UNCW
University of North Carolina Wilmington
Department of Economics and Finance
601 South College Road
Wilmington, NC 28403-5945

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DR. ADAM T. JONES
DR. CLAY MOFFETT

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Bitcoin Perceptions Across Three Continents: the Changing Attitudes Towards Digital Currencies

Aigerim Nukenova, Aalto University Finland
Olivier Maisondieu Laforge, University of Nebraska At Omaha
Yanjie Wu, South China Normal University

Abstract

This paper uses a survey conducted in mid-2017 to examine perceived risks and benefits of using Bitcoin across three continents. Using five measures of risk and four measures of benefits, we find strong differences of perceptions between Asia, Europe, and North America for users and non-users of Bitcoin. Specifically, we find that Asians and North Americans see higher risks of using Bitcoin than Europeans, but mostly similar risk benefits. Once Bitcoin has been used, risk and benefit perceptions decrease. Also, perceived risk and overall benefit constructs consisting of several selected factors each explain potential adoption of Bitcoin.

Introduction

Businesses and individuals have been looking for borderless and low-cost solutions for making online payments and transferring funds internationally over the past few years due to the high risk and expense associated with the foreign currency exchange. With the rise of the Internet, online payment systems, including both the traditional and alternatives ones, have emerged as the solution to this need. However, despite the benefits brought by the alternative online payment systems to consumers, including the possibility for instant payments and lower transaction costs, they have not gained wide public acceptance.

The low usage rate of online payment systems was blamed on the high level of risk that consumers associate with using them (Pavlou, 2001; Featherman and Pavlou, 2003). Consumer perception of high risk arises due to, for example, concerns over the security of online payments, which is an area of extensive research in the study of electronic payment systems (Abrazhevich, 2004; Ozkan et al., 2010), and lack of trust in third-party handling transactions. Besides security issues, there are other factors which influence consumer evaluation of electronic payment methods.

Previous research found that consumer attitudes towards electronic payment systems would influence their decision whether to use those systems (Ozkan et al,. 2010). The positive and negative utility factors that influence consumer evaluation of electronic payment services for potential adoption can be grouped under the concepts of perceived risk and perceived benefit (Featherman & Pavlou, 2003).

Digital currency is an emerging innovation in the field of online payments that has gained a lot of attention in the media but a low acceptance rate. Among the digital currencies, Bitcoin has the largest market share (CoinMarketCap, 2016). Previous research about Bitcoin covered its attributes and functions (Glaser et al. 2014; Dwyer 2014; Luther & White 2014); economic, legal and technical factors concerning its use (Brito et al., 2014; Raymaekers, 2014); and the factors which influence the adoption of Bitcoin by individuals and businesses (Glaser et al., 2014; Polasik et al., 2015; Spenkelink, 2014). However, none of the studies investigated how consumers evaluate Bitcoin in terms of perceived risk and perceived benefit, which consequently influence the adoption decision. This research addresses this gap.

Literature Review and Key Perceived Risks/Benefits

There has not been much research conducted on the user perceptions and adoption of Bitcoin since digital currency is still a nascent area of research. However, there were several studies done related to the adoption of Bitcoin on the following topics: (1) the factors that determine the adoption of Bitcoin by different stakeholders (Spenkelink, 2014), (2) the factors influencing the consumer choice of Bitcoin as a payment method in retail e-commerce (Polasik et al., 2014), (3) the intentions of new users when approaching Bitcoin (Glaser et al., 2014) and (4) the barriers to adoption of Bitcoin explained in terms of the network effects and switching costs (Luther, 2013). All of these studies except the one by Glaser et al. (2014) attempted to explain different aspects of the Bitcoin adoption using theoretical models, such as the Innovation Diffusion Theory (IDT), the network externality theory and the currency acceptance theory by Dowd and Greenaway (1993).

Spenkelink (2014) empirically studied the "factors influencing the adoption of cryptocurrencies in different usage scenarios for different stakeholders". He tested five different information technology (IT) adoption models to explain the individual adoption of cryptocurrencies and found that the Innovation Diffusion Theory (IDT) by Moore & Benbasat (1991) fits the best to predict the adoption of Bitcoin (ibid: 20). He used the variables of this model to develop a conceptual framework

explaining the adoption of Bitcoin. Within his conceptual framework, the factors, which were described as perceived benefits positively contributing to adoption of Bitcoin were low cost, fast transaction speed, and trialability or low barriers to entry (ibid: 34). These factors will be later adapted as the perceived benefit factors in the conceptual framework for this paper.

Several studies were undertaken to explore the influence of both positive and negative factors on the adoption of electronic methods of payment (Featherman and Pavlou, 2003; Lee, 2008). However, the risk and benefit perception in the adoption of e-services was still viewed as a field where little research was conducted (Featherman and Pavlou, 2003: 468; Lee 2008).

The perceived risk theory originates from the consumer behavior research. The theory assumes that perceived risk is a multidimensional construct consisting of different dimensions that stem from the generic sources of consumer risk (Jacoby and Kaplan 1972; Lee, 2008). Most of the reviewed studies on the role of perceived risk in e-payments used this multidimensional model of perceived risk (Lee, 2008; Featherman and Pavlou, 2003). Furthermore, it was assumed that some of the risk dimensions are more important to the consumers of e-payment services than other dimensions. These studies tended to use five of the six facets of perceived risk by Jacoby and Kaplan (1972) – physical, performance, financial, time-loss, social/psychological and security/privacy - in explaining the adoption of electronic commerce systems with variations on the included factors depending on the study (ibid). The physical or safety risk was viewed as irrelevant for the adoption of e-services since the transactions occur virtually (Lee, 2008; Featherman and Pavlou, 2003). It can be argued that the multidimensional approach to perceived risk helps to gain insight about the aspects of a specific e-payment that worry users the most and may negatively affect their decision to use the service. Furthermore, individual attitudes toward the sources of risk in general, such as security, privacy, time, and public image, can also influence their adoption of e-services (Ozkan et al., 2010).

Featherman and Pavlou studied seven e-services adoption by individual "(1) performance, (2) financial, (3) time, (4) psychological, (5) social, (6) privacy and (7) overall risk" (ibid: 455). The results of the study suggested that among other risk factors the performance-related risk factors, including time risk, privacy risk and financial risk, were the most salient inhibitors in the adoption of e-services for the research sample, whereas perceived ease of use influenced user adoption the most positively (ibid: 468).

This research uses the perceived risk facets by Lee (2008) based on the perceived risk model by Jacoby & Kaplan (1972) with the addition of regulatory risk. Thus, the risk facets are financial, security, performance (referred in this paper as technological risk), time-loss, and social.

Financial risk - The possibility of money loss due to transacting with Bitcoin constitutes financial risk. The financial risk of Bitcoin stems from high volatility of Bitcoin value and the irreversibility of transactions. Thus, the financial risk is defined in terms of two factors: the inability to cancel transactions and the instability of the daily value of Bitcoin.

Security risk - The security risk for Bitcoin is defined as security vulnerabilities of the transaction processing system, Blockchain, and the possibility of cyber threats and attacks on Bitcoin intermediaries, including payment service providers and Bitcoin exchanges. On our survey, this was the most important risk indicated.

Time-loss risk - The users of e-payment services are often concerned about the amount of time spent on installation of the needed software and learning how to use a payment system (Featherman & Pavlou, 2003). The time-loss risk in relation to Bitcoin is defined as the perception of a lot of time spent on learning how to use Bitcoin and installing the applications for making transactions, e.g., Bitcoin wallet, in comparison with the other payment methods.

Technological risk - This risk category also called performance risk is defined as the possibility of malfunction or breakdown of the Bitcoin transaction system, which may result from cyberattacks or weaknesses in the technology (Kuisma et al., 2007). According to the study by Featherman and Pavlou (2003), the users of the e-services perceived this risk facet as the most salient.

Social and psychological risks - These types of risk stem from the way a person perceives that using a certain e-service would influence perception of him or her by others (social risk) or self-perception (psychological risk) (Ho & Ng, 1994: 29). These types of risk have shown to be the least significant in the user decision to adopt an e-service. However, it was found that there is a difference in risk perception between users and non-users of e-payment services for this risk facet (ibid: 34). This study captures these types of risks under the social risk since the psychological risk can be a result of social pressure. Social risk is defined in terms of the perception of the importance of public image issues in preventing a consumer from considering using Bitcoin.

Similarly, Featherman and Pavlou (2003) and Lee (2008) used the perceived risk theory together with the technology acceptance model to study the customer intention to use online banking services. They found that that perceived benefit construct was the strongest predictor for the intention to adopt online banking (Lee, 2008).

This research involves investigating the perception of benefits related to using Bitcoin in the context of potential adoption as an online payment method. The perceived benefits of using Bitcoin were adapted from the framework of cryptocurrency adoption developed by Spenkelink (2014) that was based on the Innovation Diffusion Theory Moore & Benbasat (1991). The three benefits of adopting Bitcoin based on the Spenkelink's (2014) framework were lower transaction cost, faster transaction speed and "trialability". In addition, a fourth benefit factor was added based on an overview of the previous research - no need

for a third party to confirm transactions with Bitcoin or decentralization benefit. Hence, the four benefit factors are lower transaction cost, faster transaction speed, ease of experience or "trialability" and no need for a third party.

Lower transaction cost - Bitcoin allows money transfers at a significantly lower cost and at a higher speed than traditional payment systems (Spenkelink 2014). The cost of a typical Bitcoin transaction was 0.0001 BTC.

Faster transaction speed - Bitcoin is faster compared to the international bank transfers usually taking one to two business days, but slower compared to the e-commerce payment systems, such as PayPal and iDEAL that offer instant payments. Processing of Bitcoin transactions takes one hour at the maximum (Spenkelink, 2014).

Ease of experience – Online payments from wallet to wallet ignores country, platform, and language barriers.

No third party – Lack of oversight by a third party allows for high accessibility, freedom from oversight by any central authorities such as governments and banks, possibility for irreversible transactions, and pseudo-anonymity of transactions.

Our study examines perceived risks and benefits of Bitcoin adoption given knowledge about Bitcoin, prior experience, and demographic factors.

Independent variable	**Dependent variables**	**Dimensions of the dependent variable**
Knowledge about Bitcoin	Perceived risk	Financial risk
Prior experience with Bitcoin		Social risk
Demographic factors		Technological risk
Country of residence split into three groups based on responses: Europe North America Asia		Security risk
		Time-loss risk
		Regulatory risk
	Perceived benefit	Lower cost
		Fast transaction speed
		Ease of experience
		Lack of third-party

Results and Discussion

Since the popularity of Bitcoin is growing rapidly, attitudes about it are also changing quickly. To minimize the impact of those changes, we limited the time of our data gathering to five months in early 2017. While Bitcoin was rising during this time, our survey was conducted before the price bubble of the last five months of 2017. In addition, our survey focused on the risks and benefits of using Bitcoin, not its price volatility or its suitability as an investment vehicle. The survey was conducted online and invitations were distributed over social media to focus on those with computer access who would be most likely to have knowledge of Bitcoin. Of the roughly 2,000 people that we estimate received an invitation, 595 people responded. Of those, 469 answered a sufficient number of questions for us to analyze their responses. The survey very likely includes a significant amount of selection bias. People with no idea or opinion about Bitcoin would be less likely to fill out a survey. While this does limit the universal applicability of the survey, it does still provide insight into those who have heard of it. As with most services in the early stages of adoption, knowledge of Bitcoin is likely to increase over time. An interesting follow-up to this survey will be to gauge perceptions once its knowledge has been more fully disseminated.

Most of the respondents (55%) are young adults aged 18-24. The second largest age group (12%) represented in the sample are 25-34, and the third largest group (5%) are those between 35 and 44 years old. Only 45 of the respondents are older than 45 years old. A significant portion of respondents (25.2%) did not indicate their age. The distribution is consistent with the Pew Research Center's 2010 survey on social networking use by age distribution.

Regarding gender distribution, 60% of the respondents are female and 40% are male. Concerning the educational level, 75% of the respondents have a Bachelor's degree, 14% are high school graduates, 8% have a Master's degree, 3% have a Doctoral degree, and 2% graduated from a comprehensive school.

Figure 1: Survey respondent by location

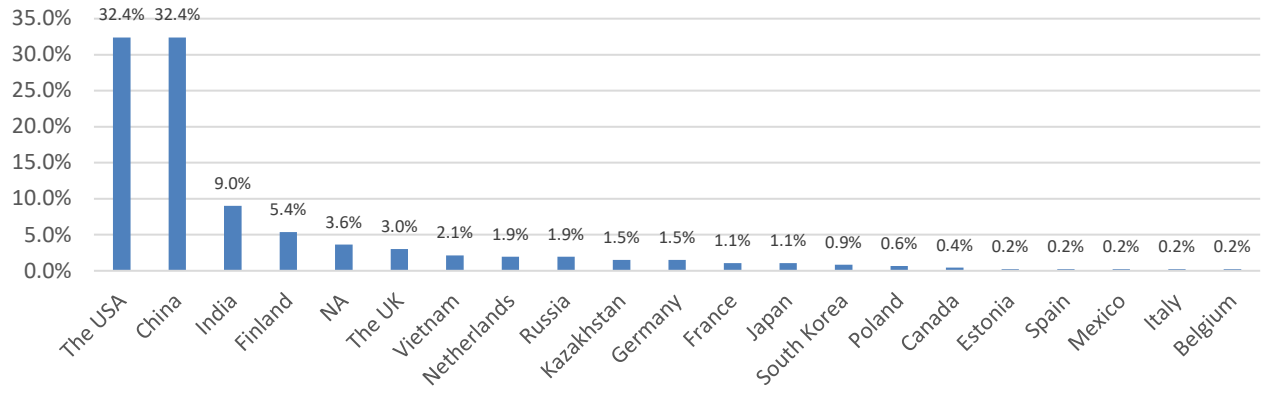


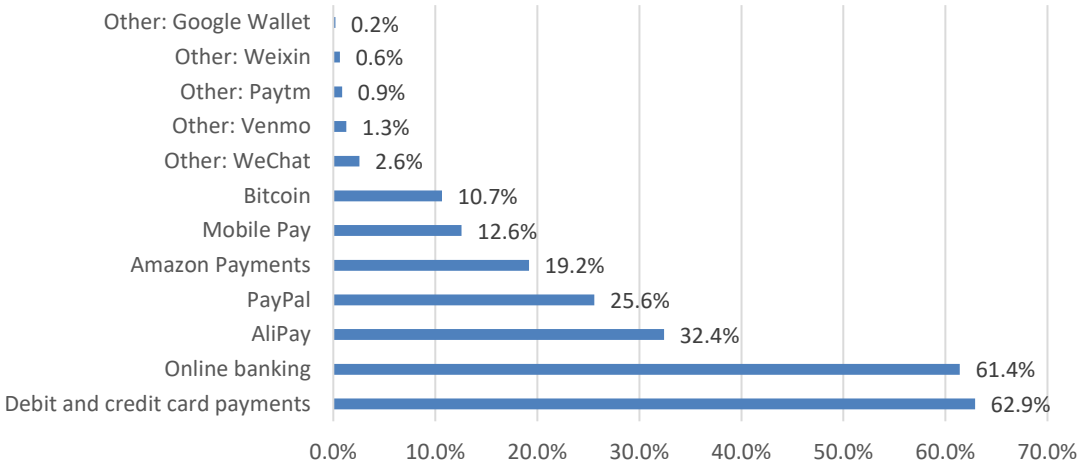
Figure 1 shows the country of residence of the respondents. About a third of the respondents are each from the US and China. The remainder are distributed among 18 countries spanning the globe. Overall, we decided to split our sample into North American users (33%), Asian users (47%), and European users (16%). This distribution provides large enough sample sizes for analysis while separating regional risks and tolerances. An ideal sample would have been much larger and been distributed according to Bitcoin use. Unfortunately, the necessary snapshot nature of our sample limited our sample size. Since Bitcoin users are for the most part anonymous, finding their distribution is challenging.

Figure 2 presents the findings regarding the online payment services used by respondents at least once a month (defined as regularly). One response to this question was missing. As shown in figure 2 below, the majority of the respondents regularly used debit and credit card payments. The second most used payment system was PayPal, followed by Amazon Payments (4.2%), and AliPay (3.3%). Bitcoin was the least used method of payment with only 2.5% of all the respondents using it on a regular basis. These findings show that the usage of Bitcoin among the respondents was relatively low but significant at 10.7%.

Most of the respondents preferred traditional and more established online methods of payment for use on a regular basis, prevalently debit and credit card payments (62.9%) and online banking (61.9%). Two alternative online payment methods – AliPay and PayPal – were popular among the respondents. Sixty-eight out of 469 respondents claimed that they had experience with using Bitcoin. Interestingly, 50 out of the 68 respondents who used Bitcoin once (74%) adopted Bitcoin for regular use.

Most respondents have never used Bitcoin. Four hundred (85.4%) respondents indicated that they have never used Bitcoin and 68 (14.5%) indicated that they have used Bitcoin. One response to this survey item was missing. Despite a relatively low percentage of respondents who had prior experience with using Bitcoin, all the respondents except for one missing response chose at least one online payment method that they use regularly. Therefore, it can be assumed that the respondents were familiar with common benefit and risk considerations in evaluating an online method of payment for potential use.

Figure 2: Online payment services regularly used by the respondents.



The choice by the respondents of more widely accepted and trusted payment methods might indicate existence of the network effects that inhibit the wider adoption of Bitcoin identified by previous research (Polasik et al., 2015; Luther, 2013). That is, low adoption rate of Bitcoin can be explained by the lack of widespread acceptance of Bitcoin among online retailers and buyers. In addition to the lack of acceptance, users may perceive the costs of switching from their current method of payment to Bitcoin as too high (Luther, 2013). However, another reason for the low adoption rate could be a perceived lack of need for Bitcoin among the respondents. Since most of the respondents resided in developed countries with a highly developed infrastructure for electronic payments, low costs and high variety of existing alternative payment methods could account for a low perceived need of switching to Bitcoin.

Responses concerning the user intentions for usage and perceived relative importance of the risk factors were analyzed only for the 68 respondents who have used Bitcoin before. It can be seen from the Figure 3 below that the top three purposes for using Bitcoin were money transfers and online payments.

Figure 3: User intentions for using Bitcoin.

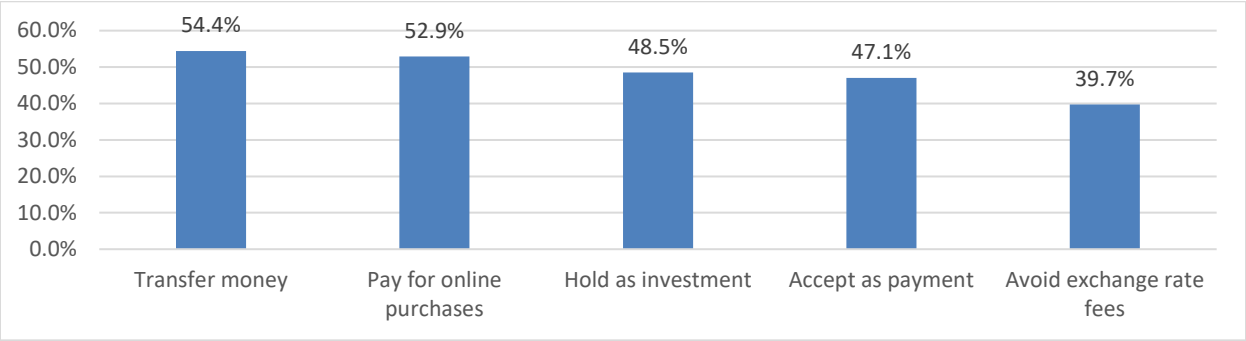


Figure 3 indicates that the sample of the Bitcoin users intended or preferred to use Bitcoin as a method of money transfer and payment rather than as an alternative investment. Such results are contradictory to the claims of the previous research suggesting that Bitcoin is currently more commonly used as an alternative speculative investment rather than as a means of payment (Luther & White, 2013).

Next, the mean levels of perceived importance for each risk dimension and each benefit factor shown in Table 1 and Table 2 are presented and analyzed for each economic zone, and for users and non-users of Bitcoin.

Looking at the overall risk perceptions (table 1), security risk had the highest mean level of perceived importance of 5.35 and social risk had the lowest mean level of 4.04. The results were consistent with the findings of the previous research. Abrazhevich (2004) cited in Ozkan et al. (2010) found that security risk was the most important concern for users of online payment services. Lee (2008) found that social and psychological risks were the least significant factors in the consumer decision to adopt an electronic payment service.

Table 1: Mean Perception of Risk and benefits of Bitcoin

		All data	Europe	Asia		North America	
Risk Measures	Financial Risk	4.73	4.30	4.47		5.34	***
	Security Risk	5.35	4.89	5.25		5.75	***
	Loss of Time	4.30	4.11	4.22		4.55	*
	Technology Risk	4.93	4.26	4.82	**	5.44	***
	Social Risk	4.04	3.58	4.30	***	3.86	
Benefit Measures	Ease of Experience	4.73	4.49	4.36		5.49	***
	Lower Trans. Cost	5.14	4.54	4.95		5.87	***
	Faster transaction	5.05	4.16	5.07	***	5.55	***
	No Third Party	4.23	4.22	4.34		4.06	
	n of observations	468	76	222		154	

Mean perceptions of risk and benefit are on a 7-point scale. *, **, *** indicate significance at the 10%, 5% and 1% level using Europe as the base.

Overall, Europe has the lowest perceived risk among most categories and North America has the highest perceived risk. This is likely due to the level of digitization of currency being the lowest in the US, thus creating more anxiety regarding cryptocurrencies. For North America, all risk factors are significantly higher than in Europe except for the social risk. In Asia, only technological risk and social risk are higher than in Europe.

The perceived benefits of Bitcoin were not the same across the geographic zones. Asia and North America appreciated lower transaction costs and faster transaction speeds. Of the three locations, North America was the most excited about the ease of use. The "no third party" benefit is very consistent across all locations with the lowest coefficient. Overall, this appears to be the least appreciated benefit of using Bitcoin.

As with the risk perceptions, the North American group had a significantly higher benefit perception than the European group. This is consistent with North Americans having less knowledge, and, therefore, exaggerated perceptions regarding Bitcoin transactions. As a robustness check, we used the Mann Whitney test and found similar results.

In table 2, we compare users versus non-users of Bitcoin across risk and benefit factors in the three areas. Specifically, we subtracted the average response for Bitcoin users minus the average response for non-Bitcoin users. A positive response shows that users of Bitcoin have a higher perception of risk or benefit to those who have not used Bitcoin.

