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Three Essays in Behavioral Economics and Macroeconomics: Unraveling Celebrity Influence on Philanthropy, Racial Disparities in Donation Decisions During the COVID-19 Pandemic, and the Impact of Foreign Direct Investment on Economic Growth in Saudi Arabia

Rawan Khalid Alothaim
Claremont Graduate University

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Approval of the Dissertation Committee

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Rawan Khalid Alothaim as fulfilling the scope and quality requirements for meriting the degree of Doctor of Philosophy in Economics.

Paul Zak, Chair
Claremont Graduate University
Professor of Economic Sciences, Psychology & Management

Pierangelo De Pace, Committee Member
Pomona collage
Professor of Economics; Chair of Economics

Yi Feng, Committee Member
Claremont Graduate University
Memorial Chair Professor

“To my roots and wings - Abdulaziz and Hind, and to my anchor in every storm - Muatasim.”

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Abstract

Three Essays in Behavioral Economics and Macroeconomics: Unraveling Celebrity Influence on Philanthropy, Racial Disparities in Donation Decisions During the COVID-19 Pandemic, and the Impact of Foreign Direct Investment on Economic Growth in Saudi Arabia

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This dissertation encompasses three chapters. Two delve into behavioral aspects of charitable donations during the COVID-19 pandemic, investigating celebrity influence and racial disparities, as well as risk preferences. The third chapter shifts to macroeconomics, examining the relationship between Foreign Direct Investment (FDI) and economic growth in Saudi Arabia over a long-term horizon.

The first chapter investigates the effectiveness of celebrity endorsements on charitable giving during the COVID-19 pandemic. Participants' donation decisions were compared after exposure to celebrity and non-profit expert endorsements. Logistic regression and Ordinary Least Squares regression were used to analyze the impact of independent variables on the likelihood and total amount of donations. Findings suggest that celebrities did not significantly affect overall donation behavior, consistent with previous research. The study found no significant difference between celebrity and expert endorsements in terms of donation decisions, underscoring that the primary challenge for

non-profit organizations is outreach, as the choice of messenger appears to have minimal impact on donation decisions.

The second chapter investigates donation decisions during the COVID-19 pandemic, specifically examining racial disparities in charitable giving and the relationship between risk preferences and donations. The analysis is based on the financial contributions made by the average US citizen to food banks in the fourth quarter of 2020. The study finds that a substantial portion of the population (57%) was willing to support charitable causes during this challenging period. Additionally, it reveals that Black participants were more likely to donate and, on average, donate more than individuals from other racial groups. This finding aligns with previous evidence highlighting the generosity of Black individuals in charitable giving. Contrary to some prior results, the study uncovers that risk-averse individuals, as indicated by their frequent use of masks during the pandemic, were more likely to donate. These insights shed light on the role of empathy and donation motivations, offering valuable implications for fundraising campaigns targeting diverse racial groups and individuals with different risk preferences.

The third chapter explores the implications of Foreign Direct Investment (FDI) on Saudi Arabia's economic growth, a topic of critical importance amidst the country's ongoing economic diversification under Vision 2030. We employ Autoregressive Distributed Lag (ARDL) models to scrutinize the effects of FDI intensity on the Kingdom's economic performance, utilizing annual data. Results reveal no significant short-term impact of FDI on economic growth. However, there is a notable long-run equilibrium relationship among FDI, inflation, interest rates, and GDP per capita growth. Historical

crises and real interest rates also significantly influence economic growth. These findings echo the existing literature on the non-significant short-term effect of FDI on Saudi Arabia's economic growth, while pointing to potential long-term relationships.

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Chapter 1 Influences Don't Influence During COVID-19 Pandemic

I.Introduction:

Celebrities have long been utilized to influence consumer decisions and endorse products and services (Ilicic & Baxter, 2014). In the realm of charitable organizations, celebrity influencers are also frequently utilized to promote causes and increase donations (Wheeler, 2009). Studies have indicated that the appearance of celebrities in charity advertisements can increase donations (Zamudio, 2015), and positive connections between celebrities and specific non-profit organizations can also lead to higher donation amounts (Devasagayam, 2017). Bivin et al. (2017) further found that people's donations increase after celebrity endorsement, particularly among younger generations such as Millennials or Generation Y (Branigan & Mitsis, 2014). However, celebrity endorsements could also have negative effects on donations, particularly among older people who are aware of the celebrity's past scandals (Peterson et al., 2018).

The credibility of a celebrity endorser is an important factor, and previous research has shown that the endorsement's effectiveness depends on the celebrity's trustworthiness, attractiveness, and expertise (Ohanian, 1990). Some studies have found that a celebrity's experience in certified charitable work is the most important factor in their endorsement, followed by attractiveness (Wymer, 2015). Other research suggests that trustworthy third-party endorsers supporting non-profit organizations have the

primary effect on donors' decisions (Wheeler, 2009; Harris and Ruth, 2015). Additionally, influencers' credibility significantly affects donation decisions, and celebrities who share social needs similar to those of non-profits can enhance the source's credibility (Permatasari, Wahab, Widiyanti, 2019; Thamaraiselvan et al., 2017; Mitsis, 2014).

However, some studies have questioned the feasibility of using celebrities to advertise charities (Knoll et al., 2017). Celebrity endorsements may only affect audience behavior when they introduce a new object (Knoll et al., 2017), and endorsement of new products could be beneficial due to the celebrities' familiarity, making the product more accessible in memory (Erfgen et al., 2015). Conversely, some studies have found that celebrities would not affect donation decisions, and those who sympathize would donate regardless of who advertises the charity's need (Peterson et al., 2018; Morini, 2017).

During the COVID-19 pandemic, many charitable organizations utilized celebrities to encourage donations. This controlled study aims to investigate the effectiveness of celebrity endorsements on charitable giving during the pandemic by comparing celebrity influencers with non-profit experts or influencers on participants' donation behavior. The study hypothesizes that celebrities will influence participants to donate during the pandemic. By examining the impact of celebrity endorsements on donation behavior, this study will contribute to understanding the spending efficiency of non-profit organizations trying to reach people through celebrities.

II.Research Method and Analytical Approach:

2.1: Participants:

Table 1: Data Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Celebrities donation	242	0.545	0.499	0	1
Experts donation	242	0.541	0.499	0	1
Total celebrities' donation	242	2.680	3.079	0	8
Total experts' donation	242	2.711	3.156	0	8
Male	242	0.504	0.501	0	1
Female	242	0.492	0.501	0	1
Black	242	0.112	0.315	0	1
Hispanic	242	0.083	0.276	0	1
Other races	242	0.050	0.218	0	1
Age	242	49.475	16.662	18	66
Extroversion	242	19.041	7.301	0	40
Neuroticism	242	26.442	8.056	4	40
Openness	242	24.054	5.782	10	40
Earning Differences	242	0.83	0.375	0	1

Table 1: Data summary statistics

The study employed an online survey tool, Qualtrics, to distribute experiments to a representative sample of the United States between September 15 and November 9, 2020. The sample comprised 242 participants, with a mean age of 49.48 years (SD = 16.66) and included both males (123) and females (119) aged between 18 and 80 years. Each participant provided six observations, one for each video they viewed, resulting in a total of 1452 observations. A summary of the data is presented in Table 1. Prior to participating, all participants agreed to watch the six short videos, make donation decisions, and complete a survey in exchange for up to $15.

2.2: The Celebrities:

The study featured three celebrities: Ellen DeGeneres, an American comedian, television host, actress, writer, and producer; Olivia Dekker, an American sportscaster, and her husband, American professional basketball player Sam Dekker; and Russell Wilson, an American professional football player, and his wife, Ciara Wilson, an American singer, songwriter, model, and businesswoman. Celebrity endorsers are evaluated based on expertise, trustworthiness, and attractiveness according to Ohanian's (1990) Celebrity-Endorser Credibility Scale. Research indicates that trustworthiness is the most significant factor influencing donations, and it is measured using sincerity, honesty, and reliability (Wiedmann, 2021). Trustworthy celebrities are expected to provide valid information to their audience, thus enhancing their endorsement's credibility and trustworthiness (Ohanian, 1991). Donating money to a charity can also improve celebrities' reliability to the public, as demonstrated in a study by Fehrler (2010), which found that donating money increases beliefs about donors' trustworthiness. All the celebrities featured in this study are well-known in their respective fields and have donated to their endorsed organizations before urging the public to donate to these causes. Ellen DeGeneres is a renowned supporter of numerous organizations and has received several accolades for her charitable efforts. Sam and Olivia Dekker used their wedding proceeds to donate to charity. Finally, Russell Wilson and Ciara are the founders of the Why Not You Foundation, a non-profit that supports student access to equal education opportunities, children's health, and food security initiatives.

2.3: Procedure:

At the beginning of the survey and after watching each video, participants reported their feelings by filling out the Positive and Negative Affect Schedule (PANAS), a scale of different words describing feelings and emotions (Watson et al., 1988). All videos were one minute long. Each participant watched six videos that encouraged them to donate to food banks to help those in need due to the pandemic. Three videos displayed the aforementioned celebrities and three videos displayed experts on the issue of interest. The survey had three different versions, one for each possible order the participants could have had the videos presented. On all versions, the videos of celebrities and experts appear in alternating order. Participants' earnings varied with the number of questions correctly answered after each video and their donations. None of the videos were allowed to be skipped. After watching a video, participants were required to answer one simple question related to the video to earn $2.50 if answered correctly. The maximum possible amount a participant could earn was $15, so the maximum possible amount that could be donated to the groups in question (experts and celebrities) was $7.50 for each group.

The survey ended with a section that measured participant personality traits by prompting participants to answer 50 questions examining the Big Five personality traits developed by Goldberg (1992). All participant donations were sent to the respective food banks mentioned in each video, which serve various local and international locations. These food banks are Sheboygan County Food Bank (Sheboygan, Wisconsin, USA), West Houston Assistance Ministries (Houston, Texas, USA), Food Lifeline Organization (Western Washington, USA), Feeding America (various locations throughout the USA, with

headquarters located in Chicago, Illinois, USA), America's Food Fund (USA), and World Central Kitchen (various international locations, with offices in Washington DC, USA).

Participants were informed that their donations would be anonymous. This study used no deception, and the participants' donations were sent to the food banks they chose to donate to after completing the survey. Claremont Graduate University's Institutional Review Board approved this study (#3809).

