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## The Impact of FDI, Import, and Export on the Economic Growth of SAARC Countries

Saman Herath Bandara, University of Mount Olive, North Carolina

#### Abstract

The study aims to understand the impact of foreign direct investment (FDI), exports (EXP) and imports (IMP) on economic growth in South Asian countries (SAARC). A dataset for the period 2000-2020 was used for the analysis collected primarily from World Bank (WB) sources. The analysis was performed using STATA. Real gross domestic product (RGDP) was used as an indicator to measure economic growth in terms of FDI, EXP and IMP. The key findings indicate significant positive relationships between economic growth, FDI and net export (X) for SAARC countries. The results lead to trade policy suggestions to the region.

JEL Codes: E1, E7 Key words: Foreign Direct Investment, Export, Import, GDP, Economic Growth

#### Introduction

The role of exports imports and investments are some of the major drivers of economic growth of a country. According to Todaro (1997), physical capital accumulation, growth of labor force, and technological progress play a major role in an economic development of a country. Foreign direct investment (FDI) brings capital as well as technological investments that impact on economic growth by increasing productivity, and innovative technology (Thomas et al. 2008). Further, it creates competition and efficient allocation of resources for economic growth (Kobrin, 2005; Le and Ataullah, 2006; Santangelo, 2018). It plays an extraordinary role in globalization and provide new market, production, and financing facilities to the global economy. For a developing host country or a regional bloc, FDI provides capital, products, organizational techniques, technology, accounting for cross border investments, risk and regulations outside debt, and values to human resource through skill trainings (Dunning and Hamdani, 1997; Answer and Nguyen, 2011; Kok and Acikgoz, 2009; Ugochukwu et al., 2013).

Importation and exportation of goods and services of a country is influenced by increasing with other factors of population, and other factors like GDP, exchange rate, inflation, and interest rate. The international trade meets the needs and requirement of population, may be goods and services that are not produced locally or not produced adequately. Exports of a country consider an indicator of economic development (Esfahani, 1991). This growth is often attributed to the possible externalities of competition in world markets in the contexts of efficiency of resource allocation, economies of scale, and various labor training and 'demonstration' effects (Bhagwati and Srinivasan, 1979; Krueger, 1980; Helpman and Krugeman, 1985). Exports increase long-run growth to the economy to specialization with economies of scale in those sectors that arise from research and development, human capital or learning by doing, (Romer, 1987; Luca, 1988; Ali et al., 2021).

Based on the different socioeconomic conditions, economic growth may be different both in developed and developed countries as well as in different regions. Thus, the main objective of this study is to understand the economic growth of a poor region of Asia, South Asian Association for Regional Cooperation (SAARC) countries, with the impacts of FDI, importation, exportation, and labor force. The rest of the paper is organized into four sections. After a discussion of SAARC countries, the next section provides data and methods. Empirical results and analysis are presented next followed by conclusions and policy suggestions.

#### SAARC Region

South Asian Association for Regional Cooperation (SAARC) a regional alliance established in 1985, originally consisting of seven South Asian countries, namely, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan and Sri Lanka and later Afghanistan was inducted (Figure 1).

The region is full of diversities in terms of land area, geographical features, population, ethnicity, religion, natural resources, etc. The region has a total population of about 1.6 billion of which India has roughly about 75%, followed by Pakistan with 9.5%, Bangladesh 9%, and rest of the population live in other 5 countries. SAARC the regional bloc works based on eight broad objectives. These are to promote the welfare of the peoples of South Asia and improve their quality of life; to accelerate economic growth, social progress and cultural development in the region, and to provide all individuals opportunity to live in dignity and to realize their full potentials; to promote and strengthen collective self-reliance among the

member countries; to contribute to mutual trust, understanding and appreciation of one another's problems; to promote active collaboration and mutual assistance in the economic, social, cultural, technical and scientific fields; (6) to strengthen cooperation with other developing countries; to strengthen themselves to negotiate unitedly' in the international forums on matters of common interests; and to cooperate with international and other regional organizations with similar aims and purposes.



Figure 1: SAARC Countries.

**Data and Methods** 

#### Data

The analytical model comprises five variables. The dependent variable is the real gross domestic product (RGDP) of the country. The independent variables are foreign direct investment (FDI), difference between export and imports (X), population growth (POPG), and unemployment rate (UEMP). RGDP generally shows the economic health of a country. It represents a sum of a country's production which consists of all purchases of goods and services produced by a country and services used by individuals, firms, foreigners, and the governing bodies. Thus, it shows an all-inclusive picture of a country's economy that provides an insight of the trend of the economy to investors. GDP is the indicator for most governments and economic decision-makers for planning and policy formulation. The balance of trade systematically records all the economic transactions between residents of a country. It is an important indicator of the country's trade as a positive balance of trade indicates a trade surplus while a negative indicates trade deficit. Deficits and surpluses are general outcomes of economic interactions among countries. They show how much a country relies on borrowing from the rest of the world or on its share of foreign lending. Population growth (POPG) of a country leads to labor force enhancement, production as well as exportation and important indicators of economic growth. UEMP measures the share of workers in the labor force who do not currently have a job but are actively looking for a job.

As the study attempts to analyze economic growth for SAARC countries a panel data set was considered for a period of 20 years (2000-2018) based on the data availability. World Economic and Financial Survey data (World economic outlook database) was the main data source for the study.

#### Panel Data Analysis

Panel data analysis refers to the statistical analysis of data sets consisting of multiple observations on each sampling unit. This could be generated by pooling time-series observations across a variety of cross-sectional units, including countries, firms, or randomly sampled individuals (Ahn and Moon, 2001). Panel data set have both cross-sectional and time-series dimensions. The size of the time series is determined by monitoring the same cross-section units over a given time frame (Hill et al., 2008; Wooldridge, 2009). Panel data provide more informative data, more variability, more degrees of freedom, less correlation between variables, and more efficiency (Frees, 2004; Baltagi, 2010; Gujarati and Porter, 2009). Panel data can better detect and measure effects that cannot be observed in pure cross section or pure time series data (Gujarati and Porter, 2009).

When analyzing panel data, the cross-sectional units are heterogeneous and controlled for variation (heterogeneity). The analysis can control variables which are subject or time invariant (Baltagi, 2010). Further, the effect of unmeasured variables can be controlled (Hsiao, 2003). In static panel data models, that do not have any lagged values of the dependent or/and independent variables, covariance estimators (pooled panel data), fixed effects, and random effects estimators are mostly used. When the cross-sectional units are homogenous, pooled ordinary least squares panel model is used. When unit or time-specific effects are present, and assuming that these effects are fixed parameters to be estimated, the fixed effects model is used. If subject-specific effects are presumed to be random and uncorrelated with independent variables, the random effects model is used for the analysis.

#### Theoretical framework of the model

The theoretical framework for Fixed effects model and random effects model are as follows.

$$Y_{it} = \alpha + \sum_{k=1}^{k} \beta_k x_{kit} + u_{it}$$
  $i = 1, ..., N$   $t = 1, ..., T$ 

Random Effects Model

$$Y_{it} = \alpha + \sum_{k=1}^{k} \beta_k x_{kit} + (\alpha_i + u_{it}) \qquad i = 1, ..., N \qquad t = 1, ..., T$$

Where, index i differentiate the subjects and ranges from 1 to N. N is the number of subjects. Each subject is observed T times and the index t differentiates the observation times through 1 to T. K is the number of the independent variables.

#### **Empirical models**

To determine the relationship between the RGDP and the independent variables, the fixed effects model and the random effects model which are the most common static linear panel data analysis models were used.

The empirical fixed effects and random effects models used for the analysis is as follows.

Fixed Effects:

$$RGDP = \alpha_i + \beta_1 X_{it} + \beta_2 FDI_{it} + \beta_3 POPG_{it} + \beta_4 UEMP_{it} + u_{it}$$

Random Effects:

$$RGDP = \beta_1 X_{it} + \beta_2 FDI_{it} + \beta_3 POPG_{it} + \beta_4 UEMP_{it} + (\alpha_i + u_{it})$$

The i stands for the country number, t stands for the year,  $u_{it}$  is the error term for the fixed effects model and ( $\alpha_i + u_{it}$ ) is the composite error term for the random effects model. If the country effects are uncorrelated with the regressors, they are known as random effects. In the random effects model, because there is no correlation between the country specific effects and the regressors, country specific effects are parameterized as additional random disturbances. If the country effects are correlated with the regressors, then they are known as fixed effects.

#### **Results and discussion**

#### Variables and Descriptive Statistics

In this study, used database consists of the panel data set of 8 countries (N) for the period of 2000 to 2018. Dataset is a balanced panel and has 152 observations. The main variables used for the panel analysis, their description and the units are as listed in Table 1. Table 2 shows the average values for each variable for the SAARC countries for the study period. Figure 1 shows average FDI changes among SAARC countries for the studied period, that highlights the India the largest country in the group. Table 3 shows the summary statistics for each country, which shows the differences of each variable.

Table 1. Valiables and Weasuring Onits							
Variable	Description	Units					
RGDP	Real GDP	Million US dollars					
EXP	Total exports of goods and services	Million US dollars					
IMP	Total imports of goods and services	Million US dollars					
Х	EXP -IMP or BOT	Million US dollars					
FDI	Total foreign direct investment in the country	Million US dollars					
POPG	Annual Population growth	Rate					
UEMP	Unemployment rate	Percent of total labor force					

Table 1: Variables and Measuring Units

#### Table 2: Summary statistics for SAARC countries

Variable	Obs	Mean	Std. Dev.	Min	Max	
RGDP	152	247084.6	523452.6	655.103	2590899	
EXP	152	45543.85	104478.3	24.52	483147.9	
IMP	152	29589.34	69213.85	30.207	318234.1	
FDI	152	3671.027	9770.128	-16.553	44458.57	
POPG	152	1.667	0.832	0.13315	4.3859	
UEMP	152	4.981	3.245	0.4	11.7	
						_

#### Figure 2: FDI for SAARC countries for 2000-2018



Table 5: Summary statist	ics for each SAARC co	untry		
Variable	Mean	Std. Dev.	Min	Max
Afghanistan				
RGDP	13968.02	5313 773	7320 789	21144 43
FXP	6004 59	3157 182	1001.83	11998 48
IMP	579.31	381 943	95 16785	1287 167
FDI	101.06	81 13622	0.17	271
POPG	2.83	1 151446	0.440528	4 385965
1010	2.05	1.101440	0.440520	4.505705
UEMP	11.43	0.19	11.06	11.68
Bangladesh				
RGDP	144819.3	48600.21	83463.81	241804.9
EXP	26058.09	16190.23	7689.18	57834.39
IMP	19759.24	11360.02	6468.78	39741.76
FDI	1257.81	931.61	52.304	2831.15
POPG	1.23	0.90	1.03	1.85
UEMP	4.09	0.43	3.27	5
Bhutan				
RGDP	1428.01	550.81	655.10	2336.47
EXP	270.61	201 53	24 52	773.26
IMP	179.33	99.86	30.21	352.41
FDI	16.11	23 23	-16 55	75 27
POPG	1.62	1 152	0.13	3.06
	2.67	0.69	1.64	3.00
UEMIF	2.07	0.09	1.04	5.90
India	1512009	558270 (	800524.2	2500200
KGDP	1515908	558270.6	800534.3	2590899
EAP	27/608.6	15/653.9	55281.05	483147.9
IMP	188230.4	95659.78	48097.39	318234.1
FDI	25037.84	15581.62	3584.22	44458.57
POPG	1.44	0.66	1.31	1.88
UEMP	5.70	0.51	5.33	7.73
Maldives				
RGDP	3164.20	964.54	1873.70	5065.81
EXP	1151.95	614.31	322.34	2401.83
IMP	235.80	96.09	126.69	541.01
FDI	215.31	177.09	20.54	575.65
POPG	1.69	0.19	1.40	2.22
UEMP	6.49	2.54	1.97	11.7
Nepal				
RGDP	19434.58	4572.86	13462.16	28695.05
EXP	3949.33	2977.11	748.1	10134.01
IMP	839.46	208.69	602.93	1374.46
FDI	45.80	53.17	-6.64	196.26
POPG	1.49	0.31	1.127	2.17
UEMP	2.09	0.62	1.33	3.1
Pakistan	2.09	0.02	1.55	5.1
RGDP	220649	50849.02	146487.6	318956.1
FXP	35313 /2	16421.48	9940 42	61000.27
IMP	18762.27	6464 61	8776 75	27200.82
EDI	2048.05	1541 14	208	5500
POPC	2048.03	1541.14	308	3390
POPG	2.129	0.30	1.//	4.10
UEMP	1.52	1.37	0.4	4.08
Sri Lanka	50206 41	19710.00	25550.05	00000 24
KGDP	59306.41	18/10.29	35558.95	90088.34
EXP	13994.25	6075.6	5449.55	22605.41
IMP	8128.90	2296.74	4695.39	11615.89
FDI	646.22	416.25	171.79	1614.04
POPG	0.88	0.28	0.569	1.46
UEMP	5.818	1.75	3.88	8.76

 Table 3: Summary statistics for each SAARC country

#### **Regression results**

With positive signals from the basic estimations, the panel data analysis was decided. First, the stationary was checked for the variables following unit root test (Im-Pesaran-Shin unit-root test). With stationary variables both fixed effects and random effects model were tested. To decide between fixed or random effects, Hausman test was conducted where the null hypothesis is that the preferred model is random effects vs. the alternative the fixed effects. The significant p value of Hausman test rejected the null hypothesis, which alternative hypothesis was accepted. Further LM test was run for the Random effect model to decide whether polled OLS would work for the analysis, but the significant results for LM test rejected pooled OLS analysis. Thus, fixed effect model was used for the final analysis. The heteroskedasticity was checked for the fixed Effect model (Modified Wald test for groupwise heteroskedasticity), and the results suggested robust analysis for the fixed effect model.

Table 4. shows the estimations for OLS (LSDV), AREG and FE models. The least square dummy variable model (LSDV) provides a good way to understand fixed effects. Thus, LSDV was analyzed with dummies to mediate differences across countries. Then, AREG with dummy is absorbing the effects particular to each country. The LSDV estimations of table indicates that positive and significant relationship between RGDP growth and X for all the three methods. Thus, the one percent change in net exports (X) increases the RGDP by 2.97 percent for the SAARC countries in general. RGDP and FDI shows a positive and significant relationship as well, that one percent increase in FDI increases 20% of RGDP to the SAARC Region. However, this impact is highly significant with India that shows the higher percentage of FDI of the SAARC region. The dummy variables for country differences India (4) and Pakistan (7) indicate a positive relationship with RDGP. This could be several reasons for GDP-related factors in countries. Like LSDV both AREG and FE show the positive and significant results for X and FDI.

Variable	OLS -(LSDV)	AREG	FE
Х	2.975***	2.975***	2.9759***
FDI	20.468***	20.468***	20.468***
POPG	-6182.360	-6182.360	-6182.360
UEMP	1823.157	1823.157	1823.157
id(country)			
2	108071.04		
3	13516.525		
4	741566***		
5	2232.993		
6	22249.425		
7	147367.35**		
8	31086.692		
CONS	-7571.01	125690.24	125690.24
Ν	152	152	152
$\mathbb{R}^2$	0.965	0.965	0.749
R <sup>2</sup> _adj	0.9627	0.9627	0.7295

Table 4: Estimation table for OLS, AREG and FE

\*\* significant at 5% level, \*\*\*significant at 1% level

Table 5 shows the panel data analysis for both fixed effects and random effects models. The FE results indicate that the one percent change in net exports (X) increases the RGDP by 2.97 percent for the SAARC countries while FDI increases 20% of RGDP to the SAARC region.

#### **Conclusions and policy suggestions**

GDP growth is important for the economic growth of the SAARC region which is one of the poor regions in the world. The results of the analysis for the last 20 years clearly indicate the essential contribution of foreign direct investments (FDI) in economic growth of the region with efficient and effective international trade (export and import) policies. Thus, countries in the region need to work for creating better environments, effective macroeconomic strategies that invite investors and create more trade.

Tuble 0: Tullet	TE and ItE anal	<i>y</i> 010						
	Fixed Effect (r	obust)		<b>Random Effe</b>	Random Effect			
RGDP	Coefficient	t	<b>P&gt;</b>  t	Coefficient	Z	<b>P&gt; t</b>		
Х	2.975	14.95	0.000***	3.681	4.14	0.000***		
	(0.199)			(0.889)				
FDI	20.468	23.67	0.000***	34.101	10.13	0.000***		
	(0.864)			(3.3647)				
POPG	-6182.361	-1.43	0.195	-8136.359	-0.46	0.642		
	(4317.728)			(17499.92)				
UEMP	1823.157	0.76	0.469	-248.398	-0.05	0.961		
	(2384.29)			(5079.617)				
CONS	125690.2	11.55	0.000	77971.26	2.02	0.044		
	(10880.37)			(38649.98)				
sigma u	251537.34			20687.015				
sigma e	101094.52			101094.52				
rho	0.860			0.0401				

#### Table 5. Panel – FE and RE analysis

\*\* significant at 5% level, \*\*\*significant at 1% level

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#### Is Spending on Fun from a Windfall Elastic? Valrie Chambers, Stetson University Eugene Bland, H. Swint Friday, Texas A&M University – Corpus Christi

#### Abstract

Earlier research has established that people are not strictly rational in their economic decision making (Areily, 2008) and sometimes use affective tags when determining how to spend money, and in particular, a windfall. Further, the source of the refund may matter. In this paper, this line of research is extended, examining the elasticity of spending windfalls on fun. That is, to what extent do people spend money from a fun source (game show winnings) on fun as the amount of the windfall increases? People intend to spend a substantial amount of a small windfall on fun, but that the percent spent on fun decreases as the amount of the windfall rises and then levels out at just over 10% for windfalls of \$10,000 or more. Similar results were found for windfalls from bonuses and tax rebates.

JEL G40, D140

Key words: Income, Income Source, Behavioral Finance, Consumer Behavior, Mental Accounting

#### Introduction

Economic research has found that people vacillate between rational behavior, with money being strictly a medium of exchange and irrational behavior that is sometimes predictable (Ariely, 2008) and subject to our environment (Thaler, 1999). This irrational behavior in economics is a newer area of research, and there is much to learn about how rationality is bounded. We do know that affective tags for money exist (Henderson and Peterson, 1992; Winkelmann et al., 2011; Bradford, 2008; Levav and McGraw, 2009; Bland and Chambers, 2019). However, little is known about how strong or elastic those affective tags are.

The better people's economic behaviors are understood, the more individual decision-making can be optimized, and as a society, aggregate prediction and response can be made. The more individual behavior is understood, better adjustments can be made to optimize financial goals. For example, if debt reduction is a goal, earmarking a specific percentage of unknown future windfalls to debt repayment in advance predisposes persons to spending such windfalls more favorably as compared to having no plan at all.

#### **Literature Review**

Thaler (1999) established that people employ different mental accounts for, e.g. long-term savings and monthly bills, and people have a different marginal propensity to consume from each account. These accounts are periodically reconciled (Camerer et al., 1997; Heath and Soll, 1996; Read et al., 1999; and Rizzo and Zeckhauser, 2003). Past research on mental accounting theory supports that spending for regular income flow differs from that of an irregular source or windfall (Johnson et al., 2006; O'Curry, 1999; Souleles, 2002; Adamopoulou and Zizza, 2017; Arkes et al., 1994; Rucker, 1984). Whether income was earned affected taxpayer compliance after a tax audit (Boylan, 2010). When taking risks, people made riskier choices with strangers' money than with their friends' money (Trump et al., 2015). Whether earned income restored a status quo or was a windfall significantly affected the intended use of the money (Epley and Gneezy, 2007; Agarwal and Qian, 2014).

Other characteristics of mental accounts are cash spending on durable goods depends on compatible reasons for saving and the permanence of the income (Karlsson et al., 1999), math aptitude of the consumer affects mental budgeting (Abeler and Marklein, 2016; Benjamin, 2006), self-control affects mental budgeting (Cheema and Soman, 2006; Wertenbroch, 2001). The more time that cognitive reflection has occurred, the more rational the behavior (Frederick, 2005). The permanence or regularity of the income itself may also affect how that income is spent or saved (Friedman, 1957; Blinder, 1981; Parker, 1999; Hsieh, 2003; Browning and Collado, 2001; Chambers and Spencer, 2008; Baker et al., 2007; and Sahm et al., 2012). A person's predisposition to spending versus saving (Spencer and Chambers, 2012) matters, as does the framing of those payments. Hershfield et al. (2015) found that consumers were insensitive to significant interest rate differences between the mental accounts of savings and debt. Shefrin and Thaler (1988) found that more of an anticipated lump sum bonus was saved than if the same amount increased regular income.

#### Is the Source of the Income Important?

The source of income may be important. Winkelmann et al. (2011) found different marginal utilities came from spending from different sources of income. Similarly, Henderson and Peterson (1992) found that individuals were more likely to spend \$2,000 on a vacation if the source of the funds was a gift rather than a bonus. Bradford (2008) found that individuals' relationship goals affected how they allocated gifts and inherited assets. Epley et al. (2006) found that people spent more from a fixed amount and timing if the source was labeled "bonus" rather than "rebate." Similarly, Chambers et al. (2017) found that people given a hypothetical payment from one of five different sources would spend the funds differently depending on the source of the money.

#### Size of Income

The size of the income might also be significant. Rucker (1984) found that the size of a retroactive payment of a raise approved by a university, reversed by the Federal Pay Board but then reinstated by the U.S. Supreme Court was the most important factor in its use, although like Frederick (2005), the length of time that the recipient had to anticipate the income was also significant. Chambers et al. (2009) found that people seemed to deem amounts of roughly less than \$600 as immaterial and used them consistent with their spending or saving habit.

#### Affective Tags and Mental Accounting

Levav and McGraw (2009) explained the different uses of money based in part on the source of money, because people attach feelings, or an "affective tag" to a given sum of money. Further, they found that when a windfall that is tagged negatively is received, people either consumed the windfall reluctantly or virtuously in response to those negative feelings. O'Curry and Strahilevitz (2001) found that those receiving lottery payments spent it hedonistically rather than relying primarily on rationality. Bland and Chambers (2019) found that those hypothetically receiving another fun source of income, game show winnings, were more likely to spend hedonistically than other more serious sources of income like employment bonuses, and these other serious sources of income were significantly more likely to be invested than game show winnings. However, contrary to what O'Curry and Strahilevitz (2001)'s paper suggests, Bland and Chambers (2019) also found the percent of a game show winning spent on fun appeared to level off over a limited range as the amount of the winning increased, indicating that effect from the source of income affect may be bounded.

#### **Demographic Factors**

Materiality may differ based on household income, *ceteris paribus*. Other demographic factors that might be significant include gender and race (Chen and Volpe, 2002; Fisher et al., 2015), risk tolerance, age, and a person's predisposition to spend versus save (Spencer and Chambers, 2012).

#### **Hypothesis and Research Questions**

This study closer considers people's intended propensity to spend a fun source of lump sum windfall income, game show winnings, on hedonistic uses as the amount of those winnings rise. O'Curry and Strahilevitz (2001) studied lottery winnings at one fixed amount, finding that they were spent hedonistically. Bland and Chambers (2019) studied various but relatively small amounts of game show winnings and found an indication that hedonistic spending may be bounded but were unable to confirm that finding at the amounts tested. Herein, similar patterns are explored for bonuses and tax rebates, consistent with Bland and Chambers (2019).

The null hypothesis is:

H<sub>1</sub>: The percent change in hedonistic spending from a hedonistic source (game show winnings) will not significantly change as the amount of hypothetical winnings increases.

The authors believe that this hypothesis has been previously unexplored in research literature and also could help clarify the findings of O'Curry and Strahilevitz (2001) and Bland and Chambers (2019). The hypothesis will be tested across the entire usable sample; then we will look at the subsample of respondents who elected to spend no money on fun.

#### Methodology

This study examined respondents' intended uses of hypothetical windfalls from a hedonistic source, game show winnings. Intent is a strong predictor of behavior: Sheppard et al.'s (1988) meta-analysis of 86 theory-of-reasoned-action

studies found a 0.53 correlation between intention and behavior. To control for source, information on spending from hypothetical windfalls from employment bonuses and tax rebates were also gathered.

Paper instruments on the intended allocation of different amounts of game show winnings, tax rebates, and employment bonuses were gathered from students at one public and one private university in two different geographic regions of the United States. In the private university, the typical student was a traditional student, with much more limited outside work experience or responsibilities, and higher household income than at the public university. See Appendix 1 for the instrument. The researchers asked professors of several classes if they would be willing to provide time to solicit survey participants. More than a dozen professors allowed the researchers to make class presentations to solicit volunteers. In some instances, the professors provided bonus points for students that participated in the survey. In some of those classes, the professors gave the students time in class to complete the surveys and in others the researchers returned the following class period to collect surveys into the class, such as junior and senior level marketing classes (studying the survey technique) and freshman and sophomore economics classes (incorporating the survey to discuss topics such as marginal propensity to consume). Students were considered acceptable respondents per Walters-York and Curatola (1998) and Ashton and Kramer (1980).

Each participant was given one instrument and asked how she would use the funds. Unlike Bland and Chambers (2019) which only used amounts of \$300, \$600, \$1,500, and \$3,000, amounts in this study ranged from \$500 to \$1,000,000. Two similar questions with narrower ranges of amounts were also asked for income from bonuses and tax rebates, which are arguably common sources of income generated through less hedonistic means than game show winnings and therefore less likely to carry a positive affective tag. The instruments asked how much of a lump sum rebate would be used for: (1) investing, (2) paying off credit card debt, (3) paying off notes, (4) regular monthly expenses, (5) buying a durable asset, (6) used for fun, similar to Chambers and Spencer (2008).

The responses were converted to a percent of the total windfall and these percentages were analyzed using descriptive statistics. These percentages were then graphed, and regressed against the size of the winnings and the control variables including: income, whether respondents normally save or spend unexpected money received, risk-taking variable, gender, age, business experience, and education level. As a control for race, ANOVAs were performed based on the responses to the race question. The complete regression model was of the form:

Percent Spent on Fun = f (Amount, Work Experience, Gender, Age, Income, Education, Credit Card Debt, Other Debt, Spend Or Save Default, Business Experience, and Risk)

where "Amount" is the hypothetical amount of the windfall in dollars, "Income" is the respondent's income, with a control for those earning zero income. The "SpenderIsOne" variable is a dummy variable set to 1 where people responded Spend to the question "[w]hen you get 'extra money,' do you spend it or save it?" Dummy variables were included as proxies for respondents' risk preference. "Gender" was a categorical male/female variable, where female was coded as "1." "Age" was the participant's age in years, and "experience" is the respondent's perception of their experience on a scale of 1-5. Since all respondents were students, responses for Education was an ordinal variable divided into five categories: freshmen, sophomores, juniors, seniors, and graduate students. Where the Amounts were complete but some of the demographic information was missing, an average for the variable was used and then the model was re-run as a control against the use of averages skewed the overall results. Non-significant control variables were dropped from the analysis and the remaining model is:

 $H_1$ : Percent Spent on Fun = f (Amount, Gender, Education, Credit Card Debt, and Spend Or Save Default)

The entire usable sample was then divided into two subsets: those who spent no money on fun and those who spent some money on fun to explore what other behavioral differences we could tease out between these two groups.

#### **Results**

In the Spring term of 2019, approximately 600 surveys were distributed to students in the business colleges of one private and one public university. There were 379 instruments in total returned, of which 282 were usable. Some of the instruments did not have sufficient data to be processed, which is a hazard of providing extra credit for anonymous responses. However, that would bias this study against findings because of the error introduced in hastily completed instruments. Where the missing data was the dependent variable, the observation was eliminated from analysis. Where the missing data was

demographics, averages were used to produce the tables below.<sup>1</sup> All but 24 of the respondents spent at least some money on fun. A separate descriptive analysis was conducted for this subsample of respondents, labeling them the "no fun" group. It is not necessarily these respondents do not have fun; however, they seem to be unwilling to pay for fun.

	Work				Business	
	Experience Years	Age Years	Income USD	Credit Card Debt USD	Experience Years	Risk Tolerance
	5.20	22.78	84,506.62	1,376.93	3.00	3.04
Average	(6.39)	(24.69)	(51,584.44)	(799.20)	(3.12)	(3.20)
Median	4.00	21.00	30,000	0	3	3
Minimum	0.00	16.00	0	0	0	0
Maximum	30.00	48.00	5,000,000	40,000	5	5

Table 1: Descriptive Statistics for Other Control Variables

#### Table 2: How Game Show Winnings Were Spent

Table 2a: Average Percent (%) of Total Windfall Spent on Each Category\*

Amount	\$500	\$1,000	\$5,000	\$10,000	\$50,000	\$100,000	\$250,000	\$500,000	\$1 Mil
Use	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
Investments	21.06	23.73	28.80	34.97	38.42	41.51	43.73	48.94	52.10
Credit Card Debt	18.56	18.64	14.69	11.94	9.32	7.16	6.23	4.99	4.42
Long-Term Debt	11.09	14.00	16.50	16.02	16.04	15.88	15.61	13.81	11.85
Expenses	15.40	15.59	14.77	13.10	11.90	11.01	10.74	10.46	9.48
Durable Assets	4.72	5.60	7.40	9.47	13.07	13.50	12.42	10.77	9.79
Fun	29.17	22.44	17.49	14.50	11.24	10.94	11.27	11.02	12.36

\*Columns sum to 100 percent.

#### Table 2b: Average Percent (%) of Respondents Who Spent Any Money on That Category

Amount	\$500	\$1,000	\$5,000	\$10,000	\$50,000	\$100,000	\$250,000	\$500,000	\$1 Mil
Use	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
Investments	41.13	56.38	73.05	85.11	91.84	94.33	95.04	97.87	
Credit Card Debt	39.36	50.00	55.67	57.45	58.87	56.38	56.38	55.67	55.32
Long-Term Debt	31.21	42.20	55.32	56.03	64.18	67.02	68.09	71.99	70.92
Expenses	42.55	51.77	63.83	68.79	73.76	74.82	74.47	75.89	76.60
Durable Assets	19.86	28.37	41.84	54.26	68.79	74.11	74.82	77.31	80.50
Fun	58.16	62.77	73.05	78.01	81.56	83.33	84.04	83.33	90.07

#### Table 2c: Average Percent (%) Spent by Those Who Spent Any Money to That Category

		1 2		1 2	5	8	5		
Amount	\$500	\$1,000	\$5,000	\$10,000	\$50,000	\$100,000	\$250,000	\$500,000	\$1 Mil
Use	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
Investments	51.20	42.09	39.42	41.08	41.83	44.01	46.01	50.01	
Credit Card Debt	47.14	37.28	26.39	20.79	15.84	12.63	11.04	8.96	8.00
Long-Term Debt	35.55	33.17	29.83	28.59	25.00	23.70	22.93	19.19	16.70
Expenses	36.20	30.12	23.14	19.04	16.14	14.71	14.42	13.79	12.38
Durable Assets	23.76	19.72	17.68	17.46	19.00	18.13	16.59	13.87	12.17
Fun	50.16	35.74	23.94	18.51	13.78	13.01	13.41	13.17	13.72

Students responded that 7.8% were freshmen, 17.4% were sophomores, 27.3% were juniors, 41.5% were seniors, and 6.0% were graduate students. Racially, 5.2% identified as African Americans, 6.3% identified as Asians, 27.3% identified as Hispanics, 2.0 % identified as Native Americans, 53.6% identified as Caucasians, and 5.6% identified as mixed race.<sup>2</sup> Half

<sup>&</sup>lt;sup>1</sup> The tables were then re-run without averages and also to eliminate one observation whose income was an outlier. The results of these analyses were consistent with using the full data set with averages, except that education and credit card debt are no longer significant with this lack of power, so the full data set analysis is what is used here and throughout the rest of this paper.

<sup>&</sup>lt;sup>2</sup> Student class and racial identification descriptive tables with this information are omitted for parsimony.

of the respondents in the full sample identified as female, with 42% in the "no fun" sample identifying as female. When asked whether they normally saved or spent additional money, 34% said that they spent it (versus 21% in the "no fun" group). There was no significant correlation between household income and the percent spent on fun at any windfall amount, as shown in Appendix 2. Additional descriptive statistics are shown in Table 1, with the means for the "no fun" group shown in parentheses.

Those in the "no fun" group appear to have more years of work experience, be slightly older, are poorer and with less credit card debt than those in the full sample. Even so, the subsample size for the "no fun" group is small.

Next, the results for hedonistic spending from game show winnings was plotted to check for an apparent linearity. The graph presented in Figure 1 shows a curvilinear relationship for game show winnings with a kink at \$10,000 joining two quasi-linear sections above and below this point, confirming Bland and Chambers (2019). Those results, which appear more curved than linear, are shown in Figure 1.





Similar plots for the narrower ranges for spending on both bonuses and tax rebates show a similar curve leveling out at about 10%, indicating that while the source of income might produce an affective tag and a significantly different amount of spending on fun at lower levels of windfall, the positive affective tag appears to lose its influence as winnings increase.

As shown in Figure 1, the full curve does not appear to be linear, but rather a combination of two rather linear sections with an inflection point at \$10,000, confirming Bland and Chambers (2019). Consequently, two regressions were run for game show winnings: one for amounts up through \$10,000 and one for amounts \$10,000 and above. The full regression model and the efficient model were run at each level. The results of the model regressions were similar, and the efficient model results are shown in Tables 3a and 3b.

As shown in both Table 3a and 3b, the results of this regressions were highly significant at  $p \le 0.05$ , although the R-squareds and the adjusted R-squareds are small. The results of this regression for both quasi-linear sections of the curve for the amounts of spending through and including \$10,000 and \$10,000 and above indicate that the null hypothesis was rejected.

