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Faculty Forward

Dear Reader,

I am very excited to see the new issue of the Iona Journal of Economics. I acted as a reviewer for the first issue of the journal, and I was very impressed by the professionalism of the editorial board. If you haven't read it already, it's worth going back to look at the first issue. It has an amazing scope, running from an examination of policy related to the Ebola epidemic in West Africa to a philosophical discussion of David Ricardo's theories to an investigation of the role of oil price fluctuations in driving Canada's exchange rate. Each of these papers – and the others – are interesting and original contributions.

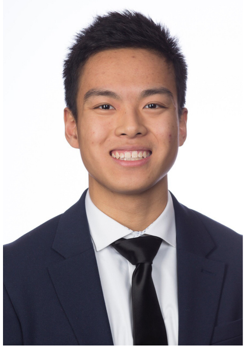
The depth and scope of the first issue reflects what the faculty already know about students at UBC: that they are engaged, intelligent, and diverse. Our goal in establishing the Vancouver School of Economics was to create better venues through which our students could become engaged. As the Department of Economics, situated on the 9th and 10th floors of Buchanan Tower, we had a real interest in our students but we were constrained both organizationally and physically from setting up the types of options we wished for them. Students would come to office hours (mainly right before exams) but there would be no place for them to hang around before or after - no place for them to study and no place for them to gather. Because of that – despite valiant efforts by the economics undergraduate association – there was no opportunity for the students to generate the kinds of synergies that led to the creation of the Iona Journal.

The move to the Iona Building was instrumental in changing all of that. For the first time, students have a space where they can hang out and talk economics (at least, that's what I assume they are talking about). Just as importantly, it means that when faculty come and go, they meet up with the students on a regular basis. That, for us, makes it feel like a real School: a place where students of economics of all levels of experience (because that is what we all are – students trying to learn more about economies and how they work) come together to study and do research and learn from each other. At the same time, the creation of the BIE program brought a new group of students into the mix, complementing the already impressive set of Majors and Honours students.

Out of that mix has emerged a much more vibrant community than we have ever had. The journal is a real reflection of that community and it is fitting that it is named the Iona Journal after the place at the heart of the community (the name also has reference to a Scottish Island and community of scholars, but I'll leave it to you to learn more about that when you go back and read the first issue).

Finally, I just want to say thank you to the set of students who have taken on the editing and running of this issue of the journal. I know from being a journal editor in the past that this is an incredible amount of work and a labour of love. A community is built by these kinds of sacrifices and we are all the beneficiaries of your efforts.

David Green
Professor and Director
University of British Columbia



Student Forward

Dear Reader,

The Vancouver School of Economics Undergraduate Society (VSEUS) would like to congratulate the IONA Journal on its third successful year as a platform for sharing knowledge and creating dialogue for young emerging researchers. As an institution that focuses on academic success and community connections, we are very proud of the work that has gone towards publishing this student-led economics journal to showcase the insightful research conducted by our fellow undergraduate students at the Vancouver School of Economics (VSE).

Many thanks and special recognition goes out to IONA Journal Editor-in-Chief, Mariam Nasser, and her entire editorial team for making this project a huge success. The IONA Editorial Board, along with VSE faculty, have put in countless hours reviewing numerous submissions and putting together a cohesive collection of some of the best Economics undergraduate research papers the VSE has seen this year. The IONA Journal of Economics highlights our students' abilities to connect what they have learned in the classrooms with today's challenging global problems. Moreover, the IONA Journal encourages students of all backgrounds with a passion for research to remain curious and speak out on issues they truly care about. VSEUS will continue to be a strong supporter of this initiative and is excited to see its continuous growth towards becoming one of the largest undergraduate economics journals in Canada.

I hope you find topics that spark your interest and challenges your way of thinking as you pick up and read through this journal. Enjoy the third installment of the IONA Journal of Economics as we celebrate the accomplishments of our remarkable students.

Cheers,

Forest Kong
President
Vancouver School of Economics Undergraduate Society

Letter from the Editor-in-Chief

Dear Reader,

Thank you so much for picking up, or viewing, the third volume of the IONA Journal of Economics. We are so excited to share the unique and brilliant work of the students, who study here at the Vancouver School of Economics, with you.

The papers within this edition of the Journal have been chosen for their intelligent use of economic theory, their exceptional ability to communicate their unique approaches, and their thoughtful applications to current and important world events. From the economics of refugees, to women's health, the softwood lumber market, online dating, and more, there is something in this Journal to peak the interest of any reader. This is, afterall, representative of our field. Economics is relevant, it is imperative, and it is all-encompassing. The seven published authors did an outstanding job proving it.

The issue of scarcity meant that only seven papers were published this year, but I feel that it is important to note that the journal received a record-breaking number of submissions this year, and each one is worthy of recognition and praise. This is a testament to both the past journals and this year's team. Unquestionably, I had an extraordinary group of people helping me throughout the entire year. To the operations and logistics team who helped promote and design the journal, the editorial team that thoroughly analyzed each sentence within it, to Forest, Pietro, and Wesley from the VSEUS who were constant sources of support and encouragement, and to the staff and faculty at VSE who provided guidance and assistance whenever needed: I thank you. I am so proud of what we have accomplished together.

To the two previous Editor-In-Chiefs, Terralynn Forsyth and Sophia Jit: I am so honoured to be able to follow in the footsteps of such brilliant and empowered women like yourselves.

Now, please: read, learn, digest, and engage with the literature that follows. You will not be disappointed.

Sincerely,

Mariam Nasser
Editor-in-Chief
IONA Journal of Economics Volume III

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I
PAPERS

Economic Recessions and Financial Reform

THE DODD-FRANK WALL STREET REFORM, CONSUMER PROTECTION ACT, AND THE UNITED STATES' SUBPRIME MORTGAGE CRISIS

Taylor Cuming

ECON 490

I. INTRODUCTION

Recent developments in American politics have reopened the debate surrounding financial sector regulation and government policy that was implemented in response to the 2008 global financial crisis. The 2008 fi nancial crisis was the United States' worst financial crisis since the Great Depression, with severe decreases in major economic health indicators and the occurrence of unthinkable events, such as the collapse of U.S. banking giant Lehman Brothers and the 700 billion USD bailout for the financial and housing markets' mortgage-backed securities. In 2010, President Obama responded to excessive risk-taking within the financial sector by signing into law the Dodd-Frank Wall Street Reform and Consumer Protection Act. Dodd-Frank placed stringent regulations on the financial sector with the stated aim of protecting American taxpayers from future bailouts, and abusive business practices. At over 2,200 pages of regulation, Dodd-Frank is by far the most comprehensive and complex government response to financial crisis. Recently elected President Donald Trump stated prior to stepping into the oval office that he would work to dismantle Dodd-Frank, as he believes the bill causes undue pressure on U.S. businesses, therefore, harms the U.S. economy. In the first month of Trump's presidency, the first piece of Dodd-Frank regulation was removed, namely the Energy Disclosure Rule. This rule required energy companies to publicly state the amount of taxes, fees, and payments made to foreign governments. It is of utmost importance to prevent yet another global financial crisis by measuring the effectiveness of the bill to shape and reshape future regulations.

This paper employs a difference-in-differences (DID) approach to analyze Dodd-Frank's effect on the price growth of securities, thereby evaluating its effectiveness at reducing the abusive behaviour of financial firms. The DID approach will examine securities in the financial sector relative to securities in sectors which were both (1) not targeted directly by the Act and (2) are less affected indirectly by the new regulatory changes. Price growth denoted as the growth rate of monthly closing prices was chosen as the measure of interest. The assumption behind this measure is that at the most superficial level the price of a security can be said to change based on simple supply and demand analysis with increased/decreased demand driving the increase/decrease in price. However, investors' attitudes about the individual security as well as their opinions about the future cash flows of the company also heavily influence market prices. This paper will expand upon the existing body of literature by testing the effect of the Dodd-Frank Act on the price growth of securities in the financial sector after controlling for macro-economic effects, sector specific effect and company specific risk factors.

Dodd-Frank added significant increases in regulation, transparency, compliance, constraints and monitoring focused on the financial sector. Therefore, if Dodd-Frank was successful at reducing abusive profit seeking behavior of financial firms, then securities in the financial sector should see a reduction in price growth after the passing of Dodd-Frank relative to sectors not targeted by the Act; namely because they are subject to far more operating and financing constraints, which adversely impacts company growth. A time period of 49 months total pre and post-Dodd Frank will allow for the effect of rolling out regulations to be captured. The time period of June 30th, 2010 to July 15th, 2010 will be removed, as although the public was aware the legislation was likely to be passed, it was not yet passed into law during this time. The structure of this paper is as follows: Section 2 presents a brief overview of the causes and effects of the 2008 financial crisis as well as an overview of the literature, Section 3 describes data measurements, Section 4 explains the methodology behind both the difference-in-differences strategy and the selection of key variables, Section 5 explains the empirical results and discussion, Section 6 tests these results against multiple other tests for robustness, and, finally, Section 7 concludes this paper with a discussion on the study's limitations and its implications for future research.

II. BACKGROUND AND EXISTING LITERATURE

2.1. A Brief Overview of the 2008 Financial Crisis

From 2000 to 2005, the United States housing market experienced a large bubble that was partially fuelled by the sale of subprime mortgages- housing loans which target consumers with poor credit scores who cannot secure conventional mortgages due to their high risk of default. Furthermore, the U.S. financial sector began to capitalize on the housing boom by offering investors collateralized debt obligation (CDO), an asset which pools together many mortgages and separates them into tranches (according to their risk profile) before being sold to investors. Sales of CDOs increased from $30 billion in 2003 to a high of $225 billion in 2006, showing that they were highly popular with investors seeking to capitalize on the housing boom. Unfortunately, the CDOs had incorrectly assigned risk profiles that were often much higher than reported to investors, which caused investors to believe they understood the risk and return of the underlying assets that were held in their CDOs when they were in fact purchasing extremely risky assets (Deng, 2008). In 2006, housing prices began to flatline and 1 out of every 92 households entered into varying stages of foreclosure (RealtyTrac). By February 2007, the financial sector had become aware of the risk associated with mortgage-backed securities, as evidenced by Freddie Mac (Federal Home Loan Mortgage Corporation) unexpectedly refusing to buy mortgage-related securities. In September 2008, banking giant Lehman Brothers filed for Chapter 11 bankruptcy protection and in 2009 the devastation caused by the financial sector's mismanagement was realized with 40,000 layoffs nationwide in a single day in January, Chrysler filing for bankruptcy protection in April, and GM filing for bankruptcy in June. In response to the crisis, the Dodd-Frank Wall Street Reform and Consumer Protection Act was introduced by President Obama in June 2010, before being passed by the House and issued into law in July 2010.

Dodd-Frank aims "to promote the financial stability of the US by improving accountability and transparency in the financial system, to end 'too-big-to-fail,' to protect the American taxpayer by ending bailouts, to protect consumers from abusive financial services practices, and for other purposes" (Dodd-Frank Wall Street Reform and Consumer Protection Act). Dodd-Frank includes 16 major titles and 243 rulemakings, although the following regulations are the most significant for this study: (1) Increased the monitoring and management of overall systematic risk by establishing the Financial Stability Oversight Council (FSOC). The FSOC focuses primarily on large banks, defined hereafter as banks with total consolidated assets over $50 billion USD, as well as other large financial firms that may affect systematic risk, (2) Said large banks and financial firms are now regulated more strictly on their permitted levels of capital, leverage and liquidity, (3) Addressed ending the "too-big-to-fail" risk by requiring banks to submit plans detailing how the bank would efficiently close down in the event of a future bank failure, and (4) Placed restricting regulations on banks, including a significant rule dubbed the modified Volcker Rule, which disallows large banks and financial institutions from proprietary trading if they have access to Federal Reserve funds or deposits insured by the Federal Reserve. Effectively, Dodd-Frank enacted laws that monitored and placed significant regulatory pressure on the financial sector.

2.2. Existing Literature

Years after the passing of Dodd-Frank, there is controversy over whether or not the Act has had a sufficient impact on the financial sector post financial crisis. Akhigbe et al. (2016) examined the Dodd–Frank legislation and risk in the financial services industry to conclude that "discretionary risk taking by financial institutions has declined following the passage of Dodd–Frank," and that this change is most pronounced for the largest institutions, which supports the view that the added regulatory strictness for firms based on total consolidated asset levels was successful. Columbia Law School Professor John C. Coffee Jr. (2011), on the other hand, claims that despite Dodd-Frank's extensive nature, "the political economy of financial regulation ensures that there will be an eventual relaxation of regulatory oversight". Greene (2011) and Prasch (2012) both cite an absence of both explicit rules and comprehensive resolution mechanisms to deal with the failure of large institutions; thus, large banks are still likely to believe that the government will not allow them to fail and will not alter their excessively risky behaviour as a result. In agreement with Greene, Wilmarth (2009) points to the fact that the global financial crisis was largely caused by big banks facing unsustainable losses, totalling over $8 trillion USD between 2007-2012; and thus the fact that they are still permitted to exist at all shows that the main cause of systematic risk was not addressed by the Act. Kim and Muldoon (2015) expand on the findings of Wilmarth by noting the new competitive advantage large banks are given. This competitive advantage makes it so that large banks are now essentially partnered with the US government, so as to be able to borrow more cheaply than other institutions and therefore "will not be allowed to fail." Other sceptics of Dodd-Frank, Simpson (2016) and Nwogugu (2015), found that Dodd-Frank's attempt to address the "too-big-to-fail" issue merely institutionalized the problem by increasing regulatory and compliance costs in the financial services industry. This literature, then, makes it clear that no consensus has been reached as to whether or not the Act was successful in its stated aim. However, a general consensus has been reached in regards to faulting excessive risk taking and abusive financial practices as major causes of the crisis.

III. DATA

This paper uses data from 74 securities listed on the New York Stock Exchange, which was downloaded through Bloomberg. To limit selection bias, securities were selected at random, subject to the following constraints: securities must not have had any missing data points during the sample period, they may not have had an initial public offering (IPO) after the year 2005 (to ensure start-up companies which operate under different risks and have different growth patterns than established companies were excluded), and must still be in business today. Price growth is represented by daily closing price data for each of the 74 different securities across a time period of 49 months. Data for the company specific risk measure was downloaded from Bloomberg in three parts: the country risk premium, the risk-free rate, and the beta of security i in period t for each of the 74 securities across 49 consecutive months. Data for inflation was downloaded from the Federal Reserve Bank of St. Louis' Economic Research Division and was reported monthly using the Consumer Price Index including all items, indexed at the year 2010=1, and was not seasonally adjusted. Data for the Dow Jones Industrial Average was provided by the S&P Dow Jones Indices and was reported in monthly averages. Data for the price of crude oil was provided by Thomson Reuters and downloaded from the U.S. Energy Information Administration (EIA). Monthly averages for West Texas Intermediate (WTI) crude oil spot prices (in US dollars per barrel) were used, as WTI is the most popularly used benchmark for oil prices.

IV. METHODOLOGY

4.1. Difference-in-Differences (DID) Strategy

Past research by Levchenko et al. (2009) utilized a DID strategy to exploit variation in industry characteristics to obtain difference-in-differences estimates for the effects of financial liberalization on growth and risk. Similarly, in an effort to determine the effect of new future trading legislation on spot price volatility, Xie and Mo (2014) employed a DID approach to examine the volatility of stocks before and after the introduction of CSI 300 index futures in Chinese stock exchanges. This paper will utilize the strategy of Levchenko et al. (2009) and the methodology of Xie and Mo (2014) as a starting point for a basic regression model with additional controls to account for macroeconomic stability and the exogenous shock effects of oil price swings.

The DID strategy is used to determine if Dodd-Frank was successful by testing for a difference between the treatment group (the financial sector) and the control group (unaffected sectors) after the passing of the Act. The control group is composed of sectors that were least affected by potential omitted variables and exogenous price shocks such as oil price swings. Securities in healthcare, public utilities (excluding energy and alternative energy related securities), and the consumer non-durables sectors serve as a strong control group because they were not overtly targeted by Dodd-Frank, were not major players in the financial crisis, and are not as directly affected as other sectors by major exogenous shocks. For example, the energy sector is extremely sensitive to oil price swings (see Figure 3), while the industrial sectors (such as the lumber, construction, and manufactured housing sectors, etcetera) and the real estate sectors are extremely sensitive to the effects of mortgage-backed securities specific to the 2008 crisis and the housing bubble bursting. Thus, securities in the healthcare, public utilities, and consumer non-durables sectors will act as a suitable control group. The effect of Dodd-Frank can then be determined through the change (or lack thereof) in the difference between the two groups after the legisla tion was passed. The basic regression model for the DID approach is shown below:

$$PG_{i,t} = \propto + \beta_1\, DF_t + \beta_2\, TREAT_i + \beta_3\, (DF^{*}TREAT)_{i,t} + \varepsilon_i$$

$PG_{(i,t)}$ (price growth) is the natural logarithm of the mean monthly closing prices of security i during period t (i.e. $PG_{(i,t)}$=ln (mean closing price)$_{(i,t)}$). DF_t is a period dummy variable which takes the value of 1 during months post-Dodd-Frank and the value of 0 during months in the pre-Dodd-Frank time period. $TREAT_i$ is an individual dummy variable which takes the value of 1 for securities in the financial sector (treatment group) and the value of 0 otherwise. (DF^* TREAT)$_{(i,t)}$ is an interaction term of DF_t and $TREAT_i$ which equals 1 for securities in the financial sector during the time period post-Dodd-Frank and 0 otherwise. The coefficient on the interaction term (DF^* TREAT$_{(i,t)}$) is the coefficient of primary interest. β_3 is expected to be negative if the Dodd-Frank regulations were successful in their stated aim of sufficiently regulating the financial sector during the examined time period; this result would be interpreted as Dodd-Frank causing a reduction in stock price growth among securities in the financial sector. If β_3 is found to be positive, then the result supports the claim made by many critics of the Act that Dodd-Frank is ineffective at properly regulating the financial sector, and that mismanagement is still too common in the financial sector.

However, the estimates given by the basic regression model have the potential for errors due to the impact of company specific risk factors, macroeconomic stability and overall market trends on the price growth of individual securities. To account for the issues above, a modified version of the basic regression model is employed as:

$$PG_{i,t} = \propto + \beta_1 DF_t + \beta_2 TREAT_i + \beta_3 (DF^{*}TREAT)_{i,t} + \beta_4 RISKP_{i,t} + \beta_5 ln(INFL_t) + \beta_6 lnDJIA_t + \beta_7 lnOILP_t + \varepsilon_i$$

Where $RISKP_{(i,t)}$ is the equity risk premium of security i in period t such that

$RISKP_{(i,t)}$=(U.S.Risk $Premium_t$-Risk Free $Rate_t$)($Beta_{(i,t)}$)

Where the U.S. risk premium is the premium paid to investors according to the risk associated with American investments, the risk free rate is measured by the 10 year U.S. treasury bond, and the beta of security i is the measure of risk of that security in comparison to the market as a whole. ln($INFL_t$) is the natural logarithm of the consumer price index (CPI) in period t, ln($DJIA_t$) is the natural logarithm of the Dow Jones Industrial Average, and ln($OILP_t$) is the natural logarithm of the monthly averages for WTI crude oil prices.

4.2. Methodology behind the Selection of Variables

The dependent variable in this study is the growth in closing prices of securities, expressed as $PG_{(i,t)}$. To accept the methodology behind using price growth as the dependent variable, it must be assumed that government regulations which target the financial sector have a definite impact; otherwise, there would be no argument for causation in the regression model between Dodd-Frank and the price growth of securities. Some financial economists, however, subscribe to Eugene Fama's Efficient-Market Hypothesis (EMH) and the theory that stock prices instantly reflect all available information, including insider information which is not publicly available (Fama, 1970). This school of thought must be mentioned because its theory refutes the cause and effect relationship assumption that was made above, instead implying that increased transparency will not change securities' prices, as insider information was already built into the stock price. In response to the EMH, we need not look any further than the 2008 financial crisis, which was caused by hidden insider information that was known only to financial firms which distorted the price of CDOs. Additionally, the real estate bubble in the same time period saw prices that were inflated by overconfidence in ever-rising real estate prices, representing another example of imperfect information in the financial sector. To highlight this, the former chairman of the Federal Reserve, Paul Volcker, stated that it is “clear that among the causes of the recent financial crisis was an unjustified faith in rational expectations and market efficiencies” (2012). The main limitation to using price growth over alternative measures such as price to earnings (P/E) ratios or price to book (P/B) values is that some securities or sectors may have inherently higher rates of price growth than others for known or unknown reasons. For example, the growth in the share price of technology stocks during the late 90’s and early 2000s far superseded any other sector due to the technology bubble, not due to the fundamentals of these companies.

This study favoured broad economic measures as explanatory variables, since the aim of the study was to examine general, sector-wide effects and not company specific effects. The rationale behind the measure constructed for risk premium has to do with investors requiring compensation in return for taking on risk, by holding stocks over risk-free investments such as government bonds and/or other foreign investment vehicles. Depending on the individual company and market conditions, investors will require more or less compensation in return for purchasing the security, which determines part of the demand for a stock and the potential growth rate of the stock. This relationship is demonstrated through models such as the Free Cash Flow to Equity (FCFE) model:

$$E_0 = \sum_{i=1}^{N} \frac{FCFE_i}{(1+K_E)^i}$$

Where E_o is the estimated stock price, $FCFE_i$ is the amount of free cash flow available to the company in period i and K_E is the cost of equity for the company. As the equity risk premium increases, investors require more compensation in return for purchasing the stock and the cost of equity K_E increases. This discounts the amount of free cash flow available to the company and reduces the estimated stock price in any given time period. Thus, if constructed correctly, the coefficient on company specific risk premium is expected to be negative, as an increase in the riskiness of a security should decrease the demand and price growth of that security over time.
Controlling for inflationary effects on price growth of securities is necessary for two reasons. Firstly, historically inflation has had a strong relationship with stock price valuations. When investors at-

tempt to determine a correct valuation for a company's stock price it is necessary to calculate the present value of the future streams of cash flows they expect to receive from the investment. One of the most popular methods of valuation is the discounted cash flows (DCF) model, which can be used to calculate the expected real cash amount of the investment as shown below:

$$DCF_n = \frac{CF_n^{real}}{(1+r_n^{real})^n}, \text{ where } CF_n^{real} = \frac{CF_n^{nominal}}{(1+i)^n}$$

Where DCFn is the discounted future cash flows for period n, CF_n^{real} is the real cash flow in period n, r_n^{real} is the real discount rate for period n, and i is the inflation rate. To arrive at the present value, the DCF values are then summed with the inclusion of the real terminal value (TV) of the sale of the security:

$$PV = DCF_1 + DCF_2 + \ldots + DCF_n + TV$$

Higher inflation rates decrease discounted cash flows, which decrease the valuation multiple and in turn lowers both demand by investors for the stock and the security's price growth. Similarly, low inflation rates typically lead to high valuation multiples, which increases investors' demand for stocks and leads to high price growth.

Secondly, the impact of an increase in inflation rates has been shown to cause a decrease in price-to-earnings ratios of securities (Feldstein, 1983). The price-to-earnings ratio is another widely used price multiple by investors to signal if a company's stock price is over or undervalued, or has a high price-to-earnings ratios, signalling high growth stocks. Thus, the coefficient on inflation must be negative, as an increase in inflation rates decrease the price growth of stocks in the model.

To account for the effect of the growth rate of the overall market on the price growth of individual securities, the logarithm of the Dow Jones Industrial Average (DJIA) is used in the regression model. The Dow is a price-weighted index composed of 30 blue-chip companies from multiple sectors that is used as a proxy measure for general market health by investors. The coefficient on the Dow variable is expected to be positive, as an increase in overall market growth trends should have a positive effect on individual stocks.

Lastly, the price of oil is often thought to have some effect on the stock market, but only varying levels of positive correlation have been found. However, oil is traded in USD which means the strength of the American dollar has a direct impact on relative crude oil prices. Furthermore, as oil is a globally traded commodity, and the US economy is to some degree reliant on oil, a drastic price change may serve as an exogenous shock and impact stock closing prices over time. Thus, the price of WTI crude oil has been included as an additional control in the regression model to account for the possible effects on the price growth of securities.

V. RESULTS AND DISCUSSION

5.1. Difference-in-Differences Results on the Effects of Dodd-Frank on Price Growth

A table of summary statistics for all key variables used in this study is shown in Table 1. On average, security prices grew approximately 3.4 percent, reflecting the trend of the entire market during the observed time period. For example, when indexed at 100, at the start of the time period (June 2008), the S&P 500 (500 leading companies in leading industries, covering 75% of equities) had a value of 102 at the end of May 2012 and 106 at the end of June 2012 (S&P Dow Jones Indices LLC).

The table for the DID estimation results for the sample period of 49 months from June 2008 to June 2012 (with data from June 30, 2010 to July 21, 2010 removed) are shown in Table 2. Both the basic regression model and the modified regression model with additional controls are tested in stages to ensure the validity of the results. The coefficient on the interaction dummy variable DF*TREAT (which equals 1 for financial sector securities in the post-Dodd-Frank period and 0 otherwise) was, from the outset, the coefficient of interest for this study. The coefficient is negative and stable across all five models, varying in statistical significance from a p-value of 0.056 in the basic regression model (1) to significance at the 1% level in models (3) through (5). The negative coefficient on the interaction dummy variable supports the claim that the Dodd-Frank Act was indeed successful in its stated aim of curtailing the reckless behaviour of financial firms. The regression results suggest that the price growth of these financial firms was negatively impacted by the passing of Dodd-Frank to the tune of a -13% impact on price growth for securities in the financial sector after the passing of the Act. The mean price growth for the study was 3.44%. Thus, the magnitude of a change of 13% on price growth is substantial.

To illustrate, take the example of Goldman Sachs. At the time of this paper, Goldman Sachs is valued at over $90 billion. Goldman's share price was trading at $150.82 per share at the beginning of the study (June 2008) and closed at $95.87 per share at the end of the 49 months, a mere 63% of its original value. According to the results of this study, without the passing of Dodd-Frank, it is possible that Goldman's price growth could have decreased by 13% less; giving Goldman a hypothetical closing price of $114 per share had the Act never been passed. With Goldman's approximately 400 million shares outstanding, the firm would have been worth a staggering $7.25 billion more at the end of the 49 months without the Dodd-Frank intervention; quite a substantial difference.

The coefficients on all added controls are as expected. The coefficient on risk premium is negative and is accurately measured as the results show consistent statistical significance at the 1% level. Increasing risk premium by 1 unit led to a decrease in price growth between 3.8% and 4.6%, which is as expected due to the increased compensation investors require to buy more risky securities. The coefficient on the Dow Jones variable is positive and consistently statistically significant at the 1% level, which is expected as market sentiments often drive the price growth of individual securities. A 1% increase in the growth of the Dow results in approximately a 0.7% increase in price growth for securities in the sample group. The coefficient on inflation is negative as expected, although only significant at the 10% level, and as such the result may not be as accurate as one might like. At this significance level, the results state a 1% change in the inflation index, resulting in a 2.5% decrease in price growth for securities. As previously stated, correlations have been found between oil prices and stock market trends, but there has been little empirical evidence showing a causal relationship between the two. Unsurprisingly, then, is that the coefficient on oil price was found to be positive, but was not statistically significant at any level and little weight should be given to its predictive power in this model.

VI. ROBUSTNESS CHECKS

6.1. Testing for the Common Trends/Parallel Paths Assumption with a Placebo DID

The first concern presented by the model is related to the nature of the DID methodology itself; namely, accepting the common trend or parallel paths assumption. With this DID strategy, it must be assumed that without the Dodd-Frank Act, the trend in price growth between the financial firms and the firms in the control group would have been more or less the same. A placebo DID test is helpful as a falsification check for the common trend assumption. Thus, to test for this, the pre-Dodd-Frank time period was divided into two separate time periods with the post-Dodd-Frank time period being excluded from this regression model. PTIME (placebo-time) is a dummy time variable that takes the value of 0 for the first half of the original pre-Dodd-Frank time period and takes the value of 1 for the latter half of the original pre-Dodd-Frank time period. PTIME*TREAT is an interaction term that takes the value of 1 for financial securities in the second half of the pre-Dodd-Frank time period and equals 0 otherwise. If the common trend assumption is to be upheld there should be no effect from the new interaction dummy variable, PTIME*TREAT, on price growth. The results of this test are shown in Table 3. The coefficient on the placebo interaction term is positive across all models, but is not significant, nor close to being significant even at the 10% level in any of the 5 models, even with robust standard errors. For example, the 95% confidence interval on the placebo interaction term in model (1) ranges from -0.054 to 0.163; it is not clear if the effect will be strictly positive or negative. Similarly, in the full regression model (5), the 95% confidence interval for the interaction term is -0.020 to 0.196. Although the result from the 95% confidence interval is mostly positive this result is likely capturing the natural business cycle as the National Bureau of Economic Research (NBER) reported that the recession officially began in December of 2007 and ended in June of 2009 (the exact middle date of the placebo time period), at which time an economic expansion began (NBER, 2010). Thus, there is likely no definitive effect and no predictive power on the interaction term for the placebo DID and the common trends assumption is sufficiently satisfied.

6.2. Testing for Multicollinearity between Predictors

Multicollinearity is a problem for any regression as it can increase the variance of the regression coefficients, which makes them difficult to interpret. Testing for the variance inflation factor (VIF) is one method that can be used to test for multicollinearity between predictors. A VIF score of 1 equals no correlation, a VIF score between 1 and 5 equals moderate correlation and VIF scores that are substantially larger than 5 signal high correlation and cause for concern. Results of the test for VIFs are reported in Table 4. The largest VIF score was on the Dow Jones explanatory variable with a VIF of 7.44. As the Dow is an index and represents the overall market trend, this relatively higher VIF is to be expected, as the securities used in the sample are part of the same market the Dow tracks. Thus, the relatively higher VIF score on the Dow variable is not a major methodological concern. All other explanatory variables have reasonably low VIF scores with five of seven predictors scoring below 5. The mean VIF score was 3.94, which is an indication that the coefficients can be interpreted accurately without glaring concerns.

6.3. Testing for the Impact of the Strictness of Regulation on Price Growth

The third concern with the results of this study have to do with the distinctions made in the Act between both the strictness and number of regulations banks and large financial institutions must adhere to, according to their total consolidated assets. Section 165(a) of the Dodd-Frank Act states the Fed will have "enhanced supervision and prudential standards" for financial firms and banks with more than $50 billion total consolidated assets. These standards will be stronger than those applied to smaller firms and will increase in strength with each company's individual level of riskiness. The most significant difference for banks and financial firms above the $50 billion consolidated asset threshold is the requirement for an independent risk committee to be established, which reports directly to the board of directors (Dodd-Frank Wall Street Reform and Consumer Protection Act). Firms below the $50 billion threshold are not subject to this third-party risk committee requirement. If the methodology behind this study is correct, such that increased regulations from Dodd-Frank successfully curtailed abusive profit seeking behaviour and decreased the price growth of financial firms, then the effects of regulation on price growth should differ in strength depending on the level of regulatory strictness and quantity of regulations firms must adhere to. Table 5 presents the results of the first robustness test for differences in the effect of Dodd-Frank on financial firms according to their total consolidated asset level with financial firms below the $50 billion threshold excluded from the sample. >50B is a dummy variable which takes the value of 1 for financial firms above the $50 billion threshold and the value of 0 otherwise. DF*>50B is an interaction dummy variable which takes the value of 1 for financial firms above the $50 billion threshold in the time period post-Dodd-Frank and 0 otherwise. As expected, for financial firms above the $50 billion threshold the effects of Dodd-Frank are more pronounced. The financial firms which must adhere to more stringent regulations post-Dodd-Frank saw a 10% further decrease in their price growth (model (1)) and an approximately 15% further decrease in model (5) compared to the original regression results which included all firms regardless of asset level. The results are statistically significant at the 1% level across all models and are consistently stable, which supports the view that the Dodd-Frank Act was successful in meeting its stated aim.

Financial firms with over $700B in total consolidated assets are subject to the strictest regulations, including being required to report to the Large Institution Supervision Coordination Committee (LISCC), as well as be subjected to additional capital and leverage restraints and surcharges (among others). Table 6 presents the results of the second robustness test for differences in the effect of Dodd-Frank on financial firms according to their total consolidated asset levels, including only those financial firms with greater than $700 billion total consolidated assets. >700B is a dummy variable which takes the value of 1 for financial firms above the $700 billion threshold and the value of 0 otherwise. DF*>700B is an interaction dummy variable which takes the value of 1 for financial firms above the $700 billion threshold in the time period post-Dodd-Frank and 0 otherwise. As expected, the effects of the Dodd-Frank Act are more pronounced for financial firms subject to the highest level of regulatory strictness. Financial firms which must adhere to highest level of stringent regulations post-Dodd-Frank saw a 20% further decrease in their price growth in model (1) and an approximately 30% further decrease in model (5) compared to the original regression results, which included all firms regardless of asset level. The results are statistically significant at the 1% level across all models and are relatively stable. It can thus be concluded that increased regulation unambiguously reduced abusive profit seeking behaviour and financial sector mismanagement as measured by a reduction in price growth.

VII. CONCLUSION, STUDY LIMITATIONS AND IMPLICATIONS FOR FUTURE RESEARCH

The model employed in this study measured the effects of the Dodd-Frank Act on the price growth of securities in the financial sector and sectors that were both (1) not targeted directly by the Act and (2) are less affected directly by the new regulatory changes. A decrease in the price growth of securities targeted by the Act in the financial sector was found after the legislation was introduced and determined to increase in size according to the strictness of regulation each company was subject to. All four controlling variables have results consistent with both financial theory and the literature: risk and inflation had negative impacts on price growth and both oil price and the overall market trend had positive impacts. All except oil price controls are highly significant, with all controls' standard errors consistent and stable in both the basic and modified regression model.

This study was limited by time and logistical constraints, as many explanatory variables that were laborious and time consuming to construct were passed over in the construction of a unique dataset that favoured broader measures. For example, the price growth of specific securities is likely affected by numerous other factors, including, but not limited to: their comparative strength in relation to similar companies (determining similarity requires lengthy valuations of each firm), the availability of substitutes for their stock (cash savings, bonds, derivatives, commodities, futures, physical real estate and the substitutes of all foreign investment vehicles listed on other exchanges), the liquidity of the stock (i.e. very low daily trading volume signals a less liquid security), quarterly and annual earnings reports, stock splits and reverse splits, mergers and buyouts, as well as good or bad publicity in the press. Future studies would benefit from the inclusion of one or more of the above mentioned factors as additional explanatory variables, as their exclusion may have inflated the magnitude of the explanatory variables' effects. Another limitation to this study is in regards to the nature of legislative responses to financial crises. Often multiple legislative changes are made with fervour, which makes it difficult to deduce the impact of specific law makings. As mentioned previously, Dodd-Frank includes 16 major titles and 243 rulemakings made active on a rolling schedule. A time period sufficiently large must be used to allow for the effects of the Act to take full effect, while the time period must be sufficiently small as to ensure that no other legislation or major changes takes place. 49 total months of data were used in an attempt to allow for the full effects of the rolling legislation schedule to take place, while still omitting as many other legislative and other exogenous shock effects, on price growth, as possible. Two legislative changes that were unable to be removed from the time period were the Emergency Economic Stabilization Act of 2008 and multiple major bailouts for large U.S. firms; these may be possible omitted variables and can potentially cause possible model misspecification as controls were unable to be employed in the regression model for the impact of these changes. Due to the vast amount of over 2,400 securities listed on the NYSE, the inclusion of 74 securities may have limitations in the degree to which the results can suggest something about the overall market. Future studies would benefit from the inclusion of as many securities as possible as well as additional controls to capture the effects of other legislations and bailouts.

In conclusion, the emerging literature on the success of Dodd-Frank is split. This model provides support for the hypothesis that the Act was indeed successful in reducing abusive profit seeking behaviors of financial firms as their price growth was substantially reduced directly after the passing of the Act. As securities in the control group did not suffer the same reduction in price growth after the change in legislation it is unlikely that these effects are reminiscent of the natural business cycle. The importance of regulation to the healthy functioning of an economy is not in doubt. Regulation can provide incentives for abusive profit seeking behavior by firms at the expense of the consumer or can provide an environment where both the producers and consumers benefit. Regulation must walk a fine line between protecting consumers and allowing firms to be locally and globally competitive. The results suggest that Dodd-Frank was successful in toeing this middle line. As such, repealing the Act in its entirety, without legislation to replace, it may prove risky for the future of a healthy functioning U.S. economy.

Getting Splinters

MEASURING THE IMPACT OF CANADIAN SOFTWOOD LUMBER IMPORTS ON AMERICAN LUMBER COMPANIES

Jacob Cutts

ECON 330

ABSTRACT

This paper investigates the impact of Canadian imports of softwood lumber into the United States. This question is highly salient to ongoing debates on the regulatory frameworks that should govern cross-border trade in lumber, but has mostly been neglected by policymakers. I build a theoretical model to explain the expected behaviour of key metrics for the health of American lumber companies, then use a linear regression model to test the soundness of the theory. I find that changes in the quantity of Canadian imports of softwood lumber to the United States have no measurable impact on the health of American lumber firms, suggesting that their claims of severe harm at the hands of Canadian importers should be investigated more closely.

I. INTRODUCTION

In the midst of the 2006 negotiations over a new softwood lumber agreement between the United States and Canada, the US Senate held a hearing entitled "[The] Economic Impacts of the Canadian Softwood Lumber Dispute on U.S. Industries." One of the key witnesses was Steve Swanson, the owner of a private softwood lumber company. In his testimony, Mr. Swanson effectively summarized the softwood lumber dispute in three key points, which he described as three facts. First, Canada subsidises their lumber production; second, those subsidies hurt the American economy; third, the subsidies are a violation of US trade law (United States Senate, 2006).

Swanson's first and third points have been discussed heavily by the legal community, since they form the basis of the many legal disputes surrounding the North American trade in softwood lumber. However, in all this debate, Swanson's second point is often left by the wayside – it is taken as a given that Canadian imports have a meaningful negative impact on the health of American forestry companies. In this paper, I will investigate Swanson's second claim and seek to answer the question: How have imports of Canadian softwood lumber into the United States impacted American forestry companies?

I will begin my investigation by laying out the background of this issue and explaining some of the key points and terms relevant to this issue (Section I-A). I will then conduct a brief overview of the academic literature on this topic, in an effort to place this work in the context of the current state of academic discourse (Section I-B). Next, I will outline the data that I have collected to answer this question, give an overview of the methodology used to process it, and provide a summary of the data (Section II). In Section III, I will revisit my research question, explain the theoretical underpinnings of my paper, and build an empirical model that seeks to answer my research question. Next, I will present the results of my investigation and conduct heterogeneity analysis to determine the source of variations within the regressions that I consider (Section IV). Finally, I will discuss some of the challenges faced in the investigation of this question, and how they could potentially be overcome in the future (Section V-VI).

To answer my research question, I created a linear regression model using several control variables along with the independent variable – Canadian imports of softwood lumber – to predict the dependent variables – the stock price, revenue, and income of American lumber firms. As discussed in Results (Section IV) and Discussion (Section V), the regressions were not significant, and did not show a measurable relationship between Canadian lumber imports and the health of American lumber companies. Explanations and implications of this are discussed in Section V.

II. BACKGROUND

Canada and the United States have engaged in a series of recurring trade disputes over softwood lumber since the early 1980s. Over the intervening 35 years, softwood lumber has remained one of the most problematic parts of the Canada-US trading relationship. This section will introduce relevant terminology, provide historical and current context on the North American lumber market, and review the state of the literature on this subject.

A. Context

Terminology.—Before discussing the history of softwood lumber disputes, it is important to understand what exactly softwood lumber is. Softwood refers to the wood from coniferous trees (e.g., fir or pine), and lumber refers to raw wood that has been sawn into boards[1]. In 2016, softwood lumber accounted for approximately 85% of all lumber produced, and is the main type of lumber used in construction (UNECE, 2017).

To understand the historical context of this issue, it is also important to elucidate some terms that are relevant to Canada-US trade disputes. First, the central issue of the disputes: stumpage fees. Stumpage fees are fees that companies pay to harvest timber from land. In Canada, the vast majority of timber is harvested from Crown lands, where stumpage fees are fixed and often lower than the market rate. In the United States, the majority of land used for forestry is private, thus stumpage fees are mostly set by market forces (A & A Customs Brokers, 2015).

Other relevant terms are the two types of duties that the United States can impose as trade remedies to illegal subsidies. Though anti-dumping measures and countervailing duties are similar, they differ in their details. Anti-dumping measures are targeted at individual companies that sell a product below the fair market rate, whereas countervailing duties are enacted when a foreign government is perceived to have unfairly subsidized an industry. In both cases, the duties imposed are theoretically supposed to be set so as to cancel out the impact of the subsidies (U.S. Customs and Border Protection, 2017).

Market Context.—Canada accounts for 28% of world exports of softwood lumber, while the United States absorbs 22% of world imports (United Nations, 2016). Canada and the United States combine to consume approximately 100 million cubic meters of softwood lumber every year, and are broadly trade neutral with the rest of the world in regards to softwood lumber (see Table 1). The largest driver of North American consumption is US housing starts, and 83% of consumption on the continent is in the United States (UNECE, 2017). Despite this disparity in consumption, production is roughly equal: Canada produces 46% of the lumber in North America to the United States' 54%. The unsurprising result of this disparity is that Canada exports the majority (78%) of its surplus production to the United States. Canadian lumber accounts for 96% of total US imports, and approximately one third of all US consumption of softwood lumber. Thus, Canadian lumber exports to the United States are substantial and irreplaceable[2].

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1. It may be valuable to note that softwood lumber is not necessarily softer than hardwood, the term comes exclusively from the type of tree, not the wood itself (UNECE, 2017).
2. Canada exports approximately 25.5 million m^3 of softwood to the United States – no other country exports at that volume (UNECE, 2017).

TABLE 1— SAWN SOFTWOOD BALANCE, NORTH AMERICA, 2015-2017 (THOUSAND M^3)

	2015	2016	2017f	Change (%) 2015-2016
Production	99,153	103,788	102,467	4.7
Imports	24,011	29,498	29,511	22.9
Exports	32,517	35,429	34,153	9.0
Apparent Consumption	90,648	97,848	97,825	8.0

Notes: 2017 figure is a forecast from the UN Committee on Forests and the Forest Industry. Source: Table is from UNECE Forest Products Annual Market Review 2016-2017, p. 48 (UNECE 2017).

A unique and significant trait of the North American softwood lumber market is its fragmentation. Of all companies in the sector, 87% operate only one facility, and a further third of them have less than five employees (IBISWorld, 2017). Overall, only one fifth of all revenues are accounted for by the top four companies, and when compared to the concentration in other primary industries, the fragmentation of the softwood industry becomes apparent. In the copper mining industry, for example, the top four companies account for 73% of all revenue, more than three times that in the softwood lumber industry (IBISWorld, 2017).

In addition to its fragmentation, the vast majority of the US softwood industry is private. In fact, of the top twelve US companies by softwood production, only two (#1 Weyerhaeuser and #9 Potlatch) are public, accounting for only around 13% of US production (The Sawmill Database, 2016). Many of the private firms are historically family owned, though some have privatized in recent years – the second largest producer, Georgia Pacific, was public before being acquired by Koch Industries in 2005 and being privatized (Berman & Terhune, 2005).

Historical Context.—The current series of disputes began in 1982, when US sawmill operators petitioned the US Department of Commerce to impose countervailing duties (CVDs) on the Canadian softwood industry for its stumpage fees. In 1983, the Department of Commerce found that the stumpage fees benefitted numerous industries, not just lumber manufacturers, and thus were ineligible for countervailing duties (Charron, 2005). In 1986, US industry groups made minor changes to their petition and resubmitted it. This time, the Department of Commerce found that Canada subsidized its lumber exporters the equivalent of 15% of the price. In response to this finding, Canada signed a memorandum of understanding (MOU) with the United States that they would impose a 15% duty on the export of softwood lumber to the United States (Charron, 2005).

In 1991, Canada terminated the MOU. In response, the United States imposed CVDs on Canadian lumber imports. Canada appealed under Canada-US Free Trade Agreement, and three separate panels found in favour of Canada. However, the United States refused to bow to pressure to return the duties it had collected, eventually forcing Canada to acquiesce to another five-year MOU, the Softwood Lumber Agreement (SLA). The SLA was signed in 1996; in it, Canada agreed to impose a tax on national production over a certain limit, and the US agreed to return the duties collected from 1991 to 1996. The SLA lasted until 2001, when it expired (Charron, 2005).

The fourth cycle of lumber disputes began in 2001, when the US lumber industry requested CVDs as well as anti-dumping duties against Canadian firms. The dispute remained unresolved until 2006, when another SLA was signed. That SLA included an agreement from the United States to refund the duties that had been levied over previous years, in exchange for a complex set of quotas, tariffs, and export taxes. The SLA was renewed in 2012, and expired in October 2015 (Payton, 2012).

Figure 1 shows the trend of imports of Canadian softwood lumber to the United States from 1988-2017 (more details about this data will be discussed in Section II). The graph displays a notable seasonality in the data due to the typical trend of construction demand in the northern hemisphere: construction expands in the summer and contracts in the winter (see Additional Figure 5 in Appendix B). However, other than that seasonality, the graph is perhaps most notable for its stability. After a period of growth from 1988-1995, the data is relatively stable for a decade, before a small uptick in 2007, followed by a steep slide following the bursting of the US housing bubble in 2007. Finally, there has been a stable increase in trade since 2009.