2.4: Analytical Approach:

This study analyzes participant donation decisions after celebrities' and experts' endorsements. Using a binary outcome to record donation decisions (1 if a participant donated, 0 if they did not), we applied the principle of maximum likelihood estimation (logistic regression), resulting in an odds ratio, which explains the impact of each independent variable on the respective odds ratio of the total donations (Sperandei, 2014). Moreover, this paper used a linear probability model with robust standard errors as a robustness check for logistic regression findings (Freedman, 2006). Furthermore, the study analyzes participant donation amounts after both endorsements. For the total donation amount, we used Ordinary Least Squares (OLS) regression to describe the relationship between the total amount of donations and the independent variables (Hutcheson, 2011).

2.5: Models:

$$log(\ Donate\ after\ celebrities\ endorsement) = \alpha i\ + \beta\ Xi\ + \mu\ Zi\ + \varepsilon\ i \qquad Model\ (1)$$

$$log(\ Donate\ after\ experts\ endorsement) = \alpha i\ + \beta\ Xi\ + \mu\ Zi\ + \varepsilon\ i \qquad Model\ (2)$$

$$Total\ \ donation\ \ after\ celebrities\ endorsement = \alpha i\ + \beta\ Xi\ + \mu\ Zi\ + \varepsilon\ i \qquad Model\ (3)$$

$$Total\ \ donation\ \ after\ experts\ endorsement = \alpha i\ + \beta\ Xi\ + \mu\ Zi\ + \varepsilon\ i \qquad Model\ (4)$$

The first two models used logistic regression with a binary dependent variable: Model 1 measured whether participants donated after watching at least one celebrity video, while Model 2 measured whether they donated after seeing an expert endorsement. Model 3 and Model 4 both measured the total amount of donations made by participants, with a range of $0 to $7.50, using an Ordinary Least Squares (OLS) regression model. X_i represented the treatment variables, such as an indicator variable for whether participants had donated to charity in the past six months, and Z_i represented the control variables, including race, gender, age, income, personality traits, and earning differences.

III.Results:

3.1: Overall statistics:

According to Table 1, out of 243 participants, 51.2% donated after watching both the celebrities' and experts' videos (SD=50). On average, participants donated $2.68 (SD=$3.08) after watching celebrities' videos and $2.71 (SD=$3.15) after watching experts' videos. Independent-sample t-tests did not find any significant differences in demographic factors between the two types of endorsements. However, participants who had donated to charity in the last six months were more likely to donate to both celebrities' and experts' endorsed charities. The mean donation amount for participants who donated in the last six months was $0.16 (SD=0.37) for celebrities' endorsements and $0.17 (SD=0.37) for experts' endorsements. The t-tests showed that these differences were significant

(celebrities' endorsements: M=$0.16, SD=0.37, t(592)=4.2, p<0.001; experts' endorsements: M=$0.17, SD=0.37, t(638)=5.31, p<0.001).

3.2 Trait effects:

After watching all six videos, participants answered questions measuring their Big Five personality traits. All measures were based on a Likert scale, with possible ratings from 1 to 5. Participants who donated, whether they donated after watching experts' endorsements or celebrities' endorsements, rated themselves higher on the agreeableness dimension than any of the other five traits. There was a significant difference for those who donated after the celebrities' endorsements (donated after celebrities videos: M = 15.47, SD = 14.90, t (603) = 3.40, p < .001; donated after experts' videos: M = 15.43, SD = 14.92, t(649) = 3.59, p = 0.239). Additionally, donors in both the celebrities and experts' groups rated themselves lower on the dimension of extroversion than any of the other five traits. The average extroversion score for the celebrities' group was 10.16 (SD = 10.70, t(1406) = 0.940, p < 0.292), and the average score for the experts' group was 10.12 (SD = 10.74, t(1406) = 0.55, p = .293). Regarding openness, the celebrities' group scored an average of 13.30 (SD = 12.8, t(1406) = 1.27, p = .101), while the experts' group scored a significant average of 13.10 (SD = 12.80, t(607) = 1.93, p < 0.05).For conscientiousness, the celebrities' group averaged 15.30 (SD = 14.80, t(601) = 1.71, p < 0.05), while the experts' group averaged 15.30 (SD = 14.90, t(1406) = 1.19, p = .116). Finally, for neuroticism, the donor groups scored almost identically, both scoring an average of 14.80 (celebrities donors: SD = 14.7, t(601) = 3.11, p < 0.001; experts donors: SD = 14.9, t(600) = 2.94, p < .01).

3.3: PANAS:

Previous studies have found that people who report experiencing more positive emotions are more likely to donate than those who report themselves primed to feel negative emotions (Lyrintzis, 2017; Paxton, Velasco, & Ressler, 2020).

For this study, the Positive and Negative Affect Schedule shows that participants who donate have significantly more positive feelings after the experts' videos. For the first experts video the donors positive scale is M=22.41 SD=8.005, t(229)= 3.08, p<0.01 ; non-donors M=19.06 , SD=8.5, and for second expert video positive scale for donor M= 20.93, SD=8.29 , t(233)=2.57 , p<0.01 ;and for non-donor M= 18.10, SD= 8.58. the third expert's video positive scale shows that donors M=20.9 SD= 8.49, t(235)=2.31 , p<0.05, while non-donor M= 18.28, SD=9.01. However, there was no significant difference between donors and non-donors PANAS after any of the celebrities' videos.

3.4: Predicting donation decisions for celebrities' and experts' endorsements:

Table 2: Donation Decision

	(Logit)	(Odd ratio)	(VIF)	(LPM)
Dependent variable:Celebrities donation				
Donate to charity last six months	1.036***	2.817	1.207	0.240***
	(0.301)			(0.067)
Black	0.726	2.66	1.106	0.157
	(0.488)			(0.102)
Hispanic	0.311	3.364	1.136	0.067
	(0.546)			(0.120)
Others	0.742	2.09	1.051	0.160
	(0.689)			(0.137)
Age	−0.004	0.995	1.314	−0.001
	(0.009)			(0.002)
Female	−0.081	0.921	1.028	−0.015
	(0.276)			(0.062)
Income	0.052	1.053	1.136	0.011
	(0.088)			(0.020)
Extroversion	−0.033	0.967	1.171	−0.007
	(0.021)			(0.004)
Neuroticism	0.031*	1.031	1.195	0.007*
	(0.019)			(0.004)
Openness	0.021	1.021	1.108	0.005
	(0.026)			(0.006)
Earning Differences	−0.608*	0.544	1.039	−0.141*
	(0.346)			(0.077)
Constant	−0.699	0.497		0.338*
	(0.908)			(0.204)
Multiple R-squared: 0.09616	Adjusted R-squared: 0.05294			
F-statistic: 2.225	P-value: 0.01404			
Dependent variable:Experts donation				
Donate to charity last six months	1.036***	2.817	1.207	0.240***
	(0.301)			(0.067)
Black	0.726	2.066	1.106	0.157
	(0.488)			(0.102)
Hispanic	0.311	1.364	1.136	0.067
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Earning Differences	−0.608*	0.544	1.039	−0.141*
	(0.346)			(0.077)
Constant	−0.699	0.497		0.338*
	(0.908)			(0.204)
Multiple R-squared: 0.128	Adjusted R-squared: 0.0863			
F-statistic: 3.069	P-value: 0.0007327			
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 2: Logistic and LPM regressions analysis

We conducted a logistic regression model in Table 2, to measure the relationship between donation decisions and endorsements by celebrities and experts. We used the odds ratio with a 95% confidence interval to interpret the model. Due to the high correlation between donations after celebrity and expert endorsements, we did not include the two dependent variables in one model as indicators of donation decisions. We also employed the robust linear probability model to ensure the results' robustness.

The findings in Table 2 indicate no significant effect of celebrity videos on donation decisions compared to expert videos. However, for those who reported donating in the last six months, the odds of donation increased by 2.817 ($p < 0.01$) after watching both celebrity and expert endorsements compared to those who had not donated within that time frame. With regard to the participants' Big Five personality traits, neuroticism was the only factor that showed a significant effect on donation odds compared to others. Similar results were found for both celebrity and expert videos, but only the former was statistically significant, with the odds of donation increasing by 1.031 ($p < 0.1$) after watching either type of endorsement.

3.5: Predicting the donation amount for celebrities' and experts' endorsements:

Table 3 presents the relationship between the total donation amount and endorsements from celebrities and experts. Table 3, we observed that participants who had previously donated, on average, donated more compared to those who hadn't, with an increase of ($1.117, $p<0.01$) after watching celebrities and ($1.565, $p<0.01$) after watching experts' videos. Additionally, we found that Black participants donated more compared to White participants by ($1.765, $p<0.05$) after celebrities endorsed and ($2.141, $p<0.01$) after experts endorsed.

Table 5: Total Donation

	(OLS)	(VIF)
Dependent variable:Total celebrities Donation		
Donate to charity last six months	1.117***	1.187
	(0.400)	
Black	1.760**	1.094
	(0.697)	
Hispanic	0.543	1.126
	(0.672)	
Others	0.118	1.053
	(0.730)	
Age	0.012	1.300
	(0.012)	
Female	−0.099	1.035
	(0.382)	
Income	0.092	1.144
	(0.121)	
Extroversion	−0.050*	1.142
	(0.030)	
Neuroticism	0.067***	1.182
	(0.025)	
Openness	0.031	1.108
	(0.033)	
Earning Differences	0.330	1.041
	(0.408)	
Constant	−0.967	
	(1.164)	
Multiple R-squared: 0.1252	Adjusted R-squared: 0.0833	
F-statistic: 2.992	P-value: 0.0009689	
Dependent variable:Total Experts donation		
Donate to charity last six months	1.565***	1.187
	(0.398)	
Black	2.141***	1.094
	(0.658)	
Hispanic	0.302	1.126
	(0.680)	
Others	0.479	1.053
	(0.812)	
Age	0.009	1.300
	(0.012)	
Female	−0.343	1.035
	(0.378)	
Income	0.036	1.144
	(0.118)	
Extroversion	−0.041	1.142
	(0.029)	
Neuroticism	0.078***	1.182
	(0.026)	
Openness	0.030	1.108
	(0.032)	
Earning Differences	0.399	1.041
	(0.433)	
Constant	−1.208	
	(1.147)	
Multiple R-squared: 0.1725	Adjusted R-squared: 0.1329	
F-statistic: 4.358.	P-value: 6.234e-06	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3: OLS regression analysis

IV.Discussion:

This study investigated the impact of celebrities' endorsements on people's decisions to donate to non-profit organizations. Our findings align with previous research suggesting that celebrities do not significantly affect charitable giving (Morini, 2017; Peterson et al., 2018; Knoll et al., 2017). Additionally, we observed that having a record of past charity giving predicts donation behavior, a finding that mirrors those of earlier studies (Kashif et al., 2015). In contrast to the conclusions of Branigan and Mitsis (2014) and Peterson et al. (2018), our study did not identify age as a significant determinant in donation decisions following exposure to celebrities.