At amounts of \$10,000 and less, men spent significantly more on fun than women. Less educated respondents spent more on fun than more educated respondents. Those who had more credit card debt spent more on fun than those with less debt. Generally, race did not make any significant difference in the percent of game show winnings spent on fun at the \$10,000 or below levels, but when Anovas for race were run African Americans did spend significantly more game show winnings than Asians (25.4% vs. 7.7%) at the \$5,000 level only. However, this appears to be an anomaly, so the tables are omitted and the result is left for further study. Those who self-identified as spenders spent more on fun than those who identify as savers. Most importantly, as seen in Table 2, as the amount of the winnings increased, the percent spent of fun decreased from 29.17% to 14.50% for amounts up through \$10,000.

However, the percent spent on fun only decreased from 14.50% to 12.36% when the amount of the game show winning went from \$10,000 to \$1,000,000. Further, the only factor that significantly correlated with the percent saved was the respondent's self-identification as a saver or spender. The amount of the award itself was not significant. While race did not make a difference overall, at the \$50,000 level, African Americans spent significantly more than Hispanics (19.0% v. 10.4%) and at the \$100,000 level, African Americans spent more than nearly any other racial group (21.3% v. 6.3% for Asians, 10.3% for Hispanics, and 11.1% for Caucasians). These ANOVA tables are shown in Appendix 3. No other significant

differences among races existed for game show winnings. However, these results substantiate that there may be a cultural element to spending differences, as indicated by P.J. Fisher (2010).

Regression Statistics						
R Square	0.061					
Adjusted R Square	0.052					
Standard Error	0.278					
Observations	1112					
ANOVA	df		SS	MS	F	Significance F
Regression	ľ1	5	.552437	0.504767	6.535509	1.26E-10
Residual	1100	8	4.958	0.077235		
Total	1111	9	0.51044			
	Coefficients	Std. Error	t Stat	P-value	Lower 95	5% Upper 95%
Intercept	0.319471	0.070442	4.53526	6.38E-06	0.181256	0.457686
Work Experience	0.002829	0.003375	0.838244	0.402076	-0.00379	0.009452
Female Is One	-0.04008	0.017865	-2.24375	0.025047	-0.07514	-0.00503
Age	0.002323	0.00337	0.689341	0.490754	-0.00429	0.008935
Income	-3.3E-08	2.82E-08	-1.15565	0.248075	-8.8E-08	2.28E-08
Education	-0.02724	0.008885	-3.06613	0.002221	-0.04468	-0.00981
Credit Card Debt	5.52E-06	2.48E-06	2.23079	0.025896	6.65E-07	1.04E-05
Other Debt	-1.3E-08	2.04E-07	-0.06126	0.951161	-4.1E-07	3.89E-07
Spender Is One	0.048988	0.017737	2.761972	0.005841	0.014187	0.08379
Business Experience	-0.01608	0.009839	-1.63391	0.102564	-0.03538	0.003229
Risk	0.00304	0.008006	0.379766	0.704193	-0.01267	0.01875
Amount	-1.3E-05	2.19E-06	-5.97751	3.06E-09	-1.7E-05	-8.8E-06

Table 3a: Regression of Game Show Amounts Through \$10,000 Against Percent Spent on Fun

Regression Statistics						
R Square	0.017					
Adjusted R Square	0.010					
Standard Error	0.152					
Observations	1668					
ANOVA	df	SS	MS	F	Significance	F
Regression	11	0.648409	0.058946	2.548135	0.003389	
Residual	1656	38.3084	0.023133			
Total	1667	38.95681				
	Coefficients	Std Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.220143	0.031406	7.009563	3.47E-12	0.158543	0.281743
Work Experience	0.000377	0.001508	0.250038	0.802589	-0.00258	0.003335
Female Is One	-0.01052	0.007983	-1.31797	0.187694	-0.02618	0.005136
Age	-0.00243	0.001506	-1.61603	0.106278	-0.00539	0.00052
Income	-1.1E-09	1.26E-08	-0.08795	0.929923	-2.6E-08	2.36E-08
Education	-0.00527	0.00397	-1.32635	0.184907	-0.01305	0.002521
Credit Card Debt	-5.8E-07	1.11E-06	-0.524	0.600347	-2.8E-06	1.59E-06
Other Debt	4.61E-09	9.14E-08	0.05045	0.95977	-1.7E-07	1.84E-07
Spender Is One	0.017656	0.007926	2.227736	0.026032	0.002111	0.033202
Business Experience	-0.00614	0.004396	-1.39718	0.162548	-0.01477	0.002481
Risk	-0.00401	0.003578	-1.1221	0.261982	-0.01103	0.003003
Amount	-4.3E-09	1.08E-08	-0.39812	0.690594	-2.5E-08	1.68E-08

Tobit analysis results are in Table 4, which confirms that Education, self-identification as a Spender, and Amount are statistically significant when all levels of windfall are included in the analysis.

Table 4: Toolt Analysis o	of Galile Show	Allounts Spent of	I I'ull	
Variable	Coefficient	Std. Error	z-Statistic	Prob.
Work Experience	0.002284	0.002287	0.998847	0.3179
Female Is One	-0.018791	0.012106	-1.552220	0.1206
Age	-0.002806	0.002277	-1.232389	0.2178
Income	-8.22E-09	1.87E-08	-0.438803	0.6608
Education	-0.018102	0.005975	-3.029595	0.0024
Credit Card Debt	1.81E-06	1.65E-06	1.092964	0.2744
Other Debt	7.52E-08	1.39E-07	0.540177	0.5891
Spender Is One	0.047165	0.011953	3.945999	0.0001
Business Experience	-0.008715	0.006632	-1.314100	0.1888
Risk	-0.005112	0.005417	-0.943800	0.3453
Amount	-5.47E-08	1.75E-08	-3.123984	0.0018
Constant	0.264102	0.047514	5.558459	0.0000
	Error Distrib	ution		
SCALE:C(13)	0.271753	0.004591 59.	19415	0.0000
Mean dependent var	0.155785	S.D. dependent va	r	0.224828
S.E. of regression	0.223851	Akaike info criter	ion	0.596545
Sum squared residual	124.7215	Schwarz criterion		0.626810
Log likelihood	-733.2772	Hannan-Quinn cri	teria	0.607532
Avg. log likelihood	-0.293076			
Left censored observation	602	Right censored ob	0	
Uncensored observations	1900	Total observations	3	2502

Table 4: Tobit Analysis of Game Show Amounts Spent on Fun

#### Discussion

In this study, game show winnings are used to attempt to elicit a positive affective tag for the windfall and attempt to tie the spending of that positive-affective windfall to a positive-affective spending of that money. Significant results at low amounts of winnings are found, as in Bland and Chambers (2019). As the amount of the winnings is extended, however, the proportion spent on fun becomes insensitive to the amount of winnings. Taken together, it would appear that affective tags exist confirming Levav and McGraw (2009); income with a positive affective tag will lead to significantly more spending on fun (which is an outlay with a positive affective tag, *ceteris paribus*), consistent with Bland and Chambers (2019).

However, the size of affective tags appears to be small and the strength of a positive affective tag appears to wane as the amount of the game show winning increases. That is, respondents' emotional response dissipates quickly, perhaps in favor of rationality. Rationality may be constrained by internal traits like laziness or by external characteristics like an overwhelming environment and the availability of convenient choices. With busy, stressful lives, people may want to have more fun, perhaps as a psychological release, and may lack the willpower, which is depletable, to save at smaller amounts of winnings. However, people's willpower appears to generally remain intact for larger amounts of winnings. Given that self-control is depletable, (how) do people budget that self-control resource? In any case, with windfalls that have a positive affective tag, people are more rational than not with their money when it comes to fun sources and uses, especially when the amount won is large. Perhaps people may be more influenced by negative emotions (Levav and McGraw, 2009), similar to how emotional losses loom larger than emotional gains, as found in Kahneman and Tversky's (1979) prospect theory.

Results are found to be enlightening. Respondents have separate mental accounts (Thaler, 1999) and that those accounts can get full (Chambers, Spencer and Mollick, 2009). While arguably, people cannot have too much fun, it appears that there is a satiation point where more relative spending does not yield more fun. That is, if we could spend all of our money on fun, most of us would not. Beginning at about \$10,000 of windfall, that satiation point is just over 10% of income rather than a fixed dollar amount. Increasingly smaller amounts of windfalls have increasingly larger amounts of spending on fun. These findings are important to entertainment industries, because as economic income rises, the amount of spending on fun may be more predictable than prior to this study. These findings could also important for policy makers giving out stimulus money when amounts of those stimulus checks are (normally) small and not directly tied to more serious sources of income, like lesser tax withholding from paychecks and larger income tax rebates and refunds. So, if a policy maker wanted to shore up

the restaurant industry, for example, a stimulus payment not directly processed through an employer or income tax return might be very effective.

#### **Limitations and Opportunities for Future Research**

One limitation of this paper is that it focuses on the changes in behavioral intent not the latent mental processes (or lack thereof) that are used to reach that intent. Priming from the mental accounting is not disentangled that produces the intent. Thaler and Sunstein (2009) might call priming a "nudge." For example, setting up certain financial defaults to encourage individuals to save for their retirement might be priming, whereas mental accounting is an internal construct. In this particular study, the nuance of disentangling the prime from mental accounting is not of concern; the focus is the type of stimulus and differences in intent.

It is worth noting that the data for this research was collected in the Spring of 2019, long before the arrival of Covid19. Given the restrictions put in place to deal with the pandemic, such as work from home initiatives, stay at home orders, travel restrictions (such as quarantine times), it is possible that there could exist a "shortage of fun" and that results of a similar survey conducted after the long awaited for vaccinations become available would be different. Future researchers may wish to conduct surveys as the vaccinations are beginning and again after "herd immunity," and travel restrictions subside. Whether people are saving their Fun money for later use, or whether there will be a reallocation toward fun as a reward for the sacrifices the Covid19 pandemic created may be interesting.

#### Conclusion

Confirming Levav and McGraw (2009), respondents appear to place affective tags on game show winnings. Confirming Bland and Chambers (2019), people will spend game show windfalls (which arguably has a positive affective tag, *ceteris paribus*) on fun – but only to a point. At amounts at or less than \$10,000, respondents intended to spend a significant amount of the winnings on fun. At \$10,000 and over, the amount spent on fun leveled off at just over 10%, regardless of the amount won. That is, the size of the affective tag appears to be small and the strength of a positive affective tag appears to wane as the amount of the game show winning increases. Respondents are influenced by emotion, but the emotional response dissipates quickly, perhaps in favor of rationality.

However, data for this research was collected in the Spring of 2019, before the Covid19 pandemic that left many socially isolated and arguably with fewer fun things to do. Given the restrictions put in place to deal with the pandemic, it is possible that there could exist a "shortage of fun" and that results of a similar survey conducted after the long awaited for vaccinations become available would be different. Future researchers may wish to conduct surveys as the vaccinations are beginning and again after "herd immunity," and travel restrictions subside. Whether people are saving their Fun money for later use, or whether there will be a reallocation toward fun as a reward for the sacrifices the Covid19 pandemic created may be interesting.

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#### **Appendix 1: Sample Survey Instrument**

"What would you do if ... "

Suppose you won an amount, shown in the top row, by participating in a **game show**. How much of these winnings would you plan to (fill in the amounts):

	\$500	\$1,000	\$5,000	\$10,000	\$50,000	\$100,000	\$250,000	\$500,000	\$1,000,000
Invest in stocks, bonds, savings, etc.									
Use to pay off credit card debt									
Use to pay off notes like mortgage & car notes									
Use about evenly every month for expenses									
Use for a durable asset like a car or furniture									
Use for fun									
Please list your: Years of work experience	Gender:	Female	e Ma	ale A	AgeY	early hous	ehold inco	me	
Highest education: High School Associate De	gree	_ Und	ergradua	ite G	raduate or	above			
Race Credit Card Debt \$ Other Debt	When 3	you nor	mally ge	et "extra r	noney," de	o you spend	d it or save	it? Spend	Save
I rate my level of business experience as: High	_ Fairl	y High	Mo	derate	_ Fairly L	.ow Lo	ow No	ne	
I rate my tolerance for risk as: High (risk is fine)_	Fair	ly High	Mc	derate	_ Fairly L	ow Lo	w Nor	ne (I am ve	ry risk
averse)									

"What would you do if ... "

Suppose you received an **employment bonus** of the amount shown in the top row. How much of this bonus would you plan to (fill in the amounts):

	\$500	\$1,000	\$5,000	\$10,000	\$50,000	\$100,000	\$250,000	\$500,000	\$1,000,000
Invest in stocks, bonds, savings, etc.									
Use to pay off credit card debt									
Use to pay off notes like mortgage & car notes									
Use about evenly every month for expenses									
Use for a durable asset like a car or furniture									
Use for fun									

"What would you do if ... "

Suppose you received a **tax rebate** of the amount shown in the top row. How much of this bonus would you plan to (fill in the amounts):

	\$500	\$1,000	\$5,000	\$10,000
Invest in stocks, bonds, savings, etc.				
Use to pay off credit card debt				
Use to pay off notes like mortgage & car notes				
Use about evenly every month for expenses				
Use for a durable asset like a car or furniture				
Use for fun				

#### Appendix 2: Correlation Table of Income and Percent Spent on Fun

	Income
Income	1
500	-0.03823
1000	-0.02692
5000	-0.00699
10000	-0.00142
50000	0.019252
100000	-0.03234
250000	-0.01483
500000	0.060396
1000000	0.017481

Anova: Single Factor SUMMARY		African Americ	an v. Asian Game S	Show \$100,000		
Groups	Count	Sum	Average	Variance		
G100000FUN	11	2.340706	0.212791	0.059262		
G100000FUN	16	1.00227	0.062642	0.004598		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.146959	1	0.146959	5.553236	0.02659	4.241699
Within Groups	0.661593	25	0.026464			
Total	0.808553	26				
Anova: Single Factor SUMMARY		African Americ	an v. Hispanic	GameShow	\$100,000	
Groups	Count	Sum	Average	Variance		
G100000FUN	11	2.340706	0.212791	0.059262		
G100000FUN	69	7.100976	0.102913	0.009508		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.114546	1	0.114546	7.21034	0.008851	3.963472
Within Groups	1.239134	78	0.015886			
Total	1.55508	19				
Anova: Single Factor SUMMARY		African Americ	an v. Caucasian		GameShow	\$100,000
Anova: Single Factor SUMMARY Groups	Count	African Americ	an v. Caucasian Average	Variance	GameShow	\$100,000
Anova: Single Factor SUMMARY <i>Groups</i> G100000FUN	<i>Count</i> 11	African Americ Sum 2.340706	an v. Caucasian <i>Average</i> 0.212791	Variance 0.059262	GameShow	\$100,000
Anova: Single Factor SUMMARY <i>Groups</i> G100000FUN G100000FUN	<i>Count</i> 11 133	African Americ Sum 2.340706 14.73255	an v. Caucasian <i>Average</i> 0.212791 0.110771	Variance 0.059262 0.019151	GameShow	\$100,000
Anova: Single Factor SUMMARY <i>Groups</i> G100000FUN G100000FUN ANOVA	<i>Count</i> 11 133	African Americ Sum 2.340706 14.73255	an v. Caucasian <i>Average</i> 0.212791 0.110771	Variance 0.059262 0.019151	GameShow	\$100,000
Anova: Single Factor SUMMARY Groups G100000FUN G100000FUN ANOVA Source of Variation	<i>Count</i> 11 133 <i>SS</i>	African Americ Sum 2.340706 14.73255 df	an v. Caucasian Average 0.212791 0.110771 MS	Variance 0.059262 0.019151 F	GameShow	\$100,000
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Anova: Single Factor SUMMARY <i>Groups</i> G100000FUN G100000FUN ANOVA <i>Source of Variation</i> Between Groups Within Groups Total	<i>Count</i> 11 133 <i>SS</i> 0.105744 3.120544 3.226288	African Americ Sum 2.340706 14.73255 df 1 142 143	an v. Caucasian Average 0.212791 0.110771 MS 0.105744 0.021976	Variance 0.059262 0.019151 F 4.81187	GameShow <i>P-value</i> 0.029891	\$100,000 <i>F crit</i> 3.907782
Anova: Single Factor SUMMARY <i>Groups</i> G100000FUN G100000FUN ANOVA <i>Source of Variation</i> Between Groups Within Groups Total	<i>Count</i> 11 133 <i>SS</i> 0.105744 3.120544 3.226288	African Americ Sum 2.340706 14.73255 df 1 142 143	an v. Caucasian Average 0.212791 0.110771 MS 0.105744 0.021976	Variance 0.059262 0.019151 F 4.81187	GameShow P-value 0.029891	\$100,000 <i>F crit</i> 3.907782
Anova: Single Factor SUMMARY <i>Groups</i> G100000FUN G100000FUN ANOVA <i>Source of Variation</i> Between Groups Within Groups Total Anova: Single Factor SUMMARY	<i>Count</i> 11 133 <i>SS</i> 0.105744 3.120544 3.226288	African Americ Sum 2.340706 14.73255 df 1 142 143 African Americ	an v. Caucasian <i>Average</i> 0.212791 0.110771 <i>MS</i> 0.105744 0.021976 an v. Hispanic	Variance 0.059262 0.019151 F 4.81187	GameShow P-value 0.029891 GameShow	\$100,000 <i>F crit</i> 3.907782 \$50,000
Anova: Single Factor SUMMARY Groups G100000FUN G100000FUN ANOVA Source of Variation Between Groups Within Groups Total Anova: Single Factor SUMMARY Groups	Count 11 133 SS 0.105744 3.120544 3.226288 Count	African Americ Sum 2.340706 14.73255 df 1 142 143 African Americ Sum	an v. Caucasian <i>Average</i> 0.212791 0.110771 <i>MS</i> 0.105744 0.021976 an v. Hispanic <i>Average</i>	Variance 0.059262 0.019151 F 4.81187 Variance	GameShow <i>P-value</i> 0.029891 GameShow	\$100,000 <i>F crit</i> 3.907782 \$50,000
Anova: Single Factor SUMMARY Groups G100000FUN G100000FUN ANOVA Source of Variation Between Groups Within Groups Within Groups Total Anova: Single Factor SUMMARY Groups G50000FUN	<i>Count</i> 11 133 <i>SS</i> 0.105744 3.120544 3.226288 <i>Count</i> 11	African Americ <i>Sum</i> 2.340706 14.73255 <i>df</i> 1 142 143 African Americ <i>Sum</i> 2.085	an v. Caucasian <i>Average</i> 0.212791 0.110771 <i>MS</i> 0.105744 0.021976 an v. Hispanic <i>Average</i> 0.189545	Variance 0.059262 0.019151 F 4.81187 Variance 0.049782	GameShow <i>P-value</i> 0.029891 GameShow	\$100,000 <i>F crit</i> 3.907782 \$50,000
Anova: Single Factor SUMMARY Groups G100000FUN G100000FUN ANOVA Source of Variation Between Groups Within Groups Total Anova: Single Factor SUMMARY Groups G50000FUN G50000FUN	<i>Count</i> 11 133 <i>SS</i> 0.105744 3.120544 3.226288 <i>Count</i> 11 69	African Americ Sum 2.340706 14.73255 df 1 142 143 African Americ Sum 2.085 7.173798	an v. Caucasian <i>Average</i> 0.212791 0.110771 <i>MS</i> 0.105744 0.021976 ean v. Hispanic <i>Average</i> 0.189545 0.103968	Variance 0.059262 0.019151 F 4.81187 Variance 0.049782 0.012276	GameShow P-value 0.029891 GameShow	\$100,000 <i>F crit</i> 3.907782 \$50,000
Anova: Single Factor SUMMARY Groups G100000FUN G100000FUN ANOVA Source of Variation Between Groups Within Groups Total Anova: Single Factor SUMMARY Groups G50000FUN G50000FUN ANOVA	<i>Count</i> 11 133 <i>SS</i> 0.105744 3.120544 3.226288 <i>Count</i> 11 69	African Americ Sum 2.340706 14.73255 df 1 142 143 African Americ Sum 2.085 7.173798	an v. Caucasian <i>Average</i> 0.212791 0.110771 <i>MS</i> 0.105744 0.021976 an v. Hispanic <i>Average</i> 0.189545 0.103968	Variance 0.059262 0.019151 F 4.81187 Variance 0.049782 0.012276	GameShow <i>P-value</i> 0.029891 GameShow	\$100,000 <i>F crit</i> 3.907782 \$50,000
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Anova: Single Factor SUMMARY Groups G100000FUN G100000FUN ANOVA Source of Variation Between Groups Within Groups Within Groups Total Anova: Single Factor SUMMARY Groups G50000FUN G50000FUN ANOVA Source of Variation Between Groups	<i>Count</i> 11 133 <i>SS</i> 0.105744 3.120544 3.226288 <i>Count</i> 11 69 <i>SS</i> 0.069482	African Americ Sum 2.340706 14.73255	an v. Caucasian Average 0.212791 0.110771 MS 0.105744 0.021976 an v. Hispanic Average 0.189545 0.103968 MS 0.069482	Variance 0.059262 0.019151 F 4.81187 Variance 0.049782 0.012276 F 4.066965	GameShow <i>P-value</i> 0.029891 GameShow <i>P-value</i> 0.047171	\$100,000 <i>F crit</i> 3.907782 \$50,000 <i>F crit</i> 3.963472
Anova: Single Factor SUMMARY Groups G100000FUN G100000FUN ANOVA Source of Variation Between Groups Within Groups Total Anova: Single Factor SUMMARY Groups G50000FUN G50000FUN ANOVA Source of Variation Between Groups Within Groups	Count 11 133 SS 0.105744 3.120544 3.226288 Count 11 69 SS 0.069482 1.332581 1.332581	African Americ Sum 2.340706 14.73255	an v. Caucasian Average 0.212791 0.110771 MS 0.105744 0.021976 an v. Hispanic Average 0.189545 0.103968 MS 0.069482 0.017084	Variance 0.059262 0.019151 F 4.81187 Variance 0.049782 0.012276 F 4.066965	GameShow P-value 0.029891 GameShow P-value 0.047171	\$100,000 <i>F crit</i> 3.907782 \$50,000 <i>F crit</i> 3.963472

### Appendix 3: Significant Game Show Spending Anova Race Results Over \$10,000

## Factors that Impact the Initial Public Offering Market of the Special Purpose Acquisition Company

William Cheng, Troy University Liyi Zheng, Wenzhou-Kean University

#### Abstract

Due to the dissemination of the coronavirus, the implementation of the segregation policy is not conducive to the operation of the traditional IPOs. Starting from the end of 2019, a technic named "special purpose acquisition company" (SPAC) become popular in the investment market. This paper will mainly focus on testing the factors including the overall market, regulation, and the epidemic situation impact on the performance of the SPAC IPO market in the US.

JEL Classification: L22, L53 Keywords: SPAC, Initial Public Offering, Merger and Acquisition, Epidemic

#### Introduction

The special purpose acquisition company (SPAC) is a kind of shell company with a long history. It appeared in the 1990s, but it only had sprung up in 2003 and kept silent until the end of 2019. The earliest research appears in 2007 and mainly focuses on the operation model of SPAC and its history because the SPAC does not act popular enough to attract researchers. Riemer (2007) mainly discusses the relationship between SPAC and the blank check company, which is the SPAC's predecessor and delves into the origin of the SPAC.

At the end of 2019, the SPAC experienced a resurgence because of the epidemic. In 2020 and 2021, the SPAC IPOs occupied 46% and 52% of the whole IPO market in the U.S. (SPAC Analytics, 2021), which shows the boom of the SPAC IPO market. The model of SPAC and traditional IPO are different, especially the SPAC IPO and De-SPAC take less time than the traditional IPO process. For the company that wants to list on the market, they need to hold a roadshow and nearly one year to finish the whole process. During the pandemic, it is difficult for those companies to organize the roadshow because the policy of quarantine and the eruption of the epidemic is unpredictable. The SPAC could avoid such problem because, for the companies that choose SPAC, those SPACs have already accomplished the long-winded conventional IPO process, so the De-SPAC could help companies save time and reduce the cost.

With the rebirth of the SPAC market, more and more research is being done on this area, since the SPAC is derived from the blank check company, the supervision requirements on SPAC are also becoming more comprehensive than before. Newman and Trautman (2021) detailly discussed the regulation on SPAC and the SEC's policy change of the SPAC market after its resurgence. Additionally, Bai, Ma, and Zheng (2020) test the short-term performance between companies that list on the stock market through conventional IPO and De-SPAC and conclude that the SPAC performs well than the conventional IPO company in the short-term. While Kolb and Tykvova (2016) find that the SPAC does not perform well in the long-term compared with the conventional IPO companies. Both these two research focus on the macroscopic angle and make some comparisons between the SPAC and conventional IPO, but there is still some blank areas in the research on the performance of SPAC IPO market. The first part of this paper will mainly focus on testing the factors that impact the SPAC IPO market, and the three factors are overall market condition, the regulation, and the pandemic situation. By doing some simple regression analysis, the relationship between those factors and the SPAC IPO market could become remarkable.

Except for the comparison between SPAC and the traditional IPO, the whole process of SPAC also attracts researchers' attention. It is a complicated process from SPAC IPO to De-SPAC, Gahng, Ritter, and Zhang (2021) analyze the motivation for some companies to go public through SPAC. They test the returns for investors on common shares and on warrants. Agarwal (2021) analyzes the overall valuation of the target companies in the SPAC market and finds that the valuation is at a high level in these two years acquisition process.

As Agarwal (2021) mentions, the valuation of the target company is a conundrum for most investors, so it is important for the investors to find a commonly used and reliable way to evaluate the company. Fernandez (2007) delves into six main valuation methods for enterprises and discusses the different properties of these methods. Among these methods, Mauboussin (2018) detailly studies the EV/EBITDA model and discusses the pros and cons of this method, like the elimination of the impact of different tax rates. Theoretically, the EV/EBITDA could serve as an effective and general method to evaluate the SPAC target company. In the second part of this paper, from the microscope perspective, the EV/EBITDA method will be tested through a case analysis, and all the data used in this part could be directly found through SEC—company filings.

For the connection between the two parts of this paper, the valuation of the SPAC target companies reflects the condition of SPAC IPO market, the high valuation of targets reflect the boom of SPAC IPO market, while the low valuation shows the recession of the market. The paper is aimed to verify how do the factors including overall market conditions, policy, and pandemic impact the SPAC IPO market, and testing the valuation model of the target companies.

#### **Literature Review**

#### Early Study

Compared with the research on the traditional IPO process, there are fewer academic studies on the special purpose acquisition company (SPAC). Due to the lack of attention by the overall market in the past, the sample size of the SPACs is not big enough to support further research. In the early years before 2010, most of the researchers focus more on a purely mechanical view of the operating mechanics of SPAC and its origins (Griffin, 2019). Riemer (2007) is one of the earliest researchers that notice the SPAC, he arranges a detailed process about how the SPACs borrow the technic from the blank check companies and form their system. As Riemer mentioned, after the enactment of Rule 419, the blank check companies are nearly eliminated from the U.S. market, and some of the managers mostly comply with Rule 419 to create the first generation of SPACs.

#### New Epoch of SPAC Study

Nowadays because of the impact of COVID-19, the traditional IPO process does not act as effectively as the SPACs. Comparing with the SPAC, the conventional IPO needs longer time-around nine months to complete, and it also has the roadshow, which is difficult to hold during this grave situation. However, the SPACs could help the investors avoid such problem because the essence of SPAC is an acquisition process. For the target companies, they only need to complete a kind of merger and acquisition (M&A) process but not the whole IPO, and the M&A could be completed within six months.

The SPAC is now experiencing a rebirth in the U.S. market, the number of SPAC IPO and De-SPAC have reached an unprecedented high level since 2019, nearly 70% of U.S. IPO were SPAC IPO in 2021 (Geerken et al., 2021). With the tremendous development in the SPAC market, the research on this area also transferred from only focusing on SPAC itself to the relationship between the SPAC market and some external factors.

#### Macroscopic Angle

Chong et al. (2021) design a comprehensive study of SPAC including the capital structure, market participants, and its management structure. Newman and Trautman (2021) focus on the financial reporting and audition considerations of the SPAC after the boom in the SPAC market in early 2021, because the SEC begin to pay close attention again to the SPAC market, the researchers detailly discuss what regulation changes does the SEC make to have better supervision on SPAC market. Besides, the SPACs outside of the U.S. market also attract researchers' attention. Although SPAC has already appeared in Europe and Asia in the early 2000s, few studies focused on those "sub-SPAC" markets. In recent years, the research on SPAC outside of the U.S. market becomes more. Riva and Provasi (2019) mainly focus on Italy and analyze how the SPAC could serve as an effective tool to meet the needs of the Italian companies, especially the middle and small-sized enterprises. Lai (2021) discusses that since the SPAC market in the U.S. is nearly saturated, many SPACs start turning to Asia. Lai analyzes some potential areas that are more appropriate for getting IPO through SPACs, and he also talks about the elements of risk and the laws for the SPAC in Asia. For some specific countries like China and Korea, the research on SPAC is more abundant than in other places. Shachmurove and Vulanovic (2017) focus on the Chinese SPACs, and they compare the performance of these Chinese SPAC with the SPACs listed in the U.S. and found Chinese SPACs perform better than the U.S. SPAC.

When analyzing the SPAC, it is difficult to avoid the traditional IPO. Datar, Emm, and Ince (2012) conduct the first research that focuses on the financial and operational performance of SPACs in the long-term, and they find that compare with the coeval companies that choose the traditional IPO process, those firms that chooses SPAC have lower growth opportunities. Later in 2016, Kolb and Tykvova also design the research on testing the long-term abnormal returns of SPACs. Different from the previous one that conduct by Datar, Emm, and Ince (2012), Kolb and Tykvova expand their timeline from 2011 to 2016, their research including the analysis of 127 SPAC acquisitions and 1128 SPAC IPO events, and they also conclude that the companies go public through SPAC do not perform well in long-term compare with the firms that choose conventional IPO process. Bai, Ma, and Zheng (2020) conduct their research on delving into the short-term performance of SPAC. They conclude that the firms that go public through SPAC are usually small or medium-sized companies, so

compared with the traditional IPO firms, those SPACs are risker during the listing process. However, different from the poor long-term performance, their research shows that in the short-term, the SPAC firms have a similar growth rate or even perform better than the companies that IPO traditionally at the same period.

On the macroscopic angle, the previous research has done a lot about the comparison between the different processes of SPAC and conventional IPO, the SPAC and SEC, and the long-term and short-term performance of SPAC firms. However, there is a lack of study on the relationship between the performance of the SPAC IPO market and the current situation. In order to keep track of this special technic in a general direction, it is significant to analyze and build the relationship between SPAC and the present situation. Due to the COVID-19, the SPAC market not only relates to the condition of the overall market, but also the regulations and the epidemic issue. Besides, it seems like people will live together with the epidemic in the next few years, Passador (2021) forecasts that the SPAC will definitely make some improvements in order to fit in the current and the future market because SPAC has already shown that they could work in the past and get a resurgence in nowadays market, which shows the strength of this technic.

#### Microscopic Angle

It has a long and complicated process from SPAC IPO to De-SPAC, different studies usually focus on different steps. Agarwal (2021) discusses why the SPACs could be attractive in nowadays market. Expect for making the comparison between SPAC and conventional IPO, he also talks about the incentives of founders, investors, and sponsors. Shachmurove and Vulanovic (2017) focus on the SPAC IPO and analyze the security issue related to the SPAC IPO process, they mention that the "SPACs' IPOs are much less noisy", which means the SPACs do not need to disclose much of their information when listing. Gahng, Ritter, and Zhang (2021) focus on why some companies choose the De-SPAC to get traded on the market. Since the investors could choose either to withdraw the investments or keep investing during the De-SPAC process, it is nearly risk-free for those SPAC investors. Gahng et al (2021) describe the SPAC as "a pool of cash", they believe that it is attractive to those target companies, through De-SPAC the target companies could not only get listed but also benefit from the adequate cash flow. Agarwal (2021) also delves into the "valuation conundrum" of the SPAC firms. However, his research mainly focuses on integrating the data and the trading price but does not explain how the SPAC determines the value of the target company. The trading price could directly be found in the S-1 or 8-K forms on SEC, but they do not provide how they calculate the price.

There are some kinds of literature that focus on the factors that impact the performance of SPAC firms from the microscopic angle, and the factors they choose are usually based on the SPAC itself. Hung et al (2021) design a comprehensive study on how the management factors including previous financial experience, education, experience heterogeneity, the age and size of the management team, and ownership of patent impact on the SPAC firms after acquisition. Jokelainen (2021) focuses on the specific case analysis, he chooses five SPAC from 4.1-31.3.2021 and analyzes the factors that impact the return and the trade price. Jokelainen points out that he does not test the relationship between the announcement of the merger and the stock price, which is later conducted by Cohen and Qadan (2021). Cohen and Qadan conclude that the announcement in the merger could have a significant impact on the share price of SPACs within 60 days.

#### Valuation Model

Overall from the microscopic perspective, there are still some blank areas in the research on the valuation of SPAC target companies, due to the epidemic and the quantitative easing policy, there is plenty of cash flow in the market, which make the overall valuation of the target company is at a high level. Since both the SPACs and target companies do not provide their valuation process, it is necessary to verify how the SPAC firms evaluate the target company and find a common and feasible way to get close to their trading price. Fernandez (2007) discusses four main groups of the most widely used company valuation methods, and from all these different methods, the EV/EBITDA is the most appropriate one for evaluating the SPAC target companies. Because the EV/EBITDA is more suitable for the company that has predictable cash flow, and it eliminates the impact of different tax rates and capital structure (Mauboussin, 2018). In the SPAC market, since the essence of the SPAC firms is a "pool of cash", their cash flow is always clear, and the De-SPAC process usually has different companies with different capital structures. Besides, since the SPAC is becoming popular all over the world, sometimes the SPAC and its target company may come from different countries, and the EV/EBITDA could help eliminate the impact of different tax rates.