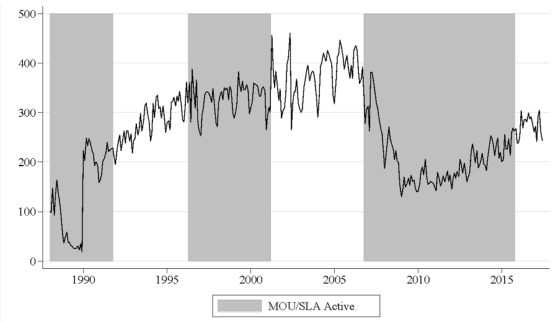


FIGURE 1. IMPORTS OF CANADIAN SOFTWOOD LUMBER TO THE UNITED STATES

Notes: Monthly and indexed, January 1988 = 100. Original units are m3 of lumber

Current Situation.—After the SLA expired in 2015, Canadian firms gained unrestricted access to the US market, and exports increased by 14% from 2015 to 2016 (UNECE, 2017). A moratorium on trade action lasted until October 2016, after which the US Lumber Coalition filed CVD and anti-dumping claims against Canada (Random Lengths, 2017). In April 2017, the Commerce Department made its interim decision on CVDs and agreed to various duties averaging 20%, to which a 7% anti-dumping duty was added in June. The Commerce Department adjusted these combined duties to around 21% in November 2017, with the decision upheld by the US International Trade Commission in December 2017 (BBC News, 2017). In April 2018, the World Trade Organization decided to officially review the American duties under its dispute settlement framework (CBC News, 2018).

B. Related Literature

The issue of the economic impacts of North American softwood lumber trade has not been extensively studied, particularly not in recent years. Even so, in a regulatory environment that changes frequently, papers rapidly become irrelevant. A 2005 thesis by Zhang (2005) at the University of Calgary considered the impacts of softwood lumber trade regimes on the welfare of Canadian lumber producers, finding that the system of quotas and tariffs set out the in the 1996 SLA was optimal for Canadian producers, over any other form of trade management. Another University of Calgary graduate, Ryan Scholefield, examined the softwood lumber disputes and concluded that "managed trade agreements are rarely favorable to all parties involved ... [but] through careful identification of priorities, potential disruptions can be minimized" (2010). Like Scholefield, the majority of recent papers in the field have focused on the time surrounding the disputes, including a paper titled "Productivity and Trade during the Softwood Lumber Dispute" by Nagubadi, Thompson, and Zhang (2009). However, none seem to have approached the topic from a long-term point of view, as I will do in this paper.

III. DATA

For this paper, I collected data from six separate sources and processed them using various methods before beginning my modelling. This section will outline the sources of my data, describe the methodology I used to process the data, and will also explain and show the patterns and trends in the data that I collected.

A. Sources

The Canadian International Merchandise Trade (CIMT) database was the key data source for the variable of interest in my paper: imports of Canadian lumber to the United States. The CIMT database includes three key axes that were essential to my paper. Firstly, it allowed breakdowns of exports using the Harmonized System (HS) of classification, down to the HS6 level. For example, in this paper I wanted to consider specifically the trade of softwood lumber. Using the HS codes, I was able to drill down all the way to HS440710, "Lumber, coniferous (softwood), of a thickness exceeding 6 mm" (Statistics Canada, 2017). The second important axis was time: the CIMT database included monthly data, beginning in January 1988. Monthly data was important in order to maximize the number of observations, and thus improve the soundness of statistical analysis. The final important axis contained within the CIMT database was state-by-state data, with monthly export data to each of the 50 states. The importance of this will be described further in Section III. All CIMT data is available in terms of quantity (in the case of softwood, m3) and value (CAD).

Next, I collected information on the location of the operations of the three companies I considered (Weyerhaeuser, Potlatch Corporation, and United Forest Products, Inc.)[3]. Using the location pages of the respective companies, I recorded their presence in each of the states using a dummy variable. I also collected quarterly data on revenue and net income from ycharts.com, a comprehensive database of historical financial information. The timespan of this information varied between the companies, as I will discuss in Subsection C of this section.

I collected several sets of financial market data for this paper: stock data for the three companies (WY, PCH, UFPI), as well as index performance (S&P 500) and the CAD/USD exchange rate (USDCAD). All of this data was collected as daily close data from Google Finance, through Google Sheets' GOOGLEFINANCE function. The time spans of these data sets also varied, as well be discussed in Subsection C of this section.

Finally, I collected economic controls data from two other sources. I collected data on the price of softwood lumber in the United States from a dataset available from the St. Louis Federal Reserve. This dataset included monthly data on a wide range of commodities from 1980-2017. In addition, I collected data on housing starts in the United States from the US Census Bureau, which records monthly housing starts going back to 1959.

3. United Forest Products, Inc. will be referred to as UFPI.

B. Processing

General Processing.—I downloaded the CIMT data from 1988-2017 and merged the data into a single Stata data file. I then selected data for HS440710, specifically the quantity values, and separated out the state-by-state data. I was then left with a data file with 354 months (January 1988 – June 2017) against 50 states. I also required quarterly data for my paper, so I used Stata's collapse function to collect mean data for each quarter, and was left with 118 quarters (1988 Q1 – 2017 Q2) against 50 states. The purpose of the quarterly data will be explained more fully in Section III. I decided to use the mean for each quarter instead of the sum, because it allows for more direct comparisons between my monthly and quarterly models, since the scales are the same.

Company location data required no manipulation, and was stored as a Stata data file with 50 states against three companies. Different companies began reporting their financial information in different years, with Weyerhaeuser and Potlatch beginning before 1988, and UFPI starting in 1993.

For financial market data, the data was converted from daily to monthly formats using Stata's collapse function using means; the same process was used to convert the data from monthly to quarterly. As a result, I was left with data from five different market variables (WY, PCH, UFPI, S&P 500, USDCAD), with beginnings ranging from 1988 to 2010, and all ending in June 2017 (a maximum of 354 months). Finally, the softwood price and housing starts data required minimal preparation, only a conversion to quarterly, using the methods mentioned above.

The datasets were combined into two main files: a monthly dataset spanning 354 months, and a quarterly dataset covering 118 months. There were gaps in the dataset (e.g., UFPI's financial information was missing prior to 1993). The company location was not transferred into the combined dataset, and was left as a separate dataset. Otherwise, the dataset included the data from the CIMT for 50 separate variables, five separate market variables, the two economic control variables, and finally the stock data (for the monthly dataset) and the financial data (for the quarterly dataset). The next step was splitting the data by company. From the main combined datasets, monthly and quarterly sets of data for each company was generated. Then, the company location data was used to drop all states that the company did not operate in.

Differencing and Indexing.—In addition to the raw data, each variable was processed in three separate ways. First, data was differenced on a period-over-period basis (i.e. month-over-month or quarter-over-quarter) using percentage values. The period-over-period differencing was conducted to help remove long term trends from the data, since much of the data experienced long term trends that would have overwhelmed any other results (this will be discussed further in Subsection C of this section). I chose to use percentage changes instead of raw changes to improve the comparability between different variables. Similarly, I prepared data that was differenced on year-over-year basis. This was created to counteract some seasonality in the data, especially in the quarterly data.

Finally, I created indexed variables, to allow for greater comparison between the different variables. Indexed data was used heavily for graphical representations of the data, as will be displayed in Subsection C of this section. The indexes took a base year, usually the first year of the relevant dataset, and set it to equal 100. Therefore, base years depend on the availability of data, and vary from dataset to dataset.

C. Key Variables

As mentioned in Subsection A of this section, the independent variable of this experiment was the import of Canadian softwood lumber to the United States, as recorded in the CIMT database. The long-term trend of this data was displayed in Figure 1. There are nine dependent variables: stock price, quarterly revenue, and quarterly income for each of the three companies I considered. Stock prices are displayed in Figure 2, and financial data are displayed in Figure 3. Finally, there are two market controls: The S&P 500 (see Figure 2) and the USD/CAD exchange rate; and two economic controls: the price of softwood lumber (Figure 4) and US housing starts (Figure 5). Summary data for this information is included in Table 2. Note that the period under consideration was set to January 1988 – June 2017 because that was the range of the independent variable – some other variables were available for longerspans, but were limited to that period.

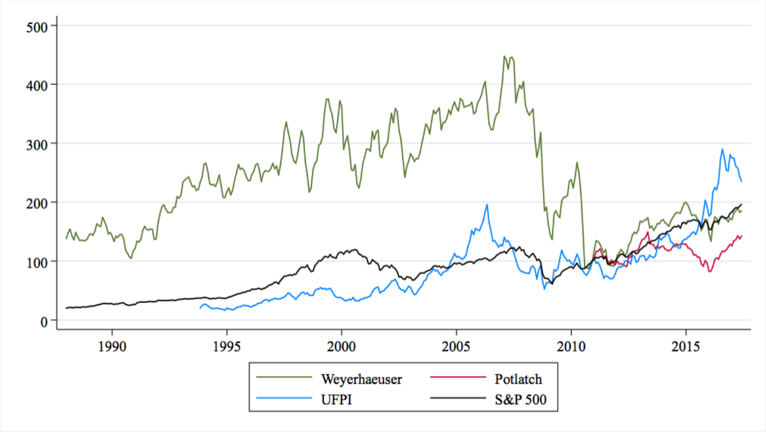


FIGURE 2. COMPANY STOCK PERFORMANCE

Notes: Indexed, December 2010 = 100. Timespan is January 1988 – June 2017 for Weyerhaeuser and S&P 500, November 1993 – June 2017 for UFPI, and December 2010 – June 2017 for Potlatch.

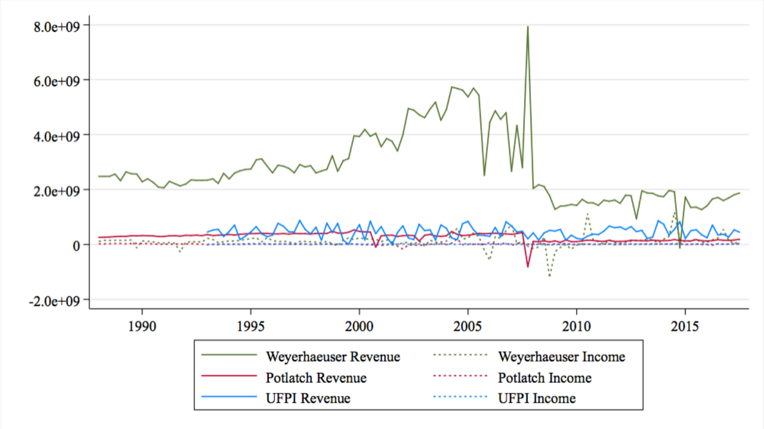


FIGURE 3. COMPANY FINANCIAL DATA

Notes: Units are US Dollars. Data for Weyerhaeuser and Potlatch are January 1988 – June 2017, data for UFPI is January 1993 – June 2017.

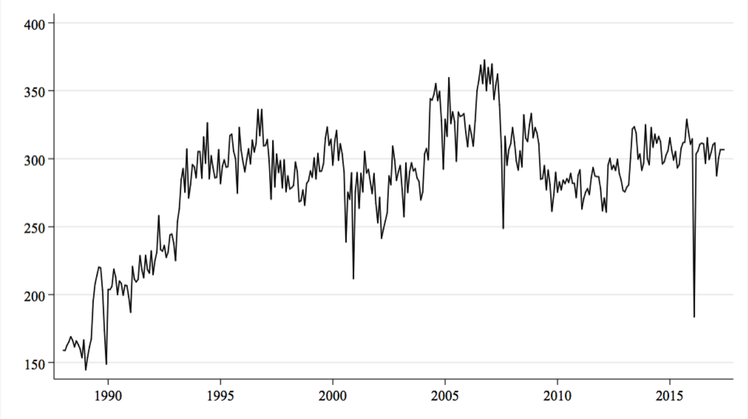


FIGURE 4. PRICE OF SOFTWOOD LUMBER

Notes: Units are US Dollars. Timespan is January 1988 – June 2017.

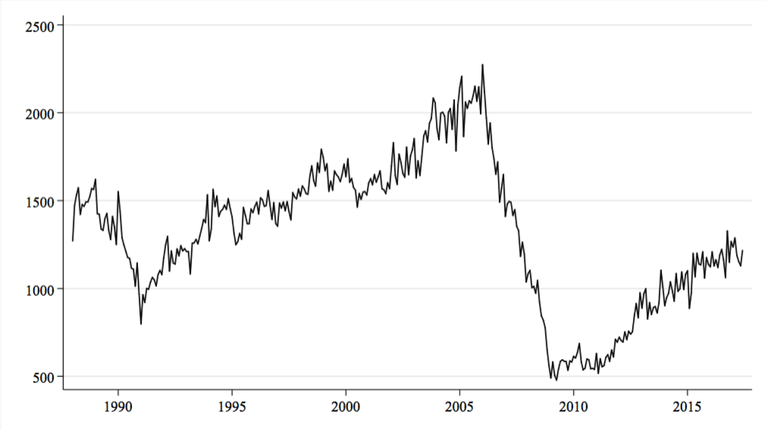


FIGURE 5. US HOUSING STARTS

Notes: Units are seasonally-adjusted annualized housing starts (in thousands). Timespan is January 1988 – June 2017.

TABLE 2— DATA SUMMARY

	Monthly Availability	Quarterly Availability	Mean	Standard Deviation	Minimum	Maximum
CIMT Trade Data^{IV}	354 months (Jan '88 – Jun '17)	118 quarters (Q1 '88 – Q2 '17)	2.71e+09†	9.51e+08†	1.91e+08†	4.72e+09†
Weyerhaeuser – Stock^{DV}	354 months (Jan '88 – Jun '17)	—	42.63	15.67	15.78	81.08
Weyerhaeuser – Revenue^{DV}	—	118 quarters (Q1 '88 – Q2 '17)	2.81e+09	1.31e+09	-1.26e+08	7.93e+09
Weyerhaeuser – Income^{DV}	—	118 quarters (Q1 '88 – Q2 '17)	1.23e+08	2.40e+08	-1.21e+09	1.16e+09
Potlatch – Stock^{DV}	79 months (Dec '10 – Jun '17)	—	37.59	5.01	26.88	48.76
Potlatch – Revenue^{DV}	—	118 quarters (Q1 '88 – Q2 '17)	2.74e+08	1.58e+08	-8.14e+08	5.32e+08
Potlatch – Income^{DV}	—	118 quarters (Q1 '88 – Q2 '17)	1.24e+07	3.07e+07	-1.67e+08	2.10e+08
UFPI – Stock^{DV}	284 months (Nov '93 – Jun '17)	—	11.01	7.30	2.07	35.90
UFPI – Revenue^{DV}	—	98 quarters (Q1 '93 – Q2 '17)	4.59e+08	2.10e+08	1.06e+06	8.72e+08
UFPI – Income^{DV}	—	98 quarters (Q1 '93 – Q2 '17)	9.38e+06	8.77e+06	-1.09e+07	3.37e+07
S&P 500^{CV}	354 months (Jan '88 – Jun '17)	118 quarters (Q1 '88 – Q2 '17)	1074.17	540.60	250.48	2433.99
USDCAD^{CV}	354 months (Jan '88 – Jun '17)	118 quarters (Q1 '88 – Q2 '17)	1.256	0.171	0.956	1.600
Price of Softwood Lumber^{CV}	354 months (Jan '88 – Jun '17)	118 quarters (Q1 '88 – Q2 '17)	282.35	45.14	144.56	372.60
Housing Starts^{CV}	354 months (Jan '88 – Jun '17)	118 quarters (Q1 '88 – Q2 '17)	1.31e+06	4.08e+05	4.78e+05	2.27e+06

Notes: † = Data from CIMT database represents the total imports to the United States, though state-by-state data was also used. IV = Independent Variable, DV = Dependent Variable, CV = Control Variable. Note that for all variables with both monthly and quarterly availability, the mean, deviation, minimum, and maximum represent the monthly figures, not quarterly.

The impacts of the bursting of the US housing bubble in 2006 are apparent on several of the graphs, most notably Figure 5: US housing starts, and in the stock prices shown in Figure 2. The same trend is also seen in Figure 1; in fact, housing starts and softwood imports mostly move in parallel (see Additional Figure 1 in Appendix A). It is also notable to highlight the relative stability of softwood prices, despite the wide variance in other measures over the same time periods.

IV. MODEL

In this section, I begin by formally presenting my research question. Then, I discuss the theoretical underpinnings of the question that I am investigating, using a simplified model of the US softwood lumber market. Finally, I explain the controls and statistical methods I used to answer my research question.

A. Research Question

As discussed previously, the objective of this paper is to determine the impact of Canadian imports of softwood lumber to the United States on American lumber companies. Formally, the research question I will be seeking to answer is the following: how have imports of Canadian softwood lumber into the United States impacted American forestry companies? For the purposes of this paper, impact will be evaluated in terms of stock price, revenue, and net income.

B. Theoretical Model

Before discussing the empirical model that I use to answer my research question, I will lay out the theoretical underpinnings of this paper. As mentioned in Subsection A, I am attempting to determine the impact of Canadian imports on US forestry companies. Thus, the market that I am considering is the US market for softwood lumber. Figure 6 displays a simplified economic model that represents the US market for softwood lumber.

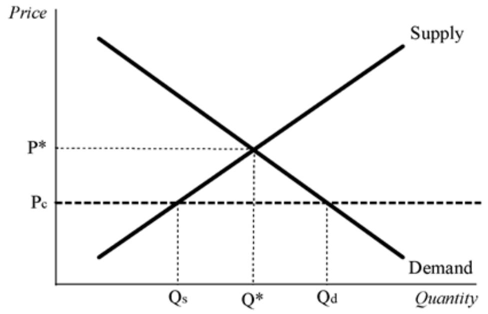


FIGURE 6. THEORETICAL MODEL OF US SOFTWOOD LUMBER MARKET

Notes: Supply and demand represent the American supply and demand (i.e. supply does not incorporate Canadian supply

According to the theory, without imports, the price of softwood lumber in the US would stabilize at the equilibrium, P*, and the quantity demanded and supplied would converge at Q*. However, since the Canadian price (Pc) is lower than the US equilibrium price, we must add that to our model.[4] Since the Canadian price is lower than the US equilibrium price, demand increases from Q* to Qd and supply falls to Qs. Since the price also falls, US firms will end up selling less, and receiving less for what they sell. The result of Canadian imports is that US forestry companies lose the producer surplus.

To consider this model in dynamic context, it is best to look at the actual data that has been collected over time. The three metrics I choose to study are all related to the benefits accruing to US softwood lumber companies. Revenue is directly apparent on this graph, as P*Qs, and the expectation is that stock prices and income will follow a similar pattern.[5] Therefore, the expectation is that as Qs or P falls, all three of the dependent variables will fall. Since we are not directly able to measure these variables, we must choose proxies for them. Since we are able to measure imports (equal to Qd-Qs), we can assume that as they increase, ceteris paribus, they must be decreasing the revenue of US firms.

As seen in Figure 7, the long-term trends of all three of the dependent variables broadly follow the trend of the independent variable – a result contrary to the theory presented earlier, which suggested that they should have an inverse relationship. However, this result can be easily explained by the fact that both US companies and Canadian exporters benefit from increased demand for softwood lumber. Since the most important end-use of softwood lumber is in construction, we can look at US housing starts (Figure 5) as a valuable indicator of the demand for softwood lumber. Unsurprisingly, there is a strong correlation between the variables seen in

4. We know that the Canadian price is lower than the equilibrium price for the simple reason that the US has non-zero imports of softwood lumber. If the price of Canadian softwood was higher than that in the United States, consumers wouldn't buy Canadian imports.
5. This is a simplifying assumption, but a discussion of the cost functions of the firms and dynamics of the equities market would be irrelevant to the core of this paper.

Figure 7 and the level of US housing starts.[6] If we return to Figure 6, US housing starts are an exogenous force that shift the demand curve left (as starts decrease) or right (as starts increase).

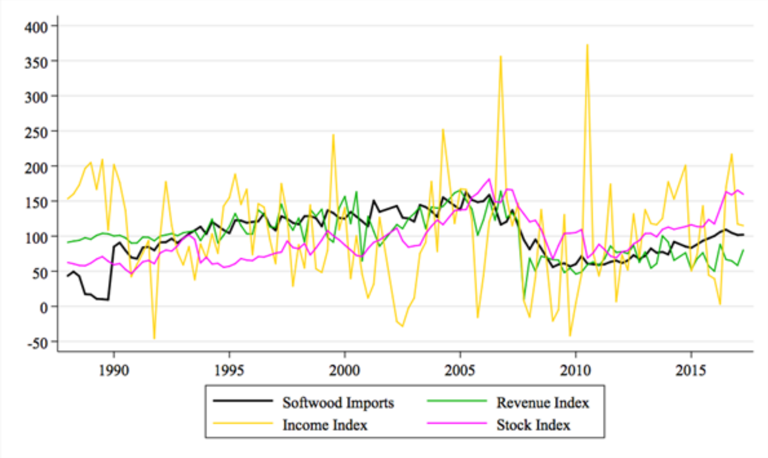


FIGURE 7. LONG TERM TRENDS OF KEY VARIABLES

Notes: Quarterly and indexed, the base of 100 is set to the average of the values over the period 1988-2017. Methodology for the creation of these indices can be found in Appendix B.

C. Empirical Model

The research question presented in Subsection A lays out the key variables under consideration in this paper. The independent variable will be the imports of Canadian softwood lumber to the United States, and the dependent variables will be the impact metrics mentioned: stock price, revenue, and net income.

This leads to two main questions: what statistical method will be used to investigate the relationship between these variables, and what controls will be used to confirm the significance of the connection? In the following section I will outline the controls and the statistical method chosen to most effectively research this question.

Controls.—The ultimate objective of these controls is to separate out the theoretical interactions described in Subsection B. An important starting point is controlling for fluctuations in the price of softwood lumber. Thus, I collected data on the price of softwood lumber in the United States, as well as the USD/CAD exchange rate, as it would impact the relative price of Canadian softwood lumber. Another important variable I sought to control was US housing starts. This is an important variable to control, since it could shift the demand curve for softwood lumber (as discussed in Subsection B). Finally, I seek to control for general economic sentiment using the S&P 500, a broad metric of the economic health

6. For further reference, see Additional Figure 1 in Appendix A, which shows the close relationship between softwood imports and housing starts.

of US companies. This is especially relevant in the consideration of stock prices, since general market stability and growth can have an exogenous effect on other stock prices, irrespective of the financial success of an individual company.

Statistical Method.— The next step is to determine the result of this interaction between the variables described above. Since my research necessitates consideration of changes in the variables, I decided to use differenced data in my approach (discussed further below). I used a linear regression because it offers the maximum interpretability of results.

I determined the appropriate lags to use in the differencing by calculating partial autocorrelation graphs for my variables and cross-referencing those results with my expectations for their seasonality. For stocks, the partial autocorrelations demonstrated a strong month-over-month correlation, but no significant correlations over longer time periods (see Additional Figure 2 in Appendix A for an example)[7]. This corroborates the efficient market hypothesis's prediction that all public information is priced into financial markets instantaneously, making future movements unpredictable (Fama, Fisher, Jensen, & Roll, 1969). Therefore, I decided to use month-over-month differencing for stock data. For financial data, the partial autocorrelation of revenue displayed a seasonal pattern, where autocorrelation was maximized quarter-over-quarter, but also saw a significant peak at lag 4, indicating a year-over-year trend (see Additional Figure 3 in Appendix A). This matches with the typical seasonality of many revenue streams – in construction, this is driven by the fact that working hours are longer and weather is more conducive in the summer, therefore construction peaks in the summer.[8] Therefore, I decided to use a year-over-year difference for revenue. The partial autocorrelations for income do not show any consistent pattern (see Additional Figure 4 in Appendix A), but for the sake of consistency, I decided to utilize a year-over-year difference.

One final consideration was how to include my independent variable (Canadian imports of softwood lumber). The CIMT database includes state-by-state breakdowns, which I decided to utilize because they allowed me to specifically target the results to the three companies I considered, and more importantly, I can conduct heterogeneity analysis on the states in the sample. Combining all of this information, I constructed an empirical model using differenced data in a linear regression, as shown below:

$$(1) \qquad y_i = \beta_0 + \beta_n m_{n,i} + \beta_{n+1} p_i + \beta_{n+2} s_i + \beta_{n+3} x_i + \beta_{n+4} h + \varepsilon_i,$$

where y is the dependent variable (either stock price, revenue, or

7. I use Weyerhaeuser's partial autocorrelations as an example, since Weyerhaeuser was the largest company I considered, but also the only one with complete stock and financial data for the entirety of the time period under consideration.

8. Additional Figure 5 in Appendix A presents a graphical representation of this phenomenon, using US housing starts as an example. The summer months show consistent and strong starts, whereas other months have lower and more variable levels of starts.

income), m_n are the imports of Canadian softwood to the states that the company operates in (separated into n states), p is the price of softwood lumber, s is the value of the S&P 500, x is the value of the USD/CAD exchange rate , and h are US housing starts.

This model assumes that my control variables (p, s, x, and h) have non-zero coefficients, the justification for this assumption was discussed under the controls header of this subsection. The main focus of my paper is on the coefficients on the independent variable (m_(n,i)): imports of Canadian softwood to the states under consideration. The coefficients (β_n) are predicted to be negative, thus indicating an inverse relationship between Canadian imports (m) and the success of US lumber companies (y).

V. RESULTS

In this section, I review the overall results of my model, finding that there is no measurable relationship between imports and revenue. I then look in more detail at the state-by-state results to ascertain whether there is a predictable intra-regression difference in the significance of the regression coefficients. Again, I find that there is no discernable pattern determining which states will be significant in the regression.

A. Summary Results

Overall, the results of the various regressions I ran were not conclusive or significant. Table 2 displays some statistics for the nine main regressions I conducted. The stock regressions were all significant at the 1% level, but as I will show later, that predictive power came almost exclusively from the S&P 500 control variable. For both revenue and income, the results were broadly not significant, with the two exceptions of Potlatch's revenue and UFPI's net income. Nonetheless, when compared to the results for the other companies, it seems likely that those results were reached by chance. Next, I will talk in more detail about the results of the regressions on each of the dependent variables.

TABLE 2—SUMMARY RESULTS FOR REGRESSIONS (SIGNIFICANCE & R-SQUARED)

	Stock (MoM)	Revenue (YoY)	Net Income (YoY)
Weyerhaeuser	0.000*** (0.342)	0.790 (-0.061)	0.828 (-0.071)
Potlatch	0.000*** (0.268)	0.078* (0.060)	0.890 (-0.044)
UFPI	0.000*** (0.245)	1.000 (-0.385)	0.001*** (0.348)

Notes: The first numbers are the significance of the total regression, as found by an F-test. The number in parentheses is the Adjusted R-squared of the regression, demonstrating the explanatory power of the regression.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

As mentioned above, the results of the stock regression were driven largely by the S&P 500 control variable (see Table 3). For each of the three regressions, it was significant at the 1 percent level. Surprisingly, the other three control variables (lumber price, exchange rate, and housing starts) were not significant. The insignificance of the softwood price variable is especially surprising, since it seems obvious that changes in the price of softwood lumber would impact forestry companies significantly.

Next, I consider the results for imports, the independent variable. Since imports were broken down by state, Table 3 provides the median coefficient and significance of all of the values. It also provides the number of the individual state coefficients that were significant at the 10 percent level. As is clear in the table, the results were mostly not significant. As a whole, imports seemed to have had no significant impact on stock price, though a small subset of them did have significant results.[9]

9. Keep in mind that since the threshold for significance was set at 10%, approximately 10% of states should be significant, simply by random chance. For example, in Weyerhaeuser's case, we would expect that 2.3 states out of each regression should have a significant coefficient, simply by random chance. The generally low numbers seen in this column suggest that the regressions are not significant.

TABLE 3—SUMMARY RESULTS FOR STOCK REGRESSIONS (COEFFICIENT & SIGNIFICANCE)

	S&P 500	Softwood Price	USD/CAD	Housing Starts	Imports (median)	Significant States† (count)
Stock Regression						
Weyerhaeuser	1.194*** (0.000)	0.015 (0.746)	-0.258 (0.228)	-0.041 (0.357)	-0.002 (0.526)	2 of 23
Potlatch	0.991*** (0.000)	0.017 (0.778)	-0.487 (0.183)	0.040 (0.523)	0.002 (0.500)	0 of 5
UFPI	1.149*** (0.000)	0.005 (0.932)	0.225 (0.419)	0.069 (0.234)	-0.003 (0.384)	5 of 29
Revenue Regression						
Weyerhaeuser	-0.323 (0.723)	0.625 (0.637)	-4.162** (0.013)	0.724 (0.529)	0.059 (0.599)	1 of 23
Potlatch	1.000** (0.010)	0.599 (0.273)	0.359 (0.623)	0.454 (0.195)	-0.001 (0.871)	0 of 5
UFPI	-1.301 (0.990)	-219.769 (0.211)	14.153 (0.941)	-101.350 (0.549)	1.324 (0.801)	0 of 29
Income Regression						
Weyerhaeuser	-0.544 (0.824)	3.352 (0.345)	11.132** (0.013)	1.196 (0.700)	-0.042 (0.623)	0 of 23
Potlatch	6.497 (0.432)	16.395 (0.168)	-11.266 (0.478)	-2.443 (0.747)	0.041 (0.762)	0 of 5
UFPI	1.369 (0.496)	5.818* (0.080)	7.065* (0.054)	-2.125 (0.504)	-0.433 (0.440)	5 of 29

Notes: The first numbers are the coefficient of the variable in the regression. The number in parenthesis is the significance of the regression, from a t-test. † = This column shows the count of states that had a coefficient significant at the 10 percent level
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.x

For revenue and net income, the results were even less substantial. None of the controls acted as consistent predictors. USD/CAD was the closest to being significant, as it was significant in three of the six regressions. The results for the independent variables were equally unpromising, with even fewer significant states than in the stock regression.

Looking at the results as a whole, they do not support the expected result that there would be significant negative correlation between Canadian imports and the company metrics. However, there was wide variability in the significance of the variables that I considered (as shown in figure 8), thus leaving open the possibility of heterogeneity analysis within the regressions, which I will conduct in Subsection B.

B. Heterogeneity Analysis

In this subsection, I will attempt to discover some underlying causes of the variability in the significance of the individual state regressions. I will do so for each company separately.

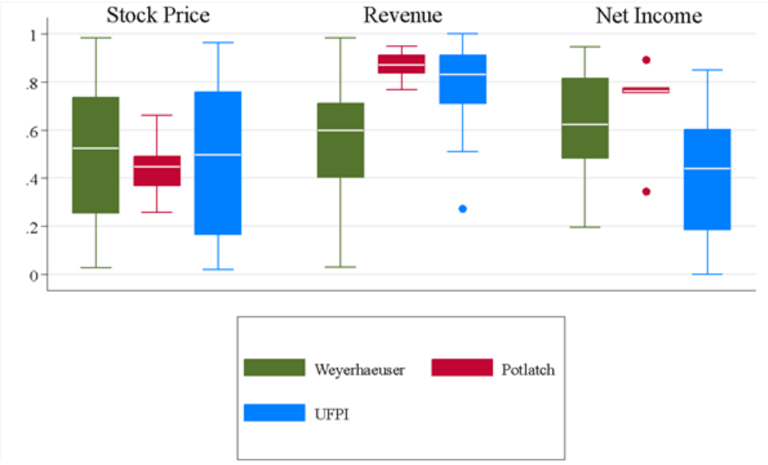


FIGURE 8. BOX PLOTS OF THE SIGNIFICANCE OF INDIVIDUAL STATE REGRESSIONS

Weyerhaeuser.—Weyerhaeuser operates in 23 states across the US, with varying levels of engagement in different states. They list 84 locations across those 23 states, divided into six types of locations ranging from sales offices to lumber mills (Weyerhaeuser, 2017). Since each state had between one and twelve Weyerhaeuser locations, the first step was to consider whether the total number of Weyerhaeuser locations in a state would increase the significance of Canadian imports to that state. However, regressions failed to show any significant relationship between number of locations and significance for any of the three dependent variables.

Next, I investigated potential differences between the different types of locations. I focused on four types of locations that I thought might be relevant, and used a regression to determine their significance. The regression took the form:

$$(2) \qquad y_i = \beta_0 + \beta_1 l_i + \beta_2 s_i + \beta_3 t_i + \beta_4 d_i + \varepsilon_i,$$

where each i represents one of the states under consideration, y is the significance of the dependent variable, l is the number of lumber mills, s is the number of sales offices, t is the number of timberlands offices, and d is the number of distribution centers. However, the results of this regression were also not significant, suggesting that the type of location was also not a utile predictor of the significance of the state coefficients. Overall, this suggests that the state-by-state results were truly random, with no discernable pattern displayed.

Potlatch.—Potlatch operates in five different states, with sawmills in four of them. Their website lists the productive capacity of their four mills, allowing for some further investigation (Potlatch, 2011). A plausible expectation would be that the larger the size of the mill, the more detrimental Canadian imports to that state would be. However, the results did not support that conclusion. The state with the largest mill (Arkansas) had an above average significance between the three metrics, whereas the state with the smallest factory actually had the strongest significance (though again, the significance was 0.52).

UFPI.—UFPI operates over 100 manufacturing and sales locations across 30 states (UFPI, 2017). As with Weyerhaeuser, I regressed the number of operations in a state against the significance of the state variable in the original regression. As with Weyerhaeuser, the result of this regression was not significant, showing no correlation between the number of operations in a state and the significance of that state's coefficient.

VI. DISCUSSION

As thoroughly discussed in the previous section, the results of this paper were almost uniformly inconclusive. Intra-regression variations discovered in Subsection A were found to have no clear predictors in Subsection B. In this section, I will further discuss this counterintuitive result, and also talk more broadly about the challenges that must be overcome to effectively answer my research question.

Analysis.—One partial explanation for the result is the fact that the model presumed that presence in a state was directly related to sales in that state, and more importantly that companies mostly sold locally. The extensive rate of Canadian imports to the United States shows that trade in lumber can easily take place across long distances, therefore suggesting that there is not an inherent connection between the location of production and the ultimate sale location. This assumption is likely more relevant for smaller firms than larger ones, since they do not have the scale and capacity to distribute their product as easily.

Another significant point is that Weyerhaeuser and UFPI, like many large North American forestry companies, operate on both sides of the US-Canada border (Potlatch, a smaller company, does not). This adds a confounding factor to this analysis since it opens up the possibility that, in the face of adverse domestic conditions, these firms could simply shift their production across the border. In fact, some imports in the CIMT database almost certainly came from Weyerhaeuser's Canadian mills. My analysis assumes that this cross-border trade by American companies was negligible, but it is possible that it was not. This would potentially explain why imports were not significant predictors of company health, and sometimes even moved in tandem with company metrics.

Another factor that may have impacted the result is the mixed use of time-series and present-day data. This is most significant in the company location data, where this paper assumes that company location has been fixed over time, where in reality it may not have been. If that data had been available, it would have benefitted the heterogeneity analysis immensely, since it would have allowed for consideration of impacts over time. For example, perhaps a company was not impacted by imports into a specific state because they only opened up a mill there within the past year (or vice versa, maybe one state was significant because for most of the period under consideration, a major mill operated there).

A surprising result of this paper was the lack of correlation between the control variables and the dependent variables. As mentioned in Section IV, it is surprising that the price of softwood lumber appeared to have no bearing on stock price, revenue, or income. It is possible that other relevant control variables were excluded, but they are not immediately apparent.

All other things considered, it is important not to underestimate the complexity of the modern economy. Without using dynamic stochastic general equilibrium models, it is challenging to accurately predict economic trends. These models require far more detailed data than was available on this topic, and would have also required much more advanced modelling techniques.

Challenges.—One of the key challenges in answering this research question is the lack of quality data. As mentioned in Section I, the three companies I considered in this paper represented less than 15% of the total US softwood lumber market. This would not be an issue if the companies I considered were representative of the market, but because of the widespread prevalence of small private companies, my selected companies are likely not representative of the market at large. It seems likely that the smaller companies would be much less able to deal with changing economic trends, so my results likely underestimate the impact of changing imports on American firms. This is for two main reasons: they are geographically diversified, exposing themselves to markets all around the continent and the world, in addition to the fact that they are also diversified within their sector. Large companies like Weyerhaeuser produce a range of products alongside softwood lumber, whereas small companies may focus exclusively on the production of one forest product.

This paucity of data also manifested itself in terms of the length and frequency of the period under consideration. When I was considering financial data, I only had 118 data points to consider, and for some variables, even less were available. For example, Potlatch only had 79 periods of stock data available. Overall, this paper would have benefited from higher frequency data, as well as a longer time-span under consideration.

A related issue in this investigation is the fluctuating regulatory framework governing the trade of softwood lumber in North America. As discussed extensively in Section I, the trade regime has changed frequently over the past three decades. This has created a variety of exogenous shocks in my data, and makes it challenging to compare time periods to one another. At various points, the system included Canadian export taxes, US tariffs, and quotas. Because of this changing regulatory environment, it is not possible to generate a consistent theoretical model to describe the state of the market. Another issue this topic suffers from is the fact that data on softwood lumber production is not readily available. Company-specific production of US firms would be invaluable in order to more accurately ascertain the crowding out effect of Canadian imports. Unfortunately, that information is not publicly accessible.

VII. CONCLUSION

In this paper, I sought to investigate Steve Swanson's claim that Canadian imports of softwood lumber hurt American forestry companies. I collected data from multiple sources and created a linear model in an attempt to respond to that statement. The results of my investigation were inconclusive, showing no measurable relationship between the variables I considered. Although this is not conclusive disproof of claims by US forestry companies that they are harmed by Canadian imports, the analysis did not support their claims, and it is a strong sign that this question should be investigated more thoroughly.

There are several areas for improvement in future papers seeking to investigate this question. Firstly, a complete answer to this question would necessitate consideration of the full breadth of American forestry companies, including the small private companies, as well as large private and public companies. If complete information could not be obtained, a more diverse sample of companies would still be useful. More advanced modelling techniques would also allow for more nuanced study of the variables under consideration, as long as the required data was available. Finally, a more complex theoretical model that better incorporates the shifting regulatory regimes could prove valuable in understanding this complex issue.

Impact of Access to Healthcare on Economic Growth

Sarayu Kantheti

ECON 490

I. INTRODUCTION

Access to healthcare is an important determinant of standard of living, which is closely related to economic progress and societal wellbeing. The focus of this paper is to investigate the relationship between access to healthcare and economic growth by testing the hypothesis that access to healthcare positively affects GDP per capita. This is an important topic of discussion because healthcare is part of a government's mandate with direct policy outcomes, and can impact the health of its society for better or for worse.

Healthcare affects economic growth through direct and indirect channels. The direct channel is that increased access to healthcare leads to an improvement in the health of the labour force. This, in turn, increases labour productivity that increases output or GDP. This chain can be continued to affect economic growth through indirect channels. When there is increased productivity, income increases. This leads to an increase in savings and investment, which, by the Solow Model, causes economic growth. When income increases, expenditure can also increase, which then stimulates aggregate demand by the multiplier effect, further leading to economic growth. In addition to productivity, improvements in healthcare can increase technological progress, which has a positive impact on growth. It can also increase life expectancy, which encourages individuals to invest in education, ultimately stimulating human capital. Increased human capital then acts as a driver of economic growth. Though access to healthcare affects economic growth through these channels, economic growth can also drive improved access to healthcare. This results in a virtuous cycle, which then pushes the economy further along the path of development.

Vaccination rate at birth has been used as a proxy for access to healthcare in this paper. This is a good measure because it is one of the most critical healthcare practices for infants, and is a good predictor of the access to medical assistance they would have as they grow older and join the labour force. It is also a consistent healthcare practice in both developed and developing countries, which would provide a suitable data set for the panel data regression used to test the hypothesis.

The economic story for the relationship between access to healthcare and GDP growth has different tones in the existing literature. Amiri and Linden (2016) argue that child health and GDP per capita have a relationship that runs in both directions, which is in alignment with the virtuous cycle argument described previously. Korkmaz and Kulunk (2016) connect healthcare to the Human Development Index, and argues that expenditure and increased access to healthcare play a role in education, human capital, and overall human development, which spurs economic growth. Jakubowska and Horvathova (2016) use human capital and the expenditure model to describe the relationship between healthcare and economic growth. They reason that improved healthcare outcomes lead to increased human capital. This increases expenditure on food and higher quality healthcare services. They also add that the impact of healthcare on developed economies may not be as evident as they already have high levels of human capital and healthcare than many countries that still struggle to meet the bare minimum. This relationship is also examined in my paper by running regressions on countries that belong to different income groups.

The empirical model used to test the hypothesis involves using panel data to run a Generalized Least Squares (GLS) regression. Control variables such as population growth, savings, human capital, and exports are added to the regression equation to maintain consistency with the long run growth accounting model for economic growth. The data sources include the Penn World Tables and the World Health Organization (WHO) Data Observatory for immunization data. Section II of this paper discusses the data sources, Section III outlines the empirical approach, Section IV compiles the results, and Section V provides the conclusions of the analysis.

II. LITERATURE REVIEW

The literature shows evidence of different approaches being taken to investigate the relationship between healthcare and economic growth that have resulted in varied interpretations.

Some papers find a positive relationship between healthcare and economic growth. Amiri and Linden (2016) find a causal relationship between child health and economic growth. They use panel data for 175 countries from 1990 to 2014 and data from the WHO data portal for infant mortality below the age of five (per 1000 live births). For economic growth, it uses the logarithmic values of GDP per capita in US prices (2000) from the ERS International Macroeconomic Data Set. The results, in terms of country groups, show that approximately 61% of countries tested exhibit either a bilateral relationship or a causal relationship between the child mortality rate and GDP per capita. 18.8% of countries show the reverse relationship and 19.43% countries show that there is no relationship between the two. They also find that cases of GDP per capita impacting child health are greater in low and middle-income countries rather than high and upper-middle income countries. The findings further suggest that cases of causality of child health affecting GDP per capita are greater in countries that are not a part of the 'low-income' category.

Korkmaz and Kulunk (2016) find a positive relationship between economic growth, life expectancy at birth, and increased schooling rates for 10 OECD countries. Panel data is used for 10 OECD countries from 2007-2013. The Granger causality test is run on this panel data to show a positive relationship between economic growth, improved life expectancy, and the schooling rate. The data for economic growth and education level (schooling rate) is taken from the OECD database. The life expectancy data is taken from the World Bank database. Their results confirm a positive relationship between the Human Development Index (HDI) variables and long-run economic growth at the 5% significance level.

Additionally, Ngangue and Manfred (2015) also find life expectancy to have a positive impact on economic growth. Their model uses dynamic panels and accounts for only fixed effects, but not random effects. The World Bank database was used for collecting data for 141 countries on variables such as GNI, life expectancy, years of schooling, quality of governance and human capital. The results indicate that life expectancy at birth has a statistically significant positive effect on GNI per capita. This result is particularly strong for the low and middle-income countries once the countries are grouped by income categories.

Weil (2014) confirms the existing literature that economic growth and population health are positively correlated. However, he states that the effects may not be very significant in terms of magnitude. His paper also explores the premise that factors such as years of schooling and life expectancy increase the productivity of workers, which results in positive outcomes for economic growth. Furthermore, he examines aggregate welfare in terms of consumption and life expectancy. The main variables considered are life expectancy, GDP, and the disability rate. The results show that the contribution of health in the 90/100-income ratio falls from 20.5 to 17.9 after health gaps have been eliminated. Ultimately, the paper discusses conclusions and methods from various papers and highlights that the economic context of the time frame being used for the analysis are important, as they could alter outcomes due to important global transitions such as demographics and industrialization.

Furthermore, Aghion (2011) uses modern endogenous growth theory to explore the relationship between health and economic growth by considering a combination of the level of health and the rate of improvement of health. Cross-country regressions are used from 1960 to 2000, where Aghion uses data for life expectancy across various age groups from 1960-2000 from the OECD health database and LMW data to find that higher initial levels and higher rate of improvement in life expectancy lead to a higher rate of growth in GDP per capita. Aghion further finds that a reduction in the mortality rate below 40 leads to more productivity, specifically in OECD countries, hinting at the positive relationship weakening once the mortality rate has steadied. The results show that developed countries with initially higher levels of health have an advantage in terms of GDP per capita growth. However, developing countries also have a higher rate of improvement of health, which has a ripple effect on the GDP per capita growth rate. It shows that the differences in health in developed and developing countries account for an annual growth gap of 2.4%.

On the other hand, some papers find minimal or no impact of healthcare outcomes on economic growth. Ashraf, Lester, and Weil (2008) find that improvements in health have minimal impact on GDP per capita in the long run, and take many years to impact economic growth. They use disease eradication and health improvements as measures for changes in health outcomes, and even control for diseases such as malaria that are responsible for disease and mortality in many poor countries. The results do not vary much even after controlling for this occurrence. The paper argues that proponents for policies for health improvements should rationalize it on humanitarian grounds rather than on grounds of a promise of economic growth in the future.

Similarly, Acemoglu and Johnson (2007) do not find any relationship between life expectancy and economic growth. Their paper examines the relationship between life expectancy and improvements in health beginning in the 1940s. A predicted mortality rate has been constructed using pre-intervention rates of mortality from various diseases. This predicted mortality is found to have a large impact on life expectancy from 1940 onwards. The study finds that a 1% increase in life expectancy leads to a 1.5% to 2% increase in the population. However, they also find that life expectancy has a relatively smaller impact on GDP. They consequently find no evidence of a positive correlation between life expectancy and GDP per capita. The paper identifies that the international epidemiological transition would probably not result in the same sort of increase in population if it occurred today.

Afonso and Sarabanda (2016) also determine that an increase in health-labour proportion of the working population has no effect on economic growth. Data for wages, the labour force, and human capital for 21 OECD countries was collected from 1991 to 2008, and the effect on growth is analyzed from a short, medium, and long-run perspective. Their paper finds that the health-labour proportion is lower in skilled labour populations of the Anglo-Saxon countries. It also shows that an increase in the health-labour share has a negative effect on the intensity of research and development. Their model computed values for various parameters, and the signs of their coefficients are analyzed to determine how the impact changed in the long run. The value of (b) stays at 0, showing that there is no impact of health on economic growth. It, however, has a negative effect on the intensity of R&D when the health-labor share in the skilled population increases.

There is also evidence of healthcare negatively impacting GDP in some literature. Hansen and Lonstrup (2015) find that countries that experienced an increase in life expectancy conversely had a lower growth rate of GDP per capita. They also find a negative relationship between life expectancy and GDP per capita. The data consists of growth rate of GDP per capita and population growth rates in 1900, 1940, and 1980. These variables are measured in two periods (1900 to 1940 and 1940 to 1980). The growth rate of life expectancy at birth and pre-intervention mortality rates are other variables used to test the hypothesis. The data collected is from Acemoglu and Johnson (2007), Maddison (2001), and Goldewijk (2010). When GDP per capita is used as the outcome variable, the OLS estimates suggest that the relationship between growth of life expectancy and GDP per capita is a negative correlation, but statistically insignificant to begin with. At the 5% significance level, the magnitude of the coefficient increases. The estimated coefficient of life expectancy is also negative. The paper looks at the spike in life expectancy in the context of the epidemiological transition. These findings cannot be used to state life expectancy to be equally important in determining the economic growth of developed countries.