Despite the studies that indicate that celebrities have a limited influence on individuals' donation decisions, nonprofit organizations continue to seek their participation in donation campaigns. This suggests that there may be underlying psychological reasons why nonprofits are still inclined to use celebrity spokespeople. One potential reason is the excitement it brings to nonprofit workers, who find it thrilling to have celebrities in their office, meet them in person, and capture memorable moments through photographs. On the other hand, celebrities themselves are often motivated to engage in donation camps as it can significantly enhance their reputation. By aligning themselves with charitable initiatives, celebrities can improve their public image and be perceived as socially responsible individuals.

Policy implications from this study suggest that non-profit organizations should adopt targeted messaging strategies beyond relying solely on celebrity endorsements.

While celebrity endorsements did not significantly impact donation decisions, organizations can still collaborate strategically with celebrities to leverage their extensive fan bases and reach new audiences. However, it is important for organizations to ensure that their messaging focuses on the cause itself rather than solely relying on celebrity endorsement. Existing studies suggest that celebrities can boost awareness around philanthropy (Knoll & Matthes, 2017).

Moreover, as this study focused exclusively on TV celebrities and athletes, future research could evaluate the impact of social media celebrities on donation decisions. Given the context of the COVID-19 pandemic in which this study was conducted, it's crucial to consider how this might have influenced people's donation decisions and attitudes toward charity. Future studies could, therefore, replicate this study under different circumstances to examine how changing contexts might affect donation behaviors.

Chapter 2 Donation Decisions During the Pandemic

I. Introduction:

During times of widespread social hardship, the need for food banks to remain stocked is even higher than usual. However, food banks rely on outside donations, and their supply is not always guaranteed, so they can often be understocked when they are needed the most. The COVID-19 pandemic significantly increased the demand for food banks, with 34.4% of families with children under 12 years old experiencing food insecurity during the pandemic, a 19.9% increase compared to 2018 (Bauer, 2020). Unfortunately, the rise in demand was hardly fulfilled, as the pandemic further strained issues of food insecurity around the world, affecting both markets and food pantries (Pattee, 2022).

The United States has a generous population when it comes to food bank donations, with increases reported every year since 1977, except in 1987, 2008, and 2009 (Giving USA, 2018). Major events that occurred during years when support declined included Black Monday in 1987, when stock markets around the world crashed, and the Great Recession of 2008-2009, when donations to food banks fell sharply by 7.2% and 8%, respectively (Rooney, 2020; Meer, 2017). However, every year had seen an increase in donations compared to the last, even in 2017 and 2018, when the United States was affected by 30 natural disasters that each caused more than one billion dollars in damage (NOAA, 2022). In fact, 26% of Americans donated specifically to support disaster aid services (Bergdoll, 2019). In 2020, there was a massive 20% increase in online giving, and the individuals who

donated this way were the sources of over 80 percent of total donations (Giving USA, 2018).

However, this increase did not occur during the beginning of the pandemic. According to a survey conducted at the end of April 2020, 63% of organizations have seen a decline in fundraising revenue since the pandemic's onset (Nonprofit Fundraising Survey, 2020). Donations began to increase at the end of the second quarter of 2020, with charitable giving by individuals growing by 5.1% between 2019 and the end of 2020 (Mesch et al., 2020). The Giving USA 2021 Annual Report also found that household contributions to charitable organizations, individuals, and businesses for COVID-19 relief rose by 9.3% between May 2020 and May 2021. The share of COVID-19 relief was higher in households where individuals had contracted COVID-19, supporting a finding by Adena & Harke (2021) that people who personally understood the COVID-19 pandemic and the severity of its impact increased their donations to various organizations. Even outside of the pandemic, empathy for others based on hardships people have faced is one factor that correlates positively with donating. Additionally, Van den Poel (2011) argued that empathy and perceived credibility are the drivers of donations, which is supported by the findings of Liu et al. (2017), Lay et al. (2020), and Chen et al. (2021).

Previous studies have investigated various factors influencing donation behavior, including donor demographics. Research has found that women tend to donate more than men (Leslie, Snyder, & Glomb, 2013; Willer et al., 2015), and individuals with higher incomes are more likely to donate (Bergdoll, 2019; Drouvelis et al., 2019). Changes in permanent household income have a more significant impact on charitable giving than the

transitory household income (Hughes, 2008). Additionally, positive correlations have been observed between donation and donor age (Saunders, 2016). However, Smith et al. (2019) found that trust in philanthropic organizations has decreased over time among individuals under 30 years old, resulting in a decline in donations from this population.

The relationship between race and charitable giving has been the subject of several studies. According to research by Gross and Wronski (2021), individuals tend to donate more often to charities that benefit their own racial group. In addition, a study by Leslie, Snyder, and Glomb (2013) found that White individuals are more likely to donate to workplace charities than other ethnic minorities. Furthermore, studies indicate that Black Americans tend to be more willing to give to charitable causes than other racial groups (Willer et al., 2015), and donate a more significant percentage of their disposable income to nonprofits compared to other races (Drezner, 2013) Hispanics to be more likely to donate to charity (Marx & Carter, 2008).

Furthermore, mask-wearing behavior may also influence donation decisions. According to several studies, people who regularly wear masks are risk-averse (Xu & Cheng, 2021; Nakayachi et al., 2020; Asri et al., 2021). However, few studies have explored the relationship between risk preferences and charitable giving. Some research suggests that risk preferences are associated with giving and donation decisions, with risk-averse individuals likely to reduce their giving when the payoff is risky (Freundt & Lange, 2017). Similarly, generosity appears to be negatively correlated with risk (Krawczyk & Le Lec, 2010; Cettolin et al., 2017).

This study aims to build on previous research by examining the extent of financial contributions made by the average U.S. citizen to food banks during the fourth quarter of 2020 amid the COVID-19 pandemic. The study will investigate racial disparities in charitable giving and explore the relationship between risk preferences and donations.

II. Method and data:

2.1 Participants and data:

The study involved a sample of 242 participants (49.6% female and 50.4% male) who were U.S. residents, with an age range of 18 to 66 years old (M = 49.475, SD = 16.67). The sample was diverse regarding race/ethnicity, with 75% identifying as White, 11% as Black, 8% as Hispanic/Latino, and 4% as other (see Table 1). The study was conducted as an online experiment, and data was collected using a Qualtrics panel during the third quarter of 2020. The study was approved by the Institutional Review Board of Claremont Graduate University (#3809). It was conducted in a computer-mediated format, with participants completing the survey in approximately 20 minutes and receiving $15 compensation for their participation. Participants were informed that the study posed no risk beyond what a typical person experiences on a regular day.

Table 1: Donation Decision Summary Statistic

Type	Name	N	Mean	St. Dev.	Min	Max
Dependent	Donate	242	0.570	0.496	0	1
Dependent	Total donation	242	5.450	6.144	0	15
Independent	Black	242	0.112	0.315	0	1
Independent	Had COVID-19 or relative had COVID-19	242	0.413	0.493	0	1
Independent	Wearing Mask	242	3.037	1.563	0	4
Control	Male	242	0.504	0.501	0	1
Control	Hispanic	242	0.083	0.276	0	1
Control	Others	242	0.050	0.218	0	1
Control	Age	242	49.475	16.662	18	66
Control	Income	242	92,210.740	65,615.260	10,000	350,000
Control	Openness	242	24.054	5.782	10	40
Control	Mask Mandatory	242	0.376	0.485	0	1

2.2 Procedure:

This study investigates the factors affecting people's decision to donate to food banks during the COVID-19 pandemic. A total of 400 participants were recruited for this study, with a balanced distribution of age, gender, and income levels. The study consisted of two sections, a video-based section, and a survey section. Participants were informed of the study's purpose and asked to provide their consent before participating. They were then asked to complete the Positive and Negative Affect Schedule (PANAS, Watson et al., 1988) to report their feelings at the beginning of the experiment. Afterward, participants watched six short videos encouraging them to donate to food banks to assist those in need due to the pandemic. After each video, they completed the PANAS schedule and were asked a simple, descriptive question about the video, and if they answered correctly, they received an incentive of $2.50. Participants were then given the option to donate all or some of their incentives to the food bank mentioned in the video.

Following the video-based section, participants were asked to complete a survey regarding their normal donation habits, demographics, and personality traits. The amount of participant earnings varied with the number of times they agreed to donate after each video. This study did not involve deception, and the money participants chose to donate was sent to the food banks at the end of the study. Food banks that were included in the study were World Central Kitchen, Feeding America, America's Food Fund, Sheboygan County Food Bank, West Houston Assistance Ministries, and Food Lifeline. Participants were informed that their donations would remain anonymous.

2.3 Analytical Approach:

This study aims to analyze two different outcomes: participants' donation decisions and the total amount of their donations. A binary outcome was used to capture the participants' donation decisions, where a value of 1 indicates that a participant donated, and a value of 0 indicates that they did not. The principle of maximum likelihood estimation, specifically logistic regression, was applied to obtain an odds ratio that explains the impact of each independent variable on the respective odds ratio of the total donations (Sperandei, 2014). To further verify the logistic regression findings, a linear probability model with robust standard errors was employed as a robustness check (Freedman, 2006). To analyze the total donation amount, Ordinary Least Squares (OLS) regression was used to describe the relationship between the total amount of donations and the independent variables (Hutcheson, 2011).