Table 2: Change in Perception After Bitcoin Use

		Europe		Asia		North America	
Risk Measures	Financial Risk	-0.68	*	-0.2		-0.8	**
	Security Risk	-1.33	***	-0.53		-0.9	*
	Loss of Time	-0.85	*	-0.34		0	
	Technology Risk	-1.14	**	-1.18		-1.1	**
	Social Risk	-0.37		0.15		-0.3	
Benefit Measures	Ease of Experience	-0.3		-0.19		-0.6	
	Lower Trans. Cost	-0.06		-0.18		-0.8	
	Faster transaction	0.35		-0.16		-0.4	
	No Third Party	0.52		0.65	*	1.23	*
	N obs. non-users	54		191		141	
	N obs. users	22		30		12	

Perceptions of risk and benefit on a 7-point scale of those who have used Bitcoin minus those who have not used Bitcoin. Difference of means tests *, **, *** indicate significance at the 10%, 5% and 1% level.

In Europe and North America, users of Bitcoin have a significantly lower risk profile than non-users for most of the measures. Since users and non-users represent different people, there are two interpretations. Either those who used Bitcoin have an inherently lower perceived risk profile, so were more likely to use it or both groups have risk profiles that are similar before Bitcoin use, and the experience of using Bitcoin changes their perceptions. Looking at the Asian results helps to clarify which interpretation is likely to be more correct. In Asia, risk perceptions are the similar for Bitcoin users and non-users. Either a priori risk perceptions do not affect adoption rates or using Bitcoin in Asia did not significantly reduce their risk perceptions. The first interpretation is only possible if a reduced risk profile affects adoption rates in Europe and North America but not in Asia, a conclusion that is internally inconsistent. The second interpretation concludes that using Bitcoin in Europe and North America provided more information, and risk profiles were adjusted downward, and that in Asia the effect was weaker.

For most of the benefit measures, using Bitcoin shows a decreasing, but not significant effect on perceptions. The "no third party" benefit, however, shows an increasing and significant effect in both Asia and North America. Of all non-cryptocurrency methods of transferring money, only cash has no third-party involvement. It is likely that most respondents did not see the benefits of excluding third parties from digital transactions until they experienced it. This does support the argument of Spenkelink (2014). He claimed that whether decentralization is seen as a benefit depends on a stakeholder group (ibid 25). That is, for the early adopters of Bitcoin, the decentralization could be a primary benefit, whereas for the average online payment user, decentralization may not have any perceived value. Using the Mann- Whitney test only changed the significances slightly, but did not alter our interpretation.

Regression Results

We use multivariate regression to examine the relationship between Bitcoin use and risk/benefit perceptions in more detail. We created a combined measure of overall perceived risk (OPR) by averaging the results of the five measures of risk for each respondent. The overall perceived benefit (OPB) measure is the average of the four measures of benefit for each user.

To measure the internal consistency of the data set and reliability of the scales, we used the Cronbach's Alpha coefficient. According to the results, the coefficient was 0.671 for the OPR scale and 0.682 for the OPB scale. Both are close to the benchmark coefficient of 0.7, indicating that the independent variables defining the overall perceived risk and the perceived benefit together formulated reliable scales. Hence, the results support the validity of using chosen independent variables for measuring perceived risk and perceived benefit of using Bitcoin.

Table 3: Regressions on Overall Perceived Risk of adopting Bitcoin

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
Variable	**Coef.**	**T stat**	**Coef.**	**T stat**	**Coef.**	**T stat**	**Coef.**	**T stat**	**Coef.**	**T stat**
Constant	4.896	***	4.759	***	4.908	***	4.490	***	4.504	***
Bitcoin User			0.623	***	0.545	***	-0.453	***	-0.824	***
Prior Know	-0.750	***			-0.055	*	-0.310			
N. Amer.							0.606	***	0.531	***
Asia							0.282	**	0.136	
User*N. Amer.									0.179	
User*Asia									0.609	*
adj. R square	1.20%		3.80%		4.10%		7.20%		7.70%	

*, **, *** indicate significance at the 10%, 5% and 1% level.

Theoretically, having prior knowledge of Bitcoin, using Bitcoin, and regional effects could explain variations in Bitcoin risk perceptions. Table 3 examines these effects. The first regression examines whether having prior knowledge, as measured in the survey, affects risk perceptions. Having stated that they had enough knowledge about Bitcoin in the survey reduced the perceived risk measures significantly by 0.75. This indicates that those with higher knowledge regarding Bitcoin perceived less risk than those with less knowledge. As regression 2 shows, using Bitcoin reduces risk perceptions by 0.623 points. As these two effects are related, regression 3 combines the effects of both having prior knowledge and actual experience. Using Bitcoin now reduces the risk perception by 0.545 and is highly significant. Having prior knowledge has less effect with a coefficient of -0.055 and significance at the 10% level. This indicates that using Bitcoin has a stronger effect on risk perceptions than stating that one has enough information to assess risk.

In regression 4, we add country components because the descriptive statistics indicated they are important contributors to risk perceptions. Using Europe as a base point, both Asia and North America, have higher risk perceptions of Bitcoin. In Asia, risk measures are higher by 0.29 and are significant at the 10% level; in North America, they are higher by 0.564 and are highly significant. While using Bitcoin continues to reduce risk perceptions, stating that one has prior knowledge of Bitcoin does not. In brief, the country factors account for prior knowledge, with Europe having a better understanding of Bitcoin risk than the other locations.

In regression 5, we interacted the location codes with Bitcoin use to separate the country effects for users and non-users of Bitcoin. In North America, risk perceptions were higher than Europe by 0.531, but for users, the risk perception was similar. This indicates that after using Bitcoin, both North Americans and Europeans had similar risk perceptions. The difference between the two is that Europeans who have not used Bitcoin were less fearful than North Americans, but after using Bitcoin, they are similar. In Asia, the effect is reversed. Users who have not used Bitcoin in Asia have similar risk profiles, but after using Bitcoin, Asian users do have a higher risk profile by .609, which is significant at the 10% level. The effect is not that Asians risk perceptions increased, but that Asian risk measures decreased less than in Europe among Bitcoin users.

In table 4, we examine the effects of prior experience, prior knowledge and gender on perceived benefit. The first regression uses prior experience of using Bitcoin and having prior knowledge. Neither is significant, indicating that having prior knowledge or using Bitcoin have no effect on the perceived benefits of Bitcoin. In the second regression, we added a gender component because our descriptive statistics indicated that women saw more benefits in Bitcoin than men. In this regression, experience with Bitcoin and prior knowledge are still insignificant, but being male showed a lower perceived benefit by 0.334 versus women. Since further regressions show this effect disappearing, we conclude that it is an artifact of the data. In the third

regression, we included the location markers for North America and Asia. North Americans were more excited about the perceived benefits than were Europeans by 0.676 overall. Asians did not see significantly better benefits than Europeans did. Bitcoin users, prior knowledge, and gender are all insignificant factors according to the results. The differences in perceived benefits appear to be purely regional in nature. Even in regression when we include interactive terms, only the country variables are significant. Although regression 4 includes interaction terms of being Bitcoin users and location markers, the results are similar. The results for both North America and Asia both became stronger once the interaction terms were included. While three benefits decreased for users, the no third party increased reducing the combined impact of the interaction term in the regression.

Table 4: Regression on overall Perceived Benefit of Adopting Bitcoin

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Variable	**Coef.**	**T stat**	**Coef.**	**T stat**	**Coef.**	**T stat**	**Coef.**	**T stat**
Constant	4.859		5.053		4.547	***	4.231	***
Bitcoin User	-0.88		0.018		0.082		0.211	
Prior Know	-0.22		-0.01		0.02			
Gender			-0.334	***	-0.203			
N. Amer.					0.676	***	1.02	***
Asia					0.204		0.445	**
User*N. Amer.							-0.338	
User*Asia							-0.179	
adj. R square	0.30%		1%		6.50%		6.20%	

*, **, *** indicate significance at the 10%, 5% and 1% level.

Tables 5 and 6 test whether OPR and OPB of Bitcoin by the respondents had an effect over potential adoption of the cryptocurrency. In table 5, linear regression analysis examined whether risk and benefit measures affect whether they were willing to use Bitcoin as answered on the survey. The response rate showed that 53% of respondents indicated they were willing to use Bitcoin, and 47% were not willing to adopt it. In regression 1, the integrated variables of OPR and OPB are both significant with the expected sign which shows that respondents were cognizant of risks and benefits in answering this question. The coefficient for benefit of 0.117 is twice as large as the risk coefficient of -.049. This indicates that benefits are perceived as more important for stating a willingness to use Bitcoin. No country indicator was significant showing that no location preference on being willing to use Bitcoin. In regression 2, we separate the risk and benefit components into their parts. The only risk factor that reduced the willingness to adopt Bitcoin was loss of time from learning the system. The ease of use and low transaction cost both increased the response rate for willingness to adopt Bitcoin.

Table 5: Regression of risk and benefit on willingness to adopt Bitcoin

	Model 1		Model 2	
Variable	**Coef.**	**T stat**	**Coef.**	**T stat**
Constant	0.213		0.214	**
Financial Risk			-0.011	
Security Risk			-0.013	
Loss of Time			-0.025	*
Technology Risk			0.006	
Social Risk			-0.011	
OPR	-0.049	**		
Ease of Experience			0.028	*
Lower Trans. Cost			0.021	
Faster transaction			0.061	***
No Third Party			0.005	
OPB	0.117	***		
Americas	-0.049		-0.062	
Asia	0.002		0.043	
adj R2	7%		9%	

*, **, *** indicate significance at the 10%, 5% and 1% level.

In table 6, we perform a logistic regression to see if these variables can predict actual Bitcoin use. We used the variables of OPB, OPR, and location markers to estimate whether people would actually use Bitcoin. The estimate for OPB is significant at 0.274 indicating that benefits do increase the odds of a respondent being a Bitcoin user. OPR is negative at -0.582, which is consistent with more perceived risk reducing Bitcoin adoption. Since the coefficient is larger for OPR than OPB, it shows that the negative effect of risk on adoption rates are larger than the effects of perceived benefits. This result is the opposite of that from regression 5 when willingness to adopt Bitcoin as a question on the survey was used. This indicates a difference between willingness to adopt versus actually adopting Bitcoin. Both North Americans, and Asians are significantly negative, indicating that they are less likely to adopt Bitcoin than are Europeans although neither indicated such in their willingness to adopt Bitcoin. Overall, this regression correctly predicted 100% of the non-Bitcoin users, but only 7 of the 67 users for a combined accuracy of 87%.

The second regression splits benefit and risk components into their parts. Only security risk and technology risk actually reduced Bitcoin use. Of the benefits, only having no third party was a significant benefit for those who used Bitcoin. There are today, many online, easy forms of payment that can move money quickly. Most of them however do use a third party such as a bank, Paypal, Alipay. Cryptocurrencies are the only one that do not use a third party, and it appears that not having a third party involved was valuable to those who chose to use Bitcoin. Not having a third party involved was the only benefit whose value increased for those who used Bitcoin. The North American and Asian coefficients are still both significantly negative indicating that those locations were less likely to adopt Bitcoin than Europe. This regression only slightly increases its prediction rate by catching 9 of the 67 users of Bitcoin.

Table 6: Logit Regression on Actual Bitcoin Adoption

	Model 1		Model 2	
Variable	**Coef.**	**T stat**	**Coef.**	**T stat**
Constant	0.274		0.002	
Financial Risk			-0.167	
Security Risk			-0.208	*
Loss of Time			-0.089	
Technology Risk			-0.154	*
Social Risk			0.015	
OPR	-0.582	***		
Ease of Experience			-0.02	
Lower Trans. Cost			0.001	
Faster transaction			0.057	
No Third Party			0.341	***
OPB	0.276	**		
Americas	-1.403	***	-1.162	***
Asia	-0.835	***	-0.897	***
Prediction of not accepting	399 of 399		398 of 399	
Prediction of accepting	7 of 67		9 of 67	

*, **, *** indicate significance at the 10%, 5% and 1% level.

Conclusion

People use their perceptions of risk and benefit when making decisions about adoption of new technologies. With any product or technology at a nascent stage of adoption, there is a greater likelihood that these perceptions are skewed due to the lack of knowledge or experience with a product. We conducted a survey of Bitcoin use to determine public perceptions and potential adoption rates of Bitcoin as a payment method. Our findings indicate that these perceptions differ both by geographic area and by whether people have chosen to use Bitcoin. Overall, Europeans see the least benefit and risk from using Bitcoin. North Americans have a highest perception of both risk and benefits of Bitcoin, which leads them to use it less frequently than the other two regions. North Americans risk and benefit perceptions both decrease after using Bitcoin the most indicating less understanding of Bitcoin prior to use than other locations. For Asians, only a few measures of risk are higher than for Europeans. Interestingly, after using Bitcoin, both North Americans and Asians see an increased benefit from having no third party indicating a displeasure with others participating in and knowing about their transactions.

The regression results of those who actually used Bitcoin differ from those who stated they were willing to use Bitcoin on the survey. Those who stated they would be willing to use it, liked that it was fast and easy to use, and only considered the learning curve as a risk. Those who actually used Bitcoin found security risk and technology risk were hindrances while no third party was the sole benefit. This indicates that education about the actual benefits and risks of using Bitcoin is still necessary.

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Appendix: Survey about Bitcoin

Dear participant,
We are a professor and an undergraduate student research team studying the understanding of public’s acceptance of Bitcoin. We are currently conducting an academic research and are kindly requesting that you complete a short survey that captures your knowledge, experience, and perceptions of Bitcoin.

Your responses are completely anonymous and will assist us in understanding Bitcoin’s adoption and longterm viability.

Thank you in advance for your time and effort!

Definition of Bitcoin:
Bitcoin is the most widely used digital currency. Its original purpose is be used as an alternative online payment system. Bitcoin is also considered to be an independent currency, which is traded on online exchanges, and used as an investment instrument.

1. Which electronic payment services do you use regularly (at least once a month)? *Check all that apply.*
   - O Debit and credit card payments

- O Online Banking
- O Bitcoin
- O PayPal
- O Amazon Payments
- O AliPay
- O Mobile Pay
- O Other:_____

2. Please assess your level of knowledge about Bitcoin. *Mark only one*

Low 1 2 3 4 5 6 7 High

3. Please specify top three purposes for which you use or would consider using Bitcoin. *Check all that apply.*

- O Pay for online purchases
- O Accept as payment
- O Transfer money
- O Hold as investment
- O Avoid exchange rate fees
- O Other:_____

How important to me are the following things in using or considering using Bitcoin for payments?

4. Ease of Experience *Mark only one*

Not Important at all 1 2 3 4 5 6 7 Very Important

5. Low transaction fees *Mark only one*

Not Important at all 1 2 3 4 5 6 7 Very Important

How important to me are the following things in using or considering to use Bitcoin for payments?

6. Fast transaction speed *Mark only one*

Not Important at all 1 2 3 4 5 6 7 Very Important

7. Transactions are not overseen by banks or other intermediaries. *Mark only one*

Not Important at all 1 2 3 4 5 6 7 Very Important

How important are the following things in making me uncomfortable with using Bitcoin?

8. Transactions cannot be cancelled *Mark only one*

Not Important at all 1 2 3 4 5 6 7 Very Important

9. The value of Bitcoin from day to day is unstable *Mark only one*

Not Important at all 1 2 3 4 5 6 7 Very Important

10. Security vulnerabilities of the transaction processing and possibility of hacker attacks on Bitcoin intermediaries, e.g. payment service providers and exchanges *Mark only one*

Not Important at all 1 2 3 4 5 6 7 Very Important

How important are the following things in making me uncomfortable with using Bitcoin?

11. Spending time to learn how to make transactions *Mark only one*

Not Important at all 1 2 3 4 5 6 7 Very Important

12. Possibility of breakdown or malfunctioning of the transaction processing system or other technical issues *Mark only one*

Not Important at all 1 2 3 4 5 6 7 Very Important

13. Issues with the public image *Mark only one*

Not Important at all 1 2 3 4 5 6 7 Very Important

14. Have you ever used Bitcoin before? ◯ Yes, ◯ No (skip to question 16)

15. Which of the risks related to Bitcoin worry you the most? *Check all that apply.*

- O Financial loss due to instability of Bitcoin value or inability to cancel payments
- O Financial or private information loss caused by the attacks due to security Vulnerabilities
- O Malfunctioning or breakdown of the Bitcoin transaction processing system
- O Increased government regulation on the Bitcoin ecosystem
- O Time loss since it may take longer to make a transaction with Bitcoin compared to other means
- O Public image of Bitcoin negatively affected by the media coverage of the past events
- O Other:_____

16. Taking into account your responses to the previous questions, will you consider using or continue to use Bitcoin for payments in the future? *Mark only one oval.*

◯ Yes ◯ No *Skip to question 18.*

17. Please specify the factors encouraging you to use Bitcoin. *Check all that apply.*

- O Fast transaction speed
- O Ease of Experience
- O Lower transaction cost
- O No third party overseeing transactions

Skip to question 19.

18. Please specify negative factors discouraging you from using Bitcoin. *Check all that apply.*

- O Financial risks
- O Security risks
- O Lack of consumer protection laws and bank guarantee for transactions
- O Spending time to learn how to make transactions
- O Possibility of malfunctioning of payment processing or other technical issues
- O Public image issues of Bitcoin

Personal information

For research purposes, you are kindly asked to answer the following questions about yourself.
This information will be kept confidential.

19. Age _____

20. Gender _____

21. What country do you currently live in? *Circle only one oval.*

China, Canada, France, Finland, Germany, Japan, Kazakhstan, Netherlands,

Russia, The UK, The USA, South Korea, Vietnam, Other _____

The Relative Tracking Ability of Exchange Traded Funds and Open-Ended Mutual Funds: Evidence from a Thinly Traded Market

Dr. Nassar S. Al-Nassar, Qassim University, Saudi Arabia, College of Business and Economics, Department of Economics and Finance, P.O. Box 6633, Buraidah 51452

Abstract

This paper investigates the relative performance of exchange-traded funds (ETFs) compared to their off-market counterparts—open-ended mutual funds listed in the Saudi stock market. The performance of both investment vehicles is gauged using several tracking-error metrics. To echo the retail investors' experience in trading ETFs, I compute tracking errors for ETFs on the basis of the secondary-market prices, in addition to the net asset value (NAV). This is to disentangle a fund manager's ability to closely mimic the performance of the underlying index from factors that affect the liquidity of the ETFs in the secondary market. The evidence reveals that the relative performances of ETFs compared to mutual funds—based on results obtained using the NAVs of the ETF—are largely mixed and inconclusive. However, the results based on the secondary-market closing prices emphatically indicate that mutual funds exhibit significantly smaller tracking errors. An important finding is that caution must be exercised when analysing the tracking errors for thinly traded ETFs, particularly those listed in emerging markets.

Introduction

The ETF industry has experienced tremendous growth in terms of asset under management (AUM) during the last two decades, overtaking the glamorous hedge-fund industry (see, Lettau and Madhavan, 2018). The popularity of ETFs among both institutional and retail investors stems from the unique characteristics that distinguish them from their rivals—traditional open-ended mutual funds. These characteristics include intraday liquidity in addition to low expense ratios and tax efficiencies.[1] Indeed, ETFs are traditionally passive investment vehicles that aim to track a market index. Therefore, the performance of ETFs is typically judged on the grounds of how accurately they track their underlying index compared to their off-market counterparts—open-ended mutual funds. The tracking accuracy can be quantified by the means of several tracking error measures.

However, the differences between the two investment vehicles should be taken into consideration when measuring their tracking ability. One important difference is that open-ended mutual funds are bought and sold at NAV, as determined at the end of each trading day; ETFs are traded intraday in the secondary market, just like an ordinary stock. The creation–redemption mechanism that operates through authorised market participants ensures that an ETF's secondary-market price is kept in sync with its NAV.

Several studies documented noticeable deviations between the NAV of ETFs and their secondary-market price; this is particularly so in the less liquid and in the international ETFs (Delcoure and Zhong, 2007; Engle and Sarkar, 2006). Poterba and Shoven (2002) indicate nontrivial year-to-year differences in tracking errors between returns calculated on the basis of NAV and those obtained using the secondary-market prices of ETFs. Since retail and institutional investors—other than authorised participants (APs)—can only transact ETFs at the prevailing secondary-market price, such a mismatch between the NAV and the secondary-market price is considered to be an extra trading cost incurred directly by an ETF's holder (DeFusco, Ivanov, and Karels, 2011).

Moreover, these deviations are exacerbated during extreme market turbulence (Ben-David, Franzoni, and Moussawi, 2017; Petajisto, 2017). Hughen (2003) documents extended large departures of the price of iShares Malaysia from its NAV during the Asian crises; Hilliard (2014) reports a similar pattern for the Egypt Index ETF (EGPT) during the Arab Spring uprisings in Egypt. Buetow and Henderson (2012), therefore, suggest the use of the secondary-market price to disentangle a manager's success in replicating the underlying benchmark, which is captured by the NAV-based tracking errors on the one hand, from the supply and demand for ETFs in the secondary market, and the efficacy of the creation-redemption mechanism; these, on the other hand, are reflected in secondary-market price-based tracking errors.

Despite the importance of secondary-market liquidity for the bulk of ETFs' investors, especially in emerging markets where the ETF industry remains in its early stages of development, subsequent emerging market-based studies relied solely on NAV-

based tracking errors (for example, Rompotis, 2011; Strydom, Charteris, and McCullough, 2015). The literature on the relative performance of ETFs compared to open-ended funds has been traditionally US-centric, focusing on domestic ETFs (Elton et al., 2002; Gastineau, 2004; Poterba and Shoven, 2002; Sharifzadeh and Hojat, 2012). Empirical work focusing on international ETFs listed in other developed markets is scant, for instance see, Blitz, Huij, and Swinkels (2012). The work on the relative performance of domestic non-US ETFs is limited to a few markets. Studies include Gallagher and Segara (2005), Rompotis (2011), and Strydom, Charteris, and McCullough (2015) who investigate the performance of ETFs compared to open-ended funds in the Australian, Greek, and South African markets, respectively.

While the empirical findings derived from these studies—which examine US-based ETFs and international ETFs listed in other markets—are informative, they do not necessarily apply to other contexts. In addition, the explanations that are regularly offered in international ETF studies for poor performance (that is, high tracking errors)—such as time-zone differences, withholding taxes, exchange-rate risk, and some regulatory restrictions—are of little relevance to the performance of domestic ETFs. Also, for domestic ETF studies, although they share common features, each market has its unique characteristics.[2] In addition, evidence on the relative performance of ETFs compared to their off-market counterparts is mixed It varies across funds, markets, time periods, data frequency, and the tracking-error measures.