In another approach, the relationship between health outcomes and economic growth has been further qualified by grouping countries into developing or developed countries. Bhargava, Jamison, Lau, and Murray (2001) find that there is a positive relationship between adult survival rate and GDP per capita growth for developing countries. The effects of health on economic growth are modelled by measuring adult surviving rates (ASR) against GDP growth rates at intervals of five years. Panel data is used to analyze GDP over a time series, which was adjusted for purchasing power and exchange rates. The data used was mainly from the Penn World Table and the World Development Indicators (World Bank). The life-expectancy-income relationship is reconsidered by building a model to capture the dynamics of GDP and the explanatory variables. Estimates of growth rates are found using GDP levels of countries and their ASRs, and confidence intervals are constructed to measure the impact of ASR on growth rates of the economies considered. The results of the paper show that in low-income countries there was a positive relationship between the ASR and growth rates.

Jakubowska and Horvathova (2016) focus on a comparison between European Union (EU) countries, that have different GDPs, to examine the relationship between years of healthy life and income levels. The countries in the EU are classified under 'old' and 'new' European Union. The dependent variables used include life expectancy and years of healthy life. The data used to determine the condition of health include life expectancy and a predicted index constructed for healthy life years. The impacts of these variables are mapped onto GDP per capita and GNI per capita. This data is obtained from the World Bank, the WHO, and the Eurostat. The results show that there is not a very favorable relationship between GDP per capita and the years of healthy life. They also show that countries with higher incomes also tend to have a lower percentage share of years of living a healthy life in their life expectancy. However, the countries that are part of the 'old' European Union show that there is no statistically significant relation between percentage of healthy years and level of income.

It is evident from the existing literature that there is not a clear consensus on the relationship between healthcare and economic growth. This research paper adds to the conversation since it uses access to healthcare as a measure for healthcare, and investigates whether it affects economic growth. Vaccination rates for measles have been used as a proxy for access to healthcare as it is administered in infancy. This will act as is a good predictor of the level of healthcare access individuals will have as they join the workforce, but is a different measure for healthcare than the ones used in the literature, that used measures such as life expectancy and mortality rate. This research could also contribute to the existing material on the subject because it controls for other macroeconomic factors influencing economic growth such as population growth, savings, human capital, and exports. These variables account for a significant level of variation in economic growth, according to the Solow Model. Adding access to healthcare, while controlling for these variables, brings originality to the research and leaves less scope for omitted variable bias.

III. DATA DISCUSSION

The two sources of data used in the analysis are the Penn World Tables and immunization data from the World Health Organization (WHO) data observatory. Within the immunization data, data for Measles Doses 1 and 2 are used. The independent variable is GDP per capita (GDP) and the explanatory variables are Shares of Measles Doses 1 and 2 (MSDOSE1, MSDOSE2). The control variables include Population Growth (GPOP), Human Capital Index (SCHOOL), Share of Gross Capital Formation at current PPPs (SAVINGS), Share of Merchandise Exports at current PPPs (EXPORTS), and Share of Measles Doses 1 and 2 (MSDOSE1, MSDOSE2).

The data in the Penn World Tables has been collated in the following way. The Human Capital Index is constructed using a combination of the average years of schooling from Barro and Lee (2013) and an assumed rate of return on education that is built on Mincer equation estimates. Share of Capital formation is savings as a share of GDP and Share of Merchandise Exports is exports as a share of GDP. Real GDP is measured at National Prices (2011 $USD in millions) and population is measured in millions. The data for Measles Doses 1 and 2 has been measured as an immunization percentage among one-year old infants. These values are converted to shares to match the manner in which SAVINGS and EXPORTS are measured. The summary statistics for the data are described below:

TABLE 1: SUMMARY STATISTICS

Variable	Obser-va-tions	Mean	Standard Devia-tion	Minimum	Maximum
GDP	5,328	14,670	19,651	310	210,102
GPOP	5,159	0.017	0.015	-0.064	0.176
SCHOOL	4,505	2.257	0.700	1.022	3.734
SAVINGS	5,328	0.210	0.100	-0.0019	0.889
EXPORTS	5,328	0.236	0.239	0.00002	2.779
MSDOSE1	5,337	0.77	0.226	0.01	0.99
MSDOSE2	1,428	0.86	0.17	0.02	0.99

For the interest of the econometric model in this paper, the following manipulations have been made to the data. GDP is calculated by taking the logarithm of real GDP at national prices, divided by the population. The Measles Data is converted to a share from percentage terms (by dividing by 100), to make it consistent with the other variables. The logarithms of these shares are taken to create MSDOSE1 and MSDOSE2. GPOP is created to measure year on year population growth. SCHOOL, EXPORTS, and SAVINGS are calculated by taking the logarithm of Human Capital Index, Share of Merchandise Exports at current PPPs, and Share of Gross Capital Formation at current PPPs.

I predict GDP and GPOP to have a negative relationship. This is because, according to the Solow Model, as population growth increases, the capital-labour ratio falls, which affects productivity and leads to a decline in economic growth. I also predict that GDP and SAVINGS will have a positive relationship. This is because when savings increases, capital accumulation increases, which increases productivity and economic growth. GDP and SCHOOL should have a positive relationship. When human capital increases, education, income, and productivity increase, leading to economic growth. This relationship finds a voice in both the original and augmented Solow model. Human capital increases total factor productivity (TFP) in the original Solow Model. In the augmented Solow model, Mankiw, Romer, and Weil (1990) construct human capital to be endogenous to their model, as they believe an increase in human capital, increases income and savings. I predict GDP and exports to also be positively correlated. This is because trade leads to allocative efficiency and specialization based on comparative advantage. This translates into increased productivity and economic gains. Lastly, I hypothesize that GDP and MSDOSE1/MSDOSE2 have a positive relationship, in that access to healthcare (using vaccination rates as a proxy) improves health outcomes for individuals which leads to increased productivity and economic growth.

The primary weakness of the data is that it was not initially available for all countries and for all the variables in the same time frame. This was on account of countries being dropped due to missing human capital data. These countries are typically countries with low incomes or low population levels, including small countries in the Caribbean and Eastern Europe. Another weakness is that, in the data for the measles vaccination, the immunization rate is only among one year-olds. A challenge here would be that the variable attempts to measure access to healthcare for individuals over the course of their lives using a metric, which is administered during infancy. However, administration of vaccines is a good predictor of the level of healthcare access those individuals would have when they are a part of the labour force and during the later parts of their lives. Since vaccination rate is only a proxy it is a suitable choice of variable. Finally, omitted variable bias is also a weakness of the data, as there could be several other factors driving economic growth that are not considered in the model.

IV. RESULTS

The Generalized Least Squares (GLS) regression model is used to determine the relationship between GDP and the explanatory variables, which are: GPOP, SCHOOL, SAVINGS, EXPORTS, MSDOSE1, and MSDOSE2. This is a suitable model for my regression as there is evidence of autocorrelation and the GLS regression corrects for it. There is also evidence for heteroskedasticity, which is corrected for in the model by using robust standard errors. Time fixed effects are used in the model to control for time specific effects that do not change over time, such as geography and culture. The country fixed effects have been included to control for country specific changes that may occur in one country but not in others, such as political turmoil. Outliers are excluded from the data by restricting the values to three standard deviations away from the mean. This is done in order to prevent the results from being skewed by extreme values on either side.

The GLS regression is described by the following equation:

$$ln(GDP_{i,t})^* = \beta_0^* + \beta_1 ln(GPOP_{i,t})^* + \beta_2 ln\,(SCHOOL_{i,t})^* + \beta_3 ln(SAVINGS_{i,t})^* + \beta_4 ln(EXPORTS_{i,t})^* + \beta_5 ln(MSDOSE1)^* + \beta_6 ln(MSDOSE2)^* + \sum_{1983}^{2014} \delta_s TF_s + \sum_{i=2}^{97} a_j EF_j + \epsilon_{i,t}$$

Where,

$$(GDP)_{i,t}^* = (GDP)_{i,t} - \rho(GDP)_{i,t-1}$$
$$\beta_0^* = \beta_0 - \rho\beta_0$$
$$X_{i.t}^* = X_{i,t} - \rho X_{i,t-1},$$

Where X is any explanatory variable

As briefly mentioned before, there was evidence of autocorrelation in the regression, which was corrected for by using the GLS regression. Autocorrelation is corrected for because it deflates standard errors in the results. The Hausman Test indicated that the null hypothesis had to be rejected, and as a result fixed effects were controlled for in the model. The Wald Test was used to test for heteroskedasticity and resulted in rejection of the null hypothesis, indicating that there is heteroskedasticity. This was corrected for by including panels heteroskedasticity in the regression equation of the model. The regression was also run with and without outliers to evaluate whether it caused the results to change. There was no indication of this, but the condition of the residuals being within three standard deviations of the mean was added to the regression equation. The test for multicollinearity offered some interesting insights. Initially, multiple vaccines were used for the regression, such as both doses of measles and polio. However, when the test for multicollinearity was run, it showed very high values of Variation Inflation Factors (VIFs) that were above 10. This meant that the vaccination values were highly correlated with each other and obscured the meaningfulness of the regression; in essence the same vaccination was being measured twice. However, the VIF values for the two doses for measles was less than 1.5 indicating that there was no multicollinearity and that they could be combined within the same regression equation. Thus, only measles vaccinations, both dose 1 and dose 2, were used for the proxy in my study.

The hypothesis for this paper is that vaccination rate (access to healthcare) positively affects GDP per capita. Vaccination rates for Measles Doses 1 and 2 have been used in the regression equation. The results from the model include the results for Measles Doses 1 and 2 for all countries, OECD countries, and non-oil countries. Both doses for measles have been included because there could be positive effects of even just the first dose of the vaccination. The number of observations for the second dose is slightly lower than the observations for the first dose. The regression has also been run for OECD countries for both doses. The OECD consists of a sample of rich countries, which provides a sample of the relationship between access to healthcare and economic growth in more developed economies. Similarly, the Non-Oil countries were separated out because oil countries have extremely large GDP and EXPORTS numbers, which skews the results of the regression. The regression has also been run on developing and developed countries. The United Nations Development Program (UNDP) Human Development Report (2014) is used to set the benchmark value of GDP per capita at $12,920 (2011 PPP $) to separate high human development countries form medium and low human development countries. The logarithm of this value is used to set the benchmark at 9.46.

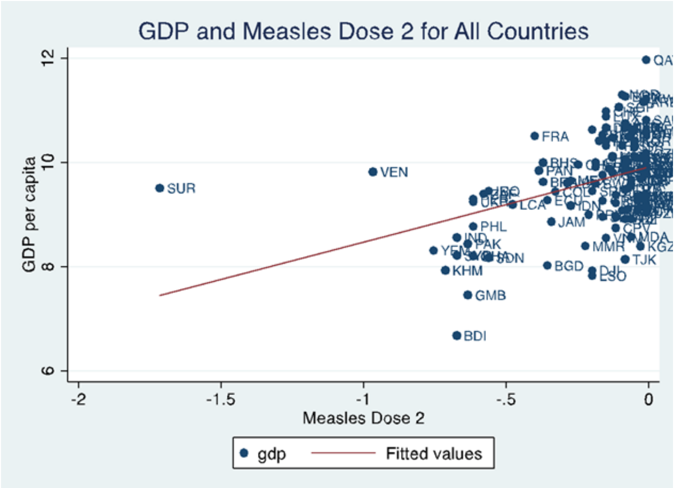
TABLE 2: REGRESSION USING MEASLES DOSES 1 AND 2 FOR ALL COUNTRIES

GDP	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
MSDOSE1	2.377*** (0.138)	1.312*** (0.159)	0.426*** (0.023)	-0.082*** (0.121)	0.156 (0.143)
MSDOSE2		0.490*** (0.052)	0.509*** (0.052)	0.232*** (0.043)	0.203*** (0.039)
GPOP		-0.030*** (0.009)	-0.021*** (0.007)	0.124*** (0.011)	0.102*** (0.013)
SAVINGS			1.207*** (0.034)	0.951*** (0.034)	0.535*** (0.041)
SCHOOL				2.278*** (0.054)	1.689*** (0.064)
EXPORTS					0.417*** (0.019)
INTERCEPT	9.686*** (0.077)	9.532*** (0.094)	11.522*** (0.096)	9.670*** (0.097)	10.116*** (0.116)
Number of Observations	937	937	937	937	937
Fixed Effects	Yes	Yes	Yes	Yes	Yes

Standard Errors in Parentheses

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

The results for all countries indicate that MSDOSE2 is significant at the 0.1% level. It implies with every 1% increase in vaccination for Measles Dose 2, GDP increases by 0.20%. MSDOSE1 is also significant until EXPORTS is added to the regression. This could be because of omitted variable bias and the crowding out effect caused by the second dose on the first dose, implying that individuals who received the second dose of the vaccine could be a subset of the first dose. Another reason could be that the variation in the second dose is much greater than in the first dose. This is likely because only countries that invest more extensively in healthcare have data for the second dose of the vaccine. Interestingly, when only MSDOSE1 was regressed with the remaining control variables, it was also significant at the 0.1% level. This validates the relationship that access to healthcare (measured using the measles vaccine) is positively correlated with economic growth.



The behaviour of the other variables is consistent with the predictions made earlier. SAVINGS, SCHOOL, and EXPORTS have a positive relationship with economic growth. Population growth is initially negatively correlated with economic growth, which is also consistent with the predictions made. However, it has a positive relationship with GDP and is significant at the 0.1% level when SCHOOL and EXPORTS are added to the regression. This could be because some of the low-income countries were dropped due to lack of data for all the variables, which leads to a positive bias for some of the countries that have high population growth rates and export-driven economies. The graph below describes the positive relationship between population growth and GDP per capita in countries that have data for MSDOSE2. Examples of countries that follow this trend include Qatar, Oman, and Kuwait. This could simultaneously explain the positive, significant relationship between MSDOSE2, GPOP, and EXPORTS in the results.

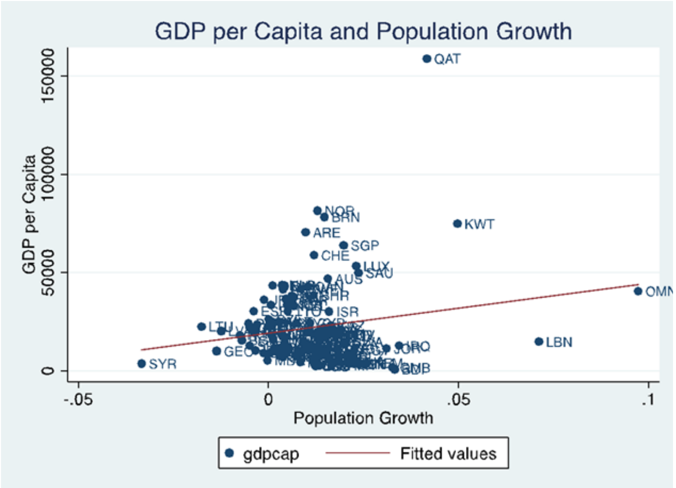


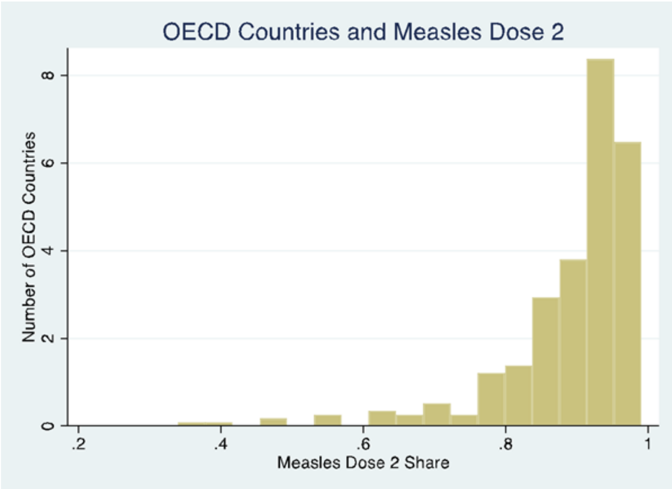
TABLE 3: REGRESSION FOR MEASLES DOSES 1 AND 2 FOR ALL, OECD AND NON-OIL COUNTRIES

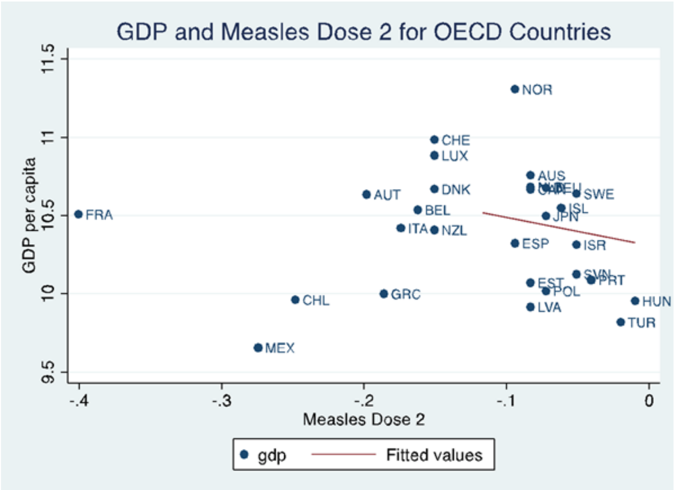
GDP	All	OECD	Non-Oil
MSDOSE1	0.156 (0.143)	-0.091*** (0.228)	-0.422*** (0.138)
MSDOSE2	0.203*** (0.039)	-0.074*** (0.090)	0.281*** (0.043)
GPOP	0.102*** (0.013)	0.070*** (0.012)	-0.004*** (0.012)
SAVINGS	0.535*** (0.041)	0.175*** (0.051)	0.558*** (0.043)
SCHOOL	1.689*** (0.064)	1.527*** (0.106)	1.672*** (0.068)
EXPORTS	0.417*** (0.019)	0.253*** (0.025)	0.355*** (0.019)
INTERCEPT	10.116*** (0.116)	9.583*** (0.170)	9.479*** (0.108)
Number of Observations	937	234	771
Fixed Effects	Yes	Yes	Yes

Standard Errors in Parentheses

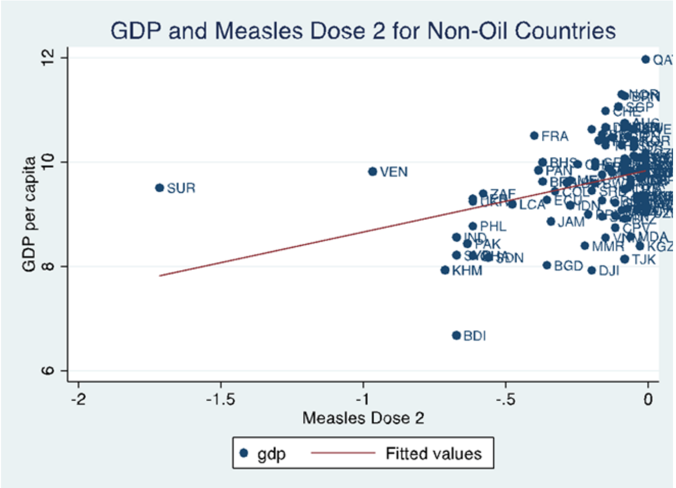
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Results for the OECD countries indicate that MSDOSE1 and MSDOSE2 are negatively correlated to GDP and are significant at the 0.1% level. This could be because the variation in the OECD countries is very minimal and that most countries already have high levels of vaccinations for measles (0.8 to 1). After a certain level of vaccination rates are achieved in a country, the impact on GDP may not be as pronounced as for countries that still struggle to meet basic vaccination levels for their populations. Additionally, since the focus of the paper is access to healthcare and not vaccines, this result possibly hints at the fact that the level of access to healthcare people have in OECD countries do not differ very much. The histogram below is indicative of this relationship.

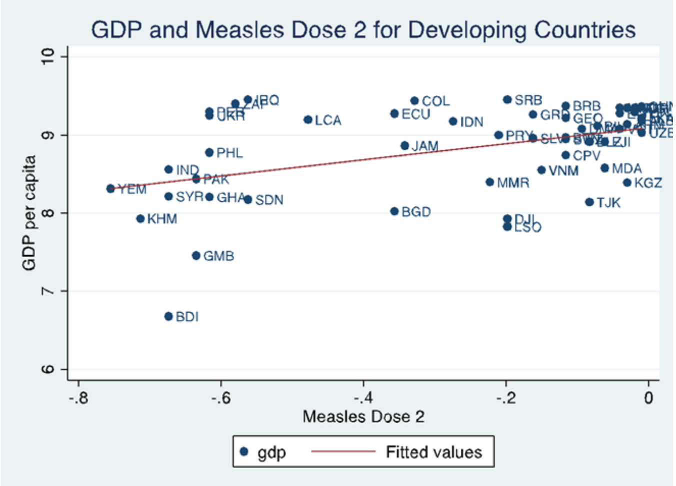


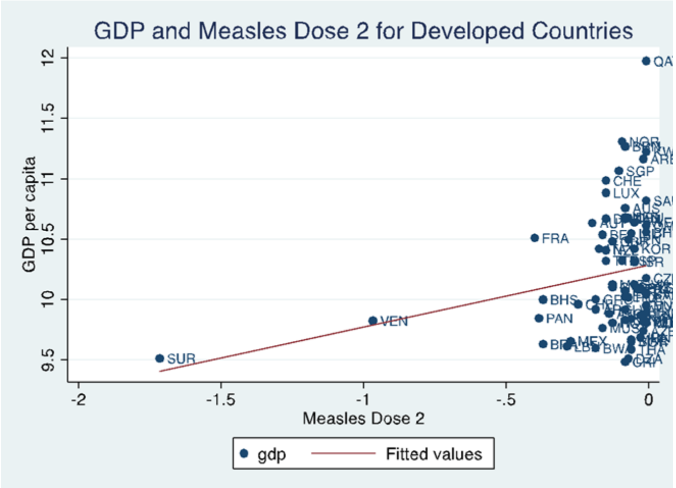


Results for the Non-Oil Countries show a positive relationship with GDP per capita. The results indicate that with every 1% increase in MSDOSE2, there is a 0.28% increase in GDP. This value is higher than the 0.20% increase for all countries. This could be explained by the removal of oil countries from the regression, which have high GDPs that are driven by oil exports. Essentially, the economies of these countries rely on resource extraction and their GDP growths do not depend as heavily on other factors such as savings and institutions. The most insightful part of the results for Non-Oil countries is that it is in alignment with the predictions made for the explanatory variables in the previous section. MSDOSE2, SAVINGS, SCHOOL, and EXPORTS are positively correlated with GDP. GPOP is negatively correlated with GDP and the results are statistically significant. This both validates the model and the hypothesis that access to healthcare positively impacts economic growth.



The relationship between access to healthcare and economic growth is further examined for countries belonging to different income groups, by separating the developing and developed countries. The logarithm of GDP per capita (2011 PPP $) for countries with high human development (Human Development Report 2014) is used as a benchmark to separate developing and developed countries. Though the relationship between access to healthcare and GDP per capita is positive for both developing and developed countries, the difference in distribution of the data points adds nuance to this interpretation. The developing countries have a more evenly scattered distribution for MSDOSE2, along the line of best fit, with a slightly greater concentration of countries at the extremes of MSDOSE2. This suggests that economic growth steadily increases with increased access to healthcare and that expenditure in increasing access to healthcare could result in positive economic gains. This result is substantiated further by the scatterplot for the developed countries. Countries with high values of GDP are almost exclusively clustered at the maximum value for MSDOSE2, implying an almost 100% vaccination rate for measles. This evidence also supports the hypothesis that increased access to healthcare leads to economic growth.





Further research can be done using the same model while controlling for expenditure on healthcare. This would provide better insight into the relationship between access to healthcare and the government's role in providing it through healthcare expenditure.

V. CONCLUSION

In conclusion, with every 1% increase in access to healthcare (immunization for Measles Dose 2), GDP per capita increases by 0.20%. This finding supports the hypothesis that access to healthcare has a positive relationship with economic growth. The relationship also holds when Non-Oil countries are separated from the data, which have a higher GDP percentage increase of 0.28%. The results for the Non-Oil countries are particularly interesting because the values for all the explanatory variables are statistically significant and support the trends predicted earlier. MSDOSE2, SAVINGS, SCHOOL, and EXPORTS are positively correlated while GPOP is negatively correlated with GDP. This indicates that the model is properly specified, and that the positive relationship between access to healthcare and economic growth is appropriately controlled for. The distribution of developing and developed countries against MSDOSE2 is also indicative of the fact that the countries with higher economic development have very high levels of access to healthcare. Additionally, widely distributed values of GDP to MSDOSE2 for developing countries indicate that increasing access to healthcare could potentially propel these economies into a virtuous cycle of economic growth. However, the direction of causality has not been tested for and thus these conclusions are purely based on correlation. It is possible that the positive relationship could run in both directions, and access to healthcare and economic growth positively affect each other (i.e. the reverse causality problem).

The existing literature uses variables such as life expectancy, mortality rate, and health improvements to measure the impact of health on GDP. Using vaccination rates as a proxy for access to healthcare is a slightly different approach than those in the papers discussed previously. However, the findings are consistent with other papers that have also found a positive relationship between healthcare outcomes and economic growth using different empirical and structural models. The findings also demonstrate resonance with some papers which determined that the impact of healthcare on economic outcomes may differ based on the income level of countries. Countries have been separated based on income groups by two methods. The first is the regression that was run for only the OECD countries. This showed a negative relationship with access to healthcare, possibly because there is such little variation in access to healthcare for these economies. The second segregation, of developing and developed countries, finds a much more clustered distribution for high-income countries with high levels of access to healthcare. This is also consistent with the literature that finds the impact of access to healthcare to be more pronounced on GDP in developing economies as opposed to developed ones.

The results offer interesting insights for policy recommendations on healthcare. There is evidence of access to healthcare being important to economic growth. However, the other important factor in increasing access to healthcare is expenditure on healthcare. More developed countries typically allocate more funds to public healthcare expenditure than developing countries. However, the impact of increasing healthcare expenditure, and conversely, access to healthcare, may have larger economic gains for developing countries than developed countries. Healthcare practices such as immunization are not always publicly funded, which implies that the probability of fundamental access to healthcare to children being denied due to negligence or poverty could be very high. This would not only hamper economic growth, but also put the health of society at risk. The positive relationship between access to healthcare and economic growth is important because it could create incentives for governments to increase healthcare expenditure, resulting in both economic and welfare gains for society.

As a result, future areas of research could include using the same model and control for expenditure on healthcare. This would provide an interesting perspective on the correlation between access to healthcare, expenditure on healthcare, and economic growth. It would build a stronger foundation to determine policy outcomes for access to healthcare and economic growth. Other macroeconomic variables such as area-wise density of doctors could also be used to measure access to healthcare to determine whether that causes the results to change. It would also be interesting to test whether there is a causal relationship between access to healthcare and GDP growth, and to check for the direction of the causality.

The Supplemental Nutrition Assistance Program (SNAP)

AN ANALYSIS OF THE SNAP'S IMPACT ON WOMEN'S HEALTH AND DIET

Natasha Laponce

ECON 490

I. INTRODUCTION

In the 2016 fiscal year, the United States federal government spent over $70 billion on the Supplemental Nutrition Assistance Program (SNAP), making it the largest federal food support program in the United States (Food and Nutrition Service [FNS], 2017b). Every year, the SNAP works to help millions of low-income families combat hunger and obtain more nutritious food. The SNAP may be better recognized by its former name, the Food Stamp Program (FSP), which distributed food stamps to Americans in need of food assistance. Food stamps were first introduced in the United States during the Great Depression in 1939 under President Roosevelt but were disbanded at the start of World War II. In 1964, food stamps were reintroduced under the Food Stamp Act in order to use excess agricultural surpluses more efficiently and make nutritious foods more widely available to low-income families ("The History of SNAP," n.d). In the early 2000s, the method of stamp distribution was replaced by the currently used Electronic Benefit Transfer (EBT) card, which functions like a debit or credit card. In 2008, FSP was renamed the Supplemental Nutrition Assistance Program (SNAP) and by 2011 it had become the largest food assistance program in the country. In the 2016 fiscal year, it helped over 43 million people every month, supplying on average approximately $125 per person (FNS, 2017c). To receive SNAP benefits, individuals have to meet a series of eligibility requirements, the most significant being an income specification, which requires households have a gross monthly income of no more than 130% of the poverty line (a maximum poverty index ratio [PIR] of 1.3). For a family of four, this amounts to $2,633 per month (FNS, 2017a).

The effectiveness of programs like the SNAP is of paramount importance for Americans, especially today with 42.2 million people living in food insecure households in addition to 36% of adults and 17% of children recorded as being obese in 2015 (Economic Research Service, 2017; Ogden, Carroll, Fryar, & Flegal, 2015). Being overweight or obese has been linked to an increased risk of developing many serious health conditions such as type 2 diabetes, coronary heart disease, high blood pressure, and some cancers (Centers for Disease Control and Prevention [CDC], 2015b). Better understanding the relationship between income and health is important, especially for women, as research has also shown that female obesity is negatively correlated with income (Ogden, Lamb, Carroll, & Flegal, 2010). For example, between 2005 and 2008, it was found that 29% of women with PIRs above or equal to 3.5 were obese, compared to 42% of women with PIRs under 1.3 (Ogden et al., 2010). Similar, but less dramatic results are evident in the data collected by the National Health and Nutrition Examination Surveys (NHANES) from 2007 to 2014 in which women of the same defined categories had obesity levels of 37% and 48% respectively (CDC, 2017).

Research on the program's effectiveness has shown mixed results. Many studies find that program participation may lead to higher obesity levels, especially among women, calling into question the program's legitimacy as a beneficial government program (Baum, 2007; Chen, Yen, & Eastwood, 2005; Gibson, 2003; Jilcott, Liu, DuBose, Chen, & Kranz, 2011; Meyerhoefer & Pylypchuk, 2008; Zargorsky & Smith, 2009). However, the belief that the SNAP may be causing women to become unhealthier is by no means unanimous. In this paper, I continue to study the impact of the Supplemental Nutrition Assistance Program using more recent data and more robust methods of estimation to determine whether it is actually improving women's health and diet or making it worse. I examine key health and nutritional indicators such as body mass index (BMI), waist circumference (WC), as well as sodium, saturated fat, vitamin A, RAE, and dietary fibre intake. In light of the fact that BMI and WC change relatively slowly, measuring the program's impact on the intake of specific dietary variables shall provide better insight into how the program is immediately affecting participants.

II. LITERATURE REVIEW

There are a handful of studies that look at the impact of the SNAP and food stamps in the US on health and diet. Many find that food stamp use may adversely impact women's health (Baum, 2007; Chen, Yen, & Eastwood, 2005; Gibson, 2003; Jilcott, Liu, DuBose, Chen, & Kranz, 2011; Meyerhoefer & Pylypchuk, 2008; Zargorsky & Smith, 2009). For example, Zargorsky and Smith (2009) who use data from the National Longitudinal Study of Youth (1979 cohort) (NLSY79), find that food stamp participation is associated with higher BMI levels in women. In contrast, Fan (2010) finds that "the FSP is not responsible for... higher BMI[s] among its female participants" (p. 1178). Ploeg, Mancino, and Wang (2007) find that although there was initially a BMI difference between female participants and non-participants in the late 1970s, this difference has evaporated when looking at more recent data taken at the turn of the century as part of a larger nationwide increase in the prevalence of obesity. In recent years, research on the SNAP has also started to look at its impact on diet and nutrient intake. Nguyen, Shuval, Njike, and Katz (2014), who use data from NHANES between 2003 and 2010, find that SNAP participants have a lower quality diet compared to income-eligible non-participants. However, Nguyen, Shuval, Bertmann, and Yaroch (2015) also find that when SNAP participation is interacted with food security, food insecure SNAP participants have lower BMIs and a healthier diet. The variety of these contrasting results indicates that further research is needed. By using more recent data from 2007 to 2014 and a regression discontinuity (RD) model of estimation, I expand upon the results of past research and provide a more up-to-date and accurate analysis on the association between food stamps and women's health and diet quality.

III. DATA

All my data comes from the National Health and Nutrition Examination Surveys (NHANES) from the periods of 2007-2008, 2009-2010, 2011-2012, and 2013-2014 (hereon called 2007 to 2014). NHANES collects demographic, socioeconomic, health, and dietary data on 5,000 nationally representative individuals every year to determine the health and nutritional status of people in the United States (CDC, 2014). The survey includes both an interview and physical examination. The sample for my standard regression includes all women aged 20-65 with a family poverty index score of less than or equal to 1.3, thereby making all women observed income-eligible for the SNAP. In practice, eligibility is determined by an index based on household conditions. However, this is not provided by NHANES and constructing a new poverty level index based on household information is very complicated given its dependence on the number of people in the household, their state of residence (not provided by NHANES), and the year the survey is conducted. Therefore, the family poverty index is used as a proxy. Women who are pregnant at the time of the survey are also excluded for accuracy. In total, my primary sample contains 3,040 observations, although this varies from regression to regression depending on the data available.

My main independent variable is current SNAP participation, determined by whether a woman has received SNAP benefits in the last 30 days. My main dependent variables include body mass index (BMI) (calculated as kg/m2), sodium intake (mg), saturated fat intake (gm), vitamin A as retinol activity equivalents (RAE) intake (mcg), and dietary fibre intake (gm). BMI is classified according to the Centers for Disease Control and Prevention (CDC) standards with indexes <18.5 classified as underweight, 18.5-24.9 as normal, 25.0-29.9 as overweight, and ≥ 30.0 as obese (Department of Health and Human Services, n.d.). Although BMI is often the favoured health indicator in studies, it fails to distinguish between excess fat, muscle, and bone mass, all of which may vary depending on a woman's activity level and ethnicity (Department of Health and Human Services, n.d.). Therefore, waist circumference (WC) (cm), which measures fat around the midsection (often considered the most dangerous), is also measured as a test for robustness (CDC, 2015a). Both BMI and WC measurements are collected in the physical examination, eliminating (or at least severely reducing) any chance that this information is misreported. Sodium, saturated fat, vitamin A, RAE, and dietary fibre intake data, however, are based on self-reported data. NHANES collects dietary intake data over the course of two non-consecutive days but only day 1 data, collected through an in-person interview, is analysed in the main regressions under the assumption that face-to-face communication renders more accurate information (Novick, 2008). Day 2 data are collected by telephone 3-10 days after the first. Although they are not used in the primary regressions, they are analysed in the interest of reaffirming day 1 generated results. Regardless of the method of collection, the fact that dietary data are self-reported poses a weakness to this study as it may be subject to both unconscious and conscious misreporting. This is taken into consideration when analysing the results.

Dietary intakes for sodium, saturated fat, vitamin A, RAE, and dietary fibre are calculated according to the USDA's Food and

Nutrient Database for Dietary Studies. These four variables are chosen based on their positive correlation with the consumption of specific foods - sodium with processed foods, saturated fat with excessive meat, cheese, and processed snacks, vitamin A, RAE with various vegetables (especially leafy greens), and dietary fibre with plant foods such as beans, fruits, vegetables, and whole grains (CDC, 2016; Dietitians of Canada, 2014; Dietitians of Canada, 2016; U.S. Department of Health and Human Services and U.S. Department of Agriculture, 2015). Consequently, sodium and saturated fat intake are negatively related to diet quality while vitamin A, RAE and dietary fibre are positively related.

My control variables include: age, ethnicity, place of birth, education, marital status, household size, health insurance coverage, employment, mental health, sedentary activity, and family poverty index. Participation in other nutrition assistance programs like the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) would have been included as a control, but data was very limited for the paper's sample of interest. Adult food security level, an index constructed by NHANES based on people's answers to food security related questions, is also added to the regression both as an additional control to test the estimate's robustness and as an interaction with SNAP participation. By controlling for these variables which may have a unique effect on women's health and diet and therefore bias results, the impact of the program is better isolated and the risk of omitted variable bias (OVB) is reduced.

Table 1 shows descriptive statistics of the dependent variables of interest for eligible versus ineligible women, and participants versus non-participants. Eligible women have a higher average BMI and WC compared to ineligible women, and participants have an even higher average BMI and WC than those who are eligible but not participants. Particularly disheartening, but not surprising given recent health trends, is that the average eligible female participant is obese according to BMI and all groups of women average a waist circumference considered a high health risk (CDC, 2015a). The relationship between participation and diet quality is less clear, but the averages of most of the dietary variables indicate that participants have the lowest quality diet (higher sodium and saturated fat intake and lower vitamin A and dietary fibre intake). Additionally, none of the groups meet the recommended intake levels for any of the dietary variables of interest leaving it to be inferred that diet quality amongst eligible and ineligible women is very poor (Food and Nutrition Board, 2005; Food and Nutrition Board, Institute of Medicine, National Academies, 2011a; Food and Nutrition Board, Institute of Medicine, National Academies, 2011b). Nevertheless, it still appears particularly bad for eligible participants. These statistics and the apparent positive correlation between SNAP participation and poor health and diet motivate this paper and suggest the need for a greater emphasis to be put on healthy eating.

IV. EMPIRICAL METHOD

$$\textbf{(1) } Y_i = \alpha_{ih} + \beta_1 SNAP_h + \delta_{ih} X_{ih} + \varepsilon_{ih}$$

My primary regression (1) uses the ordinary least squares (OLS) method of estimation to measure the impact of current participation in the SNAP (represented by the dummy variable $SNAP_h$) on the health and nutrition variables of interest. $SNAP_h$ is equal to 1 when the individual is a current participant and 0 if they are not. Y_i represents the dependent variables (BMI, WC, sodium, saturated fat, vitamin A, RAE, and dietary fibre intake), α_{ih} is the intercept, β1 is the difference in dependent variables between SNAP participants and non-participants, X_{ih} is a vector of all control variables, and ε_{ih} is the error term.

I expect β1 to be positive for BMI, saturated fat, and sodium intake and negative for vitamin A, RAE and dietary fibre intake, reflecting an overall deterioration in health and diet quality. This hypothesis is founded primarily on the theory that SNAP benefits cause an effective increase in disposable income that can be spent on food, causing women to do just that and resulting in a habit of overconsumption (Debono, Ross, & Berrang-Ford, 2012). This effect likely negatively impacts women's health given findings that suggest that food insecure individuals, many of whom are likely SNAP participants, may have a preference for low-nutrient, high calorie foods (Leung & Villamor, 2010; Nguyen et al., 2015). Junk foods and overly processed snacks can be purchased with SNAP benefits, which may also encourage such unhealthy inclinations (FNS, 2017d). This income effect may be additionally worsened by the fact that fruits and vegetables provide fewer calories per dollar and have a much shorter shelf life than other less costly, higher calorie, processed foods (Nguyen et al., 2015). Other studies have also highlighted the food stamp cycle as another way SNAP benefits may lead to weight gain (Leung & Villamor, 2010). This cycle involves binge eating right after receiving benefits, followed by severely restricting food consumption when benefits have depleted, which is an eating pattern that has been shown to potentially lead to weight gain (Leung & Villamor, 2010).

$$(2)\ Y_i = \alpha_{ih} + \beta_1 SNAP_h + \beta_2(INCELIG_h) + \beta_3(SNAP_h{*}INCELIG_h) + \delta_{ih}X_{ih} + \varepsilon_{ih}$$

I also run a regression discontinuity (2), analysing women with poverty index ratios ± 0.1 the income eligibility cut-off of PIR = 1.3. Income eligibility, indicated by the dummy variable, INCELIGh, equals 1 for women with a poverty index ratio between [1.2-1.3] (and are income eligible) and 0 for women with ratios between (1.3-1.4] (and are not income eligible). The reasoning behind this design is that women who fall right below and above the cut-off marker have similar socioeconomic characteristics. As a result, treatment, in this case SNAP income eligibility, is "as good as randomized" making them good groups to compare (Lee & Lemieux, 2010, p. 282). By narrowing the sample of observed women, the issue of omitted variable bias is somewhat alleviated. However, there are some women in the data with PIRs above 1.3 who are also SNAP participants. By nature of the eligibility cut-off, this is not possible and therefore these women are dropped under the assumption that their classification as participants is the result of inaccurate reporting. By doing this, I hope to capture more precisely the impact of the SNAP in these regression discontinuities. Like β1 in regression (1), β2 in the RD should be positive when observing BMI, sodium, and saturated fat intake, and negative for vitamin A, RAE and dietary fibre intake. However, β2 only captures the difference in dependent variables between eligible and ineligible women. Given that not all eligible women actually participate in the program (a product of the self-selection bias), β2 is unlikely to reflect the unique effect of SNAP participation. For example, of the 3,040 women eligible for the program in this paper's sample, only 1,343 are participants. β2 therefore captures the impact of the intention-to-treat (program eligibility), but this is likely an underestimate of the actual program effect (Gupta, 2011). In an effort to more accurately determine it, an additional RD is run comparing those who are income eligible and participants (the treated treatment group), represented by the interaction term, SNAPh*INCELIGh, with those who fall just above the cut-off point and are no longer eligible. I expect the new coefficient of interest, β3, to be greater than β2 given that it is likely better able to capture the true effect of the program.

Nevertheless, a few assumptions need to be made to interpret the estimates generated by the RD as valid. First, it must be assumed that women do not have precise control over their income (Lee & Lemieux, 2010). It is also assumed that there is perfect observance of the income cut-off, a problematic assumption given that income admissibility is just one of many SNAP eligibility requirements (Trochim, 1984). Finally, it is expected that there are no other causes for discontinuity between SNAP participants and non-participants (Trochim, 1984).

$$(3)\ BMI_i = \alpha_{ih} + \beta_1 SNAP_h + \beta_2 MARGINAL\_FS + \beta_3 LOW\_FS + \beta_4 VERYLOW\_FS + \beta_5(MARGINAL\_FS*SNAP) + \beta_6(LOW\_FS*SNAP) + \beta_7(VERYLOW\_FS*SNAP) + \delta_{ih}X_{ih} + \varepsilon_{ih}$$

Given the findings of past studies that have suggested that SNAP participation may affect the BMI levels of groups differently, notably individuals with different food security levels (full, marginal, low, and very low) and ethnicities (Mexican American and other Hispanic, non-Hispanic white, non-Hispanic black, or other), two more regressions which interact SNAP participation with these variables are run (Nguyen et al., 2015; Zargorsky & Smith, 2009). The sample of women observed in this analysis is the same as in regression (1) - all women with poverty index ratios of 1.3 or below. Only the equation interacting food security with SNAP participation is shown here, but a similar equation is used when ethnicity is interacted with participation. In the equation, only $\beta 1$, $\beta 5$, $\beta 6$, and $\beta 7$ are of interest. I expect $\beta 1$ to be positive based on the same theory outlined above - that SNAP benefits effectively increase income, which encourages unhealthy eating, causing BMI to increase. In contrast, I anticipate $\beta 5$, $\beta 6$, and $\beta 7$ to not only be negative (reflecting a smaller participation effect relative to that experienced by women with full food security), but increasingly negative as food security deteriorates.

This rationality is based on the assumption that benefits for women with full food security produce the greatest expansion in consumption choices leading to an overconsumption of food (captured by $\beta 1$). By comparison, food insecure women are more likely to rely on benefits to ensure food of any kind is consumed; thus, SNAP benefits are less likely to expand consumption beyond normal levels. As for the ethnicity interaction estimates, it is harder to predict how the SNAP affects different groups, especially considering that any effect is likely rooted in other socioeconomic factors. Some have hypothesized that neighbourhood conditions may lead the program to affect some communities and ethnicities more than others (Nguyen et al., 2015). For example, research has found that communities with a predominantly African American population have lower accessibility to healthy foods compared to other, predominantly white communities (Baker, Schootman, Barnidge, & Kelly, 2006; Morland & Filomena, 2007). This inconsistency may subsequently impact not only a woman's health, but also if she enrols in the SNAP and how she uses her benefits if she does. If this theory holds, the effect of SNAP participation is likely exacerbated by such neighbourhood conditions resulting in a positive coefficient on the interaction term between black women and participation (when compared to white women). This reasoning is contradicted by the results of other studies that find that white women are most affected by the SNAP - thus it is unclear how exactly the program affects the BMIs of different ethnicities (Zargorsky & Smith, 2009).

V. RESULTS AND DISCUSSION

The main regression results for BMI are listed in columns 1-5 in Table 2. The first column regresses SNAP participation on BMI with no controls. Column 2 runs the same regression, but controls for age, place of birth, education, marital status, household size, health insurance coverage, employment, mental health, sedentary activity, and family poverty index. Column 3 tests the robustness of column 2's estimates by including food security level as an additional control. Food security level is initially excluded under the assumption that SNAP participation is arguably a proxy for food insecurity (Leung & Villamor, 2010). However, some studies find that SNAP participants come from varying food security backgrounds and that program participation and food insecurity may have independent effects on health and diet (Gibson, 2003; Leung & Villamor, 2010; Leung et al., 2013). Therefore, it is included separately as a test for estimate robustness. Column 4 introduces the RD model (equation (2)), comparing the BMIs of eligible and non-eligible women with poverty index ratios between 1.2-1.4, thereby measuring the effect of SNAP eligibility. However, because eligibility does not imply participation, column 5 compares eligible SNAP participants with ineligible non-participants, capturing the effect of program participation.

Looking at the estimates in columns 1-5 in Table 2, SNAP participation appears to have a positive relationship with BMI. For example, participation is correlated with a 1.768 increase in BMI significant at the 0.1% level. When food security is controlled for, the coefficient remains relatively stable and significant, settling at 1.690. Furthermore, when income eligibility is regressed on BMI in the first RD (column 4), the resulting coefficient is -1.870. However, when SNAP participation specifically is regressed on BMI using the RD design, the new coefficient of interest in column 5 reverts to a positive 0.364. This turnaround in association makes a strong case that BMI and SNAP participation are, as my hypothesis states, positively related. This relationship is also corroborated when using WC as the dependent variable of interest (shown in Table 3). However, the statistical insignificance of the

RD estimates for both BMI and WC suggests that there may be other influencing factors.