2.4 Models:

$$log(Donate_i) = \alpha + \beta\ X_i + \mu\ Z_i + \epsilon_i \qquad Model(1)$$

$$(Total\ donations) = \alpha + \beta\ X_i + \mu\ Z_i + \epsilon_i \qquad Model(2)$$

In Model 1, the analysis focuses on whether or not participants donated after watching at least one of the videos, with the dependent variable coded as 1 for donation and 0 for no donation. Logistic regression is employed to examine the association between the donation decision and independent variables (Xi), such as participant race (Black) and risk-averse behavior (wearing a mask). Control variables (Zi), including gender, race, age, income, and Neuroticism (a personality trait), are considered. Age and income are controlled for in the model.

Model 2's analysis shifts to the total donation amount, ranging from $0 to $15, as the dependent variable. An Ordinary Least Squares (OLS) regression model is used to explore the relationship between the total amount of donations and the independent variables of interest (Xi), along with the control variables (Zi), as in Model 1.

III. Results:

3.1 Donation Behavior Among Participants:

The percentage of participants who donated after watching the presented videos was 57%. The average donation amount for the entire sample was $5.45 (SD = $6.14). There was no significant difference in donation behavior between genders. Specifically, 53% of females made donations with an average donation amount of $2.50 (SD = $5.02) (M = 0.26, SD = 0.44, t(240) = 1.260, p = 0.104), while 60.6% of males decided to donate with an average donation amount of $2.90 (SD = $5.23) (M = 0.30, SD = 0.46, t(240) = 1.149, p = 0.126). Additionally, a significant difference was found for participants who reported that they or a family member had contracted COVID-19. Those who reported COVID-19 cases were more likely to donate (M = 0.28, SD = 0.45) compared to those who did not report COVID-19 cases (M = 0.13, SD = 0.42), and this difference was statistically significant (t (240) = 2.933, p < .001). The average donation amount for those who reported COVID-19 cases was $2.67 (SD = $5.10).

73% of participants reported no change in income since the onset of COVID-19, and over half of all participants donated (M = 0.42, SD = 0.49, t(240) = 0.145, p = 0.44).

Participants with stable income donated an average of $4.25 (SD = $6.03). Among the 20% of participants who reported a decrease in income (M = 0.11, SD = 0.32, t(240) = 0.16, p = 0.43), 56% donated, with an average amount of $0.86 (SD = $2.86). Only 6% of participants reported an increase in income (M = 0.033, SD = 0.17, t(240) = 0.009, p = 0.49), and 57% of them donated, with an average donation of $0.34 (SD = $1.98).

75% of the participants reported that they regularly wear masks. Results showed a significant difference in donation decisions depending on the likelihood of participants wearing masks, with those who regularly wear masks being more likely to donate (donors: M = 2.12, SD = 1.91; non-donors: M = 1.53, SD = 1.87; t(199) = 1.67, p = 0.048). The average donation amount for those less willing to wear masks was $4.90 (SD = $5.90). Furthermore, the frequency of participants following news involving COVID-19 did not significantly affect donation decisions (M = 1.46, SD = 1.56; t(240) = 0.58, p = 0.28).

3.2 Donation Behavior Among Participants' Demographics:

The study found that 66% of Black participants donated some amount of money (M = $0.13, SD = $0.26, t(240) = 1.07, p = 0.142). Among White participants, 55.6% made donations, with an average donation amount of $0.78 (SD = $5.60, t(240) = 0.710, p = 0.239), while 50% of Hispanic/Latino participants donated, with an average donation amount of $0.07 (SD = $2.00, t(240) = 0.66, p = 0.255). The study found that there were no significant differences in donation decisions among racial groups. Age was also not found to be insignificant factor in donation decisions for the total sample, with an average age of 49.5 (SD = 16.66, t(240) = 0.821, p = 0.206).

3.3 Personality Traits and Emotional: An Analysis Using the Big Five-Factor and PANAS:

The study used the big five-factor to analyze participant traits and found that the agreeableness dimension was significantly different between donors and non-donors (donors: M = 28.9, SD = 6.24; non-donors: M = 26.5, SD = 7.24; t(202) = 2.009, p = 0.02). However, there was no significant difference in the extroversion and openness dimensions between donors and non-donors (extroversion: t(240) = 0.901, p = 0.184; openness: t(240) = 1.001, p = 0.159). The conscientiousness dimension was found to be significantly different between donors and non-donors (donors: M= 28.15, SD = 6.68; non-donors: M:27.55, SD = 6.81, t(240) =0.69, p = 0.0245). Finally, the neuroticism dimension was also found to be significantly different between donors and non-donors (donors: M:27.2, SD = 7.98; non-donors: M: 25.43, SD = 8.09, t(220) = 1.69, p = 0.045). The study's PANAS analysis revealed a significant decrease in positive feelings among donors compared to non-donors (donors M= -5.64, SD= 0.61, Non-donors M= -3.84 SD= 0.68, P-value = 0.026) after watching the videos, while there was no notable difference in negative feelings between the two groups.

3.4 Donation decisions:

Tables 2 and 3 analysis reveals interesting insights into the relationship between mask-wearing, race, personality traits, and donation behavior. Participants frequently wearing masks were 1.39 times more likely to donate ($p < 0.05$), even after accounting for mask mandate laws, income, and demographics. However, mask-wearing did not significantly affect the donation amount.

Black participants were 2.2 times more likely to donate than White participants ($p < 0.1$) and made more significant donations on average, with their contributions being $4.45 higher than those of White participants ($p < 0.01$).

Individuals with higher Neuroticism scores were found to be slightly more likely to donate (1.02 times, $p < 0.1$) compared to individuals with other omitted personality traits. Additionally, they contributed an average of $0.17 more towards donations.

Table 2: Donation Decision

	Dependent variable: Donate			
	(Logit)	(Odd ratio)	(VIF)	(LPM)
Wearing Mask	0.328**	1.387.	1.047	0.077**
	(0.166)			(0.037)
Mask Mandatory	0.163	1.176	1.083	0.038
	(0.316)			(0.074)
Black	0.787*	2.196	1.078	0.180*
	(0.478)			(0.102)
Hispanic	−0.119	0.887	1.112	−0.031
	(0.520)			(0.127)
Other races	0.676	1.965	1.065	0.151
	(0.641)			(0.133)
Male	0.238	1.268	1.027	0.055
	(0.296)			(0.069)
Age	0.006	1.005	1.100	0.001
	(0.009)			(0.002)
Neuroticism	0.033*	1.0157	1.048	0.008*
	(0.020)			(0.005)
Income	0.059	1.034	1.066	0.013
	(0.094)			(0.022)
Constant	−2.133**			0.0002
	(1.052)			(0.232)
Multiple R-squared: 0.04427		Adjusted R-squared: 0.0007695		
F-statistic:0.9829		p-value: 0.4555		
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 3: Donation Amount

	Dependent variable: Total donations	
	(OLS)	(VIF)
Wearing Mask	0.222	1.044
	(0.470)	
Mask Mandatory	0.663	1.092
	(0.921)	
Black	4.449***	1.077
	(1.420)	
Hispanic	0.116	1.114
	(1.418)	
Other races	0.406	1.059
	(1.726)	
Male	0.213	1.026
	(0.845)	
Age	0.054**	1.099
	(0.024)	
Neuroticism	0.170***	1.048
	(0.053)	
Income	0.265	1.068
	(0.271)	
Constant	−1.407	
	(2.633)	
Multiple R-squared: 0.08233	Adjusted R-squared: 0.03909	
F-statistic:1.904	p-value: 0.05351	
Note:	*p<0.1; **p<0.05; ***p<0.01	

IV. Discussion:

The findings of this study reveal that a significant portion of the population (57% of participants) demonstrated a willingness to support charitable causes during this challenging time. Furthermore, statistical analysis indicates that Black participants were more likely to donate ($p < 0.05$) and, on average, donated $4.45 more than White participants ($p < 0.01$). These findings support previous evidence suggesting that Black individuals are more generous in charitable giving, potentially due to cultural norms, social cohesion, and a stronger sense of community (Willer et al., 2015; Drezner, 2013).

Contrary to expectations, the study finds that risk-averse individuals, as indicated by their frequent mask-wearing, were more likely to donate ($p < 0.05$), contradicting previous claims (Freundt, 2017; Cettolin, 2017). The results suggest that risk aversion may be accompanied by a heightened sense of responsibility and a desire to protect others, leading to increased donation behavior. Moreover, the study emphasizes the significant role of emotions in shaping donation behavior, with donors experiencing a significant decline in positive feelings after watching the donation videos ($p < 0.05$), supporting the findings of van Dongen et al. (2021) and emphasizing the importance of understanding emotional dynamics in donation decisions.

The findings of this study hold important policy implications for fundraising organizations and non-profit entities. The study underscores the potential of videos to evoke emotions and motivate donors to give. Non-profit organizations can leverage this knowledge by creating compelling, emotional videos that inspire individuals to contribute

to their cause. Simultaneously, they could develop apps that show donors the real impact of their contributions, fostering a healthier, more engaging giving experience.

Furthermore, considering the propensity for charitable giving among Black participants and the finding by Gross and Wronski (2021) that individuals tend to donate more often to charities benefiting their racial group, strategic initiatives can be developed to foster community-based philanthropy within specific racial and ethnic groups. Non-profit organizations can establish community charitable trusts or locally-focused non-profit organizations, empowering these communities to support causes directly relevant to their cultural and social contexts.

Finally, these results contribute to understanding the interplay between risk preferences, personality traits, and emotional responses in donation decisions, warranting further investigation in future studies.

Chapter 3 The Effect of Foreign Direct Investment on the Economic Growth of Saudi Arabia

I. Introduction:

Foreign Direct Investment (FDI) holds a pivotal role in the economies of both developed and developing nations. In developed countries, FDI serves as a catalyst for increased investment, improved competitiveness, and job creation (UNCTAD, 2019). Moreover, FDI facilitates the transfer of new technologies and managerial practices, elevating productivity and sparking economic growth. For developing countries, FDI is often regarded as a crucial growth driver, offering access to capital, new technologies, and markets (OECD, 2002). This access can trigger local economic development, new job creation, stimulation of demand for goods and services, and knowledge and skill transfer.

In recent years, the Kingdom of Saudi Arabia has been navigating an economic transition under its Vision 2030. The government aims to reduce the nation's reliance on oil exports by diversifying the economy and enhancing the revenue generated from non-petroleum sectors. FDI is being harnessed as a vital instrument to achieve this goal, creating opportunities in sectors such as education, housing, energy, health, and sustainable development. The country has also lifted traditional protectionist quotas on foreign investments in retail and wholesale trading, enabling foreign investors to attain 100% ownership of assets in these sectors.