Motivated by the scarcity of evidence on the relative performance of domestic non-US ETFs, and the potential impact of the secondary-market liquidity on tracking errors, we aim to extend the literature by using data from the Saudi market to investigate the impact of ETFs' liquidity on tracking errors. The Saudi ETF industry is conducive for examining relative performance of ETFs while addressing the impact of liquidity on the tracking errors for several reasons. The first reason is the relatively small size of the fund-management industry, which is in its infancy in Saudi Arabia. The AUM in the three Saudi-listed ETFs reached 117.1 million Saudi Riyal (around USD31.2 million) in 2011, before losing 69 per cent of its value and reaching 36.5 million Saudi Riyal (around USD9.73 million) at the end of 2016 (Capital Market Authority (CMA), 2011, 2016). The second reason is the poor secondary-market liquidity for these ETFs—with a yearly trading volume for the three ETFs constituting a mere 0.09 per cent of the total trading volume in the Saudi stock market. This is less than any ordinary stock in the Saudi stock exchange (Tadawul, 2016). This could increase the overall cost of acquiring ETFs and amplify the secondary-market price deviations from NAV. The third reason is the absence of taxes, which are traditionally believed to lure investment to ETFs instead of their open-ended counterparts.

These distinctive features offer a valuable setting in which to confirm, reject, or elaborate on the conclusions reached in studies on the relative performance of ETFs compared to open-ended funds. The results that emerge from our analysis carry important implications for regulators, and for the investors who are considering the two investment vehicles.

The reminder of this article is structured as follows. In Section 2, we briefly review the extant literature; Section 3 discusses data sources; in Section 4 we develop our research design; and we report and discuss our results in Section 5. Section 6 summarises the finding of the research.

Literature Review

Several studies empirically investigated the performance of ETFs relative to their underlying index, that is, the tracking error. Early research endeavours examined the performance of S&P Depository Receipts (SPDR), the first ETF in the United States (Elton et al., 2002; Poterba and Shoven, 2002). Elton et al. (2002) examine the performance the SPDR relative to its benchmark and rivals—index funds and index futures in addition to its pricing efficiency using daily data over the period 1993-1998. The results reveal that the return generated by the SPDR persistently underperform its benchmark by an average of 28.4 basis points which is accounted for by dividends policy and the fund's expanses. Furthermore, when compared to its rivals, the Vanguard index fund available to individual investors and index futures, the return generated by SPDR fall short from its rivals, respectively, by 18.1 and 30.7 basis points. The authors attribute the difference in the case of Vanguard index fund to the value of immediacy offered by SPDR the while they suggest that large investment and expertise required to maintain a position in futures along with restrictions on holding futures for some institutional investors can explain the difference. Elton et al. (2002, pp. 471) elegantly conclude that "… exchange traded funds that offer immediacy are likely to prosper and reproduce".

Poterba and Shoven (2002), using data over the period 1994 – 2000, find evidence confirming the findings of Elton et al. (2002) that Vanguard index fund outperforms the SPDR even when return are calculated on an after-tax basis. Gastineau (2004) provides evidence on the relative performance of small cap ETFs, namely, the iShares Russell 2000 ETF against the Vanguard Small Cap Investor Shares in addition to ETFs tracking broad market indices, SPDR and iShares 500 relative to conventional Vanguard index fund over the period 1994 – 2002. The results consistently indicate that ETFs underperform their respective corresponding off-market counterpart, albeit the underperformance is considerably higher for small cap ETFs. Gastineau (2004) attributes the underperformance to the sluggishness of ETFs in acting upon changes in the constituents of their underlying index.

More recent studies, such as Agapova (2011) and Sharifzadeh and Hojat (2012), investigated a large sample of domestic US-domiciled funds. Agapova (2011) evaluates the performance 11 ETFs against 171 open-ended funds tracking the same indices and examines the implications of substitutability. The analysis spans the period 2000 – 2004 and indicates that ETFs generate superior returns and better tracking ability compared to open-ended funds. Using data spanning the period 2000 – 2010, Sharifzadeh and Hojat (2012) compare the performance of a large sample of ETFs and mutual funds that have the same investment style, resulting in 230 paired matches.[3] The results, overall, show no significant difference in performance between the two investment vehicles. that Studies that mainly focused on US-domiciled international ETFs include Harper, Madura, and Schnusenberg (2006), Johnson (2009) and Shin and Soydemir (2010). However, Johnson (2009) and Shin and Soydemir (2010) focus on the tracking ability of the ETFs relative to their underlying benchmarked without any reference to any alternative investment vehicle while Harper, Madura, and Schnusenberg (2006) compare the performance of ETFs to their exchange-traded rivals close-ended funds.

The ETF industry in European markets is predominantly international, with prevalent ETFs cross listing (Mussavian and Hirsch, 2002). Therefore, empirical evidence on the performance of ETFs in Europe mostly pertains to international ETFs invested in the other European markets (Blitz, Huij, and Swinkels, 2012) or in emerging markets (Blitz and Huij, 2012). Evidence from emerging markets includes Purohit, Choudhary, and Tyagi (2014) and Chu (2011) who analysed international and domestic ETFs listed in the emerging markets of India and Hong Kong, respectively. Wong and Shum (2010) investigated 15 worldwide ETFs from seven countries (the United States, Hong Kong, Japan, the United Kingdom, Canada, Belgium, and the Netherlands).

Gallagher and Segara (2005), Rompotis (2011), and Strydom, Charteris, and McCullough (2015) are among the few studies that solely consider domestic ETFs outside the United States, respectively, that are listed in the Australian, Greek, and South African stock markets.[4] Gallagher and Segara (2005) investigate the four ETFs and three open-ended index funds listed on the Australian stock market over the period 2002 – 2003. They find that ETFs track their benchmark indices more closely compared to index funds. Rompotis (2011) examines the relative performance of the first listed ETF in the Greek market and compares it against four open-ended funds (one index fund and three active funds) over a one-year period, spanning 2008 and 2009. The results show that ETFs display better tracking ability compared to active funds whereas they fall short from index funds. While the former studies use daily data over a relatively short sample period, Strydom, Charteris, and McCullough (2015) use monthly data in their analysis from 2001 through 2012. They compare the performances of three ETFs and four index funds listed on the South African market. The balance of evidence suggest that ETFs display superior tracking a ability compared to off-market index funds. A common feature of these studies is that they employ several tracking-error metrics.

To reiterate, the main conclusions that emerge from these studies are three-fold. First, early studies find that ETFs not only persistently underperform their underlying index, but they also produce a higher tracking error than open-ended funds that replicate the same index (Elton et al., 2002; Gastineau, 2004; Poterba and Shoven, 2002). More recent studies, however, indicate that ETFs display, on average, smaller tracking errors than their off-market counterparts (Agapova, 2011; Blitz, Huij, and Swinkels, 2012; Gallagher and Segara, 2005; Rompotis, 2011; Strydom, Charteris, and McCullough, 2015).

Second, the underperformance (tracking error) is largely explained away by dividends policy and the ETFs' expenses, while the shortfall in the ETFs' returns compared to their off-market counterparts is attributed to the value of immediacy that investors attach to ETFs (Elton et al., 2002). Gastineau (2004) confirms the findings of Elton et al. (2002) and Poterba and Shoven (2002), while attributing the underperformance of ETFs relative to conventional open-ended index funds, in part, to their organisational structure, as well as to the regulations that govern their operation and prevent them from acting upon index changes. Furthermore, the index-replication technique (full replication versus optimisation) in addition to cross-sectional dispersion in stock returns exacerbates tracking errors, particularly when an optimisation-based replication method is employed (Blitz and Huij, 2012).

Third, other factors that carry explanatory power for the tracking error, particularly for international ETFs, include dividends withholding taxes (Blitz, Huij, and Swinkels, 2012); the fluctuations in exchange rates (Shin and Soydemir, 2010); and restrictions imposed on the holding of any stock to a maximum limit that may not be sufficient to achieve full replication (Mussavian and Hirsch, 2002).

Data Sources

Our analysis is conducted over the period starting from November 20, 2011 to October 11, 2017; we have a total of 1473 daily observations. The universe of mutual funds in Saudi Arabia expanded slightly over the sample period, from 267 funds in 2011 with AUM of 82,076.4 million Saudi Riyal (64 of which are domestic equity funds with AUM of 17,135.1 million Saudi Riyal), to 271 funds with AUM reaching 87,244.2 million Saudi Riyal in 2016 (96 of which are domestic equity funds with AUM amounting to 16,703.8 million Saudi Riyal).[5] The number of ETFs, on the other hand, has not only remained the same (including two broad equity and one sectoral ETF) since their inception in 2010 and 2011 (mainly to offer access to foreign

investors), but they have also shrunk in size from 117.1 million Saudi Riyal in 2011 to 36.5 million Saudi Riyal in the 2016.[6] Because we focus on funds that track broad-market indices, we only consider the two broad-market ETFs listed on the Saudi market, namely, Falcom 30 and HSBC Saudi 20.

To maintain comparability between the performance of ETFs which trade continuously, just like a stock, to that of mutual funds, we restrict our dataset to open-ended mutual funds that stand ready to receive subscriptions and redemption applications during all trading days of the week, and that reported continuous daily NAV data from 2011.[7] Therefore, we ended up with two ETFs and six open-ended mutual funds, namely, Al Jazira AL-Taiyebat Saudi Equities Fund, Al Rajhi Saudi Equity Fund, Jadwa Saudi Equity Fund–Class B, Jadwa Saudi Equity Index Fund, Falcom Saudi Equity Fund, and Osool and Bakheet Saudi Trading Equity Fund. The reference portfolio that we use as a benchmark for these funds is the S&P Saudi Sharia Total Return Index.[8]

All the funds included in our sample are Sharia-compliant and explicitly state, in their prospectuses, that all dividend payouts, income from Murabaha accounts, and realised capital gains are reinvested in the fund. The funds' daily NAV data are obtained from the Thomson Reuters Lipper database, while the S&P Saudi Sharia Total Return Index and the ETFs' closing price levels are obtained from the Thomson Reuters Eikon terminal. Table 1 offers a profile of the ETFs and the open-ended mutual funds analysed in this study.

Table 1: ETFs and open-ended mutual funds in the sample

Fund name	Benchmark	Listing date	Expense Ratio (%)
Panel A: Mutual funds			
Al Jazira AL-Taiyebat Saudi Equities Fund	S&P Composite Shariah Index	10/21/1998	1.77
Al Rajhi Saudi Equity Fund	S&P Saudi Shariah Index	8/5/1992	4.08
Jadwa Saudi Equity Fund - Class B	S&P Saudi Sharia Domestic Index	6/30/2007	1.93
Falcom Saudi Equity Fund	All shares index TASI	4/22/2007	1.46
Osool & Bakheet Saudi Trading Equity Fund	S&P Saudi Shariah Index	3/31/2007	3.5
Jadwa Saudi Equity Index Fund	S&P Saudi Sharia Total Return Index	6/29/2008	2.12
Panel B: ETFs			
Falcom 30	Falcom 30 Saudi Equity index	3/16/2010	1
HSBC Saudi 20	HSBC Saudi 20 Equity Index	11/24/2011	0.75

Sources: The Saudi Stock Exchange (Tadawul) and the Thomson Reuters Lipper database.

Research Design

Active Returns

To obtain the relative performance of funds compared to their underlying index, we first calculate the simple returns for the funds and the underlying index, respectively, as follows:

$$R_{i,t}^{fund} = \frac{NAV_{i,t} - NAV_{i,t-1}}{NAV_{i,t-1}} \times 100 \quad (1)$$

$$R_{t}^{index} = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100 \quad (2)$$

where $R_{i,t}^{fund}$ and R_{t}^{index} are, respectively, the simple return on fund i and the underlying index on day t. In the spirit of Elton et al. (2002) and Agapova (2011), the active returns, $AR_{i,t}$ of fund i tracking the underlying index are given by:

$$AR_{i,t} = R_{i,t}^{fund} - R_{t}^{index} \quad (3)$$

Elton et al. (2002) and Agapova (2011) use the mean of the active return and call it the effectiveness measure, while Blitz, Huij, and Swinkels (2012) opt for the use of the median of active returns to account for the influence of the first and last observations in the sample. We utilise both (the mean and the median) to ensure that results are not driven by outliers.

To ascertain whether any of the funds in our sample persistently outperform or underperform their underlying index, following Gallagher and Segara (2005) and Agapova (2011), we test the hypothesis that active returns are not different from

zero. We do this by the means of two statistical tests: the standard parametric *t*-test, and the Wilcoxon signed-rank non-parametric test.

Tracking error

While there exists a trade-off between active returns that eventuate when the fund outperforms, or underperforms, its underlying index on the one hand, and the tracking error which is captured by the volatility of active return on the other, the performance of passively managed funds is more likely to be judged on the basis of its tracking error (Agapova, 2011, pp. 332).

In a relevant paper, Bong-Soo (1992) argues that tracking error—which represents the departures of the funds' return from its respective benchmark—is a sensible approach to evaluate the performance of fund managers.[9] To maintain compatibility with prior studies, *inter alia*, Gallagher and Segara (2005), Shin and Soydemir (2010), Chu (2011), Rompotis (2011) and Strydom, Charteris, and McCullough (2015), we employ four commonly used tracking-error metrics listed in Narat and Peter (2013, pp. 434).

The first metric is the mean absolute deviation (MAD) of active return, which we refer to as $TE_{1,i}$. This measure is expressed as:

$$TE_{1,i} = \frac{\sum_{t=1}^{T}\left|R_{i,t}^{fund} - R_t^{index}\right|}{T} \qquad (4)$$

Here, T is the sample period over which the performance of the fund is evaluated.[10] As in the preceding section, we compute the standard deviation, and the maximum and minimum values of the absolute value of active returns.

The second metric is based on the standard deviation (SD) of active return, $TE_{2,i} = \sigma\left(R_{i,t}^{fund} - R_{j,t}^{Index}\right)$, which can be calculated as follows:

$$TE_{2,i} = \sqrt{\frac{\sum_{t=1}^{T}\left[\left(R_{i,t}^{fund} - R_t^{Index}\right) - \left(\bar{R}_i^{fund} - \bar{R}^{index}\right)\right]^2}{T-1}} \qquad (5)$$

where $\bar{R}_i^{fund}$ and $\bar{R}^{index}$ are, respectively, the sample mean returns on the fund i and the underlying index on day t. While this metric is widely adopted as measure of tracking error, it is calculated under the assumptions that active returns are neither autocorrelated nor different from zero on average. It is documented that daily active returns, in particular, are significantly autocorrelated, which introduces bias into this metric (Pope and Yadav, 1994).[11] Further, when active returns significantly differ from zero, this metric fails to discern the performance of a fund that persistently outperforms another that persistently underperforms its benchmark (Alexander, 2008, pp. 33-36).

To overcome this concern, we use the square root of the mean squared differences, $TE_{3,i}$, which is obtained by mean-adjusting the $TE_{2,i}$ as follows:

$$TE_{3,i} = \sqrt{\frac{T-1\left(TE_{2,i}{}^2\right)}{T} + \left(\bar{R}_i^{fund} - \bar{R}^{index}\right)^2} \qquad (6)$$

Indeed, for a large sample T, the value of $TE_{3,i}$ will be close to $TE_{2,i}$ if the mean of active returns is very close to zero. Finally, the fourth metric, $TE_{4,i}$ is the standard error of the regression (SER) of the estimated residuals of the single-index model of Sharpe (1963), which is expressed as:

$$R_{i,t}^{fund} = \alpha + \beta R_t^{index} + e_{i,t} \qquad (7)$$

where α is the intercept which captures the returns generated above or below the underlying index due to the fund manager's choices, and β is beta for fund i which measures the (systematic) risk of the fund with respect to its underlying index. Aroskar and Ogden (2012), Rompotis (2011) and Strydom, Charteris, and McCullough (2015) test the restriction that $\beta = 1$ in order to find out whether or not the fund employs a full-replication method to track the underlying index.

If the intercept α and the slope β, respectively, are equal to zero and unity, then $TE_{2,i}$ and $TE_{4,i}$ become identical.[12] The R^2 from a single-index model is shown to be a valid measure of mutual-fund diversification; that is, funds with a higher R^2 are found to be more diversified than funds with a lower R^2 (Cresson, 2002). Several studies interpret R^2 as a tracking-error metric, including Chu (2011), Rompotis (2011), Aroskar and Ogden (2012), and Strydom, Charteris, and McCullough (2015).

ETFs Versus Mutual Funds: The Hypotheses

The performance of ETFs is compared to that of open-ended mutual funds in two ways: first, the difference between active returns generated by each the two ETFs and mutual funds is tested for each fund separately. Second, the difference in tacking error calculated using absolute returns is tested in the same fashion. The hypotheses are expressed symbolically as:

$$H_0: AR_i^{MF} - AR_i^{ETF} = 0$$
$$H_1: AR_i^{MF} - AR_i^{ETF} \neq 0$$

where AR_i^{MF} and AR_i^{ETF} are, respectively, the active return of mutual fund i and ETF i. The tracking-error hypothesis is:

$$H_0: TE_{1i}^{MF} - TE_{1i}^{ETF} = 0$$
$$H_1: TE_{1i}^{MF} - TE_{1i}^{ETF} \neq 0$$

where TE_{1i}^{MF} and TE_{1i}^{ETF} are, respectively, the tracking error of mutual fund i and ETF i. We use the two samples' *t*-test and the Mann-Whitney test for both hypotheses to assess each test's impact on the conclusions drawn about the relative performance of ETFs compared to their open-ended counterparts.

Tracking Error Based on Market Price

Most studies base their tracking-error calculations on NAV. Poterba and Shoven (2002), DeFusco, Ivanov, and Karels (2011) and Buetow and Henderson (2012) demonstrate the importance of taking into account the potential departures of the market price of the ETF from the NAV of the constituents of the ETF. Hill, Nadig, and Hougan (2015) emphasise the relevance of trading costs that constitute a large proportion of the expenses incurred by ETF holders. Such costs are greatly exacerbated by on-screen illiquidity. Therefore, when evaluating ETFs, market price should also be considered alongside NAV, since the creation–redemption mechanism that keeps the market price in tandem with the NAV may be halted for one reason or another. Therefore, we calculate the ETFs' returns on the basis of their closing prices in the secondary market to ascertain whether the occasional deviations of the ETFs' price from its NAV alters the conclusions reached using the NAV.

Results

Tracking-error measures calculated based on daily data for the two ETFs and their six open-ended counterparts are presented in Table 2. The first four columns of Table 2 show the absolute difference in returns-based measures, including the first tracking-error metric, $TE_{1,i}$, in addition to the standard deviation of the absolute difference in returns, as well as their maximum and minimum values. Columns five to eight of Table 2 contain the statistics pertaining to the arithmetic difference in returns, including the mean and the median of the arithmetic difference (that is, the effectiveness measure) and their corresponding *t*-statistics and z-statistics (in parentheses), respectively, in addition to the tracking error based on the definitions $TE_{2,i}$ and $TE_{3,i}$. The right-hand part of Table 2 (columns nine through 12) reports the single-index model-estimation results: α, β, R^2 and SER ($TE_{4,i}$).

Based on the first definition of the tracking error, $TE_{1,i}$, the daily tracking error lies between 0.038 per cent and 0.725 per cent. While the range between the highest and the lowest tracking error is considerable, the high tracking error is specific to Fund 3. The results are mixed, as no clear pattern can be gleaned as to the relative performance of ETFs compared to open-ended mutual funds. ETF1 exhibits a smaller tracking error compared to open-ended funds, except for Fund 2 and Fund 6, whereas ETF2 generates a higher tracking error than most open-ended mutual funds in our sample, namely, Funds 1, 2, 4, and 6.

However, the results obtained from the arithmetic returns reveal a slightly different story. The mean and median of active returns (effectiveness measure) often exhibit different signs (in four out of eight cases). Moreover, the mean is predominantly higher than the median (except for Fund 6), which is indicative of positive skewness. However, both the mean and median of active returns are statistically indistinguishable from zero, except for Fund 1 and Fund 6, albeit that these funds produce inconsistent results between the two measures. Fund 1 significantly outperforms its benchmark, according to the *t*-test at the five per cent level, while no significant difference is found under the Wilcoxon signed-rank test. On the other hand, Fund 6 underperforms its benchmark at the marginal ten per cent level, according to the *t*-test, while the Wilcoxon signed-rank test finds the difference to be statistically significant at the 1 per cent level. Taken together, these findings are consistent with Gallagher and Segara (2005), in that no systematic under- or over-performance is found relative to the underlying benchmark, either for ETFs or mutual funds. This implies that long-term investors will be able reach this performance outcome.

Indeed, $TE_{2,i}$ and $TE_{3,i}$ are nearly identical, indicating that the potential bias in daily data which can be induced by serial correlation is not a concern in our sample. This is in line with Gallagher and Segara (2005). $TE_{2,i}$ ranges from 0.141 per cent to 1.205 per cent, indicating that the two ETFs display higher tracking errors compared to all open-ended funds except Fund 3. It is sufficient to say that these findings are at odds with those obtained using the absolute-return-based tracking measure, $TE_{2,i}$.

The performance of funds based on the single-index model shows that all funds except Fund 1 fail to generate significantly positive α at the five per cent level, thus corroborating the results obtained using the mean and median of the arithmetic-return differences. The systematic-risk measure β ranges from 0.390 to 0.987, and the restriction $\beta = 1$ is rejected across the board at the significance level of 1 per cent. The R^2 paints a similar story, ranging from 0.161 to 0.984. This indicates that some funds in the sample are not well-diversified, as they use sampling techniques rather than full replication to mimic their underlying benchmark. The $TE_{4,i}$ measure produces results consistent with $TE_{2,i}$.

The differences between the measures in ranking the funds in our sample (between $TE_{1,i}$ on the one hand and $TE_{2,i}$ and $TE_{4,i}$ on the other) highlight the merits of using several measures of the tracking error; this is noted in prior studies such as Strydom, Charteris, and McCullough (2015, pp. 129). These discrepancies are mainly driven by the salient features of financial data—the departure from normality and the fat tails of the returns distribution. Since the tracking-error measure, $TE_{1,i}$ is based on absolute deviations, rather than squared deviations, it is more robust to the presence of outliers. Taleb (2015, pp. 16-17) cogently argues for the use of MAD instead of the SD. He shows that the presence of even minute outliers causes MAD to be more efficient than SD.

Taken together, the performance of most funds in our sample is largely consistent with those reported in the literature. To put things in perspective, we compare our findings with those obtained in prior studies that use daily data from developed and emerging markets. Evidence from the Greek market reports smaller tracking errors compared to our findings. The absolute-return-based tracking-error measure, $TE_{1,i}$, ranges from 0.001 per cent to 0.049 per cent, and the arithmetic-return-based measure, $TE_{2,i}$, ranges from 0.445 per cent to 1.188 per cent (Rompotis, 2011). On the other hand, tracking errors in the Hong Kong stock market are substantially higher than the tracking errors that we calculate, as Chu (2011) shows that $TE_{1,i}$ ranges from 0.278 per cent to 2.173 per cent, and $TE_{2,i}$ ranges from 0.394 per cent to 3.523 per cent. Evidence that emerges for developed markets indicates that $TE_{1,i}$ for Australian ETFs ranges from 0.016 per cent to 0.703 per cent, and $TE_{2,i}$ ranges from 0.036 per cent and 0.925 per cent. For open-ended funds, $TE_{1,i}$ and $TE_{2,i}$ fall between 0.025 per cent and 0.096 per cent, and 0.111 and 0.499 per cent, respectively (Gallagher and Segara, 2005).