Estimates for BMI begin to change when SNAP participation is interacted with food security level (displayed in column 6 of Table 2). The results show that women with full food security appear to be the most affected by the SNAP, whereas women with a marginal level appear to be the least. This is reflected by the substantial increase in the coefficient on the original SNAP variable (now representative of the impact of SNAP participation on the BMIs of women with full food security) from 1.690 to 2.496 (also significant at the 0.1% level). In contrast, the coefficient on the marginal food security interaction term, is -2.199 and significant at the 5% level implying that women with marginal food security are likely unaffected or affected to a very small degree by the program. The estimates on the other interaction terms are not statistically significant and smaller in magnitude, but both are negative suggesting that participating women with full food security are driving the initial positive correlation. These results are also supported when running the regression with waist circumference (shown in column 6 of Table 3).

Such a dramatic increase in the SNAP coefficient is arguably caused by the previously discussed income effect, whereby women consume more food with more money. As hypothesized, this effect appears to be more acute for women with full food security who, upon receiving benefits, likely experience a greater expansion of consumption choices. It is of course possible that SNAP benefits lead women to consume healthier or higher quality food which would align with the goals of the program, but these results and the results for the dietary intake variables do not reflect that. Such a theory would explain why women with full food security are affected more than women with marginal. However, the fact that the SNAP does not appear to impact women who are even more food insecure in a diminishing manner challenges this theory and suggests that other factors such as the food stamp cycle or omitted variables may be influencing the results.

Looking now at the impact of SNAP participation dependent on ethnicity (presented in column 7 of Table 2), the most striking result is that white women appear to be the most affected by the program, especially when compared to black women who appear almost entirely unaffected. The coefficient on the original SNAP variable (now representative of the effect of SNAP participation on BMI levels for white women) has increased substantially to 2.160 significant once again at the 0.1% level. In comparison, the coefficient on the interaction term between black women and SNAP participation is -2.041 and significant at the 5% level, indicating that the SNAP may be having an extremely small to negligible impact on black women. These results are also supported when WC is analysed (also shown column 7 in Table 3).

One interesting observation is that the coefficients on the ethnicity interaction terms for white and black women appear to resemble the coefficients on the full and marginal food security level interaction terms. In fact, when looking at eligible women with full food security, approximately 46.3% are white and 37.5% are black. In contrast, approximately 16.5% of eligible women with marginal food security are white and 22.3% are black. These statistics suggest that food security level may be driving the ethnicity interaction coefficients. However, even when food security is controlled for in the regression interacting ethnicity and participation, these estimates remain relatively constant, essentially dismissing such a possibility. It could also be that participating white women are financially better off than black women, triggering an income effect similar to that described in relation to food security level. In this context, women with higher ratios who, without SNAP benefits, are financially better off, experience a larger expansion in their consumption choices when they do receive benefits, thereby resulting in a greater increase in BMI. The data appears to mildly support this theory with participating white women averaging a family PIR of around 0.05 points higher than black women. Therefore, it may be that the SNAP's differential impact on black and white women is in part the result of differences in income. However, this income disparity is relatively small, thereby signifying that other unaccounted socioeconomic factors may be driving this relationship, such as the number of children living in the household and whether a woman is living in an urban or rural environment. Data on both of these variables are not provided by NHANES for the time period analysed in this paper, but both potential relationships should be explored in the future.

Diet quality estimates (see Tables 4.1-4.4) are more variable than BMI, but on the whole, SNAP participation is associated with a lower quality diet. For example, participation is correlated with a lower dietary fibre intake of -1.564 gm, significant at the 0.1% level (when all controls are included). This result is replicated and similarly statistically significant using a RD (see Table 4.4) with the coefficient on the SNAP participation variable decreasing even more to -2.529 gm. Generating statistically significant estimates using a RD is rare in this study making this result, which also aligns with the paper's hypothesis, particularly noteworthy. These results are supported when analysing day 2 intake, although the RD estimate is no longer statistically significant. The coefficients for vitamin A, RAE reflect a similar negative correlation (see Table 4.3). Saturated fat intake also appears to align with my hypothesis, which generates a significant positive coefficient of 1.691 (taking into account all controls) on the SNAP participation variable (see Table 4.2). The RD estimate is not significant, but it remains positive. From these results alone, it appears that contrary to its intended effect, the SNAP may be causing women to consume a less nutritious diet that is higher in saturated fat and lower in plant-based foods.

These results are contrasted by the negative estimates generated when looking at sodium intake (see Table 4.1). However, when consulting day 2 interview data, this relationship has reversed with all participation coefficients displaying a positive sign. The extreme variability of these estimates, especially when compared to the estimates generated by the other dietary variables, indicates that either a correlation between sodium intake and SNAP participation does not exist, or that the dietary data are inaccurate. It may also be that sodium intake is too broad of a proxy for the intake of processed foods, and that a more specific measure such as consumption of pre-prepared or packaged foods may be needed to more accurately determine how the program is influencing the consumption of particularly unhealthy foods.
One limitation with the regressions run thus far is that there is still the potential for reverse causality, a scenario in which dependent variables like BMI and diet cause a woman to participate in the SNAP rather than vice versa as hypothesized. To control for this, another RD is run comparing women who are income-eligible but choose not to participate in the SNAP (the new treatment group) with ineligible women (the original control group). The sample of interest is the same as the original RD with only women with PIRs between 1.2-1.4 observed. If the estimates generated are similar to those produced by the original RD (shown in columns 5 of Table 2 and Tables 4.1-4.4), then the program is impacting eligible participants and non-participants in the same way. Under the assumption that the program cannot impact non-participating women, such a result would imply that reverse causality may be driving the initial estimates.

The generated estimates (shown in Table 5) for this reverse causality test are once again variable. When comparing Table 5 coefficients with those in columns 5 of Table 2 and Tables 4.1-4.4, results for BMI, saturated fat intake, and dietary fibre intake appear to confirm my hypothesis that the SNAP is driving deteriorations in health and lowering diet quality. For example, the SNAP coefficient for saturated fat is negative in the RD testing for reverse causality but positive in the initial RD. From these opposing estimates, it may be inferred that reverse causality is not the source of the original positive correlation. However, other coefficients like that for vitamin A, RAE, are similar to the initial RD coefficients, fuelling the possibility that reverse causality may be an issue. Interestingly, the variables that confirm my hypothesis in this robustness test are the same ones that generated statistically significant results in the first few regressions (see columns 1-3 in Table 2, Table 4.2, and Table 4.4) once again suggesting that these variables simply have a stronger correlation with SNAP participation.

VI. LIMITATIONS

There are a few limitations of this paper that need to be discussed. First, this study does not use panel data. As a result, BMI and WC cannot be observed before and after program participation. This is problematic, not only because these measures change relatively slowly, but also because without panel data, this paper cannot determine causality (only correlation) between SNAP participation and the health and diet variables of interest. Furthermore, there is still the potential for reverse causality and omitted variable bias. While this paper attempts to test and reduce both by running various regression discontinuities, neither can be confidently ruled out. One potential omitted variable includes how busy women are, which may impact the foods they eat and whether they choose to enrol in the SNAP. Especially since the program encourages people to eat more home cooked meals that may take longer to prepare, this factor could confound results. The 2008 financial crisis may also have increased not only the number of women eligible and registered in the SNAP, but also women's stress levels which may uniquely impact their health and diet. It is very plausible that the recession exacerbated the original impact of the SNAP, causing the generated coefficients to be overestimated.

As mentioned earlier, given that all information other than BMI and WC is self-reported, data may also be misreported or misclassified, especially if participants want to hide or justify other aspects of their lives (CDC, 2014). For example, a woman receiving SNAP benefits may be hesitant to report that she is eating more unhealthy foods. An overweight woman may also be more uncomfortable reporting the food she eats if she does overeat or consume food in an irregular pattern. These are just two possible reasons why a woman may want to misreport information, but any misreporting, intentional or unintentional, would render the data inaccurate and confound the generated estimates.

A final potential limitation is this paper's use of family poverty index to determine program eligibility. In practice, eligibility is determined by an index based on household conditions. Although household and family statistics are likely very similar, if not identical in most cases, there is the chance that the two may not be equal, which may have led to inaccuracy determining who is eligible and who is ineligible.

VII. CONCLUSION

This paper expands upon previous research analysing the effectiveness of the Supplemental Nutrition Assistance Program in improving women's health and diet, ultimately determining that, on the whole, SNAP participation appears to negatively impact both. Although my results predominantly corroborate those of past academic studies, by using more recent data from NHANES and two methods of estimation (OLS and RD), I have contributed to the growing academic discussion surrounding this very important issue program. Not only do I find that the relationship between SNAP participation and women's health and diet quality is primarily negative, but I also find convincing evidence to suggest that white women and women with full food security are the most adversely affected by the program.

Future research on this topic may want to further examine the relationship between ethnicity, food security, and SNAP participation to help the program target particularly vulnerable groups. It may also be worth exploring the relationship between participation and consumption patterns more in an effort to establish whether the program is actually helping participants attain a more nutritious diet. Given the unpredictability of consumption habits, a longer-term study examining participants' consumption of food may be worth undertaking.

In an effort to encourage healthy eating, some have recommended the program restrict what participants are able to buy with SNAP benefits (Alston, Mullally, Sumner, Townsend, & Vosti, 2009). However, such changes that limit what people can purchase may also have adverse effects such as lowering program participation or increasing the prices of healthy foods (Alston et al., 2009). Nevertheless, it is clear that education on healthy eating, in addition to programs like the SNAP, need to be prioritized at this time to help alleviate hunger and improve the health and nutrition of all Americans.

Helping or Hurting?

THE CROSS-COUNTRY EFFECT OF REFUGEES ON ECONOMIC GROWTH

Lindsey Oglivie

ECON 490

I. INTRODUCTION

The recent and ongoing refugee crisis in Syria has torn apart countless families and forced individuals to migrate to the surrounding countries of Turkey, Jordan, and Lebanon. Since 2011, 1.7 million Syrian refugees have landed in Turkey alone, making up 2.3% of the country's population (Bahcekapili & Cetin, 2015). Accepting refugees can often have significant economic repercussions for host countries. In some cases, refugees displace native labour forces, leading to increased unemployment for native workers (Bahcekapili & Cetin, 2015). This is particularly prominent in the low-skilled labour market, in which refugees are often willing to accept a lower wage rate than native workers for the same work (Ruiz & Vargas-Silva, 2016). In other cases, host labour markets are able to absorb large labour shocks without experiencing adverse effects (Braun & Mahmoud, 2014). The impact that refugees have on economic growth in a host country depends largely on how the refugees behave in the host labour market.

When refugees enter the labour market in a host country they can act as either substitutes for or compliments to the host country's labour force. If refugees behave as substitutes for native workers they compete with these workers in the labour market, driving down wages and displacing native workers from employment. Additionally, the increase in the size of the labour force (due to the increased stock of refugees) dilutes the stock of capital in the host country, leading to a lower capital-labour ratio. A decrease in the capital-labour ratio decreases the productivity of the labour force and ultimately leads to lower economic growth. Thus, if refugees are substitutes to the host labour force they negatively affect

GDP per capita. Contrarily, if refugees behave as compliments in a host labour market – for example, by filling skill shortages in the host country – an increase in the stock of refugees makes native workers more productive, which increases the demand for both foreign and native labour. This increased demand leads to an increase in wage rates, while the highly productive workforce increases economic output. Consequently, if refugees are compliments to the host labour force they have a positive effect on GDP per capita.

The level of substitution or complementarity that occurs also depends on the skill level of refugees relative to native workers. Depending on the skill composition of refugees and the composition of a host country's labour force, an increase in the stock of refugees in a country can cause significant displacement in labour activities where there is a high degree of substitutability, while having insignificant or even positive effects in other areas of employment. This occurred in West Germany, after World War II, where East German expellees caused displacement in specific state-occupations that experienced large inflows of refugees, while other state-occupations that did not receive many refugees were unaffected (Braun & Mahmoud, 2014). Bahcekapili and Cetin (2015) look at the impact of Syrian refugees on unemployment in south-eastern Turkey and find that refugees compete with native workers, particularly in the prominent unskilled labour market, and consequently increase the unemployment rate in many regions. Similarly, Ruiz and Vargas-Silva (2016) find that Burundian and Rwandan refugees displace native Tanzanian workers in agricultural occupations, attributable to the high degree of substitutability between the three labour forces in this area of employment. On the other hand, Muysken and Ziesemer (2013) find that, in the long run, immigrants can fill labour shortages in many OECD countries, which increases productivity and leads to higher GDP per capita. This paper looks at the effects of refugees on cross-country variations in per capita income. By using a long-run growth accounting model to measure variable effects on economic growth, I expect that across countries refugees behave as complements to host labour forces. As such, I predict that an increase in the stock of refugees in a host country leads to an increase in GDP per capita in that country.

II. LITERATURE REVIEW

Existing literature on the economic consequences of refugee movements focuses on the regional impact of refugees on a host country's labour market. These studies use instances of mass forced migration as natural experiments to analyze the impact of refugees on unemployment, wage rates, and productivity in host countries. Braun and Mahmoud (2014) analyze the impact of post-World War II East German expellees on the labour market of West Germany. They predict that expellees have a negative effect on unemployment in West Germany due to the high degree of substitutability between East and West German workers, who share a language and have similar levels of education. Braun and Mahmoud divide the labour market into sectors according to state and occupation using data from the German occupation and population census of 1950. They find that a 10% increase in the proportion of expellees in a specific state-occupation leads to a 4% decrease in the native employment rate for the same state-occupation (Braun & Mahmoud, 2014). However, the displacement effects are not long term and diminish with time. Furthermore, if the share of expellees does not exceed 15%, expellee inflows do not affect the native employment rate, suggesting that the West German labour market is able to take in expellees up to a certain point without experiencing adverse effects (Braun & Mahmoud, 2014).

Bahcekapili and Cetin (2015) and Tumen (2016) look at the impact of Syrian refugees on the Turkish labour market. Bahcekapili and Cetin retrieve their data on labour from TurkStat and their data on refugees from the Disaster and Emergency Management Authority (AFAD) and the United Nations High Commissioner for Refugees (UNHCR) (Bahcekapili & Cetin, 2015). They use a cross-section differencing method to compare results from before the migration period (2010-2012) and after the migration period (2013-2014). They find that in three of the seven sub-regions studied, unemployment decreased after the migration period, while unemployment increased in the other four regions (Bahcekapili & Cetin, 2015). The displacement was largest among unskilled workers, which suggests that refugees compete against native workers for low-skill jobs. Conversely, Tumen compares pre- and post-migration labour statistics of treatment regions, which experience inflows of refugees, and control regions which do not receive refugees. The use of treatment and control regions allows Tumen to analyze the effect of refugees on labour markets without using data on refugees; he only uses data on labour and population, which he retrieves from the Labour Force Survey and TurkStat (Tumen, 2016). Tumen finds that refugee inflows decrease the likelihood of informal employment for native workers by 2.26% and lead to an increase in the proportion of the population that is unemployed by 0.77% (Tumen, 2016).

Ruiz and Vargas-Silva (2016) study the impact of Rwandan and Burundian refugees on the Tanzanian labour market in the 1990s. They use data from the Kagera Health and Development

Survey to test whether workers in temporary employment before the refugee shock are more or less likely to be self-employed in agricultural work, non-agricultural work, or employed outside of the household after the shock (Ruiz & Vargas-Silva, 2016). They find that natives who are employed in temporary work before the shock are more likely to be self-employed in non-agricultural work, and less likely to be self-employed in agricultural work after the shock, suggesting that refugees and natives are substitutes in the agricultural labour market (Ruiz & Vargas-Silva, 2016). Further, Tanzanians that are employed as casual workers before the shock are employed in other activities after the shock (Ruiz & Vargas-Silva, 2016). These results support the findings of literature on voluntary migration which suggest that native workers will change their employment activities to adjust to immigration flows (Ruiz & Vargas-Silva, 2016).

While voluntary migration has a different effect on labour markets than forced migration, as voluntary migration is usually a response to economic opportunities and forced migration is often a response to threats to personal safety, studies of voluntary migration provide insight into the effects of forced migration on economic growth. Feridun (2005) tests the effects of immigration on GDP per capita and unemployment in Norway. He aims to determine if immigration is capable of offsetting the anticipated decrease in the Norwegian labour supply as a consequence of an aging population. Using data from the World Bank's World Development Indicators Database over the period of 1983 to 2003, Feridun uses an OLS regression to test Granger Causality between immigration and GDP per capita and unemployment in Norway. He finds that immigration has no effect on unemployment and leads to an increase in GDP per capita (Feridun, 2005). These results oppose the common assumptions in Norway that immigration increases competition in the work force and decreases wage rates, while simultaneously putting pressure on social programs (Feridun, 2005).

Similarly, Muysken and Ziesemer (2013) propose that immigration can compensate for labour shortages in most Western countries that arise because of their aging populations. To test this theory, they use data on the Netherlands from the KLEMS (capital (K), labour (L), energy (E), materials (M), and service inputs (S)) database, World Development Indicators (WDI), the Central Planning Bureau (CPB), and the Central Bureau of Statistics (CBS) during the period of 1973 to 2009 (Muysken & Ziesemer, 2013). They find that in the short run, unemployment increases, and activity and wages fall, while GDP per capita increases slightly (Muysken & Ziesemer, 2013). In the long-run, a temporary increase in immigration of 10% causes an increase in the activity ratio of 0.4% and an increase in GDP per capita of about 0.33% (Muysken & Ziesemer, 2013). This supports the theory that immigration can have positive and permanent effects on the activity rate and economic growth of a country. Boubtane, Dumont, and Rault (2016) aim to test the theory that the negative effects of capital dilution on GDP per capita caused by immigration may be offset by migrants' positive contribution to capital accumulation, based on the framework of the augmented Solow-Swan model. The model predicts that high levels of human capital, similar to physical capital, increase output and consequently increase income per worker. They create a unique data set that differentiates between the skill levels of native and foreign-born migrants. Boubtane, Dumont, and Rault retrieve their data from border statistics, population censuses, the OECD (Organization for Economic Cooperation and Development) Population and Vital Statistics dataset, and the OECD database (Boubtane, Dumont & Rault, 2016). They find that the contribution of positive net migration to capital dilution negatively affects GDP per capita, while its contribution to capital accumulation positively affects GDP per capita, as predicted (Boubtane, Dumont & Rault, 2016). Further, the positive effects of capital accumulation are enough to offset the negative effects of capital dilution in most OECD countries (Boubtane, Dumont & Rault, 2016). Overall, an increase in foreign-born net migration of 50% leads to a long-run increase in GDP per capita of approximately 2% (Boubtane, Dumont & Rault, 2016).

Aleksynska and Tritah (2009) analyze the impact of immigration on output per worker and labour productivity in host countries. They create a unique dataset for 20 OECD countries over the period of 1960 to 2005 (Aleksynska & Tritah, 2009). Aleksynska and Tritah decompose immigrants by age and education and use a development accounting framework to evaluate the impact of immigration on human capital, physical capital, unemployment, and total factor productivity. They find that a 1% increase in the proportion of immigrants to natives causes a 0.13% increase in output per worker, which can be attributed to total factor productivity (Aleksynska & Tritah, 2009). Unskilled immigrants have the largest impact on productivity and income, which is negative in the short-run but positive in the long-run due to the adjustment of total factor productivity (Aleksynska & Tritah, 2009). The effect of immigration on employment is insignificant, suggesting that natives are not crowded out of the labour market by immigration (Aleksynska & Tritah, 2009).

Mankiw, Romer and Weil (1992) propose an augmented Solow growth model that accounts for investment in human capital to look at cross-country variations in GDP per capita. They use annual data over the period of 1960 to 1985 from the Real National Accounts composed by Summers and Heston (1998) (Mankiw, Romer & Weil, 1992). They find the effects of population growth on GDP per capita to be larger than proposed in the textbook Solow model. In addition to diluting the stock of physical capital, population growth dilutes human capital as well, further decreasing factor productivity (Mankiw, Romer & Weil, 1992). The R2 of 0.78 – which measures how well-fitted the data is to the regression line – indicates that almost 80% of the variation in GDP per capita across countries can be attributed to the variations in savings, population growth, and investment in human capital, suggesting that the augmented Solow model is a very good predictor of the cross-country variations in GDP per capita. My paper adds to the existing research on the economic impacts of hosting refugees by providing a cross-country evaluation of these effects, with the goal of improving general understanding of the consequences of hosting these migrants.

III. DATA

The long-run growth accounting model measures the amount of cross-country variation in GDP per capita that can be attributed to variations in population growth, savings rates, human capital accumulation, and openness to trade. This paper utilizes the long-run growth accounting model, adding a measure for the stock of refugees in a host country to analyze variations in GDP per capita across 126 countries over the period of 1975 to 2013. Data on income, population growth, savings rates, and openness to trade is retrieved from the Penn World Tables 9.0 (Feensta, Inklaar & Timmer, 2015), while the measure for human capital accumulation is retrieved from Barro and Lee (2013). Data on the stock of refugees in a country or territory of asylum is taken from the UNHCR Database. Real GDP at constant national 2011 prices divided by the population is used to calculate GDP per capita (GDP). Savings is measured as the share of gross capital formation at current PPPs (SAVINGS). Share of merchandise exports at current PPPs is used to measure openness to trade (EXPORTS). Human capital (SCHOOL) is retrieved from a human capital index which combines average years of schooling and average returns to education. Population growth (GPOP) is measured as the year-on-year growth in population. Finally, stock of refugees per capita (REFS) is defined as the number of refugees or people in refugee-like situations (individuals residing outside of their country of origin due to protection risks, like those of refugees, who cannot obtain refugee status for some reason) per 1,000,000 of the population in the country of asylum.

TABLE 1 SUMMARY STATISTICS

	Observations	Mean	Std. Dev.	Minimum	Maximum
GDP	4,492	14,685	19,492	162	210,103
REFS	4,492	5,684	15,146	0[1]	269,401
GPOP	4,267	0.017	0.016	-0.064	0.18
SAVINGS	4,492	0.21	0.10	-0.0020	2.01
SCHOOL	4,132	2.23	0.73	1.02	3.73
EXPORTS	4,492	0.24	0.24	0.00015	2.78

I expect population growth to negatively impact GDP per capita. A positive growth in the population of a country decreases the amount of capital per worker, which makes the labour force less productive. Lower productivity leads to lower economic growth, thus population growth negatively affects GDP per capita. In contrast, the savings rate of a country is positively related to GDP per capita. An increase in a country's savings rate leads to greater investment in capital, which improves the capital-labour ratio. As a result, workers become more productive, causing an increase in GDP per capita. Openness to trade is also positively related to economic growth as it allows countries to specialize in productive activities in which they have a competitive advantage. This enables countries to produce more output with the same amount of inputs, and simply trade to acquire the goods that they are not efficient at producing. As a result, all countries involved in the trade increase their productivity, which leads to positive economic growth. Furthermore, human capital accumulation, much like the accumulation of physical capital, increases the productivity of a labour force. Individuals with more skills, knowledge, and education are more productive workers, which leads to greater GDP per capita. Lastly, I expect refugees to act as compliments to host labourers by filling skill shortages in a host country, enabling native workers to seek employment in more productive activities, and potentially bringing assets with them to host countries in the form of physical and human capital, all of which increases the productivity of the host labour force (Boubtane, Dumont & Rault, 2016). Thus, I predict that an increase in the stock of refugees in a host country will lead to an increase in GDP per capita in that country.

IV. RESULTS

To estimate the effect of refugees on host economies I per-

1. Countries with zero refugees included in the summary statistics are excluded from the regression. These countries are: Aruba, 2010; British Virgin Islands, 2013; Grenada, 2012; Haiti, 2010; Madagascar, 2010; Myanmar, 2013; Saint Lucia, 2010; Vietnam, 2012.

formed a GLS regression of the natural log of GDP in country i at time t on the natural logs of REFS, GPOP, SAVINGS, SCHOOL, and EXPORTS, and included controls for time-fixed and year-fixed effects. The regression equation is:

$$(1)\quad ln(GDP_{i,t})^* = \beta_0^* + \beta_1 ln(REFS_{i,t})^* + \beta_2 ln(GPOP_{i,t})^* + \beta_3 ln(SAVINGS_{i,t})^* + \beta_4 ln(SCHOOL_{i,t})^* + \beta_5 ln(EXPORTS_{i,t})^* + \sum_{1975}^{2013} \delta_S TF_S + \sum_{2}^{126} a_j EF_j + \varepsilon_{i,t}$$

where: $GDP_{i,t}^* = GDP_{i,t} - \rho GDP_{i,t-1}$

$$\beta_0^* = \beta_0 - \rho\beta_0$$

$$X_{i,t}^* = X_{i,t} - \rho X_{i,t-1} \text{ where } X \text{ is any explanatory variable}$$

I used a fixed effects regression, which controls for the effects of variables that are fixed over time. As I am conducting a cross-country analysis, and countries have numerous time-invariant characteristics such as geographical position or culture, adding a measure for time-fixed effects reduces the risk of obtaining biased parameter estimates. I used a GLS regression to correct the standard errors of each coefficient, as there is evidence of heteroskedasticity and serial correlation in my model. In a standard panel data regression with serial correlation, standard errors are underestimated, which leads us to believe that parameter estimates are more precise than they are in reality. Further, heteroscedasticity can lead to biased estimations of standard errors. Thus, a GLS regression provides the best unbiased estimates of the coefficients in my model. Additionally, I added a measure for year-specific effects, which controls for cross-country variations in GDP per capita over time that are not attributed to variations in population growth, savings rates, human capital accumulation, openness to trade, or stock of refugees. Similar to controlling for time-fixed effects, controlling for year-fixed effects reduces the risk of obtaining biased parameter estimates. Further, I identified 39 outliers[2], which I excluded from my regression due to their significant deviation from the average values of GDP and REFS. These outliers are either extremely rich countries with refugee stocks significantly below the average, or extremely poor countries with incredibly large stocks of refugees. Finally, I found no evidence of multicollinearity in my model.

Moreover, it is important to note that refugee flows may not be entirely exogenous. It is probable that some refugees self-select into the countries that they take refuge. Eighty-four percent of refugees are hosted by developing nations, and while this is primarily due to the fact that refugees typically take refuge in neighbouring countries and many countries which experience conflict are surrounded by developing nations (Khoudour & Andersson, 2017), it also suggests possible reverse causality. Refugees may choose to go to less developed countries because they often have less restrictive

2. The outlying observations include: Iraq 1994-96; Kuwait 2004-08, 2011-12; Liberia 1994-99; Qatar 1981-84, 2000-02, 2004; Sudan 1989; United Arab Emirates 1977-85, 1994-95; Zimbabwe 2006-08.

immigration policies, and lower costs of living which may make it easier for refugees to establish themselves in the host country. Additionally, refugees may choose to go to countries in which they have existing connections – countries where they have relatives or friends – or countries that have better economic opportunities. The possibility of self-selection suggests the presence of endogeneity in my model and undermines the causal interpretation of my results. As such, any relationship between stock of refugees and economic growth should be interpreted as correlational.

Table 2 shows the results of the regression for all 126 countries. Figure 1, found in Appendix A, illustrates the relationship between REFS and GDP. In the first regression, refugees have a significant negative effect on GDP per capita because the measure for population growth is not yet included. As a result, an increase in the stock of refugees in a country has the same effect as a positive growth in the population, which we know negatively affects economic growth. After including population growth, savings, human capital, and openness to trade, the effect of refugees on GDP per capita is positive but insignificant. This refutes my hypothesis and suggests that refugees do not behave as substitutes or compliments to host labour forces in any significant way. However, population growth, savings rates, human capital accumulation, and openness to trade all behave in the expected directions and are statistically significant at the 0.01% level. Although it is not a perfect estimate, the R2 from a standard panel data regression of the model is 0.502, suggesting that 50.2% of the variation in GDP per capita across countries can be attributed to variations in population growth, savings rates, human capital accumulation, openness to trade, and the stock of refugees in a country.

Table 3 shows the results of the regression for 32 OECD countries, while Figure 2, found in Appendix B, illustrates the relationship between REFS and GDP in OECD countries. The effect of refugees on GDP per capita is positive and statistically significant at the 0.01% level. A 1% increase in the number of refugees per million of the population causes GDP per capita to grow by 0.065%. This result supports my hypothesis, suggesting that in OECD countries refugees act as compliments to host labour and increase productivity in host countries. This finding is similar to the findings on immigration in OECD countries. Many OECD countries have aging populations and declining fertility rates, which causes labour shortages in these countries (Feridun, 2005; Muysken & Ziesemer, 2013). As such, refugees may replenish the labour forces of OECD countries, filling skill shortages in the labour market, and ultimately increasing productivity. For these same reasons, population growth is positive and statistically significant for OECD countries, which opposes my prediction. A positive growth in the population serves to sustain the labour force in these countries and increases productive activity. Savings, human capital accumulation, and openness to trade behave as predicted and are all statistically significant at the 0.01% level.

Table 2 – The Effect of Refugees on GDP per Capita for All Countries

GDP	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
REFS	-0.0163***	0.0103***	0.0168***	0.0116***	0.00268
	(0.00235)	(0.00275)	(0.00275)	(0.00245)	(0.00227)
GPOP		-0.603***	-0.448***	-0.0481***	-0.0236***
		(0.0121)	(0.00992)	(0.00673)	(0.00572)
SAVINGS			0.928***	0.399***	0.330***
			(0.0175)	(0.0167)	(0.0144)
SCHOOL				2.764***	2.284***
				(0.0241)	(0.0261)
EXPORTS					0.350***
					(0.00776)
INTERCEPT	8.640***	6.112***	8.237***	7.459***	8.525***
	(0.0808)	(0.103)	(0.101)	(0.0765)	(0.0696)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	3550	3550	3550	3550	3550

Standard errors in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001

Table 3 – The Effect of Refugees on GDP per Capita for OECD Countries

GDP	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
REFS	0.108***	0.0901***	0.109***	0.0754***	0.0647***
	(0.00279)	(0.00377)	(0.00325)	(0.00374)	(0.00394)
GPOP		0.0180***	-0.00233	-0.00375	0.0130***
		(0.00525)	(0.00540)	(0.00505)	(0.00504)
SAVINGS			0.669***	0.664***	0.596***
			(0.0321)	(0.0289)	(0.0275)
SCHOOL				1.034***	0.884***
				(0.0402)	(0.0405)
EXPORTS					0.111***
					(0.00862)
INTERCEPT	9.158***	9.429***	10.00***	9.245***	9.654***
	(0.0346)	(0.0518)	(0.0623)	(0.0639)	(0.0669)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1142	962	962	962	962

Standard errors in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001

Table 4 shows that refugees have a negative and statistically significant effect on GDP per capita in non-oil countries.[3] Figures 3 and 4, found in Appendix C and D respectively, illustrate the relationship between REFS and GDP for oil and non-oil countries. A 1% increase in the stock of refugees per million of the population causes a 0.00804% decrease in GDP per capita. This finding refutes my hypothesis and suggests that refugees behave as substitutes for host labour in non-oil countries.

3. I retrieved the list of oil countries from Mankiw, Romer and Weil (1992). They are: Afghanistan, Bahrain, Barbados, Cyprus, Fiji, Gabon, Gambia, Guinea, Guyana, Iceland, Iran, Iraq, Kuwait, Lesotho, Luxembourg, Malta, Oman, Saudi Arabia, Surinam, Swaziland, Taiwan, United Arab Emirates, and Yemen.

Table 4 – The Effect of Refugees on GDP per Capita for Non-Oil Countries					
GDP	**Regression 1**	**Regression 2**	**Regression 3**	**Regression 4**	**Regression 5**
REFS	-0.0302*** (0.00196)	-0.0212*** (0.00280)	0.00283 (0.00273)	0.00593* (0.00251)	-0.00804*** (0.00223)
GPOP		-0.652*** (0.0132)	-0.467*** (0.0105)	-0.0598*** (0.00690)	-0.0609*** (0.00605)
SAVINGS			0.858*** (0.0165)	0.330*** (0.0156)	0.280*** (0.0135)
SCHOOL				2.905*** (0.0261)	2.405*** (0.0266)
EXPORTS					0.298*** (0.00753)
INTERCEPT	8.780*** (0.0805)	6.016*** (0.103)	8.060*** (0.0991)	7.226*** (0.0773)	8.152*** (0.0712)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	4017	3442	3442	3204	3204

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

These results are quite different than the results in Table 2, in which refugees do not have a significant effect on GDP per capita. Since economic growth in oil countries is predominantly influenced by variations in the oil market, refugees may have little effect on growth even though oil countries, on average, host significantly more refugees than non-oil countries, as shown in Table 5. In non-oil countries, where economic performance is dependent on a greater variation of productive activities, refugees may have a larger impact on growth. As a result, including oil countries in the regression in Table 2 may have biased its predictions. Additionally, refugees may be less substitutable for native labourers in oil countries than they are in non-oil countries, as oil countries focus on oil-related productive activities while non-oil countries may focus more on agricultural production, for example. This further explains why excluding oil countries from the regression leads to the significant negative results found in Table 4.

TABLE 5 - OIL VS NON-OIL

Variable	Observations	Std. Dev.	Minimum	Maximum	Mean
Oil					
GDP	459	35,301	859	210,103	29,659
REFS	459	17,474	0.54	132,590	8791
Non-Oil					
GDP	4,033	15,913	162	159,010	12,981
REFS	4,033	14,819	0	269,401	5330

Table 6 – The Effect of Refugees on GDP per Capita

GDP	All Countries	OECD Countries	Non-Oil Countries
REFS	0.00268 (0.00227)	0.0647*** (0.00394)	-0.00804*** (0.00223)
GPOP	-0.0236*** (0.00572)	0.0130** (0.00504)	-0.0609*** (0.00605)
SAVINGS	0.330*** (0.0144)	0.596*** (0.0275)	0.280*** (0.0135)
SCHOOL	2.284*** (0.0261)	0.884*** (0.0405)	2.405*** (0.0266)
EXPORTS	0.350*** (0.00776)	0.111*** (0.00862)	0.298*** (0.00753)
INTERCEPT	8.525*** (0.0696)	9.654*** (0.0669)	8.152*** (0.0712)
Fixed Effects	Yes	Yes	Yes
N	3550	962	3204
Countries	126	32	110

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Overall, population growth, savings, and human capital accumulation are significant contributors to cross-country variations in GDP per capita, as found in Mankiw, Romer and Weil (1992). The finding that an increase in the stock of refugees in non-oil countries negatively impacts economic growth is important and suggests that refugees behave as substitutes to native workers in many countries. However, as I do not categorize refugees in terms of skill or education level, this finding does not indicate in which labour markets (i.e., skilled or unskilled) refugees have the largest negative impacts. We know from numerous regional studies on refugee movements, as well as studies on immigration, that migrants often displace native workers in some areas of employment more than others (Braun & Mahmoud, 2014; Bahcekapili & Cetin, 2015; Ruiz & Vargas-Silva, 2016; Aleksynska & Tritah, 2009). As such, my findings could be improved upon if the skill composition of the stock of refugees is taken into account, and their displacement effects in different host labour markets are determined.

V. CONCLUSION

It is evident that refugees have varying effects on host economies. I predicted that refugees would behave as compliments to host labour forces, causing an increase in GDP per capita in host countries. This was the case for OECD countries, most of which have declining labour forces due to low fertility rates and aging populations. In these countries, refugees may fill labour shortages, thus increasing productivity and leading to positive economic growth. This finding is consistent with literature on immigration in OECD countries, where positive net migration increases GDP per capita, as immigrants replenish the diminishing labour forces of these countries (Feridun, 2005; Muysken & Ziesemer, 2013). However, in non-oil countries, refugees negatively affect GDP per capita, which refutes my hypothesis. This suggests that in many countries, refugees behave as substitutes for host labour and consequently lead to lower productivity in host countries. This finding is consistent with the results of Ruiz and Vargas Silva (2016) and other regional studies on the impacts of refugees on host labour markets, which find that refugees displace host labour, often leading to increased unemployment, and ultimately lower productivity and economic growth.

In many countries, native populations believe that hosting refugees is an economic burden. It is a common opinion in developed countries that refugees increase unemployment by increasing competition in the labour market and taking jobs away from native workers, leading to lower productivity and a decline in economic growth (Feridun, 2005). Additionally, the nature of refugee movements, which often involve large and rapid flows of refugees into surrounding countries, can put an unmanageable strain on host economies. As a result, many countries close their borders to these stateless individuals. My findings suggest that in countries that are experiencing labour shortages akin to those of OECD countries, adopting welcoming refugee policies may actually have a positive effect on economic growth.

While most previous literature on the effects of refugees on economic growth focuses on regional impacts, my research offers a unique look at these effects across countries. However, I do not differentiate refugees by skill level, which would make my analysis more descriptive. Future research should be conducted on the cross-country effects of skilled and unskilled refugees on economic growth, as this would lead to a more thorough understanding of the impacts of refugees on host labour markets and determine which labour market segments are most affected by refugees. Moreover, the potential for self-selection in my model makes the causal relationship between stock of refugees and economic growth ambiguous. It is possible that a country's level of economic development influences the number of refugees that choose to go to that country; this is another area of interest for future research. Altogether, this information could inform decisions on refugee policies. Countries would be better able to predict how receiving refugees will impact their economies, and which labour segments will experience the greatest displacement. Ultimately, this research may allow host countries to anticipate the impacts of hosting refugees and prepare themselves so they can help individuals in need of refuge, while also protecting the economic interests of their own people.

II

HONOURS THESIS'

Life Gambles: Affect, Probability Weighting, and Risk Preferences in Medical Decision Making

AN ANALYSIS OF PROSPECT THEORY, GENDER, AND EMOTION IN MEDICAL DECISIONS UNDER RISK

Andrew Shields

ECON 499

ABSTRACT

The following article applies Cumulative Prospect Theory (CPT) to decisions in the medical domain. Specifically, it evaluates CPT's predictions of an S-shaped value function distinguishing gain and loss domains, and non-linear probability weighting in choices between medical treatments. Furthermore, the article examines whether parameters of the value function and probability weighting function in this domain are influenced by gender and incidental emotion. The current study employed a non-parametric estimation methodology to address the two research goals presented above. The results of the experiment provide compelling evidence to support both differentiated risk preferences between gains and losses, as well as robust non-linear probability weighting, among medical decision tasks. Additionally, the evidence suggests that gender and incidental emotion significantly affected probability weighting: females were associated with more markedly non-linear probability weighting and incidental happiness was associated with more linear probability weighting. Taken together, the findings support CPT's applicability in modeling medical decision-making, and casts doubt on previous findings that implied consistent risk preferences across gain and loss domains in medical settings.

I. INTRODUCTION

My research investigates a descriptive model of medical decision-making under risk, and explores individual heterogeneity in risk preferences and probability weighting. I apply Prospect Theory (PT) (Kahneman & Tversky, 1979), which supplements Expected Utility Theory (EUT) with the additional concepts of loss aversion and probability weighting, to medical contexts involving treatment decisions with outcomes in terms of years of life. Specifically, my research poses the following question: are PT's predictions regarding utility curvature and probability weighting applicable to medical decisions under risk, and how do gender and incidental emotion moderate individuals' risk preferences and assessment of probability weights?

The motivation behind this research is threefold. The primary motivation is to assess the generalizability of PT, and its later development, Cumulative Prospect Theory (CPT)[1] (Tversky & Kahneman, 1992) in relation to medical decision making. Previous research has largely applied these theories in relation to monetary decisions in laboratory settings (Abdellaoui, Vossmann, & Weber, 2005; Etchart-Vincent, 2004; Gonzalez, & Wu, 1999), and in financial markets (Jegers, 1991; Ljungqvist & Wilhelm, 2005), yet has offered scarce attention to decision making in alternative domains. Furthermore, early research efforts to assess CPT's predictions within a medical context did so primarily from a psychological framework, focusing on the influence of heuristics and framing in the decision processes, rather than quantitative assessments (Schroth, Riegelman, & Blacklow, 1994; Treadwell, & Lenert, 1999). After a seminal paper by Bleichrodt and Pinto (2000) investigated CPT's predictions among medical decisions from a more quantitative and utility-based modeling perspective, we have seen a recent surge of quantitative analyses addressing CPT's generalizability (Attema, Brouwer, & l'Haridon, 2013; Pachur, Hertwig, & Wolkewitz, 2014; Attema, Brouwer, l'Haridon & Pinto, 2016), which has demonstrated both the applicability and limitations of CPT predictions within the medical domain. Evidence of applicability is found in the presence of non-linear probability weighting in medical decision tasks (even more pronounced than in financial decisions). Inconsistencies, however, are found in risk preference predictions across gain and loss domains in the medical context. This lack of consensus reflects the limited scope of research assessing CPT's generalizability, and suggests the necessity of a more comprehensive analysis of CPT predictions within the medical domain. Through my research, I hope to address previous inconsistencies and ambiguous experimental design choices, to provide a more thorough assessment of

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1. This paper will refer to CPT henceforth, given that CPT is just a later extension of PT.

CPT in medical decision-making.

A second source of motivation for my research is to examine moderators of individual heterogeneity in risk preferences and probability weighting, namely incidental emotion and gender. Given the psychological foundations of CPT, research has suggested that emotions play a significant role in determining the shape of the probability weighting function. For instance, research has proposed that the presence of lower and upper subadditivity in the probability weighting function is derived from the anticipated elation of an unexpected win and the anticipated disappointment of an unexpected loss, respectively (Brandstätter, Kühberger, & Schneider, 2002). Furthermore, recent research has demonstrated that incidental emotion – emotion unrelated to the decision at hand – can influence the shape of the probability weighting function in monetary decisions (Schulreich et al., 2013). Gender may also represent an important driver of the heterogeneity of both risk preferences and probability curvature within a monetary context (Fehr-Duda et al., 2011). Due to the potential significance of such factors in medical decision-making, my research assesses whether similar patterns of heterogeneity hold true in medical contexts.

A third objective of my research is to inform medical practitioners of biases that may result in suboptimal medical decision strategies. One of the main utility models implemented within health economics, the quality-adjusted life-years (QALY) model, relies on assumptions of expected utility to provide a single utility-based index of health status and life duration. The QALY model suffers from strong preference assumptions, however, such as time-linearity in utility, which may be less valid than time-non-linear models under rank-dependent utility theories (Bleichrodt, & Pinto, 2005). Therefore, to address potentially flawed recommendations due to invalid assumptions, it is critical to investigate CPT models of medical preferences.

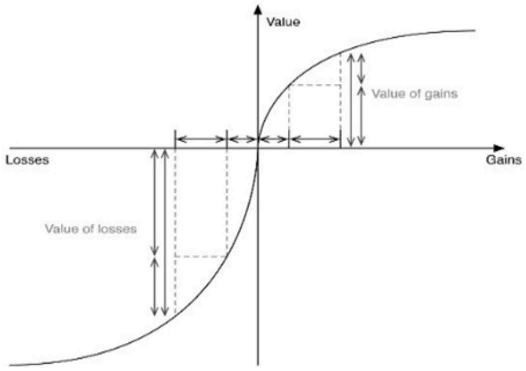
This paper is structured as follows: Section 2 will provide an overview of the economic theory employed (CPT), Section 3 will review the previous literature surrounding CPT and its applicability to the medical domain, Section 4 will describe the theoretical framework of the experimental design, Section 5 will detail the methodological procedure administered, Section 6 will analyze the results of the experiment, Section 7 will interpret and consider the implications of the results, and Section 8 will conclude.

II. ECONOMIC THEORY AND FRAMEWORK

My research relies on the theoretical framework of CPT, which was originally developed by two psychologists, Kahneman and Tversky (1979), to address paradoxes of risky decision behaviour unaccounted for by EUT. Incorporating relevant aspects of cognitive psychology within an economic framework, CPT has been extremely influential in modeling decision-making under risk, to some extent replacing EUT as a descriptive model of such decision behaviour (Bruhin, Fehr-Duda, & Epper, 2010). CPT differs from EUT in two key concepts, which form the foundation for its behavioural predictions: a differentiated value function between gains and losses from a reference point, and subjective non-linear probability weighting.

There are three noteworthy features of the value function that differentiate CPT from EUT. First, the origin (reference point) of the function does not have to equate to an objective outcome of zero. Instead, it is subjectively defined within the decision process, rendering it malleable to framing and contextual cues. Second, the value function predicts different behavioural preferences among prospects involving gains versus losses. In gains, CPT incorporates concave utility and thus models risk-averse behaviour, similar to EUT. In losses, however, CPT predicts convex utility, which implies risk-seeking behaviour that is counter to standard EUT predictions. Third, the value function is steeper in losses than in gains, indicating that losses loom larger than equivalently sized gains - a concept known as loss aversion. Figure 1 provides an illustration of CPT's value function.

Figure 1.

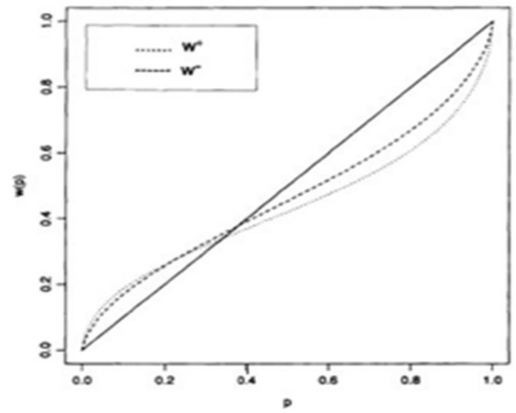


The second key concept CPT postulates is that probabilities among risky choices are not applied linearly, but are rather transformed in the choice process into non-linear subjective decision weights. Two important characteristics define such decision weights during choice: lower and upper subadditivity[2], and sub-cer-

2. Such terms are defined in the Section II: Economic Theory and Framework (pp.7).

tainty. Lower and upper subadditivity lead to the overweighting of low probabilities and the underweighting of high probabilities, respectively, which results in an inverse S-shaped weighting function. Sub-certainty states that the sum of complementary decision weights is less than one, such that two complementary probabilities totalling 100% are interpreted in choice to represent less than 100%. This phenomenon is indicated graphically by the probability weighting curve crossing the 45-degree line at $p < 0.50$. Both features are illustrated in Figure 2:

Figure 2.