However, despite the strategic role of FDI in promoting economic growth, the implications for Saudi Arabia's economy remain somewhat ambiguous. The few studies that have explored the relationship between FDI and economic growth in Saudi Arabia present mixed results. For instance, research conducted by Al Khathlan (2013) and Alkofahi and Riyadh (2022) found no correlation between FDI and economic growth. Meanwhile, the 2018 study by Belloumi and Alshehry suggested a negative relationship between non-oil GDP growth and FDI in Saudi Arabia. In contrast, Alshehry (2015) identified a long-term relationship between FDI inflows and economic growth. These varying findings highlight the need for further investigation into this pivotal subject.

Therefore, given the variation in results regarding FDI's impact on Saudi Arabia's economic growth, this paper will delve into the effects of FDI on the country's GDP per capita by utilizing annual data. The findings will assist policymakers in assessing the efficacy of promoting foreign investment. We aim to shed light on this important area, hoping that our contribution will fill a gap in the existing body of knowledge and spur further discussion and research on this vital topic.

II. Literature review:

2.1 General Literature on the Impact of FDI on Economic Growth:

Empirical studies suggest that Foreign Direct Investment (FDI) generally propels economic growth in host countries. FDI is often perceived as a solution to the economic challenges faced by developing countries (Mencinger, 2003). Despite extensive research

on FDI's impact on economic growth, its actual effects still harbor some ambiguity (Wang, 2009). Numerous studies report a positive correlation between FDI and economic growth (Bird & Choi, 2020; De Gregorio & Lee, 1998; Al-Mamun & Sohag, 2015; Cheng & Shen, 2003; Wang, 2009; Andraz & Rodrigues, 2010; Agrawal & Khan, 2011), while others found no significant link (Carkovic & Levine, 2002; Alfaro et al., 2004; Albassam, 2015). Some studies even contend that FDI can exert adverse effects on host countries (Mencinger, 2003; Kohpaiboon, 2003; Omran & Bolbol, 2003).

Scholars have found that the variance in the effects of FDI on a host country's economic growth is contingent on the domestic circumstances of the host country (Forte & Moura, 2013; Hermes & Lensink, 2003; OECD, 2002). A myriad of domestic conditions, such as the country's achievement of a certain level of wealth (Blomstrom et al., 1994), a specific level of human capital (Borensztein et al., 1998), the degree of openness (Forte & Moura, 2013), or financial development (Hermes & Lensink, 2003; Alfaro et al., 2004), have been advanced to account for the positive impact of FDI. Choong et al.'s (2004) study emphasized that the domestic financial system is a crucial prerequisite for FDI to have a positive effect on economic growth.

However, FDI can exert negative impacts on the economies of host countries with poor infrastructure, low education levels, and limited absorptive capacity. A significant technological gap between the multinational's home country and the host country might also hinder the transfer of advanced technologies and limit the positive impact of FDI. Regulatory impositions on foreign investors, such as technology transfer requirements,

minimum exports from production, or joint ventures, can deter the use of advanced technology. Glass and Saggi (1998) noted that a large technology gap makes it less likely for the host country to possess the requisite human capital or physical infrastructure to attract FDI, influencing the decision to invest and the type of technology transferred.

2.2 The literature review about the FDI and Economic growth in Saudi Arabia:

Saudi Arabia occupies a unique position in the Middle East and North Africa (MENA) region, attracting a significant proportion of regional FDI inflows, notably in the sectors of oil, retail, wholesale trading, entertainment, and renewable energy. This is largely due to its robust economic status as a top oil exporter, complemented by structural and institutional improvements which have rendered it an attractive environment for foreign investors (UNCTAD, 2018). Historical milestones, such as the accession to the World Trade Organization (WTO) in 2005 and responses to global crises, have significantly shaped FDI behavior in the country. Joining the WTO considerably amplified FDI inflows by enhancing the business environment, increasing transparency, reducing corruption, and harmonizing Saudi regulations with other states (Allee & Scalera, 2012; Aziz & Mishra, 2016; Alfalih & Bel Hadj, 2020). Additionally, the Global Financial Crisis (GFC) from 2007 to 2009 did not significantly deter FDI in Saudi Arabia, primarily due to the high energy prices and resilience of the economy to the crisis (Brach & Loewe, 2010).

This backdrop contextualizes the specific literature on the effects of FDI on Saudi Arabia's economy. Samargandi et al. (2022) investigated the factors that attract FDI

inflows to Saudi Arabia. They found that the country's WTO membership, institutional quality, resilience during the GFC, and trade openness were conducive to FDI inflows. Elimam (2017) identified growth rate, GDP, exports, and imports as influencing factors for FDI flow in Saudi Arabia. Mahmood et al. (2018) determined that oil price and financial market development positively influence FDI inflows, while domestic investment, viewed as a substitute for FDI, negatively impacts it.

Mixed results exist regarding the relationship between FDI and economic growth in Saudi Arabia. Some studies, such as Alkofahi and Riyadh (2022), Belloumi and Alshehry (2018), and Alkathlan (2013), found no significant relationship between FDI and economic growth, utilizing various data sets and methods. In contrast, Alshehry (2015) determined that FDI inflows promote economic growth in the long term. These disparate findings underscore the need for further studies on this topic, particularly considering the continued economic diversification and modernization in Saudi Arabia.

Given these differing conclusions drawn by various studies, our paper will delve into the effects of FDI on Saudi Arabia's GDP per capita, by analyzing annual data. We aim to contribute to this literature, providing findings that can inform policy decisions and investment strategies, thereby enriching our understanding of the intricate dynamics between FDI and economic growth.

III. Data and Methodology:

3.1 Data Descriptions:

This research investigates the impact of foreign direct investment (FDI) on economic growth in Saudi Arabia, utilizing annual time series data from 1970 to 2022. The data for this study were sourced from organizations such as the World Bank, International Monetary Fund (IMF), CEIC, SAMA, and the PRS Group. Table 4 below outlines the main variables used in the analysis, their details, types, and sources.

Table 4: Variables Description and Sources

Variable	Description	Type	Source
RFDI_INTENSITY	The ratio of real FDI inflows (RFDI) to real gross domestic product (RGDP)	Explanatory	World Bank& CEIC
FDI_ transformed	Calculated by sign (FDI)*log(1+|FDI|)	Explanatory	World Bank& CEIC
RFDI	Real FDI inflows	Explanatory	World Bank& CEIC
GROWTH_RGDP_PC	The growth rate of real GDP per capita	Response	SAMA
L_Oil prices	Logarithm of the average oil prices	Control	CEIC data, and OPEC
DUMMY_70s	1973-1975 Oil Embargo Dummy: Assigned a value of 1 for the crisis years from 1973 to 1975, and 0 otherwise.	Control	-
DUMMY_80s	1980s Crises Dummy (Oil Glut): Takes a value of 1 for the crisis years of 1981-1986, and 0 otherwise	Control	-
GFC	Global Financial Crisis Dummy: Assigned a value of 1 for the crisis years of 2007-2009, and 0 in all other years.	Control	-
LN_OPENNESS	Logarithm of the openness	Control	SAMA
LN_GOV_EXPENTURE	Logarithm of the government expenditure	control	SAMA
Real INTREST_RATES	US. Lending rate	Control	FRED

INFLATION	Inflation rate	Control	FRED

3.2 FDI Transformations:

In our analysis, we prioritize real FDI intensity, defined as the ratio of real FDI inflows to real GDP, as the key independent variable. This approach provides several advantages. It positions FDI inflows in relation to the size of the economy, providing a more comprehensive view of FDI's impact (Alfaro et al., 2004; Bevan & Estrin, 2004; Nunnenkamp, 2002; Zhang, 2001). Also, this approach recognizes the intensity of FDI within an economy, enabling a more precise examination of its potential growth impact (Durham, 2004). Originally, the transformation proposed by Levy-Yeyati et al. (2007) was considered for the FDI data to reduce skewness and kurtosis. This transformation is defined by the formula: FDI_transformed= sign(FDI)*log(1+|FDI|). However, upon application, this transformation yielded highly fluctuating values, raising concerns about its

reliability and interpretability, as Figure 1 shows.

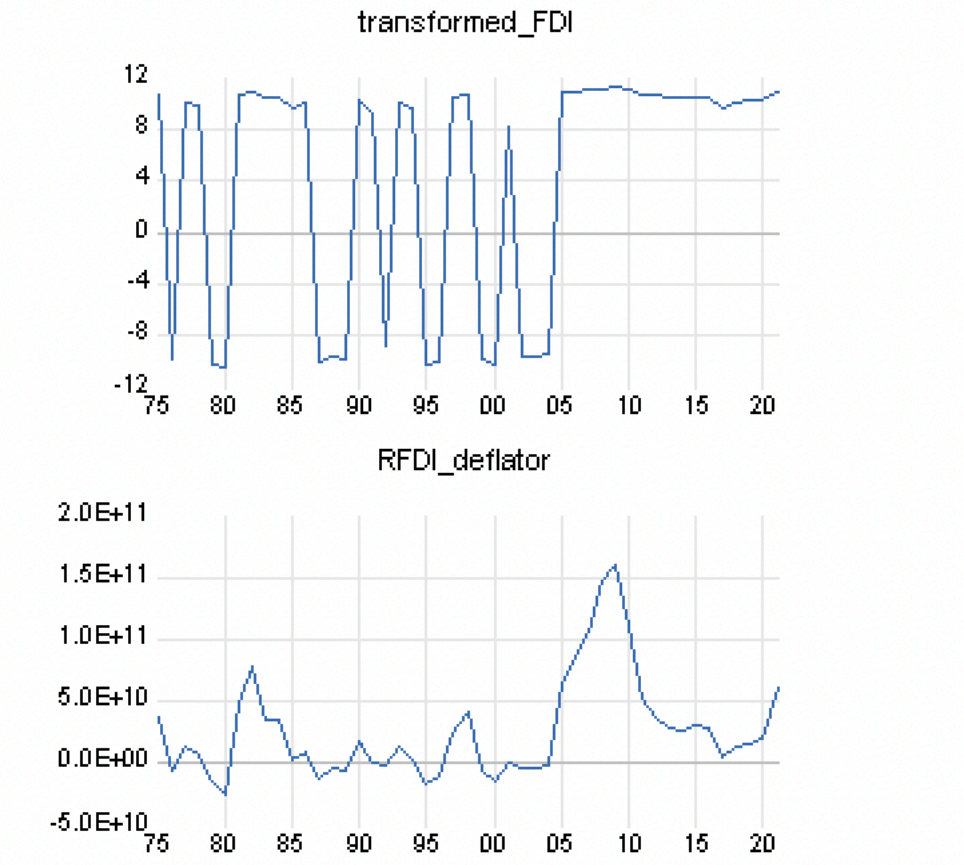

Figure 1: RFDI after applying transformation.

