SVI, the lagged effect is significant and indicates the delayed attention-driven decisions. These results indicate that the SVI, as a direct measure of public interest, can be a powerful short-run predictor of investment activity with varying sensitivity depending on cultural differences.

6. Conclusions

The use of Google search data on a cross-country basis has been gaining major interest in investment literature. Our novel study presents and estimates the effect of the Search Volume Index on the FDI outflow based on the two-step GMM estimation. Using data from a sample of 69 countries over 2004–2022, the empirical evidence shows that Google search data contributes to increased FDI outflow. The estimates also suggest that this effect differs in countries with respect to their cultural dimension and uncertainty avoidance. The one-year time lag of SVI shows that the effects are stronger for high uncertainty (HUACs) and insignificant for low uncertainty countries (LUACs). This implies that cultural factors could place investors in a position of weakness due to uncertain or unknown situations, possibly causing them to hesitate in investing through internet search queries. These results are in line with the findings of the literature from other disciplines exploring how cultures influence the behaviour of tourists.

Our study makes a significant contribution to economic literature by being the first to empirically test the association between Search Volume Index (SVI) and Foreign Direct Investment (FDI) outflow, addressing an important gap, as no previous studies have explored this link. Additionally, it highlights the role of the cultural factors, particularly uncertainty avoidance, in the link between SVI and FDI outflow, which this aspect has been overlooked. Lastly, it incorporates real-time data from Google Trends and introduces a novel methodological approach to testing the mediating factor of the cultural dimensions on the association between SVI and FDI outflow.

From a policy implication perspective, investors can focus on encouraging Google Trends as a reliable source, and in doing so, they can reduce the significant amount of time spent planning their FDI investment in other countries. However, this depends on the countries in which the investors live. Future research is needed, particularly to consider how long such a time lag should be. For instance, it can be measured weekly, and thus, this can help investors save time on their investment planning in other countries.

Despite the rigorous methodology and careful selection of the sample, the study is subject to several data-related limitations. First, the measurement of the Search Volume Index (SVI) is very dependent on the selection of keywords; even slight variations can lead to different empirical conclusions, which makes the study highly dependent on the selected keywords. Additionally, the temporal scope of the study is reduced by the availability of SVI (2004–2022), which is only available from 2004 onward. FDI outflow data by the WB for 2023 is not available yet, limiting the analysis to the most current available year. These temporal constraints may influence the ability of the proposed econometric model to investigate the most recent global investment trends, especially considering the economic disruptions caused by COVID-19 and political tensions in the world. Second, as FDI outflow and other model variables are available on a yearly basis, we used the yearly aggregated value of SVI by taking the average of monthly values of the SVI index, which leads to a decrease in the frequency of data provided by Google Trends. Third, the SVI data from Google Trends is based on the randomized sampling process, which can lead to some minor differences across downloaded data. Although this study mitigates this problem by taking the average values from nine separate samples, the potential for sampling bias remains. Fourth, the SVI data can suffer from abnormal jumps, time trends, or seasonality issues, which require more effective technical transformations to neutralize their negative consequences in empirical findings. Fifth, Hofstede's UAI data is available for 69 countries, which reduces the sample size significantly. Exclusion of a noteworthy number of countries from the study may limit the deeper analysis of cross-country cultural heterogeneity and complex cultural dynamics in the world. Finally, the SVI in this study is collected by considering the search activity in English only, using the keyword "investment". This approach may cause a linguistic and cultural bias, particularly in non-English-speaking countries.

Future research on the relationship between SVI and FDI outflow may be extended as follows. First, the use of several measures of investment in SVI is needed to ensure the robustness of the results. The term "investment" cannot adequately capture that individuals or investors are searching to make outward FDI. FDI is a distinct category of investment typically undertaken by companies in establishing foreign operations, usually through acquisitions. Some may argue that it is unlikely that prospective investors would simply search for the term "investment" on Google and make their decision to establish a foreign subsidiary. Second, some countries can have the highest SVI as they have high levels of internet penetration (e.g., wide internet access and a high population), and they would also have high FDI. This can show a correlation, but it may be spurious. Future research needs to control for these factors in its models. Finally, another point of discussion relating to causality could be analysed, subject to the availability of reliable data.

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Authors contributions

Vusal Mammadrzayev played a key role in conceptualizing the study and was responsible for developing the methodology and conducting the data analysis. Orkhan Nadirov was responsible for data collection and did the revision. Drahomira Pavelkova contributed to the review and editing of the paper.

Disclosure statement

The authors have no conflict of interest to declare

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