Table 2: Tracking errors for ETFs and open-ended mutual funds in the sample based on NAV

Fund	Absolute difference in returns				Arithmetic difference in returns				Single index model			
	Mean (TE1)	SD	Min	Max	Mean	Median	SD (TE2)	TE3	α	β	R^2	SER (TE4)
Panel A: Mutual funds												
Fund 1	0.243	0.229	0.000	2.429	0.021**	0.004	0.333	0.333	0.023***	0.906***	0.91	0.316
					(2.39)	(1.35)			(2.80)	(-12.71)		
Fund 2	0.177	0.182	0.000	1.863	0.006	-0.010	0.254	0.254	0.008	0.912***	0.95	0.234
					(0.86)	(0.71)			(1.31)	(-16.07)		
Fund 3	0.725	0.963	0.001	12.693	0.031	0.009	1.205	1.205	0.046*	0.390***	0.16	0.995
					(0.97)	(0.48)			(1.78)	(-26.20)		
Fund 4	0.242	0.252	0.000	3.699	-0.002	-0.003	0.350	0.349	-0.001	0.954***	0.90	0.346
					(-0.22)	(0.14)			(-0.10)	(-5.73)		
Fund 5	0.271	0.285	0.000	3.286	0.005	-0.012	0.393	0.393	0.008	0.886***	0.88	0.372
					(0.46)	(0.30)			(0.79)	(-13.14)		
Fund 6	0.038	0.136	0.000	2.401	-0.007*	-0.007***	0.141	0.141	-0.007*	0.987***	0.98	0.140
					(-1.89)	(13.20)			(-1.81)	(-4.11)		
Panel B: ETFs												
ETF1	0.206	0.374	0.000	5.351	0.001	-0.003	0.427	0.427	0.003	0.922***	0.86	0.418
					(0.08)	(1.07)			(0.27)	(-7.95)		
ETF2	0.250	0.401	0.000	4.844	0.003	-0.009	0.473	0.473	0.005	0.919***	0.83	0.464
					(0.27)	(0.59)			(0.44)	(-7.44)		

Notes: *t*-statistics and z-statistics in (). ***,**,* denote statistical significance at the 1%, 5% and 10% levels, respectively.

We also compare the estimation results of the single-index model with those reported by Wong and Shum (2010) who use daily data from 15 worldwide ETFs. They find that R^2 ranges from 0.653 for the QQQQ to 0.968 for IVV in the United States, and from 0.69 for the iShares Nikkei 225 to 0.992 for Nikko ETF 225. Chu (2011) reports a wider range for ETFs listed in Hong Kong, where R^2 ranged from as high as 0.956 to as low as 0.000; Rompotis (2011) finds that the R^2 for Greek ETFs' index and active mutual funds falls between 0.903 and 0.988, and the restriction $\beta = 1$ is rejected across the board. Overall, these results are in agreement with our findings.

Table 3: Test of equality of active returns and MAD estimates across ETFs and open-ended mutual funds based on NAV

Fund	ETF1				ETF2			
	Arithmetic		Absolute		Arithmetic		Absolute	
	Mean diff	Median diff	Mean diff	Median diff	Mean diff	Median diff	Mean diff	Median diff
Fund 1	0.020	0.008	0.037***	0.075***	0.017	0.013	-0.008	0.054***
	(1.40)	(1.08)	(3.24)	(11.34)	(1.15)	(0.97)	(-0.65)	(5.90)
Fund 2	0.005	-0.007	-0.028***	0.015***	0.002	-0.001	-0.073***	-0.007**
	(0.37)	(0.01)	(-2.59)	(3.25)	(0.17)	(0.05)	(-6.37)	(2.36)
Fund 3	0.030	0.012	0.012***	0.302***	0.027	0.018	0.474***	0.281***
	(0.89)	(0.21)	(19.27)	(26.58)	(0.81)	(0.13)	(17.44)	(22.79)
Fund 4	-0.003	0.001	0.001***	0.072***	-0.005	0.006	-0.008	0.051***
	(-0.21)	(0.13)	(3.11)	(11.70)	(-0.35)	(0.00)	(-0.68)	(6.14)
Fund 5	0.004	-0.008	0.065***	0.088***	0.001	-0.003	0.021	0.066***
	(0.25)	(0.29)	(5.34)	(13.69)	(0.09)	(0.32)	(1.60)	(8.25)
Fund 6	-0.008	-0.003	-0.168***	-0.101***	-0.010	0.002	-0.213***	-0.122***
	(-0.67)	(0.43)	(-16.17)	(34.17)	(-0.80)	(0.22)	(-19.28)	(36.70)

Notes: *t*-statistics and z-statistics in (). ***,**,* denote statistical significance at the 1%, 5% and 10% levels, respectively.

The results of the hypothesis testing for the performance of ETFs compared to open-ended funds are presented in Table 3. The arithmetic and absolute return differences of the two ETFs are compared to the six open-ended funds using the two sample tests, the *t*-tests and the Mann-Whitney test. A look at Table 3 reveals that the results based on the arithmetic mean of active returns (effectiveness measure) consistently show that there is not sufficient evidence to reject the null that active returns differ between ETFs and open-ended funds.

On the other hand, the results based on the absolute return differences are mixed. The two tests (t-test and Mann-Whitney test) arrive at conflicting conclusions. Absolute returns differences are positively skewed, which invalidates the *t*-test.[13] Therefore, we use the Mann-Whitney test to judge the performance of the ETFs compared to their open-ended rivals. The results show that ETF1 exhibits significantly smaller tracking errors than all open-ended funds, except Fund 6, while ETF2 significantly falls short from Fund 2 and Fund 6. These results indicate that ETFs predominantly produce significantly smaller tracking errors than most open-ended funds; this is in accord with the findings of Gallagher and Segara (2005) and Strydom, Charteris, and McCullough (2015). This conclusion is expected to hold if the market price of ETFs is kept in line with the its respective NAV. However, the market price can deviate from NAV, and the greater the departure and the longer it takes to be corrected by arbitragers via the creation–redemption mechanism, the more suspect are our results. Therefore, we calculate tracking-error measures and tests based on market price as a robustness check. The results are reported in Table 4 and Table 5.

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Table 4: Tracking errors for ETFs in the sample based on market price.

Fund	Absolute difference in returns				Arithmetic difference in returns				Single index model			
	Mean (TE1)	SD	Min	Max	Mean	Median	SD (TE2)	TE3	α	β	R^2	SER (TE4)
ETF1	0.690	0.831	0.002	11.962	0.003	-0.014	1.080	1.080	0.013	0.617***	0.325	0.993
					(0.12)	(0.26)			(0.51)	(26.59)		
ETF2	0.847	1.129	0.002	18.723	0.007	-0.067	1.411	1.411	0.028	0.235***	0.052	1.124
					(0.20)	(1.44)			(0.95)	(8.95)		

Notes: *t*-statistics and z-statistics in (). ***,**,* denote statistical significance at the 1%, 5% and 10% levels, respectively.

Comparing the results reported in Table 2 Panel B and Table 4, it can be clearly seen that all tracking-error measures are higher when calculated based on the market closing price instead of NAV. Moreover, all tracking-error measures are consistent in showing that ETFs exhibit larger tracking errors than their off-market counterparts (with only one exception, ETF1 versus Fund 3). Indeed, it is important to note that the mean and median of active returns remain statistically indistinguishable from zero, whereas the β and R^2 are found to be drastically smaller, due to the staleness of the market prices.

Table 5: Test of equality of active returns and MAD estimates across ETFs and open-ended mutual funds based on market price

Fund	ETF1				ETF2			
	Arithmetic		Absolute		Arithmetic		Absolute	
	Mean diff	Median diff	Mean diff	Median diff	Mean diff	Median diff	Mean diff	Median diff
Fund 1	0.017	0.018	-0.447***	-0.263***	0.013	0.071***	-0.604***	-0.351***
	(0.59)	(1.32)	-(19.90)	(21.73)	(0.35)	(3.31)	(-20.09)	(24.70)
Fund 2	0.002	0.004	-0.512***	-0.324***	-0.002	0.057***	-0.669***	-0.412***
	(0.08)	(0.77)	(-23.10)	(27.60)	-(0.03)	(3.07)	(-22.42)	(29.94)
Fund 3	0.027	0.023	0.035	-0.037	0.023	0.076*	-0.122***	-0.125***
	(0.65)	(0.58)	(1.05)	(0.81)	(0.49)	(1.73)	(-3.15)	(4.64)
Fund 4	-0.005	0.011	-0.448	-0.267***	-0.009	0.064**	-0.604	-0.355***
	(-0.18)	(0.42)	(-0.18)	(22.00)	(-0.25)	(2.55)	(-0.25)	(24.87)
Fund 5	0.001	0.002	-0.42***	-0.251***	-0.003	0.055***	-0.576***	-0.339***
	(0.05)	(0.51)	(-18.28)	(19.93)	(-0.06)	(2.58)	(-18.94)	(23.00)
Fund 6	-0.010	0.007	-0.652***	-0.439***	-0.014	0.060***	-0.809***	-0.527***
	(-0.36)	(0.56)	(-29.70)	(42.94)	(-0.39)	(2.80)	(-27.26)	(43.49)

Notes: *t*-statistics and z-statistics in (). ***,**,* denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5 shows that the results pertaining to the absolute returns differences reach the opposite conclusion to that reached in Table 3. I find that that ETFs produce significantly higher tracking errors than open-ended funds, with only one exception (ETF1 versus Fund 3 where no statistically significant difference is found), based on the Mann-Whitney test at the 1 per cent level. These findings indicate the presence of substantial pricing inefficiencies due to the ineffectiveness of the creation–redemption mechanism in keeping the market prices of ETFs in line with their fundamental value—that is, NAV.

Conclusion

This paper examined the relative performance of ETFs on the Saudi stock exchange compared to their off-market counterparts. The performance of these funds is gauged using four tracking-error measures. The tracking-error analysis for the ETFs is based on both the NAV and the closing secondary-market price to address the impact of the secondary-market liquidity on tracking errors.

The results reveal that tracking-error measures arrive at inconsistent conclusions. The reason is that the leptokurtic distribution of returns undermines the accuracy of the SD tracking-error measure. Based on the MAD tracking-error measure calculated using NAV, I find that ETFs predominantly display smaller tracking errors compared to open-ended mutual funds, and the difference is statistically significant at least at the five per cent level using the Mann-Whitney test.

However, when the tracking-error calculation is carried out using the market price of ETFs, the conclusion is altered. ETFs generate larger tracking errors across the board in comparison to open-ended mutual funds, and the difference is strongly significant at the one per cent level, with only one exception.

Overall, while the NAV-based tracking errors show that ETFs managers are successful in replicating their underlying benchmark, illiquidity has a large and detrimental effect on their secondary-market price-based tracking errors. These findings are consistent with the decline in the ETF industry in Saudi Arabia. Among the potential reasons for that decline is the absence of the main advantage that distinguishes these instruments from traditional open-ended mutual funds—tax efficiencies—in addition to the large and extended discrepancies between NAV and market prices. The latter arise due to the failure of APs to arbitrage away such discrepancies via the creation-redemption mechanism. The ability of APs to eliminate mispricing is also undermined by the prohibition of short selling that has recently been revoked in the Saudi market. An important finding to take from this is that caution must be exercised when analysing tracking errors for ETFs, particularly for those listed in emerging markets.

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Notes

1. Several research articles have investigated the differences between ETFs and open-ended mutual funds. These articles include Dellva (2001), Kostovetsky (2003), and Guedj and Huang (2009). These studies delineate and analyse management fees, transaction costs, and taxes incurred by the ETFs' investors compared to those who hold open-ended funds. The thrust of their findings is that the choice between the two investment vehicles is mainly based on the investors' liquidity needs, the amount invested, and the investment horizon. Agapova (2011) showed that ETFs and open-ended funds are not perfect substitutes that target different market niches. While there exists a substitution effect, ultimately based on the funds' returns and fees, there is also a clientele effect that mainly stems from tax efficiency and other qualitative factors, such as liquidity and trading flexibility.

2. Mussavian and Hirsch (2002) highlight the impact of regulations in some European countries on the tracking error. An example of such regulations is that some countries restrict the holding of any stock to a maximum of 10 per cent.

3. Sharifzadeh and Hojat (2012) measure the performance of ETFs and open-ended funds using the Sharpe ratio and risk-adjusted buy and hold total returns instead of the tracking error.

4. Elton et al. (2002) distinguish between the returns due to changes in the NAV of the ETF (SPDR) and the temporary departures of the ETF's price from its underlying NAV, which are inevitably eliminated via the creation–redemption mechanism. Further, they state that using the returns generated by changes in the NAV of the ETF enables the comparison between the performance of ETFs and other passive index funds that track the same underlying benchmark. While subsquent studies use NAV changes to calculate the returns on ETFs, Poterba and Shoven (2002) indicate nontrivial year-to-year differeces in tracking errors between returns calcualted on the basis of NAV and those obtained using the closing prices of the ETFs. Further, these studies use different metrics in the calculation of tracking errors. Elton et al. (2002), Poterba and Shoven (2002), and Gastineau (2004) use the differences between yearly returns on the fund and the underlying benchmark and average these difference over the sample period. Blitz, Huij, and Swinkels (2012) employ the

median 12-month returns differences, while Gallagher and Segara (2005), Shin and Soydemir (2010), and Chu (2011) utilise the average absolute value of returns differences, in addition to the volatility of the return differences.

5. See the annual reports issued by the Capital Market Authority (CMA)—the capital-market regulatory body in Saudi Arabia: Capital Market Authority (CMA) (2011, pp. 49); Capital Market Authority (CMA) (2012, pp. 45); and Capital Market Authority (CMA) (2016, pp. 68-69).

6. See Capital Market Authority (CMA) (2011, pp. 60-61) and Capital Market Authority (CMA) (2016, pp. 72).

7. Most funds in Saudi Arabia limit their dealing days to only two days in the week.

8. The selection of the present benchmark index for our analysis is motivated by several reasons: first, the index that I have chosen covers a comparable stock universe to the funds under investigation—the benchmark like the funds includes only Shariah complaint stocks and assigns higher weights to large capitalisation firms. Second, all the funds that I examine reinvest all dividend payouts, income from Murabaha accounts, and realised capital gains back into the fund which motivate the use of a total return index—not all the prospectus's benchmarks in Table 1 satisfy this requirement. Third, all ETFs in the Saudi market use tailor-made indices that are not publicly available. Fourth, it is not uncommon for managed funds to change their underling benchmark and Gastineau (2004, pp. 98) suggest that analyst will still use both the old and the new benchmark when they evaluate the performance of a fund that changed its benchmark. Fifth, (Elton et al., 2002) uses two benchmark indices (i.e. the S&P500 and the CRSP index) to judge the performance of the SPDR.

9. Narat and Peter (2013) distinguish between the temporary deviations of the ETF's price from its NAV, which are quickly corrected via the creation–redemption mechanism, and the deviations from the underlying benchmark which could accumulate over time and could significantly undermine the long-term performance of the ETF.

10. While several studies (for example Elton et al. (2002)) use average tracking error, which is simply obtained by averaging active returns, Roll (1992) posits that longer sample periods are required to obtain a statistically valid estimate of this metric, particularly in volatile markets. Therefore, practitioners as well as academics have become more focused on the volatility of active returns instead of the average.

11. Using the approximation suggested by Lo and MacKinlay (1988), Pope and Yadav (1994) show that, in the presence of negative autocorrelation in active returns, daily TE_2 is biased upward compared to its monthly counterpart. By the same token, positive autocorrelation in active returns will induce a downward bias.

12. Pope and Yadav (1994, pp. 32) suggest that this metric is flawed as long as the residuals from the regression in eq. (7) differ from active returns (that is, the differences between the return on the fund and its underlying benchmark).

13. Sheskin (2011, pp. 261) posits that 'some statisticians believe that if one or more of the assumptions of a parametric test … are saliently violated, the test results will be unreliable; because of this, under such conditions, it is more prudent to employ the analogous nonparametric test'.

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Overall and Regional Fan Preferences for ECHL Hockey

Rodney J. Paul, Syracuse University

Abstract

An attendance model for the ECHL was specified using Ordinary Least Squares regression. Fans of the ECHL were shown to respond positively to teams that tend to both win and fight. Other factors shown to significantly impact attendance were weekend games, weather factors, promotions such as special jerseys, and city demographics. When comparing teams in the south to teams outside the south in this minor league, fans of southern teams were shown to be more responsive to fighting, while fans in the non-south were more responsive to winning.

Introduction

The ECHL is the AA-level of minor league hockey serving as part of the farm system for NHL teams. Each ECHL team is affiliated with an NHL team. NHL teams provide part of the roster of the ECHL teams as they play during the season. ECHL players are routinely moved up and down to the AAA-level of hockey development, the American Hockey League, and many players have progressed from the ECHL to become regular NHL players.

In 2015-16 the structure of minor league hockey changed when the American Hockey League started the Pacific Division, moving minor league affiliates closer to their NHL parent cities and teams. In the process, some former ECHL cities became AHL cities and the ECHL looked to find different cities to cover their affiliations and round out their league. Part of this was achieved by the absorbing of former Central Hockey League (CHL) teams into the ECHL and the rest was achieved through new cities becoming part of the league. After this minor league transformation, the Western U.S. representation of the ECHL was considerably lessened and the league attracted more teams in the U.S. Southeast.

This research studies the 2016-17 ECHL season and models attendance based upon a variety of factors including team performance, game timing, and promotions. Beyond previous studies of the ECHL and other minor leagues, this study adds game day weather and detailed promotional categories as explanatory variables. The main goal of the research is to determine the role that both winning and fighting plays in attracting fans to the league, in addition to identifying other key factors that are successful in boosting attendance.

Beyond the overall regression results and their implications, the sample is then split into teams based in the U.S. South compared to the rest of the league (non-South). The rationale behind this split is to determine if fans in the American South, thought of as a non-traditional hockey audience, is more attracted to the violent and physical nature of the sport, proxied by on-ice fights during the game, compared to team success. An examination of these differences could help evaluate changes in the game would could alter the frequency of fighting and better understand the underlying preferences different types of fans may desire from hockey as a form of in-person entertainment.

The paper is structured as follows. Part II serves as a literature on economic research on hockey attendance and related fan activity. Part III presents the regression model and its results for the league overall and for the grouping of teams in the South vs. teams in the non-South. Part IV discusses the findings and concludes the paper.

Literature Review

Fighting has played a major role in economic studies of hockey attendance at both the major and minor league levels. The role of fighting in the NHL has been studied by Jones (1984), Jones, et al. (1993), Jones, et al. (1996) and Paul (2003). In each of these studies, a positive and significant effect on attendance was seen with an increase in fighting by the team in both Canadian and American cities.

In the minor leagues of North America, fighting has been found to increase attendance in both the American Hockey League (Paul, et al., 2013) and in the ECHL (Paul, et al., 2015). At both the AAA-level (AHL) and AA-level (ECHL) fighting had a positive and statistically significant effect on attendance. Other factors that were found to influence attendance in these studies of minor league hockey were weekends, city demographic effects, and various promotions.

Although fighting is not permitted in the DEL league in Germany, evidence was found that penalty minutes increased attendance in this league (Coates, et al., 2012). However, penalty minutes, as a proxy for physical and violent play, was not found to significantly impact attendance in the SM-Liiga in Finland (Coates, et al., 2012). Fighting was not shown to have an impact on attendance in junior hockey in the Quebec Major Junior Hockey League (Paul and Weinbach, 2011).

The link between fighting and winning hockey games has also been investigated by researchers. Leard and Doyle (2011) studied winners and losers of hockey fights in the NHL and did not find a statistically significant relationship between winning fights and overall team success. Coates, et al. (2012) found a negative relationship between fighting and team success in the NHL.

Other research on hockey attendance and overall fan interest has been performed through surveys. Zhang, et. al (1996) found that hockey knowledge was important in forecasting game attendance and ticket purchases for International Hockey League games. Zhang, et al (2001) also found that health-promoting, achievement seeking, and stress & entertainment factors should be part of the marketing strategies of minor league teams. In a survey of fans of the Southern Professional Hockey League (SPHL), violence was found to be important in explaining why fans attended games, although results differed by both gender and the level of ticket purchase (Damon, et. al, 2009).

Minor league hockey attendance has also been researched by Rascher, et al. (2009) and Hong (2009). Rascher, et al. (2009) studied the impact of the NHL lockout in 2004-05 and found increased attendance for minor league hockey while the NHL was not in play. In a study of marketing of minor league hockey games, it was discovered that teams with success at the gate had winning teams, star players, good fan relations, affordable prices, and substantial community involvement (Hong, 2009).

Attendance Model and Results

The goal of this research is to model attendance for the ECHL using data from the 2016-17 season. This research not only updates previous findings on the ECHL from five years prior (Paul, et al., 2015), but adds additional factors to the research which may impact attendance such as weather conditions and investigates teams in the South versus those in the non-South that participate in the ECHL.

The dependent variable in the regression model is game-by-game team attendance for the ECHL for the 2016-17 season. The data on attendance was gathered from the box scores of ECHL games on www.ECHL.com. The results are shown in levels, although a log specification was also tried without much change in overall results.

The independent variables are arranged by category. Dummy variables for the day of the week are the first category of independent variables, with Wednesday used as the reference category. Weekend days are expected to be more popular than weekdays due to the opportunity cost of fans' time. The second category is monthly dummies, with January as the reference category. Higher attendance is expected greater as the year progresses and the hunt for the playoffs intensifies.

The third category of independent variables are related to team performance. These variables consist of the points per game earned in the season heading into the current game and the number of fights per game heading into the current game. The ECHL uses a points-based system to determine the standings, like other hockey leagues, with two points earned for a win, one point earned for an overtime or shootout loss, and zero points earned for a regulation loss. If fans of the ECHL prefer to see more successful team play, we would expect this variable to have a positive and significant coefficient. Fighting is a unique attribute to hockey as a team sport and, as mentioned in the literature review, has been shown to play a significant role in determination of attendance in hockey leagues. If fans enjoy fighting, it is anticipated that this variable will have a positive and significant effect on attendance.

Weather-related variables are included in the regression model to account for conditions which may impact the decision of fans to attend games. Although ECHL games are played indoors, weather factors could discourage travel and heavily influence day of game sales. The weather-related variables included in the model are temperature, humidity, barometric pressure, and the amount of precipitation (in inches) on the day of the game. This information was gathered from www. weatherunderground.com.