Based on this finding, we have decided to examine the real Foreign Direct Investment (FDI) intensity. This approach aligns with our research objectives and allows us to provide meaningful insights into the impact of FDI on Saudi Arabia's economic growth.

Subsequently, summary statistics and a correlation matrix for the variables used in the analysis are provided in Table 5 and Table 6, offering a comprehensive understanding of the data and relationships among the variables.

Table 5: Summary Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
RFDI_INTENSITY_GDP	11479.99	6926.34	84963.52	-82187.8	28782	51
RFDI	2.17E+10	1.26E+10	1.60E+11	-8.51E+1	4.38E+10	51
GROWTH_RGDP_PC	0.288086	0.321644	17.78578	-24.4307	8.554246	51
Dummy_70s	0.076923	0	1	0	0.269069	51
DUMMY_80s	0.098039	0	1	0	0.300327	51
GFC	0.058824	0	1	0	0.237635	51
INFLATION	3.676252	1.22207	34.57611	-3.203331	7.471203	51
REAL_NTREST_RATES	3.758719	4.939533	16.07102	-6.7136	8.226921	51

Table 6: The Correlation Matrix

	RFDI_INTENSITY	RFDI	GROWTH_RGDP_PC	LN_OPENNESS	INFLATION	REAL_INTREST_RATES
RFDI_INTENSITY	1.00000	0.94953	-0.42952	0.51174	-0.10920	-0.07896
RFDI	0.94953	1.00000	-0.27535	0.57761	-0.05598	-0.22758
GROWTH_RGDP_PC	-0.42952	-0.27535	1.00000	-0.29944	0.21124	-0.27418
INFLATION	-0.10920	-0.05598	0.21124	-0.27190	1.00000	-0.01695
REAL_INTREST_RATES	- 0.065402	-0.22758	-0.305051	-0.28926	-0.01695	1.00000

3.3 Dummy Variables:

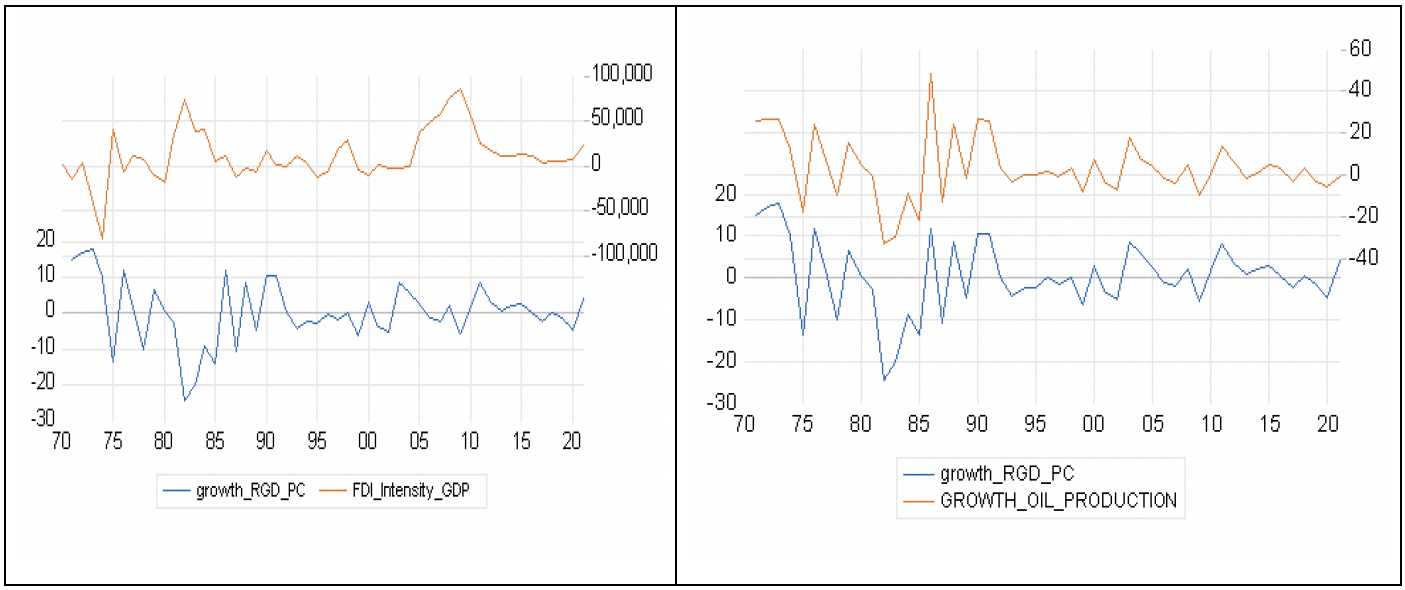

Figure 2: FDI, Oil Production, and Growth rate of RGDP per capita over the time

In the analysis, we further account for external factors by creating dummy variables for key periods that have seen major economic events affecting Saudi Arabia, specifically, the 1973 Oil Embargo, the 1980s Oil Glut, and the 2008 Global Financial Crisis.

The 1973 Oil Embargo, triggered by Arab oil-producing countries, led to a significant increase in oil prices, substantially boosting oil revenues for oil-exporting nations such as Saudi Arabia. During this period, both RGDP growth and RFDI in Saudi Arabia experienced a sharp decline.

The 1980s Oil Glut, marked by an oversupply of oil globally, resulted in a drop in oil prices. Interestingly, while the RGDP growth decreased during this time, there was a noticeable increase in RFDI. This could be attributed to various factors, including Saudi Arabia's diversification initiatives and increased openness to foreign investments.

Lastly, the 2008 Global Financial Crisis, known for its broad impact on the global economy, potentially affected both FDI and RGDP growth. However, during this period, Saudi Arabia witnessed a significant jump in RFDI, contrary to the trend of declining RGDP growth. This surge in RFDI could be partly explained by Saudi Arabia's accession to the World Trade Organization in 2005, which may have increased investor confidence and attracted more FDI to the country.

Including these dummy variables allows for control over the unique economic fluctuations during these periods, yielding a more nuanced comprehension of the relationship between FDI and economic growth in Saudi Arabia.

3.4 Control Variables:

To further refine our analysis, we control key economic indicators such as real GDP per capita, , inflation, and real interest rates. By accounting for these variables, we ensure that our evaluation of the relationship between FDI and economic growth in Saudi Arabia is not skewed by these potential influencing factors.

3.5. Autoregressive Distributed Lag Methodology (ARDL):

In our research, the ARDL methodology is utilized to investigate both the immediate and long-term impacts of FDI on Saudi Arabia's economic growth. This approach enables an in-depth analysis of the dynamic interplay among variables across varied time scales, a critical aspect for developing effective policy recommendations. A significant advantage of the ARDL model, highlighted by Mahran and Al Meshall (2014), is its efficiency and consistency when applied to smaller data samples, like our dataset that spans from 1970 to

2021. Moreover, the ARDL method can accommodate variables with different orders of integration (i.e., I(0), I(1), or a mix), increasing its adaptability for our research. Importantly, the ARDL methodology preserves the depth of long-term equilibrium relationships between variables by bypassing unnecessary differencing and allowing for flexible lag structures. It also reduces endogeneity concerns by considering each variable within its own equation, which limits the potential for residual correlation (Nkoro & Uko, 2016).

3.5.1. Stationarity Test:

Firstly, the stationarity of the time series data is confirmed using the Augmented Dickey-Fuller (ADF) unit root tests (Dickey and Fuller 1979). Stationarity ensures that the series do not exhibit any trend or seasonality, which is a prerequisite for further steps of ARDL.

3.5.2. ARDL Bounds Testing Cointegration:

Following this, a cointegration test is applied to identify potential long-term relationships among the variables. This is conducted by estimating the unrestricted error-correction models:

Model 1:

$$\Delta RGDP_P C_t = \beta 0 + \sum_{i=1}^{p} \beta i\, \Delta GRGDP_P C_{t-1} + \sum_{i=1}^{p} \beta i\, \Delta RGDP_P C_{t-1} + \sum_{i=0}^{q1} \gamma j\ \Delta RFDI_{t-1} + \sum_{i=0}^{q1} \delta k\, \Delta INFLATION_{t-1} + \sum_{i=0}^{q1} \mu l\, \Delta INTEREST_R ATE_{t-1} + \sum_{i=0}^{q1} \lambda m\, \Delta DUMMY_{t-m} + \sum_{i=0}^{q1} \varepsilon n\ \Delta GFC_{t-n} + \theta_1\ GRGDP_P C_{t-1} + \theta_2\ GRGDP_P C_{t-1} + \theta_3\ RFDI_{t-1} + \theta_4\ INFLATION_{t-1} + \theta_5\ INTEREST_R ATE_{t-1} + \theta_6\ DUMMY_{t-m} + \theta_7\ GFC_{t-n} + \eta$$

Equation 1: The Model

In the given model, β0 is the constant term. The parameters βi, β2, β3, β4, βm, and βn represent the short-run coefficients for the respective variables and their lags. These coefficients capture the immediate impact of a change in these variables on the dependent variable. Meanwhile, the parameters θ1, θ2, θ3, θ4, θ5, and θ6 are the long-run coefficients associated with the lagged level variables. These coefficients represent the equilibrium or long-term relationship between these variables and the dependent variable. The term η represents the error term in the model, which captures any unexplained variation in the dependent variable by the model's predictors.

The selection of the lag lengths, namely p, q1, q2, q3, q4, and q5, is a crucial part of the model specification. These determine the number of previous periods of each variable to be included in the model. In this model, these lag lengths are chosen based on the Akaike

Information Criterion (AIC). The AIC is a widely used statistical method for model selection, balancing the trade-off between the goodness-of-fit of the model and the complexity of the model.