To sum up, both the performance of the SPAC IPO market and the high valuation of the target companies relate to the current situation including the overall market condition, regulations, and the severity of the epidemic. This paper is aimed to build a relationship between the three factors and the performance of the SPAC IPO market and verify a common way to evaluate the target companies.

#### Methodology

This paper is aimed to find two things: first, the relationship between three factors and the performance of the SPAC IPO market; second, whether the EV/EBITDA could serve as a feasible and reliable way to evaluate the SPAC target company.

#### The Impact of Market Factors

In the first part of this paper, the literature survey and regression analysis will be used in the analysis. The key data included in this part are the yearly number of SPAC IPO number from 2003 to 2021, and it serves as the dependent variable.

In order to analyze the relationship between the SPAC IPO market and the overall market condition, the federal fund rate, and the 10-year U.S. treasury rate are chosen as the independent variables, because the federal fund rate is one of the most important indices of the market, and the 10-year treasury rate is the benchmark of some other rate as the mortgage rate. The SPAC market does not perform actively enough before 2019, the monthly data cannot be used because for many months, the SPAC IPO number is zero, so when analyzing the relationship of these two things, the interval is in yearly units.

The polynomial regression model is used in this part, which aimed to find how the overall market condition impact on the SPAC IPO market and which kind of index is more significant in this case. The SPAC IPO number is the dependent variable and federal fund rate as well as 10-year treasury rate are the independent variables, the discount rate, 1-year treasury rate and 5-year treasury rate are the control variables in this regression model. Because the life cycle of a SPAC is around 2 years, bonds with a maturity of less than five years can influence investors' decisions in this case, so the "2 years" just serve as a kind of "median", the 1-year/ 5-year rates are chosen.

#### The Impact of Policy

To find an effect of the policy issue, the key is about the regulation on the SPAC company. Since it is difficult to find or create an index to represent the regulation, and the policies do not contain any measurable variable, it is difficult to do the dummy variable assignment. So in this part the literature survey along with the policy recommendation will be performed.

#### The impact of Epidemic

To test the pandemic issue that impacts the SPAC IPO market, the monthly number of new infections need to be collected, from Jan. 2020 to Oct. 2021. The number of new infections together with the monthly number of SPAC IPO, serve as the second set of numbers for analyzing the impact of the epidemic issue. The monthly number of SPAC IPOs cannot be found in one database because most of the available data sources only have the yearly number. It comes from multiple sources including SPAC analytics, Bloomberg, and SPACtrack, and some simple filtration and calculation are required. In this part, a traditional linear regression model is used, and the natural log of the monthly SPAC IPO number is used to make the result become more significant.

#### The Valuation Model and Data

For the second part of the thesis, the mathematic mean is mainly used in this section, and all of the calculation is based on the formula:

EV/EBITDAEV (enterprise value) = market value of the company + value of debt – total cashflow

EBITDA = earnings before tax, interest, depreciation, amortization.

Instead of another two wildly used valuation methods P/E and P/S, the EV/EBITDA is the most appropriate mean in evaluating the SPAC target company. Based on the operation of the SPAC, the essence of the SPAC is a shell company, and its unique mission is to acquire a company. The acquisition process may not just be limited to a single country, especially during the pandemic period, the SPAC appears all around the world. The P/E and P/S cannot avoid the impact of the tax.

EV/EBITDA also includes shareholder' return and creditors' return in EBITDA and contains equity market value and debt market value in EV part. P/E ratio only contains the shareholders' return in "E" and equity market value in "P", without the part of creditors. In other words, the calculation of EV/EBITDA considers different levels of leverage. When acquisition happens, two enterprises with the same profitability may have different financing levels, for the industries with high leverage like the energy industry, EV/EBITDA is more accurate than P/E and P/S.

In this part, the EV/EBITDA will be tested through a case analysis called the Newfrontier's acquisition of United Family Healthcare (UFH). All data come from the SEC, which is the companies' filing because this paper aims to provide a general and accessible way for all the investors to evaluate the target company. From the file named "PREM14A" (a preliminary proxy statement), "DEFM14A" (definitive proxy statement relating to a merger or acquisition), and the "Form S-4".

#### Results

#### The Impact of Overall Market Conditions

#### Unit Root Test

Overall there are six variables in this part, to make the result become more significant, the natural log of the dependent variable is used, which means generate lny=ln(SPAC IPOs). For the dependent variable, first order difference is performed on the data to make the data become stationary. For the independent variables, the federal fund rate needs second difference and the 10-year treasury rate need first difference.

Table 1: Uni	t root test for the numbe	r of SPAC IPO						
Dickey-Fulle	r test for unit root		Nu	mber of obs $=$ 17				
			Interpolated Dickey-Fuller					
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value				
Z(t)	-4.124	-3.750	-3.000	-2.630				
MacKinnon a	pproximate p-value for	Z(t) = 0.0009						
Table 2 and '	<b>Table 3</b> : Unit root test for	or independent variables						
Dickey-Fulle	r test for unit root		Nu	mber of obs $=$ 16				
			Interpolated Dickey-Fuller					
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value				
Z(t)	-3.652	-3.750	-3.000	-2.630				
MacKinnon a	pproximate p-value for	Z(t) = 0.0048						
Dickey-Fulle	r test for unit root		Nu	mber of obs $=$ 17				
5			Interpolated Dicker	y-Fuller				
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value				
Z(t)	-4.133	-3.750	-3.000	-2.630				
MacKinnon a	pproximate p-value for	Z(t) = 0.0009						

#### **Result of Regression**

To make the result more significant, the natural log of the SPAC IPO number is used. Although the R-squared is low and shows the insignificant relationship between those variables, the P-Value and t-Value indicates the federal fund rate and 10-year treasury rate have significant impact on SPAC IPO market, the SPAC IPO market has a negative relationship with the overall market condition, and 10-year treasury rate is more significant than federal fund rate.

	Table 4	1: T	he	resul	t of	ft	he	regression	on	mar	ket	cond	lit	ion	part
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	8	1				
SPAC IPOs	Coef.		St.Err	t-value	p-value	Sig.
Fed fund rate	1.190		0.481	2.47	0.029	**
10-year Treasury rate	-1.766		0.584	-3.02	0.011	**
1-year Treasury rate	-0.658		0.403	-1.63	0.128	
5-year Treasury rate	1.262		0.411	3.07	0.010	**
Discount rate	-0.427		0.348	-1.23	0.243	
Mean dependent var		0.220	SD depender	nt var		1.093
R-squared		0.564	Number of o	bs		17.000
F-test		3.100	Prob > F			0.050
Akaike crit. (AIC)		46.854	Bayesian cri	t. (BIC)		51.020
*** .0.01 *** .0.05 *	-0.1					

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

#### **Robustness Test**

Initially the traditional polynomial regression is used, to do the robustness test, the model need to be changed. By using the OLS regression model, although the significance level becomes lower than before, it could still provide the same result.

 Table 5: The robustness test result

SPAC IPOs	Coef.		St.Err	t-value	p-value	Sig.
Fed fund rate	1.156		0.517	2.24	0.047	**
10-year Treasury rate	-1.733		0.621	-2.79	0.018	**
1-year Treasury rate	-0.652		0.420	-1.55	0.149	
5-year Treasury rate	1.265		0.428	2.95	0.013	**
Discount rate	-0.406		0.370	-1.10	0.296	
Constant	0.061		0.234	0.26	0.799	
Mean dependent var		0.220	SD depender	nt var		1.093
R-squared		0.548	Number of o	bs		17.000
F-test		2.663	Prob > F			0.082
Akaike crit. (AIC)		48.750	Bayesian crit	t. (BIC)		53.749
****						

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

#### **Policy Impact**

On April 12,2021, the SEC issued a series of guidance on SPAC, the most important of which was the need for future SPAC warrants granted to early investors to be documented on its balance sheet in the form of debt rather than equity as originally assumed. Based on the new guidance, all of the SPAC, either lining up to go public or having completed listing and mergers, will need to readjust their statements under the new accounting rules.

Figure 1: Number of SPAC IPOs



In the same month, Reuters published that the U.S. regulator mulls guidance to curb SPAC projections, liability shield sources. For SPAC IPO, the company could make projections on their future performance, which could attract more investors. And the projection is also a significant difference between SPAC IPO and conventional IPO.

#### **Epidemic Impact**

<b>Table 6:</b> The result of the regression	in epidemic part	t				
SPAC IPOs	Coef.		St.Err	t-value	p-value	Sig.
Newinfections	0.000		0.000	3.28	0.004	***
Constant	2.132		0.330	6.45	0.000	***
Mean dependent var	2	.916	SD dependen	ıt var		1.296
R-squared	0	.350	Number of ol	bs		22.000
F-test	10	).762	Prob > F			0.004
Akaike crit. (AIC)	67	.343	Bayesian crit	. (BIC)		69.525
*** $n < 0.01$ ** $n < 0.05$ * $n < 0.1$						

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

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There is a significant decrease in the number of SPAC IPO in April, notice that the SPAC IPO number kept increasing before April, and reached a peak in March. However, just in April, it decreased from 109 to 13.

As Table 6 shows, the R-squared shows the significance between epidemic issue and SPAC IPO market is low, but the tvalue and p-value as well as the coefficient could show the significant positive relationship between the epidemic and SPAC IPO market.

#### **Results of Valuation**

Before the calculation, there is an important statement in the company's Form S-4, which mainly state that some of the financial measures including the adjusted EBITDA, that were not calculated in accordance with the International Financial Reporting Standards as issued by the International Accounting Standards Board.

#### The Calculation

To get the enterprise value (EV), the details of agreements, investments, unredeemed shares are needed. Those items mainly measure the stock value of the company, which refers to the company's market cap. For this specific case, the transaction including two types of agreements—forward purchase agreement and subscription agreement, along with a reinvestment and unredeemed shares commitment. Then refers to the financial statement in 2019 to get the debt, and the debt financing within the transaction should also be included. To get the EBITDA, usually the company filings directly provide this number although it may not be absolutely accurate. The acquisition happened in Nov. 2019, the company's filings provide the EBITDA for 2018, along with forecasts for 2019 and 2020. To get close to the official M&A multiple, the 2019E should be used.

#### Table 7: Calculation of EV

	Official Guide Price	Own	
EV	1,302 million (Max)	1,305.8 million	
EBITDA	Unknow	20.3 million	
M&A Multiple	70.1x	64.4x	

EV=\$190m (Forward Purchase Agreements) + \$711.5m (Subscription Agreements) + \$167.6m (re-investments) + \$90m (unredeemed shares) + \$26.7m (debt)+\$300(loan) -\$180m (cashflow)= \$1,305.8m

#### Valuation of the Overall Industry

The case shows the high valuation of the SPAC target company although there is a small discrepancy between the calculation with the official guidance. The following Figures 2 and 3 show the comparison between the valuation of SPAC target company and the overall industry.



#### Figure 2: M&A Multiples: EV/EBITDA for SPAC Targets

#### Figure 3: M&A Multiples: Average EV/EBITDA for Industries



The industries including medical, Technology and Software, Finance (including Fintech), and Media and Entertainment. Because those industries are the most popular industries in SPAC market, more than 90% of the De-SPAC take place within those areas. The results show the valuation of SPAC target companies are always higher than the industries' average level, especially in Q2 2021.

#### Conclusion

This paper finds that the performance of SPAC IPO market has a negative relationship with the overall market condition. When the federal fund rate and 10-year treasury rate decrease, people prefer to spend their money rather than saving in the bank. Since the treasury yield decrease, the investors tend to choose other investment product than the treasury bonds. The reason why treasury rate is more significant than federal fund rate is, the SPAC is more about an investment decision. From 2006 to 2008, the 10-year treasury rate and the interest rate also decreased a lot, at that period, the number of SPAC IPO had an increase rate of 32.1% in 2006 and 78.3% in 2007, which means without the impact of COVID, the relationship between these factors is also reasonable.

Although the SPAC market is impacted by many different factors, it is a strong policy-oriented product. In the absence of major changes in other conditions, the policy changes had a drastic impact on SPAC IPO market—a -88.1% decrease from March to April. Oddly, the SPAC market began to grow again just after April, which means the stringent regulations have some potential benefits on SPAC IPO market. Although this policy has largely taken the heat out of the SPAC, it has also helped to screen out unqualified companies. It is bad for the SPAC market in the short term, but it is good in the long term.

The COVID-19 outbreak is a direct factor behind the rise of SPACs, which are simpler than traditional IPO process. First, the life cycle for conventional IPO is much longer than M&A process, the time cost for SPAC is much lower. Second, the outbreak of epidemic is unpredictable, which means the quarantine could take place at anytime and anywhere, and that restrict the roadshow of conventional IPO process. Third, the normalization of COVID also increase the people's confidence on SPAC. The performance of SPAC during epidemic period demonstrates the feasibility and the superiority of the SPAC technic.

The high valuation of the SPAC target company shows the boom of SPAC IPO market. In this position, the SPAC act as a supply and need to fund a target company to do M&A, and the target company is the demand side. When more and more SPAC finish IPO and start searching for target company, the demand part has the bargain power. However, since more and more SPAC finished IPO and search for target company, the market has already unbalanced, so investors may be looking away from IPOs to search for target company for a while.

This paper mainly focuses on the SPAC IPO market, and it does not as attractive as other SPAC parts, and this paper helps fill this vacancy slightly. Besides, through the case analyses by testing the EV/EBITDA, it provides a general way for investors to get close to the valuation of the target company and could help them make their investment decisions.

#### limitations and Futures

There are three limitations in this paper, especially for the monthly number of SPAC IPOs. From all of the specific SPAC database, including SPAC analytics, SPACinsider, and SPACtrack, they all have the number of yearly SPAC IPO since 2003, and all the data from different sources could match. However, when it comes to the monthly data, most of these data sources do not have this number. The number of monthly SPAC IPO in this paper comes from Bloomberg and the SPACtrack. On Bloomberg, it shows 238 SPAC IPO events in 2020, but the accurate number is 248. And on SPACtrack, it provides 437 SPAC IPO events in 2021, while the true number is 450. Although the errors are limited since the sample is big, the results could be more accurate if the exact number could be used.

Besides, in the first part of this paper, when analyze the impact of the regulation on the SPAC IPO market, the thesis only uses the literature survey method. If some indexes could be developed in this part to measure the regulation could help make the analysis become more reasonable and visual. This part only considers the impact from the SEC regulation but does not contain other policy issues like the quantitative easing. In real world, especially during the epidemic time, the exact performance of the SPAC IPO market could be affected by many other factors.

In the second part of the thesis, the result has a little discrepancy between the official guidance, this paper only tests the EV/EBITDA. And the reason for choosing this valuation method is all based on the theoretical concepts that be provided in the previous literatures. This paper only tests that the EV/EBITDA could be a feasible way for all the investors to evaluate the target company, but some other methods may serve as more accurate way in valuation. For the future research, more new method and model could be created to evaluate the SPAC target company.

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## The Impact of Northbound Cash Flows on the Investor Sentiment of Mainland Chinese A-share Investors

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#### Abstract

Nowadays, Shanghai Hong Kong Stock Connect and Shenzhen Hong Kong Stock Connect have run smoothly for many years. Overseas capital is increasingly widely used in Chinese mainland stock market. Some ordinary investors will choose northbound cash flow (overseas capital) as the wind vane to guide their investment behavior. This study will analyze whether northbound cash flow impacts investor sentiment in China's stock market in recent years. Moreover, this paper will classify the data from different kinds of markets and different market sentiment conditions. Analyze the impact of changes in market investor sentiment by northbound cash flow under different circumstances.

JEL Codes: G15, G41 Keywords: Chinese Stock Market, Investor Sentiment, Northbound Cashflow, Overseas capital

#### Introduction

For developing countries, the opening of financial markets is conducive to broadening the financing channels of enterprises and plays a very positive role in national economic growth (Gaies and Nabi, 2019). As the second largest economy in the world after the United States, China has been actively improving the openness of its financial market in recent years. Two typical examples are Shanghai Hong Kong Stock Connect (SH-HK-SC) opened on November 17, 2014, and Shenzhen, Hong Kong stock connect (SZ-HK-SC) opened on December 5, 2016. These two signifies those overseas investors and Hongkong investors can participate in the A share trading in Chinese mainland through the interoperability mechanism. Moreover, Northbound Cash flow usually refers to the A-share purchased by overseas investors through the Shanghai-Hong Kong stock connect and Shenzhen-Hong Kong stock connect. In many Chinese news media and financial publications, northbound cash flow is always called "smart capital." Due to the relatively stable long-term investment style of northbound cash flow, the return rate of northbound cash flow as a wind vane to guide their investment behavior due to the relative lack of information and the lack of ability to analyze the company's financial indicators independently. This paper will analyze whether the change of northbound cash flow will affect the extensive Imitation Behavior of investors from the perspective of investor sentiment.

This study can effectively fill the gap on the impact of foreign capital on investor sentiment in China's stock market and has the following signs for future research. Firstly, the results of this research may help me make better investment decisions when I invest in the future. If the quantitative relationship between the inflow proportion of northbound and the rise and fall of stocks on the second day is found in this study, it will help me control my cost price in short-term trading. Secondly, Chinese mainland stock investors are mainly nonprofessional retail investors. When the hype behavior blindly follows the trend, it will have a significant impact on the stability of the financial market. Influential investors may try to control these market indicators and affect the behavior of retail investors to achieve profit. This study may help analyze the risk that China's stock market is facing "holding the market" by some investors. Thirdly, this study will help to explore how to continuously improve the maturity of the stock market in the future and improve the level of independent analysis of investors.

Based on the research of Baker and Wurgler (2007), this study takes the stock turnover rate as the proxy variable of investor sentiment to build a vector autoregressive (VAR) model and a linear regression model, respectively. The daily market transaction data of SH-HK-SC and SZ-HK-SC from the establishment date (due to the lack of previous data at wind financial terminal, the data of SH-HK-SC began on January 4, 2016) to September 10, 2021, were used for linear regression. Combined with the loss aversion theory, this study classifies the primary sentiment conditions of the market by using the ISI comprehensive investor sentiment index data and exploring the impact of northbound cash flow on investor sentiment under different market basic sentiment conditions. In addition, considering the differences between Shanghai and Shenzhen markets, this paper will explore whether there are differences in the sensitivity of investor sentiment affected by events in the large-cap stock market and small and medium cap stock market.

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This paper will involve three main hypotheses: 1. Northbound Cash Flow has a positive correlation with investor sentiment in the Chinese mainland. 2. When the overall market sentiment is negative, the impact of northbound cash flow on investor sentiment will be more obvious than when the overall market sentiment is positive. 3. The investor sentiment of the Shenzhen Stock Exchange, a market dominated by medium and small-cap stocks, is more sensitive to the changes of northbound cash flow than that of the Shanghai Stock Exchange dominated by large-cap stocks. In the second section of this paper, the literature related to the above factors will be reviewed. In the third section, the above assumptions will be described in more detail, as well as the research methods and data will be introduced in detail. The fourth section will show the results of data processing and research. The fifth section will conclude the study and a series of problems existing in the study.

#### **Literature Review**

At present, there is a considerable body of literature on Shanghai-Hong Kong and Shenzhen-Hong Kong Stock Connect (SH-HK-SC and SZ-HK-SC) programs. However, most of them focus on the impact of the connect program on the effectiveness of China's stock market and AH share premium. Few papers focus on the inflow of northbound cash flow. In addition, there are abundant papers on stock investor sentimental measures. This paper will measure the impact of the inflow of northbound cash flow on investor sentiment in the A-share market based on previous literature.

#### Shanghai-Hong Kong and Shenzhen Hong Kong Stock Connect Programs

Existing studies have found that Shanghai-Hong Kong Stock Connect (SH-HK-SC) programs have significantly strengthened mainland China's stock market (Huo and Ahmed, 2017). Ma et al. (2019) used a series of GARCH models to study the market linkage between SH-HK-SC and Hong Kong and Shanghai. They found that the period during the stock market crash mainly reflects the market linkage between the two places after the launch of SH-HK-SC. Other researchers use the panel data of listed companies to find that SH-HK-SC reduces the A-H Share Premium and strengthens the effectiveness of China's stock market (Fan and Wang, 2017). Another study uses multifractal cross-correlation analysis (MFCCA) to find that there is a solid continuous positive correlation between the inflow of northbound and the return of stocks (Ruan et al., 2017). Through research, Jiang et al. (2020) found that implementing SH-HK-SC and SZ-HK-SC strengthens the freedom of China's stock market and reduces the tax avoidance phenomenon of Chinese enterprises.

Moreover, this phenomenon is significantly reflected in non-state-owned enterprises and companies with weak external supervision, low transparency, and strong financial constraints. Another group of researchers found that the government can use foreign investors to help screen out companies with more development potential through SH-HK-SC (Chen et al., 2020). According to these studies, SH-HK-SC and SZ-HK-SC are indeed beneficial to improve the effectiveness of China's stock market and play a very positive role in the rationality of stock price pricing. The positive correlation between the inflow of northbound cash flow (foreign capital) and income has not been proved. Compared with local investors, foreign capital has disadvantages in information acquisition capability because of language time differences. Therefore, the reason why northbound cash flow can bring benefits may be reflected in the positive change of northbound cash flow's investor sentiment in the Chinese mainland. This study aims to fill the gap in the impact of northbound cash flow on investor sentiment in SH-HK-SC and SZ-HK-SC.

#### **Investors Sentiment and Stock Return**

At present, there has been pervasive research on the relationship between stock investor sentiment and return. Through Granger causality tests, Kling and Gao (2008) found that the emotions and noise of small investors will significantly affect the fluctuation of stock prices. In addition, they also found that the positive feedback of emotions to the stock price is mainly reflected in the short-term dynamics. This has played an excellent guiding significance for my research. This study will focus on the observation of short-term indicators. In addition, Yang and Zhou (2016) combined the crowded trading of individual stocks and investor sentiment. They found that the combined effect of the two has a highly significant impact on the yield of individual stocks. Li et al. (2017) used the quantitative Granger non-causality test to find that investor sentiment can provide incremental predictability for stock returns and explained this finding with loss aversion and herd behavior. Ahmed (2020) used EGARCH parameter estimation in his research. He found that investor sentiment in the market played a significant role in promoting the change of stock price and found that the driving of sentiment on the market was asymmetric in a bull market and bear market. The emotion-driven trading behavior would be more significant in a bear market. Zhu and Niu's (2016) research also proves the impact of investor sentiment on the market will be much weaker under optimism. In addition, Ni et al.'s (2015) research show that investor sentiment's impact on the return of stocks of small and medium-sized growth

enterprises is more significant than that of value stocks. This study will focus on observing the short-term indicators of the overall market and study the short-term investor sentiment of the market and the short-term fluctuations of the Shanghai index and Shenzhen index. Furthermore, considering the asymmetry of the impact of investor sentiment on stock prices and the differences between Shanghai and Shenzhen markets (Shanghai Stock Exchange is dominated by large-scale value stocks and Small and medium-sized growth stocks dominate Shenzhen stock exchange), this study needs to analyze the investor sentiment in different markets and different market situations respectively. This will help to reconfirm the relationship between investor sentiment and stock market returns.

#### Measure of Investors Sentiment

On the measurement of investor sentiment, the existing literature and have conducted extensive research. The research of Baker and Wurgler had a broad impact on the later research. Baker and Wurgler (2007) analyzed six emotional indicators, including closed-end fund discount, stock trading volume, number of initial public offerings and average first-day return, shares of newly issued shares, and dividend premium, to form a comprehensive emotional indicator. This also has great reference value for my research. However, because the object of this research is investor sentiment in China's stock market, some sentiment indicators will no longer be effective in China's stock market because of some institutional differences. According to the research mentioned by Yao and Zheng (2021), in 2012, the regulatory authorities restricted the IPO issue price not to exceed 125% of the average P/E ratio of the same industry and the strict issuance ceiling of 23 times the P/E ratio. The direct result is that the return on the first day of IPO is maintained at a very high level. Therefore, it is challenging to measure investor sentiment in China's stock market effectively. In addition, Liang et al. (2020) Studied social media, newspapers, and Internet media news and found that the index constructed by social media and Internet media news can effectively predict the volatility of the Shanghai stock index and Shenzhen stock index. Other researchers try to use the users' comment data on the stock market social networking website to analyze the sentiment of stock market investors (Guo, Sun, and Qian, 2017). According to the above existing studies, considering that this study uses the daily data of northbound cashflow inflow to study the short-term impact on investor sentiment, this study will exclude other indicators that cannot be quickly reflected in the market and select the variables directly related to trading, namely stock trading volume (stock turnover ratio) as the ultra-short-term proxy variable of investor sentiment. The closed-end fund discount, number of initial public offers and average first-day return, shares of newly issued shares, and divided premium are effective only on a monthly or longer time scale and cannot accurately reflect the changes in investor sentiment on an ultra-short time scale of days. This study takes the ISI comprehensive sentiment index, including these factors as a medium- and long-term measurement index as control variables in the linear regression model.

#### Vector Autoregression (VAR)

VAR model was originally proposed by Sim (1980) to capture the relationship between multiple variables over time and is widely used in economic research. Based on the VAR model, the Granger causality test can usually be used to predict the future values of another time series through the prior values of one-time series, to judge whether the two variables statistically reflect causality (Granger, 1969). In addition, the Impulse response function (IRF) can be used to measure the response of other variables when one variable in VAR is impacted (Pesaran et al., 1998). This study will use the net inflow of northbound cashflow and sentient to construct a VAR model and conduct a Granger causality test to explore whether there is a certain correlation between the two variables. In addition, IRF will be used to quantitatively detect the response of investor sentiment when the net inflow of northbound cash flow is impacted.

So far, the goal of this study has become apparent. According to the existing research, optimistic investor sentiment has a positive relationship with the rise of stock price and increased return. In addition, among many panel indicators, stock trading volume (turnover rate) is an excellent indicator to measure investor sentiment. This study combines this to study whether there is a specific relationship between northbound cash flow and Chinese A-share investor sentiment in SH-HK-SC and SZ-HK-SC.

#### Methodology

This study collects all the daily trading data of Shanghai index and Shenzhen index from the operation of mechanism SH-HK-SC and SZ-HK-SC to September 10, 2021 (All the data is collected from the Wind Financial Terminal. In addition, due to the limitation of data availability, the data of Shanghai market has been from January 2016 to now). According to the panel data of the Shanghai index and Shenzhen index and the daily flow data of northbound cash flow, this paper will test the impact of northbound cash flow on the sentiment of A-share investors.
# Dependent Variable: Sentiment $_{t+1}$

This paper considers referring to the commonly used investor sentiment measurement model from Baker and Wurgler:

 $SENTIMENTt = -0.241CEFD_t + 0.242TURN_{t-1} + 0.253NIPO_t + 0.257RIPO_{t-1} + 0.112S_t - 0.283P_{t-1}^{D-N}$ 

CEFD: the closed-end fund discount TURN: the natural log of the raw turnover ratio NIPO: number of IPOs RIPO: the average first-day returns

 $S_t$ : sentiment index  $P^{D-ND}$ : dividend premium

This study is based on daily data to study the ultra-short-term impact of the inflow of northbound cash flow on investor sentiment. Other variables lack statistical significance on the scale of day or are difficult to respond to quickly in the stock market. This paper chooses turnover ratio as the proxy variable of investor sentiment (Monthly-data of other variables as the control variables in the regression). In addition, based on the research of Chen et al. (2014), using the ratio of the daily turnover rate to the average turnover rate of the previous 100 days can better measure the relative size of the daily turnover rate data. In addition, multiplying this value by the rise and fall of the index on that day can better help us judge whether the short-term investor sentiment on that day is positive or negative.

 $Market Turnover_{t} = \frac{Turnover_{t}}{Average Turnover for Previous 100 Trading Days}$ Exchange Related Sentiment<sub>t+1</sub> = Market Turnover<sub>t+1</sub> × Pct Chg<sub>t+1</sub> × 100

(In the following, Exchange Related Sentiment $_{t+1}$  will be abbreviated as Sentiment $_{t+1}$ )

## Independent Variable: Net Inflow of Northbound Cashflow

The independent variable of this study is the net inflow of northbound cash flow, which is recorded in millions of yuan. After the closing of each trading day, the data will be reported in China's main financial databases.

## **Control Variables**

**Main Capital Inflow:** In China's securities market, the securities trading software will classify the traded transactions according to the size of a single transaction. The transactions with a single comparison transaction of more than 500,000 yuan will be defined as main capital. Some ordinary individual investors will also consider this indicator as one of the criteria because they believe that the large proportion of main capital in the market means the entry of institutional investors. Therefore, in this study, I take this variable as the control variable, which is also conducive to the comparison with the net inflow of northbound cash flow.

**Sentiment**<sub>t</sub>: Because the sentiment of one day and the sentiment of the next day are not independent of each other, the emotion of one day has a specific conduction effect on the emotion of the next day, so the sentiment<sub>t</sub> is also included in the control variable.

**ISI index (turnover ratio excluded, z-score normalization):** ISI index is the monthly data of comprehensive investor sentiment index calculated based on Baker and Wurgler model and combined with the characteristics of the Chinese market. All original data are from the CSMAR database. In this study, the index is recalculated after excluding the influence of turnover ratio and doing Z-score normalization to the data.

ISI Index =  $\frac{\text{turnover ratio excluded ISI index} - \mu}{\sigma}$ 

μ: The mean value of turnover ratio excluded ISI index

 $\sigma$ : The standard deviation of turnover ratio excluded ISI index

The normalized ISI index data can represent the basic investor sentiment within a certain time range in linear regression. This operation is conducive to separating the basic investor sentiment (including macroeconomic conditions) in a long time range from the investor sentiment fluctuations caused by transactions and capital changes in the ultra-short term. In addition, normalization divides ISI index into positive and negative parts, which is conducive to the classified discussion of the impact of northbound cashflow under different basic investor sentiment in linear regression.

## Data Sorting and Summary

Based on the original data, various calculations and results are summarized in Table 1.

	<b>u</b> 1 j				
Date	Net Inflow of Northbound Cashflow (million)	Main Capital Inflow (million)	Sentiment t	ISI Index	Sentiment t+1
2021-09-09	2422.87	-12179.59	83.89	0.79	48.55
2021-09-08	-2883.61	-18403.70	-6.29	0.79	83.89
2021-09-07	3593.72	4615.75	235.94	0.79	-6.29
2016-01-05	1429.38	-15200.23	-21.71	-0.84	169.87
2016-01-04	31	-27769.37	-394.62	-0.84	-21.71

Through Stata, the data of SH-HK-SC and SZ-HK-SC are summarized and sorted, respectively. The results are shown

in Table 2:

Table 1: Data	Summarv	of SH-HK-SO	C and SZ-SK-SC
1	~ willing		

Table 1: Data Summary

Obs	Mean	Std. Dev.	Min	Max
1323	493.42	2261.62	-10553.88	16811.77
1323	-7316.74	8707.73	-59001.16	26308.08
1323	4.06	150.09	-1304.8	1841.66
1323	0.04	1.016	-1.354	3.041
Obs	Mean	Std. Dev.	Min	Max
1108	680.66	2068.86	-12389.09	11615.6
1108	-5972.85	8062.33	-55338.21	21142.61
1108	7.521	184.00	-973.44	1835.47
1108	.052	1.04	-1.354	3.04
	Obs 1323 1323 1323 1323 1323 Obs 1108 1108 1108 1108	Obs         Mean           1323         493.42           1323         -7316.74           1323         4.06           1323         0.04           Obs         Mean           1108         680.66           1108         -5972.85           1108         7.521           1108         .052	Obs         Mean         Std. Dev.           1323         493.42         2261.62           1323         -7316.74         8707.73           1323         4.06         150.09           1323         0.04         1.016           Obs         Mean         Std. Dev.           1108         680.66         2068.86           1108         -5972.85         8062.33           1108         7.521         184.00           1108         .052         1.04	Obs         Mean         Std. Dev.         Min           1323         493.42         2261.62         -10553.88           1323         -7316.74         8707.73         -59001.16           1323         4.06         150.09         -1304.8           1323         0.04         1.016         -1.354           Obs         Mean         Std. Dev.         Min           1108         680.66         2068.86         -12389.09           1108         -5972.85         8062.33         -55338.21           1108         7.521         184.00         -973.44           1108         .052         1.04         -1.354

The number of observations in the Shenzhen market is larger than that in the Shanghai market. This is mainly because SZ-HK-SC in the Shenzhen market was founded in December 2016, while the data of the Shanghai market compiled by me started on January 4, 2016 (in fact, SH-HK-SC was founded in 2014, but I can't obtain earlier data due to data availability problems). In addition, it can be clearly noted that the capital scale of net inflow of northbound cash flow and main capital inflow in the Shanghai market is significantly larger than that in the Shenzhen market. The main reason is that the overall scale of the Shanghai market is relatively more extensive than that in the Shenzhen market, and the Shanghai market is also the main listing concentration of China's super-large companies. From the perspective of sentiment, the standard deviation of sentiment in the Shanghai market is less than that in the Shenzhen market, which also shows that the volatility of investor sentiment in the Shanghai market is also less than that in the Shenzhen market.

In addition, the line plot drawn according to the data of net inflow of northbound cashflow and investor sentiment in the two markets is shown in the figure below:



From the line plot, there is a certain correlation between the fluctuation of net inflow of northbound cash flow and the fluctuation of sentiment in the two markets. The period of sharp fluctuation of sentiment often occurs near the period of sharp fluctuation of net inflow of northbound cash flow.