To account for differences across cities, a variety of demographic data is included in the regression model. Population and Population^2 is included to account for differences in city sizes. Presumably, larger metro areas would have more potential hockey fans to attract and, therefore, would likely lead to higher attendance figures. It is possible, however, that bigger cities may have many more entertainment options and lower-level minor league hockey may not be much of a draw in these cities. To account for differences in income across cities, the per-capita income of each city and its square are included in the regression model. These variables will help to identify if ECHL hockey is a normal or inferior good and if there tends to be an optimal level of income where ECHL games are popular forms of entertainment within a city.

Other demographic variables included in the regression model attempt to identify some key attributes of hockey fans. Many hockey fans are assumed to be male and predominantly white, so the percentage of the population that is male and the percentage of the population that is a minority are included in the model. In addition, the percentage of the population that is married and the average age of the population are included to determine if marital status or age plays any role in the popularity of ECHL hockey in a city. All this information on city demographics was obtained from www.city-data.com.

Promotional activities involved on game day were gathered from the individual team websites of the ECHL and included in the regression model as a series of dummy variables. These promotions were grouped, as close as possible, into

different categories that appeared to be common across teams. Promotional categories consisted of home opener, theme nights, charity nights, special jerseys, skate with the team, teddy bear toss, discounted tickets, giveaway items, group nights, autograph nights, dogs to the rink, party nights, discounted or free food, discounted or free drink (alcohol), and indoor fireworks. If these promotions attracted more fans to ECHL games, they should have a positive and significant result.

The last category of independent variables included in the model are road dummy variables. Different teams, based upon history, geographic considerations, or team success may have an impact when they are the road team. If any team attracts a higher following on the road than others in the ECHL, the dummy variable for this team will be statistically significant.

The following table shows the summary statistics for the key non-binary variables in the regression model of ECHL attendance. The table shows the variable name, mean, median, and standard deviation.

Table 1: Summary Statistics: ECHL 2016-17

Variable	***Mean***	***Median***	***Standard Deviation***
Attendance	4,251.84	4061.5	1,852.58
Population	210,139.70	130,113	191,963.30
Per Capita Income	28,466.44	27,069.00	7,771.24
Male %	49.08	49.10	1.26
Age	35.95	34.70	6.43
Minority %	34.29	35.90	14.63
Married %	42.73	41.70	9.68
Temperature	43.91	44.00	16.56
Humidity	66.02	67.00	15.22
Barometric Pressure	29.98	30.09	1.69
Wind Speed	8.07	8.00	4.21
Precipitation (in)	0.06	0.00	0.21
Fights Per Game	0.64	0.59	0.28

The following table shows the frequency of the use of the different types of promotions during the 2016-17 ECHL Season.

Table 2: Frequency of Promotions: ECHL 2016-17

Promotion	***Frequency***
Theme Night	367
Charity Night	51
Special Jersey	87
Skate with Team	51
Teddy Bear Toss	20
Discounted Ticket	67
Giveaway Item	161
Group Night	12
Autograph Night	29
Dogs to the Rink	10
Party Night	8
Discounted Food	33
Discounted Drink (Alcohol)	60
Indoor Fireworks	6

The following table presents the regression model results. Due to heteroskedasticity and autocorrelation being present in the initial regression run, the results are shown using HAC standard errors and covariances using the Newey-West method for correction. The coefficient, standard error, t-statistic, and probability value for each independent variable are shown.

Table 3: Regression Model Results for ECHL Attendance: 2016-17 - Dependent Variable: Per-Game Attendance

Variable	***Coefficient (t-stat)***	***Variable***	***Coefficient (t-stat)***
C	20745.73*** (5.78)	MALE	-353.43*** (-5.64)
SUN	712.02***	AGE	71.05***

	(3.87)		(2.94)
MON	788.11*	MINORITY	18.45**
	(1.89)		(2.17)
TUE	205.97	MARRIED	-28.76***
	(0.81)		(-2.41)
THU	141.76	HOMEOPEN	1459.28***
	(0.67)		(3.59)
FRI	1152.12***	THEME	8.09
	(6.96)		(0.07)
SAT	1768.88***	CHARITY	149.55
	(10.51)		(0.65)
OCT	-1203.52***	SPJERSEY	383.25***
	(-4.94)		(2.51)
NOV	-493.47***	SKATE	-270.73
	(-2.53)		(-1.28)
DEC	-208.98	TEDDY	34.88
	(-1.21)		(0.12)
FEB	-6.33	DISTIX	11.40
	(-0.03)		(0.06)
MAR	156.51	GIVEAWAY	-61.46
	(0.78)		(-0.42)
APR	620.16***	GROUP	365.71
	(2.52)		(0.80)
PPG	1053.21***	AUTO	-284.40
	(3.36)		(-1.42)
FPG	1532.34***	DOGS	-13.56
	(5.59)		(-0.04)
TEMP	7.53**	PARTY	-774.42
	(1.94)		(-1.25)
HUM	-1.55	FOOD	1349.15***
	(-0.40)		(4.68)
PRES	-77.28***	DRINK	-1248.54***
	(-4.10)		(-4.59)
WIND	-5.93	FIREWORKS	545.57
	(-0.45)		(1.06)
PRECIP	-93.15	Visiting Team Dummies	Included
	(-0.41)		
POP	0.01***		
	(6.45)		
POP^2	-1.54e-08***		
	(-7.18)		
PERCAPINC	-0.18***	R-squared	0.5451
	(-3.86)		
PERCAPINC^2	3.85e-06***	Adjusted R-squared	0.5109
	(3.56)		

* Significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level

In terms of the days of the week, Saturday and Friday were found to be the most popular days for ECHL games. Compared to the omitted daily category of Wednesday, Fridays increased attendance by over 1150 fans, while Saturday increased attendance by nearly 1770 fans (both statistically significant at the 5% level). Sunday, and surprisingly Monday, were also found to have positive and statistically significant effects on attendance, each increasing fans by over 700 compared to Wednesday, which was the lowest attended day of the week for ECHL games.

Beyond opening day, which contributed nearly 1500 more fans and was found to be statistically significant at the 1% level, early season attendance for the ECHL was considerably lower than the reference month of January. October and November each had negative and statistically significant impacts on attendance in the regression model. The end of the season playoff push was found to increase attendance for ECHL games as the April dummy variable was found to have a positive and significant effect on attendance at the 5% level.

In relation to on-ice performance variables, ECHL fans showed a considerable affinity for good and tough play. Both winning, proxied by the points-per-game average entering the game, and fighting (fights-per-game average) were shown to have positive and significant effects on attendance at the 1% level of significance. Scaling these variables to reasonable variables, a 0.1 increase in points per game was shown to add more than 100 fans in attendance, while a 0.1 increase in fights

per game added about 150 fans. Successful teams on the ice and teams who have players that ware willing to drop the gloves were both shown to positively drive attendance figures.

Although ECHL games are played indoors, outside game day weather conditions in the city significantly influenced attendance for hockey games. Temperature was shown to have a positive effect on attendance as more fans attended games on warm (or in the case of winter, less-cold) days. Humidity and wind gust speed were shown to have negative coefficients, but were not statistically significant. Barometric pressure, on the other hand, was shown to have a negative and significant effect on attendance. On high pressure days, people are generally less active as the pressure in the air makes effort more exerting. In a league where walk up sales are common and many full and partial season ticket packages offer the possibility to choose games or swap game tickets for another night, it appears the impact of high pressure reduces attendance at ECHL games.

In terms of city demographics, population was shown to have a non-linear impact on attendance. Population itself was shown to have a positive effect, but population squared was shown to have a negative impact on attendance (both significant at the 1% level). Therefore, bigger cities generally have higher attendance figures, except in the case of very large cities, where other entertainment options for sport and otherwise are likely to be close substitutes and AA-level hockey may not be as popular a choice for fans.

Per capita income in the city was also shown to have a non-linear effect on attendance, with per capita income having a negative effect and per capita income squared having a negative effect. ECHL appears, within the normal range of most city incomes in the sample, to be an inferior good, but attendance was also shown to increase in the wealthier cities. Without income distribution data, it is tough to decipher, but it is possible the lower cost of ECHL tickets in the highest income areas in the sample may be providing entertainment options to a portion of the population who is not as wealthy as the average in that city.

Both the percentage male and percentage married were shown to negatively influence attendance. These may be somewhat surprising, but could signify other entertainment options (concerts, other sports, restaurants, bars, etc.) when citizens tend to be non-married males over ECHL hockey. Age and minority percentage were both shown to have positive effects as ECHL fans look to be a bit older on the age scale and a higher percentage of minority residents (typically not thought of as a prime hockey demographic) does not seem to hinder attendance in those areas.

The only promotions that were found to have a positive and statistically significant impact on attendance were the home opener, games featuring special jerseys, and games involving free or reduced-priced food items at the game. Home openers attracted about 1,459 additional fans, on the average, for ECHL teams. Special Jersey games increased attendance by about 383, while games involving free or reduced-priced foods increased the number of fans by 1,349 fans. The only promotion that was found to have a negative and statistically significant effect on attendance was reduced-price drink (alcohol), where it reduced fans by over 1,200 fans. This result is surprising, but could represent that some fans stay away when low-priced alcohol is available at the arena due to possible negative externalities.

In terms of breaking the sample into teams in the U.S. South compared to the rest of the sample revealed some informative results. Most of the results remained the same when the sample was split. The key focus of each subsample is the impact of winning vs. fighting as to what tends to matter more in which areas of the country. The results showing the coefficients, standard errors, t-stats, and p-values for the points per game (team success) and fights per game variables in each subset are shown in the table below.

Table 4: Comparison of Impact of Winning and Fighting on Teams in South and Non-South

Variable	***Coefficient***	***Standard Error***	***t-statistic***	***p-value***
		South		
PPG	-350.48	304.96	-1.15	0.25
FPG	903.65	507.22	1.78	0.07
		Non-South		
PPG	1074.14	511.95	2.10	0.04
FPG	114.41	281.79	0.41	0.68

As can be seen in the table, there are considerable differences as it relates to team performance and attendance for the Southern teams in the ECHL vs. the rest of the league. In the south, fighting has a big impact on attendance and is statistically significant, while winning (PPG) does not have a statistically significant effect. In the Non-South for the ECHL, however, it is the exact opposite. Team success as measured by points per game (winning) has a big positive and significant effect on attendance, while fights per game, although still positive, does not have a statistically significant effect. It appears that fans of the teams in the South in the ECHL care more about seeing fights as part of the hockey game than overall team success, while in the more traditional hockey markets (Non-South), team success is a much more important driver of attendance than fighting.

Conclusions

An attendance model for ECHL hockey for the 2016-17 season was specified and run to test for significant determinants of fan demand for the league and sport. Many results followed closely to that of other leagues and other sports. Weekend days were much more popular with fans than weekdays and attendance was poor early in the season (other than opening night) and better later in the season as the playoffs approached. Team performance was important for ECHL attendance as both points-per-game (measure of winning) and fights-per-game were found to have positive and significant effects on attendance.

Despite being played indoors; weather-related variables did have an impact on ticket sales. Temperature was found to have a positive and significant effect, while barometric pressure was shown to have a negative and significant effect on attendance. The impact of weather, as it relates to attending a game, is likely stronger in leagues such as this, where many sales occur on the day of the game.

Demographic variables illustrated the best locations for ECHL hockey in terms of attendance. Population and population squared were both found to have a positive and significant effect on attendance, as this league attracted more fans in (relatively) bigger metro areas. Per capita income was found to have a non-linear effect on attendance as it showed a negative influence with the level of per capita income (suggesting ECHL as an inferior good to an extent) coupled with a positive effect of per capita income squared which implies that teams were also successful in the highest per capita income cities as well (this may not necessarily mean the wealthiest people were ECHL fans, but could also imply that it provided an inexpensive option for sports entertainment for those not as wealthy residents within these cities).

Although hockey is commonly thought of as a sport with fans being primarily male and white in origin, the regression results showed that higher female and minority populations did not hurt attendance, but seemed to help increase attendance. The average age within a city had a positive and significant effect on ECHL attendance and a higher percentage of single (non-married) population also had a positive and significant effect.

In terms of game promotions, only three categories showed statistically significant returns, two positive and one negative. Games involving special jerseys and games with free or discounted food showed large boosts to attendance on those days. Perhaps somewhat surprisingly, discounted drink (alcohol) had a negative and significant effect on attendance. This suggests some fans may stay away on these nights, as cheap alcohol can induce negative externalities in terms of enjoyment of a game.

With the ECHL moving away from Western U.S. cities due to the AHL moving the NHL's top farm teams closer to their parent squads, the ECHL has staked more of a claim in the Southeastern U.S. This allowed for a comparison between teams in the South and those in the rest of country as it relates to the importance of different aspects of team performance. Southern U.S. cities are typically thought of as "non-traditional" markets for hockey and could depend upon the physical nature of the game, particularly fighting, to spur attendance. The results from the ECHL confirm this hypothesis as fans of the teams in the South were much more responsive in buying tickets to teams that fought more often and team success was not found to be statistically significant. In the other cities in the ECHL, however, team success was found to have a positive and significant effect on attendance, but fighting (although having a positive coefficient) was not found to be statistically significant.

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The Effects of Foreign Direct Investments and Foreign Aids on Energy Needs

M.Emre Görgülü, Afyon Kocatepe University, Turkey

Abstract

The increased international financial movements as a result of globalization, brings forth many necessities. One of those needs is the need for efficient energy usage. Long-term international capital movements have created an increase in demand for efficient energy usage. However the real question is, do the foreign capital receiving countries have the power to translate this international capital inflow into a boost in economic performance through increased energy usage? In this direction, this study aims to empirically reveal the true nature of the relationship between long-term foreign capital - in the forms of foreign direct investments and foreign aid - and the energy needs in the long road of economic development. On one hand, as the energy need could be expressed as a function of foreign direct investments and foreign aids, as well as economic growth, the economic growth could be foreign direct investment and foreign aid dependent on the other. Therefore, it is needed to investigate the abovementioned relationship. The study is conducted for countries with different levels of development. The results confirm that either or both forms of long-term international capital movements plays an important role in determining countries' energy needs with respect to economic growth given that they would have necessary levels of absorptive capacities.

Introduction

The era of globalization have increased international financial movements and those movements have served the purpose of augmenting the globalization at the same time (Gorgulu, 2015a). Whatever the direction of this relationship is, as a result international financial movements have increased and it created many new necessities for countries. One of those needs is the need for energy. International capital movements, either in the form of Foreign Direct Investments (FDI) or foreign aids, have created an increase in demand for efficient energy usage. However the real question is does this increase in energy demand induce an augmented economic growth? In other words, do the foreign capital receiving countries have the power to translate this international capital inflow into a boost in economic performance through increased energy usage?

Therefore, specifying the relationship between country specific energy needs of countries from different levels of development and FDIs along with foreign aids gains importance and forms the main rationale for this study. Studying countries from various levels of development groups allows us to observe the varied effects of FDIs and foreign aids on countries with different development structures. With this aim, the energy need could empirically be expressed as a function of FDIs and foreign aids. Also, the energy need or consumption can be an indicator for the economic development. By this way, it is aimed to reveal the role played by FDIs and foreign aids in determining countries' energy needs and thus their development.

Moreover, to the best of my knowledge there are no studies concerning FDIs' and foreign aids' effects on development through an energy consumption perspective at the same time. Also, using an absorptive capacity measure which was previously introduced by Gorgulu (2015b), would allow this study to investigate the subject matter in a more detailed way, thus allowing it to contribute the existing literature. Additionally, the study aims to enable the policy makers to have a better view on maximizing their utility on international capital movements in the forms of FDIs and foreign aids from the energy perspective.

The structure of the study is constructed by putting forward the theoretical framework in which one can find theoretical fundamental information about the FDIs and foreign aids along with absorptive capacities in the next section. Also the literature dealing with FDIs and foreign aids and their effect on development mostly through infrastructural perspectives are handled in the same section. In the following section, the analysis to serve finding the role of FDIs and foreign aids on energy consumption is presented. Finally, the results of the analysis are evaluated and policy implications on the regarding matter are dealt with in the conclusion part.

The Theoretical Framework

Theoretically, foreign capital flows consists of three basic elements: Portfolio investments, FDIs and foreign aid. Portfolio investments and FDIs are private international capital flows and they differ mainly on control power. As FDIs generate control power - according to IMF (1993, pp. 86), above 10% of shares or voting power enables control power - over an investment in a foreign country, portfolio investments does not offer such power. And that is the major difference between the two. While

FDIs could be made in different ways from Greenfield investments to Brownfield investments and mergers and acquisitions, portfolio investments mainly cover the investments made on stock markets. In that way, FDIs are considered as a long-term investment whereas portfolio investments regarded as short-term ones. Foreign aids on the other hand are primarily financial flows - in the form of grants or subsidized loans – or technical support programs and transfer of resources, mainly undertaken by governments or international agencies in which government resources are pooled together and channeled to countries in need in forms of many different projects. Plus most of the foreign aids are in the forms of Official Development Assistance (ODA) and Official Assistance (OA) with the only difference among them being the 25% grant element which the former of the two meets this requirement, whereas the latter does not (OECD, 2010, pp. 271-276). Also foreign aids are formed in a way that they yield results more in long-term. Those long-term capital flows either in the form of FDIs or foreign aids are more prone to country specific effects in one way or another, than those in short-term. Therefore, portfolio investments are left unattended for the purposes of this study.

The absorptive capacity framework first was put forward as an ability to absorb know-how for businesses through which usage of new technologies are spread (Cohen and Levinthal, 1989; Cohen and Levinthal, 1990). In time, absorptive capacities have evolved from a business perspective to a more general equilibrium focused one and reached to a concept measuring the ability of the countries to internalize and utilize international capital flows. As this ability increases countries would be much more able to translate international capital flows into their economic development figures (Alfaro, Chanda, Kalemli-Ozcan, and Sayek, 2004; Alfaro, Chanda, Kalemli-Ozcan, and Sayek, 2006; Gorgulu and Akcay, 2015). In the literature, the absorptive capacities are measured in several ways from financial development to the development of human capital and to the technology gap existent in the host country (e.g., Blomstrom, Lipsey and Zejan, 1994; Li and Lui, 2005; Borensztein, De Gregorio and Lee, 1998; Durham, 2004; Hermes and Lensink, 2003; Krogstrup and Matar, 2005; Globerman and Shapiro, 2004; Busse and Groizard, 2008).

Even though there is a vast literature on FDIs, on foreign aids or on their separate effects on economic development, the literature dealing with both FDIs' and foreign aids' effects on economic development through an energy consumption perspective at the same time, is very limited. However, there are some remarkable studies regarding the infrastructural development effects of FDIs and foreign aids. Among those, Dastidar (2013) studies the role of foreign aids and many other factors on FDI inflows and puts forward that foreign aids once channeled to infrastructural development may augment FDI inflows to that country. Moreover, Amusa, Monkam and Viegi (2016) investigated the effects of foreign aids on infrastructural development on Sub-Saharan Africa and concluded that foreign aids directed particularly to energy infrastructure would have increasing effects of FDI inflows. Additionally, Selaya and Sunesen (2012) have found that once the foreign aid is channeled to government infrastructure and to human capital it can create FDI increasing effects. In short, the same result that once foreign aids is channeled to infrastructural development projects is confirmed by many other researchers (i.e. Kapfer, Nielsen and Nielson, 2007) as well. On the other hand, Yousaf, Khan, Erum and Rasul (2016) asserted that foreign capital in the form of foreign aids can lead to environmental degradation in Pakistan. As observable from the literature the lack of studies dealing with FDIs' and foreign aids' effects on development at the same time, enables this study to inventively identify the roles of FDIs and foreign aids on countries energy needs thus on their development.

The Analysis

As its methodology this study uses multiple OLS regressions in a general equilibrium model. This way, having multiple models and imposing certain independent variables - namely the absorptive capacity variable - in one model and omitting in the other makes us enable to comment about the effect of that specific variable. The sample of this study consists of country groups from different levels of development. In forming the sample of this study, level of income is used as a proxy for level of development and the World Bank classification is used (the World Bank, 2018a). Accordingly, the analysis is applied to low-income, lower-middle-income, upper-middle-income and high-income country groups for the period of 1997-2014 due to data limitations. Also, having country groups from diversified levels of development allows us to observe different effects of FDIs and foreign aids on energy needs of those countries with different development structures. With this aim, the energy need could empirically be expressed as a function of FDIs and foreign aids. Also, the energy need or consumption can be a proxy for the economic development. In the model, the energy needs of countries in the form of energy consumption per capita would be a proxy for the economic development and thus becomes the dependent variable. FDI inflows per capita, foreign aid inflows per capita and previous year's energy consumption per capita take their place in the model as independent variables. The imposed absorptive capacity variable on every alternative model – namely Model 2 - for each country group is also another independent variable. Using per capita terms is to reflect the standard of living measure in each country group.

As mentioned above, this study uses two simple empirical regression models and the OLS regression analyses are performed separately for each country group using the specified Model 1 and Model 2 below. Accordingly Model 1 and Model 2 are as follows:

$$EC_{it} - EC_{it-1} = \alpha + \theta(EC_{it-1}) + \beta(FDI_{it}) + \Omega(FA_{it}) + \varepsilon_i \quad \text{(Model 1)}$$

$$EC_{it} - EC_{it-1} = \alpha + \theta(EC_{it-1}) + \beta(FDI_{it}) + \Omega(FA_{it}) + \delta(AC_{it}) + \varepsilon_i \quad \text{(Model 2)}$$

In Model 1, $EC_{it} - EC_{it-1}$ is specified as the dependent variable, where EC_{it} is the value of per capita energy consumption and is calculated through the weighted average of the sum of electric power consumption per capita and oil equivalent energy use per capita (The World Bank, 2018b). Per capita energy consumption differences between consecutive years shows the growth in energy need from year to year. As for independent variables; while EC_{it-1} shows the per capita energy consumption of the previous year - calculated as explained above - and takes its place in the model as a generic value (The World Bank, 2018b), FDI_{it} is the annual per capita FDI inflows (The World Bank, 2018b), and FA_{it} is the foreign aid per capita received by host country groups and is calculated by the sum of ODA per capita and OA per capita. In addition to Model 1, Model 2 introduces the AC_{it} independent variable to the model that represents the absorptive capacities of the host countries which is obtained by a series of calculations explained below (Gorgulu, 2015b; The World Bank, 2018b). All variables except the AC_{it} variable in Model 2 are in current USD terms in order to capture the effects of inflation indirectly.