The Bounds test is then employed to confirm cointegration among the variables. The F-statistic, as developed by Wald, is the determinant for cointegration. The decision on cointegration depends on the location of the F-statistic in relation to the critical values provided by Pesaran et al. (2001) and supplemented by Narayan (2005) for small samples. If the F-statistic exceeds the upper bound, cointegration is inferred; if it is below the lower bound, non-cointegration is concluded. If it falls within the bounds, the outcome remains inconclusive.

3.5.3. Model Estimation and Diagnostic Tests

Once we confirm cointegration, we proceed to estimate coefficients, shedding light on the magnitude and direction of relationships, both in the short and long term. To ensure the robustness of our model, we conduct diagnostic tests. These include the CUSUM and CUSUMSQ to ensure stability, checking for the presence of heteroskedasticity, serial correlation, model specification errors, and normality of residuals.

These checks confirm that our estimators are efficient, unbiased, and consistent. We address heteroskedasticity using the Breusch-Pagan Godfrey test and check for serial correlation using the Breusch-Godfrey Serial Correlation LM Test. Additionally, we verify the correct model specification using the normality of residuals with the Jarque-Bera test. All these measures enhance our model's reliability and the credibility of our findings.

IV. Empirical Results and Discussion:

4.1: Results of Unit Root Tests:

Table 7 presents the results of the Augmented Dickey-Fuller (ADF) stationarity test applied to our time series variables. The test outcomes demonstrate that all series are stationary at either the level or first difference, thus satisfying the prerequisites for applying the ARDL methodology.

Table 7: The Results of the Unit root tests.

Variable	**AD test at level**		**AD test -at 1st different**	
	t-test	Prob.*	t-test	Prob.*
Growth rate of GDP per capita	-5.591987	0.0000	-12.12941	0.0000
Growth non-oil GDP per capita	-3.093191	0.002	-7.06692	0.0000
FDI_ Intensity	-3.428067	0.001	-9.091931	0.0000
Transformed_FDI	-5.856532	0.0000	-9.650768	0.0000
Real FDI	-2.05767	0.03	-7.566646	0.0000
Real_Intrest_rates	-2.330608	0.1666	-5.668895	0.0000

Inflation	-2.158253	0.0000	-5.540194	0.0000
GDP deflator	1.637308	0.9738	-6.448036	0.0000

4.2. Results of ARDL Models

Table 8 illustrates the outcomes of the diagnostic tests conducted on the three models. The Jarque-Bera normality, Breusch-Godfrey serial correlation LM, and Breusch-Pagan-Godfrey tests collectively establish that the error terms within all three models are normally distributed, serially independent, homoscedastic and that the parameters are stable (as demonstrated by the CUSUM tests).

Table 8: The Results of the Diagnostic Tests

	Model 1	**Model 2**	**Model 3**
Selected Model: ARDL	(4,1,0,3,0)	(1, 3, 2, 0)	(3,0,1,2)
Breusch-Godfrey Serial Correlation LM test	F-statistic: 0.729409, p-value: 0.4903	F-statistic: 0.441472, p-value: 0.6465	F-statistic: 0.922918, p-value: 0.6465
Heteroskedasticity Test: Breusch-Pagan-Godfrey	F-statistic: 1.189937, p-value: 0.3276	F-statistic: 1.357173, p-value: 0.2328	F-statistic: 1.566185, p-value: 0.1476

Normality Test **Jarque-Bera Test**	Jarque-Bera:1.886, p-value: 0.3381	Jarque-Bera: 0.5038, p-value: 0.77737	Jarque-Bera: 2.66, p-value: 0.335
CUSUM	Stable	Stable	Stable

4.3 ARDL Bounds Test and R-Squared Results

Table 9: ARDL bound test and R- squared.

	Model 1	**Model 2**	**Model 3**
F-Bounds Test	10.99791***	12.73278***	12.03836***
R-squared	0.674825	0.423978	0.586543
Adjusted R-squared	0.396660	0.239651	0.466858

Table 9 shows the ARDL Bounds test results for each model, along with the R-squared and Adjusted R-squared values. The results reveal a long-run relationship between the overall growth rate of real GDP per capita and the explanatory variables—foreign direct investment inflows, inflation, interest rates, government expenditure, and trade openness—at a 1% level of significance. This relationship may offer valuable insights into the factors contributing to Saudi Arabia's economic growth and the possible impact of FDI inflows.

4.4 Long- and Short-Run Estimates (ARDL Error Correction Model)

Table 10: Long Run Estimation

Variable	Model 1	Model 2	Model 3
RFDI_INTENSITY_GDP	-5.25E-05 (4.25E-05)	-	-4.89E-05 (3.96E-05)
RGDP_PER_CAPITA(-1)	-203.0905** (83.95162)	-64.47736 (46.45037)	-
REAL_INTREST_RATES	0.103126 (0.237536)	0.209795 (0.189155)	-0.010308 (0.253213)
INFLATION	1.575035*** (0.450464)	1.043445** (0.458919)	0.498229 (0.344904)
C	12.90229** (5.806725)	2.776827 (2.955613)	0.577993 (1.867216)
Significance levels: *p<0.1; **p<0.05; ***p<0.01.			

Table 11: Results from Short Run Estimation

Variable	Model 1 Coeff. (SE)	Model 2 Coeff. (SE)	Model 3 Coeff. (SE)
D(GROWTH_RGDP_PC (-1))	0.240877* (0.136591)	-	0.107314 (0.147049)
D(GROWTH_RGDP_PC (-2))	0.364427** (0.122864)	-	0.194872* (0.105732)
D(GROWTH_RGDP_PC (-3))	0.161928* (0.090822)	-	-
D(RGDP_PER_CAPITA (-1))	-	558.5889* (307.7815)	-
D(RGDP_PER_CAPITA (-2))	-	74.95722 (109.0280)	-
D(RGDP_PER_CAPITA (-3))	-	-277.1044** (106.7829)	-
D(RFDI_INTENSITY_GDP)	-8.20E-06 (3.02E-05)	-	-
D(REAL_INTREST_RATES)	1.081574*** (0.179667)	0.708473* (0.304297)	1.496979** (0.464290)
D(REAL_INTREST_RATES(-1))	-0.065462 (0.158741)	-0.1555038 (0.301305)	-0.559525** (0.171520)

D(REAL_INTREST_RATES(-2))	0.774446*** (0.153813)	-	-
D(INFLATION)	-	-	2.168432*** (0.519234)
DUMMY_70S	-39.58686*** (5.115593)	-	-20.40831*** (3.625305)
DUMMY_80	-5.289607** (2.129259)	-13.51903*** (2.993174)	-13.34620*** (2.703728)
GFC	-16.828551 (2.726176)	-10.45561** (3.277318)	-1.268609 (3.121830)
CointEq(-1)	-1.434595*** (0.153170)	-1.701197*** (0.273756)	-1.347024*** (0.175196)
Significance levels: *p<0.1; **p<0.05; ***p<0.01.			

Tables 7 and 8 display the results of our research, which uses three Autoregressive Distributed Lag (ARDL) models to examine the effect of Foreign Direct Investment (FDI) intensity on Saudi Arabia's economic growth. Each model employs different variables, facilitating robustness checks on our results. Model 1 positions economic growth as the dependent variable with independent variables including FDI intensity (RFDI_INTENSITY), , inflation, real interest rates, and control factors for historical crises such as the Global Financial Crisis, the oil glut in the 1980s, and the oil embargo in the 1970s. Also, we add lagged Real GDP per capita to control for control the convergence effect. Model 2 mirrors Model 1 but excludes RFDI_INTENSITY, while Model 3 incorporates RFDI_INTENSITY but omits Real GDP per capita, serving as additional robustness measures.

In the long run, all models demonstrate the presence of a cointegrating relationship among the variables, as indicated by the F-statistic surpassing the upper bound at a 1% significance level. This suggests a long-run equilibrium relationship among the variables.

In the short run, the first and second lags of the real GDP per capita growth showed significant positive coefficients of 0.240877 and 0.364427, respectively ($p < 0.05$), indicating that growth rates in previous periods positively impact current ones. Historical crises have consistently suppressed growth. Specifically, the Global Financial Crisis (GFC) reduced growth by about 6.17 percentage points ($p=0.0307$). The 1980s Oil Glut (DUMMY) similarly curtailed growth by approximately 5.29 points ($p=0.0186$). The 1970s oil crisis (DUMMY_70S) had the most drastic effect, slashing growth by nearly 39.59 points ($p < 0.0000$), underscoring the substantial negative impact of historical crises on growth. The real interest rates variable exhibited a significant effect ($p < 0.05$), where an increase in real interest rates corresponds to an upswing in the growth rate of real GDP per capita. Specifically, the coefficients for real interest rates at the current period and the second lag are 1.081574 and 0.774446 respectively, suggesting that a robust economy, as indicated by higher interest rates, stimulates economic growth.

Turning to the Error Correction Term (ECT), all models exhibit coefficients with absolute values exceeding -1 but less than -2, signifying an overshooting adjustment process. This suggests the system oscillates around its long-run equilibrium before stabilizing. In particular, the ECTs for Models 1, 2, and 3 stands at -1.434595, -1.701197, and -1.347024, respectively. Despite appearing atypical, such phenomena are not uncommon in empirical economic research. Existing literature associates ECTs with absolute values between -1 and -2 with overshooting adjustment behavior, which is consistent with our models (Litavcov et al., 2021; Odugbesan & Rjoub, 2020).

To conclude, the ARDL models offer insights into the short and long-term dynamics of Saudi Arabia's economy under the influence of FDI and other key macroeconomic variables. FDI intensity does not significantly contribute to short-term economic growth, whereas inflation has a significant impact on long-term economic growth. Additionally, certain historical crises, particularly the oil embargo of the 1970s and the oil glut of the 1980s, have a significant negative impact on economic growth. Lastly, our models indicate an overshooting adjustment process, wherein the economy fluctuates around the long-run equilibrium before eventually stabilizing.

v. Discussion:

The present study investigated the impact of Foreign Direct Investment (FDI) on economic growth in Saudi Arabia. Our analysis revealed that there is no significant effect of FDI on economic growth in the short run. However, in the long run, the bound test and the significance of the error correction term suggest a long-term relationship between FDI, inflation, interest rates, government expenditure, and the growth of the Real Gross Domestic Product per capita. These findings align with the existing literature on the subject, which has also reported no significant relationship between FDI and economic growth in Saudi Arabia in the short term but a relationship in the long term (Alshuhry, 2015).