According to the two correlation matrices, there is always a very significant relationship between net inflow of northbound cashflow and sentiment<sub>t</sub>, sentiment<sub>t+1</sub>, and main capital inflow. The main capital inflow is more closely related to ISI Index.

#### Table 2: Correlation Matrix of SH-HK-SC

Variables	(1)	(2)	(3)	(4)	(5)
(1) Net Inflow of Northbound Cashflow	1.000				
(2) Main Capital Inflow	0.399***	1.000			
(3) Sentiment <sub>t</sub>	0.376***	0.696***	1.000		
(4) ISIIndex	-0.055**	-0.242***	0.046*	1.000	
(5) Sentiment <sub>t+1</sub>	0.140***	0.055**	0.017	0.035	1.000
*** p<0.01, ** p<0.05, * p<0.1					

Table 3.	Correlation	Matrix	of SZ-HK-SC

Variables	(1)	(2)	(3)	(4)	(5)
(1) Net Inflow of Northbound Cashflow	1.000				
(2) Main Capital Inflow	0.519***	1.000			
(3) Sentiment <sub>t</sub>	0.427***	0.694***	1.000		
(4) ISIIndex	-0.042	-0.265***	0.011	1.000	
(5) Sentiment <sub>t+1</sub>	0.142***	0.094***	0.054*	0.004	1.000

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

According to the two correlation matrices, there is always a very significant relationship between net inflow of northbound cashflow and sentimentt, sentimentt+1, and main capital inflow. The main capital inflow is more closely related to ISI Index.

# Regression

#### VAR Model

In this study, sentiment and the net inflow of northbound cash flow are used as two variables of a vector autoregression. The regression models of these two-time series are as follows:

$$\begin{bmatrix} N_t \\ S_t \end{bmatrix} = a_0 + A_1 \begin{bmatrix} N_{t-1} \\ S_{t-1} \end{bmatrix} + \dots + A_k \begin{bmatrix} N_{t-k} \\ S_{t-k} \end{bmatrix} + \begin{bmatrix} \epsilon_1, t \\ \epsilon_2, t \end{bmatrix}$$

Nt: The net inflow of Northbound cashflow at t

 . .

**S**<sub>t</sub>: The sentiment at t

. .

Since the basic assumption of the VAR model is based on stationary time series, for these data, sentiment<sub>t</sub> and the net inflow of northbound cashflow must be stationary time series. Therefore, out unit root tests are performed for these two time series.

D'1 E 1	1 4 4 6 - 14 4	т	4 14 1D'1 - E	11
Dickey-Ful	ler test for unit root		nterpolated Dickey-Fu	ller
-	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-25.495	-3.430	-2.860	-2.570
MacKinnon	approximate p-value for	r Z(t) = 0.0000		
Table 6: Sen	timent (Shanghai)			
Dickey-Ful	ler test for unit root	I	nterpolated Dickey-Fu	ller
-	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-39.655	-3.430	-2.860	-2.570
MacKinnon	approvimate n-value for	r Z(t) = 0.0000		
Wackinnon				
Table 7: The Dickey-Ful	e net inflow of Northbour ler test for unit root	nd cashflow (Shenzhen)	nterpolated Dickey-Fu	ller
Table 7: The Dickey-Ful	e net inflow of Northbour ler test for unit root Test Statistic	nd cashflow (Shenzhen) I: 1% Critical Value	nterpolated Dickey-Fu 5% Critical Value	ller 10% Critical Value
Table 7: The Dickey-Ful Z(t)	e net inflow of Northbour ler test for unit root Test Statistic -26.893	nd cashflow (Shenzhen) If 1% Critical Value -3.430	nterpolated Dickey-Fu 5% Critical Value -2.860	ller 10% Critical Value -2.570
Table 7: The Dickey-Ful Z(t) MacKinnon	e net inflow of Northbour ler test for unit root Test Statistic -26.893 approximate p-value for	nd cashflow (Shenzhen) If $1\%$ Critical Value -3.430 r Z(t) = 0.0000	nterpolated Dickey-Fu 5% Critical Value -2.860	ller 10% Critical Value -2.570
<b>Table 7:</b> The Dickey-Ful Z(t) MacKinnon	e net inflow of Northbour ler test for unit root Test Statistic -26.893 approximate p-value for	nd cashflow (Shenzhen) 1% Critical Value -3.430 r $Z(t) = 0.0000$	nterpolated Dickey-Fu 5% Critical Value -2.860	ller 10% Critical Value -2.570
Table 7: The Dickey-Ful Z(t) MacKinnon	e net inflow of Northbour ler test for unit root Test Statistic -26.893 approximate p-value for timent (Shenzhen)	nd cashflow (Shenzhen) 1% Critical Value -3.430 r $Z(t) = 0.0000$	nterpolated Dickey-Fu 5% Critical Value -2.860	ller 10% Critical Value -2.570
Table 7: The         Dickey-Ful         Z(t)         MacKinnon         Table 8: Sen         Dickey-Ful	e net inflow of Northbour ler test for unit root Test Statistic -26.893 approximate p-value for timent (Shenzhen) ler test for unit root	nd cashflow (Shenzhen) If 1% Critical Value -3.430 r $Z(t) = 0.0000$	nterpolated Dickey-Fu 5% Critical Value -2.860 nterpolated Dickey-Fu	ller 10% Critical Value -2.570 ller
Table 7: The         Dickey-Ful         Z(t)         MacKinnon         Table 8: Sen         Dickey-Ful	e net inflow of Northbour ler test for unit root Test Statistic -26.893 approximate p-value for timent (Shenzhen) ler test for unit root Test Statistic	nd cashflow (Shenzhen) I: 1% Critical Value -3.430 r $Z(t) = 0.0000$ I: 1% Critical Value	nterpolated Dickey-Fu 5% Critical Value -2.860 nterpolated Dickey-Fu 5% Critical Value	ller 10% Critical Value -2.570 ller 10% Critical Value

The results of the unit root test show that both time series are stationary time series, so the VAR model is effective in this situation.

#### **Linear Regression Equation Model**

 $Sentiming_{t+1} = \beta_1 \times Net Inflow of Northbound Cashflow_t + \beta_2 \times Main Capital Inflow_t + \beta_3 \times Sentiment_t$ 

 $+ \beta_4 \times ISI_t + \varepsilon$ 

MacKinnon approximate p-value for Z(t) = 0.0000

The purpose of this model is to test the impact of net inflow of northbound cash flow on investor sentiment the next day. Since the data of main capital inflow, like northbound cash flow, will appear on the pages of major securities trading websites, it is also used as a control variable. Moreover, due to the continuity of investor sentiment, this study also consider the investor sentiment of the day, the overall market sentiment of the month, and the sentiment affected by macroeconomic conditions in the model.

Table 5: SH Collinearity Diagnosis		
SH-HK-SC	VIF	1/VIF
Main Capital Inflow	2.350	0.425
Sentiment <sub>t</sub>	2.180	0.458
Net Inflow of Northbound Cashflow	1.220	0.822
ISIIndex	1.170	0.853
Mean VIF	1.730	

# Table 5: SH Collinearity Diagnosis

#### Table 10: SZ Collinearity Diagnosis

SZ-HK-SC	VIF	1/VIF
Main Capital Inflow	2.560	0.390
Sentiment <sub>t</sub>	2.110	0.474
Net Inflow of Northbound Cashflow	1.400	0.716
ISIIndex	1.180	0.849
Mean VIF	1.810	

According to the collinearity diagnosis in Table 9 and Table 10, the VIF values of all variables in the two markets are less than 5; that is, there is no multicollinearity between the variables in the linear regression model. Then the regression equation can be effective.

# Results

## VAR

#### Granger Causality Test

This study uses the Granger causality test program in Stata to test and obtains the following two tables:

Table 6: Granger causality Wald tests	(SH-HK-SC)			
Equation	Excluded	chi2	df	Prob>Chi2
Sentiment <sub>t</sub>	Net Inflow of Northbound Cashflow	12.293	1	0.000
Sentiment <sub>t</sub>	ALL	12.293	1	0.000
Net Inflow of Northbound Cashflow	Sentiment <sub>t</sub>	2.4864	1	0.115
Net Inflow of Northbound Cashflow	ALL	2.4864	1	0.115
Table 7: Granger causality Wald tests	(SZ-HK-SC)	ahi2	df	Droh\Chi2
Equation	Excluded	cn12	ai	Prob>Cni2
Sentiment <sub>t</sub>	Net Inflow of Northbound Cashflow	16.706	1	0.000
Sentiment <sub>t</sub>	ALL	16.706	1	0.000
Net Inflow of Northbound Cashflow	Sentiment <sub>t</sub>	30.784	1	0.000
Net Inflow of Northbound Cashflow	ALL	30.784	1	0.000

The results of these two tables are obtained according to the Akaike Information Criterion (AIC) minimization principle to ensure the optimal statistical model fitting. The lag orders selected for the Shanghai market and Shenzhen market are 2 and 1, respectively. According to the results, the net inflow of northbound cash flow is the Granger cause of sentiment<sub>t</sub> in both markets. In both Shanghai and Shenzhen markets, changes in investor sentiment will be affected by northbound cash flow. *Impulse Response Function (IRF)* 

This study uses the impulse response function in Stata to export the following two figures:







The ordinates of the two figures represent a percentage, while the abscissa represents time in days. The two figures show that when the northbound cash flow is impacted, investor sentiment will produce a response in the same direction, and the overall trend of this response will decline over time. However, there are some differences in the specific responses in the two markets. In the Shanghai market, when the northbound cash flow is impacted by a standard deviation, investor sentiment will immediately respond with about 50% standard deviation, while in the Shenzhen market, this data is 70% standard deviation. In addition, there are some differences in the duration of response after the impact of northbound cash flow in the two markets. In the Shanghai market, the response after the impact can last for more than five days, while in Shenzhen, the response caused by the impact will completely disappear after three days.

#### **Linear Regression Equation Model**

The linear regression results of the Shanghai market and Shenzhen market are derived as shown in the tables below:

Table 15. OLD Results, SIT Market			
SH market	(Overall)	(ISI +)	(ISI -)
	Sentiment <sub>t+1</sub>	Sentiment <sub>t+1</sub>	Sentiment <sub>t+1</sub>
Net Inflow of Northbound Cashflow	.01***	.006**	.015***
	(.002)	(.003)	(.003)
Main Capital Inflow	.001*	.001	.002
	(.001)	(.001)	(.001)
Sentiment <sub>t</sub>	097**	04	133***
	(.04)	(.065)	(.051)
ISI Index	9.854**	15.501*	21.895
	(4.337)	(8.851)	(15.802)
cons	9.563	802	18.818
	(6.888)	(12.679)	(14.073)
Observations	1323	593	730
R-squared	.026	.018	.043

 Table 13: OLS Results. SH Market

Standard errors are in parentheses. \*\*\* p<.01, \*\* p<.05, \* p<.1

SZ market	(Overall)	(ISI +)	(ISI -)
	Sentiment <sub>t+1</sub>	Sentiment <sub>t+1</sub>	Sentiment <sub>t+1</sub>
Net Inflow of Northbound Cashflow	.011***	.008**	.019***
	(.003)	(.004)	(.006)
Main Capital Inflow	.002	.001	.002
	(.001)	(.001)	(.002)
Sentiment <sub>t</sub>	049	021	09
	(.043)	(.07)	(.057)
ISI Index	4.861	13.338	-1.27
	(5.672)	(10.942)	(20.542)
cons	9.334	895	3.664
	(9.358)	(16.446)	(19.378)
Observations	1108	508	600
R-squared	022	024	028

Standard errors are in parentheses. \*\*\* p<.01, \*\* p<.05, \* p<.1

For the two markets of Shanghai and Shenzhen, the same linear regression equation is used three times, respectively. The regression data in the first column is the regression result of the overall data, while the second and third columns are based on the positive or negative classification discussion of the overall market sentiment considering the macroeconomic situation.

Firstly, in all classification discussions, the impact of net inflow of northbound cash flow on sentiment is always significant, and the value of the coefficient is always greater than 0. This proves that the inflow of Northbound Cashflow by the Chinese mainland stock market will play a positive role in promoting investor sentiment in the whole market. In addition, comparing the impact of northbound cash flow with that of main capital inflow, we can find that the impact of main capital inflow on sentiment is not significant. This also means that judging the trend of market investor sentiment through the data of main capital inflow is of little significance. The possible reason is that the real main capital, that is, large professional investors or institutional investors, use the program to split a transaction into multiple small transactions with an amount of less than 1 million yuan today, to hide their real large-scale buying or selling behavior.

Secondly, compare the difference of results brought by the positive and negative of basic investor sentiment (ISI Index), including macroeconomic conditions, over a period. In Shanghai and Shenzhen stock markets, the impact of northbound cash flow on sentiment is stronger than that in the period of high market sentiment. From the perspective of efficiency, the value of efficiency under negative sentiment in the Shanghai market is 150% higher than that under the positive sentiment, while in the Shenzhen market, the figure is 137.5%. This result can be explained by the theory of myopia loss aversion of Thaler et al. (1997). Thaler pointed out that when investors do not often evaluate their investments, it often means that they are more

willing to accept risks. When the overall market sentiment is high, most investors benefit from the stock market, and investors will show confidence in their investment decisions. At this time, investors are often more willing to accept risks and pay less attention to external information. When the market sentiment is depressed, and investors suffer losses, investors are more likely to doubt their investment decisions, reassess their investments frequently, and hope to rely on external information to make trading decisions. In this case, the change of northbound cashflow data is more likely to attract the attention of investors, thus more significantly affecting investor sentiment.

Thirdly, compare the regression results of the Shanghai and Shenzhen markets. Under the regression of three different categories, the investor sentiment in the Shenzhen market is more sensitive to northbound cash flow than that in the Shanghai market. According to the research results of Ni et al., the stock prices of enterprises with large scale, strong profitability and long profit history, especially state-owned enterprises, are not easy to be affected by the sentiment of market investors. The Shanghai Stock Exchange happens to be the main position for the listing of China's large state-owned enterprises and giants in traditional industries such as banking, oil, and mining. There are many innovative enterprises with a relatively small market value on Shenzhen Stock Exchange. Therefore, we can also judge that the investor sentiment of large companies and state-owned enterprises in traditional industries is also relatively weak affected by northbound cash flow. On the contrary, the investor sentiment of innovative growth enterprises will be more sensitive to the impact of northbound cash flow.

#### Robustness

In this study, the residuals of the linear regression model were suppressed, and OLS regression was performed again as the robustness test. Results as shown in Table 15 and Table 16, the positive and negative and relative size relationships of all coefficients remain unchanged, so the model passes the robustness test.

<b>Fable 15:</b> Robustness, SH Market									
SH market	(Overall)	(ISI +)	(ISI -)						
	Sentiment <sub>t+1</sub>	Sentiment <sub>t+1</sub>	Sentiment <sub>t+1</sub>						
Net Inflow of Northbound Cashflow	.011***	.006**	.015***						
	-0.002	-0.003	-0.003						
Main Capital Inflow	0.001	0.001	0.001						
	0	-0.001	-0.001						
Sentiment <sub>t</sub>	068**	-0.041	111**						
	-0.034	-0.06	-0.049						
ISI Index	8.257**	15.251*	5.168						
	-4.183	-7.916	-9.66						
Observations	1323	593	730						
R-squared	0.025	0.019	0.041						

Standard errors are in parentheses. \*\*\* p<.01, \*\* p<.05, \* p<.1

### **Conclusion** and Limitations

## Conclusion

Based on the daily trading data of northbound cash flow in Hongkong and Shanghai Stock Exchange, the paper explores the impact of northbound cash flow's change on short-term investor sentiment in the Chinese mainland market based on the Shanghai and Shenzhen two cities. According to the results of the Granger causality test and impulse response function, it is confirmed that there is a specific causal relationship between northbound cash flow and investor sentiment from a statistical point of view. And when the northbound cash flow is impacted, the impact on investor sentiment may last for several days. Based on the linear regression function constructed according to northbound cash flow and sentiment, it is proved again that there is a positive correlation between northbound cash flow and sentiment. In addition, according to the normalized ISI data, this study found that when the overall market investor sentiment is depressed, sentiment is more significantly affected by the change of northbound cash flow. The sentiment is more sensitive to the change of northbound cash flow. Finally, this study also found differences in the stability of investor sentiment in different markets. Compared with the Shanghai market dominated by large enterprises and state-owned enterprises, the investor sentiment in the Shenzhen market is more sensitive to the changes of northbound cash flow. This study fills the gap in the study of the impact of a unique cash flow in securities trading on ultra-short-term investor sentiment in the market. This has a specific reference significance for ordinary investors to trade in the A-share market. When we decide to buy stock shortly, we may have a greater probability of obtaining a

favorable purchase price by buying the stock one day after the outflow of northbound cash flow. On the contrary, when deciding to sell stocks, it may be more appropriate to sell at the time point after the capital inflow to the north.

SZ market	(Overall)	(ISI +)	(ISI -)
	Sentiment <sub>t+1</sub>	Sentiment <sub>t+1</sub>	Sentiment <sub>t+1</sub>
Net Inflow of Northbound Cashflow	.013***	.008**	.02***
	-0.003	-0.004	-0.005
Main Capital Inflow	0.001	0.001	0.002
-	-0.001	-0.001	-0.002
Sentiment <sub>t</sub>	-0.03	-0.022	-0.088
	-0.038	-0.066	-0.055
ISI Index	3.36	13.088	-4.23
	-5.469	-9.924	-13.285
Observations	1108	508	600
R-squared	0.023	0.025	0.031

#### Table 16: Robustness, SZ Market

Standard errors are in parentheses. \*\*\* p<.01, \*\* p<.05, \* p<.1

# Limitations and Future Steps

There are still many defects in this study. Firstly, to simplify the classification and discussion of the study on the overall investor sentiment of different societies, the data of the normalized ISI index is divided into positive and negative parts. In future research, there should make a more refined classification. Alternatively, filtering the data of some abnormal periods for separate analysis can be considered. For example, the A-share market plunged in 2015. In future research, some of the data should be screened for abnormal periods and analyzed separately. For example, the A-share market plunged in 2015. Or since 2019, the global economy has been influenced by COVID-19 and the quantitative easing policy of central banks. In addition, in dealing with the overall market sentiment, this study simply substitutes the monthly data of the data into the daily model. An important problem brought about by this is that there will be a sudden change in the data of the overall economic situation from the end of each month to the beginning of the next month, but there will be no change in each month. This is different from the actual situation. There may be better models to measure the daily socio-economic and investor sentiment in future research.

Secondly, this study takes the whole market as the research object to analyze investor sentiment. In the real market, the investor sentiment of individual stocks is likely to deviate from that of the whole market. Moreover, northbound cash flow's shareholding ratio in the overall A-share market is not significant. In addition, northbound cash flow is not balanced for the inflow of Chinese mainland stocks. When the concentration of funds into several stocks leads to high investor sentiment in some stocks, the impact is likely not enough to cause significant changes in investor sentiment in the whole market. In future research, select stocks may be examined to study the relationship between northbound cash flow and investor sentiment.

Thirdly, the linear regression model of this study selects the relationship between the inflow day of northbound cash flow and the 2nd-day investor sentiment as the research object. According to the conclusion of the impulse response function, the impact of northbound cash flow on investor sentiment will last for several days. In future research, different hysteresis periods can be used for testing.

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# **Does Financial Development Cause Economic Growth? Time-Series Evidence from Sri Lanka**

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# Abstract

The objective of this study is to investigate the relationship between financial development and economic growth in Sri Lanka over the period of 1980-2019. Instead of using several financial development indicators, a recently developed financial development index was used to capture the role of financial development. Using the Autoregressive Distributed Lag (ARDL) bounds test technique and an Error-Correction Model, we have found evidence that financial development has a positive impact on economic growth in Sri Lanka both in the short-run and the long-run.

JEL Codes: C32, G20, O47 Keywords: Economic growth, financial development, ARDL model, Sri Lanka

#### Introduction

The relationship between financial development and economic growth has been studied theoretically and empirically since as early as the 1900s. Empirical studies have been conducted either on an individual country or on geographic regions, or on countries by income-groups, among others. Empirical approaches to these studies are equally varied relying on cross-country or on a combination of cross-section and time-series methods panning across ordinary least squares (OLS), generalized least squares (GLS), two-stage least squares (TSLS), non-linear autoregressive distributed lag model (ARDL), fully modified ordinary least squares (FMOLS); vector error-correction model (VEC), generalized least squares (GLS) method, generalized method of moments (GMM), and bootstrap panel Granger causality.

Early studies have concluded that financial development predicts growth, but they were not able to investigate causality and direction in this relationship. In addition, these studies often ignored stationarity or cointegration of variables in the long run. As time-series studies became more widespread, analysts refocused their attention on the direction and causality between financial development and economic growth using multiple regression estimation methods. There are no previous studies on the relationship between the financial development and economic growth in Sri Lanka. Recent trends in economic growth and financial development are presented Figure 1. The objective of this study is to fill the gap in the literature by investigating the nexus between financial development in economic growth in Sri Lanka from 1980-2019.

The paper is organized as follows. The next section presents the review of literature while the following section presents the methodology and data sources. Empirical results then a discussion of the results and conclusion follows.

### **Literature Review**

A rich variety of studies could be found in literature on the relationship between economic growth and financial development. Hsueh, Hu, and Tu (2013) have used the method of bootstrap panel Granger causality which was proposed by Konya (2006) to analyze causal relations of financial development and economic growth among ten OECD countries over 27 years between 1987 to 2007. Issues of slope heterogeneity and cross-sectional dependency were simultaneously considered by this method. The study found that the causality direction between financial development and economic growth is responsive to financial development variables used.

Botev, Egert and Jawadi (2019) have done a study in developing, emerging and advanced economies using sample countries to analyze the relationship between financial development and economic growth. Three main areas were focused using nonlinear techniques. The areas were to identify whether the relationship between financial development and economic growth become negative at high developed financial levels, to identify whether the effect of financial development on economic development is subject to the trade openness, human capital, and overall economic development level. From the results obtained, the study could not confirm the hypothesis that the relationship between financial development and economic growth become clearly negative beyond a given level of financial development. Further it is founded that the banking and market finances are complementary. Finally, as per the results the effects of bank and market finance have not seem to be subjected to economic development and trade openness.



Figure 1. Financial Development and Economic Growth in Sri Lanka, 1980-2019

Song, Chang, and Gong (2021) have analyzed the causality and cointegration among broad money, gross domestic product and corruption using data from 142 developed and developing countries from 2002 to 2016. Panel cointegration test was used and the results confirmed that significant cointegration relationship are existed among the three variables irrespective of whether the full sample or developing country sub sample is used. Further the "Fully Modified Ordinary Least Square" method has shown that corruption has negative effect on broad money for both samples while GDP has positive effect on broad money only for developed country sample. Finally for the full sample and developing country sample, broad money is impacted by gross domestic product and corruption only in the long term when using VECM estimation.

A study done by Osei and Kim (2020) has shown that a well-developed financial sector is a significant foundation for the growth of Foreign Direct Investment (FDI). However, it has provided evidence that FDI is subject to reduced returns with the increased financial market development. In other words, the study shows that a potential maximum financial development threshold is exceeded the economic growth impact of FDI becomes insignificant.

Mollaahmetoglu and Akcali (2019) have done research to analyze how financial innovation impacts on economic growth as another link beside financial development which is represented with financial access, efficiency, depth, and stability variable using panel data analysis that covers 15 countries from 2003-2016. The study has statistically proven the fact that the higher financial innovation is significantly and positively related with higher macro-economic growth.

A paper done by Christopoulos and Tsionas (2004) has investigated the long-term relationship between financial depth and economic growth using panel root tests, panel cointegration analysis, threshold cointegration tests, Fully Modified Ordinary Least Square method (FMOLS) and dynamic panel data estimation for 10 developing countries. The evidence supports the hypothesis that a single equilibrium relationship is existed between financial depth, growth, and ancillary variables. Further, a unidirectional causality from financial depth to growth is implied by the cointegrating relation.

Cheng, Chien, and Lee (2021) have contributed to find how ICT diffusion and financial development influence on economic growth using an economic growth model considering the joint effect of these two factors. Principal Component Analysis (PCA) and Generalized Method of Moments (GMM) have been used to catch the universal effect of financial development on economic growth and the three variables have been combined into a broad index. The study has used a wider dataset consisting of 72 countries from 2000-2015 with the purpose of getting the impact of different income level countries. The three-fold result evidenced from the study was that the financial development is always unfavorable for economic growth irrespective of income level, ICT diffusion can enhance the economic growth in high income countries and finally the interaction effects between ICT and financial development are positively related in all income levels.

A paper written by Yang (2019) has been tested how financial system development is positively influenced to economic development of a nation among different economies. By augmenting the previous research studies, the research has found

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that the financial development is significantly contributed to economic growth through channels of physical capital stock and total factor productivity, Granger causality is existed between economic growth and equity market development, a reverse causality is existed between economic growth and equity market development in high income economies and specifically in trapped middle-income economies, Granger causality and feedback between inflation and banking system development is found.

Pradhan, Arvin, and Bahmani (2018) have employed panel unit root and panel cointegration tests to determine the interactions between financial development, economic growth, and innovation. The study has used data from 49 European countries between 1961 and 2014. The results of the study have suggested a cointegrating relationship between the three variables. It is shown that financial development and innovation are causative factors of economic growth in the long term by estimating a vector error-correction model. Finally, the research has recommended to have policy focus on financial development and innovation to enhance the economic performance.

By the time Sobiech (2019) has done this paper, the impact of remittances on economic growth has been relatively a new topic in the literature. Sobiech (2019) has contributed by creating a brand-new index of overall financial development and two other estimation methods called QML- FE (Quasi-Maximum Likelihood for dynamic panel data with Fixed Effects) and GMM (Generalized Method of Moments). The research results have suggested that important poverty alleviating advantages can be obtained by encouraging migrants' transfers in short term, while in the long term it is more advantageous for government to enhance financial sector development.

Comprehensive work could be found in literature in different countries of the world such as Saudi Arab, Ghana, Kenya, Korea, Russia, Tunisia, and Egypt on the relationship between economic growth and financial development.

Samargandi, Fidrmuc, and Ghosh (2014) have found that financial development has a positive impact on the non-oil sector growth while having a negative impact for oil sector growth in the context of Saudi- Arab which is an oil rich economy utilizing the Autoregressive Distributed Lag (ARDL) Bounds test technique. The study has concluded that the relationship between financial development and growth is subject to resource dominance in economies.

Adu, Marbuah, and Mensah (2013) have investigated the long-term growth effects of financial development in Ghana. Eight alternative proxy indicators have been used in this analysis. Principal Component Analysis (PCA) has been used to reduce the dimension of the proxies from eight to four while retaining the total variance in the data at approximately 95%. It is found that the growth effect of financial development is dependent to the proxy choice. Important finding in the research was that the credit to the private sector as ratios to total domestic credit and GDP were growth inducing while Broad Money stock (BM) to GDP ratio is not growth inducing.

A study by Uddin, Sjo, and Shahbaz (2013) when the economy of Kenya is developing, to reinvestigate the relationship between financial development and economic growth over the period of 1971-2011 in Kenya using the Cobb-Douglas production function. Gregary and Hansen's structural break cointegration approaches and a simulation based ARDL bounds testing have been used for the analysis. The research has found that the financial sector development has a positive impact on economic growth in the long term.

Yang and Yi (2008) have done research to examine the causal relationship between financial development and economic growth using annual data for Korea from 1971-2002 utilizing the super exogeneity methodology. During the period used, Korea has experienced a variety of financial liberalization, reforms, and phenomenal economic growth. The study has found that the financial development control causes economic growth. Further the evidence of the study has accepted the view of "finance causes growth" while rejecting the view of "growth causes finance". Further, this study has suggested to prioritize financial reform in policy perspective rather than economic growth because a sustainable growth in the medium or long term can be achieved only by having a decisive and accelerated speed of financial restructuring.

Ono (2017) has done a study to investigate the finance growth nexus in Russia considering oil prices and foreign exchange rates using the vector autoregression model. Two sub periods were analyzed: namely 1999-2008 (sub period 1) and 2009-2014 (sub period 2). The results have suggested that causality exists from economic growth to money supply and bank lending for the sub period 1 while no causality exist from money supply to economic growth indicating that economic growth granger causes bank lending for sub period 2. The study has related the results for the dramatic reduction in foreign exchange market interventions.

Jedidia, Boujelbène, and Helali (2014) have done a study using Autoregressive Distributed Lag method to examine the finance growth relationship considering financial development indicators namely private credit, value traded and issuing bank's securities on the financial market in Tunisia. The results have suggested that the domestic credit to private sector effects positively on the growth of economy. Finally, the research recommends to Tunisia to prioritize on the financial reforms of the stock market in Tunisia to encourage long term economic growth and to contribute to mobilize savings.

Abu-Bader and Abu-Qarn (2008) have done a study to examine the causal relationship between financial development and economic growth, and investment being the additional variable within a Trivariate Vector Autoregressive framework (VAR) during the period 1960 - 2001 in Egypt. The results have supported strongly to the view that financial development and economic growth are mutually causal bi-directionally. The study finally recommends prioritizing on financial reforms and to improve the efficiency of financial system for long term growth prospects.

### **Methodology and Data**

# **Model Specification**

Drawing on the existing empirical literature (see, for example, Botev, Egert, and Jawadi (2019) and Hassan, Sanchez, and Yu (2011)), the starting point is to specify the following growth regression:

$$GROWTH_t = f(GRK_t, GRL_t, GHC_t, OPEN_t, GOV_t, INF_t, FD_t)$$
(1)

where  $GROWTH_t$  is the growth rate of real GDP per capita; t = 1, 2, ..., 40;  $GRK_t$  is the growth rate of capital stock;  $GRL_t$  is the growth rate of labor;  $GHC_t$  is the growth rate of human capital;  $OPEN_t$  is the exports plus imports as a share of GDP;  $GOV_t$  is the government expenditure as a share of GDP;  $INF_t$  is the inflation rate measured using the consumer price index (CPI); and  $FD_t$  is a variable representing financial development.

In addition to the explanatory variables included in Equation (1), we have also introduced a dummy variable (WAR) to account for the ethnic war in Sri Lanka that lasted from 1977 to 2009. Assuming that the model specified in Equation (1) is linear, we can write the following empirical specification of our growth model:

$$GROWTH_t = \beta_0 + \beta_1 GRK_t + \beta_2 GRL_t + \beta_3 GHC_t + \beta_4 OPEN_t + \beta_5 GOV_t + \beta_6 INF_t + \beta_6 FD_t + \beta_7 WAR_t + \varepsilon_t$$
(2)

where  $\varepsilon_t$  is the error term. Other variables are defined earlier. *A priori*, the signs of variables  $GRK_t$ ,  $GRL_t$ , and  $GHC_t$  are expected to be positive. The expected sign of  $OPEN_t$  variable is also positive. The expected sign of  $GOV_t$  variable can be either positive or negative. The expected sign of  $INF_t$  variable is negative. The expected sign of  $FD_t$  variable can also be either positive or negative depending on whether financial development enhance or deter economic growth. The expected sign of  $WAR_t$  variable is also negative.

## Definition of Variables, and Data Sources

The dependent variable, GROWTH, is the growth rate of real GDP per capita. The growth rate of physical capital (GRK) is measured by gross fixed capital formation as a percent of GDP. The growth rate of labor (GRL) is measured by a proxy variable, namely, the growth rate of population. Trade openness (OPEN) variable is measured as exports plus imports) divided by GDP. GOV is measured as the government expenditure as a share of GDP. The growth rate of human capital (GHC) variable is defined as the growth rate of average years of schooling. Inflation (INF) variable is measured as the annual percentage change in the consumer price index. The data on GROWTH, GRK, GRL, OPEN, GOV, GHC, and INF variables were collected from the World Bank, *World Development Indicators 2021 database*. Data on the financial development index (FD) were collected from the International Monetary Fund, *Financial Development Index database*.

#### **Summary and Conclusions**

The objective of this study is to investigate the relationship between financial development and economic growth in Sri Lanka over the period of 1980-2019. Unit root tests confirm that all variables non-stationary at the levels but are stationary at the first difference. Johansen cointegration test confirms that the Trace test indicates three cointegrating equations at the 1% level of significance, implying that the eight variables are cointegrated. The Maximum Eigenvalues test also shows evidence for the presence of two cointegrating equations. The results of the OLS, FMOLS, and DOLS show that all variables included in the model have the expected signs and most of the variables are statistically significant either at the 1% or the 5% level of significance. Financial development variable (FD) has a positive sign in all three models, and it is also statistically significant in two of the three models estimated.

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# A Panel Data Analysis of the Growth Effects of Workers' Remittances and Financial Development: Empirical Evidence from Asian Countries

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## Abstract

The objective of this study is to investigate the relationship between workers' remittances, financial development, and economic growth in Asian countries. The study uses a panel data set covering 10 Asian countries during the period 1980-2018. We have carried out panel unit-root tests and panel cointegration tests before estimating the specified models using different estimation methods. Three estimations methods were used to estimate the specified model. The results of the study provide evidence to conclude that there is a direct relationship between workers' remittances and economic growth as well as between financial development and economic growth in Asian countries.