In this study, the absorptive capacities of the host countries are calculated by an alternative method introduced by Gorgulu (2015b). According to this method; first the weighted average of gross capital formation relative to GDP, domestic credit to private sector relative to GDP and government expenditure on education relative to GDP (The World Bank, 2018b) has been calculated for each country group. The first two components of this measure reflect the financial development aspect of the absorptive capacities whereas the last component reflects the human capital perspective of absorptive capacities. The technology gap measure (The World Bank, 2018b) has been obtained for each country group as a ratio of difference of GDP per capita between US and the host countries, relative to host country GDP per capita (Li and Lui, 2005) Then the technology gap measure is negatively multiplied - as the technology gap would negatively affect the growth of host countries - with one minus the previously obtained weighted average, in order to assure that a high average would diminish the technology gap's negative effects on growth. Theoretically with a perfect score of the weighted average -average of 1, it is even possible to offset the technology gap's negative effects on growth - since the gap value would be multiplied by 0 in this case. Thus, as the absorptive capacity value gets closer to 0 from the negative space, host countries perform better because they would become more able to eliminate the effects of the technology gap. Moreover, an absorptive capacity value greater than 0 would imply the economy is roughly performing better than that of US. At least the county has no technology gap, but instead would have a technology surplus in this case. By doing so, technology gap, human capital development and financial development aspects of absorptive capacity concept are all captured in the analyses. That way, the method aims to nullify the negative effects of technology gap through absorptive capacities and as the value gets higher absorptive capacity level of the host countries gets better (Gorgulu, 2015b, pp. 9).

The results of the analyses for each model are summarized in Table-1 and Table-2 below respectively. As last year's energy consumption per capita is a generic value, it does not rank among the summary of the results tables.

Table 1: Summary of the Results-Model 1

Country Groups	FDI		Foreign Aid	
	Coef.	Significance*	Coef.	Significance*
H-I	0.301431	√	49.31037	X
U-M-I	1.645056	√	12.72914	√
L-M-I	0.029217	√	0.384991	X
L-I	0.003861	X	-0.030575	√

*Significance only at the 5% level

Table 2*:* Summary of the Results-Model 2

Country Groups	FDI		Foreign Aid		Absorptive Capacity	
	Coef.	Significance*	Coef.	Significance*	Coef.	Significance*
H-I	0.344486	√	30.65709	X	1592.186	√
U-M-I	1.726588	√	12.86148	√	3.962456	√
L-M-I	-0.519535	√	0.775877	X	2.056972	√
L-I	-0.591559	√	-0.486797	√	0.114024	√

*Significance only at the 5% level

Furthermore, to prove that the energy needs can be used as an indicator of economic growth the following simple model - in which Y_{it} is the GDP per capita - is used and simple OLS regression has been conducted for each country groups.

$$Y_{it} - Y_{it-1} = \alpha + \theta(Y_{it-1}) + \beta(EC_{it}) + \varepsilon_i \qquad \text{(Model 3)}$$

According to the results of the analyses; on Model 3 it is shown for each country group that in fact energy consumption can be used as an indicator for economic growth under ceteris paribus assumption. For all country groups the energy consumption positively affects the absolute growth in GDP per capita.

Also the results for Model 1 and Model 2 show that; for the 1997-2014 period, all models are statistically significant. Additionally, in Model 1 the effects of FDIs turned out to be significant except only those are in low-income countries. The effects of FDIs are at the highest level for upper-middle-income countries. Also, as foreign aid flows move opposite direction to the level of development of countries, higher-income countries have no significant effect from those flows in both models. Moreover, it is evident that foreign aids have negative effects on low-income countries, have no significant effect on lower-middle-income group and have positive effects on upper-middle-income countries.

For Model 2, the results reveal that the effects of FDIs vary depending on absorptive capacities at diverse levels in subject countries. Generally, with all country groups having significant absorptive capacities ranking directly proportional to their income and development level – for low-income countries being the lowest and for high-income countries being the highest - high-income and upper-middle-income economies have higher absorptive capacities above a certain threshold have better FDI contributions to development, whereas lower-middle-income and low-income countries fail to seize development augmenting effects of FDIs as they lack such absorptive capacities. In fact, in both low-income and lower-middle-income countries FDIs have adverse effects on development - it is worse for low-income countries than the lower-middle-income group - due to lack of necessary levels of absorptive capacities. It is clear to see that as the level of absorptive capacities increase in country groups their FDI performances gets better from negative to positive effects. Also, the effects of FDIs on energy needs and development are higher in upper-middle-income countries than they are on high-income group. This shows us that after some threshold of development, FDIs start to lose their momentum and given that most of the upper-middle-income countries being developing economies, it can be said that they work more efficiently on those countries.

As for foreign aids, it is observed from the analyses that, once absorptive capacities are in play, for low-income countries they have negative effects and for lower-middle-income group it has no significant effect. Also, aid flows could be beneficial for upper-middle-income countries for their development but for high-income countries as most of them being donors instead of hosts; foreign aids have no significant effect on energy needs therefore on development.

One another aspect to note about the role of absorptive capacities is that, through the transformation from Model 1 to Model 2, it is observed that in Model 2, FDI and Foreign Aid variables have gained more significance and on overall it yielded better and more meaningful results.

Conclusion

The results confirm that either or both forms of long-term international capital movements plays an important role in determining countries' energy needs with respect to economic growth given that they would have necessary levels of absorptive capacities. As the absorptive capacity of the FDI and foreign aid hosting countries increases, the effects of FDIs and foreign aids would be more beneficial due to increasing industrialization observed through augmented energy needs. In other words, as energy consumption on these countries increases due to FDI and foreign aid inflows, it is possible to say that host countries can develop more, given that they have necessary levels of absorptive capacities.

With the findings of its analyses of a 17 year span, this study enables the policy makers to equip with a more informed decision set when it comes down to making a decision about FDI and foreign aid inflows. That is, having more inflows of the two given a sufficient level of absorptive capacity can benefit the country, but with the lack of necessary absorptive capacities having international capital inflows in the forms of FDIs and foreign aids would be pointless or even harmful under some circumstances. Therefore, the first thing the policy makers should consider is to find ways to enhance their countries' absorptive capacities if they seek to reap more benefits out of FDIs and foreign aids. These improvements can range from improving institutional quality but not limited to easing business environment or to improving transparence and rigidity of financial markets.

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Students' Perspective of Technology Use in the Classroom

Shishu Zhang, Yingying Pang, and Michael McGuire, University of the Incarnate Word
Jia Wang, University of Dayton
Albert Xin Jiang, Trinity University

Abstract

The purpose of this article is to explore college students' perception of technologies used in the economics classroom. This article tested 247 students on their demographic information such as gender, major, school distance, work hour, and parents' educational level, etc. The study uses several econometric and statistical analyses to reach and confirm the results. Results show that differences in the education levels of the students' fathers and the students' schools influence students' perceptions of technologies used in the classroom. The higher the fathers' education level, the lower the students' ratings about the technology used in the classroom. Students also consider 'posting the grades online' to be very important. The authors discuss possible reasons for the results, identify limitations of the study, and suggest future lines of research. Results recommended get to know your students and employ technology accordingly.

Introduction

With technology playing an increasing role in our lives, educators have thought of ways to incorporate it into instruction (Al-Bahrani et al., 2015c). Even though the average economics teacher is slow to adopt new technology, recent literature has proposed excellent ways to use social media (Facebook, YouTube, etc.) and other tools in teaching economics (Al-Bahrani et al., 2015a). Compared with the traditional "chalk and talk" method, technology use is sometimes perceived to be beneficial. It enhances communication between instructors and students, serves as alternative platforms for course materials, and engages students inside and outside the classroom (Manning, 1996; Osgerby and Rush, 2015). Technology use, however, does come with costs. It takes time to get familiar with new technology and tailor it to specific courses. Further, there could be privacy concerns depending on the type of technology used (Al-Bahrani et al., 2015c).

Despite the large body of literature on the pros and cons of incorporating technology into classrooms, the efficacy of such pedagogy regarding students' learning outcomes is not clear (Kader, 2012; Cameron, 2012). More importantly, students' opinions about technology use are under-researched. The effectiveness of technology as a complement to "chalk and talk" may be diminished if students do not view its use as important. Economics is distinct from many other social science disciplines in that it is more mathematically based, while it emphasizes more real-world applications when compared with mathematics. This poses unique challenges for instructors of economics when considering technology use.

This paper evaluates the importance of technology use in economics education from students' perspectives and extends existing literature in several ways. Instead of focusing on a specific type of technology (for example, social media), it surveys students' opinions about all major technology use and identifies the relative importance of each. Further, the paper investigates whether students' preferences for technology differ by demographic characteristics and undergraduate course level (introductory versus upper level). Findings of the paper shed light on which type of technology students value more and are of practical importance to educators who consider complementing traditional classroom teaching with technology. Using technology that students consider to be more important may enhance the effectiveness of such pedagogies.

Our findings are based on a survey administered to students enrolled in Principles of Microeconomics, Principles of Macroeconomics, Econometrics, Latin America Economics, and International Economics at two institutions: Sewanee - The University of the South and the University of Incarnate Word during the 2016–2017 academic year~~s~~. The results identify which technology use students consider important and not important in traditional classroom teaching. More specifically, we find that for students, posting their grades online is the most important use of technology. However, both the class subject and demographic information on age, gender, education and work status of student's father, and living distance from school could influence student opinion about the importance of technologies used in the classroom. The two schools evaluate the use of technology differently. With one exception, Sewanee students consider the use of technology in the classroom to be less important than UIW students; the one exception is that Sewanee students consider document sharing to be more important than UIW students. Further, the higher the education level of the student's father, the less important-the less important the use of technology in the classroom. For teachers considering incorporating more up-to-date technologies into traditional economic courses, our results provide new insights into what students consider to be most effective.

Literature Review

As technology becomes increasingly integrated into people's lives, educators have found ways to incorporate technology into teaching face-to-face classes. A variety of tools have been discussed in the literature, including but not limited to emailing, learning management systems (LMS) and social media. For economics teachers, Sheridan, Hoyt, and Imazeki (2014) pointed out that PowerPoint was the most commonly used technology and other popular tools included clickers and blogs. More recent literature elaborated on how to integrate other media into teaching. For example, Al-Bahrani and Patel (2015b) documented how to use film clips from *ESPN 30 for 30* as real-world examples to supplement classes. Al-Bahrani et al. (2016b) outlined ways to turn a "selfie" into an instructional tool for students to demonstrate their understanding of economic concepts. Al-Bahrani et al. (2016a) also illustrated how video scrapbooking could be integrated into the economics curriculum.

Nevertheless, no consensus has been reached regarding the efficacy of alternative pedagogical tools (anything but "chalk and talk"). Researchers do agree that technological tools can engage students better than just lecturing. Manning (1996) reported that using e-mail in economics classes enhanced teacher-student relations and information provision. Discussion lists promoted group discussion and improved communication among students. Agarwal and Day (1998) found a positive influence of internet use class mailing list and web projects on student grades and retention of concepts. More recent studies findings continued to support earlier findings that using technology enhances student engagement. Junco, Heibergert, and Loken (2010) used controlled experiments to study the effect of Twitter on a sample of pre-health major students. They found a positive impact on both college student engagement and grades. The Twitter experiment conducted by Kader (2012) led to increased student engagement with mixed results on learning outcomes.

Barczyk and Duncan (2013) found that Facebook enhanced a sense of classroom community through social learning and connectedness. When Alpert, Harmon, and Histen (2013) used Facebook as additional online discussion forums, they found that a positive association between student participation and exam scores. Cameron (2012) used a blog assignment for a small (40-60 students) introductory economics course and found that student performance was positively correlated with the quality of their blog participation and with a favorable response from students about the blog assignment/experience. Non-traditional teaching generally provides additional opportunities for students to participate in the discussion and share their ideas outside the classroom. Potential benefits aside, there are costs involved in adoption (Cameron, 2012; Barczyk and Duncan, 2013; Al-Bahrani and Patel, 2015a). Adopting technology in economics courses requires a time commitment from both instructors and students, especially when they are not familiar with the technology. In the primer for new teachers of economics, Sheridan, Hoyt, and Imazeki (2014), therefore, recommended that new teachers should not try to do too much at once given the costs of incorporating technology.

Further, Cameron (2012) mentioned that the effect of incorporating blogs on teaching and learning relies heavily on buy-in from the students. This is likely to be true for whatever technology the instructor contemplates using. However, this important aspect of technology use has been largely ignored in the literature. A few studies examined the issue for specific technology uses. For example, Barczyk and Duncan (2013) surveyed business students from two large public universities and found that students are inclined to use Facebook to complement face-to-face classroom teaching. Osgerby and Rush (2015) used a small sample of accounting students to explore students' perceptions of using Twitter as a learning support tool. They concluded that students' opinions were mixed and educators should plan with caution despite Twitter's communication and pedagogical potential. Herman et al. (2010) surveyed students and faculty at a midsized southern university and found that students were more receptive to using Facebook and similar technology as educational tools while faculty preferred traditional technologies like email. Al-Bahrani, Patel, and Sheridan (2015c) examined social media uses and concerns among students. They found that Instagram, Facebook, and YouTube were the top three popular sites and students accessed social media sites more frequently than school email or Learning Management Systems (LMS).

Our research adds to the existing literature by examining students' perceptions regarding various types of technology use in the economics classroom and how those perceptions differ by demographic characteristics of students. By learning which technology use was important in students' eyes, the authors are able to provide suggestions on effective uses of technology, given the long list of technologies available and the costs of adoption. Picking a technology that students view as important could lead to better learning outcomes.

Methodology

An in-class survey was distributed to undergraduate students enrolled in introductory and upper-level economic courses at two private liberal arts colleges – The University of the South (Sewanee) and University of Incarnate Word (UIW) in the academic year of 2016–2017. The survey was administered during the week before final exams. To meet the

Institutional Review Board (IRB) standards, students understood that participation in the survey was voluntary and there would be no negative impact on their grades if they did not participate.

The University of the South (Sewanee) is a private liberal arts college owned and governed by dioceses of the Episcopal Church. With its setting in rural Tennessee (90 miles to the southeast of Nashville), it has the enrollment of 1734 undergraduate students with most of them from Tennessee, Georgia, Texas, North Carolina, and Alabama. It operates on a semester schedule, and all students are required to live on campus unless they are granted an exception. At Sewanee, the survey was administered in three courses: two sections of Principles of Microeconomics and one section of Principles of Macroeconomics in the fall 2016 semester (as shown in Table 3).

The University of Incarnate Word is a private university founded in 1881 by the Sisters of Charity of the Incarnate Word. There are more than 6,000 graduate, and undergraduate students enrolled on its main campus in San Antonio, Texas, and more than 11,400 students enrolled globally. It is the largest Catholic university and the third-largest private university in Texas. The student body is 60 percent female, 52 percent Hispanic, 8 percent Black or Afro-American, and 4 percent Asian. The data was administered during two semesters and in nine courses taught by two professors in the University of the Incarnate Word (as shown in Table 3).

The researchers applied several statistical analyses to analyze the relationship between students' demographic features and their perspectives on technology. The analyses include descriptive statistical analysis of means, one-way analysis of variance (ANOVA), t-Test, correlation analysis, and multiple regression analysis. The descriptive statistical analysis explored the traits of student demographic variables and the overall students' responses to technologies used in the classroom. The ANOVA analysis compared the means of different answers of technology questions for students from different demographic groups. After exploring the mean difference through ANOVA, the researchers used Tukey comparison analysis to discover which specific demographic subgroups had different answers for technology questions. For demographic variables with only two subgroups, we used the t-Test to compare the means between different groups. To fully explore the research questions, the authors used correlation analysis to demonstrate the correlation among different answers for technology questions, among different demographic groups, and the correlation between students' perspectives on technologies and students' demographic characters. Finally, we applied multiple regression analysis to determine the possible influence of demographic traits on students' perspectives on technologies.

Results

Results from Descriptive Statistics

Table 1 is the description of variables. The researchers labeled each individual with a number to account for one observation. Each participant's number was based on the order in which the researcher entered the data. The number assigned to each individual does not affect the results. In order to analyze the difference between each class, the researcher also provided each class with a numerical label. The class number also depended on the order in which the researcher entered the data. In short, the ID variable was to identify each survey response and the class variable was to distinguish the class from which the response came. A total of 247 volunteers participated in this survey. The data was collected during two semesters. The first data collection was conducted in Spring, 2016; there were six classes with 87 students. The classes included Dr. McGuire's two Macroeconomics classes, one Microeconomics class, and one Latin America Economics class. Dr. Shishu Zhang's one Microeconomics and one Econometrics class. The second data collection was in the Fall semester, 2016; data were collected from 8 classes with 160 students. Three of Dr. Shishu Zhang's microeconomics classes participated. Dr. McGuire's Microeconomics class and his Public Finance class participated. Dr. Jia Wang who is from Sewanee University participated in the research in the Fall semester, 2016. The three participating classes of Dr. Jia Wang were one Macroeconomics and two Microeconomics classes.

Table 1 (Description of Variables) shows that the sample size is 247. A large group of participants belonged to the class of Macroeconomics, and the majority of the data was collected from UIW: 184 participants were from UIW, and 63 participants were from Sewanee. Table 1 also shows the enrollment from each professor's class: 95 were from Shishu Zhang's classes, 89 were from Michael McGuire's classes, and 63 were from Jia Wang's classes.

The data included 154 male and 93 female participants. Among the participants, 103 were freshmen, 66 were sophomores, 37 were juniors, and 37 were seniors. Two hundred and thirty-five of the participating students were single, and 12 were married. Most of the students (122) did not work when the surveys were collected. Forty-four students worked between 5 and 10 hours per week, 45 students worked between 11 and 20 hours per week, and 34 students worked more than 20 hours per week. Most of the respondents were living close to the school. Eighty-eight students lived within walking distance from school, twelve students drove 5 to 10 miles, 18 students drove 10 to 15 miles, and 41 students drove 15 miles or more to school.

The age of research participants ranged between 20 and 40 years. To enable an ANOVA analysis of age, the researcher created the variable, “Age2”. We put each age into one group. For instance, age 18 ~~as~~ is group 1, age 19 is group 2, etc. There are 7 categories in the “Age2” variable as shown in Table 1. Participants of the same age were grouped into one category if the category had more than 10 observations. The rest of the age groups where there were less than 10 observations were all put into the “other” category. The variable “Major” included 37 different groups, and some of the groups had only one or two observations. In order to perform the ANOVA analysis, as shown in Table 1, the researchers created the variable “Major2” consisting of six categories of majors; each of the categories contained at least 15 observations. The authors also created another variable, “Major3,” which consisted of nine categories of majors. Each category of “Major3” had at least 10 observations.

As for mothers’ and fathers’ education, the survey question was designed so that *1* represents high school, *2* represents two-year College, *3* was four-year College, and *4* signifies graduate school. The average of mothers’ education (Mother Edu) was 2.44, and that of the fathers’ education (Father Edu) was 2.50. From the results, we could see that most of the students’ parents had some high school or college education. Table 1 shows that two hundred and forty-one participants answered the question about mother’s education: ninety-three students indicated that their mothers had 4-years of college, and seventy-two students responded that their mothers had some high school. Two hundred and thirty-seven participants answered the question about father’s education. Seventy-six students indicated that their fathers had 4-years of college, while the fathers of seventy-two students had some high school education.

Table 1: Description of Variables

Variable Names	**Definitions**	***M***	***SD***	***N***
Subject	=0 if the individual belongs to the class of Macroeconomics; =1 if the individual belongs to the class of Microeconomics; =2 if the individual belongs to the class of Econometrics; =3 if the individual belongs to the class of Latin American Economics; =4 if the individual belongs to the class of International Economics	0.89	1.160	247
School	=1 if the individual comes from the University of the Incarnate Word (UIW); =2 if the individual comes from Sewanee: The University of the South (Sewanee)	1.26	0.437	184 63
Name	=0 if the individual belongs to Shishu Zhang’s class; =1 if the individual belongs to Michael McGuire’s class; =2 if the individual belongs to Jia Wang’s class	0.87	0.791	95 89 63
Age	Age of the individual	20.40	2.889	247
Age2	=1 if the individual is 18 years old; =2 if the individual is 19 years old; =3 if the individual is 20 years old; =4 if the individual is 21 years old; =5 if the individual is 22 years old; =6 if the individual is 23 years old; =0 otherwise	2.54	1.617	247
Gender	=0 if the individual is male; =1 if the individual is female	0.38	0.485	154 93
School Year	=1 if the individual is freshmen; =2 if the individual is sophomore; =3 if the individual is junior; =4 if the individual is senior	2.03	1.090	103 66 37 37
Major2	=1 if the individual’s major is Business; =2 if the individual’s major is International Business; =3 if the individual’s major is Management; =4 if the individual’s major is Sports Management; =5 if the individual’s major is Computer Information System; =0 otherwise	1.61	1.767	223

Note: Age2 is based on Age divided data into 7 groups, each group contains more than 10 data. Major2 is based on Major divided data into various groups. Major2 divided data into 6 groups, each group contains 15 or more data.

Table 1: Description of Variables (Continued)

Variable Names	Definitions	*M*	*SD*	*N*
Major3	=1 if the individual's major is Business; =2 if the individual's major is Economics; =3 if the individual's major is Finance; =4 if the individual's major is International Business; =5 if the individual's major is Management; =6 if the individual's major is Marketing; =7 if the individual's major is Sports Management; =8 if the individual's major is Computer Information System; =0 otherwise	3.08	2.676	223
Mother Edu	=1 if respondent's mother has some high school;	2.44	1.098	72
	=2 if respondent's mother has 2-year college;			33
	=3 if respondent's mother has 4-year college;			93
	=4 if respondent's mother has graduate school degree			43
Father Edu	=1 if respondent's father has some high school;	2.50	1.159	72
	=2 if respondent's father has 2-year college;			32
	=3 if respondent's father has 4-year college;			76
	=4 if respondent's father has graduate school degree			57
Marital Status	=0 if the individual is singled;	0.05	0.215	235
	=1 if the individual is married			12
Work Hour (per week)	=1 if the individual did not work;	1.96	1.114	122
	=2 if the individual works 5 to 10 hours per week;			44
	=3 if the individual works 11 to 20 hours per week;			45
	=4 if the individual works above 20 hours per week			34
School Distance	=1 if the individual lives within walking distance from school;	2.08	1.305	88
	=2 if the individual needs to drives 5 to 10 miles to school;			12
	=3 if the individual needs to drives 10 to 15 miles to school;			18
	=4 if the individual needs to drives more than 15 miles to school			41

Note: Major3 divides data into 9 sub-majors, each one of which contains 10 or more cases.

The survey contains 19 questions which are listed in Table 2 (Survey Questions). Each question has five different levels of importance represented by the numbers 1 through 5, with 1 indicating *very important*, 2 *important*, 3 *neutral*, 4 *not very important*, and 5 *not important at all*. The nineteenth question was an open question: "Do you have any specific technology (hardware/software) you would like the teachers to use in the classroom? If you have, please explain how the teacher could use it". Participants were asked to write down their answers for this question in words.