My research will examine the hallmark shapes of CPT's value and probability weighting predictions within a medical domain where individuals make choices regarding medical treatments. It will assess both the value and probability weighting functions under gains and losses to accurately capture any differentiation in risk preferences between such domains. It is worth noting that this study will not measure loss aversion, given that the experimental design does not allow for relative comparisons in the magnitude of gains or losses in utility in concordance with a constant outcome change.

III. LITERATURE REVIEW

The motivation of my research derives itself from literature largely categorized along three dimensions: applications of CPT within the medical domain, the effect of incidental emotions on risk preferences and probability weights, and gender differences among risk preferences and probability assessment.

The primary motivation for my research was that much of the previous literature on CPT applies its theoretical predictions in relation to monetary decisions in laboratory settings (Abdellaoui, Vossmann, & Weber, 2005; Etchart-Vincent, 2004;) and in financial markets (Jegers, 1991; Ljungqvist & Wilhelm, 2005). Only a select few studies have investigated whether CPT predictions hold within medical contexts, by quantitatively modeling CPT's value and probability weighting functions among medical decision tasks.

This research includes pioneering attempts by Bleichrodt and Pinto (2000), and more recent efforts by Attema, Brouwer, and l'Haridon (2013) and Pachur, Hertwig, and Wolkewitz (2014), all of whom assess medical decision-making under a CPT framework and lay imperative foundations for my own research. As defined later, Bleichrodt and Pinto's (2000) investigation consisted of non-parametrically eliciting utility and probability weighting functions, through a series of hypothetical, binary treatment options, which each produced uncertain[3] years of additional life. The non-parametric elicitation method, derived from Wakker and Deneffe (1996), allowed the authors to model CPT's value and probability weighting functions without imposing prior assumptions to avoid restricting analysis of behaviour. Their study was limited, however, by their restriction of decision tasks within a single domain (loss), which curtailed their ability to derive the entire value function, that is predicted to differ between losses and gains. Attema et al. (2013) conducted a similar experiment, assessing medical risk preferences in both gain and loss domains, thus addressing previous limitations. The authors assessed such preferences through a semi-parametric approach developed by Abdellaoui et al. (2008), in which subjects decided between treatment outcomes for a series of hypothetical, binary treatment options that differed from Bleichrodt and Pinto's (2000) method in one critical aspect: one option produced a certain gain (loss) in life years, while the other option produced an uncertain gain (loss) in life years. Such an approach is less robust, since its semi-parametric method imposes certain parametric assumptions within the analysis, and preferences elicited may be distorted by the presence of a certain option, known as the 'certainty effect' (Kahneman & Tversky, 1979). The 'certainty effect' is problematic because it may produce results that misconstrue an individual's true risk preferences, as recent research has suggested that risk preferences may be inconsistent between certain and uncertain choices (Andreoni & Sprenger, 2010). Pachur et al. (2014) investigate CPT's predictions for medical decisions in a decidedly different manner, through the evaluation of subjects' willingness to pay (WTP) to avoid various medical side effects. After eliciting each subject's WTP, binary lotteries were constructed involving uncertain outcomes of the side effects to determine medical preferences. To compare this with preferences among monetary choices, analogous

3. Two outcomes associated with given probabilities.

lotteries were constructed using participants' elicited WTP. Although Pachur et al.'s (2014) method allows for direct comparison between medical and monetary decisions among equally valued lotteries, it imposes strong parametric assumptions and restricts the analysis of medical decision making to the loss domain.

The results from the previous three studies show both the applicability and the limitations of CPT in modelling medical decision-making behaviour. Evidence of applicability is found in the presence of non-linear probability weighting in medical decision tasks, consistent with previous findings within monetary contexts. Bleichrodt and Pinto's (2000) assessment of probability weighting may be considered the most robust of the three, given that it assesses a large range of probability values (0.10-0.90) independently of utility curvature. Their results indicate that probability weighting is substantial among medical decision tasks, with participants demonstrating even greater non-linear probability curvature (γ=0.55) than comparable results found in monetary decision tasks (γ=0.832) (Abdellaoui et al., 2005). The analyses of both Attema et al. (2013) and Pachur et al. (2014) are limited by the fact that they measure probability weighting simultaneously with utility curvature, resulting in possible collinearity issues in measurement. In addition, Attema et al. (2013) only assess probability weighting at one probability value (0.50), whereas Pachur et al. (2014) assess probability values ranging from 0.05-1.00. Despite these limitations, Attema et al. (2013) obtain curvature results of γ=0.46 - 0.49, which are very similar to that of Bleichrodt and Pinto (2000), providing further evidence of substantive probability curvature. Interestingly, Pachur et al.'s (2014) analysis also indicates significant probability weighting. However, the probability curvature values they attain, of γ=0.001), are markedly and significantly different than the previous two studies. Although this may reflect the differences in questions posed (drug side effects versus treatment options that affect life years), it more likely reflects weaknesses of the WTP procedure, given that a curvature value of γ=0.001 is well below the range of values found in monetary tasks and implies virtually no sensitivity to probability differences. Although all studies support qualitative predictions of CPT's probability weighting function, the consistency of values found between Bleichrodt and Pinto (2000) and Attema et al. (2013) suggests that non-parametric and semi-parametric elicitation methods may be more valid and reliable measures of CPT functions than WTP procedures. Therefore, my research will incorporate Bleichrodt and Pinto (2000)'s elicitation method (given its further merit of independent utility and probability assessment) to further investigate the 'appropriate range' of probability curvature values, in both gains and losses, within a medical context.

CPT's applicability within the medical domain has been challenged with respect to differentiated utility curvature between gains and losses, which is predicted by CPT's value function. The most robust test of CPT's value function was conducted by Attema et al. (2013), who manipulated the reference point of their decision tasks to present medical choices as both gains in life years (gain domain) and losses in life years (loss domain). In their analysis, they find compelling evidence to reject CPT's value function predictions,[4] indicated by the presence of utility concavity (risk aversion) in both gain ($\alpha=0.25$) and loss ($\delta=-1.24$) domains.[5] As previously noted, however, such results may be misinterpreted given the authors' simultaneous estimation of utility and probability weighting parameters, which does not account for collinearity effects. Bleichrodt and Pinto (2000) and Pachur et al.'s (2014) analyses of CPT's value function are more limited, since they only analyze decisions within a loss domain. Furthermore, Bleichrodt and Pinto (2000) fail to justify why their treatments should be considered 'loss decisions,' given that they always provide gains in additional life years, similar to Attema et al.'s (2013) gain condition. Within a loss context, Pachur et al.'s (2014) findings contradict those of Attema et al. (2013), with one experiment yielding utility linearity (risk neutrality) in losses ($\alpha=1$), and a repeated experiment indicating utility convexity (risk-seeking) ($\alpha=0.388$).[6] The large range of variance found in utility curvature between the two equivalent experiments, however, undermines the reliability and validity of the authors' WTP procedure, and does not establish compelling evidence to reject Attema et al.'s (2013) findings, nor confirm CPT predictions. Bleichrodt and Pinto's (2000) results are also inconclusive, for while they find evidence of utility concavity ($\theta = 0.779$)[7] in losses, similar to Attema et al. (2013), they fail to justify why such decisions represent losses despite describing gains in life years. Thus, the results may actually support CPT's applicability, if such decisions were perceived as gains by participants. My research aims to address the methodological weaknesses and inconsistent results found in the literature, by assessing utility independently of probability weighting, in both gains and losses, through an extension of Bleichrodt and Pinto's (2000) study that effectively manipulates the reference point of decision tasks.

The second objective of my research is motivated by recent research that has investigated the role of incidental emotions – emotions unrelated to the task at hand – in altering risk preferences and probability weighting among monetary decisions. Research that has examined the influence of incidental emotion on CPT predictions includes Campos-Vazquez and Cuilty (2014) and Schulreich et al. (2013). The two studies differ in the focus of incidental emotion, with the former analyzing its effect on risk-preferences, and the lat-

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4. CPT's value function predicts utility concavity in gains and utility convexity in losses.
5. Attema et al.(2013) utilize an exponential function for utility specification, where α is associated with utility curvature in gains, while δ is associated with utility curvature in losses: $\alpha>0$ $\delta<0$ indicate utility concavity.
6. Pachur et al. (2014) utilize a power function for utility specification, where: $\alpha<1$ indicates utility convexity in losses. Power function in losses: $y=-(-x)\alpha$.

ter examining its effect on probability weighting – differences later reflected in their respective methodologies. Campos-Vazquez and Cuilty (2014) analyzed risk preferences and probability weighting with lotteries developed by Tanaka, Camerer, and Nguyen (2007), which measure such parameters through switching behaviour between both gain and mixed lotteries.[8] The inclusion of mixed lotteries allows Campos-Vazquez and Cuilty (2014) to evaluate the influence of emotion on both utility curvature (in gains) and loss aversion. In contrast, Schulreich et al. (2013) employ the Random Lottery Pairs procedure (Hey & Orme, 1994), which only consists of gain lotteries, yet contain much greater variance in probabilities, allowing them to discern the influence of incidental emotion on probability weighting more precisely. The two studies also differ in their experimental manipulation of emotion prior to decision tasks: Campos-Vazquez and Cuilty (2014) had university subjects read stories of Mexico's gang violence and youth unemployment to elicit anger, sadness, and fear, whereas Schulreich et al. (2013) presented 'sad' or 'happy' musical stimuli. Schulreic et al.'s (2013) manipulation may be more valid than Campos-Vazquez and Cuilty's (2014), since it is based on previous emotional elicitation research (Juslin & Laukka, 2004; Koelsch, Rohrmeier, Torrecuso & Jentschke, 2013), while Campos-Vazquez and Cuilty's (2014) manipulation is not. Furthermore, Campos-Vazquez and Cuilty's (2014) measure of emotion after manipulation is extremely constraining, asking participants to identify with a single emotional state among the following: anger, sadness, fear/uncertainty, and indifference. Schulreich et al.'s (2013) emotional measurement, in contrast, is based on an empirically validated emotional scale (Izard, Libero, Putnam, & Haynes, 1993), and consists of a series of 9-point Likert questions to assess the degree of different emotions experienced.

The two studies, nonetheless, provide complementary insights regarding the influence of incidental emotion on CPT's value and probability weighting functions. Campos-Vazquez and Cuilty (2014) discovered that incidental sadness significantly increased risk aversion (utility concavity) among gain lotteries (baseline: α=0.47, interaction: α=-0.08) and that anger significantly decreased loss aversion in mixed lotteries by over 52%. These findings indicate that emotion completely unrelated to the gambles at hand had significant effects on risk preferences of subjects, with different emotions affecting different aspects of CPT's value function. In Schulreich et al.'s (2013) analysis, the authors found that induced happiness significantly increased the elevation of the probability weighting curve in comparison to the control sound condition (interaction δ= +0.0576) and sadness significantly decreased its elevation from the no music control condition (interaction δ= -0.0615).[9] The authors

7. Bleichrodt and Pinto (2000) utilize a power function for utility specification, where: $\theta<1$ indicates utility concavity in losses.
8. Mixed lotteries refer to those where one outcome is a gain and the other is a loss.
9. Probability elevation is measured in concordance with Gonzalez & Wu's (1999) specification; where the greater the δ, the greater the elevation.

found no evidence of specific incidental emotions significantly altering probability weighting curvature compared with control conditions. Schulreich et al.'s (2013) results are particularly compelling, as the authors accounted for the elapsed time between emotional manipulation and decision points, which Campos-Vazquez and Cuilty (2014) fail to do – potentially rendering underestimations of incidental emotion's true effect on risk preferences. Both studies shed light on possible moderators of individual heterogeneity in risk preferences and probability weighting, which can be incorporated with a more nuanced framework of CPT. My research will pioneer a similar analysis (albeit investigating a correlational link between emotion and decision parameters) within a medical context to more comprehensively assess medical decision making, and determine how moderators of individual heterogeneity may hold or differ across contexts.

Research on gender differences within CPT's framework parallels research efforts on incidental emotion, both of which aim to extrapolate potential moderators of individual heterogeneity in decision behaviour. Fehr-Duda, Epper, Bruhin, and Schubert's (2011) formative analysis of gender differences, in conjunction with incidental emotion, among risk preferences and probability weighting in monetary decisions, exemplifies this objective. The authors employ binary lotteries in both gain and loss domains that vary in probability between 0.05-0.95, to effectively capture both CPT's value and probability weighting function. In addition, the authors measured incidental mood through a questionnaire that assessed participant's mood relative to their average mood. Despite the study's comprehensive analysis of CPT and incidental emotion, limitations exist in their lottery choices and mood evaluation. First, the lottery choices always contained a certain (100%) option, which may not accurately measure risk preferences due to the certainty effect discussed earlier. Second, the mood parameter was constructed as a binary variable, which may constrain the analysis of emotion. Their results, nonetheless, provide significant insights into the moderating variables of interest. In terms of gender differences, Fehr-Duda et al. (2011) found no significant difference among risk preferences in gains nor losses. Women, however, weighted probabilities significantly more non-linearly than males in both gains and losses (γ=0.306-0.320,vs.0.546-0.547) and had significantly lower probability elevation (more pessimistic) than men (δ=0.662,1.082). With respect to the effect of incidental emotions, the authors found that good mood was only significantly correlated with the probability weighting function in women, associated with increases in probability elevation (interaction,δ= +0.143), and decreases in curvature (interaction γ=+0.152). Although Fehr-Duda et al.'s (2011) analysis of emotion is correlational, and therefore less comprehensive than the literature previously discussed, it suggests that good mood is associated with more economically 'rational' decision behaviour among women. By assessing both moderating variables, the Fehr-Duda et al. (2011) study provides greater descriptive, and prescriptive, evaluation of CPT as a model of decision behaviour, which my research aims to replicate and extend to the medical realm.

My research contributes to all three facets of previous literature in the following ways: first, it addresses inconsistencies and weaknesses in experimental procedures previously used to assess CPT's generalizability to the medical domain; second, it builds on pioneering research on the effect of incidental emotion and gender differences in medical decision making within a CPT framework. Through this, my research aims to provide a more comprehensive model of medical decision behaviour within the realm of behavioural health economics.

IV. EXPERIMENTAL FRAMEWORK: TRADE OFF METHOD

In order to investigate a descriptive model of medical decision-making under risk, I employed a non-parametric elicitation procedure to independently determine the utility and probability weighting functions in the domain of life years for individual subjects. Utility functions were elicited through the trade-off method originally develop by Wakker and Deneffe (1996), and subsequently updated by Abdellaoui (2000). My experiment will implement Abdellaoui's (2000) revised method, since it evaluates indifference values through a more experimentally valid procedure (Bostic et al, 1990) – applying a bi-sectional,[10] rather than matching,[11] approach. I elicited probability weighting functions through a similar procedure, utilizing Bleichrodt and Pinto's (2000) adaption of the trade-off method to assess subjective probability weighting. The trade-off method to elicit both utility and probability weighting functions can be formalized as follows:

Part 1- Utility: The first step is to establish two reference outcomes, R and r, where $R \succcurlyeq r$, and a third initial outcome, x_0, where $R \succcurlyeq r \succcurlyeq x_0$. These values produce a decision task, in which the participant must determine whether he/she prefers $[p, R; 1-p, x_0]$ or $[p, r; 1-p, x_{1a}]$. The fourth outcome, x_{1a}, begins as the midpoint between x_0 and r, yet endogenously updates itself through various rounds of choices made by the participant. For instance, if the participant shows preference for the second prospect in the first round, i.e. $[p, R; 1-p, x_0] \preccurlyeq [p, r; 1-p, x_{1a}]$, then in the

10. The bi-sectional approach assesses decision preferences by asking subjects to state their preference between binary lotteries.
11. The matching approach assesses decision preferences by asking subjects to determine a value within the decision scenario that makes them indifferent between binary lotteries.

next round, the participant faces a prospect choice between [p, R; 1-p, x_0] and [p, r; 1-p, x_1b], where x_1b is the midpoint of x_0 and x_1a. Eventually x_1 reflects an indifference value between prospects [p, R; 1-p, x_0] and [p, r; 1-p, x_1], with R ≽ x_0 and r ≽ x_1 to ensure comonotonic preferences. In all rounds, p is held constant at 0.50. A second indifference value can be similarly determined such that the participant is indifferent between [p, R; 1-p, x_1] and [p, r; 1-p, x_2]. The first indifference yields the following if rank-dependent utility holds:

$$[p,\ R;\ 1\text{-}p,\ x_0] \sim [p,\ r;\ 1\text{-}p,\ x_1]$$

$$\Leftrightarrow w(p)U(R) + [1 - w(p)]U(x_0) = w(p)U(r) + [1 - w(p)]U(x_1)$$

$$\Leftrightarrow w(p)[U(R) - U(r)] = [1 - w(p)][U(x_1) - U(x_0)] \qquad \textit{(Equation 1)}$$

The second indifference yields a similar outcome

$$[p,\ R;\ 1\text{-}p,\ x_1] \sim [p,\ r;\ 1\text{-}p,\ x_2]$$

$$\Leftrightarrow w(p)[U(R) - U(r)] = [1 - w(p)][U(x_2) - U(x_1)] \qquad \textit{(Equation 2)}$$

Since the LHS of the Equations 1 and 2 are equal, combining these results in the following:

$$U(x_2) - U(x_1) = U(x_1) - U(x_0) \qquad \textit{(Equation 3)}$$

Therefore, if comonotonic assumptions continue to hold, a sequence of indifference values can be elicited until $U(x_n)$- $U(x_{n-1})$= $U(x_{n-1})$- $U(x_{n-2})$, where n=5. Since the difference in utility between every indifference point is constant, the utility function can be scaled such that $U(x_o)$=0,and $U(x_n)$=1, and thus $U(x_j)$- $U(x_i)$=1/n.

Part 2- Probability Weighting: To assess probability weighting, I will employ an analogous elicitation approach, incorporating the indifference values found in the Part 1, and varying probability values. For probabilities of p' ≤0.5, an indifference value (z_r) will be elicited such that the participant is indifferent between [p', x_i; 1-p', x_j] and [p', x_k; 1-p', z_r], where $x_k \geq x_i \geq x_j$ and are a subset of the standard sequence previously elicited. For probabilities of p' >0.5, an indifference value (z_s) will be elicited such that the participant is indifferent between [p', x_m; 1-p', x_n] and [p', z_s; 1-p', x_q], where $x_m \geq x_n \geq x_q$, and such values represent the complementary subset of the standard sequence previously found (two different equations are necessary to address boundedness problems in elicited probability weights).

This results in:

$$w(p') = \frac{u(x_j)-u(z_r)}{[u(x_j)-u(z_r)+u(x_k)-u(x_i)]} \; for\ p' \le 0.5 \qquad \textbf{(Equation 4)}$$

$$w(p') = \frac{u(x_n)-u(x_q)}{[u(z_s)-u(x_m)+u(x_n)-u(x_q)} \; for\ p' > 0.5 \qquad \textbf{(Equation 5)}$$

Where w(p')= subjective decision weight of probability p', for p'= 0.10, 0.25, 0.50, 0.75, 0.90.

It is important to note that the elicitation method described above is not perfect, and does impose some limitations. The first limitation of the approach is that z_r and z_s in equations (2) and (3) do not necessarily have to belong to the utility sequence elicited through Part 1, and in many cases, will not belong to the sequence. Therefore, the utility values corresponding to z_r and z_s need to be estimated – I will determine such values through power estimation, given similar procedures used in previous studies (Bleichrodt & Pinto, 2000). The second limitation of the procedure is of boundedness concerns when assessing subjects' weighted probabilities. Close inspection of equations (2) and (3), in conjunction with assumptions of comonotonic preferences, reveals that w(p') is bounded between zero and $\frac{u(x_j)}{[u(x_j)+u(x_k)-u(x_i)]}$ for p'≤0.5, and bounded between $\frac{u(x_n)-u(x_q)}{[1-u(x_m)+u(x_n)-u(x_q)}$ and one for p'>0.5.

Therefore, the procedure may constrain the behaviour of individuals who weigh probabilities in extreme fashion. The third limitation of the procedure is the possibility of error propagation from early estimates to later estimates that could undermine the validity of the results. Given that both the utility and probability weighting functions rely on an iterative process of decisions to determine indifference values, errors in the recording, or interpretation, of decision tasks can lead to error-filled utility and probability weighting sequences.

V. EXPERIMENTAL PROCEDURE

Subjects

There were 69 subjects employed for the experiment, consisting of undergraduate commerce students from the University of British Columbia. 35 of these subjects were randomly assigned to the 'gain condition' and 34 to the 'loss condition'. The subjects in the gain condition consisted of 14 males and 21 females, whereas the loss condition consisted of 11 males and 23 females. The average age among these subjects was 20 years old. The subjects were compensated with class credit, and did not receive additional financial compensation.

Procedure

The experiment was conducted in small experimental groups, in which initial instructions were read aloud and subjects completed decision tasks using a well-known online survey software (Qualtrics). Due to the ethical constraints in measuring the utility of life years, all decision scenarios within the study were hypothetical, and therefore no decision choices posed 'real' consequences (contrary to many financial decision experiments). Despite the absence of 'real' incentives within the study, evidence from previous research suggests that hypothetical and 'real' incentives produce similar results in experiments assessing decision-making under risk (Tversky & Kahneman, 1992).

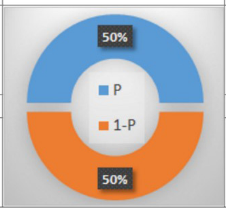
The experiment's primary objective was to assess CPT's (Tversky & Kahneman, 1992) applicability in relation to medical decision-making, and its secondary objective was to determine moderators of individual heterogeneity within probability weighting and utility, namely incidental emotion, and gender. In order to accomplish the first objective, the experiment manipulated the reference point of decision tasks to produce a 'gain' and 'loss' condition. The two conditions differed in the presentation of decision tasks, with the 'gain condition' emphasizing how medical treatments can produce beneficial outcomes and the 'loss condition' emphasizing how medical treatments can minimize negative outcomes.[12] This reference point manipulation was necessary to effectively assess CPT's generalizability within the medical domain, given that it predicts different behavioural responses between decisions involving gains and those involving losses. In order to accomplish the second objective, I measured the emotional state of subjects prior to the experiment, utilizing a two-dimensional framework proposed by Feldman, Barrett, and Russell (1998). The two-dimensional framework offers a more compressive account of subject's emotional state than typical valence frameworks – positive versus negative – since it also adds an arousal dimension – activated versus deactivated – that can account for more covarying effects. Since emotions are measured passively and are not actively manipulated during the experimental, all analyses involving incidental emotions (and gender) are correlational in nature and not causal.

Part 1: The study commenced with an explanation of its purpose – to assess medical decision-making under risk – and proceeded to describe the 40 decision scenarios related to medical

12. See appendix for exact reference manipulation details.

choices that subjects would complete during the study. Subsequently, the study asked subjects to assume a hypothetical role as a physician treating a fifteen-year-old patient for an illness. The physician's role and patient's illness were characterized in general terms to avoid unnecessary complications, yet the instructions specified that based on the symptoms present, the patient needed immediate treatment to survive – alternatively, in the absence of treatment, the illness would result in immediate death. The instructions next detailed that the subject (as the 'hypothetical' physician) must recommend a course of treatment, and would be given a choice between two treatment options (Treatment Q and Treatment R), each of which was associated with two uncertain outcomes. These outcomes represented the life years bestowed upon the patient by the treatments, and the probabilistic nature of these outcomes reflected the uncertainty of how the treatments would interact with individual health factors. The treatment options, and their associated outcomes, were presented in an equivalent format throughout the 40 decision scenarios, which reflect the trade-off method described above (ie. [p, R; 1-p, x_0] vs [p, r; 1-p, x_{1a}]). The presentation of decision scenarios implemented within the experiment are depicted in Figure 3 (gain condition).

Figure 3.

Treatment Q: Patient's Additional Life-Expectancy	Probability	**Treatment R:** Patient's Additional Life-Expectancy
42 year gain with Probability = 50%		**34** year gain with Probability = 50%
OR		**OR**
2 year gain with Probability = 50%		**18** year gain with Probability = 50%

After establishing the context of the study, and the subject's role within it, the subjects were taken through a practice scenario, which outlined the different aspects of each decision they would face during the experiment, and posed questions to assess their comprehension before proceeding.

The first decision scenario was held constant for all participants, which set R= 42 year gain, r= 34 year gain, and x_0= 2 year gain, forming the following decision problem: Treatment Q= [p, R; 1-p, x_0] versus Treatment R = [p, r; 1-p, x_{1a}].[13] These values were established after pilot testing discovered that outcomes greater than 42 additional life years were too heavily discounted to be considered in subjects' decision processes, and setting x_0=0 produced extreme

13. These values refer to the gain condition. For the loss condition, analogous values are set, however, are presented inversely. For example, instead of R = 42 year gain in life expectancy compared to 15 years (patient's current age), in the loss condition, R = 4 year loss in life expectancy compared to 61 years (patient's life expectancy without disease). Both lead to the same total survival age = 57.

risk-averse behaviour due to the possibility of certain death. Given these values, I set x_{1a} = 18 year gain, since it represented the midpoint between r= 34 years gain, and x_o=2 year gain. From this initial decision scenario, each subject's treatment preference modified the subsequent decision scenarios he or she faced, until the subject arrived at a value of x_1 such that he or she was indifferent between Treatment Q = [p, 42; 1-p, 2] and Treatment R = [p, 34; 1-p, x_1]. The value of x_1 was determined after the subject's fourth decision task, and represented the fifth midpoint iteration of the bi-sectional approach. Given the initial values of r= 34 years gain, and x_o=2 year gain, the fifth midpoint represented the last successive midpoint iteration that still resulted in an integer. This process is depicted in Figure 4:

Figure 4.

Decision Task	Treatment Q: Upper Bound (R)	Treatment Q: Lower Bound (x_o)	Treatment R: Upper Bound (r)	Treatment R: Lower Bound (x_{1a} =midpoint)	Interval of possible indifference values	Preference: Given these values, the subject chooses
1	42	2	34	(2+32)/2 =18	[2, 34]	Treatment R (influences interval of next round)
2	42	2	34	(2+18)/2 = 10	[2, 18]	Treatment R
3	42	2	34	(2+10)/2 = 6	[2, 10]	Treatment Q
4	42	2	34	(6+10)/2 = 8	[6, 10]	Treatment R
5	n/a	n/a	n/a	x_1= (6+8)/2 = 7	[6, 8]	n/a
6. Hypothetical round; if subjects chose Treatment R in 5				→ no longer integer	[6, 7]	

After determining x_1, the subjects undertook a second round of decision scenarios, which were initially characterized by the choice between Treatment Q = [p, R; 1-p, x_1] and Treatment R = [p, r; 1-p, x_{2a}]. The same procedure employed to establish x_1 unfolded to produce an indifference value of x_2. This iterative approach was repeated for a total of five rounds until a sequence of indifference values was elicited from $x_1, x_2,...,x_5$. Since the utility difference between adjacent indifference values remained constant throughout the sequence, utility functions could be scaled to 1, and derived for each indifference value, such that $U(x_j)=j/5$.

Part 2: In the second part of the experiment, subjects continued to face decision scenarios similar to those described in Part 1, with two significant departures: the probabilities of the two outcomes associated with each treatment now varied between $0.10 \le p \le 0.90$, and the treatment outcomes incorporated the indifference values found in Part 1. Probabilities of 0.10, 0.25, 0.50, 0.75, 0.90 were implemented to assess subjects' probability weighting functions given that similar values have been used in prior literature (Bleichrodt & Pinto, 2000), and since such a range encapsulates probability values that are typically over-weighted (0.10 and 0.25) and underweighted (0.50, 0.75, and 0.90), per CPT predictions. In total, there were five rounds in Part 2, one round corresponding to each of the five probabilities values listed above – thereby each round featured a unique p', which was held constant throughout the round. The decision tasks for $p \le 0.50$ were characterized as Treatment Q = [p', x_4; 1-p', x_3] versus Treatment R = [p', x_5; 1-p', z_r], with z_r representing the indifference value to be found through an iterative bi-sectional approach (as described earlier). Values z_1, z_2, and z_3 denoted the indifference values corresponding to p' = 0.10, 0.25, and 0.50, respectively. For $p > 0.50$, the decision scenarios took the form of Treatment Q = [p', x_3; 1-p', x_2] versus Treatment R = [p', z_s; 1-p', x_1], where z_s represents the final indifference value found in each round. Values z_4 and z_5 denoted the indifference values corresponding to p' = 0.75 and 0.90, respectively. In all scenarios, it is given that $x_5>x_4>x_3>x_2>x_1$, as defined earlier by the structure of the indifference sequence. After the five indifference values (z_i) were elicited, Equations (4) and (5) were used to determine the subjective weightings of the five probabilities listed. Each subject's probability weighting function were subsequently constructed from such weighted probability values.

In sum, each subject participated in two parts, with each part consisting of five rounds and each round consisting of four decision scenarios. Part 1 was necessary to determine utility curvature concerning years of life, with each round determining the indifference value necessary to construct the utility curve, and each decision scenario pinpointing the indifference value of interest. Part 2 was necessary to determine probability weighting in the context of life years, with each round establishing the subjective weighting of an objective probability, and each decision scenario pinpointing the indifference value of interest.

VI. RESULTS

Reliability

Given that the data below represents 'initial' experimental trials[14], there were a considerable number of subject exclusions, largely due to violations of comonotonicity (indifference values exceeded initial upper limits of the trade-off method implemented ($x_i \geqslant r$), and a few due to programming errors within the experimental software. Violations of comonotonicity occurred due to constraints within the methodology's 'event space' – the range in which indifference values could fall without violations of assumptions. Given that for comonotonicity to hold, $r \geqslant x_i$, and r within the experimental procedure was set to 34 years, the event space of the experiment was defined as 2 (x_0) through 34 years (r). Therefore, the five indifference values elicited per subject necessarily had to fall within such a range. Such requirements were often violated when the difference between subject's initial indifference values ($x_0 \rightarrow x_1, x_1 \rightarrow x_2$) were large, thus taking up a substantial portion of the event space. This has resulted in the exclusion of 4 out of 35 subjects from the gain condition (exclusion rate = 11.4%), and the exclusion of 22 out of 34 subjects from the loss condition (exclusion rate = 64.7%). The extremely high exclusion rate from the loss condition likely reflects the greater difficulty in computing expected life years of the patient compared to gains due to framing effects, and a failure of subjects to appreciate how treatments will impact the entire lifespan of the patient (the data suggests that subjects focused too heavily on reducing the minimum life years lost, rather than considering both the minimum and maximum).

Therefore, while the results from the gain condition can be defended as valid and reliable, the results from the loss condition must be interpreted with caution, and are described below as a tentative initial analyses. It is important to note that for the loss condition, the subjects that weren't excluded represent a minority of the overall sample, which, given the structure of the experiment, implies that the retained participants are less risk-seeking than those who did violate the assumptions (since large differences between initial indifference values were significantly associated with risk seeking preferences). As such, an 'extended' analysis of the loss condition is also provided, which includes subjects in the original loss analysis (12 subjects), plus those who violated the comonotonicity assumption only on the last round of indifference value elicitation (9 subjects), resulting in the ability to construct utility functions over the majority of elicited indifference values that did not violate

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14. A second round of experiments is being conducted using a different presentation of decision tasks that are designed to be more intuitive and require less mathematical computations on the subject's behalf.

assumptions. This extended analysis is included to provide a more robust estimation and to demonstrate how the majority of those in the loss condition behaved in ways consistent with greater risk seeking than the 12 subjects who did not violate any assumptions. In addition to the high exclusion rate in the loss condition noted above, another area of possible concern is the 'chained' nature of the elicited indifference values in both the utility and probability weighting phases of the experiment. Given that the subjects were not individually monitored during the experiment to provide corrective feedback of possible recording errors, there remains a strong possibility that such errors occurred during the course of utility and probability weighting function elicitations, causing errors to propagate through subsequent decision tasks. As Wakker and Deneffe (1996) note, the combination of a bi-sectional approach with the trade off method increases this possibility, given the higher number of decisions tasks involved. Although no robust consistency checks were enacted to test for the prevalence of these errors, close examination of data patterns in subjects' responses yielded limited instances of erratic choice patterns that may indicate such error propagation.

The results are detailed as follows: an assessment of the utility function precedes that of the probability weighting function. Within each assessment, the discussion commences with a non-parametric analysis of the function (all conditions), followed by a parametric analysis (all conditions), and concluding with relations of the parameters of interest to moderating variables (all conditions).

Utility Curvature

Utility curvature was determined individually for each subject, through both non-parametric and parametric methods.

Non-Parametric Analysis

To non-parametrically determine a subject's utility curvature, I denoted $\Delta_{(j-1)}{}^{j}$ as the difference between pairs of adjacent indifference values, ie. $(x_{(i+1)} - x_i) - (x\_{}_i - x_{(i-1)})$, for all pairs of indifference values elicited. Therefore, if $\Delta_{(j-1)}{}^{j}>1$, this segment of the utility curve corresponded to concave utility, if $\Delta_{(j-1)}{}^{j}=1$, it corresponded to linear utility, and if $\Delta_{(j-1)}{}^{j}<1$, it corresponded to convex utility. Given that five utility indifference points were elicited during the experimental procedure, this allowed for the calculation of four $\Delta_{(j-1)}{}^{j}$'s per subject. Each subject's $\Delta_{(j-1)}{}^{j}$'s were assigned a value of 1 (concavity = risk averse), 0 (linearity = risk neutral), or -1 (convexity = risk seeking), and then were subsequently aggregated per subject determined the subject's classification. If the sum was greater than 0, then the subject was classified as risk averse, if the sum was equal to 0, then the subject was classified as risk neutral, and if the sum was less than 0, the subject was classified as risk seeking.

Gains – Table 1 (Tables and Figures) provides the results of this measure for subjects in the gain condition, which finds that 39.7% of subjects demonstrated risk aversion, 38.7% displayed risk neutrality, and 22.6% showed risk seeking tendencies. This analysis suggests that risk preferences were relatively uniformly dispersed across categories, though on aggregate, subjects demonstrated slightly risk averse behaviour in gains. Graphs 1.1 and 1.2 (Tables and Figures), which non-parametrically plot a utility curve derived from the aggregate mean and median indifference values, respectively, support this conclusion, as they depict utility curvature as linear (Graph 1.1) or slightly concave (Graph 1.2). Results of risk aversion in gains reflect previous findings of utility curvature within a medical context (Attema, Brouwer, & l'Haridon, 2013; Attema, Brouwer, l'Haridon & Pinto, 2016). However, previous studies have generally found much more pronounced risk aversion than demonstrated in this study. This is most likely due to the different methodologies employed, as previous studies have used methods that are more constraining in terms of parametric assumptions and prospect structure (i.e. certainty equivalents).

Losses – Tables 2 and 3 (Tables and Figures) provide analogous results for the loss condition and the 'extended' loss condition, respectively. Results from the loss condition reveal that 16.7% of subjects displayed risk aversion, 50.0% demonstrated risk neutrality, and 33.3% displayed risk-seeking tendencies. Such results are complementary to the results of the gain condition, and suggest that on aggregate, subjects displayed slight risk-seeking tendencies in losses. Graphs 1.3 and 1.4 (Tables and Figures) support this conclusion, as they both depict utility convexity in the non-parametric plots of mean and median indifference values. This is a significant finding, as it provides evidence of CPT's applicability within the medical domain, and contradicts previous studies that have found risk aversion in apparent losses (Attema, Brouwer, & l'Haridon, 2013; Attema, Brouwer, l'Haridon & Pinto, 2016). Although this finding cannot be considered robust given the caveats discussed previously, it does provide initial insights into a plausible relationship. Furthermore, Table 3 demonstrates that the results of Table 2 represent a minority of less 'risk loving' individuals within the loss condition. In the 'extended' analysis of the loss condition, only 14.3% of subjects demonstrated risk aversion, while 42.9% displayed risk neutrality, and 42.9% risk seeking preferences. Graphs 1.5 and 1.6 (Tables and

Figures), provide further evidence of such risk seeking preferences, as both the mean and median indifference utility plots for the extended loss condition show more exaggerated utility convexity than the respective plots of the loss condition (non-extended). This suggests that the majority of participants in the loss condition were more risk seeking than those who did not violate any comonotonicity assumptions (depicted in Table 2), and illustrates a stronger contrast between risk preferences in gain and loss conditions, as per CPT predictions.

Parametric Analysis

Utility curvature was also analyzed parametrically for both gains and losses. Utility is commonly assumed to take the form of a power function in CPT literature ($y=bx^{\sigma}$) (Tversky & Kahneman, 1992), and therefore non-linear least squares ($\Sigma_{(i=1)}{}^{5}(x_i-(x_i)\hat{})^2$) was used to estimate the parameter of interest: sigma (σ). Under the power function specification, the results sigma > 1, sigma = 1, or sigma < 1, imply risk seeking, risk neutrality, and risk-averse preferences, respectively. Given that parameter (b) is also estimated in the process, $\Sigma\_{(i=1)}{}^{31}(b_i\, x^{\sigma i}) \neq \Sigma_{(i=1)}{}^{31}(b_i) \times \Sigma_{(i=1)}{}^{31}(x^{\sigma i})$, and therefore estimates of sigma using aggregated data, versus estimates of sigma using individual data and subsequently aggregated, can be very different. I employed the latter (individual-based) approach in my parametric estimations of sigma, given that it is more common in CPT literature (Bleichdrot & Pinto, 2000; Fehr-Duda, Epper, & Bruhin, 2011) and it allows for examining the relations between individual sigma values and other variables of interest. Given that the x_o values were exogenously determined by the experiment, I employed two different specifications of the power function relating X and Y. Specification (1) added a floating intercept term 'a' ($y=a+bx^{\sigma}$), while Specification (2) employed the original power function form ($y=bx^{\sigma}$), yet scaled indifferences values relative to their distance from x_o, thus equating $x_o=0$.

Gains – Table 1 provides both the mean and median estimations of sigma for subjects in the gain condition, for both specifications described above. Under both specifications, the mean sigma lies above one (Specification (1) =1.05, Specification (2) =1.03), which suggests slight utility convexity (sigma > 1), and thus slight risk-seeking preferences. When sigma is estimated through median values, however, slightly different risk preferences emerge, with Specification (1) sigma = 1, and Specification (2) sigma = 0.93. Thus, the median sigma values imply risk neutrality (Specification (1)) or risk aversion (Specification (2)). Subjects were then categorized individually per their estimated sigma value, which resulted in the following for Specification (1): 48.4% were classified as risk averse, 12.9% as risk neutral, and 38.7% as risk seeking. For Specification (2), 54.8%, 16.1%, and 29.0% were classified as risk averse, risk neutral, and risk seeking, respectively. Categorizations of subjects based on the two parametric classifications map relatively well to those of the non-parametric classification (despite a dissipation of risk neutral subjects), which suggests that the specifications do a relatively good job in capturing risk preferences, and that the majority of subjects in the gain condition displayed risk averse preferences. To further determine the accuracy of these parametric estimations, Graphs 2.1, 2.2, 2.3, and 2.4 (Tables and Figures) plot the estimated parametric utility curve over the non-parametric utility curve for mean and median estimates of both specifications. Graphs 2.1 and 2.2 show that Specification (1), in both mean and median sigma estimations, produces a curve that is far too convex in comparison to the non-parametric plot of indifference values, whereas Graphs 2.3 and 2.4, depicting the mean and median sigma estimates of Specification (2), portray curves that map onto the non-parametric utility curve relatively well. The median parametric estimate in Graph 2.4 appears to capture the non-parametric curve most accurately, only slightly deviating from the curve due to its smaller degree of concavity. Thus, the median sigma estimate of Specification (2), which implies risk-aversion, can be considered the most reflective of the subjects' true risk preferences.

Losses – Table 2 (and Table 3) contains the parametric estimates of sigma for the loss condition. The estimated mean sigma values of both specifications for subjects in the loss condition lie substantially above 1 – suggesting pronounced risk-seeking preferences. In Table 2, the aggregate mean sigma value is 1.68 (Specification (1)) and 1.61 (Specification (2)), which is far above the mean sigma values of 1.05 and 1.03 found in the gains condition, but is likely exaggerated by outliers having a strong pull on the small sample size (given its large standard error). However, the median individual estimates of sigma for the loss condition continue to hold above one at sigma = 1.14 (Specification (1)) and sigma = 1.23 (Specification (2)). This represents a stark divergence from the median values found in the gain condition, which equalled 1 and 0.93, respectively, and corroborates the non-parametric finding of differentiated risk preferences between the two conditions. The divergence in preferences is also reflected in the classification of subjects according to their sigma value, with the majority of subjects in the loss condition (50.0% Specification (1), 75.0% Specification (2)) displaying risk seeking preferences. The estimates in Table 3 (extended loss condition) also support the previous suggestion that risk seeking preferences increase in the loss condition as subjects are added to the analysis, as the number of subjects classified as risk seeking climbs to 81.0% (Specification (2)). Furthermore, in Table 3, the mean sigma value becomes significantly greater than one ($p < 0.05$), providing robust evidence of risk-seeking in losses. Lastly, if we examine Graphs 2.5-2.10 (Tables and Figures), which are analogous to Graphs 2.1-2.4 in gains, we find that the median sigma value of Specification (2) = 1.23 provides the best fit for the loss analysis, while the median sigma value of Specification (2) = 1.24 provides the best fit for the loss extended analysis (although it slightly under exaggerates the degree of risk seeking, as depicted by the curve lying below the non-parametric plot). Again, the specifications utilizing mean sigma values are far too convex to capture the non-parametric curve accurately. Cumulatively, these analyses provide compelling evidence that risk seeking preferences are more prevalent in the loss condition versus the gain condition, a foundational prediction of CPT. A summary of the parametric differences between conditions can be found in Table 6 (Tables and Figures).

Moderators of Utility Curvature

Tables 7-8 (Tables and Figures) analyze potential moderators of sigma, such as emotion, gender, and language. The correlation matrices indicate that the only significant correlation with sigma ($p < 0.10$), are estimates of gamma-1 (curvature in the one-parameter specification of probability weighting). The significant negative correlation between sigma and gamma-1, indicates that increases in a subject's risk seeking preferences are associated with higher levels of probability curvature. This is an interesting insight, as it suggests that risk seeking individuals are less discerning of probabilistic values. It is hard to compare such a result to previous literature, since most literature on CPT estimates probability weighting simultaneously with utility curvature, and therefore independent analyses of such correlations are not possible. The limited number of variables that covary with sigma is not surprising given the small sample size and that utility curvature has been found to be less susceptible to moderating influences than that of probability weighting (Fehr-Duda, Epper, & Bruhin, 2011).

Conclusion

Evidence from non-parametric and parametric analyses of utility curvature in both gains and losses supports CPT's prediction of differentiated risk preferences between the two domains – risk aversion in gains and risk seeking in losses. Although the difference in mean sigma values found between the two conditions is not statistically significant, this appears be a consequence of large standard errors in losses (due to small sample size), rather than a reflection of undifferentiated responses. Evidence from median sigma values, as well as non-parametric classifications, all indicate that the majority of subjects in the gain condition exhibited risk averse preferences, whereas the majority of subjects in the loss condition demonstrated risk seeking preferences.

Probability Weighting Function

In order to obtain probability weights from the indifference values (z_i) found in Part 2 of the experimental procedure, it is necessary to estimate and correct for the utility of such values based on the indifference values (x_i) found in Part 1. Similar to Bleichdroit and Pinto (2000), I estimated such utility values based on each individual's parametric power function (Specification (1)) derived from Part 1. Therefore, the analyses that proceed reflect the weighted probabilities found through power estimation.

Non-Parametric Analysis

Gains – Table 4 (Tables and Figures) provides a non-parametric analysis of the probability weighting function under gains, finding evidence of lower and/or upper subadditivity among the majority of subjects – a hallmark of CPT's probability weighting function. Lower subadditivity was defined as w(0.10)>0.10 and upper subadditivity as 1-w(0.90)>0.10, following Tversky and Fox's (1995) non-parametric method of analysis. In gains, 50.0% of subjects displayed lower subadditivity, 97.6% upper subadditivity, and 46.4% both. Such results argue that the majority of participants systematically overweight low probabilities (ie. 0.10), or underweighted high probabilities (ie. 0.90), compared to their objective value, yet only about half of participants did both. Although these findings represent less significant departures from objective probability weighting than found in similar literature in a medical context (Bleichrodt & Pinto, 2000), such results are likely underestimations as evidenced from the relatively small choice space participants with tightly sequenced indifference values faced in Part 2 of the experimental procedure, which may have constrained probabilistic assessments. Additionally, the large difference between the percentages of lower versus upper subadditivity may reflect the overall 'pessimistic' weighting of probabilities found amongst the majority of participants, evidenced in the parametric findings which follow. Despite slight divergences in individual classifications, aggregate evidence of significant lower and upper subadditivity is clearly visible in Graph 1.7 (Tables and Figures) which plots the mean and median probability weights against objective probability values, portraying the characteristic inverse S-shaped probability weighting function of CPT. Tversky and Fox's (1995) method of analysis also allows for the assessment of the 'possibility effect' versus the 'certainty effect', which compares the value of w(0.10) and 1-w(0.90). If w(0.10)> 1-w(0.90), then the possibility effect exceeds the certainty effect, and vice-versa. For 75.0% of subjects, the certainty effect exceeded the possibility effect, supporting a well-documented phenomenon of sub-certainty among probabilistic values (Kahneman & Tversky, 1979).