#### JEL Codes: C33, F24, G20, O47

Keywords: Economic growth, financial development, remittances, panel data models

#### Introduction

The relationship between workers' remittances and economic and the relationship between financial development and economic growth have been studied theoretically and empirically since as early as the 1900s. Empirical studies have been conducted on either an individual country or on geographic regions or by income-groups, among others. Empirical approaches to these studies are equally varied relying on the type of data utilized such as time-series data, cross-sectional data, or panel data. They also differ based on the different estimation methods used. Financial development variables used in these studies have included either or a combination of domestic credit provided to the private sector, domestic credit provided by the banking sector, liquid liabilities, gross domestic savings, stock market capitalization, and the bond market. In this study, a financial development index developed by Sviydzenka (2016) and Sahay et al. (2015) is used. The selection of 10 Asian countries includes both emerging markets and low-income countries. The 10 countries are Bangladesh, China, India, Indonesia, Malaysia, Nepal, Pakistan, the Philippines, Sri Lanka, and Thailand.

Early cross-country studies have concluded that financial development predicts growth, but they were not able to investigate causality and direction in this relationship. In addition, these studies often ignored stationarity or cointegration of variables in the long run. As time-series studies became more widespread, analysts refocused their attention on the direction and causality between financial development and growth using panel regressions estimation methods. While consensus exist on causality, the direction of that causality seems to differ by region, with well-developed high income countries demonstrating causality from financial development to growth. On the other hand, causality could go either or both ways in developing countries, depending on the use of financial development proxies and the maturity of the financial sector. The relationships between workers' remittances and economic growth have also drawn great attention in recent years. However, the literature is ambivalent on the nature of these relationships. Some studies have found evidence to suggest that workers' remittances have a negative effect on economic growth.

There appears to be no previous study that has investigated the relationship between workers' remittances, financial development, and economic growth focusing on the Asian region. The objective of this study is to fill the gap in the literature by investigating the nexus between workers' remittances, financial development, and economic growth in 10 developing countries in Asia from 1980-2018. Moreover, the impact of the financial/banking crises on economic growth in these countries is explored. This study investigates this relationship in a few steps. First, the presence of panel unit-roots for each of the variables included in our specified models is considered. Second, a test for panel cointegration among the variables included in the specified model is performed. Finally, the specified model using different estimation methods is estimated to test for sensitivity of results to methodology employed. In addition to this contribution to the literature, the focus on an important region that has been receiving an increasing share of worldwide workers' remittances flows.

The results of the study provide evidence of a direct relationship between workers' remittances and economic growth and between financial development and economic growth in Asian countries. Results further reveal that the financial/banking crises had negatively impacted economic growth in the pooled sample of 10 Asian countries.

The paper is organized as follows: the next section presents the review of literature while the methodology and data sources follows. Next, empirical results and a conclusion are provided.

#### **Literature Review**

In the review of literature, first the focus is on the studies that investigate the effects of financial development on economic growth and focus on studies that explore the effects of workers' remittances on economic growth. The relationship between economic growth and financial development has been the focus of a rich variety of studies and include famous scholars such as Schumpeter (1911), Kuznets (1955), Lewis (1956), and Rostow (1959) who saw varying importance of the role of financial development on economic growth but did not view financial development as endogenous to growth. Early empirical studies (Robinson, 1952; Patrick, 1966) reinforced this claim based on the conventional wisdom that developing countries' financial systems were underdeveloped (Lewis, 1956; Adu et al., 2013; Hsueh, 2013), contending that technology was the prime determinant in economic growth, and that financial development followed as a result of this growth. By the 1980s, however, research actively investigated the economic growth-financial markets nexus. The reasoning behind this approach is that a well-greased financial system offers increased pooling of resources, reduced risks, reduced transaction and costs and interest rates, increased investments, increased allocation of resources to more profitable organizations, enhanced entrepreneurship, and therefore, greater economic efficiency and growth (Bekaert et al., 2005). Henceforth, most studies, based on varying sample sizes, countries, regions, income groups, time periods, and empirical approaches focused on correlation vs causation and the direction of the FD and growth relationship and causality.

While many studies support the FD to economic growth causality, they also contend that unsustainable credit liberalization has a huge cost to growth. For example, Ibrahim and Alagidede (2018), relying on panel data for 29 Sub-Saharan African countries between 1980–2014, reveal that while financial development supports economic growth, the extent to which finance helps growth depends crucially on the synchronized growth of the real and financial sectors, and that the financing of risky and unsustainable investments adversely affects economic growth.

Destek et al. (2020) extend the financial development and economic inequality nexus in Turkey from 1990 to 2015, based on Rostow's theory of Growth and Kuznets' inverted-U curve (Kuznets, 1955) hypothesis. Unlike most other studies, they include the bond market as a component of financial development. Utilizing the ARDL bound testing procedure, their results confirm the inverted U-shaped relationship between financial development overall and income inequality, implying a positive relationship between financial development overall and economic growth. They contend that income distribution is adversely affected by financial development in the initial stages of the development of the banking sector, but as economic growth increases, financial risk is mitigated by the banking sector, and this facilitates accessibility to credit by low-income segments of the population. At the same time, they conclude no statistical significance of the bond market with inequality and therefore, economic growth. Their study further provides evidence that low-income segments benefit more than high-income segments of the population as a result of financial development and economic growth. The implication of Destek et al. (2020), Tiwari et al. (2013), and Pradhan (2009) to our study is that developing countries, in particular in South Asia and Sub-Saharan Africa, have large rural populations and a large degree of income inequality.

The relationships between workers' remittances and economic growth have drawn great attention in recent years; however, the literature is ambivalent on the nature of these relationships. Some studies have found evidence to suggest that remittances promote economic growth, while others found evidence to suggest that remittances have a negative effect on economic growth. Though there are a large number of studies on the remittances-growth nexus, for this review we have selected the few recent studies. As pointed out by Glytsos (2005), considering the dependence of remittance flows on complex factors related to the nature and purpose of migration, the changing migrant flows entail complex and multidimensional effects of remittances, which make their role difficult to detect and evaluate.

The motivation to conduct this study arose because there is no consensus in policy debates on the impact of workers' remittances on economic growth, and because the number of studies that have examined these issues in the Asian region is relatively small. Considering the growing economic importance of remittance flows to Asian region, this paper attempts to fill this gap in empirical research. This paper employs panel least squares and panel fully modified least squares (FMOLS) methods to estimate the effects of workers' remittances on economic growth in 10 Asian countries using a newly available dataset. In addition, bounds testing or the Autoregressive Distributed Lag (ARDL) approach is employed to co-integration analysis to empirically assess the effects of remittance flows on the economic growth in individual countries. The paper also assesses the role of the institutions in determining the relative effectiveness of remittance flows to the region. The specific objectives of this study are to explore the hypotheses that (a) workers' remittances will enhance economic growth in Asian countries, and (b) financial development will enhance economic growth in Asian countries. These hypotheses are tested at two levels. First, the effects of workers' remittances on economic growth and financial development is explored considering all countries as a group. In the second step, the effects of workers' remittances and financial development on economic growth for each individual country is considered. Another innovation of the paper is that it has incorporated the institutional environment, which is vital for enhancing growth and the development impact of workers' remittances in Asia. Thus, the findings reported in this study represent a significant contribution to the existing literature, particularly because they have been derived using recently developed econometric techniques and a larger dataset.

This paper adopts the methods presented in Botev, Egert, and Jawadi (2019) and Hassan, Sanchez, and Yu (2011), that integrates the assumption of coefficient heterogeneity and cross-sectional dependency concurrently, while examining the test of panel data causality. This approach is carried out using Pedroni's Heterogeneous Panel Cointegration Test, Johansen-

Fisher Panel Cointegration Test, and Kao Residual Panel Cointegration Test. Using these methods for developing countries is appropriate because of the different degrees of economic development among the different regions.

### **Methodology and Data**

## Model Specification

The objective of this study is to investigate the nexus among workers' remittances, financial development, and economic growth. Drawing on the existing empirical literature (see, for example, Botev, Egert, and Jawadi (2019) and Hassan, Sanchez, and Yu (2011)), the starting point is a growth regression including the following explanatory variables: (a) growth rate of physical capital (investment as a percent of GDP; GRK), (b) growth rate of labor force (GRL), and (c) growth rate of human capital (GHC). This specification of the growth regression can be extended by adding the following control variables: (a) trade openness (measured as exports plus imports as a percent of GDP; OPEN), (b) the inflation rate measured using the consumer price index (INF). Adding two variables representing workers' remittances (REM) and financial development (FD) yields the following empirical specification:

$$GROWTH_{i,t} = f(GRK_{i,t}, GRL_{i,t}, GHC_{i,t}, OPEN_{i,t}, REM_{i,t}, INF_{i,t}, FD_{i,t})$$

$$\tag{1}$$

where *GROWTH* is the growth rate of real GDP per capita; *i* and *t* subscripts are defined as i = 1, 2, ..., 10 and t = 1, 2, ..., 39; *GRK<sub>i,t</sub>* is the growth rate of capital stock; *GRL<sub>i,t</sub>* is the growth rate of labor force; *GHC<sub>i,t</sub>* is the growth rate of human capital; *OPEN<sub>i,t</sub>* is the exports plus imports as a share of GDP; *GOV<sub>i,t</sub>* is the government expenditure as a share of GDP; *INF<sub>i,t</sub>* is the inflation rate measured using the consumer price index (CPI); and *FD<sub>i,t</sub>* is the variable representing financial development.

In this study a financial development index developed by Sviydzenka (2016) and Sahay et al. (2015) is used. In addition, a dummy variable is included to represent a banking or economic crisis (BCD). Assuming the model specified in Equation (1) is linear, the empirical specification of the growth model is as follows:

$$GROWTH_{i,t} = \beta_0 + \beta_1 GRK_{i,t} + \beta_2 GRL_{i,t} + \beta_3 GHC_{i,t} + \beta_4 OPEN_{i,t} + \beta_5 REM_{i,t} + \beta_6 INF_{i,t} + \beta_6 FD_{i,t} + \beta_7 BCD_{i,t} + \varepsilon_{i,t}$$

$$(2)$$

where *i* and *t* subscripts are defined as i = 1, 2, ..., 10 and t = 1, 2, ..., 39;  $BCD_{i,t}$  is a dummy variable representing a banking or economic crisis; and  $\varepsilon_{i,t}$  is the error term. Other variables are defined earlier. *A priori*, the signs of variables  $GRK_{i,t}$ ,  $GRL_{i,t}$ , and  $GHC_{i,t}$  are expected to be positive. Since the economies that are more open tend to grow faster than the relatively closed economies, the expected sign of  $OPEN_{i,t}$  variable is also positive. The expected sign of  $INF_{i,t}$  variable is negative. Since any banking or economic crisis tend to lower the economic growth, the expected sign of  $BCD_{i,t}$  variable is negative. The expected sign of  $REM_{i,t}$  variable can be either positive or negative. The expected sign of  $FD_{i,t}$  variable can also be either positive or negative depending on whether financial development enhance or deter economic growth.

# Definition of Variables, and Data Sources

The dependent variable, *GROWTH*, is the growth rate of real GDP per capita. The growth rate of physical capital (*GRK*) is measured by a proxy variable, namely, gross fixed capital formation as a percent of GDP. The growth rate of labor (*GRL*) is measured by a proxy variable, namely, the growth rate of population. Trade openness (*OPEN*) variable is measured as (exports + imports)/GDP. Human capital (*GHC*) variable is defined as the growth rate of average years of schooling. Inflation (*INF*) variable is measured as the annual percentage change in the consumer price index. The data on *GROWTH*, *GRK*, *GRL*, *OPEN*, *GHC*, and *INF* variables were collected from the World Bank, *World Development Indicators 2021* database. Data on the financial development index (FD) were collected from the International Monetary Fund, *Financial Development Index* database. In addition, we have included a dummy variable to represent a banking or economic crisis (*BCD*). Information on banking crisis dummy was collected from the World Bank, *Global Financial Development Database* (*GFDD*) 2019.

#### **Summary and Conclusions**

This study investigates the nexus between financial development in economic growth in Asian developing countries. The study uses a panel data covering 10 developing countries during the period 1980-2018. Before estimating the specified models, all variables were tested for panel unit-roots using four different methods before carrying out panel cointegration tests. Panel unit-root tests confirmed that all the variables are stationary at the first difference. Two different methods of

testing the panel cointegration are used, namely, Kao Residual Panel Cointegration Test and Johansen-Fisher Panel Cointegration Test. The panel cointegration tests show clear evidence of cointegration among nine variables.

Then the specified model was estimated using three estimation methods, namely, Panel LS, Panel FMOLS, and Panel DOLS. Results indicate that for all estimation methods, GRK and GRL are significant for all countries pooled sample. GHC is also positive and significant under all estimation methods. The results also show that regardless of which estimation method is used, estimated coefficients of FD are positive and statistically significant confirming a long-run positive relationship between financial development and economic growth in Asian countries. The coefficient for REM is positive and significant at the 1% level or 5% level in all three cases. These values are consistent with the contribution of workers' remittances to economic growth in developing countries. BCD is negative as expected, but not statistically significant.

A future study could focus on a large group of developing countries covering all world regions. This paper does not also consider the stock and bond markets, even though other studies have demonstrated that they play key roles in a country's financial development and economic growth and, therefore, should be considered in future studies. In addition, poverty and inequality are prevalent in developing countries, and therefore should be considered in future studies.

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# **Teaching Finance and Business Analytics Using Data** Visualization of Financial Data

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# Abstract

With increasing amounts of financial data and the advent of user-friendly data visualization software, there is synergy between teaching finance and business analytics. This paper discusses the use of data visualization programs to analyze and visualize financial data. The module can be incorporated in a business analytics course, in which the real-world financial data provides motivation for students to learn the material. The module also can be incorporated in a finance course, where it can not only help students acquire practical skills that they might need to deal with data, but also help students to understand the concepts.

JEL Codes: I20 Keywords: finance education, data analytics, data visualization

## Introduction

With ubiquitous usage of personal computing devices such as smart phones, and with the frequent use of apps for social networking, banking, shopping, communication, and investment, there is an endless amount of data in the business world. (Gupta and George, 2016). Given its importance in the business world, data analytics is becoming an increasingly important subject in business schools (Cegielski and Jones-Farmer, 2016).

In terms of economics and finance, there is an explosion of data just like other areas of business. Therefore, data analytics can go hand in hand with finance and economics.

In particular, this paper addresses how the teaching of foundational business courses can work synergistically by incorporating data visualization into finance courses, and vice versa, by incorporating financial data in business analytics courses.

An important learning objective of business analytics courses is to teach students to become proficient at dealing with real-world data. Even though made-up textbook data can be useful for educational purposes, students need to become familiar with real-life data. Further, using real-life data can be much more interesting to students. Knowing that the data has practical applications, students may be more motivated to study and to learn the material in a "boring" class like data analytics.

Financial data is not only important, but also relatable and interesting to students. One example of this would be stock market data. For many students, this data is interesting for both corporate finance and personal finance reasons.

There are many platforms and tools of data analytics, ranging from the most foundational tools such as Excel to the most cutting-edge artificial intelligence tools. This paper will specifically discuss a set of tools known as data visualization software. This will be followed by an overview of data visualization software, and a discussion of the potential benefits of employing this software in the classroom.

# **Overview of Data Visualization Software**

Data visualization software is also known as business intelligence tools (Albright and Winston, 2020). As opposed to data analytics platforms that are spreadsheets or programs that rely on users to write program code, data visualization programs allow users to analyze and interact with data with a graphical user interface.

Data visualization software has several other advantages relative to the alternatives. For instance, Excel and PowerPoint have difficulty handling large amounts of data, have limited analytics capabilities, and generally are considered relatively static. By way of contrast, data visualization software can handle larger amounts of data, has more advanced analytics capabilities, and generally is considered more dynamic and interactive. Writing programs, such as R and Python, are highly versatile, but tend to have a steep learning curve, which can lead to users – and especially inexperienced users such as students learning a program for the first time – getting lost in the technical details. Data visualization software, on the other hand, generally is considered easier to learn, thus freeing up the instructor and the students to focus more of their attention on whatever questions or issues the program is being used to analyze in a given situation.

The most popular data visualization software programs include Tableau, Microsoft Power BI, Qlik, Google Data Studio, and SAS Visual Analytics. This paper will use Tableau as an example, although the principles can be applied to any data

visualization program. An advantage of Tableau is that it can be run both on Mac computers and on PC with Windows. Specific uses of Tableau include the abilities to import substantial amounts of data in various formats, to create and customize tables and charts, to perform geographical analysis, to aggregate data, to perform calculations, to filter data, and to join data.

## Pedagogical Benefits of Finance Data Visualization

As alluded to above, finance data visualization provides a potentially symbiotic intersection of finance material and data analytics material, which can be useful in teaching a class in either area. For instance, consider the use of finance data visualization in a data analytics course. For a nontrivial number of students, the use of a "dollars and cents" example seems likely to provide greater motivation than would a "standard statistics example" that, fairly or unfairly, would likely be viewed by many students as boring and/or contrived. In addition to the motivational factor, there is arguably a tangible benefit to having the students acquire experience in dealing with real-life data, as opposed to textbook data.

Likewise, the intersection of finance with data analytics has the potential to make a finance data visualization example useful in a finance class. The hands-on experience with real-life data is likely to provide meaningful added value. In addition, the old saying that "a picture is worth a thousand words" would seem to apply.

## Example of Use of Finance Data Visualization: Individual Stock Data Over Fixed Time Periods

In the interest of space, the discussion below will omit the various figures that comprised a significant amount of the paper as presented at the conference and will instead rely on a description of what would be seen from those figures.

Suppose that the instructor wishes to introduce the use of data visualization with a simple example, employing tracking the price of an individual stock, such as Boeing. To start, the student would download (for instance) 5-year daily close or daily adjusted close data for Boeing and place it in an Excel file. The next step would be to connect to the Excel file from Tableau. The instructor or the student would then go to the Tableau worksheet, drag "date" to "Columns," and drag the daily adjusted close price to "Rows."

Tableau's default display would then show the average daily adjusted close price for each year. The graph that is displayed as a result of this operation would generally be rather plain. In this example, the graph first displays a series of consecutive increases, including an especially steep increase from 2017 to 2018. This is followed by a sharp decline from 2019 to 2020, and then a partial rebound from 2020 to 2021. The student can readily see that the graph provides summary information regarding the movement of average daily adjusted closing prices, but not much more.

Now, suppose that the instructor wants to show the benefits of adding detail to the figure. The instructor can use the drop-down menu over "Year" to adjust the time scale. A first step might be to change from yearly averages to monthly averages. Here, the student has the opportunity to see a bit more of the "up and down" pattern that stock prices typically follow. For instance, consider the year between 2017 and 2018, the one-year period noted above as a year featuring a sharp overall increase in the average daily price. Here, the student can readily observe that while the progression in the stock's average monthly price is not linear, it does show a rather consistent upward trend. This is a detail that was not available from observing only the year-over-year change. By way of contrast, between 2018 and 2019 (a period for which the annualized graph simply showed a slight increase), the monthly graph reveals a somewhat erratic pattern. Between 2019 and 2020, where the annualized graph shows only a steep overall decline, the monthly graph shows an early pattern of up-and-down movements, followed by a sharp decline toward the end of the year.

Taking things a step further, the instructor can then change the period from monthly to weekly. Here, a more detailed and nuanced pattern is revealed. Even during the aforementioned 2017-2018 interval, in which the primary change among the monthly progressions was simply a change in the rate of improvement from one month to the next, the weekly figures clearly indicate a more typical pattern of back-and-forth movement in the stock price. Finally, the period can be changed to daily, in which case the graph includes the adjusted closing price for every trading day.

#### **Second Example: Moving Averages**

In the set of examples described above, the student can see the differences produced in the graphs, based on how finely the instructor divides the time periods for the data. In addition, however, the student can see that even in the monthly data, and to some extent even in the weekly data, the graphs display rather rough transitions from one time period to the next. For instance, "Here was the average daily adjusted close for 2018 as compared to 2017." Or, "Here was the average daily adjusted close for 2018." This is due to the use of fixed time periods for the averages.

This recognition allows the instructor to transition to another feature of Tableau: the ease of creating moving averages. For instance, suppose that the instructor wishes to illustrate the creation of a series of 20-day moving averages. In order to do this, the instructor or the student will first access the "table calculation" feature in Tableau. For "calculation type," the user will then select "moving calculation." The user would then select the "Average" option. When asked how many previous values to include, the user would choose 19. The user would then check the box to include the current value; this current value, combined with the previous 19 values, would provide the information necessary to calculate a 20-day moving average. This calculation can be performed for a variety of lengths of time, as desired.

In addition, Tableau allows the user to overlay multiple charts in a single figure. For instance, one could overlay daily numbers, 50-day moving average numbers, and 100-day moving average numbers. The daily numbers will display the greatest volatility, the 100-day moving average numbers will display the least volatility, and the 50-day moving average numbers will be somewhere in between. This can be compared to the aforementioned rough transitions that were observed in the initial set of visualization examples.

#### **Third Example: Portfolio Diversification**

One key topic in an introductory corporate finance course, an investments course, and or even a personal finance course is the concept of portfolio diversification. There are numerous ways to illustrate this, but the use of data visualization arguably has some advantages over the more traditional approach.

Suppose, for instance, that in addition to Boeing, the instructor tracks Walmart. And, in addition to looking at the raw stock price, the instructor illustrates cumulative return on investment. For starters, Tableau can be instructed, with a given stock, to track the cumulative return over a given period of time by comparing adjusted closing prices and calculating a percentage change. A graph can be created in which cumulative returns are overlaid for two separate stocks. In addition, however, Tableau can be instructed to include a third item in the graph: the return on a portfolio consisting of "X" proportion of the first stock, and "1-X" proportion of the other stock.

A couple of things become clear from these graphs. First, as with the graphs that typically are shown in a finance textbook (albeit oftentimes with hypothetical stocks), the student can readily see that the returns for the portfolio as a whole, while highly variable, display far less volatility than is seen in the returns of the individual stocks. To be specific, the graph will illustrate that the cumulative returns for the overall portfolio will always, by definition, fall between the cumulative returns for the two individual stocks. And, this will result in a more muted pattern of cumulative returns for the portfolio, as compared to the patterns of cumulative returns for the individual stocks.

However, unlike what one typically sees in a finance textbook example, Tableau allows the instructor to quickly and easily display the impact of changing the percentage allocations within the portfolio. The impact on portfolio volatility of changes in the allocations may sometimes surprise even the instructor!

For instance, over the 5-year time period used in this paper, the authors began by constructing a portfolio that consisted of a 70% allocation to Boeing and a 30% allocation to Walmart. The curve for the cumulative portfolio returns, while lying between the curves for the cumulative returns on the individual stocks as mentioned above, would obviously be expected to lie closer to the curve for Boeing than it does to the curve for Walmart. But, the degree to which that was true came as a surprise; the visual impact was actually somewhat striking.

On the other hand, when the allocation was shifted to 40% Boeing and 60% Walmart, there was a dramatic shift. Again, the surprise was related not to the direction of the change, which was completely predictable, but rather to the degree of change. Of course, with this allocation it would be expected that the curve displaying the cumulative returns for the portfolio as a whole would lie closer to the middle than in the previous example. However, whereas the visual appearance of the 70-30 graph looked much closer to a 100-0 allocation than one might have expected, the visual appearance of the 40-60 graph looked much closer to a 50-50 allocation than one might have expected.

Different pairs of stocks might very well display markedly different patterns, but the point is that the instructor can use a data visualization to demonstrate, far more effectively than might be done with a mere numerical example, the potentially dramatic impact on portfolio volatility of even a slight shift in the asset weightings.

#### Conclusion

This paper has presented an overview of finance data visualization for teaching and learning, both in data analytics courses and in finance courses. It is argued that the use of "dollars-and-cents" data may be more motivating for students in a data analytics course, as opposed to the standard examples that one might find in statistics textbooks. It is further argued that for finance students, the use of data visualization may make it easier for students to grasp and then to apply the concepts that are being introduced.

Three specific scenarios were described. In the first example, students can be shown how moving from yearly to monthly, weekly, and eventually daily information can provide a more detailed view of the progress of the price of a given firm's stock.

In the second example, the instructor can show how the rather stark visual impact created by using fixed time periods can be smoothed out by creating moving average data. In addition, different moving averages for a single set of numbers can be overlaid on a single graph. This allows the instructor to demonstrate how the degree of volatility may be perceived differently, due to differences in the length of the time periods employed.

In the third scenario, the topic moves from the average adjusted closing price of a single stock to the cumulative returns on two separate stocks, and then to the cumulative returns on portfolios comprised of varying proportions of those two stocks. This tool – particularly when the instructor notes the impact of changes in how the assets are weighted on the overall volatility of the portfolio – can be an effective means of illustrating the concept of portfolio diversification in general, and the importance of asset allocation in particular.

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# U.S. Investor Sentiment and Stock Returns in the Americas; a Study of the U.S. Financial Crisis and Beyond

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## Abstract

We assess the impact of individual and institutional investor sentiments as sources of financial contagion from the U.S. to the Americas during the U.S. Financial Crisis. We estimate the effects of the perceived U.S. market volatility, individual investor sentiment, and institutional investor sentiment on financial contagion. We break our observations into three periods using NBER turning points for U.S. business cycles and employ DCC-GARCH models to obtain the dynamic conditional correlations. We identify the significant influence of institutional investors on international market returns during the Financial Crisis and their possible role as financial contagion agents.

JEL Classification: G15, G40 Keywords: Financial Contagion, U.S. Financial Crisis, Investor Sentiment, Behavioral Finance.

## Introduction

The 2008-2009 U.S. financial crisis is critical because it represented the most extensive U.S. stock market decline since the great depression of the early 20th century and the rapid spread to other economies worldwide. The financial contagion observed during this period challenges the ability to build diversified portfolios by investing in different global stock markets during times of crisis and prompts us to investigate the sources of this contagion.

In addition to the fundamentals-based contagion theories of Kaminsky and Reinhart (2000), other authors identify that investor behavior can also accentuate financial contagion. Investors may attempt to mitigate the risk of their international holdings by withdrawing their funds from countries with high economic ties to the country in crisis, resulting in increased correlations between the country in crisis and its trade partners (Yuan, 2005; Pasquariello, 2007). Kodres and Pritsker (2002) develop a rational expectations model that explains financial market contagion, identifying that investors transmit shocks from one market to another when they rebalance their portfolios to adjust their exposure to macroeconomic risks.

Markowitz (1952) defines investors as well-informed and rational when building efficient portfolios to maximize expected returns for any given risk. Modern Financial theory states that individual investors are rational utility maximizers who care about their investment risks and returns and make investment decisions based on economic fundamentals (Fama, 1970). Traditional Efficient market theory states that markets are rational and that stock values are equal to discounted future cash flows. It also says that any deviation from fundamental values should be eliminated in a short time by arbitragers, reducing the effects of investor sentiment (Fama and Macbeth, 1973)

De Long et al. (1990) highlight the role that rational and noise traders play in stock pricing, arguing that limitations to arbitrage allow for noise traders and that stock prices consist of two elements; a fundamental value given by rational investors and a risk premium attributed to noise traders. Baker and Wurgler (2006, 2007) identify two types of investors: rational traders, also known as arbitrageurs, and sentiment traders. Arbitrageurs make informed decisions to determine expectations about the future value of an asset. At the same time, sentiment traders (i.e., noise traders) could be optimistic or pessimistic about the market, leading them to either under-estimate or over-estimate asset prices.

Most investor sentiment literature focuses on the U.S. markets and finds evidence that investor sentiment affects securities pricing and stock returns. The literature also finds that investor sentiment is driven by demand shocks and/or arbitrage limitations (Lee, Shleifer, and Thaler, 1991; Lee, Jiang, and Indro, 2002; Brown and Cliff, 2004; Baker and Wurgler, 2007; Verma, Baklaci, and Soydemir, 2008; Ho and Hung, 2009; Baker, Wurgler, and Yuan, 2012; Huerta, Egly and Escobari, 2016).

A growing branch of literature investigates the effects of international investor sentiment on a country's stock valuation. The definition of investor sentiment is: "a belief about future cash flows and investment risks that is not justified by the facts at hand" (Baker and Wurgler, 2007). Lee et al. (2002) find that changes in investor sentiment and excess stock returns are positively correlated. They also find that bullish shifts in investor sentiment are inversely correlated to market volatility. Verma and Soydemir (2006) investigate how U.S. investor sentiment propagates to other countries, finding that U.S. investor sentiment influences international stock market returns, varying significantly across countries. They also find that changes in institutional investor sentiment have a more substantial influence than individual investor sentiment. Both are driven by rational and irrational factors but conclude that U.S. investor sentiment can be an essential spillover factor. Investor sentiment

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can influence trading decisions, at both the firm and market levels, especially for firms that are difficult to value or arbitrage (e.g., Baker and Wurgler, 2007). Rodriguez-Nieto and Mollick (2020) identify that increases in U.S. stock volatility contributed to the financial contagion to the major markets in the Americas during the U.S. financial crisis.

Schmeling (2009) uses consumer confidence as a proxy for individual investor sentiment and assesses its impact on the stock returns of 18 industrialized countries. He finds a causal effect, between investor sentiment and stock market returns, from t to  $t_{t+1}$ . He observes that individual investor sentiment negatively forecasts stock market returns and suggests that this is stronger for countries that are culturally more prone to overreaction and herd-like behavior.

Hwang (2011) finds that U.S. investor sentiment can influence the demand for foreign securities, affecting their price and deviating from their fundamental value. Baker et al. (2012) find evidence that investor sentiment can influence market volatility and that return predictability is consistent with over-reaction corrections. They also find that investor sentiment comprises two factors, namely "global" and "local," and that global investor sentiment is spilled across markets through capital flows.

Sayim and Rahman (2015) find significant spillover from U.S. individual and institutional investor sentiment to the Turkish stock market returns. Perez-Liston, Huerta, and Gutierrez (2015) use a vector autoregressive model (VAR) to identify U.S. investor sentiment spillover to Mexican investor sentiment and the Mexican stock market returns. They attribute this spillover to the cross proximity, strong trade ties, ease of capital flows, and exchange rates.

We apply the multivariate DCC–GARCH model, introduced by Engle (2002), to identify the role of U.S. market volatility and U.S. investor sentiment as sources of contagion from the U.S. to the Americas during the 2008-2009 financial crisis. We first assess contagion from the U.S. to Argentina, Brazil, Canada, Chile, Colombia, Mexico, and Peru. We use the CBOE Volatility Index®, or VIX, to control the impact of market volatility on the conditional correlations obtained from the DCC-GARCH between the U.S. and each stock market. We then assess the effects of investor sentiment on these conditional correlations by using survey-based proxies used in the literature (Brown and Cliff, 2004; Huerta, Egly, and Escobari, 2016) as direct measures of investor sentiment. We distinguish the effects of the Individual Investor Sentiment, represented by the American Association of Individual Investors (AAII) survey, and Institutional Investor Sentiment, using the Investor Intelligence (II) Survey.

This essay contributes to the investor behavior literature by identifying the role of the perceived market volatility *VIX*, individual investor confidence *AAII*, and institutional investor confidence *II* on the stock market returns of the major markets in the Americas during the U.S. financial crisis. We find that the institutional investor sentiment not only has a more substantial influence than the individual investor sentiment on the stock returns of the U.S. but also applies to the largest markets in the Americas.

#### **Individual and Institutional Investor Sentiment**

To capture the effect of the institutional and individual investor sentiments on the stock returns of the major stock markets in the Americas, we use two sentiment indexes widely used in the literature. Following Brown and Cliff (2004) and Huerta et al. (2016), we first use a survey performed by the American Association of Individual Investors AAII to proxy individual investor sentiment. The American Association of Individual Investors is a nonprofit corporation that provides education, information, and research to individual investors. Since 1987, Individual investors are pooled weekly to measure the percentage of bullish, bearish, or neutral about the stock market's short-term performance. Those who are said to be bearish are individual investors who are pessimistic about the stock market performance in the next six months, and bullish investors expect the stock prices to rise. Neutral investors expect the stock prices to remain unchanged. Following Brown and Cliff (2004), we build the *AAII* index by calculating the difference between bullish and bearish investors; the result is the bull-bear spread, commonly used as a proxy for individual investor sentiment.

We then use the Investors Intelligence (II) survey to build a proxy for institutional investors' Intelligence. The Investors Intelligence Survey analyses the market views of more than 100 investment advisor newsletters and interprets them as bullish, bearish, and those that expect a correction or neutral. Since professional advisors are the authors of these letters, we follow Brown and Cliff (2004) and use this survey to build a proxy for Institutional Investor Sentiment. The Investor Intelligence index, II, represents the spread between the percentage of bullish and bearish newsletters.

Since individual and institutional investor sentiments positively affect U.S. stock returns, we hypothesize that investor sentiment will also impact international markets. We define three hypotheses based on individual and institutional investor sentiments:

H1: Increases in the Individual Investor Sentiment (AAII will have positive and statistically significant effects on the stock returns of Canadian and Latin American stock markets.

H2: Increases in the Institutional Investor Sentiment (*II*) will have positive and statistically significant effects on the stock returns of Canadian and Latin American stock markets.

H3: Institutional Investor Sentiment (*II*) will have a more substantial influence than Individual Investor Sentiment (*AAII*) on the stock returns of the markets in the Americas.

## **Data and Descriptive Statistics**

We collect country-specific data from DataStream, consisting of weekly closing prices from Argentina (BURCAP), Brazil (BOVESPA), Canada (S&P/TSX Composite Index), Chile (IPSA), Colombia (IGBC), Mexico (BOLSA), Peru (ISBL), and the United States (S&P 500). Data are in U.S. Dollars, from January 1, 2002, through December 31, 2015.

We use three proxies to measure sentiment; we first use the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) to proxy implied market volatility. The VIX is widely used as a fear gauge since it represents the market's expectation of stock market volatility for the next 30-day period. Following Brown and Cliff (2004), we employ two survey-based weekly sentiment measures collected by the American Association of Individual Investors (*AAII*) and Investor's Intelligence (*II*).