Based on the information about the means presented in Table 2, if the average of the answers was between 1 and 2, this meant that participants felt the question was between *important* and *very important*. The smaller the average, the more importance the participants attributed to that question. Similarly, if the average was between 2 and 3, the participant felt neutral. When the average was between 3 and 4, the participant believed that the statement was not very important. In this research, the survey did not find any question whose average was between 4 (not very important) and 5 (not important at all). By looking at the average of the scores from Table 2, we could see that students found it more important to have course materials shared and grades made available online (Q1, Q3, Q5, Q18). In particular, students felt that posting their grades online (Q18) was most important; the use of social media for online discussion (Q16) was least important for them, and the use of other faculty's lecture recording/real-time broadcast for classroom teaching (Q12) was *neutral.*

The Means of table 2 show that students found it *somewhat important* to use online resources and videos in teaching: the average scores of the eleven questions dealing with online resources fall between 2 and 3. Respondents felt the following technologies to be not very important: using social media for online discussion (Q16), and having a course website posted on social media (Q17).

Table 2: Survey Questions

Questions	***M***	***SD***	***N***
Q1. Use emails to send students slides and other course materials.	1.77	0.820	247
Q2. Uses share documents (like google doc.) to share documents for teaching.	2.12	1.041	247
Q3. Uses online course management system (e.g. blackboard) for online grading.	1.52	0.753	247
Q4. Uses online course management system for online discussion.	2.66	1.107	247
Q5. Uses online course management system for slides.	1.85	0.820	247
Q6. Uses online course management to post videos for students to watch after class (either self-made or made by others).	2.47	1.136	247
Q7. Uses any publishers' websites for teaching.	2.62	0.976	247
Q8. Uses any publishers' tools for online grading (e.g., aplia, Econ Lab).	2.66	1.061	245
Q9. Uses existing video (e.g. YouTube) for classroom teaching.	2.17	0.897	245
Q10. Uses apps (skype) online tools for distance teaching for flipped classrooms which only meet once a week.	2.85	1.106	245
Q11. Uses automated response system (e.g. clickers) in classroom in large classes.	2.70	1.665	246
Q12. Uses Other faculty's lecture recording/real time broadcast (e.g. skype, facetime) for classroom teaching.	3.00	1.016	246
Q13. Have the option for eBooks rather than printed textbooks.	2.29	1.146	245
Q14. Post other faculty's video to teach before/after class.	2.80	1.022	246
Q15. Uses online test system rather than in-class testing.	2.76	1.138	246
Q16. Uses social media (e.g. Facebook, twitter) for online discussion.	3.43	1.177	245
Q17. Have a course website posted on social media.	3.26	1.207	246
Q18. Post students' grade online.	1.33	0.654	245

Notes: From Q1 to Q18 contain 5 levels of importance, they are: =1 very important; =2 important; =3 neutral; =4 not very important; =5 not important at all. Question 19 is an open answer question: Do you have any specific technology (hardware/software) you would like the teachers to use in the classroom? If you have, please explain how the teacher could use it.

Table 2.5 is a recoded version of Table 2. We recoded ~~the~~ "very important" and "important" into 1 and "neutral," "not very important," and "not important at all" into 0 to investigate the overall perspectives from participants. This implies that if a question's mean is over 0.5, more participants were holding a positive opinion on this question. The majority of the participants from our sample believed this survey statement was important. Likewise, if the question's mean is below 0.5, the majority of the participants considered this survey question unimportant. If the score is exactly 0.5, each side contained exact same number of participants.

The results from Table 2.5 showed that participants were holding a positive opinion on the importance of Q1, Q2, Q3, Q5, Q6, Q9, Q13, Q18 and a negative opinion on Q4, Q7, Q8, Q10, Q11, Q12, Q14, Q15, Q16, Q17. None of the questions hold a score of 0.50. This indicates that most of the participants considered "use emails to send students slides and other course materials," "uses share documents (like google doc.) to share documents for teaching", uses online course management system (e.g. blackboard) for online grading", "uses online course management system for slides", "uses online course management to post videos for students to watch after class (either self-made or made by others)", "uses existing video (e.g. YouTube) for classroom teaching", "have the option for eBooks rather than printed textbooks", "and post students' grade online" to be important.

Among all the questions, students considered that *post students' grade online* was the most important (M=0.94) and *uses social media for online discussion* the least important (M=0.20).

Table 2.5: Survey Questions (Recoded)

Questions	***N***	***Mean***
Q1. Use emails to send students slides and other course materials.	247	0.85
Q2. Uses share documents (like google doc.) to share documents for teaching.	247	0.66
Q3. Uses online course management system (e.g. blackboard) for online grading.	247	0.89
Q4. Uses online course management system for online discussion.	247	0.43
Q5. Uses online course management system for slides.	247	0.81
Q6. Uses online course management to post videos for students to watch after class (either self-made or made by others).	247	0.54
Q7. Uses any publishers' websites for teaching.	247	0.45
Q8. Uses any publishers' tools for online grading (e.g. aplia, Econ Lab).	245	0.42
Q9. Uses existing video (e.g. YouTube) for classroom teaching.	245	0.66
Q10. Uses apps (skype) online tools for distance teaching for flipped classrooms which only meet once a week.	245	0.33
Q11. Uses automated response system (e.g. clickers) in classroom in large classes.	245	0.49
Q12. Uses Other faculty's lecture recording/real time broadcast (e.g. skype, facetime) for classroom teaching.	246	0.27
Q13. Have the option for eBooks rather than printed textbooks.	245	0.62
Q14. Post other faculty's video to teach before/after class.	246	0.36
Q15. Uses online test system rather than in-class testing.	246	0.41
Q16. Uses social media (e.g. Facebook, twitter) for online discussion.	245	0.20
Q17. Have a course website posted on social media.	246	0.26
Q18. Post students' grade online.	245	0.94

Notes: This table recoded the levels of importance into 1 and 0 from the original survey. 1= very important; 0= neutral, not very important, and not important at all. Q1 to Q18 from original survey contain 5 levels of importance, they are: =1 very important; =2 important; =3 neutral; =4 not very important; =5 not important at all. Question 19 is an open answer question: Do you have any specific technology (hardware/software) you would like the teachers to use in the classroom? If you have, please explain how the teacher could use it.

Table 3: Survey Responses based on Class Subjects and Academic Semesters

		Semesters		**Total**	
Professor	**Class Subject**	**Spring 2016**	**Fall 2016**	**Counts**	**Percentage (%)**
	Macroeconomics (1)	11		11	4.45%
	Macroeconomics (2)	17		17	6.88%
Dr. McGuire	Microeconomics	21	11	31	12.55%
	Latin America Economics	10		10	4.05%
	International Economics		19	19	7.69%
	Macroeconomics		18	18	7.29%
Dr. Wang	Microeconomics (1)		23	23	9.31%
	Microeconomics (2)		22	22	8.91%
	Macroeconomics (1)		19	19	7.69%
	Macroeconomics Class (2)		24	24	9.72%
Dr. Zhang	Macroeconomics Class (3)		24	24	9.72%
	Microeconomics	18		18	7.29%
	Econometrics	10		10	4.05%
Total		**87**	**160**	**247**	**100%**

Table 3 (Survey Responses based on Class Subjects and Academic Semesters) shows that the survey was conducted in Dr. Zhang and Dr. McGuire's spring 2016 and fall 2016 classes, and in Dr. Wang's Fall 2016 classes. There were 87 respondents for Spring 2016 classes, and there were 160 respondents from Fall 2016 classes. The highest percentage of respondents were from Dr. McGuire's Microeconomics classes (both Spring and Fall) with 31 respondents. The lowest respondents were from Dr. Zhang's Econometrics class (spring) with 10 respondents. The class size was a factor that affected the number of respondents.

Table 4 (Survey Respondents' Majors) shows the number of respondents from each major for both Spring and Fall semesters of 2016. As expected, most respondents were majoring in Economics (12.96%). There was only one respondent from several majors such as Asian Studies, Banking, and Finance, Chemical Engineering, etc. There was a total of 247 survey respondents from more than 40 majors, and they were unevenly distributed among different majors.

Table 4: Survey Respondents' Majors

	Academic Semesters			**Total**
Major	**Spring 2016**	**Fall 2016**	**Counts**	**Percentage (%)**
Economics	12	20	32	12.96%
General Business	15	15	30	12.15%
International Business	10	18	28	11.34%
Unspecified	1	23	24	9.72%
Computer Information Systems	7	10	17	6.88%
Management	7	9	16	6.48%
Sports Management	7	9	16	6.48%
Marketing	7	7	14	5.67%
Finance	2	8	10	4.05%
Accounting	6	2	8	3.24%
Engineering	1	4	5	2.02%
Biology	1	3	4	1.62%
Biochemistry		3	3	1.21%
Communication Arts		3	3	1.21%
Criminal Justice		3	3	1.21%
English		3	3	1.21%
Fashion Management	2	1	3	1.21%
Fashion Merchandising	3		3	1.21%
Mathematics	1	2	3	1.21%
Chemistry		2	2	0.81%
Computer Science		2	2	0.81%
Natural Resource Management		2	2	0.81%
Asian Studies		1	1	0.40%
Banking and Finance	1		1	0.40%
Chemical Engineering		1	1	0.40%
Cyber Security Systems		1	1	0.40%
Design, Media, & Technology Studies	1		1	0.40%
Environmental Science and Sustainability		1	1	0.40%
Fashion Design		1	1	0.40%
History		1	1	0.40%
International Affairs		1	1	0.40%
Kinesiology		1	1	0.40%
Management Information Systems	1		1	0.40%
Nutrition and Dietetics	1		1	0.40%
Nutrition Science		1	1	0.40%
Philosophy	1		1	0.40%
Physics		1	1	0.40%
Politics		1	1	0.40%
Total	**87**	**160**	**247**	**100%**

ANOVA Results (Tables 5-5.8)

Table 5 (ANOVA Analysis) shows the results of a one-way analysis of variance (ANOVA). The analysis proved that all questions were statistically significant for different variables at a 95 percent level of significance ($\alpha<0.05$). The analysis found that the answers for Q15 and Q18 were significantly different among different categories. The answers for Q3, Q4, Q5, and Q15 were found to be significantly different for "Subject (courses)." The answers for Q6, Q10 to Q16 and Q18 were significantly different for "Names (professor names)". Answers for Q3, Q12, and Q14 were shown to have significant differences among different age groups (Age2). The answers for Q11, Q15, Q17, and Q18 had significant differences for different "Major2"; the answers for Q4, Q7, Q10, Q11, and Q15 were significantly different for different "Father Edu"; answers for Q15 and Q18 were significantly different for students with different "Work Hour"; and answers for Q9, Q11, and Q15 were significantly different for students with different "School Distance".

Table 5: ANOVA Analysis

	df	*F*	*p*		*df*	*F*	*p*
Class				**Major 2**			
Q15	232	6.570***	0.000	Q11	216	2.926*	0.014
Q18	231	2.387**	0.005	Q15	216	3.323**	0.007
Subject				Q17	216	2.904*	0.015
Q3	242	2.591*	0.037	Q18[c]	216	2.683*	0.022
Q4[a]	242	2.604*	0.037	**Father Edu**			
Q5	242	4.196**	0.003	Q4	233	4.987**	0.002
Q15	241	6.356***	0.000	Q7	233	4.541**	0.004
Name				Q10	231	5.711**	0.001
Q6	244	4.547*	0.012	Q11	232	3.274*	0.022
Q10[b]	242	3.271*	0.040	Q15	232	2.970*	0.033
Q11	243	4.289*	0.015	**Work Hour (per week)**			
Q12	243	3.712*	0.026	Q15	240	3.265*	0.022
Q13	242	4.910**	0.008	Q18	239	2.912*	0.035
Q14	243	3.245*	0.041	**School Distance**			
Q15	243	30.811***	0.000	Q9[d]	154	3.156*	0.027
Q16	242	3.259*	0.040	Q11	154	3.003*	0.032
Q18	242	5.553**	0.004	Q15	154	3.433*	0.019
Age 2							
Q3	240	2.372*	0.030				
Q12	239	2.819*	0.011				
Q14	239	2.371*	0.030				

Notes: *p<0.05, **p<0.01, ***p<0.001

[a, b, c, d] Found no significant relationship exist in Tukey HSD Comparison Analysis

All the significant results found through ANOVA were tested using the posthoc tests with Tukey HSD comparison analysis. Four questions were found to have significant differences through ANOVA but not found to be statistically different through the Tukey HSD comparison analysis: Q4 for Subject, Q9 for School Distance, Q10 for Name, and Q18 for Major2. For demographic variables which contained only two groups, we conducted a t-Test analysis; the results are shown in Table 6.

Tables 5.1 through 5.8 explain the results of the Tukey HSD comparison analysis for questions tested to be significantly different through ANOVA. Tukey HSD comparison analysis determined the mean differences within each demographic subgroup. For example, Table 5 shows that there were significantly different answers for Q15 (online testing) depending on "Father Edu." To explain which subgroups within "Father Edu" answered Q15 differently, the Tukey HSD comparison analysis shown in Table 5.6 (Tukey HSD Comparison for Father Edu) found that students whose father's education was "high school" and those with father's education of "graduate school" answered Q15 differently: students felt that Q15 was significantly less important if their fathers' education was graduate school than students whose fathers' education was high school.

Table 5.1 (Tukey Comparison Analysis for Different Classes) indicates that, compared to participants from UIW, the participants from Sewanee think that "uses online test system rather than in-class testing" is less important. Respondents from Dr. Jia Wang's class considered "post students' grade online" to be less important than one of Dr. McGuire's International classes (class 11), and three of Dr. Shishu Zhang's classes (classes 1, 7, and 8). Compared to class 12 (Dr. Jia

Wang's Macroeconomics), class 13 (Dr. Jia Wang's Microeconomics) also considered "post students' grade online" to be less important.

Overall, most of the significant results explain the differences between Dr. Wang's classes and both Dr. McGuire and Dr. Zhang's classes. The same conclusion follows from the t-Test (Table 6) between the two schools. Also, in Dr. Jia Wang's class, students of Macroeconomics have a different perspective than students of Microeconomics class on "post students' grade online." This means that differences between the two schools have a strong influence on student perspective. Moreover, it shows the possibility of course content influencing students' perspective.

Table 5.1: Tukey HSD Comparison for Class

	(I) Class	**(J) Class**	**Mean Difference (I-J)**	***SE***	***p***
Q15	1	12	-1.222*	0.338	0.025
	2	12	-1.600*	0.398	0.006
	4	8	1.065*	0.299	0.029
	5	12	-1.636*	0.387	0.003
	6	12	-1.647*	0.343	0.000
		13	-1.212*	0.320	0.014
	7	12	-1.789*	0.334	0.000
		13	-1.355*	0.310	0.002
		14	-1.153*	0.313	0.020
	8	12	-1.875*	0.317	0.000
		13	-1.440*	0.292	0.000
		14	-1.239*	0.295	0.003
	9	12	-1.708*	0.317	0.000
		13	-1.274*	0.292	0.002
		14	-1.072*	0.295	0.023
	10	12	-1.364*	0.387	0.033
	11	12	-1.789*	0.334	0.000
		13	-1.355*	0.310	0.002
		14	-1.153*	0.313	0.020
Q18	1	13	-0.691*	0.198	0.038
	7	13	-0.808*	0.196	0.004
	8	13	-0.788*	0.184	0.002
	11	13	-0.808*	0.196	0.004
	12	13	-0.726*	0.205	0.032

Notes: *$p<0.05$;
[a] Based on one-way ANOVA, $F=6.57$, $p<0.001$; [b] Based on one-way ANOVA, $F=2.39$, $p=0.005$.

Table 5.2 (Tukey Comparison Analysis for Class Subjects) shows that the answers for Q15 were significantly different depending on different "subjects" (Macroeconomics, Microeconomics, Econometrics, Latin American Economics, and International Economics). The mean scores for the answers of Q15 (use online testing system) for Microeconomics class (M = 3.18, SD = 1.11) were significantly higher than both Macroeconomics class (M = 2.52, SD = 1.15) and International Economics class (M = 2.21, SD = 0.86). This means that respondents from Microeconomic class considered Q15 less important than respondents from Macroeconomics and International Economics classes.

Table 5.2: Tukey HSD Comparison for Class Subjects

	(I) Subject	**(J) Subject**	**Mean Difference (I-J)**	***SE***	***p***
Q3[a]	Macroeconomics	Microeconomics	-0.307*	0.104	0.027
Q5[b]	Macroeconomics	Microeconomics	-0.399*	0.111	0.004
Q15[c]	Microeconomics	Macroeconomics	0.661*	0.152	0.000
		International Economics	0.968*	0.274	0.004

Notes: *$p<0.05$
[a] Based on one-way ANOVA, $F=2.59$, $p=0.037$; [b] Based on one-way ANOVA, $F=4.20$, $p=0.003$;
[c] Based on one-way ANOVA, $F=6.36$, $p<0.001$.

The results in Table 5.2 view the classes by class subject to discover whether differences in class content affect students' perspective on technology. The results show that the Microeconomics category had a different perspective than either the Macroeconomics group or the International Economics group in "uses online test system rather than in-class testing." These results enhance the possibility that course content can influence students' perspective. However, it will important to investigate whether this influence is caused by students' school distance.

In addition, the results of Table 5.1 and Table 5.2 show that the students from Macroeconomics scored lower than Microeconomics for both Q3 (online grading) and Q5 (online slides). This result indicates that Macroeconomics students think that using an "online course management system for online grading" and an "online course management system for slides" is more important than do the Microeconomics students. The results show that the Microeconomics students scored higher than both Macroeconomics and International Economics students for Q15; this means that the students from both Macroeconomics and International Economics believe that "use online test system rather than in-class testing" is more important than do the Microeconomics students.

Table 5.3 (Tukey Comparison Analysis for Different Professors) shows that the respondents from Dr. Jia Wang's classes (one Macroeconomics and two Microeconomics classes) scored significantly higher than Dr. Shishu Zhang's classes (three Macroeconomics classes, one Microeconomics class, and one Econometrics class) for Q6, Q12, Q14, and Q16. The respondents from Dr. Jia Wang's class scored significantly higher than both Dr. Shishu Zhang and Dr. McGuire's classes for Q11, Q13, Q15, and Q18. This indicates that compared to Dr. Shishu Zhang's class, Dr. Jia Wang's respondents believe that "use videos and social media for discussion" is less important. Dr. Jia Wang's respondents considered that "uses automated response system in classroom in large classes," "have the option for eBooks rather than printed textbooks," "use online test system rather than in-class testing," and "post students' grade online" were all less important, compared to both Dr. Shishu Zhang and Dr. McGuire's respondents. Table 5.3 investigates the influence of different professors' teaching styles on students' perspective. However, the results show that the influence of differences between the two schools outweigh professor teaching style.

Table 5.3: Tukey HSD Comparison for Respondents from Different Professors' Classes

	(I) Name	**(J) Name**	**Mean Difference (I-J)**	***SE***	***p***
Q6[a]	Shishu Zhang	Jia Wang	-0.520*	0.182	0.013
Q11[b]	Jia Wang	Shishu Zhang	0.647*	0.268	0.044
		Michael McGuire	0.754*	0.272	0.016
Q12[c]	Michael McGuire	Jia Wang	-0.436*	0.166	0.025
Q13[d]	Jia Wang	Shishu Zhang	0.530*	0.184	0.012
		Michael McGuire	0.507*	0.187	0.020
Q14[e]	Shishu Zhang	Jia Wang	-0.400*	0.165	0.043
Q15[f]	Jia Wang	Shishu Zhang	1.276*	0.167	0.000
		Michael McGuire	1.006*	0.169	0.000
Q16[g]	Shishu Zhang	Jia Wang	-0.459*	0.191	0.044
Q18[h]	Jia Wang	Shishu Zhang	0.347*	0.105	0.003
		Michael McGuire	0.254*	0.107	0.047

Notes: *$p<0.05$
[a] Based on one-way ANOVA, $F=4.55$, $p=0.012$; [b] Based on one-way ANOVA, $F=4.29$, $p=0.015$;
[c] Based on one-way ANOVA, $F=3.71$, $p=0.026$; [d] Based on one-way ANOVA, $F=4.91$, $p=0.008$;
[e] Based on one-way ANOVA, $F=3.25$, $p=0.041$; [f] Based on one-way ANOVA, $F=30.81$, $p<0.001$;
[g] Based on one-way ANOVA, $F=3.26$, $p=0.040$; [h] Based on one-way ANOVA, $F=5.55$, $p=0.004$.

Table 5.4 (Tukey Comparison Analysis for Age) indicates that the 19-year-old individuals scored Q3 significantly lower than did those of 20 years of age. Compared to the other ages, the 19-year-old individuals scored both Q12 and Q14 higher than other ages (excluding the students' ages of 18, 19, 20, 21, 22, and 23). This shows that 19-year-old individuals think that "uses online course management system for online grading" is more important than 20-year old. Moreover, those of 19 years answered that "uses other faculty's lecture recording/real-time broadcast for classroom teaching" and "post other faculty's video to teach before/after class" was less important than the other ages.

The different perspective of 19-year old students could have multiple causes. The first difference could be caused by the differences between traditional students (age 18-23) and non-traditional students (age over 24). The second difference could be caused by different school years (freshmen, sophomore, junior, senior). These possibilities need more testing to confirm these explanations.

Table 5.4: Tukey HSD Comparison for Age2

	(I) Age2	(J) Age2	Mean Difference (I-J)	*SE*	*p*
Q3[a]	19	20	-0.466*	0.146	0.026
Q12[b]	19	other	0.750*	0.242	0.035
Q14[c]	19	other	0.793*	0.245	0.023

Notes: *p<0.05
[a] Based on one-way ANOVA, F=2.37, p=0.030; [b] Based on one-way ANOVA, F=2.82, p=0.011;
[c] Based on one-way ANOVA, F=2.37, p=0.030.

Table 5.5 (Tukey Comparison Analysis for Majors) shows that General Business students think that "uses automated response system in classroom in large classes" is less important compared to both International Business and Computer Information System students. It also shows that Sports Management students think that "uses online test system rather than in-class testing" is less important compared to both General Business and International Business students. The mean scores for the International Business major (M = 2.79, SD = 0.96) is significantly lower than the mean scores for the Computer Information Systems major (M = 4.00, SD = 1.17). This indicates that International Business students think that "have a course website posted on social media" is more important compared to Computer Information Systems students.

In Table 5.5 the researchers investigate whether differences in student majors influence students' perspectives on technology. The results in the table prove that technology needs vary between majors. Professors should consider specific technology used in the classroom based on the major of most of the students in the class. For example, if most of the students in the class are General Business majors, professors should consider using online testing and avoid using automated response systems even in a large class.