Losses – Tables 5 contains the non-parametric analysis of the probability weighting function under losses – reflecting similar results to those found in gains. Table 5 reports that 58.3% of subjects displayed lower subadditivity, 66.7% upper subadditivity, and 36.4% both. In comparison with gains, these classifications reflect a slightly greater tendency of subjects to overweight low probabilities, and a lesser tendency to underweight high probabilities. Evidence of a similar problem to gains arises in that some subjects may have been constrained in probabilistic assessment due to tightly sequenced indifference values derived in Part 1, and therefore such percentages may represent an underestimation of true levels of upper an lower subadditivity. Graph 1.8 (Tables and Figures) demonstrates the clear presence of lower and upper subadditivity in the aggregated plots of mean and median weighted probability values across subjects. In terms of the possibility versus certainty effect, only 55.0% of participants in losses demonstrated the certainty effect as exceeding the possibility effect, compared to 75.0% in gains. This is likely due to the decreased tendency of subjects in losses to underweight higher probabilities, while slightly exaggerating lower probabilities, thus making complementary probabilities more attractive. A comparison of the mean weighted probability values plots between gains and losses is depicted in Graph 1.9 (Tables and Figures), which provides a clear visual of the slight differences in non-linear probability weighting between the two conditions noted above. Although slight divergences exist, no fundamental departure in the shape between the two probability weighting functions does, as both display robust non-linear weighting reflecting the presence of lower and upper subadditivity.

Parametric Analysis

While non-parametric assessments of the probability weighting function provide intuitive and clear insights, parametric estimations are necessary to identify definitive differences between the two conditions and provide appropriate comparison to previous CPT literature that largely relies on parametric analyses. Since the weighted probability values in this study are elicited non-parametrically, it is possible to estimate various functional forms to model the probability weighting function. In CPT literature, two specifications largely dominate the debate concerning the weighting function's parametric form, a one-parameter model proposed by Tversky and Kahneman (1992) and a two-parameter model proposed by Gonzalez and Wu (1999) (both of which are described in Table 6). The one-parameter model only allows for changes in the function's curvature (gamma), whereas the two-parameter specification allows for changes in the function's curvature (gamma) and elevation (delta). The parameters of both specifications in this study are estimated through non-linear least squares ($\Sigma_{(i=1)}^{5}$ $(w(p_i)-(w(p_i)\hat{\ })^2)$).

Table 6 provides a comparison of parametric estimations across conditions. Confirming initial impressions formed through the non-parametric analyses, there are no significant differences between the parameter values of the probability weighting function between gain and loss conditions. The mean estimates of probability curvature (gamma) for the one-parameter specification are 0.52 in gains and 0.65 in losses, suggesting robust non-linear weighting (1 = linear, 0 = constant) in both conditions. The slightly higher parameter estimates in losses likely captures the decreased tendency for subjects in that condition to underweight higher probabilities, thus resulting in slightly more linear weighting functions as found non-parametrically. When assessing the two-parameter model, mean curvature estimates (gamma) range from 0.58-0.64 for gains and losses, respectively, and mean elevation estimates (delta) range between 0.66-0.68. The two-parameter gamma values imply, similarly to the one-parameter estimation, robust non-linear weighting, while the delta values of 0.66-0.68 imply strongly pessimistic probability assessment (delta < 1 = pessimistic). Such values are statistically similar to previous studies of similar methodology found in the medical domain (Bleichrodt & Pinto, 2000) and in the financial domain (Abdellaoui, 2000).

To determine which parametric form fits the data the best, Graphs 2.11-2.14 (Tables and Figures) provide a visual comparison between the non-parametric weighted probability plots (average and median values) and parametric plots across both conditions. In all cases, the two parametric functions fit the data very well, and do not fundamentally deviate, as seen in some of the parametric utility estimates. In all but one of the cases (loss - average weighted probability values), the one-parameter model appears to fit the aggregate data best, although the differences in fit are too small to validly determine visually.

Moderators of the Probability Weighting Function

Tables 7-8 provide correlational analyses of potential moderating factors, such as gender and emotion, with the parametric estimations of the probability weighting function. In gains, there exists both significant correlations among moderating variables – such as gender and happiness – and probability parameters, and between probability parameters themselves. In terms of moderating variables, 'pleasant' is significantly positively correlated with gamma-2 (curvature in the two-parameter specification) ($p < 0.05$) and gender is significantly negatively related to gamma-2 ($p < 0.10$). Utilizing the two-dimensional affect scale of Feldman Barrett and Russell (1998), 'pleasant' refers to the aggregated position of a subject on Unpleasant/Pleasant scale ranging from -15 to 15, constructed from six emotional items reflecting happiness, and rated on a 5-point Likert scale. The positive significant correlation between 'pleasant' and gamma-2 depicts that happier subjects were associated with more linear probability weighting – a finding that supports previous correlational findings of good moods in women and greater probability linearity (Fehr-Duda, Epper, & Bruhin, 2011). The rationale behind why good moods are associated with greater probability linearity is not clear, yet the external validity of the effect appears to be strong, as previous research regarding market transactions and probability weighting find greater probability curvature on highly cloudy days, and during the fall when daylight becomes scarce – both scenarios signifying negative moods accompanied by seasonal effects (Kliger & Levy, 2008). Additionally, the negative relationship found between gender and gamma-2, which suggests that female subjects weighted probabilities more non-linearly than males, also supports previous findings (Fehr-Duda, Epper, & Bruhin, 2011). Concerning the covariation between parameter values themselves, strong positive correlations exist between gamma-1 and delta ($p < 0.05$), and moderately between gamma-1 and gamma-2 ($p < 0.05$). This suggests that gamma-1 may more closely reflect the elevation parameter delta than curvature itself, which the two-parameter model allows gamma-2 to isolate. This suggestion is further evidenced in the significant negative relationship between gamma-2 and delta ($p < 0.05$), which indicates that non-linear probability weighting is associated with probability optimism.

When comparing correlations among potential moderating variables in the loss condition, differing patterns arise. In the loss domain, there is no significant relationship between 'pleasant' and probability weighting, nor gender and probability weighting, as found in the gain condition. Instead, a significant positively relationships exist between gender and delta ($p < 0.10$), implying that female subjects weighted probabilistic values more optimistically than males. This finding departs significantly from previous CPT literature, which consistently finds that females are generally more pessimistic about probabilities than males (Booij, Van Praag, & Van De Kuilen, 2010; Fehr-Duda, De Gennaro, & Schubert, 2006).

Therefore, this finding likely derives from the small sample size rather than a true relationship. Additionally, the loss condition conveys an extremely high positive correlation between gamma-1 and gamma-2 ($p < 0.05$), yet no correlation between gamma-1 and delta, as found in the gain condition. While the finding supports cross correlation between the two curvature parameters as denoted in gains as well, it is improbable that the correlation between the two would be as high as 0.92 if the sample size increased, given the differences in what the variables capture (gamma 1 = curvature and elevation, versus gamma 2 = only curvature).

Summary

Cumulatively, the analyses of the probability weighting function in gain and loss domains support CPT's postulation of non-linear probability weighting, and the presence of lower and upper subadditivity. Such analysis, however, do not find significant differences in probability weighting parameter estimations between gain and loss conditions, suggesting that the reference point manipulation does not play the same significant role it does in utility curvature. Lastly, correlations between different emotional dimensions and probability weighting parameters suggests that emotion and gender play a significant moderating role in the shape of individual's probability weighting function.

VII. DISCUSSION

The results above demonstrate the applicability of CPT to the medical domain and the importance of recognizing both the presence of differentiated risk preferences between gains and losses, and non-linear probability weighting, when considering medical decisions.

An important contribution of this paper is the support it lends to a differentiated value function between gains and losses among medical decision tasks, with gains invoking risk-averse preferences in the majority of participants and losses producing risk seeking preferences. The distinction found in risk preferences between gains and losses represents an imperative finding within the literature given the limited number of studies which have directly tested this core facet of CPT within medical decision making, and more significantly, it provides a refutation to the studies which have tested for a differentiated value function and have found CPT's prediction to not hold (Attema, Brouwer, & l'Haridon, 2013; Attema, Brouwer, l'Haridon & Pinto, 2016). The divergent findings of the current report and previous literature likely arises due to the different methodologies employed, with previous literature utilizing less noisy, yet more constraining, methods of analysis than the experiment administered in this study. Previous literature which imposed parametric assumptions, and/or certainty equivalents, may have altered risk preferences to cause an appearance of risk aversion in losses, while masking the true preferences of their subjects. Furthermore, as the parametric analyses of the current report suggest, many parametric estimations (of mean values) do no adequately capture the 'true' non-parametric risk preferences given by subjects, and yet in many of studies mentioned above, this is the only analysis upon which their assessment and conclusion rely. Hence, without reference to a non-parametric plot, different parametric forms and calculations may lead to erroneous risk preference models, simply due to measurement error. My analysis, therefore, provides preliminary support of CPT's differentiated value function, and maintains that methodological choices in the measurement of risk preferences are of key concern when evaluating and comparing outcomes.

The current research also contributes to the literature in its assessment whether CPT's postulation of non-linear probability weighting holds amongst medical decisions. The first significant finding is that of robust non-linear probability weighting in both gain and loss domains, which confirms previous findings from an array of methodological implementations in medical (Bleichdroit and Pinto, 2000; Pachur, Hertwig, & Wolkewitz, 2014, Attema, Brouwer, l'Haridon & Pinto, 2016) and financial (Abdellaoui, 2007; Abdellaoui, Vossmann, & Weber, 2005) domains. These findings demonstrate the significant prevalence of subjective probability weights across contexts, and the appropriateness of considering such tendencies when evaluating medical choices. A second, and more novel, finding is that of gender and incidental emotions moderating the shape of an individual's probability weighting function under medical decisions. Evidence from the gain condition suggests that probability weighting is more susceptible to the influence of moderating variables than utility curvature and that factors, as incidental as one's current emotional state, can have significant sway over probabilistic assessment. The current study found that females weighed probabilities more non-linearly than males, which previous research has suggested is the result of males employing expected value strategies more frequently (Fehr-Duda et al., 2011). Furthermore, incidental happiness predicted more linear probability weighting than incidental sadness, which corroborates previous findings in the financial domain (Fehr-Duda et al., 2011; Kliger & Levy, 2008), but has yet to be explained. Therefore, the results of the present experiment demonstrate the robustness of non-linear probability weighting across contexts, while also addressing the need for further research to disentangle moderating variables of probability weighting to more comprehensively capture and model heterogeneity in probabilistic assessment.

The current report, and previous CPT literature within the medical domain, are of vital importance to understanding the impact of risk preferences and probability assessment in how one perceives medical decisions under risk. This has important implications beyond just theoretical considerations, as many real-world health measures, such as the QALY model, are based on potentially erroneous assumptions under EUT that may lead to recommendations and decisions which poorly reflect the preferences of the individual in question. Therefore, while the present study is limited in its applicability to real-world medical decision scenarios, given the hypothetical nature of the questions, the amount of information provided, and the demographics of the sample itself, it does provide a blueprint for baseline behavioural tendencies and potential moderating variables to account for during medical decision making processes.

Although this report provides compelling insights into medical decision processes, it suffers from two significant limitations, which I hope to address in subsequent research. As previously mentioned in my results section, the high number of subject exclusions in the loss condition render some of the conclusions tentative at best, and such exclusions must be mitigated for further research to deliver definitive results. Possible solutions to this problem may be: conducting the experiment among smaller groups with more feedback, providing more intuitive interface designs, and establishing better incentives to ensure quality responses. A second limitation of the current report is the hypothetical nature, and 'unrepresentative' sample, employed within the experiment, which may render the results less generalizable to an applied setting. The first concern, the hypothetical nature of the experiment, is not limiting when one interprets the subject's response not as representative of a true 'physician,' but merely as their objective assessment of medical decisions without confounding influences associated with subjects assuming the role of a patient (different ages, different present life experiences, etc). The second concern, undergraduate commerce students being unrepresentative of the general public in risk and time preferences, is more valid, and harder to mitigate. Research has shown that young adults tend to have significantly divergent risk and time discounting preferences than older adults (Gardner & Steinberg, 2005; Green, Fry, & Myerson, 1994), who will more frequently face medical decisions. Although it is impossible to determine how divergent the risk preferences of the current subjects are to comparable older adults, in terms of time discounting, this may be less influential, as a medical time discounting assessment within the experiment did not correlate significantly to the subject's risk preferences or probability weights. A more representative sample, however, could solve both issues, and should be implemented in further research.

VIII. CONCLUSION

The extent of CPT's applicability within the medical domain has yet to be determined. As discussed in the literature review and throughout the results, incomplete and contradictory findings in previous literature have not clearly established whether CPT's postulation of differentiated value functions between gains (utility concavity) and losses (utility convexity), and non-linear probability weighting, hold in medical as they do within monetary contexts. The goal of the present research was to provide a robust test of both predictions, and to clarify contradictory findings of previous reports. By employing an experimental design that manipulated the reference point of decision scenarios among medical tasks, the present research allowed for both non-parametric and parametric analyses of CPT's differentiated value and probability weighting functions, while simultaneously testing for moderating influences of both. Through this, I found significant evidence to support the core predictions of CPT – the presence of differentiated value function, and non-linear probability weighting – which corroborates, and refutes, previous CPT research within this domain. It validates previous studies that have found robust non-linear probability weighting among medical decisions, yet counters research that has suggested undifferentiated utility curvature across gains and losses. Furthermore, the current report established pioneering research in regards to moderating influences of the probability weighting function within the medical domain, and found compelling evidence of moderator variables found in the financial domain, such as gender and happiness, influencing the shape of the probability weighting function. The report makes clear, above all else, that current research regarding CPT's generalizability to the medical domain is still within its infancy, and thus further research employing a variety of methodological designs is required to determine the extent to which its predictions hold.

Who Wants to Find a Lover Online and Why?

A Study of The Determinants of Online Dating Usage and The Effect of First-Time Meeting Venue on Relationship Outcomes

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ABSTRACT

Online dating (OD) has gained increasing popularity in the marriage market. While previous scholars have studied various aspects of online dating such as personal and demographic characteristics of online daters, efficient matching algorithm, and factors affecting the quality of relationships, there is still space for expansion of knowledge in this field. This paper is therefore an integrated investigation on the determinants of OD usage and the effect of online vs. offline first-time meeting venue on the quality and long-term stability of relationships. I use data from a national telephone survey conducted from April 17th to May 19th in 2013 by Princeton Survey Research Associates International for the Pew Research Center's Internet & American Life Project to explore the issues. Economic models based on expected utility theory are constructed to predict the decisions on dating activities. Binary choice model and Probit regression are utilized to estimate the average marginal effects (AME) of demographic and social determinants on the propensity to use OD services and involve in certain OD related activities. Results suggest behavioural and perceptual sociability online is positively correlated with OD usage, and some demographic effects are not robust when sociability is controlled. First-time meeting venue does not affect the quality and long-term stability of relationships. This paper helps discover the decision-making process on OD usage and sheds light on the improvement of online matching algorithms.

I. INTRODUCTION

With the advent of the internet in the mid-1990s, online dating (OD) has gained increasing popularity. It is estimated that a Canadian-based dating website, PlentyOfFish, has around 100 million users worldwide ("10 Online", 2017). While the traditional offline meeting venue still dominates the dating market, the modern online meeting venue is on its way of catching up or even surpassing its predecessor. As more and more dating intermediaries establish online sites and mobile apps with special algorithms to facilitate the searching and matching process, agents who are interested in mating start to consider the online options. Economists have studied how agents make decisions with multiple available options using expected utility theory. In the realm of dating markets, for example, Adachi (2003) uses threshold crossing rule based on expected utility to model matching decisions. To explore the underlying dynamics that motivate agents' usage of OD services, this paper proposes theoretical decision making models that predict individuals' propensity to use OD services. Through regression analysis, the model predictions are tested and some possible determinants of OD usage are identified.

Besides the determinants of OD usage, the matching efficiency and effectiveness of OD sites and apps are also of interest. It is reported that the proportion of marriages in 2015 in which the couples met on dating sites is 17% ("Why man", 2017). Does this suggest OD has the potential to reach stable matching outcomes? Scholars from various disciplines employ scientific methods to decipher the underlying matching patterns of relationships and marriages (Becker, 1973; Kalmijin, 1998; Browning, Chiappori, & Weiss, 2008). In the field of economics, Gale and Shapley (1962) construct deferred acceptance algorithm (DDA) which can lead to efficient and stable matching outcomes. Following Gale and Shapley, other scholars have furthered the study on matching in marriage markets by applying search models (Adachi, 2003) and exercising econometric methodology (Wong, 2003; Choo & Siow, 2006; Flinn & Boca, 2006). Even though research suggests that scientific algorithms, in theory, lead to matching outcomes with higher stability, there is yet to be an investigation conducted to evaluate the relationship outcomes of OD using empirical data. This paper, therefore, aims to fill the gap.

The paper proceeds as follows: Section II gives an overview of the motivational and topical literature in the field, Section III introduces the theoretical framework based on expected utility theory, Section IV describes data source and summary statistics, Section V discusses the binary choice econometric model and estimation strategy, Section VI presents estimation results and discussion, and Section VII gives concluding remarks.

II. LITERATURE REVIEW

Two distinct types of literature motivate this research. The first is the vast body of literature on expected utility theory and consumer choice theory, which ties closely to my first research question regarding the decisions regarding, or the determinants of, OD usage. The second is the literature on matching theory and mechanism design, which inspires my second research question regarding the matching efficiency and effectiveness measured by quality and long-term stability of relationships.

Expected utility theory has been widely used to model the underlying mechanisms of decision making under uncertainty since the mid-20th century, and the literature in this field is vast. Bernoulli is the pioneer in the 18th century who brought in the concept of probability into the profit maximization problem under uncertainty. The 19th century saw an explicit adoption of the concept of utility, thanks to the theoretical advancement by Bentham, the "Philosophical Radicals", mainstream classical and neoclassical economists. After heated scholarly debates over the comparison of interpersonal utility, revealed preference theory gained popularity. In the mid-20th century, Samuelson developed welfare economics, while von Neumann and Morgenstern revitalized theory of choice under risk.

The gradual development of economic theory suggests that expected utility is legitimate in its consideration for agents' decision making (Quiggin, 2012). However, due to certain limitations of expected utility theory, scholars have also developed a few alternatives. For example, Starmer (2000) points out that many observed decisions made by agents do not align with the specification by expected utility theory. He thus proposes an alternative non-expected utility theory to address the issue, including conventional strategies featured by the "fanning out" hypothesis and theories with decision weights, as well as unconventional theories featured by the procedural approach, reference dependence, and non-transitive preference theory. Furthermore, prospect theory, which models the dynamics of decision making on probabilistic options with risks, was created and developed by Kahneman and Tversky (1979) and remains one of the most popular alternatives to expected utility theory. A wider variety of factors, such as psychological ones, are considered for the analysis of expected utility as well. For instance, Caplin and Leahy (2001) incorporate anticipatory psychological emotions such as anxiety into the formulation of their model and coin it as psychological expected utility model. This paper, therefore, includes psychological effects in the formulation of the economic model as well. However, since the decision on OD usage involves risk that is less salient than that of medical or financial investment decisions, this paper tentatively refrains from applying prospect theory. To focus on the general structure of the decision on OD usage, this paper simplifies the modelling framework by neglecting factors such as social stigma that affect the decision, and focuses on the application of expected utility theory.

Consumer choice theory is another way to approach the decision on OD usage. If we regard dating activities as consumer goods, then daters, by assumption, would choose to maximize his or her expected utility subject to resource constraints by optimally allocating consumption on online and offline dating. Previous scholars have researched consumer choice on online and offline platforms. For example, Guo, Wang, and Leskovec (2011) investigate the role of social networks on consumer choice in online shopping. Degeratu, Rangaswamy, and Wu (2000) study the effects of brand name, price, and other search attributes of consumer choice behaviour in online and offline supermarkets, and they find that the value of brand names varies across categories depending on the availability of information, that sensory (e.g. visual cues) and non-sensory (e.g. nutrition facts) search attributes have different levels of impact on consumer choice, and that consumers tend to be more sensitive to the price online. An analogy to OD can be made here — since the build-up of personal brands tends to be more important in the creation of online profiles, the potential value of a well-polished personal brand may affect agents' decisions on OD usage; visual and non-visual information in online and offline profiles may also affects agents' dating and settlement decisions; agents' mating criteria may serve as their "ask price" for their potential mates, so the difference in availability of information about daters' "ask price" may also affect agents' decision on OD usage. In terms of resource allocation, Okada (2005) finds that people are willing to pay more in time for hedonic goods and more in money for utilitarian goods, which also has implication on the resource allocation of dating activities. If agents use OD services for entertainment purpose, that is, if they treat OD as a hedonic good, does it imply that they tend to allocate more time on OD usage? On the other hand, if their intentions for OD usage is to find a long-term partner for a committed relationship, that is, if they treat OD as a utilitarian good, does it suggest that they tend to invest more money in OD usage? A hypothesis could be made, but this paper does not aim to test the hypothesis due to the lack of information on the purpose of OD usage.

The second realm of literature that motivates this research is related to matching theory and market design. Matching occurs in numerous aspects of our lives, such as job searching and school enrolment. Relationships are also a type of matching in marriage markets. As mentioned in Section I, scholars have done research on the underlying patterns of marriages and constructed efficient matching algorithms to facilitate the matching process. Moreover, Becker (1973) focuses on the examination of household production within, and outside of, marriage and further explores how it helps determine optimal sorting and assortative mating in marriage markets. Having realized the promising potential of scientific mechanisms to improve matching outcomes in marriage markets, previous intellectuals invented and patented mechanisms to facilitate matching in OD (Collins, 1999; Collins, 2000; Brown, 2009), in the era of technology when OD sites and apps are remarkable platforms in which efficient algorithms and mechanisms can be applied. As OD gains increasing popularity and scientific mechanisms gain increasing favor by OD sites and apps, scholars have started to explore the matching effectiveness of OD services. For example, Hitsch, Hortaçsu, and Ariely (2010) use a novel data set from an OD site to test the prediction accuracy of Gale-Shapley algorithm and report first-date matching efficiency of the site studied. Furthermore, Lee (2009) utilizes a dataset from a South Korean matchmaking service to track a sequence of dates and possibly until marriage to explore the long-term stability of matching outcomes.

Motivated by the two types of literature mentioned above, I pinpoint my two research questions, which include: (1) what are the determinants of OD usage and deeper OD usage? (2) what is the difference in quality and long-term stability of relationships initiated from online and offline meeting venues? To further grasp the current state of knowledge, more literature related to my specific research questions is reviewed and presented below.

First, scholars have conducted research to investigate demographic and social characteristics of online daters. In the case of demographic attributes, for instance, Sautter, Tippett, and Morgan (2010) analyze 3,215 respondents from the first nationally representative U.S. survey of internet dating by using multivariate logistic regression. They find sociodemographic factors have strong effects on internet access and single status but weak effects on usage of internet dating services once the sample is conditioned on these factors, and the likelihood of internet dating is strongly influenced by computer literacy and social networks. In the case of Canada, Brym and Lenton (2001) report that online daters are more likely to be male, younger, single, divorced, employed, urban, better educated, and enjoy higher income, according to their analysis of data from a telephone survey of 1,200 Canadians conducted in 2000 for

MSN.CA. In the case of social attributes, for example, Kim, Kwon, and Lee (2009) explore how the three-way interaction between self-esteem, involvement in romantic relationships, and sociability affect OD usage. Their data were collected from the 2004 DDB Needham Life Style Survey with a quota sample composed of 3,345 respondents aged from 19 to 89 with a mean age of 48, which was representative of the U.S. adult population. They find a positive correlation between sociability and OD usage. Moreover, for sociable people, the more they consider relationships as an important contributor to their happiness, the more likely they choose to use OD services if they have higher self-esteem, and the less likely they choose to use OD services if they have lower self-esteem. This pattern is explained by the concept of contingency of self-worth — when they consider relationships as the domain for the realization of self-worth, high self-esteemed people will tend to use OD as a venue to further boost their success through online self-promotion, whereas low self-esteemed people will tend to avoid failure in the domain by distancing themselves from public self-presentation. On the other hand, if those sociable people did not view relationships as crucial, that is, if they were not as involved in romantic relationships, then those with low self-esteem tend to use OD services more frequently than their higher self-esteemed counterparts, which requires more explanation acknowledged by the authors. For the less sociable people, there are no significant patterns found in the interaction between self-esteem and involvement in relationships.

Following Kim, Kwon, and Lee (2009), Gatter and Hodkinson (2016) designed and analyzed questionnaires answered by 75 voluntary respondents recruited through Facebook to compare characteristics between individuals who used Tinder and who used OD agencies. They find no differences between the two groups in motivation to use OD services, sociability, and self-esteem, while differences are shown in sexual permissiveness, likely due to the age difference between the groups. That is, on average, Tinder users are younger and more sexually permissive than OD agency users. Since there is little difference in certain attributes of users of dating apps and agencies, I group users of dating apps and sites together for neatness to conduct my research, even though my data allows me to explicitly distinguish them. Furthermore, Valkenburg and Peter (2007) also explore characteristics of online daters by using data from an online questionnaire with 367 single Dutch Internet users between 18 and 60 years old. They find the most active online daters tend to be low in dating anxiety in terms of psychological traits; in terms of demographic characteristics, online daters between 30 and 50 years old are the most active dating group, and OD usage is unrelated to income and educational level.

To provide the topic of interest with more evidence and insights, my research also explores whether demographic characteristics, including physical attributes, geographic locations, assets and human capital, mating history and preferences, and social characteristics, including behavioural and perceptual sociability, are correlated with the propensity to use OD services. My research findings may support, supplement or contradict the previous scholars' conclusions.

To focus more on social determinants, additional literature regarding online sociability is reviewed. Incentives and predictors to use the internet and social networking services (SNS) are studied. For instance, Papachrissi and Rubin (2000) investigate the predictors of internet usage based on data from a survey with a total of 279 student participants enrolled in an introductory communication class, at a large midwestern university in the U.S. They find contextual age, unwillingness to communicate, social presence, and Internet motives can predict outcomes of internet exposure, affinity, and satisfaction. Similarly, Bonds-Raacke and Raacke (2010) recruited a total of 201 students at a four-year public, east coast university in the U.S. for their study to identify dimensions of uses and gratifications for users of friend networking sites. The information, friendship, and connection dimensions are found, and sex differences are also identified — men are more likely to use the sites for dating purposes and women are more likely to set their accounts to private. Other scholars also use data from surveys to explore motives for the use of social networking sites (Lin & Lu, 2011; Kim & Sohn, & Choi, 2011; Xu & Ryan & Prybutok, & Wen, 2012), and Facebook particularly (Hunt & Atkin & Krishnan, 2012; Quan-Haase & Young, 2010). However, whether the active involvement in SNS and certain online activities (i.e. behavioural online sociability) and opinions about OD (i.e. perceptual online sociability) would infer a stronger tendency of the usage of OD services is barely studied by previous scholars; therefore, my research aims to fill the gap.

In addition to the determinants of OD usage, the quality and long-term stability of relationships formed through OD are also of interest. Previous scholars have investigated the factors that affect the quality of relationships in general. For example, Sprecher (2001) utilizes a volunteer sample of 101 romantic couples from a midwestern university in the U.S. in 1988, with additional follow-ups in the following four years, to study long-term stability of relationships. By using multiple regression, she reports correlation between relationship satisfaction and commitment, as well as with social exchange variables such as under-benefiting and over-benefiting inequity, rewards, investments, and alternatives. Similarly, Kurdek and Schnopp-Wyatt (1997) study how intrinsic (e.g. inner satisfaction) and extrinsic (e.g. social distinction) values couples place on their relationships act as predictors of relationship stability and commitment. By surveying university students and their partners, the researchers collected data from 130 heterosexual, non-cohabiting, primarily white, exclusively dating couples, and analyzed their 6-month relationship stability. One of their findings is that relationship stability is predicted by female partners' low extrinsic values and an interaction between both partners' intrinsic values. None of these research findings implies the difference in quality and long-term stability of relationships initiated from different first-time meeting venues. Hence, I will research on the effect of first-time meeting venue to expand our knowledge on this topic.

III. UNDERLYING ECONOMIC MODELS

To better understand agents' decision making process on OD usage, I construct the economic model outlined below. First, I assume agents make a series of rational decisions along the dating process based on expected utility. Essentially, they decide whether to use OD services by comparing expected utilities generated by alternative options. I use a similar threshold crossing rule by Adachi (2003) to model the decision. This model is tested by the empirical results of the determinants of OD usage. Second, once they decide to use OD services, they face a consumption allocation problem since they need to decide whether to engage in deeper OD usage, given some offline options that are still available to them. Assuming $x_1 \neq 0$, agents choose a consumption bundle between OD (x_1), including not only dating activities online but also offline interaction initiated online, and offline dating (x_2) to maximize utilities subject to resource constraints. This model is tested by the empirical results of the determinants of deeper OD usage. Third, once agents have tried some preliminary dates, they decide whether to settle or not for a committed long-term relationship or marriage based on the comparison of expected utilities associated with different options of mates. The settlement decision is closely governed by the expected quality and long-term stability of to-be-committed relationships, which provides information for the evaluation of matching outcomes. This model is tested by the empirical results regarding the comparison of the quality and long-term stability of relationships resulting from online and offline first-time meeting venues. This section will proceed by describing the underlying economic models of these three decisions one by one.

i. Decision on OD Usage – Threshold Crossing Rule

I assume individuals make ex ante decisions based on their evaluation of expected utilities of uncertain future events in OD usage. When individuals make decisions on OD usage, they do not know the actual to-be-realized payoffs and the probabilities of getting the payoffs for sure, so they form beliefs about the values of these parameters, which affect their decision making. Theories of self-enforcing expectation in economics and self-fulfilling prophecy in psychology explain how beliefs play a crucial role in shaping individuals' decisions and actions, so perceived payoffs and probabilities (which are influenced by these beliefs) are parameters integrated in this model; besides, the value of parameters representing real payoffs and probabilities are determined by the physical structure of the dating markets. Thus, let $E[\pi_k]$ and $E[Prob_{(i,k)}$ (matched)] be the expected payoffs and probabilities that individual i gets matched on dating venue k∈(online,offline) respectively, each of which consists of its real and perceived components; $E[\pi_k]$ may be affected by the real and anticipated quality and long-term stability of relationship (utilitarian goods) and/or the entertaining nature of dating (hedonic goods). Since costs are less uncertain than dating outcomes, this model constructs costs without the expectation operator, so let $TC_k=C_k^{sub}+C_k^{psy}$ be the total costs consisting of substantial costs such as money, time, and psychological costs such as vulnerability of self-disclosure. Then the expected utility that individual i gets from dating through venue k is the following:

$$EU_{i,k} = E[\pi_k] * E[Prob_{i,k}(matched)] - TC_{i,k} \quad = 1 \backslash * \text{ GB2 } (1)$$

where

$$E[Prob_{i,k}(matched)] = \alpha_{i,k} + v_{i,k} - \gamma_{i,k} - \delta_{i,k} + \sigma_{i,k} + Prob_{i,k}^{perceived}(matched) \quad = 2 \backslash * \text{ GB2 } (2)$$

where $\alpha_{(i,k)}$ is the baseline probability of i being matched, which could be determined by certain personality and demographic attributes of individual i in venue k. $\alpha_{(i,onine)}$ might be lower due to adverse selection, that is, individuals who have difficulties finding a partner offline tend to resort to OD, but this paper does not consider this scenario for simplicity. $v_{(i,k)}$ is individual i's mating visibility, which represents the likelihood that i's mating interest and relevant personal information are revealed to his or her potential mates. $\gamma_{(i,k)}$ indicates search friction in i's network in k; it might be the case that $\gamma_{(i,online)}$ is lower since the internet relaxes the geographical and occupational constraints. $\delta_{(i,k)}$ represents the substitutability of i in k, which is the probability that i can be substituted by other candidates in the market k. Since online personal profiles are more visible than offline personal introduction through daily interaction with people, it could be presumed that $v_{(i,online)}$ tends to be higher than $v_{(i,offline)}$, thus individual i's attributes, experiences, and other relevant information are more likely to be thoroughly learned if he or she uses OD, but the opposite could be true as well since it is easier for some people to get familiar with others offline. Since the internet environment is generally the same for everyone, the index i could be withdrawn for search friction online γ_{online}, however, $\gamma_{offline}$ may vary across individuals since the level of difficulties to meet people in town is perceived differently by different people, thus the index i should be kept for $\gamma_{(i,offline)}$. Since there is a larger pool of potential mates online, the choice set online for any other individual j is relatively larger than that offline, so i's potential mate j is more likely to switch away from i since j can find another potential mate who has similar attributes to i more easily online, that is, since sorting is more efficient online, the supply of j's potential mates of j's preferred type is relatively higher online, so I presume $\delta_{(i,online)}$ is higher than $\delta_{(i,offline)}$. Finally, $\sigma_{(i,k)}$ represents the dating activeness of individual i in dating venue k.

Furthermore,

$$C_{online} = c_{fee} + c_{profile} + c_{browse} \cdot m + c_{email} \quad = 3 \backslash * \text{ GB2 } (3)$$

$$C_{offline} = c_{social} + c_{intro} \cdot n + c_{screen} + c_{know} \cdot m + c_{contact} \cdot h \quad = 4 \backslash * \text{ GB2 } (4)$$

where c_{fee} captures any potential fee that individual i has to pay to use OD services, and c_social indicates the cost that individual i has to make to socialize for the search for a potential mate offline. $c_{profile}$ is a once-for-all cost of creating an online personal profile, which may include own cost and cost of asking others to help create or review the profile. Correspondingly, c_{intro} is the cost of introducing oneself to others in an offline scenario, and n is the number of people to whom individual i introduces him or herself. c_{browse} is the cost of browsing a profile of a potential mate online, while c_{know} is the cost of getting to know a potential candidate offline, and m is the number of people that individual i studies. c_{screen} is the cost of screening for preferred potential mate, and since this cost is minimized in online scenarios due to the fact that computer algorithms can automatically do the screening for users, I do not include the cost in the online scenario. c_{email} represents the cost of sending an email or an online message to ask a potential mate out, which is assumed to be a fixed cost because once an email is written, it can be carbon copied or copied and pasted to multiple recipients with slight modification. $c_{contact}$ is the cost of asking someone out for a date in an offline scenario, which is considered to be a marginal cost, and h is the number of people to whom individual i asks out.

In the actual process towards a confirmed relationship or marriage, more costs and investments may occur in the continuing interaction between partners. For example, each partner may need to make some efforts to maintain the relationship and preserve his or her own market value so that the utility he or she gives to his or her partner does not degrade to the partner's reservation utility where the partner prefers to stay single, so ongoing investment on preferred personal attributes such as intellectual ability and physical shape is possibly needed to counteract the natural depreciation of these attributes. Nevertheless, the theoretic model I propose here tracks the dating process only until a first date for simplicity, so the potential costs and investments mentioned in the continuing dating process are out of consideration.

In this proposed model, I assume individual i chooses to use OD services if and only if

$$EU_{i,online} \geq EU_{i,offline} \quad = 5 \backslash * \text{ GB2 } (5)$$

Given the knowledge of the variables and parameters mentioned above, individual i's propensity to use OD services can be predicted by

$$Propensity_i = Prob_i(EU_{i,online} \geq EU_{i,offline}) \quad = 6 \backslash * \text{ GB2 } (6)$$

In practice, however, most of these variables and parameters are less observable or measurable. Therefore, I will use Probit regression model which will be presented in Section V to estimate the propensity of interest.

ii. Decision on The Level of Involvement of OD Usage – Consumption Allocation

Once an agent decides to use OD services, he or she solves the following consumption allocation problem:

$$max_{x_{1,i},\ x_{2,i}} (a_i ln\, x_{1,i} + b_i ln\, x_{2,i}) \quad = 7 \backslash * \text{ GB2 } (7)$$

$$s.t. \quad t_{1,i} + t_{2,i} \leq T_i$$

$$and \quad s_{1,i} + s_{2,i} \leq S_i$$

where $x_{(j,i)}$ is person i's involvement in online/offline dating activities, $t_{(j,i)}$ is the time that person i spends on online/offline dating, T_i is the total time that i allocates to dating activities, $s_{(j,i)}$ is the money spent on each dating venue, and S_i is the total money allocated to dating activities. a_i and b_i capture how much individual i values online and offline dating, respectively, each of which can be viewed as a collection of all the relevant parameters (i.e. π_k, $\alpha_{(i,k)}$, $v_{(i,k)}$, $\gamma_{(i,k)}$, $\delta_{(i,k)}$) mentioned in sub-section ii. Individuals with different demographic and social attributes generally have different values of a_i, b_i, and different budgets T_i and S_i, so the model suggests that certain demographic and social characteristics may determine agents' decisions on deeper OD usage through the utility maximization process.

iii. Decision on Settlement – Conditional Expectation

The settlement decision by a couple w_iand m_j is represented by the following indicator function:

$$Y_{i,j} = 1\{settle \mid w_i, m_j \ \forall\ i,j\} = 1\{EU_i(rel_{i,j}) \geq EU_i(rel_{i,j'})$$

$$and\ EU_j(rel_{i,j}) \geq EU_j(rel_{i',j}) \ \forall\ i' \neq i\ and\ j' \neq j \mid w_i, m_j \ \forall\ i,j\} \ = 8 \backslash *\ GB2\ (8)$$

Woman w_i and man m_j will decide to settle for a committed relationship if and only if each of them can obtain his or her highest expected utility from the relationship conditional on all the available choices. If an agent anticipates non-satisfactory expected utility from a potential match based on his or her observation of the potential mate's attributes and their preliminary interaction, he or she will decide not to settle for the match regardless of the meeting venue. If a couple ever decides to settle, their settlement decision elicits information about their anticipatory satisfaction with the relationship already. Since the first-time meeting venue is just a channel through which two people are brought together, and further commitment decision need to be made for a settled relationship after several rounds of interaction, the model suggests that first-time meeting venue does not have determining power for the quality and long-term stability of committed relationships.

iv. Model Prediction and Hypotheses

Based on the economic models outlined previously, I hypothesize that certain demographic and social characteristics determine agents' OD usage by determining the values of parameters proposed in those same economic models, and that first-time meeting venue is a non-determinant of the quality and long-term stability of relationships. Detailed model prediction and hypotheses are presented below.

First, the observed higher proportion of males within online daters could be attributed to the fact that men tend to be more sociable online than their female counterparts. Specifically, if males are more likely to flirt with someone online, then it might suggest that they gain entertaining utility from romantic activities such as flirting online, which increases their expected utility from OD (i.e. $EU_{(i,online)}$) by increasing the expected payoff of OD activities (i.e. $E[\pi_{(online}]$), hence it is more likely for males to cross the baseline utility threshold and to choose to use OD services. If males are more likely to initiate a date through virtual aid, then their dating activeness online $\sigma_{(i,online)}$ is higher than that offline, which suggests that their expected probability of getting matched online (i.e. $E[Prob_{(i,on-}$

$_{line)}$ (matched)]) would be higher, so males are more likely to choose an online dating venue. If men and women are equally sociable online, then there should be no pure gender difference in OD usage. Second, the elderly (i.e. people who are over 56 years old) have a higher propensity to use OD services. The key reasoning here is that the probability of being matched offline $Prob_{(i,offline)}$ (matched) is lower than the probability of being matched online $Prob_{(i,online)}$ (matched) for the elderly, assuming the related costs are the same for all ages. To be more specific, the mating visibility offline $v_{(i,offline)}$ for the elderly is likely lower than $v_{(i,online)}$, because it is generally harder for the elderly to reveal their singleness and/or mating intention offline than online and it is harder to detect potential mates' singleness and/or mating intention offline than online as well. Furthermore, it is also likely that the offline meeting venue exhibits a greater search friction (i.e. $\gamma_{(i,offline)} > \gamma_{(i,online)}$) for the elderly, because as people get older, they tend to interact with only a certain circle of friends that they have established previously and thus lack the opportunities to get to know people outside their established network. For example, if a person has been working in a certain industry for decades, then it is likely that most of his or her friends or acquaintances are workers in that industry as well. In this case, the elderly are rather constrained by a relatively rigid network, which creates a greater offline search friction for them to find a mate. Fortunately, OD makes it easier for the elderly to establish new relationships by increasing their mating visibility and decreasing search friction, so it is understandable that they are more likely to choose to use OD services.

Third, if urban folks account for a statistically larger proportion of OD users, and if assortative mating leads them to prefer mates that are urban as well, then their perceived probability of getting matched through OD (i.e. $Prob_{(i,online)}^{perceived}$ (matched)) will likely be higher because they believe the larger pool of urban users online would give them a better chance to find a suitable mate. If urban people tend to be more comfortable and confident about online self-disclosure, then the psychological cost of vulnerability and anxiety resulted from OD usage (i.e. C_online^psy) would be lower for the urban user. These two forces together will increase the expected utility of OD (i.e. $EU_{(i,online)}$) for the urban individual, so they will be more likely to cross the threshold to use OD services, should the conjectured parameter values are applicable to them. Similarly, if the psychological cost of online disclosure is higher for the rural cohort, then it should be less likely for them to use OD services. If they ever choose to use OD services, it should be the case that their $E[\pi_{online}]*E[Prob_{(i,online)}$ (matched)] is high enough to overturn the negative effect of C_{online}^{psy}, so that the rural user crosses the threshold to use OD services, which suggests that their a_i (i.e. how much they value OD in the consumption allocation model) would be higher, leading them to allocate more resources to OD if they ever to choose to be involved in OD. Thus the model predicts that rural people are more likely to engage in deeper OD usage if they ever decide to use OD services.

Lastly, this economic model is an extremely simplified one and is by far only able to make a few primitive predictions of OD usage based on conjectured parameter values, leaving some other decision making mechanisms unexplained. The main reasons why this model is not sophisticated enough to account for all the dynamics undergoing decision makers' minds are the following: (1) we have limited knowledge of the underlying parameter values of each agent; (2) there are unidentified parameters that might affect agents' decision making; (3) factors outside the rational economic model such as habits and social conformity may also play a role in leading agents to make irrational decisions. To address the limitation of the presented economic model, more research in behavioural economics, microeconomics, psychology, sociology, neuroscience, and other disciplines is needed to help us fully understand the mechanisms that drive agents' decision making.

IV. DATA SOURCE AND DESCRIPTION

My data come from a national telephone survey conducted by Princeton Survey Research Associates International for the Pew Research Center's Internet & American Life Project from April 17 to May 19 in 2013, among a sample of adults at age 18 or older. The unit of observation is individual. The cross-sectional data includes 2,252 observations comprised of 1,125 landline respondents and 1,127 cell phone respondents. Survey Sampling International provides the sample, generated through the random digit dialing (RDD) method used among both landline and cellphone users to systematically represents American adults who have access to either a landline or cellular phone. From active blocks (area code + exchange + two-digit block number) with three or more residential directory listings, numbers for the landline sample were drawn with equal probabilities. The cellphone sample was drawn through a systematic sampling from dedicated wireless 100-blocks and shared service 100-blocks with no directory-listed landline numbers. Margins of error attributed to the sampling are plus or minus 2.3, 2.5, 2.9, and 7.4 percentage points for results based on the entire sample (n=2,252), all internet users (n=1,895), all non-single individuals (n=1,428), and users of OD services (i.e. dating sites or apps) (n=223), respectively. Additional errors may also occur due to the difficulties encountered in the implementation process of the telephone survey.

To compensate for sample designs and patterns of non-response that might skew results, a two-stage weighting procedure was used. Specifically, the first-stage consists of correction for different probabilities of selection associated with the number of adults in each household and each respondent's telephone usage patterns, and adjusts for the overlapping landline and cell sample frames and their relative sizes. The second stage matches sample demographics to national population parameters. The basic weighting parameters, the population density parameter, and the telephone usage parameter were obtained by the organization from the US Census Bureau's 2011 American Community Survey data, Census 2010 data, and an analysis of the January-June 2012 National Health Interview Survey, respectively. Weights are included in the downloadable data package, and the standard weight variable instead of the weight variable is used as probability weight for this paper.

The questionnaire is comprised of eight modules with different designed topics that focus on: the level of satisfaction of life and family, patterns of internet usage, involvement in certain online activities, relationship status, OD behaviours, internet's effect on relationships, demographic characteristics, and administrative information. A certain subset of data was selected to suit my research purpose. In general, this paper aims to examine the effect of demographic characteristics and involvement in certain online activities on agents' OD behaviours, as well as the effect of dating behaviours on the level of satisfaction of life, family, and relationship conditions.

For statistical analysis, certain variables in the dataset were transformed, recoded, or grouped. For example, due to the nature of the multiple-choice questionnaire, values of almost all the variables are categorical, so they were transformed to dummy variables for the sake of regression analysis. Furthermore, the numerical values of the age variable are grouped and transformed into categorical dummy variables and then dummy variables. Some categories of educational attainment, household income, employment status, and marital status were grouped to reduced the number of variables used in the regression. To answer my first research question regarding the demographic and social determinants of OD usage, data of sample demographics and factors of respondents' sociability and dating activeness online are carefully selected. To devise indicators for online sociability, each survey question was closely examined, and discretion was exercised to extract core themes from certain questions that demonstrate similar latent patterns, from which higher order categories were formed to represent certain behavioural online sociability. To present descriptive statistics, more details are shown in Table 1, which summarizes the demographics and sociability of sample online daters as compared to the total sample population. Table 2 presents certain relevant demographic and social attributes of online daters who were more involved in OD activities and Table 3 shows the level of satisfaction of life and family of the Non-Singles with different first-time meeting venues.

V. ESTIMATION STRATEGY

To predict the propensity to use OD services conditional on individuals' demographic characteristics and sociability, a Probit multiple regression model is utilized, and the average marginal effect (AME) of each relevant demographic or social variable is estimated. Furthermore, an ordered Probit model is used to estimate the effect of meeting venue on the quality of relationships, since the measure of quality of life and family, which serves as a proxy of quality of relationships, is a five-point scale index ranging from excellent to poor, and only its order matters. Moreover, a stability index is constructed to represent the stability of relationships. Since the index is a continuous variable that takes numerical values, an Ordinary Least Square (OLS) estimation is used to estimate the effect of meeting venue on the stability of relationships. This paper intends to identify certain patterns of correlation suggested by the regression analysis. Empirically, the professional data analysis software Stata is used to process data and run the regressions. In this section, I will first present the theoretical econometric framework, and then introduce my empirical estimation strategy.