Table 1 reports the descriptive statistics for the pooled dataset, both in levels and in returns for the country stock indexes and the first differences for *VIX*, *AAII*, and *II*. We first report the data in levels and provide statistics about the mean, standard deviation, variance, skewness coefficient, kurtosis coefficient, the Shapiro-Wilk normality test, and the Ljung–Box autocorrelation test. Except for *AAII*, the Shapiro-Wilk test statistic suggests that the series are non-normally distributed. The Ljung–Box test statistics indicate that all return series are auto-correlated except for Argentina and Peru.

For the data reported in returns and differences, we observe that Colombia and Peru report the highest means at 0.24, with standard deviations of 3.91 and 4.15, respectively. They are followed by Mexico with mean returns of 0.17, Argentina at 0.16, and Chile at 0.12, respectively, with standard deviations of 3.83, 5.1, and 2.92. Brazil and Canada report identical mean returns of 0.09; however, their standard deviations are quite different at 4.77 and 3.20, respectively. We observe that except for *AAII*, the series are non-normally distributed; except for Argentina and Peru stock returns, all series are auto-correlated.

Table 2 reports the unconditional correlation between the pooled sample's stock index returns,  $\Delta$ VIX,  $\Delta$ AAII, and  $\Delta$ II. We find that all pairwise correlations amongst the stock returns are positive and significant. The highest correlations are between the U.S., Canada, Mexico, and Brazil, with pairwise correlations ranging between 0.6487 and 0.7818. Correlations between the stock index returns and changes in VIX are negative and significant. It is not surprising to find a high correlation between the U.S. and  $\Delta$ *VIX* of -0.7976. Still, it is interesting that the highest correlations are with Mexico, Canada, and Brazil at -0.6934, -0.6655, and -0.5594, respectively, since they represent the largest stock markets in the Americas. The relationship between investor sentiment indexes and country-specific stock indexes is positive and significant. The individual investor sentiment AAII ranges from a high of 0.1919 for Canada, Chile with 0.1633, the U.S. with 0.1566, and 0.1038 for Colombia. The institutional investor sentiment *II* presents larger correlation coefficients with stock returns than the individual investor sentiment *AAII* in all cases, ranging from a high of 0.4090 for the U.S., 0.3154 for Mexico, and 0.3057 for Canada, with the lowest pairwise correlation being that of Peru at 0.2009. We also find a low correlation coefficient of 0.2074 between *II* and *AAII*, highlighting the importance of including both sentiment measures in the empirical model.

Table 3 includes the results of the stationary tests for the country stock indexes expressed in returns and VIX, individual investor sentiment *AAII*, and institutional investor sentiment *II* expressed in first differences. We perform the ADF, KPSS, and Philips-Perron tests, identifying that all series are stationary.

#### The DCC Model and Estimation Results

We use a DCC-GARCH model, introduced by Engle (2002), to assess the changes in the conditional pairwise correlations between the stock market returns, the difference in market volatility  $\Delta VIX$ , changes in the individual investor confidence  $\Delta AAII$  and institutional investor confidence  $\Delta III$ .

The model used in this study is as follows:

We model the return dynamics by using an autoregressive model in the form of:

$$r_{t} = \gamma_{0} + \gamma_{1} r_{t-1} + \gamma_{2} r_{t-1}^{\Delta VIX} + \gamma_{3} r_{t-1}^{\Delta AAII} + \gamma_{3} r_{t-1}^{\Delta II} + \varepsilon_{t} (3.1)$$

The vector of returns is:

 $r_{t} = (r_{Argentina,t}, r_{Brazil,t}, r_{Canada,t}, r_{Chile,t}, r_{Colombia,t}, r_{Mexico,t}, r_{Peru,t}, r_{U.S.,t})'$ 

and the vector of error terms is:

# $\varepsilon_{t} = \left(\varepsilon_{Argentina,t}, \varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Chile,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{Peru,t}, \varepsilon_{U.S,t}\right)'$

The results for the multivariate DCC–GARCH model are reported in Table 4. The results for the mean equations indicate that the constant term  $\gamma_0$  is positive and statistically significant for all markets. The AR(1) term  $\gamma_1$  yields mixed results, being positive and statistically significant for Colombia and negative and statistically significant for the U.S. and Canada. We find that the  $\Delta VIX$  term is only statistically significant and positive for Brazil, Colombia, and Mexico. The Individual Investor Sentiment  $\Delta AAII$  is not significant for any country. The Institutional Investor Sentiment  $\Delta II$  is positive and significant for Peru and the U.S., and for Argentina is positive but not significant.

We look at the parameter estimates of the mean and conditional variance equations to verify the appropriate use of the GARCH specification. We confirm that all coefficients are significant, thus ensuring the proper use of the specification. The volatility persistence (a + b) is near one (1) in all cases, varying from a high of 0.99 for Argentina and 0.98 for the U.S. to a low of 0.86 for Colombia, indicative of high volatility persistence. The lambda1 and lambda2 parameters are statistically significant at 1%, verifying the appropriate use of the DCC-GARCH over a CCC model.

Table 5 includes the DCC-GARCH-based correlations between  $\Delta VIX$ ,  $\Delta AAII$ ,  $\Delta II$ , and the stock returns during the pooled data period. As expected, we see that correlations between the  $\Delta VIX$  and stock market returns are negative and significant, indicating that the greater the volatility in the U.S., the lower the returns of these markets. We observe that the pairwise correlations between  $\Delta VIX$  correlations are greater for the U.S at -0.838, followed by those of Mexico at -0.715, Canada with -0.697, and the lowest being Argentina at -0.512. The pairwise correlations with the individual investor sentiment AAII are all positive and significant, ranging from 0.292 for II, Canada at 0.213, the U.S. at 0.196, with the lowest being Peru at 0.179; this indicates that positive individual investor confidence is associated with positive stock market returns. We also observe that the magnitude of these coefficients is greater than the estimated coefficients for the individual investors. We notice that the highest pairwise correlation coefficients between II and the stock market returns are those associated with the U.S., Canada, and Mexico, ranging from 0.603 for the U.S, 0.499 for Mexico, and 0.468 for Canada.

Further, the correlation between  $\Delta VIX$  and  $\Delta II$  is negative and statistically significant at -0.507, which is greater than that observed between the  $\Delta VIX$  and  $\Delta II$  at -0.143, indicating a more substantial inverse relation between the fear index and institutional investor confidence when compared to individual investors. We also observe that the pairwise correlations amongst countries are all positive and significant. It becomes clear that the highest correlations are those between the most developed countries, namely the U.S., Canada, Mexico, and Brazil. We identify the highest pairwise correlations between Brazil-Canada at 0.839, followed by U.S.-Canada at 0.825, U.S.-Mexico at 0.806, Brazil-Mexico at 0.794, and U.S.-Brazil at 0.711.

# Explaining the conditional correlation coefficients

One advantage of the DCC-GARCH model is that we can obtain the dynamic correlations between  $\Delta VIX$ ,  $\Delta II$ , and  $\Delta AAII$ and the stock market returns and represent them graphically. Figure 1 includes the dynamic conditional correlations between  $\Delta VIX$  and the various stock market returns. We observe a general downward trend during the pre-crisis period, indicating that the inverse relationship between  $\Delta VIX$  and each stock market grew from approximately -0.1 to levels greater than -0.5 in all cases. We observe a slight correction in the opposite direction during the financial crisis, which sharply reverts and remains at the highest negative levels. For the post-crisis period, the dynamic conditional correlations between  $\Delta VIX$  and stock returns stay at lower levels than during the pre-crisis period, with the most notorious being those of Canada and Mexico at around -0.7 and the U.S. at -0.9.

Figure 2 documents the conditional correlations for all pairs between  $\Delta II$  and the stock markets. We observe that correlations are positive and with an upward trend during the pre-crisis period; these correlations remain at around the highest level reached during the financial crisis but with increased volatility. We observe that correlations during the post-crisis period remain higher than in the pre-financial crisis, with a notorious upper trend for the U.S., Canada, and Mexico, with dynamic conditional correlations reaching around 0.5 for the U.S. and 0.4 for Canada and Mexico.

Figure 3 includes all pairwise dynamic conditional correlations between individual investor sentiment  $\Delta AAII$  and the stock markets. We observe positive pairwise correlations, with upward trends in most cases, during the pre-crisis period. We then detect a slight downward trend after the beginning of the financial crisis period, followed by a sharp correction. We observe that during the post-crisis period, the correlations remain positive and, in most cases, higher than the levels observed during the pre-crisis period; however, they behave erratically, with similar patterns for Brazil, Canada, Chile, Mexico, Peru, and the U.S.

We are interested in defining if the financial crisis affected the conditional correlation coefficients between the stock market returns,  $\Delta VIX$ ,  $\Delta AAII$ , and  $\Delta II$ . To capture the effect of the financial crisis on these pairwise conditional correlations, we use the following regression model:

$$\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DSCRISIS_t + \epsilon_{ij,t}, \text{ for } i \neq j$$
(3.2)

We identify two periods in the sample: the first runs from January 1, 2002, to December 31, 2007, and we define it as the pre-crisis period. We describe the second period as since-the-crisis because it begins in the wake of the financial crisis on January 01, 2008, and continues until the end of the pooled sample (December 31, 2015). We create a dummy variable (DSCRISIS) for the since-the-crisis period, which is set equal to one for such period and zero otherwise. We regress the predicted dynamic conditional correlation coefficients  $\hat{\rho}_{ij,t}$ , between markets and sentiment indexes *i* and *j* at time *t*, with dummy variable DSCRISIS for the since-the-crisis period (January 1, 2008, to December 31, 2015).

The estimation results in Table 6 indicate that the financial crisis has a significant impact on the conditional correlation for all the pairwise correlations. We first examine the effects on the pairwise correlations between the stock markets in the Americas and  $\Delta VIX$  and observe that the financial crisis has an inverse and significant impact in all cases, indicating the relationship between  $\Delta VIX$  and each stock index increases after the financial crisis begins. We identify that  $\Delta VIX$  has the highest negative pairwise correlations with the U.S. at -0.8157, Mexico at -0.6963, Canada at -0.6628, Chile at -0.5662, Brazil at -0.5648, Peru at -0.5106, Colombia at -0.4954, and Argentina at -0.4876.

We observe that the pairwise correlations between these stock market indexes and the individual investor confidence *AAII* increase significantly. We identify that the correlation with the U.S. has the largest coefficient at 0.1902, followed by Canada at 0.1858, Chile at 0.1682, Argentina at 0.1635, Brazil at 0.1551, Mexico at 0.1493, Peru at 0.1330, and Colombia at 0.1202. This confirms that the contemporaneous relationship between individual investor confidence and stock market returns increase during the U.S. financial crisis.

We identify that the effect on the relationship between the institutional investor confidence *II* and the stock market returns is also significant and larger than the coefficients observed for the pairwise correlations between *AAII* and each stock index. The correlation coefficients range from a high of 0.4899 with the U.S., Mexico at 0.3780, Canada at 0.3627, Brazil at 0.3060, Chile at 0.2713, Colombia at 0.2580, Argentina at 0.2413, to Peru at 0.2306.

In an attempt to capture the effects of the financial crisis period and the following post-crisis period in more detail, we break the since-the-crisis period into two. We redefine the resulting subsamples as pre-crisis, crisis, and post-crisis. The precrisis period runs from January 1, 2002, to December 31, 2007. The crisis period starts in the wake of the financial crisis on January 01, 2008, and ends on June 30, 2009. The post-crisis period includes data from July 1, 2009, and ends on December 31, 2015.

To differentiate the effect of the financial crisis and the post-crisis on the pairwise correlations between  $\Delta$ VIX,  $\Delta$ AAII,  $\Delta$ II, and the country-specific stock markets, we use the following regression model:

$$\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}, \text{ for } i \neq j$$
(3.3)

We create dummy variables for the crisis period (*DCRISIS*) and the post-crisis period (DPOSTCRISIS), which are set equal to one for each respective period and zero otherwise. We regress the predicted dynamic conditional correlation coefficients  $\hat{\rho}_{ij,t}$ , between markets and sentiment indexes *i* and *j* at time *t*, with dummy variable *DCRISIS* for the crisis period and dummy variable DPOSTCRIS for the post-crisis period.

The estimation results for equation 5 are reported in Table 7. Panel A includes the regression results for the pairwise correlations between the stock returns of the U.S. and each of the other countries. We observe that  $\lambda_0 C$  aptures the pre-crisis period is positive and significant for all the pairs with coefficients ranging from a high of 0.6354 for Canada, followed by Mexico at 0.6304, Brazil at 0.5340, Chile at 0.4694, Argentina at 0.4132, and Colombia at 0.3789. The effect of the financial crisis  $\lambda_1$  is also positive and significant, with coefficients ranging from a high of 0.1933 for Peru, 0.1848 for Colombia, 0.1747 for Mexico, 0.151 for Argentina, 0.1359 for Brazil, 0.1354 for Chile, and 0.1007 for Canada. The effect of the post-financial crisis, as indicated by  $\lambda_2$ , is positive and significant, ranging from a high of 0.1795 for Peru, 0.1562 for Canada, 0.1427 for Colombia, 0.1400 for Mexico, 0.1365 for Argentina, 0.1251 for Chile, and 0.1147 for Brazil. We interpret a strong correlation between the stock returns of the U.S. and each of the countries in this study. We observe that all countries increase their correlations with the U.S. during the financial crisis, indicative of contagion. Except for Canada, which continues to strengthen its co-movements with the U.S. after the financial crisis had ended, the other countries maintain higher correlations than those observed before the start of the financial crisis. Yet, they are smaller than those from the crisis.

In table 7, panel B, we report the effects of the financial crisis on the pairwise correlations between the stock markets in the Americas and  $\Delta VIX$ . In all cases, we observe negative and statistically significant coefficients for the constant  $\lambda_0$  that indicates a strong inverse relationship during the pre-crisis period. The  $\lambda_0$  coefficients range from -0.6818 for the U.S., -

0.5532 for Mexico, -0.5301 for Canada, -0.4507 for Brazil, -0.4299 for Chile, -0.3715 for Peru, -0.3646 for Colombia, and -0.3512 for Argentina. We observe that the effect of the financial crisis  $\lambda_1$  is also negative and significant for all pairs, indicating contagion since the inverse correlations increase during this period. The  $\lambda_1$  coefficients range from Mexico at -0.1683, Argentina at -0.1592, Colombia at -0.1448, Chile at -0.1434, Peru at -0.1374, the U.S. at -0.1318, Brazil at -0.1303, and Canada at -0.877. The effect of the post-crisis period  $\lambda_2$  is negative and significant in all cases, with most cases being smaller in magnitude than  $\lambda_1$ , such as Mexico at -0.1372, Chile at -0.1346, Argentina at -0.1312, Colombia at -0.1276, and Brazil at -0.1104. In the cases of Canada at -0.1460, Peru at -0.1394, and the U.S. at -0.1343, the post-financial crisis coefficients for  $\lambda_2$ , are larger than those observed during the financial crisis. We identify the long-term effects of the financial crisis on the correlations between VIX and each country in the study.

The results for the effects of the financial crisis on the individual investor confidence *AAII*, and each of the countryspecific stock returns, are included in Table 7, panel C. We first observe positive and significant coefficients for  $\lambda_0$  ranging from 0.1651 for the U.S, followed by Canada at 0.1542, Chile at 0.1369, Brazil at 0.1312, Argentina at 0.1176, Mexico at 0.1151, Peru at 0.1083, and Colombia at 0.095. We observe mixed effects of the financial crisis on these pairs, with five countries presenting inverse and statistically significant coefficients, like Peru at -0.0324, Canada at -0.0320, the U.S. at -0.0201, Brazil at -0.0131, and Chile at -0.0059. The other pairs observe positive and significant coefficients, ranging from 0.0153 for Mexico, 0.0052 for Colombia, and 0.0041 for Argentina. The effect of the post-crisis period is positive and significant for all pairs, indicating that increases in individual investor confidence are associated with increases in stock returns. The coefficients range from 0.0555 for Argentina, 0.0462 for Canada, 0.0398 for Chile, 0.0386 for Mexico, 0.0378 for Peru, 0.0355 for the U.S., and 0.0331 for Brazil.

The last panel for Table 7 is panel D, which includes the results of the regressions for the pairs composed of the institutional investor confidence II and the stock returns for each country. We first observe that the constant term $\lambda_0$ , which represents the pre-crisis period, is positive and significant for all the pairs. We find that higher institutional investor confidence is correlated to positive stock market returns in the Americas during the pre-crisis period. The coefficients range from a high of 0.3590 for the U.S., followed by Mexico at 0.2833, Canada at 0.2602, Colombia at 0.2333, Brazil at 0.2208, Chile at 0.2107, Argentina at 0.1490, and Peru at 0.1477. The table then reports the effect of the U.S. financial crisis, represented by  $\lambda_1$ , is positive and significant for all the pairs. This suggests contagion, with coefficients ranging from a high of 0.0996 for the U.S., followed by Mexico at 0.0854, Peru at 0.0789, Brazil at 0.0684, Canada at 0.0654, Argentina at 0.0604, Colombia at 0.0413, and Chile at 0.0283. Finally, the effect of the post-crisis period on the pairs is positive and significant, with coefficients that are larger than those from the crisis period in most cases except for Colombia, which is smaller than the effect from the crisis. The  $\lambda_2$  coefficients range from a high of 0.1381 for the U.S., Canada at 0.1111, Argentina at 0.0997, Mexico at 0.0969, Brazil at 0.0891, Peru at 0.0838, Chile at 0.0680, ad Colombia at 0.0208.

We compare the coefficient of determination  $R^2$  for each of the stock market returns, the U.S., VIX, *AAII*, and *II*, identifying the regression with the highest explaining value for each regression model. For Argentina, we recognize that *II* has the highest  $R^2$  value of 0.5602, followed by VIX at 0.4153, the U.S. at 0.3867, and *AAII* at 0.3751. For Brazil, we identify that the highest  $R^2$  value is from *II* at 0.4995, VIX at 0.2918, the U.S at 0.2537, and *AAII* at 0.1579. For Canada, we observe a similar pattern, with a  $R^2$  value for *II* at 0.5685, followed by VIX at 0.4402, followed by the U.S at 0.3784, tailed by *AAII* at 0.3613. For Chile, we identify that the highest  $R^2$  value is that of VIX at 0.4402, followed by the U.S. at 0.4141, *II* at 0.4019, and *AAII* at 0.115. The U.S. leads the case of Colombia with a  $R^2$  of 0.4834, VIX at 0.4349, *AAII* at 0.1246, and *II* at 0.0786. For Mexico, we find the highest  $R^2$  value with *II* at 0.4467, VIX at 0.4266, and *AAII* at 0.3069, and *AAII* at 0.0884. For Peru, the highest  $R^2$  is for *II* at 0.5531, the U.S. at 0.4767, VIX at 0.4266, and *AAII* at 0.279. The Case of the U.S. has the highest  $R^2$  value with *II* at 0.5531, VIX at 0.2748, and *AAII* at 0.1608.

Our findings support the flight to safety theory indicating that investor confidence played a significant role in the contagion from the U.S. stock market to the major stock markets in the Americas during the U.S. financial crisis. We also identify that the institutional investor confidence II's level of influence is significantly higher than that of the individual investor confidence *AAII*. These findings align with Verma and Soydemir (2006) that institutional investor sentiment has a more considerable impact than individual investor confidence on international markets. Our results are related to the observations made by Huerta, Egly, and Escobari (2016) that large institutional investors influence the U.S. markets at a greater rate than individual investors do, attributing this to their greater access to capital and their tendency to trade in large blocks. We contribute to the literature by identifying that U.S. institutional investors have greater influence than individual investors of the largest markets in the Americas. We observe that this influence increased during the U.S. financial crisis.

### **Summary and Conclusions**

We examine U.S. investor sentiment as a source of contagion from the U.S. to the largest stock markets in the Americas during the U.S. financial crisis. We use a DCC-GARCH model to obtain the dynamic conditional correlations between the U.S. market volatility, individual and institutional investor sentiments, and the stock indexes of Argentina, Brazil, Canada, Chile, Colombia, Mexico, Peru, and the U.S.

We use weekly data to analyze the relationship between U.S. market volatility, individual investor sentiment, institutional investor sentiment, and the stock returns from eight countries in the Americas before and after the U.S. financial crisis. In addition to using the perceived market volatility index VIX, we use the bull-bear spread from the American Association of Individual Investors *AAII* as a proxy for individual investor sentiment and the bull-bear spread from the Investor Intelligence *II* survey proxy for institutional investor sentiment. We obtain the dynamic conditional correlations between the investor sentiments and the various stock market indexes to identify the effect of the financial crisis on these pairwise correlations. We use two models to regress the predicted dynamic conditional correlation coefficients, using dummy variables for the periods that include the crisis and post-financial crisis. The dummy variables get a value of one during their period and zero otherwise. We observe a significant increase in the correlation coefficients, maintaining their sign, between U.S. stock returns, *VIX*, *AAII*, *II*, and the stock market returns, due to the financial crisis.

We also observe a negative and significant correlation between changes in *VIX* and the stock market returns. Institutional investor confidence has a more substantial influence on the international stock markets than individual investor confidence. We also observe a significant increase in the correlation coefficients, among the various sentiment indexes, due to the U.S. financial crisis.

We contribute to the literature by identifying the influence that U.S. investor sentiment plays on the stock returns of the largest stock markets in the Americas. By recognizing that the U.S. institutional investor sentiment has more substantial influence than the U.S. individual investor sentiment on the international markets of the Americas and that this influence increases significantly during the U.S. financial crisis. We caution about the consequences of block trading by institutional investors during times of crisis since this flight to safety behavior can result in financial contagion.

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Levels	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru	U.S.	VIX	AAII	II
Observations	730	730	730	730	730	730	730	730	730	730	730
Mean	1930.15	391.68	10198.77	1191.24	4.56	2170.68	899.30	1333.68	19.97	6.86	21.82
Standard Dev.	898.52	202.55	3071.00	483.43	2.56	937.89	483.31	340.36	9.25	18.19	14.78
Variance	807340.00	41027.22	9431054.00	233704.20	6.56	879631.90	233593.10	115841.80	85.49	331.05	218.58
Skewness	0.02	-0.03	-0.60	-0.09	-0.19	-0.43	-0.15	0.79	2.33	0.03	-0.90
Kurtosis	2.31	1.88	2.11	2.02	1.79	1.72	1.65	2.88	10.89	2.91	3.58
Shapiro-Wilk (Normality)	6.405***	7.354***	9.061***	6.847***	8.465***	9.491***	8.827***	8.718***	11.256***	-1.05	8.013***
Ljung-Box test (Auto Correlation)	20045.81***	21420.17***	20977***	24122.14***	23943.21***	23931.28***	23237.52***	22284.44***	8672.29***	1946.80***	6091.48***
Returns/Difference	es										
	RET ARG	RET BRA	RET CAN	RET CHI	RET COL	RET MEX	RET PER	RET U.S.	$\Delta$ VIX	$\Delta$ AAII	$\Delta II$
Observations	730	730	730	730	730	730	730	730	730	730	730
Mean	0.16	0.09	0.09	0.12	0.24	0.17	0.24	0.08	-0.01	-0.05	-0.02
Standard Dev.	5.1	4.77	3.20	2.92	3.91	3.83	4.15	2.44	3.16	14.37	4.83
Variance	26.04	22.75	10.24	8.55	15.32	14.67	17.24	5.94	9.98	206.59	23.35
Skewness	-1.92	-0.71	-1.33	-1.68	-1.18	-0.64	-0.59	-0.85	0.73	0	0.04
Kurtosis	15.21	7.93	13.53	18.49	9.23	13.13	8.46	11.2	13.73	3.46	3.94
Shapiro-Wilk (Normality)	0 706***	7 066***	0 (01***	0 412***	9 501***	0 224***	7 720***	0 601***	0 702***	1	2 201***
	9.790	/.900	9.001***	9.415	8.301	9.524	1.139	0.004	9./95	1	5.201

**Table 1:** Descriptive Statistics (Weekly Data from Jan. 2002 to Dec. 2015)

Notes: All stock indexes in levels represented in U.S. Dollars. All variables are in returns except VIX, AAII, and II, which are in differences. Sharpe Ratio = Mean/Standard-Dev.

	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru	U.S.	VIX	AAII	II
In Levels											
Argentina	1										
Brazil	0.6572***	1									
Canada	0.8741***	0.8809***	1								
Chile	0.7267***	0.8869***	0.8823***	1							
Colombia	0.7043***	0.865***	0.8858***	0.9648***	1						
Mexico	0.883***	0.8236***	0.9511***	0.9111***	0.9169***	1					
Peru	0.7618***	0.9022***	0.8885***	0.9644***	0.9307***	0.9244***	1				
U.S.	0.8234***	0.2533***	0.6345***	0.4132***	0.422***	0.6951***	0.4627***	1			
VIX	-0.295***	-0.0061***	-0.2842***	-0.142***	-0.152***	-0.2409***	-0.0729***	-0.5016***	1		
AAII	-0.0832***	-0.2382***	-0.1379***	-0.1332***	-0.1422***	-0.1403***	-0.162***	0.0796***	-0.3911***	1	
II	0.1752***	-0.0818***	0.129***	0.0641***	0.0679***	0.1257***	0.0344***	0.3789***	-0.7017***	0.5906***	1
<u>Returns/Differe</u>	enced										
	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	RET_U.S.	VIX_CHG	AAII_CHG	II_CHG
RET_ARG	1										
RET_BRA	0.5741***	1									
RET_CAN	0.5844***	0.7537***	1								
RET_CHI	0.486***	0.6761***	0.6591***	1							
RET_COL	0.4015***	0.5508***	0.5539***	0.5423***	1						
RET_MEX	0.5346***	0.741***	0.7454***	0.6678***	0.5802***	1					
RET_PER	0.5059***	0.6769***	0.7568***	0.5785***	0.4932***	0.6651***	1				
RET_U.S.	0.519***	0.6487***	0.7818***	0.5966***	0.506***	0.7731***	0.562***	1			
VIX CHG	-0.4453***	-0.5594***	-0.6655***	-0.5573***	-0.4913***	-0.6934***	-0.532***	-0.7976***	1		
AAII CHG	0.1525***	0.1354***	0.1919***	0.1633***	0.1038***	0.1264***	0.1494***	0.1566***	-0.0798***	1	
II CHG	0.2037***	0.265***	0.3057***	0.2516***	0.2381***	0.3154***	0.2009***	0.4090***	-0.3253***	0.2074***	1

Table 2: Correlation Coefficients of Weekly Stock Index Returns, TED, AAII, and II - (Weekly Data from Jan, 2002 to Dec, 2015)

<u>*II\_CHG\_0.2037\*\*\*\_0.265\*\*\*\_0.3057\*\*\*\_0.2516\*\*\*\_0.2381\*\*\*\_0.3154\*\*\*\_0.2009\*\*\*\_0.4090\*\*\*\_-0.*</u> Notes: All variables are in returns except *VIX, AAII,* and *II,* which are in differences. \*, \*\*, and \*\*\* significant at 10%, 5% and 1%, respectively

Series	ADF(k)	KPSS(19)	PHILLIPS-PERRON(
RET_ARG	-14.833 (2)***	0.0552	-28.642***
RET_BRA	-14.497 (2)***	0.0738	-29.400***
RET_CAN	-19.193 (1)***	0.0385	-28.760***
RET_CHI	-14.262 (2)***	0.0593	-28.560***
RET_COL	-12.769 (2)***	0.0599	-26.996***
RET_MEX	-15.498 (2)***	0.0519	-29.485***
RET_PER	-26.325 (0)***	0.0359	-26.328***
RET_U.S.	-27.962 (0)***	0.0578	-27.976***
VIX_CHG	-20.078 (1)***	0.0253	-32.042***
AAII_CHG	-20.806 (2)***	0.0188	-44.237***
II_CHG	-17.761 (1)***	0.0296	-23.538***

Table 3:	Unit Root Tests on Weekly I	Data - January 1, 2	002 to December 31, 2015
Series	ADF(k)	KPSS(19)	PHILLIPS-PERRON(k)

Notes: The lag length (k) is selected as follows: the null hypothesis is the unit root for the ADF test. We use the Campbell and Perron (1991) data-dependent procedure starting with an upper bound  $k_{max} = 2$  on k. if the last lag is significant, choose  $k = k_{max}$ ; if not, we reduce k by one and continue this process until this is satisfied, or else k = 0. The KPSS assumes a null that the series is stationary. We use the Bartlett-Kernel criteria to select k = 19 as truncating parameter. The critical values for the KPSS test are 0.119 (10%), 0.146 (5%), and 0.216 (1%). The Phillips-Perron test has a null hypothesis of unit root and uses the equation  $k = 4(T/100)^{2/9}$  to select the maximum lag, in this case k = 7. \*, \*\*, and \*\*\* significant at 10%, 5% and 1%, respectively.

		, , ,			/			
	RET_U.S.	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER
Mean Equations								
Y0	0.33738*** (0.0575)	0.42810*** (0.1390)	0.49117*** (0.1299)	0.38381*** (0.0799)	0.30679*** (0.0826)	0.52815*** (0.1213)	0.50810*** (0.0977)	0.45549*** (0.1223)
Υ1	-0.10692*** (0.0321)	-0.04435 (0.0364)	-0.04263 (0.0271)	-0.09703*** (0.0257)	0.03277 (0.03164)	0.07279** (0.0368)	-0.03726 (0.0294)	0.01583 (0.0299)
$\Upsilon 2 (\Delta VIX)$	0.04792 (0.0293)	-0.02693 (0.0515)	0.10258** (0.05176)	0.01466 (0.0347)	0.05366 (0.0336)	0.16285*** (0.0476)	0.10037** (0.0427)	-0.00924 (0.0089)
$\Upsilon 3 (\Delta AAII)$	-0.00296 (0.0043)	0.00595 (0.0096)	0.00941 (0.0097)	-0.00403 (0.0059)	0.00683 (0.0059)	-0.00720 (0.0087)	-0.00244 (0.0071)	0.01623 (0.0286)
Υ3 (ΔΙΙ)	0.02714* (0.0152)	-0.00849 (0.0299)	0.03564 (0.0310)	0.03094 (0.0197)	0.01281 (0.0192)	0.02623 (0.0285)	0.01213 (0.0238)	0.09922** (0.0496)
Variance Equations								
Cons	0.18749*** (0.0427)	0.76925*** (0.2682)	1.48375*** (0.3519)	0.41229*** (0.0886)	0.74120*** (0.2158)	2.8151*** (0.9571)	0.74069*** (0.1633)	0.76746*** (0.2371)
Arch	0.13326*** (0.0167)	0.13804*** (0.0232)	0.07856*** (0.0128)	0.08243*** (0.0124)	0.12714*** (0.0265)	0.18973*** (0.0517)	0.11673*** (0.0168)	0.06522*** (0.0135)
Garch	0.85070*** (0.0167)	0.85274*** (0.0231)	0.85933*** (0.0224)	0.88087*** (0.0164)	0.79129*** (0.0437)	0.67330*** (0.0871)	0.84416*** (0.0204)	0.89298*** (0.0220)
Persistence								
	0.98396	0.99078	0.93790	0.96330	0.91843	0.86302	0.96089	0.95820
Multivariate DCC Eq	uation							
Lambda1	0.01079*** (0.0014)							
Lambda2	0.97745*** (0.0026)							
Observations	729							
χ2	364.19							
χ2 (p-value)	0.000							

Table 4: DCC Estimations for Stock Returns, VIX, AAII, and II (weekly data from Jan. 2002 to Dec. 2015)

Notes: Robust standard errors are in parentheses. \*pb.10, \*\*pb.05, \*\*\*pb.01. The mean equation is  $r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{\Delta VIX} + \gamma_3 r_{t-1}^{\Delta AII} + \gamma_3 r_{t-1}^{\Delta III} + \varepsilon_t$ 

where  $r_t = (r_{Argentina,t}, r_{Brazil,t}, r_{Canada,t}, r_{Chile,t}, r_{Colombia,t}, r_{Mexico,t}, r_{Peru,t}, r_{U.S.,t})'$ ;  $\varepsilon_t = (\varepsilon_{Argentina,t}, \varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Chile,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{Peru,t}, \varepsilon_{U.S.,t})'$ and  $\varepsilon_t | I\Omega_{(t-1)} \sim N(O, H_t)$ . The variance equations are  $h_{ii,t} = c_i + a_i \varepsilon_{i,t-1}^2 + b_i h_{ii,t-1}$  for i = 1, 2, ..., n. The null for the  $x^2$  test is  $H_0 : \alpha = \beta = 0$ . Persistence is calculated as the sum of the coefficients in the variance equation (Arch and Garch).