Table 5.5: Tukey HSD Comparison for Major2

	(I) Major2	(J) Major2	Mean Difference (I-J)	*SE*	*p*
Q11[a]	General Business	International Business	0.786*	0.271	0.047
		Computer Information System	0.941*	0.313	0.035
Q15[b]	Sports Management	Business	0.890*	0.273	0.016
		International Business	1.007*	0.278	0.005
Q17[c]	International Business	Computer Information System	-1.214*	0.362	0.012

Notes: *p<0.05
[a] Based on one-way ANOVA, F=2.93, p=0.014; [b] Based on one-way ANOVA, F=3.32, p=0.007;
[c] Based on one-way ANOVA, F=2.90, p=0.015.

Table 5.6 (Tukey Comparison Analysis for Fathers' Education) suggests that when participants' fathers had graduate degrees, the participants felt that Q7 ("uses any publishers websites for teaching") was less important than those whose fathers' were less educated. Also, the participants felt Q4 ("uses online course management system for online discussion") and Q10 ("uses apps online tools for distance teaching for flipped classrooms which only meet once a week") to be less important when the participant's father held a graduate degree compared to students whose father held either a high school degree or a 2-year college degree. Participants whose "Father Edu" was high school level considered Q11 ("uses automated response system in classroom in large classes") and Q15 ("uses online test system rather than in-class testing") to be more important than did the participants whose "Father Edu" was at the graduate level. However, the analysis did not find any significant result on the participants' "mother Edu".

Researchers investigated whether the father's edcuation level influences a student's perspective on technology. Many student statements show that their perspectives are indeed influeniced by their father's education level. Table 5.6 shows that the higher the father's education level, the less importance given to Q7, 10, 11, 15 by students. In addtion, researchers did not find a significant relationship between the mother's education level and the student's perspective on technology used in the classroom.

le 5.6: Tukey HSD Comparison for Father Edu

	(I) Father Edu	(J) Father Edu	Mean Difference (I-J)	*SE*	*p*
Q4[a]	Graduate School	High School	0.643*	0.191	0.005
		2-year College	0.674*	0.238	0.026
Q7[b]	Graduate School	High School	0.444*	0.171	0.049
		2-year College	0.719*	0.213	0.005
		4-year College	0.461*	0.169	0.035
Q10[c]	Graduate School	High School	0.758*	0.192	0.001
		2-year College	0.629*	0.238	0.044
Q11[d]	High School	Graduate School	-0.835*	0.296	0.027
Q15[e]	High School	Graduate School	-0.522*	0.199	0.046

Notes: *$p<0.05$
[a] Based on one-way ANOVA, $F=4.99$, $p=0.002$; [b] Based on one-way ANOVA, $F=4.54$, $p=0.004$;
[c] Based on one-way ANOVA, $F=5.71$, $p=0.001$; [d] Based on one-way ANOVA, $F=3.27$, $p=0.022$;
[e] Based on one-way ANOVA, $F=2.97$, $p=0.033$.

Table 5.7 (Tukey Comparison Analysis for Work Hours) indicates that non-working individuals answered Q15 ("uses online test system rather than in-class testing") to be more important than "working 5 to 10 hours per week" individuals did. The non-working individuals considered Q18 "post students' grade online" to be more important than did individuals who worked 11 to 20 hours per week. Table 5.7 showed that non-working students cared more about the choice of test system and ability to access grades any time more than did the students who work. This could indicate working students are distracted by their work life, or that the purpose of working students who enroll in the undergraduate degree may differ from that of non-working students.

Table 5.7: Tukey HSD Comparison for Work Hour

	(I) Work Hour	(J) Work Hour	Mean Difference (I-J)	*SE*	*p*
Q15[a]	None	5-10 hours	-0.614*	0.198	0.011
Q18[b]	None	11-20 hours	-0.306*	0.114	0.038

Notes: *$p<0.05$
[a] Based on one-way ANOVA, $F=3.27$, $p=0.022$; [b] Based on one-way ANOVA, $F=2.91$, $p=0.035$.

Table 5.8 (Tukey Comparison Analysis for School Distances) shows that respondents who lived within walking distance scored Q11 (use automated response system) higher than did the respondents who drove 10 to 15 miles to school. They also scored Q15 (use online testing system) higher than the respondents who drove 5 to 10 miles to school. These responses indicate that the respondents who lived within walking distance from school assumed "uses automated response system in classroom in large classes" to be less important than did the respondents who drove 10 to 15 miles to school. Compared to the respondents who drove 5 to 10 miles to school, the respondents who lived within walking distance also considered "uses online test system rather than in-class testing" to be less important. As a result, students who live far from campus had a higher opinion about using online testing and automated response systems in classrooms.

The results in Table 5.8 show that students who live farther away will rely more on the technology that helps with long-distance communication. Also, an online test system doesn't require students to drive to school and sit in the classroom, thereby creating for students who live far away from school.

Table 5.8: Tukey HSD Comparison for School Distance

	(I) School Distance	(J) School Distance	Mean Difference (I-J)	*SE*	*p*
Q11[a]	Walking Distance	Drive 10 -15 miles	1.305*	0.490	0.042
Q15[b]	Walking Distance	Drive 5 – 10 miles	1.011*	0.362	0.030

Notes: *$p<0.05$
[a] Based on one-way ANOVA, $F=3.00$, $p=0.032$; [b] Based on one-way ANOVA, $F=3.43$, $p=0.019$.

Table 6 (t-Test results). Unlike the ANOVA analysis, the t-Test analyzes only the demographic variables that contain no more than two subgroups. The table demonstrates that, on average, the UIW students found it more important to be engaged with online teaching technology than Sewanee students. UIW students gave a lower score to Q4, Q6, Q10, Q11, Q12, Q13, Q15, and Q 18, but scored Q2 higher than Sewanee students. This result indicates that UIW students considered "uses share documents to share documents for teaching" to be less important, compared to Sewanee students, but UIW students considered other technology questions more important than Sewanee students considered them. The conclusions of the t-Test are similar to those of Table 5.1 (Tukey Comparison Analysis for Different Classes) and Table 5.3 (Tukey Comparison Analysis for Different Professors). Many participants from different schools had different perspectives on technology.

Table 6: t-Test Table

	School	***N***	***M***	***t***	***p* (2-tailed)**
Q2[a]	UIW	184	2.20	2.164	0.032
	Sewanee	63	1.90		
Q4[b]	UIW	184	2.58	-2.011	0.047
	Sewanee	63	2.89		
Q6	UIW	184	2.38	-2.124	0.035
	Sewanee	63	2.73		
Q10[c]	UIW	184	2.75	-2.799	0.006
	Sewanee	61	3.16		
Q11	UIW	184	2.53	-2.900	0.004
	Sewanee	62	3.23		
Q12	UIW	184	2.90	-2.670	0.008
	Sewanee	62	3.29		
Q13	UIW	183	2.16	-3.137	0.002
	Sewanee	62	2.68		
Q15	UIW	184	2.47	-7.608	0.000
	Sewanee	62	3.61		
Q18[d]	UIW	184	1.26	-2.433	0.017
	Sewanee	61	1.56		

Notes: [a] In the Levene's Test for Equality of Variances, F=7.374, p=0.007
[b] In the Levene's Test for Equality of Variances, F=3.969, p=0.047; [c] In the Levene's Test for Equality of Variances, F=4.318, p=0.039;
[d] In the Levene's Test for Equality of Variances, F=27.492, p<0.001.

Table 7.1: Correlations (Demographic Information vs. Demographic Information)

	Class	Subject	School	Name	Age	Major	School Year	Gender	Mother Edu	Father Edu	Marital Status	Work Hour	School Distance
Class			+**	+**	-**	+**	-**		+**	+**			-**
Subject				+*	+**	-**	+**					+*	
School	+**			+**	-**	+**	-**		+**	+**	-*		-**
Name	+**	+*	+**		-*	+**			+**	+**			-**
Age	-**	+**	-**	-*			+**	-*			+**	+**	+**
Major	+**	-**	+**	+**									
School Year	-**	+**	-**		+**				-**	-**	+**	+**	+**
Gender					-*						-*		
Mother Edu	+**		+**	+**			-**			+**		-*	-**
Father Edu	+**		+**	+**			-**		+**				-*
Marital Status	+**		+**	+**	-*	+**	-**		+**	+**			-**
Work Hour		+*			+**		+**		-*				
School Distance	-**		-**	-**	+**		+**		-**	-*	+**		

Note: *p<0.05, **p<0.01

Table 7.2: Correlations (Questions vs. Questions)

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18
Q1		+**	+**	+**	+**	+**	+**	+**	+**	+**	+*	+*		+**	+**	+**	+**	+*
Q2	+**		+**	+**	+**	+**	+**	+**	+**	+**		+**	+*	+**	+**	+**	+**	+*
Q3	+**	+**		+**	+**		+**	+**	+**	+**			+**		+*	+*		+**
Q4	+**	+**	+**		+**	+**	+**	+**	+**	+**		+**	+*	+**	+**	+**	+**	+**
Q5	+**	+**	+**	+**		+**	+**	+**		+**		+*	+*	+**	+**	+**	+**	+**
Q6	+**	+**		+**	+**		+**	+**	+**	+**	+*	+**	+*	+**	+**	+**	+**	
Q7	+**	+**	+*	+**	+**	+**		+**	+**	+**		+**	+**	+**	+**	+**	+**	
Q8	+**	+**	+**	+**	+**	+**	+**		+**	+**	+**	+**	+*	+**	+**	+**	+**	+**
Q9	+**	+**	+**	+**		+**	+**	+**		+**	+**	+**	+**	+**	+**	+**	+**	+*
Q10	+**	+**	+**	+**	+**	+**	+**	+**	+**		+**	+**	+**	+**	+**	+**	+**	
Q11	+*					+*		+**	+**	+**		+**	+**	+**	+**	+**		+*
Q12	+*	+**		+**	+*	+**	+**	+**	+**	+**	+**		+**	+**	+**	+**	+**	
Q13		+*	+**	+*	+*	+*	+**	+*	+**	+**	+**	+**		+**	+**	+**	+**	
Q14	+**	+**		+**	+**	+**	+**	+**	+**	+**	+**	+**	+**		+**	+**	+**	
Q15	+**	+**	+*	+**	+**	+**	+**	+**	+**	+**	+**	+**	+**	+**		+**	+**	+**
Q16	+**	+**	+*	+**	+**	+**	+**	+**	+**	+**	+**	+**	+**	+**	+**		+**	
Q17	+**	+**		+**	+**	+**	+**	+**	+**	+**		+**	+**	+**	+**	+**		
Q18	+*	+*	+**	+**	+*			+**	+*		+*				+**			

Notes: *p<0.05, **p<0.01

Table 7.3: Correlations (Demographic Information vs. Questions)

	Class	Subject	School	Name	Age	Major	School Year	Gender	Mother Edu	Father Edu	Marital Status	Work Hour	School Distance
Q1	-*								-*				
Q2	-*												
Q3													
Q4				+*						+**			
Q5										+*			
Q6			+*	+**						+*			
Q7				+*						+*			
Q8													
Q9				+*						+*			-*
Q10			+*	+*						+**			
Q11			+**	+*						+**			-*
Q12	+*	-*	+**		-*								
Q13	+*		+**	+**						+*			
Q14				+*									
Q15	+**		+**	+**		+*				+*	-*		
Q16				+*						+**			
Q17										+*			
Q18			+**	+**									-*

Notes: *p<0.05, **p<0.01

Correlation Results (Tables 7.1-7.3)

Table 7.1 (Correlations between Demographic Variables) shows the inter-correlation between demographic variables: more than half of the variables were positively correlated. For example, when the participant's "father Edu" was at the higher education level, it was more likely that the participant is married. However, there were still some variables that were negatively correlated with other variables. Gender and age, for example, were negatively correlated. This meant that if a participant was 18 years old, the person was more likely to be female, and if the participant was 21 years old, the person was more likely to be a male. Table 7.2 (Correlations between Survey Questions) indicates that each of the survey questions was positively correlated (if a participant scored higher for one question, he was more likely to score higher for other questions as well). This is to be expected since all the questions were about the technology used in the classroom.

Table 7.3 (Correlation between Demographic Information and Survey Questions) shows that most correlations were positive, but a few of them were negative. For instance, Father Edu is positively correlated with Q16 (use social media for online discussion) indicating that as the Father Edu of a participant increased, the student attributed less importance to using "social media for online discussion." On the other hand, Mother Edu was negatively correlated with Q1 (use email to send slides and other course materials) indicating that the higher the Mother Edu, the more importance attributed to the "use emails to send students slides and other course materials" by the respondents."

Regression Results (Table 8)

This article uses ordinal logistic regression to further analyze the relationship between demographic variables and the answers to all the survey questions. The general model used in this paper is:

$$\text{logit(Survey Question)} = \text{Intercept} + \text{Participant's Demographic Information} * \text{Slope of the Line} \quad (1)$$

In the above equation, the value assigned to each survey question is its level of importance, where "1 = very important" and "5 = not at all important". The survey collected twelve categories of the participants' demographic information: class, subject, name, age, major, school year, gender, mother Edu, father Edu, marital status, work hour, and school distance. The completed model was the following:

$$\text{logit}(Y_i) = \ln\left(\frac{\pi}{1-\pi}\right) = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} \ldots + \beta_{12} X_{12i} \quad (2)$$

Table 9 (Ordinal Logistics Results) finds that the demographic variables are statistically correlated with questions Q4, Q6, Q10, Q15, and Q17 (other questions are not significantly associated with demographic variables). In Table 9, an ordinal logistic regression was run to determine the effects of Gender, Father Edu, and Work Hour on Q4 (uses online course management system for online discussion). Male students believed Q4 was less important than female students. When a respondent's father education level was higher, the respondent answered Q4 to be less important. The longer the respondent's working hours per week, the less important the respondent felt online discussion to be. The demographic variables mentioned above (Gender, Father Edu, and Work Hour) were all significant predictors of Q4 (uses online course management system for online discussion). We find that School Year, Father Edu, and Work Hour had a significant effect on Q6 (uses online course management to post videos for students to watch after class). As the respondent's school year grew higher, the importance of Q6 declined. Also, as the education of a respondent's father increased, the importance attributed to Q6 declined. Finally, as a respondent's working hours per week increased, the importance of "uses online course management to post videos for students to watch after class" declined.

Table 8: Ordinal Logistic Regression Results

Variables		***Coefficient***	***SE***	***Wald χ^2***	***p***	***OR***	***95% CI OR***
Q4	Gender	-0.797	0.367	-2.17	0.030	0.451	[-1.516, -0.078]
	Father Edu	0.424	0.177	2.40	0.016	1.528	[0.078, 0.770]
	Work Hour (per week)	0.431	0.181	2.38	0.017	1.539	[0.076, 0.787]
Notes: Log Likelihood=-167.13, Pseudo R^2=0.074, χ^2=26.71, p=0.014, # of Obs=124							
Q6	School Year	0.576	0.274	2.110	0.035	1.779	[0.040, 1.113]
	Father Edu	0.434	0.178	2.440	0.015	1.543	[0.085, 0.783]
	Work Hour (per week)	0.390	0.180	2.170	0.030	1.477	[0.038, 0.742]
Notes: Log Likelihood=-165.80, Pseudo R^2=0.075, χ^2=26.80, p=0.013, # of Obs=124							
Q10	Father Edu	0.704	0.184	3.830	0.000	2.023	[0.344, 1.065]
Notes: Log Likelihood=-169.42, Pseudo R^2=0.069, χ^2=24.96, p=0.023 # of Obs=123							
Q15	Dr. Zhang	-4.777	1.397	-3.420	0.001	0.008	[-7.515, -2.038]
	Dr. McGuire	-3.532	1.211	-2.920	0.004	0.029	[-5.906, -1.158]
	Gender	-0.791	0.366	-2.160	0.031	0.453	[-1.509, -0.074]
	Work Hour (per week)	0.435	0.188	2.320	0.020	1.545	[0.068, 0.803]
Notes: Log Likelihood=-155.50, Pseudo R^2=0.150, χ^2=54.99, p<0.001, # of Obs=123							
Q17	Father Edu	0.369	0.177	2.090	0.037	1.447	[0.023, 0.715]
	Work Hour (per week)	0.480	0.186	2.580	0.010	1.615	[0.115, 0.844]

Notes: Log Likelihood=-177.66, Pseudo R^2=0.070, χ^2=26.76, p=0.013, # of Obs=123

Note 1= very important, 5= not important at all; Gender: Male=0, Female=1; Father Edu: 1=high school, 2= two year college, 3= four year college, 4= graduate school degree; School Year: 1=freshman, 2=sophomore; 3=junior, 4=senior.

Table 9 shows that Father Edu had significant effects on Q10 (uses online tools for distance teaching for flipped classrooms which only meet once a week). This means that the higher the education level of the father, the lower the importance of "uses apps (skype) online tools for distance teaching for flipped classrooms which only meet once a week" to the respondent. We find that Dr. Zhang, Dr. McGuire, Gender, and Work Hour had significant effects on Q15 (uses online test system rather than in-class testing). Compared with Dr. Wang Jia's class, students in Dr. McGuire and Dr. Zhang's classes considered Q15 to be more important. Male students considered "uses online test system rather than in-class testing" less important than female students. When respondent's working hours were longer, he or she believed Q15 to be less important.

Table 9 shows the results of an ordinal logistic regression that was run in order to determine the effect of Father Edu and Work Hour on Q17 (have a course website posted on social media). The effect is found to be significant: as the education level of a respondent's father increases, the importance of Q17 declines. As the respondent's working hours per week increase, the importance "have a course website posted on social media" declines.

Conclusion and Discussion

The results of the ANOVA and the independent t-Tests show~~ed~~ that for half of the questions student perspectives depended upon the institution attended by the participants. Overall, UIW students attributed more importance to all those questions than did the Sewanee students. However, the Sewanee students attributed more importance to using shared documents than did UIW students as shown by the t-Test.

For different classes, the results of ANOVA analysis also showed that in comparison to Microeconomics students, Macroeconomics students cared more about using an online course management system for slides and using online grading. International Economics students considered using online testing more important than did Microeconomics students. International Business students attached more importance to questions about the automated response system, online testing, and posting course websites on social media than did Business majors, Computer Information System majors, and Sports Management majors.

As for students of different ages, the ANOVA found that 19 years old participants felt "posting grade on online course management system" to be more important than did the 20-year-old participants. The 19-year-old participants considered "using other faculty's lecture recording/real time broadcast for classroom teaching" or "posting other faculty's video to teach before or after class" less important than did the participants whose ages were not from 18 to 23 years old. Other important ANOVA results included: students who lived within walking distance from school cared less about long-distance technology since they can access or interact in the classroom; the non-working individuals were more concerned about putting grades online than were the individuals who worked. Interestingly, when father's education reached the graduate school level, the participants attributed less importance to most of the technology questions asked in the survey. Based on the results of regression, the females assigned more importance to online discussion and online testing than did males. The longer participants work per week, the less importance they gave to online discussion, online testing, and posting a website on social media. The regression results indicated that when the respondents' school year was higher, they assigned less importance to "post video on online course management system". For all the survey questions, which showed significant regression results, the higher the Father Edu, the less importance the participants assigned to the questions 4, 6, 10, and 17. Fifteen students commented on Question 19. Three of them emphasized how important it was to use technology in the classroom. Two of the students suggested using smart boards as teaching tools; another two students recommended more use of online tools in the classroom. Ideas for using hardware included the use of personal computers and Xbox Live. Software suggestions included more online testing, recording systems, Webex, eBooks, and Khan Academy. One student expressed the hope of more study resources and more slideshows for the classroom.

This research showed that father's education was an interesting factor that influenced students' opinions about use of technology in the classroom. However, not all the responses for the survey questions were usable. For example, one participant wrote "why" as his/her response to all the questions except Mother Education.

Students of Sewanee: The University of the South did not think it as important to "post grades online" or "engage with online teaching technologies" as did the students of the University of the Incarnate Word. Could this be due to the smaller class size at University of South? If the class size was smaller at University of South, it probably meant easier interaction among students or between students and teachers. The students could easily get their grades directly from their teachers.

The researchers expected that those who work would find it more valuable to have online testing and posting grades online. However, our results suggested that students who worked while going to a school rated those two items lower than students who did not work at the time we conducted the survey. One explanation may be that there was a trade-off between students' work and their academic efforts. The working students might be too involved in their work, and they were lacking the focus on their academic success and did not care about the technology used in the classroom.

Another interesting result is that the older the students were, the more likely it was that they would be male and vice versa. First-year students were more likely to be female (since 18-year-old were more likely to be female). One interpretation is that females were more likely to drop out of college or not be in economics classes by the time they were in the junior year (since 21-year-old were more likely to be male).

Suggestions

One of the most important findings from the survey questions was that the students considered "posting their grades online" to be most important with a mean 1.33 as shown in Table 2. Therefore, the researchers suggest that the professors post the up-to-date grades online so that students could view them at any time.

Based on the results of the ANOVA tests, t-Tests, and the multiple regression analyses, students had different opinions about technology use in the classroom based on students' age, gender, majors, father education, the classes, and the universities they attended. The researchers recommend that the professors adjust the types of technology used in the class based on what class the professor is teaching, and which students comprise the class majority, and also based on students' background such as their age, gender, majors, whether they worked or not, and how far they lived from school.

Limitation

The researchers collected the data from UIW and University of the South (Sewanee). Due to the differences between the two schools, students held different perspectives on technology use in the classroom. It indicated that if the sample changed, the students' responses for technology used in the class might also change.

If we conducted the surveys in a different environment, the correlation tables might indicate different results. Therefore, the results of this research might not be generalized. In other words, if future researchers apply the same survey in other institutions (e.g., future research that contains all the higher education institutions in San Antonio), that would disclose more generalized results.

Another limitation of this research is that the sequence of the data collection process could affect the results of the analysis. UIW required students to take the course of Macroeconomics first and then the Macroeconomics. Sewanee had no requirements as for the order of the economic classes. As a result, students can enroll in both Microeconomics and Macroeconomics in the same semester. Since we collected the data anonymously from spring and fall of 2016 without recording respondents' name, both UIW and Sewanee could have some student participants who responded twice.

Future Research

The researchers analyzed students' opinion about the technology used in the classrooms in two private universities. Notably, students' opinion could change based on the sample. Therefore, we suggest that future researchers extend this research to other universities to validate our findings.

Future researchers could also conduct qualitative research by interviewing students about the technology used in the classroom. In this study, we did not conduct further research to explain some of the results from the survey. For example, future researchers can discover why 19-year-old students attributed more importance to grades, why different majors and classes expressed different needs for online testing, why students who worked care less about the grades, and why students' Father Education influenced their perspectives on using technology in the classroom in an unexpected way.

In the future, researchers could analyze the key elements between different institutions that affect student opinions about using technology in the classroom. Researchers could also conduct researches to compare the opinions of professors and students concerning technology used in the classroom to see whether they have different perspectives.

Moreover, future researchers could discover whether financial constraint (family or personal income level) is a factor that influences student's opinions about the technology used in the class. One participant in the survey who commented on Q13 (have the option for eBooks rather than printed textbooks) wrote that: "eBook is cheaper!"

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