Consider the following binary choice model: let X_i be a column vector that captures the demographic and social characteristics of individual i, θ_i^k be a row vector of coefficients that determines individual i's expected utility from dating venue k and $\theta_{(o,i)}^k$ be a scalar intercept term, u_i^k be the random variable that represents the unobservable factors of i in dating venue k, then the econometric specification of individual i's expected utility function is

$$F(X_i, \theta_i^{on}) = \theta_{0,i}^{on} + \theta_i^{on} * X_i + u_i^{on}$$

through OD, and

$$H(X_i, \theta_i^{off}) = \theta_{0.i}^{off} + \theta_i^{off} * X_i + u_i^{off}$$

through offline dating. Let OD_i be the binary choice variable that indicates whether individual i chooses to use OD services. Then i's choice is represented by the following indicator function:

$$OD_i = 1\{F(X_i, \theta_i^{on}) \geq H(X_i, \theta_i^{off})\} = 1\{\theta_{0,i}^{on} - \theta_{0,i}^{off} + (\theta_i^{on} - \theta_i^{off}) * X_i \geq u_i^{off} - u_i^{on}\} \quad = 9 \backslash * \; GB2 \; (9)$$

Let $\beta_{0,i} = \theta_{0,i}^{on} - \theta_{0,i}^{off}$, $\beta_i = \theta_i^{on} - \theta_i^{off}$, $v_i = u_i^{off} - u_i^{on}$, then the model becomes

$$OD_i = 1\{\beta_{o,i} + \beta_i * X_i \geq v_i\} \quad = 10 \backslash * \; GB2 \; (10)$$

Assumption 1: $v_i | X_i \sim N(0,1)$, that is, conditional on X_i, v_i is normally distributed with mean zero and variance one.

Assumption 2: $P(OD_i = 1 | X_i) \in (0,1)$ and $Var(X_i) > 0$, which are trivially satisfied.

Then we transform the indicator function to conditional expectation function:

$$E[X_i = x] = P(X_i) = P(X_i) = P(\beta_{o,i} + \beta_i x \geq v_i) = \Phi(\beta_{o,i} + \beta_i x) \quad = 11 \backslash * \; GB2 \; (11)$$

where Φ is the standard normal cumulative distribution function (cdf). Thus, we have

$$\Phi^{-1}(E[X_i]) = \beta_{o,i} + \beta_i X_i \quad = 12 \backslash * \; GB2 \; (12)$$

which is the Probit regression model that is used in this research.

The parameter of interest is the average marginal effect (AME), which is expressed as:

$$AME = E[x = X_i] = E[\phi(\beta_{o,i} + \beta_i X_i) * \beta_i] \quad = 13 \backslash * \; GB2 \; (13)$$

The ordered Probit model is essentially the same as the Probit model. The major difference is that the dependent variables in ordered Probit model take ordinal values, which is that case of the quality of life and family dependent variable which takes the values of *excellent, very good, good, fair,* and *poor*. The stability index is formulated as

$$Stab = \frac{years\ been\ in\ the\ relationship}{age - 16} \quad = 14 \backslash * \; GB2 \; (14)$$

which represents the fraction of adulthood that is committed to the current relationship. Since the internet was invented in the mid-1990s, and OD did not gain significant popularity until the onset of the 21st century (i.e. 2001, approximately speaking), relationships that started before 2001 and continued until the time of the survey (i.e. 2013) did not have the OD option to consider, so their relationship stability is not relevant for the comparison of online and offline dating venues. Additionally, relationships that had lasted less than a year at the time of the survey are too short to give an effective measure of the couples' stability potential, since we would not have a good idea about whether the relationships would last long after the survey. Given the two concerns mentioned above, I keep only the observations whose years been in the current relationships were between one to twelve years for the analysis of relationship stability.

Furthermore, probability weight (i.e. sampling weight) is included in the regressions to ensure the representativeness of the dataset. Most of the variables from the raw data were grouped and re-categorized based on social and conceptual similarities to increase the compactness of the analysis. Regressions that are with and without controlling for certain demographic and/or social characteristics are run and compared to identify the severity of omitted variable bias and the role certain variables play in determining the usage of OD services.

VI. RESULTS AND DISCUSSION

The regression results suggest that some specific attributes have significant predicting power on OD usage while others do not, part of which is explained by the model prediction. Moreover, first-time meeting venue is a non-determinant of the quality and long-term stability of relationships, which aligns with the model prediction regarding settlement decision. The results are outlined ing greater detail below.

i. Determinants of OD Usage (Table 4)

Gender Difference Is Explained by Online Sociability Males are consistently around 3%-4% more likely to use OD services than their female counterparts, without controlling for social covariates, as shown in Table 4.1 Column (1) - (2), but their higher propensity to use OD services becomes insignificant when variables indicating sociability are added in the regression, as shown in Column (3). To explicitly show how gender difference is absorbed by social determinants, regressions of sociability on gender were run. Appendix 1 shows that gender difference repeatedly appears in various indicators of behavioural and perceptual sociability. That is, males tend to be more social online, not only behaviourally (i.e. more likely to flirt with someone online and ask someone out on a date using the internet, email, a social networking site, or a cellphone), but also perceptually (i.e. tend to agree on opinions that seem to be more in favour of OD such as "OD is a good way to meet people", "OD allows people to find a better match for themselves because they can get to know a lot more people", and "OD keeps people from settling down because they always have options for people to date"). Further, these sociability factors that are more likely to be related to males are positively correlated with OD usage as shown in Table 4.5. This pattern suggests that males appearing to have a higher propensity to use OD services is explained by their corresponding higher sociability online. Thus, I confirm the hypothesis that there is no pure gender difference in OD usage.

a. OD is Favoured by the Elderly

Column (3) in Table 4.1 shows that individuals in the "18-20 years" and the "21-35 years" age groups are 12% and 5% less likely to use OD services than the "over 56 years" age group, respectively. And the insignificance in the "36-55 years" age group suggests that there is little difference between them and the "over 56 age group" in the propensity to use OD services. This result seems to be striking and counter-intuitive at the first glance, but it turns out to be a logical outcome based on the proposed threshold crossing model, as mentioned in Section III.

b. Race Difference is Explained by Online Sociability

Compared to those who are white, it seems that Asian or Pacific Islanders are 10%-13% less likely to be engaged in OD when only demographic characteristics are considered, as shown in Table 4.1 Column (1) - (2). However, this observation is misleading because the regressions suffer from omitted variable bias, indicated by the fact that the significance disappears when we control for social characteristics in Column (3). The results suggest that there is no significant difference between whites and Asian or Pacific Islanders in the propensity to use OD services, if they have the same online sociability. To explore why sociability matters, regressions targeting the correlation between being an Asian or Pacific Islander and certain social characteristics were run. As illustrated in Appendix 1.2, Asian or Pacific Islanders are 15% more likely to agree that "OD keeps people from settling down because they always have options for people to date". Even though Table 4.6 does not show that the agreement on this opinion has significant effect on the propensity to use OD services, it is plausible to speculate that Asian or Pacific Islanders' higher tendency to agree on the opinion may contribute to their lower tendency to use OD services as suggested in Column (1) - (2) in Table 4.1.

Similarly, online sociability plays an important role in revealing the difference in the propensity to use OD services between those who are white and who are mixed. In Table 4.1 Column (3), we observe that those of mixed race are 6% less prone to use OD services than their white counterparts if they are equally sociable online. The different results between the regressions with and without social determinants as explanatory variables suggests that there exist omitted variable bias in the regressions shown in Column (1) - (2), and therefore it is inaccurate to believe that there is no significant difference between whites and those of mixed race in the propensity to use OD services. In Appendix 1.1, we observe that those of mixed race are 11% more likely to be involved in certain online activities, 11% more likely to pay attention to interested persons' digital profiles, 9% more likely to flirt with someone online, 14% more likely to ask someone out on a date through digital communication, and 7% more likely to maintain a long-distance relationship by virtual aid, compared to their white counterparts. All these behavioural social determinants mentioned are positively correlated with OD usage, as indicated in Table 4.5. Therefore, it is reasonable to conjecture that the mixed people's 6% lower propensity to use OD services is compensated by their higher online sociability so that there exhibits no significant difference from whites in propensity to use OD services when only demographic determinants are considered. However, it is not clear how the expected utility model can explain the phenomenon, so it is a potential issue for future research. A possible conjecture could be that the social, cultural, racial, or psychological concerns of the mixed peoples dominate their economic rationality.

c. Location Matters

In Table 4.2, it is observed that compared to people from the "South" census region, individuals who are in the "Northeast" are consistently 5%-6% less inclined to use OD services. When compared to people who are suburban, individuals from rural areas are 4% less prone to use OD services, and the urban cohorts are 3% more likely to use OD services. It is also unclear how the underlying economic model can explain the pattern, however. A possible speculation could be that agents make irrational decisions under the influence of regional and community cultures, which can be tested by future research.

d. The Role of Assets and Human Capital

It seems that individuals who have a postgraduate degree are 5%-7% more likely to use OD services without controlling for online sociability. Column (3) in Table 4.3, however, shows that there is no significant difference between them and people who graduate from high school or have some college education if they are equally social online. Moreover, the affluent, that is, people who have higher annual household income (i.e. $100,000 or more), are 6% less likely to use OD services than the upper middle class (i.e. people with $40,000 to $100,000 annual household income), as shown in Column (3) in Table 4.3 when online sociability is controlled. Similarly, online sociability again plays a role in determining the propensity to use OD services of the careless, that is, those who don't know their income. The insignificant results shown in Column (1) - (2) in Table 4.3 are deceitful due to omitted variable bias. The fact is that, from Column (3) in Table 4.3, we observe that people who do not keep track of their household income are shown to be 7% more likely to use OD services than the upper middle class (i.e. the base group). Furthermore, the non-employed includes those who are retired, not employed for pay, disabled, or students, and they are consistently less inclined to use OD services compared their employed counterparts. From Table 4.3 Column (3), we see that the magnitude of their lower tendency to use OD services is 4%.

e. Rekindle Relationships of the Broken Hearted

The higher propensity of the "Divorced, or Separated, or Widowed (DSW), AND non-single" group to use OD services compared the "Married or Cohabited" group is diluted when social determinants are controlled. 7% is the magnitude of the difference in the propensities when all demographic and social determinants are considered. One thing that should be kept in mind is the timing of using OD services. The fact that the "Divorced, or Separated, or Widowed, AND non-single" group is more likely to use OD services does not necessarily mean that they are more inclined to use OD services when they are in a committed relationship. Their relationship status (i.e. non-single) was specific to the time when the survey was conducted. Their usage of OD services is captured by the survey question "have you ever used an OD site or app", which means that their past usage of OD services was included. Therefore, the results shown in Table 4.4 only mean that people who were divorced, separated, or widowed, and were currently in a committed relationship were more likely to use OD services in their past lives. To further check whether the non-single DSW are more likely to use OD services concurrently with being in a committed relationship, Probit regression with "profile currently posted in an OD site" as the dependent variable was run, and the results show that the non-single DSW are truly more likely to have a profile posted when they were in a committed relationship compared to their married or cohabited counterparts, which implies that they might not be fully committed to their current relationships. It is sentimentally disappointing but also sympathetically understandable, because a broken heart may not firmly believe in love anymore. A possible reason why the non-single DSW do not fully withdraw from the OD markets could be that the potential utility from being matched to different mates varies, and their continuing presence in the OD markets opens the opportunities for them to jump from one relationship to another should they find a better match that can potentially give them higher utility than what their current partners offer. Similarly, people who are divorced, separated, or widowed, and single are 18% more prone to use OD services than the married or cohabited. The magnitude of the difference is much larger than their non-single counterparts mentioned above. In contrast, people who have never been married and were in a committed relationship show no significant difference in propensity to use OD services than their married or cohabited counterparts.

f. Parental Status Does Not Matter

It is shown that parental status has no significant effect on the propensity to use OD services. There is no significant difference between parent and non-parent in OD usage.

g. OD Attracts People Who Have Ambiguous Sexual Orientation

It appears that gay, lesbian, or bisexual people are more inclined to use OD services than their heterosexual counterparts when online sociability is not controlled, as shown in Column (1) - (2) in Table 4.4. However, this seeming higher propensity is absorbed by social determinants, and Column (3) in Table 4.4 suggest that they are not more likely to use OD services when sociability is controlled. Interestingly, people who do not know their sexual orientation, that is, who have ambiguous sexual orientation, are 19% more prone to use OD services when online sociability is controlled for.

h. Behavioural Sociability Seems to Matter More Than Perceptual Sociability

In Table 4.5, it is found that the following behaviours that are associated with online sociability have positive correlation with the usage of OD services: involvement in certain online activities (9%), attention to interested persons' digital profiles (5%), flirting online (8%), dating initiative (10%), and maintenance of long-distance relationship by virtual aid (8%). However, the regressions may suffer from endogeneity problem arisen from omitted variable bias. For example, a possible omitted variable could be the desire to date online, which is likely to be correlated with some of the explanatory variables regarding sociability and is thus likely to affect the propensity to use OD services.

Looking at Column (3) in Table 4.6 only, where all possible demographic and social determinants are considered in the regression, we find that people who agree that "OD is a good way to meet people" are 4% more likely to use OD services as compared to people who disagree on the opinion. People who do not know their standpoint on the statement show no difference from the base group (i.e. people who disagree on the opinion) in propensity to use OD services. The attitudes towards other opinions about OD (i.e. "OD allows people to find a better match for themselves because they can get to know a lot more people", "people who use OD sites are desperate", "OD keeps people from settling down because they always have options for people to date") seem to have no impact on the propensity to use OD services, either.

ii. Determinants of Deeper OD Usage (Table 5)

The economic model regarding consumption allocation suggests that individuals with different values of parameters (i.e. a_i, b_i, T_i, S_i) will allocate resources differently into online and offline dating activities. Even though we do not have the exact data on the time and money spent on online and offline dating activities by agents, the deeper OD usage observed can serve as proxies of time and money spent on OD activities. For instance, if an individual pays to use an OD site or app, then it suggests that he or she allocates more money into OD usage; if an individual asks others to help create or review his or her OD profiles, then it suggests that he or she allocates more time into OD usage. Empirically estimating the determinants of deeper OD usage facilitates the inference of parameter values of agents in the economic model. The types of deeper OD usage are presented as the following order: (a) pay to use an OD site/app; (b) ask other to help create or review OD profile; (c) attend a group outing or event organized by an OD site/app; (d) go on a date with someone met through an OD site/app; (d) have a long-term relationship or marriage through an OD site/app; (e) involve in deeper OD usage (i.e. involve in at least one of (a) – (d)).

a. Pay to Use an OD Site/App

Compared to people who are over 56 years old, individuals who are between 18 to 20 years old and those who are between 21 to 35 years old are 43% and 23% less prone to pay to use an OD site or app, respectively. People who pay attention to interested persons' online profiles, that is, use the internet or a social networking site to search for information about someone they dated or had a relationship with in the past, are currently dating or are about to meet for a first date, or are interested in dating, or 'follow' or 'friend' someone online because their friends suggest they might want to date that person, are 24% more likely to pay to use an OD site or app compared to people who do not pay this sort of attention. Moreover, those who have flirted with someone online are 15% less likely to pay to use an OD site or app than people who have not flirted online.

b. Ask Others to Help Create or Review OD Profile

People who are 18 to 20 years old are 24% more likely to ask others to help them create or review their OD profiles. In addition, those who are careless enough to never bother to keep track of their household income are 24% more inclined to ask others to help them create or review OD profiles than people who have an idea about their household income, presumably because careless people tend to rely on others to help them deal with trivial matters. Moreover, people who show initiative in dating, that is, who have used the internet or email or a social networking site to ask someone out on a date, or have used a cellphone to ask someone out on a date by calling or texting, are 13% more likely to ask others to help them create or review OD profiles, possibly because they are more proactive and serious about OD.

c. Attend a Group Outing or Event Organized by an OD Site/App

Younger cohorts (i.e. 18-20 years old) are 10% more likely to attend a group outing or event organized by an OD site or app than the elderly (i.e. over 56 years). People who pay attention to interested persons' digital profiles are 12% more likely to do so, and people who flirt with others online are 7% less likely to do so.

d. Go on a Date With Someone Met Through an OD Site/App

The lower middle class, that is, people who have $20,000 to $40,000 annual household income, are 14% less likely to go on a date with someone met through an OD site or app than the upper middle class (i.e. people who have $40,000 to $100,000 annual household income). Those who do not know their income are 27% less likely to do so than the upper middle class. Bisexual cohorts are 24% more likely to go on a date with someone met through an OD site or app than their heterosexual counterparts. Those who pay attention to interested persons' digital profiles are 19% more likely to do so, and people who have dating initiative online are 25% more likely to do so.

e. Have a Long-Term Relationship or Marriage Through an OD Site/App

The "36 to 55 years" age group is 15% less likely to have a long-term relationship or marriage through an OD site or app than the elderly (i.e. "over 56 years"). Furthermore, people who flirt with others online are 19% more likely to do so.

f. Involve in Deeper OD Usage

Even though people from rural areas are 4% less likely to use OD services than those in suburban areas, Column (3) in Table 5 suggests that once they decide to use OD services, they are 16% more likely to engage in deeper OD usage than their suburban counterparts.

The lower middle class, again, is 16% less likely to be very engaged in deeper OD usage than the upper middle class. People who do not know their income are also less likely (19%) to get involved in deeper OD usage. People who pay attention to interested persons' digital profiles, who flirt with others online, and who show dating initiative online, are 11%, 11%, and 17%, respectively, more likely to be involved in deeper OD usage.

iii. Quality and Long-term Stability of Relationships (Table 6 & 7)

Table 6 and Table 7 show that there is no significant difference in quality and long-term stability of relationships between individuals who first met their partners online or offline. If they first met their current partners online, then it does not matter whether they met through OD sites or some other way. Therefore, first-time meeting venue is not a determinant of relationship outcomes measured by quality and long-term stability, which supports the model prediction and confirms the hypothesis.

However, the insignificant effect of first-time meeting venue on relationship outcomes does not necessarily rule out the effect of dating venue on the efficiency of the searching and screening process. It still might be the case that online dating venues help reduce search friction and speed up the search process. It might be true that searching channel does not directly affect the matching outcomes because everyone has his or her own standard to make the settlement decisions, however, technology and advanced algorithms may increase searching efficiency by exposing seekers to a larger pool of potential matches in a shorter time period. Even though the enlargement of qualified pools in online platforms may increase seekers' expectation and standards for settlement, which may potentially increase the relationship outcomes through the online dating venue, the simultaneous increase of the standards of all agents will end up having no real effect on the market equilibria, just as the universal increase of nominal value does not affect the real value of the economy. Alternatively, the reluctance to settle because of the expectation of better matches in the next search may also exert negative effect on relationship outcomes, which could balance out the potential positive effect of increasing standards of settlement decision and leave the effect of first-time meeting venue insignificant for relationship outcomes. However, the effect of first-time meeting venue on searching efficiency is not studied by this research due to the lack of data on (1) online and offline searching time; (2) number of searches and dates needed to make a settlement decision; (3) level of satisfaction of online and offline searching experience. Therefore, another set of survey collecting feedback from daters on their online and offline searching experience may help us evaluate the efficiency of online dating venue, which is left as a potential area for future research.

VII. CONCLUSION

This paper mainly investigates two issues: (1) the decisions on OD usage by agents with different demographic and social attributes, which is studied through the exploration of the determinants of OD usage; (2) the matching effectiveness and efficiency of OD, which is examined through the investigation on the quality and long-term stability of relationships resulted from online and offline meeting venues. Some estimation results are supported by the proposed economic models and the hypotheses are confirmed, but some of the results suggest unknown dynamics of agents' decision making process, which is a potential area for future research. It should be stressed that this paper investigates only the correlation, instead of causation, between interested variables. Besides, any potential endogeneity problem can also be addressed by further studies. The answer to my first research question helps elicit the determinants of online dating usage. My results confirm some previous findings regarding the correlation between certain demographic and social characteristics and OD usage while contradicting others. Since datasets from different regions in different time periods provide different demographic information and the survey respondents differ, it is not surprising that my research produces different results than previous scholars'. My findings, however, contribute to the discussion by adding diversity and providing skepticism for established conclusions. In addition, by knowing attributes associated with higher propensity to use OD services, we can better understand what determines individual daters' decisions on dating, and mechanism designers can construct more customized matching mechanisms to enhance users' matching experience and outcomes. For instance, since the elderly, the divorced, separated, and widowed, as well as people with ambiguous sexual orientation, seem to be more in favour of OD platforms, more specialized dating sites/apps could potentially be created to facilitate the mating process of these groups.

The answer to my second research question provides insights on OD's correlation with the quality and long-term stability of users' relationships, which helps expand our knowledge on the effectiveness and efficiency of online dating in general and its matching algorithms in real-life practice. Even though OD sites/apps and some previous scholars report that certain matching algorithms lead to better matching outcomes, the results that there is no significant difference in the matching outcomes through online and offline meeting venues, which is presented by this paper, suggests more research needs to be done to potentially improve the design of online matching mechanisms. However, the searching efficiency of OD still needs further investigation. The original goal of this research is to contribute to the increase of efficiency and economic surplus in the marriage markets by identifying the needs of agents and evaluating relationship outcomes. To help agents find partners faster, with lower costs and better outcomes, intellectuals need to optimize the search process by minimizing searching costs, improve matching mechanisms by increasing the probabilities of getting matched, and facilitate relationship maintenance by maximizing relationship satisfaction and stability.

III
REFERENCES AND APPENDICES

Contents

REFERENCES AND APPENDICES

B. HONOURS THESIS'

Economic Recessions and Financial Reform: The Dodd-Frank Wall Street Reform, Consumer Protection Act, And The United States' Subprime Mortgage Crisis

Taylor Cuming

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B. APPENDICES

a. Figures and Tables

TABLE 1. SUMMARY STATISTICS FOR KEY VARIABLE

Variable	Notation	Mean	Standard Deviation
Price Growth	$PG_{(i,t)}$	3.43	0.77
Risk Premium	$SRISK_{(i,t)}$	9.12	3.36
Dow Jones	$lnDJIA_t$	9.27	0.15
Inflation	$lnINFL_t$	1.01	0.02
Oil Price	$lnOILP_t$	4.38	0.26

Notes: $PG_{(i,t)}$=ln (mean closing price)$_{(i,t)}$, inflation is indexed at the year 2010.

TABLE 2. DIFFERENCE-IN-DIFFERENCES RESULTS ON THE EFFECTS OF DODD-FRANK ON PRICE GROWTH

	(1) PG	(2) PG	(3) PG	(4) PG	(5) PG
DF	0.219 *** [-.032]	0.234*** [0.031]	0.069* [0.039]	0.114** [0.047]	0.120*** [0.047]
DF*TREAT	-0.010 ** [0.050]	-0.139** [0.050]	-0.132*** [0.049]	-0.138*** [0.049]	-0.132*** [0.049]
TREAT	0.281*** [0.035]	0.439*** [0.041]	0.412*** [0.041]	0.413*** [0.041]	0.414*** [0.041]
RISKP		-0.046*** [0.004]	-0.038*** [0.004]	-0.038*** [0.004]	-0.039*** [0.004]
DJIA			0.765*** [0.122]	0.940*** [0.160]	0.737*** [0.222]
INFL				-2.51* [1.295]	-2.50* [1.296]
OILP					0.120 [0.090]
Observations	3626	3626	3626	3626	3626

Robust standard errors in brackets
**p<0.1, ** p<0.05, *** p<0.01*
*Notes: The sample is a period of 49 months: June, 2008-June, 2012 (with data from June 30th, 2010-July, 21st 2010 removed). The dependant variable PG is the price growth of securities. DF is a period dummy variable which takes the value of 1 during the post-Dodd-Frank period and the value of 0 during the pre-Dodd-Frank time period. TREAT is an individual dummy variable which takes the value of 1 for securities in the financial sector (treatment group) and the value of 0 otherwise. DF*TREAT is an interaction term of DF_t and $TREAT_i$ which equals 1 for securities in the financial sector during the time period post-Dodd-Frank and 0 otherwise. RISKP is the equity risk premium, INFL is the inflation rate, DJIA is the Dow Jones Industrial Average and OILP is WTI crude oil prices.*

TABLE 3. PLACEBO DIFFERENCE-IN-DIFFERENCES RESULTS ON PRICE GROWTH, POST-DODD-FRANK PERIOD EXCLUDED

	(1) PG	(2) PG	(3) PG	(4) PG	(5) PG
PTIME	-0.080 [0.348]	-0.114*** [0.034]	-0.038 [0.035]	-0.047 [0.035]	-0.053 [0.036]
PTI- ME*TREAT	0.054 [0.056]	0.096* [0.055]	0.088 [0.055]	0.088 [0.055]	0.087 [0.055]
TREAT	0.220*** [0.360]	0.347*** [0.0356]	0.322*** [0.036]	0.321*** [0.036]	0.322*** [0.035]

	(1) PG	(2) PG	(3) PG	(4) PG	(5) PG
RISKP		-0.047*** [0.004]	-0.038*** [0.004]	-0.037*** [0.004]	-0.037*** [0.004]
DJIA			0.780*** [0.089]	1.021*** [0.178]	0.773*** [0.221]
INFL				-1.390 [1.048]	-1.249 [1.050]
OILP					0.107 [0.091]
Observations	1813	1813	1813	1813	1813

Robust standard errors in brackets
**p<0.1, ** p<0.05, *** p<0.01*
*Notes: The sample is a period of 24 months: June 1st, 2008-June 31st, 2010. PTIME (placebo-time) is a dummy time variable that takes the value of 0 for the first half of the original pre-Dodd-Frank time period (June 2008- June 2009) and takes the value of 1 for the latter half of the original pre-Dodd-Frank time period (June 2009-June 2010). PTIME*TREAT is an interaction term that takes the value of 1 for financial securities in the second half of the pre-Dodd-Frank time period and equals 0 otherwise. All other variables are as before.*

TABLE 4. RESULTS OF TESTING FOR MULTICOLLINEARITY USING THE VARIANCE INFLATION FACTOR (VIF)

Variable	VIF
DF	4.23
TREAT	2.31
DF*TREAT	2.98
RISKP	1.37
DJIA	7.44
INFL	5.42
OILP	3.81
Mean VIF	3.94

TABLE 5. DIFFERENCE-IN-DIFFERENCES RESULTS, FINANCIAL FIRMS ACCORDING TO ASSET LEVEL, $50B THRESHOLD

	(1) PG	(2) PG	(3) PG	(4) PG	(5) PG
DF	0.219*** [0.032]	0.240*** [0.030]	0.099** [0.039]	0.148*** [0.049]	0.158*** [0.049]
DF*>50B	-0.236*** 0.064	-0.304*** [0.062]	-0.296*** [0.061]	-0.297*** [0.061]	-0.298*** [0.061]
>50B	0.395*** [0.045]	0.736*** [0.055]	0.696*** [0.055]	0.697*** [0.056]	0.700*** [0.056]
RISKP		-0.067*** [0.005]	-0.059*** [0.005]	-0.059*** [0.006]	-0.060*** [0.006]
DJIA			0.652*** [0.133]	0.844*** [0.172]	0.556** [0.238]
INFL				-2.337* [1.363]	-2.200* [1.364]
OILP					0.165* [0.096]
Observations	2548	2548	2548	2548	2548

Robust standard errors in brackets
**p<0.1, ** p<0.05, *** p<0.01*
Notes: The sample is a period of 49 months: June, 2008-June, 2012 (with data from June 30th, 2010-July, 21st 2010 removed). This table presents the robustness test for differences in the effect of Dodd-Frank on financial firms according to their total consolidated asset level, including only financial firms with above the $50 billion threshold in the treatment group. >50B is a dummy variable which takes the value of 1 for financial firms above the $50 billion threshold and the value of 0 otherwise. (DF>50B) is an interaction dummy variable which takes the value of 1 for financial firms above the $50 billion threshold in the time period post-Dodd-Frank and 0 otherwise. All other variables are as before.*

TABLE 6. DIFFERENCE-IN-DIFFERENCES RESULTS, FINANCIAL FIRMS ACCORDING TO ASSET LEVEL $700B THRESHOLD

	(1) PG	(2) PG	(3) PG	(4) PG	(5) PG
DF	0.219*** [0.032]	0.241*** [0.030]	0.131*** [0.040]	0.152*** [0.051]	0.158*** [0.051]
DF*>700B	-0.335*** [0.087]	-0.485*** [0.085]	-0.472*** [0.085]	-0.472*** [0.085]	-0.472*** [0.085]
>700B	0.333*** [0.061]	0.800*** [0.075]	0.759*** [0.076]	0.759*** [0.076]	0.761*** [0.076]

	(1) PG	(2) PG	(3) PG	(4) PG	(5) PG
RISKP		-0.072*** [0.006]	-0.065*** [0.006]	-0.065*** [0.006]	-0.065*** [0.006]
DJIA			0.510*** [0.141]	0.594*** [0.183]	0.386 [0.256]
INFL				-1.013 [1.461]	-0.910 [1.462]
OILP					0.119 [0.102]
Observations	2156	2156	2156	2156	2156

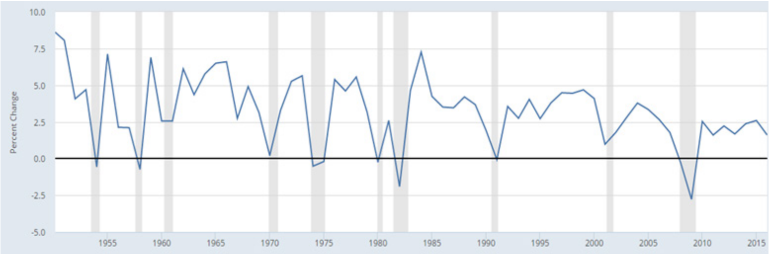
Robust standard errors in brackets

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

Notes: The sample is a period of 49 months: June, 2008-June, 2012 (with data from June 30th, 2010-July, 21st 2010 removed). This table presents the robustness test for differences in the effect of Dodd-Frank on financial firms according to their total consolidated asset levels, including only those financial firms with greater than $700 billion total consolidated assets in the treatment group. >700B is a dummy variable which takes the value of 1 for financial firms above the $700 billion threshold and the value of 0 otherwise. (DF>700B) is an interaction dummy variable which takes the value of 1 for financial firms above the $700 billion threshold in the time period post-Dodd-Frank and 0 otherwise. All other variables are as before.*

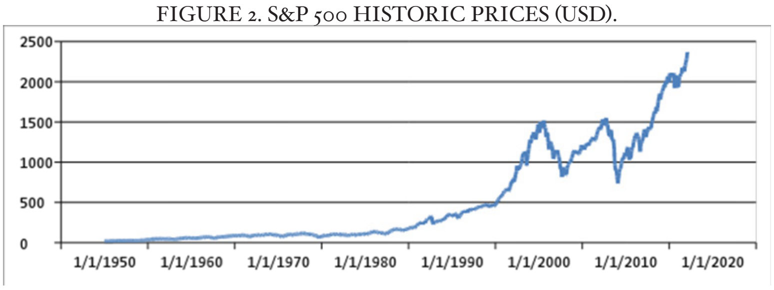
b. Graphs

FIGURE 1. ANNUAL AVERAGE PERCENT CHANGE IN REAL GROSS DOMESTIC PRODUCT (RECESSIONS SHADED).



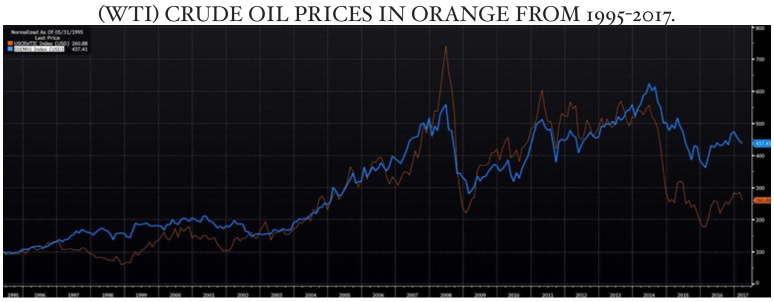
Source: U.S. Bureau of Economic Analysis via FRED, Federal Reserve Bank of St. Louis. U.S. RGDP Series.

FIGURE 2. S&P 500 HISTORIC PRICES (USD).



Source: U.S. Bureau of Economic Analysis via FRED, Federal Reserve Bank of St. Louis. SP500 Series.
Notes: The S&P 500 is a market value weighted index and serves as a general health indicator for the United States' stock markets.

FIGURE 3. COMPARISON BETWEEN THE S5ENRS INDEX (UNITED STATES ENERGY INDEX) IN BLUE AND WEST TEXAS INTERMEDIATE (WTI) CRUDE OIL PRICES IN ORANGE FROM 1995-2017.



Source: Bloomberg.

Getting Splinters: Measuring the impact of Canadian softwood lumber imports on American lumber companies

Jacob Cutts

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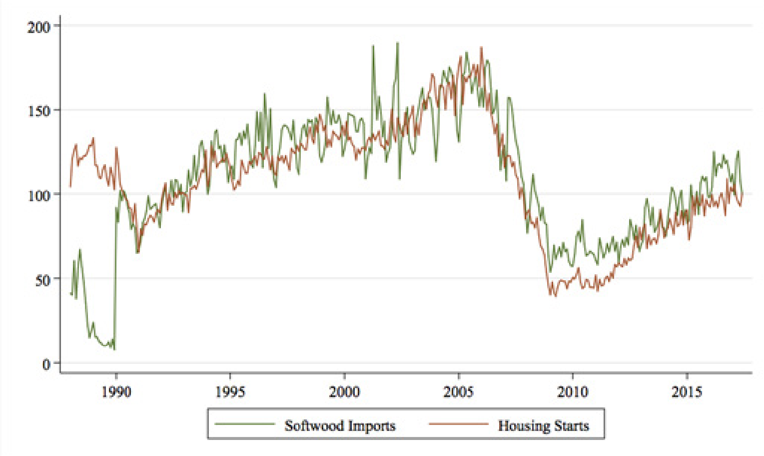
B. APPENDICES

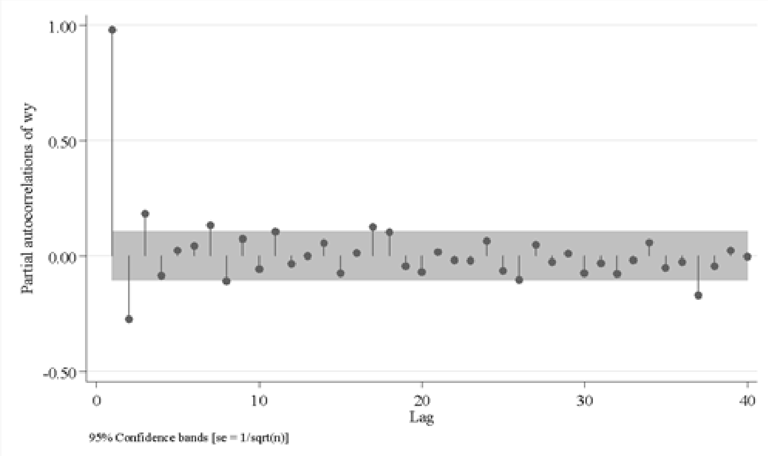
a: Additional Figures

ADDITIONAL FIGURE 1. CANADIAN SOFTWOOD IMPORTS VS US HOUSING STARTS

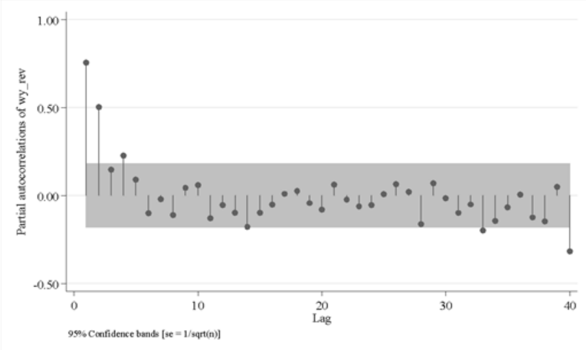


Notes: Indexed, June 2017 = 100. Original units for softwood imports were m3 of softwood lumber, original units for housing starts were seasonally-adjusted annualized housing starts.

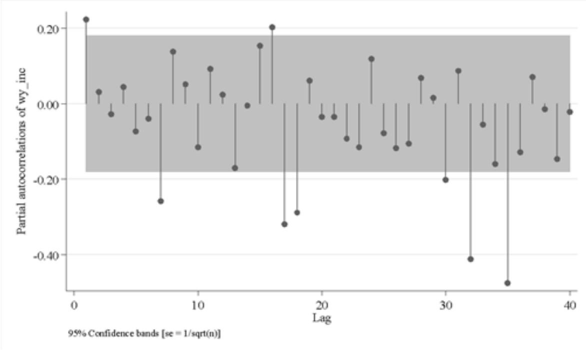
ADDITIONAL FIGURE 2. PARTIAL AUTOCORRELATION OF WEYERHAEUSER'S MONTHLY STOCK PRICE



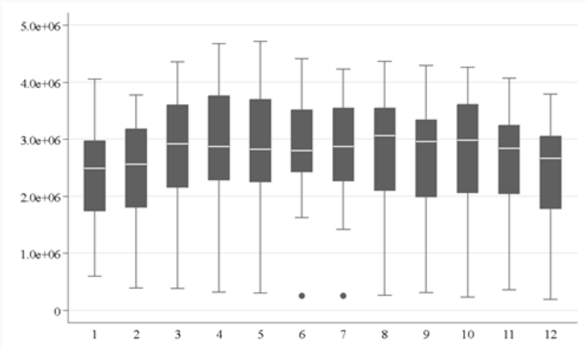
ADDITIONAL FIGURE 3. PARTIAL AUTOCORRELATION OF WEYER-HAEUSER'S QUARTERLY REVENUE



ADDITIONAL FIGURE 4. PARTIAL AUTOCORRELATION OF WEYER-HAEUSER'S QUARTERLY NET INCOME



ADDITIONAL FIGURE 5. BOX PLOT OF US HOUSING STARTS BY MONTH



b. Methodology for the Calculation of Figure 7

(i) The mean for each variable (stock price, revenue, and income for each of the three companies, plus the total imports of Canadian softwood lumber to the United States) was calculated.

(ii) The quarterly value for each of the variables was divided by their mean, then multiplied by 100.

(iii) For imports, this in itself formed the indexed value, but for the three company metrics, the indexed values were averaged together to form a composite value.

(iv) In cases where one or more of the companies' data was not available, the index was composed of the available data.

Due to the issues raised by point (iv), the data is not perfectly comparable over the span considered. However, the data is sufficient for broad comparison.

Impact of Access to Healthcare on Economic Growth

Sarayu Kantheti

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The Supplemental Nutrition Assistance Program (SNAP): An Analysis of the SNAP's Impact on Women's Health and Diet

Natasha Laponce
ECON 490

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B. APPENDICES

a. Tables

TABLE I SUMMARY STATISTICS OF INELIGIBLE, ELIGIBLE NON-PARTICIPANTS, AND PARTICIPANTS FOR ADULT WOMEN AGED 20-65: NHANES, 2007– 2014

	Body Mass Index	Waist Circumference (cm)	Sodium Intake (mcg)	Saturated Fat Intake (gm)	Vitamin A, RAE Intake (mcg)	Dietary Fibre Intake (gm)
Ineligible	28.86072	94.972357	3061.6835	22.432734	588.73709	15.649424
Eligible - Non-SNAP Participant	29.79051	97.00502	2953.6466	21.583691	523.71293	14.729452
Eligible - SNAP Participant	31.76974	101.83608	2987.4072	23.375599	508.26108	12.764204
Observations	8330	7995	7819	7819	7819	7819

Note: Each cubicle represents one average. Ineligible = all women with PIR > 1.3; eligible = all women with PIR ≤ 1.3; participant = eligible woman who has received SNAP benefits within the last 30 days. BMI is classified according to the CDC standards with indexes <18.5 classified as underweight, 18.5-24.9 as normal, 25.0-29.9 as overweight, and ≥ 30.0 as obese (Department of Health and Human Services, n.d.). A woman with a waist circumference over 88.9cm (35in) is also classified by the CDC as at a higher health risk (CDC, 2015a). The National Institutes of Health daily recommendations of the dietary variables of interest are as follows: 1300-1500mg of sodium, as little as possible saturated fat, 700mcg of vitamin A, RAE, and 21-25g of fibre (Food and Nutrition Board, 2005; Institute of Medicine (US) Committee to Review Dietary Reference Intakes for Vitamin D and Calcium, 2011a; Institute of Medicine (US) Committee to Review Dietary Reference Intakes for Vitamin D and Calcium, 2011b).

TABLE 2: MULTIVARIATE REGRESSION ANALYSIS ON THE ASSOCIATION OF SNAP PARTICIPATION, SNAP PARTICIPATION INTERACTED WITH FOOD SECURITY (FS), AND SNAP PARTICIPATION INTERACTED WITH ETHNICITY ON BODY MASS INDEX (BMI) FOR ADULT WOMEN AGED 20-65: NHANES, 2007– 2014

	(1) BMI	(2) BMI	(3) BMI	(4) BMI	(5) BMI	(6) BMI	(7) BMI
SNAP	1.977*** (0.317)	1.768*** (0.364)	1.690*** (0.364)		0.364 (1.200)	2.496*** (0.563)	2.160*** (0.575)
Income Eligibility				-1.870 (1.469)	-1.976 (1.520)		
Marginal FS x SNAP						-2.199* (0.907)	

	(1) BMI	(2) BMI	(3) BMI	(4) BMI	(5) BMI	(6) BMI	(7) BMI
Low FS x SNAP						-0.186 (0.904)	
Very Low FS x SNAP						-1.643 (0.998)	
Mexican or Other Hispanic x SNAP							-1.438 (0.757)
Black or Other Hispanic x SNAP							-2.041* (1.002)
Other x SNAP							2.734 (1.628)
Observations	2920	2496	2494	417	417	2496	2494

*Note: SNAP is a dummy variable for SNAP participation; standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Each column represents one regression. Respondents in columns 1-3, 6, and 7 have PIRs of 1.3 or below. Respondents in columns 4 and 5 have PIRs between 1.2-1.4. Only the coefficients on the variables of interest are listed. Column (1) regresses SNAP participation on BMI with no controls. Column (2) regresses SNAP participation on BMI, controlling for age, race, education, marital status, number of people in the household, depression, health insurance, employment, minutes sedentary, and poverty index. Column (3) regresses SNAP participation on BMI controlling for all the variables in column 2 and food security level. Column (4) regresses SNAP income eligibility on BMI using a regression discontinuity (RD) including all controls from column (3). Column (5) regresses SNAP participation on BMI using an RD including all controls from column (3) and income eligibility. Column (6) regresses SNAP participation on BMI interacting participation with food security level (full, marginal, low, and very low) including all controls from column (3) except food security level. Full food security is left out of the regression; consequently, its impact is captured by the estimate on the SNAP variable. Column (7) regresses BMI on SNAP participation, interacting participation with ethnicity (White, Mexican or other Hispanic, black, and other/mixed race) including all controls from column (3) except ethnicity. White is left out of the regression; therefore its impact is captured by the estimate on the SNAP variable.*

TABLE 3: MULTIVARIATE REGRESSION ANALYSIS ON THE ASSOCIATION OF SNAP PARTICIPATION, SNAP PARTICIPATION INTERACTED WITH FOOD SECURITY (FS), AND SNAP PARTICIPATION INTERACTED WITH ETHNICITY ON WAIST CIRCUMFERENCE (WC) FOR ADULT WOMEN AGED 20-65: NHANES, 2007– 2014

	(1) WC	(2) WC	(3) WC	(4) WC	(5) WC	(6) WC	(7) WC
SNAP	4.814*** (0.688)	4.607*** (0.736)	4.449*** (0.764)		0.812 (2.635)	6.340*** (1.205)	5.503*** (1.258)
Income Eligibility				3.173 (1.707)	3.007 (1.789)		
Marginal FS x SNAP						-4.366* (1.953)	
Low FS x SNAP						-0.410 (1.928)	
Very Low FS x SNAP						-4.845* (2.025)	
Mexican or Other Hispanic x SNAP							-3.170 (1.656)
Black or Other Hispanic x SNAP							-4.745* (2.060)
Other x SNAP							5.454 (3.258)
Observations	2787	2436	2434	412	412	2436	2434

*Note: SNAP is a dummy variable for SNAP participation; standard errors in parentheses; * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Each column represents one regression. Each regression (and column) is identical to the regression displayed in the identically numbered column presented in Table 2 except WC replaces BMI as the dependent variable of interest. For example, column (1) regresses SNAP participation on WC with no controls. Column (2) regresses SNAP participation on WC, controlling for the same variables controlled for in column 2 of Table 2. Column (3) regresses SNAP participation on WC, controlling for all the variables in column 2 and food security level. Refer to Table 2 note for a more comprehensive outline of the regressions run in the remaining columns, replacing BMI with WC where appropriate.*

TABLE 4.1: MULTIVARIATE REGRESSION ANALYSIS ON THE ASSOCIATION OF SNAP PARTICIPATION ON SODIUM INTAKE (BASED ON DAY 1 DIETARY DATA) FOR ADULT WOMEN AGED 20-65: NHANES, 2007– 2014

	(1) Sodium Intake (mcg)	(2) Sodium Intake (mcg)	(3) Sodium Intake (mcg)	(5) Sodium Intake (mcg)
SNAP	27.05 (62.65)	-7.667 (68.12)	-10.25 (67.81)	-39.30 (202.5)

	(1) Sodium Intake (mcg)	(2) Sodium Intake (mcg)	(3) Sodium Intake (mcg)	(5) Sodium Intake (mcg)
Observations	2732	2732	2440	412

*Note: SNAP is a dummy variable for SNAP participation; standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Each column represents one regression. Only the coefficient on SNAP participation is displayed. The regressions in columns (1), (2), (3), and (5) all align in structure with regressions (1), (2), (3), and (5) outlined in Tables 2 and 3. For example, column (1) regresses SNAP participation on sodium intake including no controls. Column (2) regresses SNAP participation on sodium intake controlling for age, race, education, marital status, number of people in the household, depression, health insurance, employment, minutes sedentary, and poverty index. Column (3) regresses SNAP participation on sodium intake, controlling for all the variables in column (2) and food security level. Column (5) regresses SNAP participation on sodium intake using a RD including all controls from column (3) and income eligibility.*

TABLE 4.2: MULTIVARIATE REGRESSION ANALYSIS ON THE ASSOCIATION OF SNAP PARTICIPATION ON SATURATED FAT INTAKE (BASED ON DAY 1 DIETARY DATA) FOR ADULT WOMEN AGED 20-65: NHANES, 2007– 2014

	(1) Saturated Fat Intake (gm)	(2) Saturated Fat Intake (gm)	(3) Saturated Fat Intake (gm)	(5) Saturated Fat Intake (gm)
SNAP	1.764**	1.700**	1.691**	1.353
	(0.591)	(0.637)	(0.636)	(2.218)
Observations	2732	2732	2440	412

*Note: SNAP is a dummy variable for SNAP participation; standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Each column represents one regression. Only the coefficient on SNAP participation is displayed. The regressions in columns (1), (2), (3), and (5) all align in structure with regressions (1), (2), (3), and (5) outlined in Tables 2 and 3. Refer to Table 4.1 note for a more comprehensive outline of the regressions run in each column, replacing sodium intake with saturated fat intake in the explanation.*

TABLE 4.3: MULTIVARIATE REGRESSION ANALYSIS ON THE ASSOCIATION OF SNAP PARTICIPATION ON VITAMIN A, RAE INTAKE (BASED ON DAY 1 DIETARY DATA) FOR ADULT WOMEN AGED 20-65: NHANES, 2007– 2014

	(1) Vitamin A, RAE Intake (mcg)	(2) Vitamin A, RAE Intake (mcg)	(3) Vitamin A, RAE Intake (mcg)	(5) Vitamin A, RAE Intake (mcg)
SNAP	-15.92	-28.75	-26.43	-25.10
	(24.22)	(33.18)	(32.06)	(53.29)
Observations	2732	2732	2440	412

*Note: SNAP is a dummy variable for SNAP participation; standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Each column represents one regression. Only the coefficient on SNAP participation is displayed. The regressions in columns (1), (2), (3), and (5) all align in* *structure with regressions (1), (2), (3), and (5) outlined in Tables 2 and 3. Refer to Table 4.1 note for a more comprehensive outline of the regressions run in each column, replacing sodium intake with vitamin A, RAE intake in the explanation.*

Table 4.4: Multivariate Regression Analysis on the Association of SNAP Participation on Dietary Fibre intake (based on day 1 dietary data) for Adult Women aged 20-65: NHANES, 2007– 2014

	(1) Dietary Fibre (gm)	(2) Dietary Fibre (gm)	(3) Dietary Fibre (gm)	(5) Dietary Fibre (gm)
SNAP	-1.969*** (0.353)	-1.516*** (0.397)	-1.564*** (0.395)	-2.529* (1.208)
Observations	2732	2732	2440	412

*Note: SNAP is a dummy variable for SNAP participation; standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Each column represents one regression. Only the coefficient on SNAP participation is displayed. The regressions in columns (1), (2), (3), and (5) all align in structure with regressions (1), (2), (3), and (5) outlined in Tables 2 and 3. Refer to Table 4.1 note for a more comprehensive outline of the regressions run in each column, replacing sodium intake with dietary fibre intake in the explanation.*

DIETARY FIBRE INTAKE (BASED ON DAY 1 DIETARY DATA) FOR ADULT WOMEN AGED 20-65: NHANES, 2007– 2014

	(1) BMI	(2) Waist Circumference (cm)	(3) Sodium Intake (mcg)	(4) Saturated Fat Intake (gm)	(5) Vitamin A, RAE Intake (mcg)	(6) Dietary Fibre Intake (gm)
SNAP-Non Participants	-1.404 (1.662)	-1.981 (3.540)	37.73 (287.2)	-0.684 (2.715)	-36.93 (96.17)	-1.623 (1.865)
Observations	350	348	346	346	346	346

*Note: SNAP-Non Participants is a dummy for SNAP eligibility for non-participants: it equals 1 for women who are eligible, but not participating in the SNAP with PIRs between 1.2-1.3, and 0 for ineligible women with PIRs between 1.3-1.4; standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Each column represents one regression, which regresses the SNAP-Non Participants variable on BMI, WC, sodium, saturated fat, vitamin A, RAE, and dietary fibre intake shown respectively in columns (1), (2), (3), (4), (5), and (6). Each regression controls for age, race, education, marital status, number of people in the household, depression, health insurance, employment, minutes sedentary, poverty index, and food security level. Estimates in this table should be compared with the estimates generated in columns 5 of Tables 2, 3, and 4.1-4.4. If they are significantly smaller in magnitude or contradict the results in those tables, reverse causality can be ruled out.*

Abbreviations and Acronyms:

BMI = body mass index; **CDC** = Centers for Disease Control and Prevention; **FNS** = Food and Nutrition Service; **FSP** = Food Stamp Program; **NHANES** = National Health and Nutrition Examination Survey; **OVB** = omitted variable bias; **PIR** = poverty index ratio; **RD** = regression discontinuity; **SNAP** = Supplemental Nutrition Assistance Program; **USDA** = United States Department of Agriculture; **WC** = waist circumference.