To support our findings, we conducted a comprehensive review of the relevant literature on the effect of FDI on Saudi Arabia's economic growth. The literature indicates that Saudi Arabia has attracted substantial FDI inflows, particularly in sectors such as oil, retail, wholesale trading, entertainment, and renewable energy. Factors such as the

country's accession to the World Trade Organization (WTO) and its response to global crises have contributed to Saudi Arabia's attractiveness as a destination for foreign investors. However, despite these factors, the literature generally agrees that FDI has not shown a significant impact on economic growth in Saudi Arabia (Samargandi et al., 2022; Elimam, 2017; Mahmood et al., 2018).

Regarding the specific factors influencing economic growth in Saudi Arabia, our analysis revealed that inflation and interest rates have a positive influence on RGDP growth. These findings are consistent with economic theory and empirical evidence from other studies. It suggests that inflation and interest rates play a crucial role in shaping the short-term dynamics of economic growth in Saudi Arabia.

We must acknowledge the limitations of our study, notably the length of the data, which is annual and covers only 51 observations. This limited time series data may not fully capture the complexities of the relationship between FDI and economic growth. Therefore, caution should be exercised when generalizing the results to longer time periods or different economic conditions.

Future research should address these limitations by utilizing high-frequency data to capture the dynamic nature of the relationship between FDI and economic growth in Saudi Arabia. Additionally, exploring other potential factors that could explain the long-term dynamics of RGDP growth would contribute to a more comprehensive understanding of the Saudi Arabian economy.

Based on our findings, several policy recommendations can be proposed. Firstly, despite the non-significant effect of FDI on short-term economic growth, its positive

influence in the long term suggests the need for consistent policy efforts to attract and retain foreign investment. These policies may include the enhancement of institutional quality, further liberalization of the economic sectors, and investment in human capital to boost Saudi Arabia's absorptive capacity.

Additionally, since the real interest rate positively impacts economic growth, monetary policy should be designed in such a way that stimulates investment while keeping inflation under control. Therefore, the Saudi Arabian Monetary Authority could consider an interest rate policy that maintains an optimal level of real interest rate, conducive to investment and economic growth.

Moreover, the results of our study emphasize the substantial negative impact of historical oil crises on Saudi Arabia's economic growth. Given this, and Saudi Arabia's ongoing diversification efforts under Vision 2030, there should be continuous initiatives to diversify the economy away from oil, reducing its vulnerability to oil market volatility. It could involve promoting investments in non-oil sectors, encouraging innovation, and fostering entrepreneurship.

VI. References

Agrawal, G., & Khan, M. (2011). Impact of FDI on GDP growth: A panel data study. European Journal of Scientific Research, 57(2), 257–264.

Alfaro, L. (2006). How does foreign direct investment promote economic growth? Exploring the effects of financial markets on linkages. National Bureau of Economic Research.

Alkathlan, K. (2013). Foreign direct investment inflows and economic growth in Saudi Arabia: A co-integration analysis. Review of Economics and Finance, 4, 70-80.

Alkofahi, K., & Riyadh, K. S. A. THE DETERMINANTS OF FOREIGN DIRECT INVESTMENT: EMPIRICAL INVESTIGATION FROM KINGDOM OF SAUDI ARABIA.

Alshehry, A. S. (2015). Foreign direct investments and economic growth in Saudi Arabia: A cointegration analysis. Developing Country Studies, 5(6), 69-76.

Andraz, J., & Rodrigues, P. (2010). What causes economic growth in Portugal: Exports or inward FDI? Journal of Economic Studies, 37(3), 267–287.

Belloumi, M. (2014). The relationship between trade, FDI and economic growth in Tunisia: An application of the autoregressive distributed lag model. Economic Systems, 38, 269-287.

Bengoa, M., & Sanchez-Robles, B. (2003). Foreign direct investment, economic freedom, and growth: New evidence from Latin America. European Journal of Political Economy, 19(3), 529-545.

Bird, G., & Choi, Y. (2020). The effects of remittances, foreign direct investment, and foreign aid on economic growth: An empirical analysis. Review of Development Economics, 24(1), 130.

Borensztein, E., De Gregorio, J., & Lee, J.-W. (1998). How does foreign direct investment affect economic growth? Journal of International Economics, 45, 115–135.

Carkovic, M., & Levine, R. (2005). Does foreign direct investment accelerate economic growth? Does foreign direct investment promote development, 195, 220.

Cheng, H., & Shen, Y. (2003). Foreign direct investment and economic growth: The importance of institutions and urbanization*. Economic Development and Cultural Change, 51(4), 883–896. https://doi.org/10.1086/375711

Choong, C. K., Yusop, Z., & Soo, S. C. (2004). Foreign direct investment and economic growth in Malaysia: The role of the domestic financial sector. Singapore Economic Review, 50, 245.

Devasagayam, R., Meyers, M., Ashline, K., Baker, M., Moss, M., & Venkatakrishnan, R. (2017). Brand endorsers and cause-related marketing: An empirical investigation. International Journal of Academic Research in Business and Social Sciences, 7(9), 137-144.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366a), 427–431.

Degasperi, N. C., & Mainardes, E. W. (2017). O que motiva a doação de dinheiro? Estudo sobre motivadores externos. Revista de Administração (São Paulo), 52(4), 363-373.

Durham, J. B. (2004). Absorptive capacity and the effects of foreign direct investment and equity foreign portfolio investment on economic growth. European Economic Review, 48(2), 285-306.

Elsadig, M. A. (2012). Are the FDI inflow spillover effects on Malaysia's economic growth input driven? Economic Modelling, 29, 1498-1504.

Elimam, H. (2017). Determinants of foreign direct investment in Saudi Arabia: A review. International Journal of Economics and Finance, 9(7), 222-227.

Erfgen, C., Zenker, S., & Sattler, H. (2015). The vampire effect: When do celebrity endorsers harm brand recall?. International Journal of Research in Marketing, 32(2), 155-163.

Fehrler, S. (2010). Charity as a Signal of Trustworthiness. IZA Discussion Paper No. 5299, Available at SSRN: https://ssrn.com/abstract=1708745 or http://dx.doi.org/10.2139/ssrn.1708745

Forte, R., & Moura, R. (2013). The effects of foreign direct investment on the host country's economic growth: Theory and empirical evidence. The Singapore Economic Review, 58(03), 1350017.

Goldberg, L. R. (1992). The development of markers for the Big-Five factor structure. Psychological Assessment, 4(1), 26–42. https://doi.org/10.1037/1040-3590.4.1.26

Hailpern, S. M., & Visintainer, P. F. (2003). Odds Ratios and Logistic Regression: Further Examples of their use and Interpretation. The Stata Journal, 3(3),213–225. https://doi.org/10.1177/1536867X0300300301

Harris, E. E., & Ruth, J. A. (2015). Analysis of the Value of Celebrity Affiliation to non-profit contributions. Nonprofit and Voluntary Sector Quarterly, 44(5), 945–967.

Hermes, N., & Lensink, R. (2003). Foreign direct investment, financial development and economic growth. Journal of Development Studies, 40(1), 142–163.

Ilicic, J., & Baxter, S. (2014). Fit in celebrity-charity alliances: When perceived cyanthropy benefits nonprofit organizations. International Journal of Nonprofit and Voluntary Sector Marketing, 19(3), 200–208. doi:10.1002/nvsm.1497.

Knoll, J., Matthes, J. (2017). The effectiveness of celebrity endorsements: A meta-analysis. Journal of the Academy of Marketing Science, 45(1), 55–75.

Kohpaiboon, A. (2003). Foreign trade regimes and the FDI-growth nexus: A case study of Thailand. Journal of Development Studies, 40(2), 55–69.

Li, S., Liu, X., & Li, J. (2021). The Contagion of Donation Behaviors Changes Along With the Abatement of the COVID-19 Pandemic: An Intertemporal Survey Experiment. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.585128

Li, X., & Liu, X. (2005). Foreign direct investment and economic growth: An increasingly endogenous relationship. World Development, 33(3), 393-407.

Love, J. H., & Lage-Hidalgo, F. (2000). Analysing the determinants of US direct investment in Mexico. Applied Economics, 32(9), 1259-1267.

Mainardes, E. W., Teixeira, A. I., & Romano, P. C. D. (2017). Stakeholder theory: A bibliometric analysis. BAR - Brazilian Administration Review, 14(1).

McCracken, G. (1989). Who is the celebrity endorser? Cultural foundations of the endorsement process. Journal of Consumer Research, 16(3), 310–321.

Naude, W., & Krugell, W. (2007). Investigating geography and institutions as determinants of foreign direct investment in Africa using panel data. Applied Economics, 39(10), 1223-1233.

Ndongko, W. A. (1980). The effects of foreign direct investment on the growth of the manufacturing sector in Cameroon. The Journal of Modern African Studies, 18(3), 429-443.

Nelson, C. R., & Plosser, C. I. (1982). Trends and random walks in macroeconmic time series: Some evidence and implications. Journal of Monetary Economics, 10(2), 139–162.

Romano, P. C. D., Mainardes, E. W., & Grigório, C. M. (2018). Retenção e lealdade de doadores em organizações não governamentais: proposta de um modelo conceitual. Revista de Administração (São Paulo), 53(2), 175-188.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. The Stata Journal, 9(1), 86–136.

Saha, S., & Yap, G. (2014). The moderation effects of political instability and terrorism on tourism development: A cross-country panel analysis. Journal of Travel Research, 53(4), 509–521.

Seddon, P. B., & Kiew, M.-Y. (1996). A Partial Test and Development of DeLone and McLean's Model of IS Success. Australian Journal of Information Systems, 4(1). https://doi.org/10.3127/ajis.v4i1.378

Varma, S., & Kapur, A. (2012). Impact of FDI on GDP: A Comparative Study of China and India. International Journal of Business and Management, 7(10), 52-59.

Wei, Y., & Liu, X. (2001). Foreign direct investment in China: Determinants and impact. Edward Elgar Publishing.

Zhang, Q., Felmingham, B. (2002). The role of FDI, exports and spillover effects in the regional development of China. Journal of Development Studies, 38(4), 157–178.