Table 5: MGARCH-DCC Based Correlations Between VIX, AAII, II, and Stock Returns

	$\Delta VIX$	$\Delta AAII$	$\Delta II$	RET_U.S.	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER
$\Delta VIX$	1										
$\Delta AAII$	-0.143* (0.082)	1									
$\Delta II$	-0.507*** (0.06)	0.292*** (0.08)	1								
RET_U.S.	-0.838*** (0.024)	0.196** (0.087)	0.603*** (0.058)	1							
RET_ARG	-0.512*** (0.057)	0.182** (0.084)	0.339*** (0.072)	0.603*** (0.05)	1						
RET_BRA	-0.597*** (0.05)	0.186** (0.089)	0.419*** (0.071)	0.711*** (0.039)	0.672*** (0.047)	1					
RET_CAN	-0.697*** (0.04)	0.213** (0.087)	0.468*** (0.068)	0.825*** (0.026)	0.647*** (0.048)	0.839*** (0.024)	1				
RET_CHI	-0.575*** (0.051)	0.188** (0.087)	0.379*** (0.073)	0.635*** (0.048)	0.541*** (0.057)	0.724*** (0.04)	0.73*** (0.041)	1			
RET_COL	-0.553*** (0.054)	0.157* (0.089)	0.305*** (0.077)	0.614*** (0.052)	0.557*** (0.055)	0.751*** (0.041)	0.743*** (0.044)	0.694*** (0.046)	1		
RET_MEX	-0.715*** (0.038)	0.18** (0.089)	0.499*** (0.066)	0.806*** (0.028)	0.628*** (0.051)	0.794*** (0.029)	0.793*** (0.03)	0.73*** (0.039)	0.674*** (0.047)	1	
RET PER	-0.52*** (0.056)	0.179** (0.088)	0.324*** (0.077)	0.617*** (0.05)	0.572*** (0.055)	0.733*** (0.038)	0.782*** (0.031)	0.646*** (0.049)	0.648*** (0.052)	0.677*** (0.043)	1

Notes: Robust standard errors are in parentheses. \*, \*\*, and \*\*\* significant at 10%, 5% and 1%, respectively.
	$\Delta VIX$	$\Delta AAII$	$\Delta II$
RET_ARG	-0.4876***	0.1635***	0.2413***
	(0.0119)	(0.0042)	(0.0052)
RET_BRA	-0.5648***	0.1551***	0.3060***
	(0.0151)	(0.0048)	(0.0074)
RET_CAN	-0.6628***	0.1858***	0.3627***
	(0.0174)	(0.0054)	(0.0086)
RET_CHI	-0.5662***	0.1682***	0.2713***
	(0.0143)	(0.0052)	(0.0071)
RET_COL	-0.4954***	0.1202***	0.2580***
	(0.0122)	(0.0035)	(0.0078)
RET_MEX	-0.6963***	0.1493***	0.3780***
	(0.0183)	(0.0047)	(0.0094)
RET_PER	-0.5106***	0.1330***	0.2306***
	(0.0125)	(0.0041)	(0.0052)
RET_U.S.	-0.8157***	0.1902***	0.4899***
	(0.0225)	(0.0058)	(0.0119)

 Table 6: Regression Coefficients (Since the Crisis)

Notes: Numbers in parentheses denote standard errors. \*pb.10, \*\*pb.05, \*\*\*pb.01

(weekiy uata nom.	Jan. 2002 to De	<i>c</i> . 2013)					
Country/Index i:	RET_U.S	RET_U.S.	RET_U.S.	RET_U.S.	RET_U.S.	RET_U.S.	RET_U.S.
Country j:	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER
$\lambda_0$	0.4132*** (0.0049)	0.5340*** (0.0057)	0.6354*** (0.0054)	0.4694*** (0.0042)	0.3789*** (0.0077)	0.6304*** (0.0062)	0.3835*** (0.0053)
λ1	0.1517*** (0.0110)	0.1359*** (0.0128)	0.1007*** (0.0120)	0.1354*** (0.0095)	0.1848*** (0.0099)	0.1747*** (0.1389)	0.1933*** (0.0119)
λ2	0.1365*** (0.0068)	0.1147*** (0.0079)	0.1562*** (0.0074)	0.1251*** (0.0059)	0.1427*** (0.0061)	0.1400*** (0.0086)	0.1795*** (0.0074)
Observations	730	730	730	730	730	730	730
F	230.78	124.94	222.91	258.67	342.04	162.41	333.07
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R <sup>2</sup>	0.3867	0.2537	0.3784	0.4141	0.4834	0.3069	0.4767

Table 7A: Regression Analysis of Conditional Correlations Coefficients and the U.S. Financial Crisis (Weekly data from Jan. 2002 to Dec. 2015)

Notes: Robust standard errors are in parentheses. \*pb.10, \*\*pb.05, \*\*\*pb.01. The regression equation is  $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}$ , for  $i \neq j$ 

<b>Table 7B:</b> Regression Analysis of Conditional	Correlations Coefficients and the U.S. Financial Crisis
(Weekly data from Jan. 2002 to Dec. 2015)	

Country/Index i:	ΔVIX							
Country j:	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	RET_U.S.
$\lambda_0$	-0.3512*** (0.0046)	-0.4507*** (0.0050)	-0.5301*** (0.0044)	-0.4299*** (0.0043)	-0.3646*** (0.0042)	-0.5532*** (0.0053)	-0.3715*** (0.0045)	-0.6818*** (0.0061)
λ1	-0.1592*** (0.0102)	-0.1303*** (0.0112)	-0.0877*** (0.0099)	-0.1434*** (0.0096)	-0.1448*** (0.0094)	-0.1683*** (0.1179)	-0.1374*** (0.0101)	-0.1318*** (0.0136)
λ2	-0.1312*** (0.0063)	-0.1104*** (0.0069)	-0.1430*** (0.0062)	-0.1346*** (0.0060)	-0.1276*** (0.0058)	-0.1372*** (0.0073)	-0.1394*** (0.0062)	-0.1343*** (0.0084)
Observations	730	730	730	730	730	730	730	730
F	259.9	151.15	271.07	287.67	281.54	214.18	272.17	139.09
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R <sup>2</sup>	0.4153	0.2918	0.4256	0.4402	0.4349	0.369	0.4266	0.2748

Notes: Robust standard errors are in parentheses. \*pb.10, \*\*pb.05, \*\*\*pb.01. The regression equation is  $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}$ , for  $i \neq j$ 

weekly data from J	an. 2002 to Dec	2. 2013)						
Country/Index i:	ΔΑΑΙΙ	ΔAAII	ΔΑΑΙΙ	ΔΑΑΙΙ	ΔΑΑΙΙ	ΔΑΑΙΙ	ΔΑΑΙΙ	ΔΑΑΙΙ
Country j:	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	RET_U.S.
$\lambda_0$	0.1176*** (0.0020)	0.1312*** (0.0024)	0.1542*** (0.0021)	0.1369*** (0.0032)	0.0950*** (0.0021)	0.1151*** (0.0033)	0.1083*** (0.0022)	0.1651*** (0.0026)
λ1	0.0041*** (0.0044)	-0.0161*** (0.0054)	-0.0320*** (0.0047)	-0.0059*** (0.0071)	0.0052*** (0.0048)	0.0153*** (0.0073)	-0.0324*** (0.0049)	-0.0201*** (0.0059)
λ2	0.0555*** (0.00276)	0.0331*** (0.0034)	0.0462*** (0.0029)	0.0398*** (0.0044)	0.0298*** (0.0030)	0.0386*** (0.0045)	0.0378*** (0.0030)	0.0355*** (0.0037)
Observations	730	730	730	730	730	730	730	730
F	219.81	69.36	205.64	48.36	52.87	36.36	142.03	70.86
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R <sup>2</sup>	0.3751	0.1579	0.3613	0.115	0.1246	0.0884	0.279	0.1608

**Table 7C:** Regression Analysis of Conditional Correlations Coefficients and the U.S. Financial Crisis (Weekly data from Jan. 2002 to Dec. 2015)

Notes: Robust standard errors are in parentheses. \*pb.10, \*\*pb.05, \*\*\*pb.01. The regression equation is  $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}$ , for  $i \neq j$ 

Table 7D: Regression Analysis of Conditional Correlations Coefficients and the U.S. Financial C	risis
(Weekly data from Jan. 2002 to Dec. 2015)	

Country/Index i:	ΔII							
Country j:	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	RET_U.S.
$\lambda_0$	0.1490*** (0.0024)	0.2208*** (0.0024)	0.2602*** (0.0026)	0.2107*** (0.0022)	0.2333*** (0.0026)	0.2833*** (0.0030)	0.1477*** (0.0024)	0.3590*** (0.0033)
λ1	0.0604*** (0.0053)	0.0684*** (0.0054)	0.0654*** (0.0058)	0.0283*** (0.0050)	0.0413*** (0.0058)	0.0854*** (0.0066)	0.0789*** (0.0053)	0.0996*** (0.0075)
λ2	0.0997*** (0.0033)	0.0891*** (0.0033)	0.1111*** (0.0035)	0.0680*** (0.0031)	0.0208*** (0.0036)	0.0969*** (0.0041)	0.0838*** (0.0033)	0.1381*** (0.0046)
Observations	730	730	730	730	730	730	730	730
F	465.2	364.77	481.17	245.91	32.09	292.46	352.79	452.11
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R <sup>2</sup>	0.5602	0.4995	0.5685	0.4019	0.0786	0.4443	0.4911	0.5531

Notes: Robust standard errors are in parentheses. \*pb.10, \*\*pb.05, \*\*\*pb.01. The regression equation is  $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}$ , for  $i \neq j$ 







**Figure 2:** Dynamic Conditional Correlations –  $\Delta II$  to Stock Market Returns





**Figure 3:** Dynamic Conditional Correlations –  $\Delta AAII$  to Stock Market Returns

# Racial Composition in Advertisements and Its Effects on White Consumers' Perceptions and Purchase Intentions

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### Abstract

Previous marketing research has generally not examined how ethnic majority consumers perceive advertisements featuring mixed racial compositions of model groups. We present an investigation into how White consumers' perceptions and purchase intentions change depending on the racial composition of the people represented in an advertisement. The study uses a single 12-condition experiment, in which it examines the type of advertisement (product versus social advocacy advertising), racial composition (all-White vs. diverse mix vs. all-Black), and racial priming effects (racially-primed versus racially-neutral message). Additionally, consumers' levels of self-referencing to the ad and strength of ethnic identification are explored as possible mediation variables.

JEL codes: M31, M37 Keywords: Advertising, Branding, Ethnic Diversity, and Racial Priming

# Introduction

Advertising is an essential tool for brands to convey their values, promote their products or services, and connect with their intended audience. Brands often use visual stimuli in their marketing materials to tell stories and connect with different groups of consumers, and one common way to do so is through imagery of people. However, representations of people in advertisements have not always reflected the reality of what the larger society looks like. Historically, marketers have been reluctant to use People of Color (POC) in advertisements out of fear that they would alienate White consumers, who are still the ethnic majority group in the United States (Appiah, 2001). In fact, previous research has shown that high-prejudice White individuals respond with significantly less favorable attitudes towards advertisements featuring a Black model than low-prejudice Whites (Whittler, and DiMeo 1991). More recent studies have also shown that consumer racism negatively impacts ethnic majorities' judgements and purchase intentions of products from minority-owned businesses (Ouellet, 2007; Rao Hill and Paphitis, 2011).

Nevertheless, "diversity and inclusion" have become widely-discussed topics across organizations in the last decade. The murder of George Floyd at the hands of the Minneapolis police in the summer of 2020 marked a significant moment in the history of racial minority groups in the United States (Yang et al., 2021). After the incident, a wave of protests and social movements such as Black Lives Matter (BLM) gained traction, and not long after, the Stop Asian Hate movement also emerged in response to the racial discrimination against Asian Americans during the COVID-19 pandemic. These movements were significant in shaping racial relations in the United States (Song and O'Donnell, 2021).

In response to these events, corporate communication strategies have gone through considerable transformations in the past few years, with brands actively devoting efforts to emphasize racial diversity, equity, and inclusion (DEI) in their marketing materials to meet changing social attitudes. Customers nowadays wish to see themselves reflected in brand messages, and marketers have grown more concerned about how to target an increasingly more diverse yet polarized U.S. population (Melancon, 2021). Thus, these changes open up an opportunity to expand on previous research on ethnic perception in marketing.

The effects of ethnic perception on consumers' response to advertisements have been widely documented. Past experiments have shown that an ad spokesperson's race can significantly influence the perceptions and purchase intentions of ethnic minority consumers in product advertisements (ads promoting a product or service). Still, White consumers (the ethnic majority) generally feel indifferent towards a model's race in product ads (Lee and Kim, 2019). Additionally, past research has explored the effects of a spokesperson's race on consumer perception in social advocacy advertisements (Lee et al., 2013). Different from product ads, social advocacy advertisements allow brands to publicly support social causes that align with company values. For example, brands have recently employed social advocacy advertisements to take a stance on social causes surrounding racial injustice (Yang et al., 2021), or promoting messages of hope during the COVID-19 pandemic (Deng et al., 2022). Both product and social advocacy advertisements serve to communicate brand messages in different ways, and previous studies have shown that consumers' ethnic perceptions can significantly impact advertising effectiveness (Lee et al., 2002; White, 2007).

However, much of the existing literature has not considered the notable developments in racial relations following the summer of 2020. Consumers today have become more vocal about the lack of representation plaguing industries (Saputo, 2019). The high engagement that diverse advertisements (whether commercial or social) have garnered in recent years suggests a growing concern for brands to be more cognizant of ethnic representation in their marketing materials. Although prior studies have shown that White consumers are generally ambivalent towards ethnically-targeted advertisements, recent socio-cultural developments suggest that a shift in racial attitudes could have occurred amongst the majority ethnic group, thus changing their ethnic perceptions in advertisements (Tesler, 2020).

Previous research has however overlooked how consumers respond to larger group compositions in advertising images. Experiments on targeted ethnic advertising have only examined how individuals respond to single-model advertisements. As such, this study examines how variations in group racial compositions are perceived across two types of marketing communications: product advertising, and social advocacy advertising. Three different variations of racial composition are tested: all-White models, ethnically diverse models, and all-Black models. Through these manipulations, the paper examines the effects of non-diverse, diverse, and all-minority racial compositions. Additionally, the paper investigates how racial priming (bringing racially-charged language to consumers' attention) influences people's judgment of the ethnic composition in the advertisements. By racially priming consumers, this study contributes to an understanding how racially-charged language cues might influence behavior.

### **Literature Review**

### **Diversity in Product Advertising**

Diversity in marketing communication has been a widely discussed topic across industry and academia (Jamal, 2003; Cui and Licsandru, 2018). Marketing communication imagery has deep roots in racist and discriminatory practices dating back to the colonial period, and underrepresentation in advertising spaces has been the focus of many qualitative studies in the past (Davis, 2018). For instance, a previous study reveals that the percentage of POC represented in children's television advertising, specifically African Americans, Hispanics, and Asians, is less than proportional to the ethnic makeup of the city in which the advertisements appeared. Further analysis suggests that for sophisticated products such as toys and electronics, advertisers are more likely to use Caucasian and Asian characters, who are perceived to be more positively stereotyped (Maher et al., 2008). Other research has also examined colorism and the manifestation of whitewashing in marketing communications, showing that darker-skinned models were nine times less likely to be featured in print advertisements for beauty products than light and medium-skinned models (Mitchell, 2020).

Additionally, previous scholarship has explored the role of marketing in a multicultural society. Studies indicate that exclusionary marketing practices such as the underrepresentation of social groups can potentially motivate consumers from such groups to revolt and be frustrated with the advertised brand (Cui and Licsandru, 2018). Marketing practices have become so embedded in society that they have a significant impact on the way consumers construct and maintain their identities (Jamal, 2003). When marketing images promote exclusionary practices and interfere with people's sense of acceptance, belongingness, and equality, it leads to skewed conceptions of particular social groups and perpetuates structural social advantages (Gopaldas and Siebert, 2018).

Although the literature indicates that discriminatory practices have influenced marketing practices in the past, the rise of social movements following the events of May 2020 has pushed marketers to place a stronger focus on diversity, equity, and inclusion (DEI) (Guzmán, 2021). The BLM movement served as a wake-up call for brands in significant ways: given that BLM stands against structural racism, silence from brands on the issue was often perceived by consumers as taking the side of the oppressor (Hurst, 2020). The movement also further highlighted how structural racism and underrepresentation have suppressed marginalized voices, thus sparking a call, both from consumers and marketing managers, for more diverse racial representation in advertising imagery. A recent study involving participants from Brazil, the United Kingdom, and the United States found that 54% of consumers do not feel culturally represented in online advertising and 64% indicated they wished to see more diversity (de Lima Alcantara, 2021). In addition to satisfying customer's need and desires, DEI strategies in marketing communications are also seen as a successful tool to improve long-term brand equity by positioning the brand as emotionally competent (Poole, 2021). Brand equity is here defined as the value of a brand that is determined by consumers that speak to their morals and personal values. However, while marketers and consumers have shown growing concern for more diverse representation in contemporary advertising, there has been little research-based evidence on whether racial diversity in advertisements has a positive effect on consumer behavior.

Despite a heightened expectation for brands to embrace diversity in their marketing materials, only a few studies have examined the effectiveness of racially integrated product advertisements (ads promoting products or services) in experimental

settings. Previous work on in-group bias theory suggests that people tend to favor members of their own group more than members of the out-group (Brewer, 1979). For example, Elias et al., 2011 found that Black consumers generally rate advertisements with a Black product presenter more positively. Similar experiments have shown that other ethnic minorities, such as Asian Americans and Hispanics, also tend to prefer ads that feature an ethnic minority model (Appiah, 2001; Lee and Kim, 2019). Therefore, consumers are expected to evaluate ads featuring models of their same ethnicity more favorably. One previous study conducted in 1999 found that advertisement racial composition does not strongly influence African Americans' purchase intention of race-neutral products like perfume, but it does for race-based products like makeup foundation (Green, 1999). However, the effects of racially diverse ads (featuring models from more than just two races) on White consumers' behavior has yet to be explored. Given that such a demographic still represents the ethnic majority of American consumers, it is relevant for marketers to assess their ethnic perceptions in advertisements.

The current study aims to expand on prior work by broadening the scope of ethnic diversity and comparing White consumer responses to product ads featuring all-White versus all-Black versus diverse model compositions. These three different variations in racial composition are used to assess how racially diverse product ads (compared to non-diverse or all-minority ads) may impact consumer perceptions and purchase intentions. Results from this experiment also provide an updated examination of racial perception in product advertisements following recent developments in racial justice issues. Therefore, the following research question is proposed:

**Research Qu.1:** How does the ethnic composition in a product ad (all-White versus diverse mix versus all-Black) influence White consumers' (i) attitudes toward the brand, (ii) attitudes toward the ad, and (iii) purchase intention?

## Diversity in Social Advocacy Advertising

Social advocacy advertising is another type of communication strategy that brands often use to enhance their marketing efforts. Prior research shows that social advocacy advertising serves three main purposes: (1) to enhance an organization's image; (2) to deflect criticism of the organization and/or its products, or (3) to communicate a company's values while attempting to raise awareness of social issues (Bostdorff and Vibbert, 1994; Lee et al., 2013). Many companies today have publicly taken a stance on social issues that align with company values (e.g. gender violence, environmental sustainability, or LGBTQ+ rights) (Bharadwaj and Rodríguez-Vilá, 2017). Notable examples include Pepsi's 'Live Now' campaign meant to promote unity and Gilette's 'The Best a Man Can Get' aiming to stand against toxic masculinity. While initially aimed to promote a positive message by taking a social stance, the ads backfired as both brands failed to predict how key consumer segments would decode the advertisements (Taylor, 2017; Trott, 2020). The controversial campaigns were eventually pulled, but such cases highlight how social advocacy marketing can significantly influence consumers' perceptions of brands.

While social advocacy advertisements are less focused on selling a product or service, studies have shown that proper advocacy communication can be an effective way to foster positive brand associations and purchase intentions (Groza et al., 2011). Research indicates that brands still reap business benefits by advertising their social commitments, as today's consumers, particularly Generation Z and Millennials, are belief-driven and want to see brands that improve the world by supporting social causes (Burnett, 2019).

The effect of ethnic perception in social advocacy advertisements has been widely studied, although their effectiveness is not as easily measured as effectiveness for product advertisements. Past research suggests that consumers' perceptions of value advocacy are mediated through customers' pre-existing schemas (Groza et al., 2011; Lee et al., 2002; Lee et al., 2013). Schemas are cognitive structures that represent a person's current knowledge about certain situations or stimuli, which allow customers to encode and retrieve information that is presented to them (Dimofte et al., 2003). In the context of social advocacy advertising, a previous study showed that increased congruity of consumers' brand schemas to the fact that brands are socially responsible leads to more favorable attitudes toward the advertised message (Bhaduri and Ha-Brookshire, 2017). When customers' perceptions of a brand align with the social message being conveyed, they are more likely to have positive reactions to the advertisement.

However, schema congruity alone does not fully explain the process through which consumers perceive social cause advertising. Previous research suggests that attribution theory can be used to explain how incongruent and congruent schema influence perceptions of social cause sponsorship (Lee et al., 2013). Attribution theory posits that individuals assign an underlying cause or explanation to a certain event (Kelley, 1973). If individuals have a reason to believe that there is an alternative explanation to an event (e.g. company is motivated by profits rather than by social good), consumers minimize the explanation of the original cause (Kelley, 1973). This theory proposes that consumers can have positive or negative attributions of corporate social sponsorship, and a negative attribution indicates that they perceive the company's social commitment as self-serving rather than genuine (Bhattacharya and Du, 2010). Therefore, brands should aim for positive

attributions, so their commitment to social causes is perceived as altruistic rather than self-serving to maximize their business benefits.

Drawing from schema congruity and attribution theory, prior research has also shown that an advertising model's ethnicity can influence consumers' perceptions of social cause sponsorship. This is because people use their own ethnicity as a schema to interpret information that is presented to them (Dimofte et al., 2003). One previous experiment demonstrated that Asian consumers find more schema congruence with social advocacy ads that displayed an Asian spokesperson and Asian cultural cues, leading to more positive messaging attributions and higher purchase intentions (Lee et al., 2013). Similarly, Arpan and Wang (2008) found that African American subjects responded more favorably to HIV public service announcements (PSAs) featuring a Black spokesperson compared to PSAs featuring a White spokesperson. Moreover, African Americans participants rated the Black spokesperson as more credible than the White spokesperson (Arpan and Wang, 2008). While Arpan and Wang (2008) examine PSAs from a non-corporate source, their findings still provide relevant insights on ethnic perceptions in social advocacy messaging.

Ethnic perception processes in social advocacy ads appear to remain consistent with those of product ads amongst ethnic minority groups. Overall, ethnic minority consumers tend to positively attribute social cause advertisements when the ad triggers schematic congruence with their ethnic identity. However, limited studies have examined how White subjects attribute social advocacy advertisements featuring racially-integrated group compositions. As the ethnic majority group, Caucasian consumers are generally less aware of racial disparities affecting marginalized groups, and thus are less sensitive towards model race cues in social advocacy advertisements (Deshpandé and Grier, 2001; Lee and Kim, 2019). Nonetheless, given the recent developments of race relations in the United States, the current study seeks to update previous research findings by examining White consumers' response to different group racial compositions in social cause advertisements.

**Research Qu.2:** How does the ethnic composition in a social advocacy ad (all-White vs. diverse mix vs. all-Black) influence White consumers' (i) perceptions of the company's social cause commitment (ii) attitudes toward the brand, (iii) attitudes toward the ad, and (iv) purchase intention?

# **Racial Priming**

Discussions surrounding racial equality have become much more politicized in recent years. A year after social movements intensified in the United States to protest George Floyd's murder, data revealed that Americans were deeply divided on racial inequality issues (Pew Research Center, 2021). When asked whether paying more attention to the history of racism in the U.S. was good for society, opinions between ethnic groups differed significantly: 75% of Black adults said attention to this topic was a good thing, with 54% saying it was "very good" for society (Pew Research Center, 2021). A majority of Asian Americans and Hispanics also believed that giving more attention to the nation's racial history was a positive thing. However, only 46% of White adults said that greater attention to such topics was good for society, with 24% saying it was "very good," and 32% saying it was bad (Pew Research Center, 2021). Such data suggests that American consumers' racial attitudes could become more polarized when they are intently reminded of structural inequalities affecting ethnic minorities.

Advertisers have long employed racial priming techniques to activate latent attitudes towards specific ethnic groups (Huber and Lapinski, 2006). Past research on racial priming in political campaigns explores how White voters evaluate candidates depending on the level of racial priming embedded in the advertisement (Hutchings and Jardina, 2009). One study found that White people's negative racial attitudes can be activated by simply highlighting racially-charged topics such as affirmative action in a political advertisement (Reeves, 1997). Mendelberg (2008) argues that Caucasians are generally ambivalent to racial issues, emphasizing that although they are committed to racial equality, they still continue to unconsciously project racial prejudice and promote anti-black stereotypes. Mendelberg's findings indicate that individuals tend to reject explicit racial appeals in advertisements because people perceive the obvious racial intent. Instead, implicit racial appeals in advertisements are more effective in shaping opinion formation (Mendelberg, 2008).

While racial priming has been largely studied in political campaigns, limited scholarship examines the effects of racial priming in product and social cause advertisements. In a previous study, Forehand et al. (2002) explored the effects of embedded identity primes on spokespersons and advertisement evaluation. The study showed that Asian subjects responded most positively to Asian spokespeople and Asian-targeted advertising when they were exposed to identity primes, whereas Caucasian subjects responded most negatively to those same Asian identity primes. These results indicate that awareness of racial differences may influence how consumers perceive advertisements featuring different model racial compositions.

Building on previous research, this study employs racial priming to examine how racially-charged language can impact consumers' advertisement perceptions and purchase intentions. By exposing individuals to racially-charged stimuli prior to viewing the advertisements, the paper explores whether these cues could prompt a stronger judgment of the racial composition in an ad. Thus, racial priming in this experiment serves as a measure of how real-world conversations about racial inequality in the United States may have an impact on consumers' perceptions of different ethnic groups in advertisements. As such, the following additional research questions are posited:

**Research Qu.3:** How does prior exposure to racially-charged language influence White consumers' (i) attitude toward the brand, (ii) attitude toward the ad, and (iii) purchase intention in product advertisements featuring varied ethnic compositions?

**Research Qu.4:** How does prior exposure to racially-charged language influence White consumers' (i) perception of the company's social cause commitment (ii) attitude toward the brand, (iii) attitude toward the ad, and (iv) purchase intention in social advocacy advertisements featuring varied ethnic compositions?

# Methodology

# Design

The experiment follows a 2 (ad type: social advocacy versus product) x 3 (ethnic composition: all-White versus diverse mix vs. all-Black) x 2 (priming: racially-neutral vs. racially-charged) between-subject design to explore the research questions. The questionnaire was designed using Qualtrics (see Appendix D). The five dependent variables include (a) ad likability, (b) brand likability, (c) brand trustworthiness, (d) net promoter score, (e) perceived advertiser's motives, and (f) purchase intention. Data for mediation variables (consumers' level of self-referencing and strength of ethnic identification) was also collected. The structure of the experimental conditions is illustrated in Table 1.

Table 1: Manipulations within the Experiment

		All-White	Diverse mix	All-Black
Duadwat Ad / Sacial Causa Ad	Racially-Neutral Stimulus			
Product Ad / Social Cause Ad	Racially-Charged Stimulus			

# **Participants**

A total of 1249 participants across the United States were recruited using Amazon Mechanical Turk. In total, 62.44% of participants identified as male, 36.97% identified as female, and 0.5% identified as non-binary or did not wish to disclose. The mean age was 39, with a median of 36. From the participant sample, 83% identified as White, 7% as Black, and 10% as other people of color (POC). However, only Caucasian participants' responses (1,209 subjects) were taken into account for the analysis in this study.

# **Stimulus Materials**

The experiment consisted of two levels of stimuli: priming passage, followed by ad exposure. The passages used for racial priming were extracted from an Insider.com article (Sarkisian, 2021) discussing topics about the American entertainment industry and the Academy Awards. It is pertinent to note that these experiments were conducted in December 2021, prior to the 2022 Academy Awards ceremony taking place. Both racially-neutral and racially-charged passages had a length of fifty words. The racially-neutral passage contained general information about the Academy's mission in the film industry and the number of nominations that it gives out each year. The language employed in this first passage was neutral in the sense that racial or ethnic themes were not discussed. In contrast, the racially-charged message blatantly pointed out a diversity problem in the Oscars, stating that the nominations for the top award categories were overwhelmingly going to Caucasian creatives, clearly identifying racial inequalities in the American media industry. These passages were pretested using 15 volunteers and refined to ensure that they unanimously agreed that the priming message was effective in making participants think about issues surrounding racial injustice (see Appendix C for passages).

Six variations of full-color social media ads were created for the experiment. The advertisements were for Pompom Mobile, an imaginary smartphone manufacturing brand. A fictitious brand was used to avoid consumer bias or knowledge about existing brands. Two types of ads were created: a product commercial and a social advocacy ad. Each ad type had three variations of the models' ethnic composition (see Appendix B for ad mockups). The product ads were promoting Pompom's

new cellphone model, whereas the social advocacy ads were promoting the company's efforts in supporting healthcare workers through donations of hospital equipment. A smartphone manufacturer was selected as it is common to see technology brands employ both product and social advocacy ads on their social media. Each advertisement showed a group of six people, and the groups were either all White, ethnically diverse, or all Black. The ethnically diverse advertisements featured Asian, White, Brown, and Black models. The ad copy, brand names, and size remained consistent across all conditions.

# Procedure

Ethical clearance for the study was obtained from the author's institution. Once subjects voluntarily consented to participate in the study, they were randomly assigned to one of the twelve experimental conditions. After screening out participants that were non-White and/or failed attention checks, each condition ended up with between 67 and 84 subjects. The survey took an average of five minutes to complete and workers were compensated 50 cents for their time. Following the consent form, subjects were asked to carefully read either the racially-neutral (control condition) or racially-charged (primed condition) passage. Then, they were instructed to carefully review all components of the ad and proceed to the questionnaire. The question included items assessing attitudes toward the ad, attitudes toward the brand, purchase intention, perceived advertisers' motives, level of ad self-referencing, and strength of ethnic identification. The study concluded with demographic questions.

### Measures

The study included five dependent variables: brand likability, ad likability, brand trustworthiness, net promoter score (likelihood to recommend brand), and purchase intention. All items were measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). Question items included "Pompom Mobile is a likable brand," "I like Pompom Mobile's ad," "Pompom Mobile is a trustworthy brand," and "I would recommend Pompom Mobile to my friends/family/colleagues."

Purchase intention was measured by a 7-point Likert scale asking subjects to rate their interest in purchasing a product from the company (MacKenzie et al., 1986; Singh and Spears, 2004). For social cause ads, the perceived advertiser's motive was included as an additional dependent variable. Consumers' perceived advertiser's motives refer to how they attribute an organization's sponsorship of a social cause. According to attribution theory, consumers can have positive and negative attributions toward a cause-related sponsorship (Dean, 2002). Positive attributions signify that consumers perceive the social cause sponsorship as altruistic (caring more about social impact rather than corporate gains), whereas negative attributions indicate perceptions of the company as self-serving.

Both types of attributions can exert an influence on consumers' perceptions, behaviors, and attitudes toward a brand (Lee et al., 2013). Perceived advertisers' motives were measured with a 5-item, 7-point Likert scale based on prior studies (Dean, 2002; Lee et al., 2013). Question items measuring positive attributions included the degree to which consumers perceived the social cause sponsorship as "generous" and "based on an honest wish to do good." Items measuring negative attributions asked the degree to which consumers perceived the sponsorship as the company "acting in its own self-interest" and "having an ulterior motive."

#### Results

Tables 2 and 3 illustrate the means, standard deviations, and sample sizes as analyzed for the product and social advocacy adverts. A series of t-tests were conducted to determine significance levels in pairwise comparisons for each dependent variable. Graphs illustrating the difference in means for dependent variables are further provided in Appendix A to which the reader is referred.

# **Product** Ads

For product ads, where statistics cited are reported in the following Table 2, there was no significant difference in ad likability, brand trustworthiness, nor net promoter score across the three racial compositions in neither of the priming conditions for product advertisements. Such results indicate that variations in racial composition generally do not affect White consumers' attitudes towards the ad or the brand in product advertisements. However, significant differences were found in purchase intention under specific conditions. When White subjects were not racially primed (i.e. they were exposed to the racially-neutral passage) they had significantly higher purchase intentions when they saw the ad with all-Black subjects (M = 5.107, SD = 1.582) than the ad with an ethnically diverse group (M = 4.552, SD = 1.480, p < .05). However,

there were no significant differences in purchase intentions between the diverse vs. all-White or all-Black vs. all-White ads in the racially neutral condition. In contrast, when participants were racially primed (exposed to the racially-charged passage), they had significantly lower purchase intent for the all-Black ads (M = 4.479, SD = 1.681) than the all-White ads (M = 5.102, SD = 1.410, p < .05), but with no significant differences between the diverse vs. all-White or diverse vs. all-White ads. Interestingly, White subjects' purchase intentions for all-Black ads significantly decreased when they were racially primed (M = 5.107, SD = 1.582), compared to when they were not (M = 4.479 SD = 1.681, p < .05).

Table 2. Responses to 1100	aut mus mean an	a Standard Dev	lation					
	Not Prime	ed (Racially-Net	utral Stimulus)	Primed (	Primed (Racially-Charged Stimu			
	All-White	Diverse	All-Black	All-White	Diverse	All-Black		
	(N=72)	(N=67)	(N=75)	(N=84)	(N=76)	(N=71)		
Ad likability	4.89	4.94	5.16	5.17	5.34	5.23		
-	(1.66)	(1.31)	(1.46)	(1.24)	(1.44)	(1.41)		
Brand likability	5.29	5.13	5.32	5.18	5.18	5.00		
-	(1.28)	(1.24)	(1.38)	(1.27)	(1.42)	(1.52)		
Brand trustworthiness	4.94	5.10	5.00	4.93	5.16	4.97		
	(1.47)	(1.16)	(1.43)	(1.31)	(1.43)	(1.45)		
Net Promoter Score	4.74	4.73	4.88	5.00	5.00	4.56		
	(1.63)	(1.53)	(1.55)	(1.54)	(1.67)	(1.85)		
Purchase Intention	4.85	4.55 <sup>b</sup>	5.11 <sup>a,b</sup>	5.01°	4.86	4.48 <sup>a,c</sup>		
	(1.77)	(1.48)	(1.58)	(1.41)	(1.69)	(1.68)		

Table 2: Responses to Product Ads Mean and Standard Deviation

*N.B.*: each entry lists averages on a 7-point Likert scale (strongly disagree - strongly agree). The values in parentheses are SD. Pairs of cells with the same superscript index differ significantly according to pairwise comparisons. a, b, c : p < .05

*Purchase Intention:* Consumers showed higher purchase intentions when the ad featured all-Black models (M = 5.241, SD = 1.407) than when it featured all-White models (M = 4.726, SD = 1.742, p < .05) in the non-primed condition. When primed, the same effect was seen but with a higher degree of significance (M = 5.143, SD = 1.502) and (M = 4.370, SD = 1.882, p < .01) respectively. However, there were no differences in purchase intention between the all-White vs. diverse or all-Black vs. diverse comparisons in neither of the priming conditions.

*Positive attributions:* Significant differences were found in positive attributions (i.e. attributing the social sponsorship as altruistic rather than self-serving). When White participants were racially primed and viewed all-White ads (M = 4.938, SD = 1.315), their perceived brand altruism was lower than when they were not racially primed and viewed all-Black ads (M = 5.462, SD = 1.058, p < .01). However, the higher positive attributions for all-Black ads became no longer significant once White subjects were racially primed.

### Social Advocacy Ads

For social advocacy ads, where statistics cited are reported in the following Table 3, significant differences were found across all dependent variables in both priming conditions.

Ad Likability: When White subjects were not racially primed, ad likability was higher for the all-Black composition (M = 5.582, SD = 1.336) than for the all-White composition (M = 5.123, SD = 1.509, p < .05), but no significant differences were seen between the all-White vs. diverse or all-Black vs. diverse compositions. When racially primed, ad likability was significantly lower for the all-White composition (M = 4.616, SD = 1.861) than for the ethnically diverse composition (M = 5.494, SD = 1.404, p < .01) and the all-Black composition (M = 5.377, SD = 1.246, p < .01), but there were no significant differences in ad likability between the all-Black and diverse compositions.

Brand Likability: When not racially primed, Whites showed significantly lower brand likability when the advertisement featured all-White subjects (M = 4.959, SD = 1.628) than when it featured ethnically diverse (M = 5.419, SD = 1.020, p < .05) or all-Black subjects (M = 5.557, SD = 1.206, p < .05). Similarly, when participants were racially primed, they showed significantly lower brand likability when the advertisement featured an all-White group (M = 4.726, SD = 1.465) than when it featured an ethnically diverse group (M = 5.342, SD = 1.358, p < .01) or all-Black group (M = 5.325, SD = 1.250, p < .01). However, there were no significant differences in brand likability between diverse and all-Black ads in either of the priming conditions.

Brand Trustworthiness: When not racially primed, brand trustworthiness was significantly higher when it featured all-Black (M = 5.443, SD = 1.196) subjects than when it featured all-White (M = 5.123, SD = 1.509, p < .01) subjects. Similarly, when White subjects were exposed to racially charged-language, brand trustworthiness scores were higher when

ads featured all-Black (M = 5.416, SD = 1.140) subjects than when they featured all-White (M = 4.794, SD = 1.424, p < .01) subjects. Nonetheless, no differences in brand trustworthiness were seen between the all-White vs. diverse or all-Black vs. diverse comparisons in neither of the priming conditions.

*Net promoter score:* White subjects' likelihood to recommend the brand (net promoter score) was significantly higher when the ad showcased all-Black models (M = 5.026, SD = 1.376) than when it featured all-White models (M = 4.288, SD = 1.911, p < .01), but only when racially primed. There were no differences in net promoter score between the diverse and all-White ads in the racially-primed condition, nor across any of the three racial compositions in the racially-neutral condition

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	Not Prime	d (Racially-Ne	utral Stimulus)	Primed	(Racially-Charg	ed Stimulus)
	All-White	Diverse	All-Black	All-White	Diverse	All-Black
	(N=73)	(N=74)	(N=79)	(N=73)	(N=79)	(N=77)
A d Librahility	5.12 <sup>a</sup>	5.28	5.58ª	4.62 <sup>b,c</sup>	5.49 <sup>b</sup>	5.38°
Ad likability	(1.51)	(1.31)	(1.34)	(1.86)	(1.40)	(1.25)
Duan d Litrahility	4.96 <sup>d,e</sup>	5.42 <sup>d</sup>	5.56 <sup>e</sup>	4.73 <sup>f,g</sup>	5.34 <sup>f</sup>	5.33 <sup>g</sup>
Brand likability	(1.63)	(1.02)	(1.21)	(1.47)	(1.36)	(1.25)
D 14 (1)	4.82 <sup>h</sup>	5.16	5.44 <sup>h</sup>	4.74 <sup>i</sup>	5.17	5.42 <sup>i</sup>
Brand trustworthiness	(1.40)	(1.17)	(1.20)	(1.42)	(1.46)	(1.14)
Not Dromotor Sooro	4.77	4.77	5.15	4.29 <sup>j</sup>	4.82	5.02 <sup>j</sup>
Net Promoter Score	(1.57)	(1.46)	(1.34)	(1.91)	(1.58)	(1.38)
D	4.73 <sup>k</sup>	4.81	5.24 <sup>k</sup>	4.37 <sup>1</sup>	4.81	5.14 <sup>1</sup>
Purchase Intention	(1.74)	(1.48)	(1.41)	(1.88)	(1.69)	(1.50)
Desitive Attributions	5.17	5.25	5.46 <sup>m</sup>	4.94 <sup>m</sup>	5.22	5.28
Positive Auributions	(1.28)	(1.15)	(1.06)	(1.32)	(1.41)	(1.06)

Table 3: Responses to Social Advocacy Ads Mean and Standard Deviation

*N.B:* each entry lists averages on a 7-point Likert scale (strongly disagree - strongly agree). The values in parentheses are SD. Pairs of cells with the same superscript index differ significantly according to pairwise comparisons. *a*, *d*, *e*, *k*: p < .05; *b*, *c*, *f*, *g*, *h*, *i*, *j*, *l*, *m*: p < .01

### Discussion

This study focuses on White consumers by evaluating how they respond to ads featuring subjects that look like them (all-White ads), subjects that look like them along with a diverse crowd (Diverse ads), and subjects that do not look like them at all (all-Black ads). Findings from this experiment show that, under certain conditions, racial composition in advertisements does influence consumers' perceptions and purchase intention.

Results indicate that showcasing ethnically diverse or all minority models in product advertisements does not necessarily result in more favorable consumer perceptions. No significant differences were found for brand likability, brand trustworthiness, or likelihood to recommend the product across the different ethnic compositions. However, these results do not imply that displaying a diverse or all-minority set of subjects will lead to lower advertising effectiveness. Instead, the findings suggest that, despite heightened advocacy for racial justice in recent years, the ethnic majority (Caucasian) population of the United States still mostly feels indifferent to whether brands use diverse models or not in their product advertising. While previous research has found that consumers today claim to want more diverse representation in marketing media (de Lima Alcantara, 2021), the current study suggests that this desire could possibly be rooted in political correctness rather than in a genuine attitudinal change, as model diversity ultimately does not influence brand or ad evaluations when White consumers are evaluating product ads.

Prior scholarship has suggested that Whites are less likely to be aware of their racial identity and, therefore, less likely to notice racial differences (Appiah, 2001; Deshpandé and Stayman, 1994). This might explain why there was no difference in White subjects' brand and product ad perceptions across the three different racial compositions in this study. This paper's findings are consistent with previous ethnic research showing that White consumers generally do not vary in favorable attitudes toward advertisements based solely on the model's race (Lee et al., 2002; Lee and Kim, 2019).

However, significant effects were observed for purchase intention in product advertisements. White consumers had significantly higher purchase intentions for the all-Black ads than for the diverse ads when exposed to the neutral message. However, when racially primed, subjects' purchase intentions from the all-Black ads decreased, and consumers actually showed higher purchase intention for the all-White ads. Such results suggest that when White consumers are exposed to language highlighting racial inequality, their willingness to purchase decreases when they view an ad with all-Black subjects (compared to when racial inequality is not brought to their attention). This may be explained by Mendelberg's claim that although some Caucasians are genuinely committed to racial equality, many still unconsciously view demands for racial

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justice as illegitimate (Mendelberg, 2001). Thus, racially priming subjects could instigate racial tension or guilt amongst White consumers, leading to lower purchase intention for product ads that feature all-Black models.

In contrast, White subjects appear to be more responsive to models' racial composition for social advocacy ads. Brand likability, ad likability, brand trustworthiness, and purchase intention were all significantly higher for all-Black ads than all-White ads, both when consumers were racially primed and not. Racially diverse social ads also had higher ad and brand likability than all-White ads, but only when consumers were racially primed. The interaction effects seen in social advocacy ads suggest that Caucasian consumers tend to favor ads featuring diverse or all-minority subjects when brands are pursuing social advocacy goals. Interestingly, Caucasians were also more likely to attribute the corporate sponsorship as "genuine" and "based on an honest wish to do good" for all-Black ads when not racially primed than for all-White ads when primed. These results indicate that Whites generally favor social advocacy ads showcasing racial minority subjects in a racially neutral state; however, when reminded of racial inequality and white privilege, their altruistic attributions for all-White ads become significantly lower, yet without increasing altruistic attributions for all-Black ads. Mendelberg's claims may also apply here: given that Whites are generally ambivalent towards racial issues, they tend to reject explicit racial appeals because they violate the norm of racial equality (Mendelberg, 2001).

Such findings provide an interesting avenue for future research on recent developments in America's racial climate, stereotyping, and altruism. One recent study showed that when White individuals witnessed racism online, Whites with an empathetic emotional response to the racist content appeared to promote anti-racism advocacy more than those with a fear- or guilt-based response (Keum, 2021). It could be possible that when brands support a social cause, the sponsorship triggers an empathetic response from White consumers, which could, in effect, lead to more favorable brand perceptions and behavioral intentions when racial injustice is brought to their attention. On the other hand, racial priming can also trigger a guilt-based response, which explains the lower altruistic attributions for all-White ads when racially primed with no significant improvement in positive attributions for all-Black ads. However, this mechanism does not fully explain why Whites still have more favorable perceptions of social advocacy ads featuring all-Black models even when subjects are not racially primed and when the advertised social cause is unrelated to racial issues. As previous literature has demonstrated, ethnic effects can be moderated by other variables such as industry category, product category, or type of social cause (Green, 1999; Arpan and Wang, 2008).

Findings from the current study provide significant practical implications for how racial composition in advertisements may influence White consumers' perceptions and purchase intentions. For marketing managers, this research shows that when promoting a product or a service, showcasing a diverse set of subjects or all minority subjects does not help brand or ad evaluations more than using all-White models. In fact, displaying all-Black models in product advertisements could hurt purchase intention when racial disparity, issues, and conflict are brought to the consumers' attention. On the other hand, when promoting corporate sponsorship of a social cause, showing a diverse set of subjects provides a partial improvement in brand and ad evaluation—but does not always result in significantly higher purchase intent. Lastly, presenting all minority (all-Black) subjects in social advocacy advertising consistently improves brand and ad evaluation and purchase intention. Better results are seen when White consumers are made aware of racial injustice.

While the findings discussed in the current study only reflect Caucasians' ethnic perceptions, an analysis of the entire sample size (which includes a percentage of POC that is proportionally representative of the United States' ethnic demographics) illustrates similar overall results in consumer perceptions and purchase intentions. However, previous research indicates that consumers' ethnic identity influences their racial perception in advertisements, so it is more appropriate to examine data from subjects in the same racial category. The results are generally consistent with prior scholarship in that consumers from the majority group usually feel indifferent about whether ethnic majority or minority models are showcased in product advertisements. Still, this study provides an updated examination of how these same consumers react to racial diversity in social cause advertisements, indicating that Whites showed more favorable responses to all-Black social ads for the most part.

### **Future Research and Limitations**

Practical limitation and implications are now discussed alongside future research opportunities. As with many experimental studies, this research has limitations worth mentioning. First, ethnic perception and advertising effectiveness are influenced by external variables such as type of industry, product category, and the type of social issue being sponsored. Future research is still needed to determine the extent to which these results may be generalized across different product and industry categories. Second, given the sheer volume of White participants in the population sample (83%), race-based results cannot be objectively produced. As the study was conducted on Amazon Mechanical Turk, the ability to recruit an equal proportion of different racial demographics was limited. Future research should attempt to control for these differences better or focus deliberatively on population samples of Black or other ethnic minority groups.

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Furthermore, the results should be interpreted with acknowledgement of some minor inconsistencies across the photo montages in the ad mockups. For example, there are small variations in location (indoor vs. outdoor scenes), lighting, and models' poses. Also, the all-Black product ads feature all female models, whereas the all-Black social advocacy ads feature all male models. Given that the ad mockups were intentionally designed to preserve a realistic and natural visual composition (with little indication of photo-manipulation), the visual components were not perfectly controlled for in the experiment design. Future research could extend this work by determining whether these inconsistencies are actually significant or not.

Moreover, ad exposure in experimental settings cannot completely mimic the natural conditions in which consumers witness ads every day. Future research could perhaps replicate the study in a field experiment setting and incorporate different types of media (print or video). For instance, running a Facebook ad campaign and analyzing relevant business metrics such as click-through rate. Lastly, it would also be interesting for future research to assess perceptions of group diversity in other countries and cultures, where the ethnic majority group varies, to elucidate any universality to these results.

Thus far, the current study has examined the extent to which the independent variables influence certain aspects of consumer behavior. However, the current discussion still does not establish a full direction of causation with concrete mediating or moderating variables. Why do Whites have more favorable attitudes and purchase intentions toward all-Black social cause advertisements, but not for product advertisements? Future studies could explore mechanisms in which racial diversity impacts White consumers' perceptions. Possible mediation variables worth investigating could be prejudice level, human warmth perception, political alignment, or cultural awareness.

In an attempt to illustrate such mediating effects, an initial analysis of self-referencing and strength of ethnic identification is provided in Appendix E, using data collected during the experiment. This section whilst of great importance is not included directly within the main analysis, given the limitations derived from the small percentage of POC subjects relative to Whites in this study's population sample. As demonstrated within the previous literature, the mechanism of self-reference levels and strength of ethnic identification tend to have more consistent results with ethnic minority consumers. The preliminary mediation analysis still provides meaningful insights, but it is worth noting that Whites' level of self-referencing and strength of ethnic identification tend to vary more widely than those of ethnic minority groups.

### Conclusions

In conclusion, this study provides an initial analysis of how White consumers perceive advertisements with different variations of racial composition. The results found that for product advertisements, changes in racial composition affect White consumers' purchase intentions under certain priming conditions, but had no significant effects on attitudes toward the ad or brand. However, for social advocacy advertisements, Whites consistently show more favorable perceptions and purchase intentions for racially diverse or all-Black model compositions. These findings contribute to literature on the effects of group racial perceptions in marketing communications and provide key implications for practitioners. These findings provide a better understanding of how consumers perceive racial representation in advertising images and expands the literature on diversity and inclusion in marketing practice. The findings also contribute to previous ethnic research and provide an updated examination of racial perceptions in advertisements within the United States.

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# **APPENDIX A**

# Differences in Means: Dependent Variables for Product and Social Cause Ads



A3.

A4.

A5.



A5.



# A2.





A9.







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# **APPENDIX B**

# **Product Advertisements (all-White, Diverse, all-Black)**



Social Advocacy Advertisements (all-White, Diverse, all-Black)

**B4**.

B5.

**B6**.



# **APPENDIX C**

# **Racial Priming Passages**

**Racially Neutral (Control Condition):** "The Academy, made up of over 9,000 professionals working in the film industry, gives out awards every year to the best movies, performances, and behind-the-scenes work across the industry. Its goal, according to the organization, is to advance and "uphold excellence" within the motion picture industry."

**Racially-Charged (Primed Condition):** "When Insider looked at the nominations across best picture, best director, the top four acting categories, and the two writing categories, we found that Oscar nods were still overwhelmingly white. Only 6.3% of nominations went to Black creatives, while 2.6% went to Latinx people and 1.4% went to Asian people."

# APPENDIX D

# **Qualtrics Survey**

### Qu.1 Consent Form

Please read this form carefully. If you would like to participate in this study, please click the button below and enter your MTurk ID.

I understand that the general purpose of this study is to investigate purchase behavior and I consent to participate in this study.

My decision to consent is entirely voluntary and I understand that I am free to withdraw at any time without giving a reason. I also understand that withdrawal before completion could affect my payment. I understand that my responses will be kept completely confidential. I consent to the publication of the results of this study, so long as participant information is anonymized.

• I voluntarily consent to participate in this study.

Qu.2 MTurk ID

Please enter your Mechanical Turk Worker ID. We need this to check who successfully completed the survey and whose work should be approved

### Qu.3 Captcha Verification

This survey includes short scenarios that we ask you to read carefully.

There are no right or wrong answers, we are only interested in your honest opinion.

The questionnaire should take about 5 minutes to complete and you will receive a compensation of 50 cents for your time. Your M-Turk completion code will be provided at the end.

Please let us know that you are reading the instructions by checking the box below.

Qu. 4 Priming Passage (Only one displayed to each subject)

(Neutral Passage) Please read through the following passage very carefully:

"The Academy, made up of over 9,000 professionals working in the film industry, gives out awards every year to the best movies, performances, and behind-the-scenes work across the industry. Its goal, according to the organization, is to advance and 'uphold excellence' within the motion picture industry" (Insider, 2021)

Or: (Primed Passage) Please read through the following passage very carefully:

"When Insider looked at the nominations across best picture, best director, the top four acting categories, and the two writing categories, we found that Oscar nods were still overwhelmingly white. Only 6.3% of nominations went to Black creatives, while 2.6% went to Latinx people and 1.4% went to Asian people." (Insider, 2021)

### Qu.5 Ad Stimulus (Only one of the 6 different variations of ads is shown to each subject)

### Consider the following scenario:

You are scrolling through social media, and you come across the following sponsored ad from Pompom Mobile on your feed. Pompom is a multinational technology company specializing in smartphones. Please review all components of the advertisement

### Qu.6 Evaluation of Dependent Variables

The following questions will ask you the extent to which you agree to the statements presented:

Main DVs (Part 1) (Shown for all ads):

Based on what you saw on Pompom Mobile's ad, to what extent do you agree/disagree with the following statements?

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
Pompom Mobile is a likable brand	0	0	0	0	0	0	0
I like Pompom Mobile's ad	0	0	0	0	0	0	0
I have high interest in purchasing a product from Pompom Mobile	0	0	0	0	0	0	0
Pompom Mobile is a trustworthy brand	0	0	0	0	0	0	0
I would recommend Pompom Mobile to my friends / family / colleagues	0	0	0	0	0	0	0

Social DV 1 (Part 2) (Shown only if it is a Social Cause ad):

### Based on what you saw on Pompom Mobile's ad, to what extent do you agree/disagree with the following statements?

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
The donation by Pompom Mobile is generous	0	0	0	0	0	0	0
The donation by Pompom Mobile is based on an honest wish to do good	0	0	0	0	0	0	0
Pompom Mobile is acting in its own self-interest in making the donation	0	0	0	0	0	0	0
Pompom Mobile seems to have an ulterior motive in making the donation	0	0	0	0	0	0	0
If you are paying attention, please select two	0	0	0	0	0	0	0

# Product DV 2 (Part 2) (Shown only if it is a Product ad):

Based on what you saw on Pompom Mobile's ad, to what extent do you agree/disagree with the following statements?

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
I can easily picture myself using the advertised product	0	0	0	0	0	0	0
Pompom Mobile's ad is informative	0	0	0	0	0	0	0
Pompom Mobile's ad is pleasant	0	0	0	0	0	0	0
Pompom Mobile is a sincere brand	0	0	0	0	0	0	0
If you are paying attention, please select two	0	0	0	0	0	0	0

Qu.7 Strength of Ethnic Identification (Shown to all participants):

# The following questions will ask you the extent to which you agree to the statements presented

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
I have a clear sense of my ethnic background and what it means for me	0	0	0	0	0	0	0
I am happy that I am a member of the ethnic group I belong to	0	0	0	0	0	0	0
I have a strong sense of belonging to my own ethnic group	0	0	0	0	0	0	0
I have a lot of pride in my ethnic group and its accomplishments	0	0	0	0	0	0	0
I feel a strong attachment to my ethnic group	0	0	0	0	0	0	0

Qu. 8 Self-Referencing (Shown to all participants):

# The following questions will ask you the extent to which you agree to the statements presented

	U		1			
Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
	Strongly Disagree 1	Strongly 2 Disagree 1	Strongly     2     3       Disagree 1     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0       0     0     0	Strongly       2       3       4         Disagree 1       0       0       0       0         0       0       0       0       0         0       0       0       0       0         0       0       0       0       0         0       0       0       0       0         0       0       0       0       0         0       0       0       0       0	Strongly Disagree 1       2       3       4       5         0       0       0       0       0       0         0       0       0       0       0       0         0       0       0       0       0       0         0       0       0       0       0       0         0       0       0       0       0       0         0       0       0       0       0       0	Strongly Disagree 1         2         3         4         5         6           0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0

Qu.9 What is your year of birth?

Qu.10 Gender What gender do you identify with?

- Male
- $\circ$  Female
- Non-binary / third gender
- $_{\odot}$  Prefer not to say

Qu. 11 Race What ethnicity do you best identify with?

- $\circ$  White
- o Hispanic / Latino / Spanish origin
- Black or African American
- o American Indian or Alaska Native
- Native Hawaiian or Pacific Islander
- East Asian
- South Asian
- o Other Asian
- Two or more races
- $\circ$  Other \_

Qu. 12 Education What is your level of education?

- Less than high school
- High school graduate (or equivalent)
- $_{\odot}$  Some college
- College graduate
- Postgraduate/Professional degree
- $_{\odot}$  Prefer not to answer

# Qu.13 Effort Check

This study required substantial time and effort to put together. If for whatever reason you feel that you did not respond to the questions carefully or accurately, we would greatly appreciate you informing us of this now.

## Your answer will NOT affect your payment or reputation on Mechanical Turk.

Have you responded to the questions carefully and accurately?

- $\,\circ\,$  Yes, and my answers should be included in the analysis.
- $_{\odot}$  No, and my answers should not be included in the analysis.

### APPENDIX E

### **Exploring Mediation Variables**

Appendix E explores ethnic self-referencing and the strength of ethnic identification as possible mediating variables for why Caucasian consumers might perceive varying racial compositions differently. However, it is important to highlight that theories of self-referencing and strength of ethnic identification are more applicable to studying the behavior of ethnic minorities rather than Whites. This preliminary analysis provides an initial observation of whether such theories can also apply to Caucasian consumers, and if there is a direction of cause for why there are differences in how they perceive diversity in advertisements.

### **Ethnic Self-Referencing**

Ethnic identification is the degree to which someone identifies with their ethnicity. Identification theory states that people assess their similarities with an information source and make judgments based on these similarities (Appiah, 2001). Previous studies examining the role of consumers' ethnicity on advertisement perceptions suggest that ethnic minority groups tend to respond more favorably to advertisements featuring spokespeople of their same race (Appiah and Liu, 2009). Such findings can be explained through the process of self-referencing, a phenomenon that occurs when a consumer processes information by relating it to some aspect of themselves (Lee et al., 2002). Self-referencing allows consumers to associate a stimulus with their pre-existing schemas, and it has been shown that schema congruity, in the sense that consumers can strongly relate the advertising content to their personal experiences, leads to more favorable responses to the advertisement. (Lee et al., 2002).

Self-referencing theory is based on the concept of self, a complex memory structure containing knowledge that a person accumulates over their lifetime (Burnkrant and Unnava, 1995). Lee et al. (2002) showed that when consumers are exposed to advertisements featuring elements that are consistent with a salient dimension of their "self", they self-reference the ad. In line with this theory, ethnicity can be a strong point for self-referencing for consumers, especially for those who identify with an ethnic minority group (Hesapci et al., 2016). Past experiments have shown that ethnic minority consumers engage in stronger self-referencing when advertisements show models of their same ethnicity (Hesapci et al., 2016). In turn, stronger self-referencing leads to more favorable thoughts, attitudes, and purchase intentions (Lee et al., 2002).

However, limited scholarship examines how consumers evaluate advertisements featuring highly diverse racial compositions (e.g. White, Black, Hispanic, Asian). While self-reference theory posits that ethnic minority consumers are more likely to reference their own ethnicity in ads, little research examines how the introduction of other ethnicities into the ad's racial composition would influence consumer perception. Appiah found that Black, Hispanic, and Asian American adolescents responded more favorably to ads featuring Black characters because ethnic minorities are more likely to believe they are the intended audience of ads featuring minority characters (Appiah, 2001). Moreover, self-reference theory suggests that racial composition in social advocacy advertisements might be more meaningful to consumers when brands are advocating for social causes consistent with their concept of self. Thus, it is predicted that consumers will highly self-reference ads featuring models of their same ethnicity, whether that is White, Black, or other POC. Moreover, self-referencing will act as a mediating variable between advertisement ethnic composition and consumer perception. As such, the paper derived the following hypotheses:

H1: Levels of self-referencing will display a mediating effect between racial composition and consumers' (i) perception of the company's social cause commitment (ii) attitude toward the brand, (iii) attitude toward the ad, and (iv) purchase intention in social advocacy advertisements.

**H2**: Levels of self-referencing will display a mediating effect between racial composition and consumer's (i) attitude toward the brand, (ii) attitude toward the ad, and (iii) purchase intention in product advertisements.

### **Strength of Ethnic Identification**

Past research has also highlighted the significance of consumers' strength of ethnic identification and how it mediates their perception of promotional messages. Green showed that African American women who strongly identified with their ethnicity evaluated advertisements that featured only African American models more positively, whereas African American women who did not identify as strongly with their ethnicity had more positive evaluations of advertisements that featured only White models (Green, 1999). Similarly, another study found that Asian Americans who identify strongly with their ethnicity perceive advocacy advertisements with an Asian spokesperson more favorably than the advertisements with a White spokesperson (Lee et al., 2013).

As for the effects of an ad model's ethnicity on White consumers' advertisement perceptions, studies have pointed to less concrete results (Hong and Len-Riós, 2015; Lee et al., 2013; Watson et al., 2009). Lee and Kim (2019) showed that White Americans do not vary in self-referencing based on the model's race, nor does it affect their purchase intention or attitude towards the advertisement. This is because White consumers are considered to be the majority racial group in American society and are generally less mindful of ethnic cues in advertising images (Appiah, 2001).

However, limited scholarship examines how a consumer's strength of ethnic identification might influence their perceptions of social advocacy advertisements featuring diverse mixes of ethnic composition. A study by Arpan and Wang (2008) demonstrated that African Americans perceived HIV public service announcements more favorably when the spokesperson was African American. They also found that a spokesperson's race was a more powerful predictor of HIV PSA evaluation among African American participants than was the spokesperson's expertise. These findings suggest that ethnic minorities might perceive social cause ads that feature a higher percentage of people of color as more trustworthy and attribute altruistic motives to the brand's social advocacy.

In product advertisements, the ethnic composition of models influences consumer perception in different ways. A previous study found that African American consumers who identified strongly with their ethnic culture had higher purchase intention when viewing Black-dominant ads (a Black model placed front and center in between two White models) (Green, 1999). However, Green's study only examined mixes of White and Black models, and all participants were African American. The aim of this study is to expand on previous literature by exploring how Caucasian consumers perceive advertisements with varying degrees of ethnic diversity (all-Caucasian vs. diverse vs. all-Black). This predicts that the strength of ethnic identification is a mediator of how strongly consumers will self-reference the advertisement. Given previous demonstrated relationships between the strength of ethnic identification on different consumers' advertisement perceptions, this paper hypothesizes the following:

**H3**: Strength of ethnic identification will display a mediating effect between racial composition and consumers' (i) perception of the company's social cause commitment (ii) attitude toward the brand, (iii) attitude toward the ad, and (iv) purchase intention in social advocacy advertisements.

**H4**: Strength of ethnic identification will display a mediating effect between racial composition and consumer's (i) attitude toward the brand, (ii) attitude toward the ad, and (iii) purchase intention in product advertisements.

### **Methodology and Measures**

The measurement of the mediating variables was part of the main experiment, so the design, stimulus materials, and procedure were exactly the same. Mediation analysis with categorical variables was conducted using the product of the coefficients method with STATA.

# Self-Referencing

The degree to which participants self-referenced the ad was measured by averaging a group of 5-item, 7-point Likert scales derived from prior research (Hesapci et al., 2016). Items included statements like "I can easily form similarity judgments between myself and the advertising models," "the ad seems to be written for me," and "I can easily picture myself being a customer of this company." A reliability test of the measuring items yielded a Cronbach's alpha of  $\alpha = 0.90$ , indicating that the items were highly reliable.

### Strength of Ethnic Identification

Participants' strength of ethnic identification was measured using a 5-item, 7-point Likert scale based on Phinney's Multigroup Ethnic Identity Measure (Phinney, 1992). The scale included items such as "I have a clear sense of my ethnic background and what it means for me," "I am happy that I am a member of the ethnic group I belong to," and "I feel a strong attachment to my ethnic group." A reliability test of the measuring items yielded a Cronbach's alpha of a = 0.91, indicating that the items were highly reliable.

# Results

*N.B.* All effects detailed below are relative to the reference group (all-White ads); \*p < 0.05; \*\*p < 0.01)

	,	1110ddot 11db	
	Purchase Intent	Ad Likability	Brand Likability
Indirect Effect for Diverse Ads	.084	.061	.057
Indirect Effect for All-Black Ads	.081	.059	.055
Total Indirect Effect	.165	.121	.113
Total Direct Effect	522**	.155	248
Table 5. Coefficients for Self-Referencing	g as Mediation Variable in	n Social Advocacy Ads	
	Purchase Intent	Ad Likability	Brand Likability
Indirect Effect for Diverse Ads	.288*	.188	.168
Indirect Effect for All-Black Ads	.460**	.300**	.269**
Total Indirect Effect	.747**	.488**	.437**
Total Direct Effect	.160	.645**	.700**
Table 6. Coefficients for Strength of Ethn	ic Identification as Media	tion Variable in Social	Advocacy Ads
	Purchase Intent	Ad Likability	Brand Likability
Indirect Effect for Diverse Ads	.111	.087	.081
Indirect Effect for All-Black Ads	O 4 1 de de		
manoet Enteet for Am Black Aus	.241**	.189**	.177**
Total Indirect Effect	.241** .352*	.189** .276*	.177** .259*
Total Indirect Effect Total Direct Effect	.241** .352* .555*	.189** .276* .857**	.177** .259* .878**
Total Indirect Effect Total Direct Effect Table 7. Coefficients for Strength of Ethn	.241** .352* .555* ic Identification as Media	.189** .276* .857** ation Variable in Product	.177** .259* .878**
Total Indirect Effect Total Direct Effect Table 7. Coefficients for Strength of Ethn	.241** .352* .555* ic Identification as Media Purchase Intent	.189** .276* .857** ation Variable in Product Ad Likability	.177** .259* .878** t Ads Brand Likability
Total Indirect Effect Total Direct Effect Table 7. Coefficients for Strength of Ethn Indirect Effect for Diverse Ads	.241** .352* .555* ic Identification as Media Purchase Intent 026	.189** .276* .857** ation Variable in Product Ad Likability 021	.177** .259* .878** t Ads Brand Likability 0202
Total Indirect Effect Total Direct Effect Table 7. Coefficients for Strength of Ethn Indirect Effect for Diverse Ads Indirect Effect for All-Black Ads	.241** .352* .555* ic Identification as Media Purchase Intent 026 .087	.189** .276* .857** ation Variable in Product Ad Likability 021 .073	.177** .259* .878** t Ads Brand Likability 0202 .069
Total Indirect Effect Total Direct Effect Table 7. Coefficients for Strength of Ethn Indirect Effect for Diverse Ads Indirect Effect for All-Black Ads Total Indirect Effect	.241** .352* .555* ic Identification as Media Purchase Intent 026 .087 .062	.189** .276* .857** ation Variable in Product Ad Likability 021 .073 .052	.177** .259* .878** t Ads Brand Likability 0202 .069 .049

# Discussion

As shown in the tables above, self-referencing and the strength of ethnic identification may have a significant mediating effect between an advertisement's racial composition and White consumer's perceptions and purchase intentions. Self-referencing showed to be a significant predictor of purchase intention, ad likability, and brand likability ( $\beta = 0.460$ , p < 0.01;  $\beta = 0.300$ , p < 0.01;  $\beta = 0.269$ , p < 0.01, respectively) when White consumers viewed all-Black ads. Strength of ethnic identification also showed to be a significant predictor of purchase intention, ad likability, and brand likability ( $\beta = 0.241$ , p < 0.01;  $\beta = 0.189$ , p < 0.01;  $\beta = 0.177$ , p < 0.01, respectively) when White consumers viewed all-Black ads.

Interestingly enough, contrary to what previous literature would predict, White subjects who viewed the all-Black social advocacy ads (M = 4.312, SD = 1.646, P < .05) had significantly higher levels of self-referencing than those who viewed the all-White ads (M = 4.911, SD = 1.339). However, neither self-referencing nor strength of ethnic identification was a significant predictor of consumer evaluations and purchase intentions for product ads, regardless of racial composition. Consistent with the initial interaction effects seen in this study, the mediating mechanisms work differently depending on whether the ad is promoting a product or a social cause. However, these mechanisms still do not fully explain why White consumers have higher levels of self-referencing with all-Black ads more than all-White ads in the first place. This is a further possible avenue for future research.



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