Helping or Hurting? The Cross-Country Effect of Refugees on Economic Growth

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ECON 490

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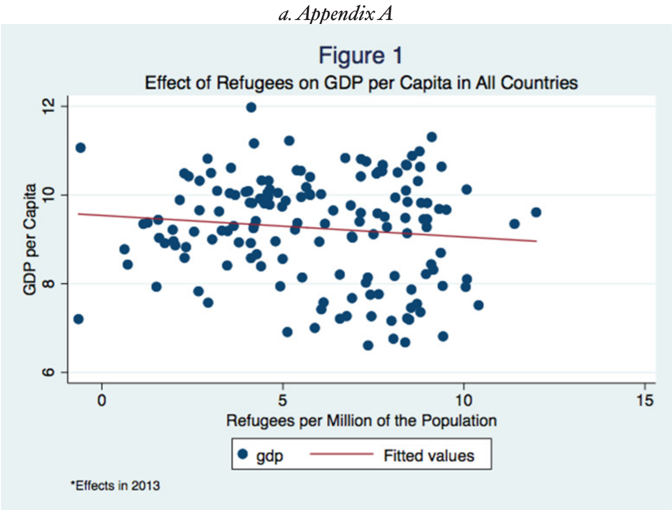
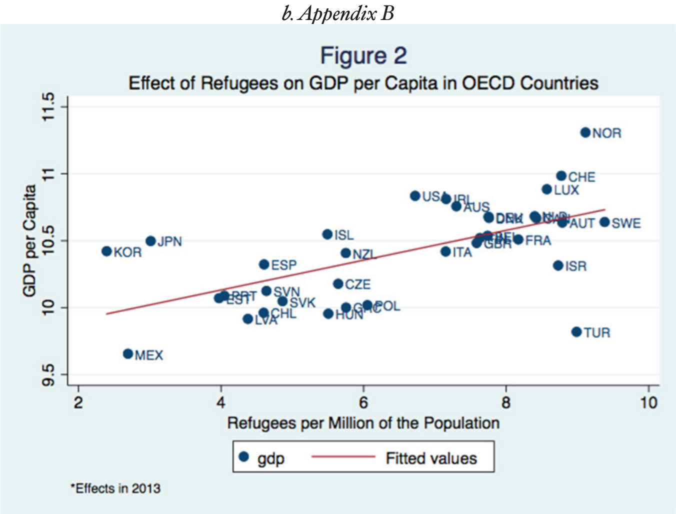
B. APPENDICES

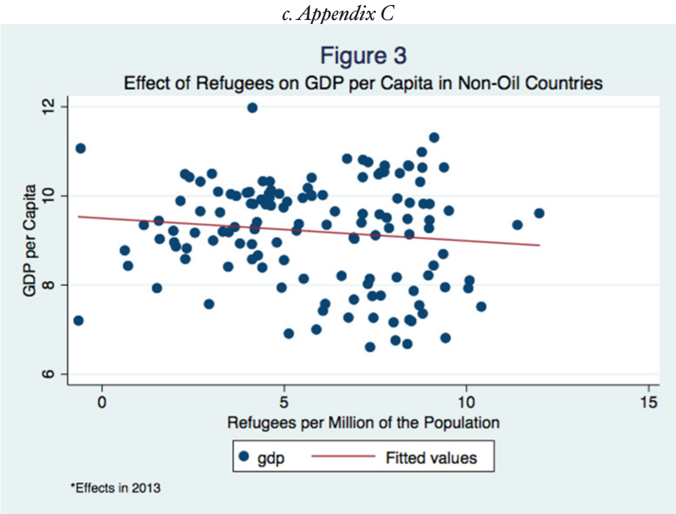
a. Appendix A



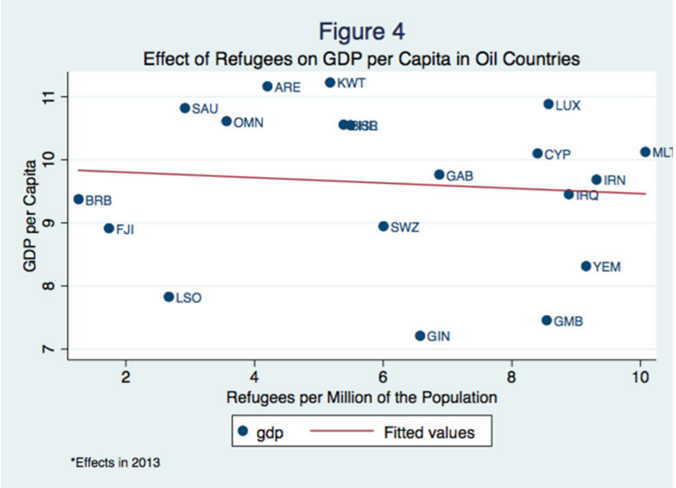
b. Appendix B



c. Appendix C



d. Appendix D



Life Gambles: Affect, Probability Weighting, and Risk Preferences in Medical Decision Making

Andrew Shields

ECON 330

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B. APPENDICES

Key Tables

Indifference Values	**Mean**	**Median**	**Obs**
x0	17 (0.000)	17	31
x1	20.77 (0.514)	20	31
x2	25.39 (0.955)	25	31
x3	30.23 (1.395)	31	31
x4	34.42 (1.677)	36	31
x5	37.94 (1.787)	42	31

Non-Parametric Classification	**# Subjects**	**Percentage**
Risk Adverse (Decreasing Slope)	12	38.71%
Risk Neutral (Linear Slope)	12	38.71%
Risk Seeking (Increasing Slope)	7	22.58%

Parametric Classification	**(1)**	**(2)**
Sigma (Mean)	1.05 (0.133)	1.03 (0.083)
Sigma (Median)	1	0.93

	Percentage (Subjects)	
Risk Adverse (Sigma<1)	48.39% (15)	54.84% (17)

Risk Neutral (Sigma=1)	12.90% (4)	16.13% (5)
Risk Seeking (Sigma>1)	38.71% (12)	29.03% (9)

Parametric Specification 1: $y=a+bx^{\sigma}$
Parametric Specification 2: $y=bx^{\sigma}$ with scaled indifference values
*Standard errors are reported in parentheses, except under 'Percentage' header, where number of subjects are presented

Table 2: Utility Curvature - Losses

Indifference Values	*Mean*	*Median*	*Obs*
x0	17 (0.000)	17	12
x1	23.83 (1.029)	22	12
x2	30.50 (1.460)	30	12
x3	35.58 (1.270)	36	12
x4	40.17 (1.106)	40	12
x5	44.83 (0.936)	46	12
Non-Parametric Classification		*# Subjects*	*Percentage*
Risk Adverse (Decreasing Slope)		2	16.67%
Risk Neutral (Linear Slope)		6	50.00%
Risk Seeking (Increasing Slope)		4	33.33%
Parametric Classification		*(1)*	*(2)*
Sigma (Mean)		1.68 (0.430)	1.61 (0.317)
Sigma (Median)		1.14	1.23
		Percentage (Subjects)	
Risk Adverse (Sigma<1)		41.67% (5)	25.00% (3)
Risk Neutral (Sigma=1)		8.33% (1)	0.00% (0)
Risk Seeking (Sigma>1)		50.00% (6)	75.00% (9)

Parametric Specification 1: [illegible]= [illegible]+ [illegible]
Parametric Specification 2: [illegible]= [illegible] with scaled indifference values

Table 3: Utility Curvature - Losses (Extended)

Indifference Values	*Mean*	*Median*	*Obs*
x0	17 (0.000)	17	20
x1	24.76 (0.774)	24	20
x2	31.86 (1.231)	32	20
x3	38.24 (1.155)	39.5	20
x4	43.52 (1.060)	46	20
x5	46.19 (0.632)	48	20
Non-Parametric Classification		*# Subjects*	*Percentage*
Risk Adverse (Decreasing Slope)		3	14.29%
Risk Neutral (Linear Slope)		9	42.86%
Risk Seeking (Increasing Slope)		9	42.86%
Parametric Classification		*(1)*	*(2)*
Sigma (Mean)		- -	1.474 (0.191)
Sigma (Median)		-	1.24
		Percentage (Subjects)	
Risk Adverse (Sigma<1)		- -	19.05% (4)
Risk Neutral (Sigma=1)		- -	0.00% (0)
Risk Seeking (Sigma>1)		- -	80.95% (17)

Parametric Specification 1: [illegible] = [illegible] + [illegible]
Parametric Specification 2: [illegible] = [illegible] with scaled indifference values

*Standard errors are reported in parentheses, except under 'Percentage' header, where number of subjects are presented

TABLE 4: PROBABILITY WEIGHTING FUNCTION - GAINS

Weighted Probability Values	Mean	Median	Obs
wp10	0.22 (0.035)	0.27	28
wp25	0.28 (0.041)	0.28	28
wp50	0.32 (0.046)	0.34	29
wp75	0.53 (0.026)	0.52	30
wp90	0.62 (0.027)	0.61	29

Non-Parametric Classification	# Subjects	Percentage
Lower Subadditivity	14	50.00%
Upper Subadditivity	28	96.55%
Lower & Upper Subadditivity	13	46.43%
PE Exceeds CE	7	25.00%
PE Equals CE	0	0.00%
CE Exceeds PE	21	75.00%

Parametric Classification	Parameter	Mean	Median
Tversky & Kahneman $w(p)= \frac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{1/\gamma}}$	Gamma	0.52 (0.026)	0.52
Gonzalez & Wu $w(p)= \frac{\delta p^{\gamma}}{\delta p^{\gamma}+(1-p)^{\gamma}}$	Gamma	0.58 (0.069)	0.50
	Delta	0.66 (0.072)	0.64

*Standard Errors are reported in parentheses
** PE refers to the possibility effect; CE refers to the certainty effect

TABLE 5: PROBABILITY WEIGHTING FUNCTION - LOSSES

Weighted Probability Values	**Mean**	**Median**	**Obs**
wp10	0.22 (0.053)	0.23	12
wp25	0.28 (0.057)	0.33	12
wp50	0.39 (0.059)	0.41	12
wp75	0.62 (0.070)	0.57	12
wp90	0.73 (0.069)	0.63	11

Non-Parametric Classification	**# Subjects**	**Percentage**
Lower Subadditivity	7	58.33%
Upper Subadditivity	8	66.67%
Lower & Upper Subadditivity	4	36.36%
PE Exceeds CE	5	45.45%
PE Equals CE	0	0.00%
CE Exceeds PE	6	54.55%

Parametric Classification	**Parameter**	**Mean**	**Median**
Tversky & Kahneman $w(p)=\frac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{1/\gamma}}$	Gamma	0.65 (0.076)	0.52
Gonzalez & Wu $w(p)=\frac{\delta p^{\gamma}}{\delta p^{\gamma}+(1-p)^{\gamma}}$	Gamma	0.64 (0.141)	0.58
	Delta	0.68 (0.118)	0.53

*Standard Errors are reported in parentheses
** PE refers to the possibility effect; CE refers to the certainty effect

TABLE 6: COMPARISON OF PARAMETRIC VALUES ACROSS CONDITIONS

Parametric Classification	*Parameter*	*Gains*	*Losses*	*Losses - Ext*
Power Function (1)	Sigma	1.05 (0.133) 1.00	1.68 (0.430) 1.14	-
Power Function (2)	Sigma	1.03 (0.083) 0.93	1.61 (0.317) 1.23	1.47 (0.191) 1.24
Tversky & Kahneman	Gamma	0.52 (0.026) 0.52	0.65 (0.076) 0.56	-
Gonzalez & Wu	Gamma	0.58 (0.069) 0.50	0.64 (0.141) 0.58	-
		0.66 (0.072) 0.64	0.68 (0.118) 0.53	

* First mean values are reported, followed by std. errors in parentheses, then median values

TABLE 7: CORRELATION MATRIX - GAINS

	Sigma	*Gamma (2)*	*Delta*	*Gamma (1)*	*Language*	*Gender*	*Pleasant*	*Activated*
Sigma	1							
Gamma (2)		1						
Delta		-0.606**	1					
	-							
Gamma (1)	0.346*	0.381**	0.8631**	1				
Language					1			
Gender		0.381**			0.094*	1	-0.123*	
Pleasant		-0.337*			-0.531**		1	
Activated							0.201**	1

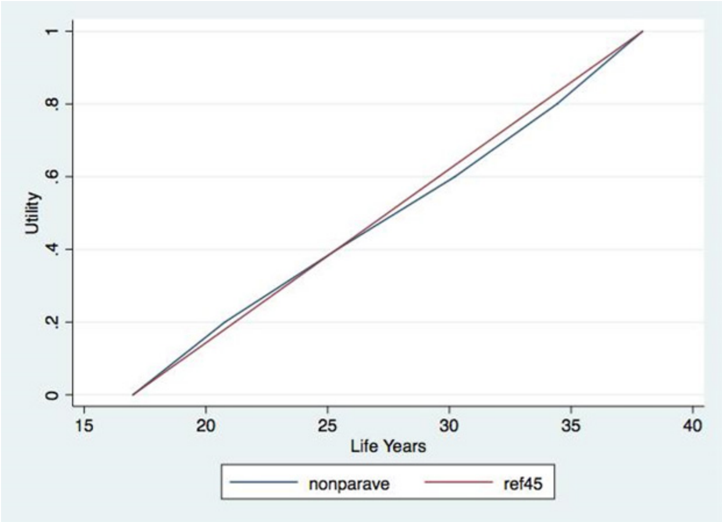
Gamma (1) - refers to Tversky & Kahneman's (1992) probability weighting specification
Gamma (2) - refers to Gonzalez & Wu's (1999) probability weighting specification
* denotes significance at a 10% level; ** denotes significance at a 5% level; insignificant values are not included

TABLE 8: CORRELATION MATRIX - LOSSES

	Sigma	*Gamma (2)*	*Delta*	*Gamma (1)*	*Language*	*Gender*	*Pleasant*	*Activated*
Sigma	1							
Gamma (2)		1						
Delta			1					
	-							
Gamma (1)		0.918**		1				
Language					1			
Gender			0.565*		0.154*	1		
Pleasant					-0.268**	-0.183*	1	
Activated					-0.193**		.490**	1

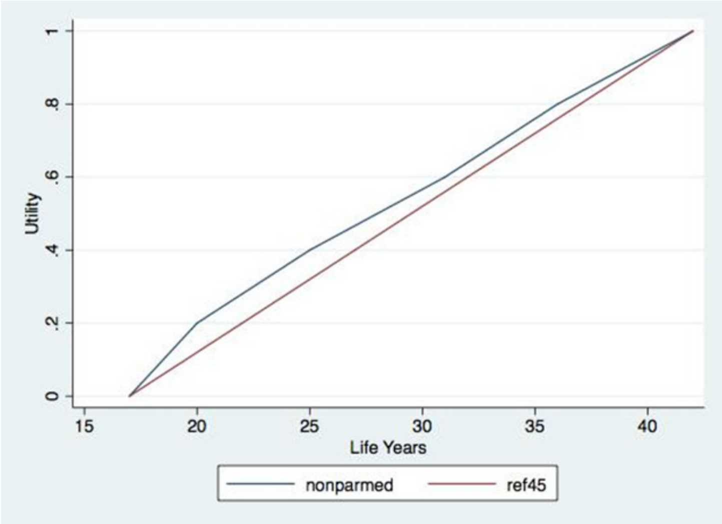
Gamma (1) - refers to Tversky & Kahneman's (1992) probability weighting specification
Gamma (2) - refers to Gonzalez & Wu's (1999) probability weighting specification
* denotes significance at a 10% level; ** denotes significance at a 5% level; insignificant values are not included

Key Graphs

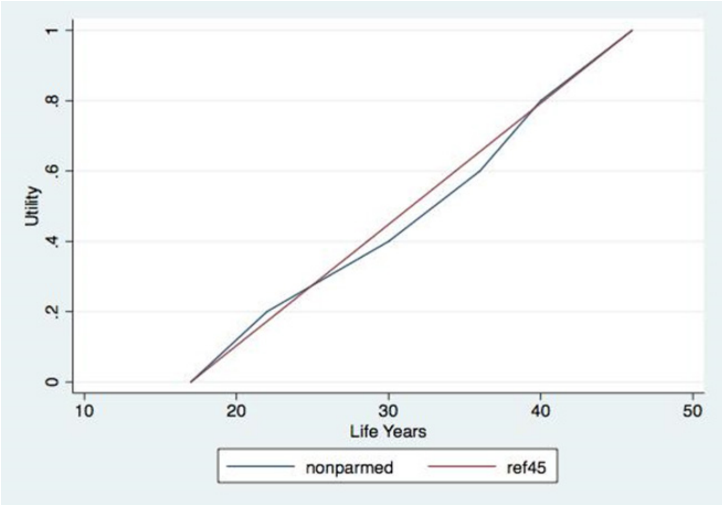


Graph 1.1: Non-Parametric Utility Plot (Ave) - Gains

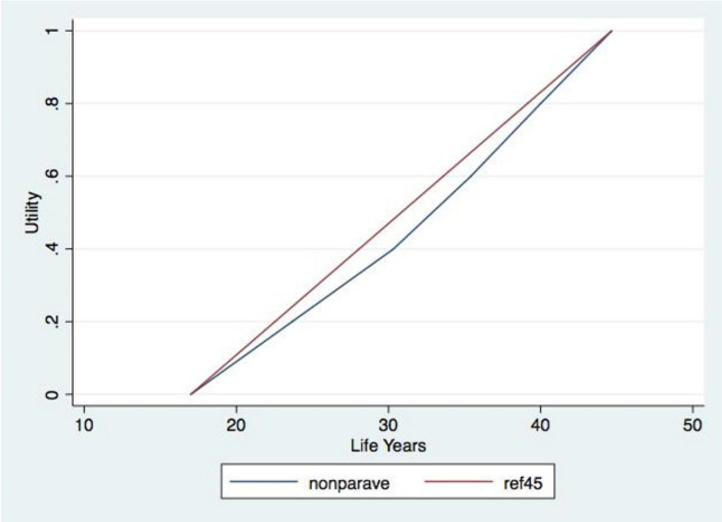
**nonparave- refers to the non-parametric plotting of mean indifference values*



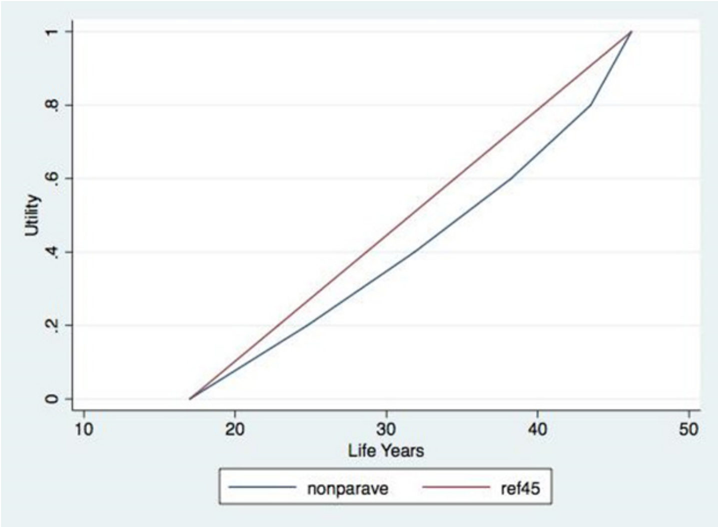
Graph 1.2: Non-Parametric Utility Plot (Med) - Gains
**nonparmed- refers to the non-parametric plotting of median indifference values*



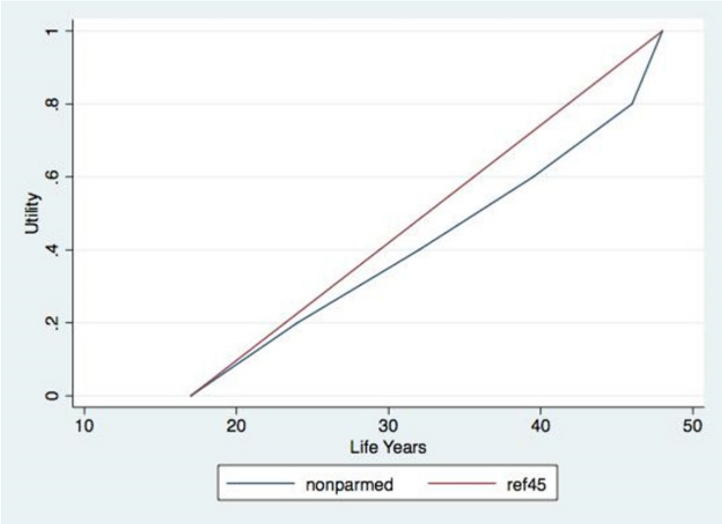
Graph 1.3: Non-Parametric Utility Plot (Ave) – Losses
**nonparmed- refers to the non-parametric plotting of median indifference values*



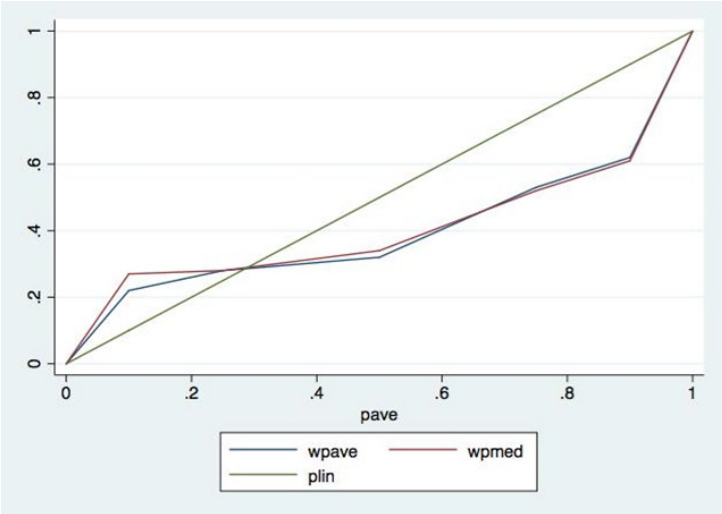
Graph 1.4: Non-Parametric Utility Plot (Med) – Losses
**nonparave- refers to the non-parametric plotting of mean indifference values*



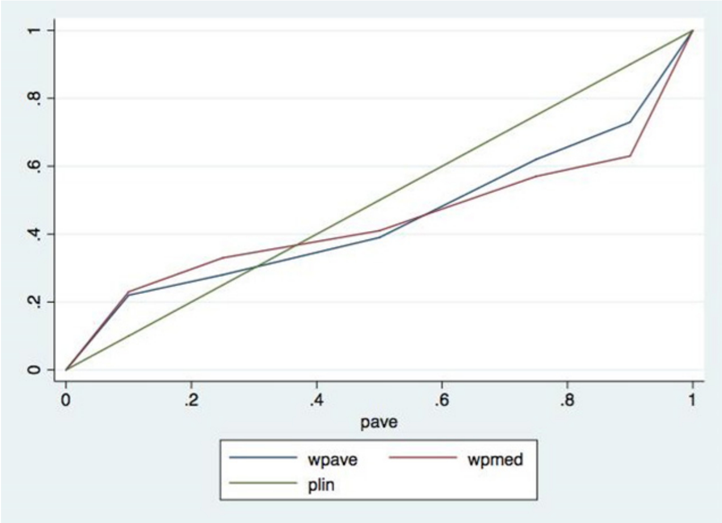
Graph 1.5: Non-Parametric Utility Plot (Ave) – Losses (Ext)
**nonparave- refers to the non-parametric plotting of mean indifference values*



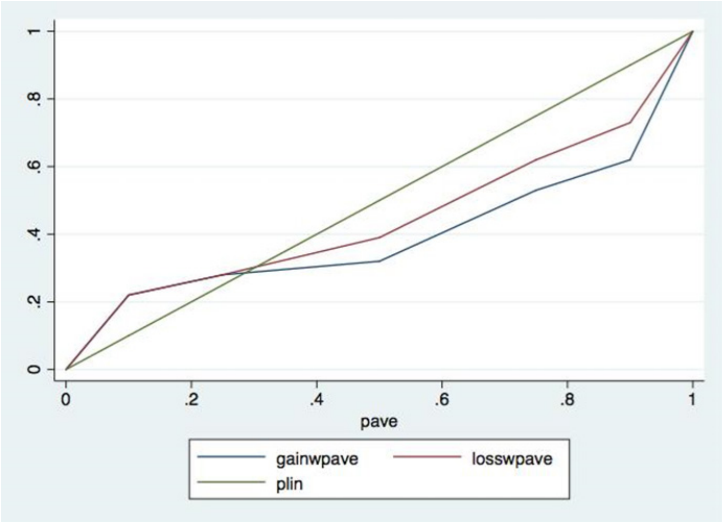
Graph 1.6: Non-Parametric Utility Plot (Med) – Losses (Ext)
**nonparmed- refers to the non-parametric plotting of median indifference values*



Graph 1.7: Non-Parametric Weighted Probability Function Plot - Gains

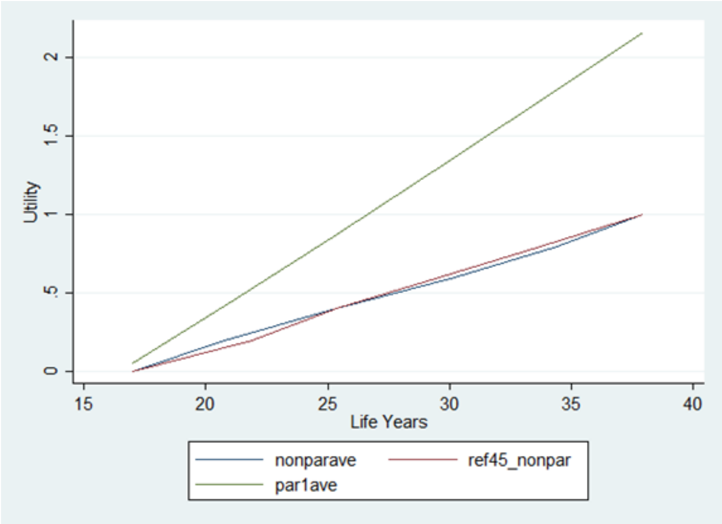


Graph 1.8: Non-Parametric Weighted Probability Function Plot - Losses
** pave - refers to objective probability; wpave - refers to the non-parametric plotting of mean weighted probability values; wpmed - refers to the non-parametric plotting of median weighted probability values.*



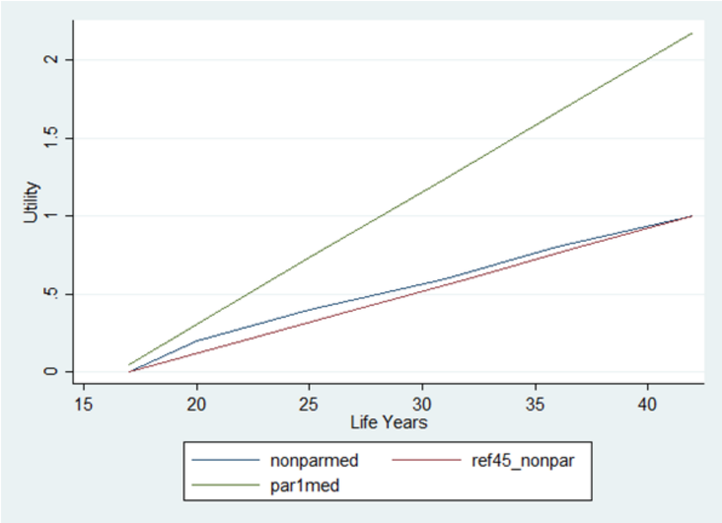
Graph 1.9: Non-Parametric Weighted Probability Function Plot - Gains vs. Losses
** pave - refers to objective probability; gainwpave - refers to the non-parametric plotting of mean weighted probability values for the gain condition; losswpave - refers to the non-parametric plotting of mean weighted probability values for the loss condition.*

Supplementary Graphs



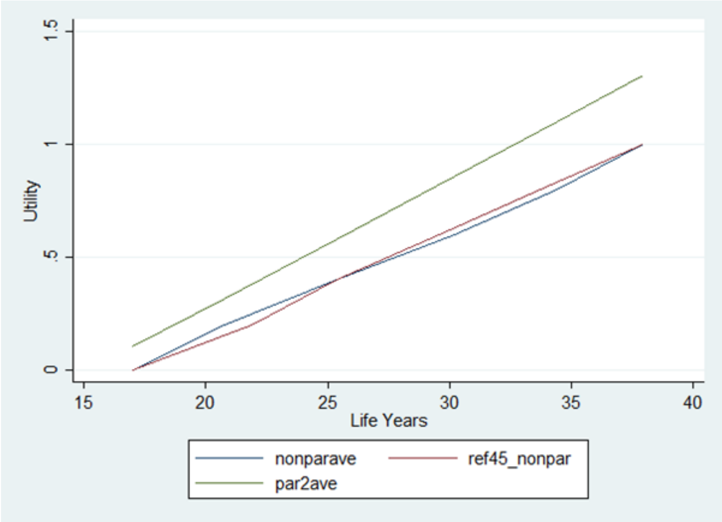
Graph 2.1: Parametric Utility Plot (Specification 1, Ave) - Gains

** nonparave - refers to the non-parametric plotting of mean indifference values. parave- refers to the plotting of the derived mean parametric curve per parametric specification 1*

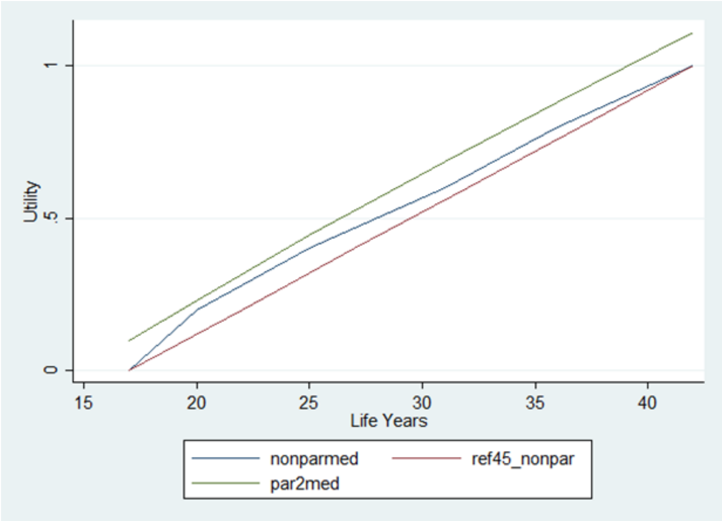


Graph 2.2: Parametric Utility Plot (Specification 1, Med) - Gains

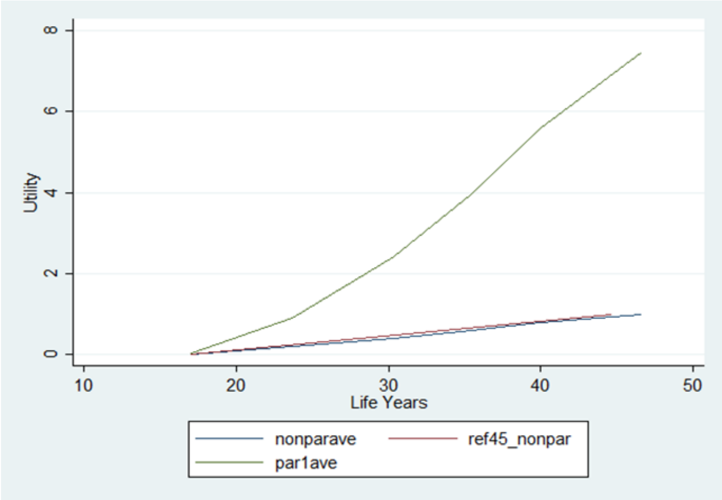
** nonparmed - refers to the non-parametric plotting of median indifference values. parmed- refers to the plotting of the derived median parametric curve per parametric specification 1*



Graph 2.3: Parametric Utility Plot (Specification 2, Ave) – Gains
** nonparave - refers to the non-parametric plotting of mean indifference values. par2ave- refers to the plotting of the derived mean parametric curve per parametric specification 2*

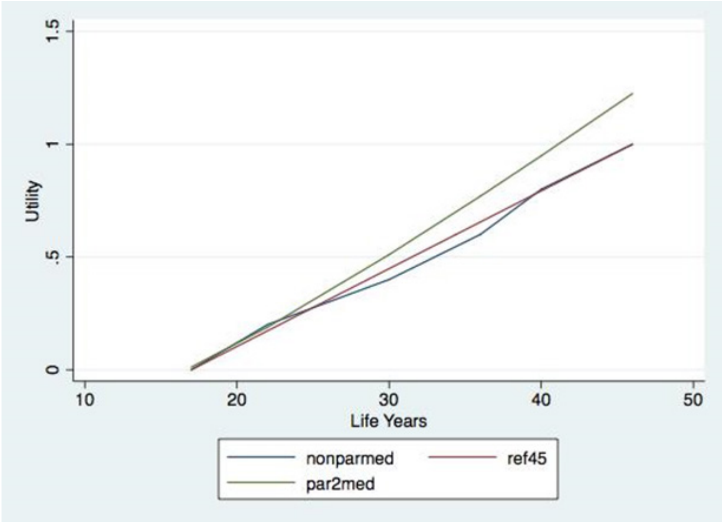


Graph 2.4: Parametric Utility Plot (Specification 2, Med) – Gains
** nonparmed - refers to the non-parametric plotting of median indifference values. par2med- refers to the plotting of the derived median parametric curve per parametric specification 2*



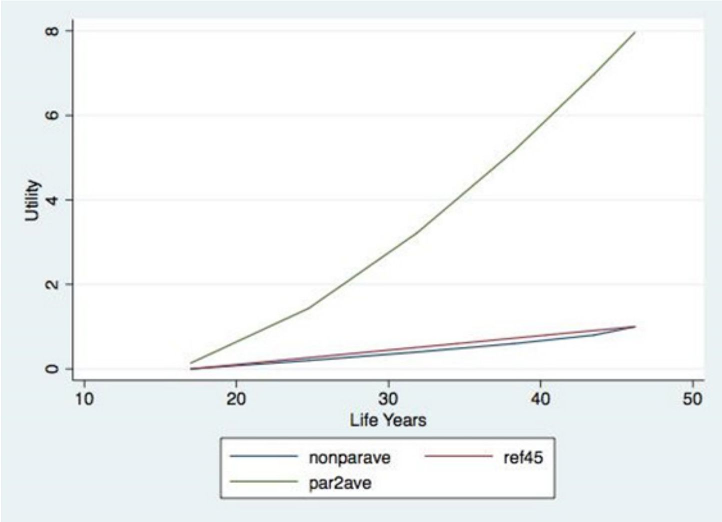
Graph 2.5: Parametric Utility Plot (Specification 1, Ave) – Losses

** nonparave - refers to the non-parametric plotting of mean indifference values. parave- refers to the plotting of the derived mean parametric curve per parametric specification 1*



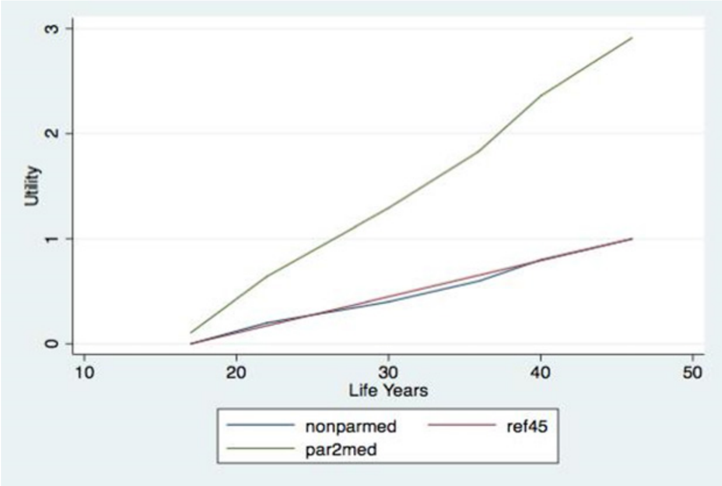
Graph 2.6: Parametric Utility Plot (Specification 1, Med) – Losses

** nonparmed - refers to the non-parametric plotting of median indifference values. parmed- refers to the plotting of the derived median parametric curve per parametric specification 1*



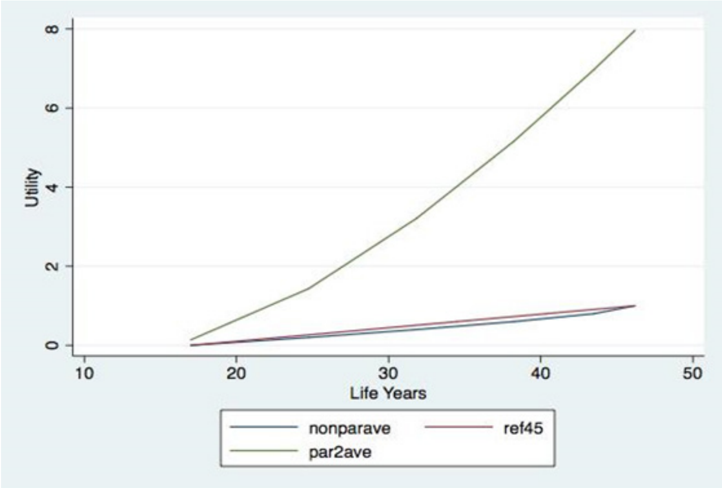
Graph 2.7: Parametric Utility Plot (Specification 2, Ave) – Losses

** nonparave - refers to the non-parametric plotting of mean indifference values. par2ave- refers to the plotting of the derived mean parametric curve per parametric specification 2*



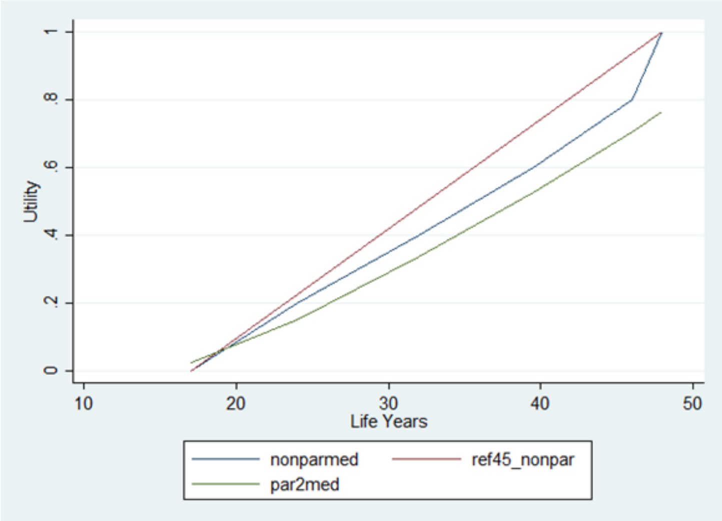
Graph 2.8: Parametric Utility Plot (Specification 2, Med) – Losses

** nonparmed - refers to the non-parametric plotting of median indifference values. par2med- refers to the plotting of the derived median parametric curve per parametric specification 2*



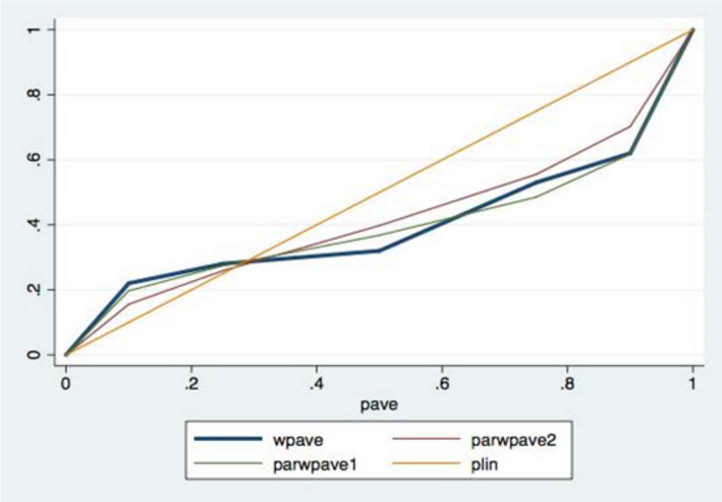
Graph 2.9: Parametric Utility Plot (Specification 2, Ave) – Losses (Ext)

** nonparave - refers to the non-parametric plotting of mean indifference values. par2ave- refers to the plotting of the derived mean parametric curve per parametric specification 2*

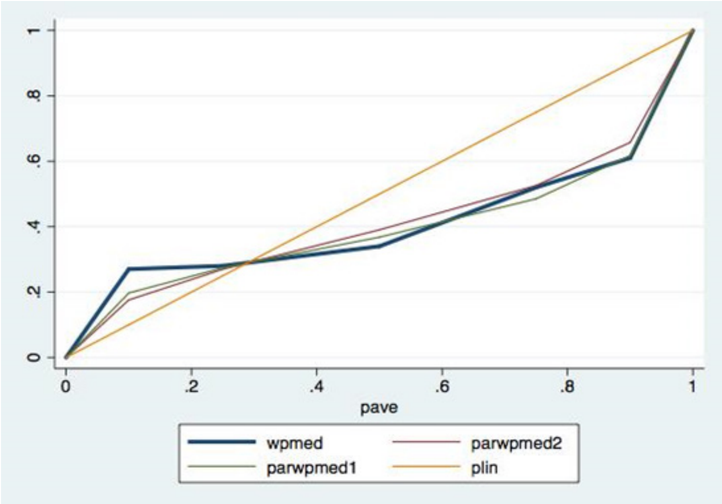


Graph 2.10: Parametric Utility Plot (Specification 2, Med) – Losses (Ext)

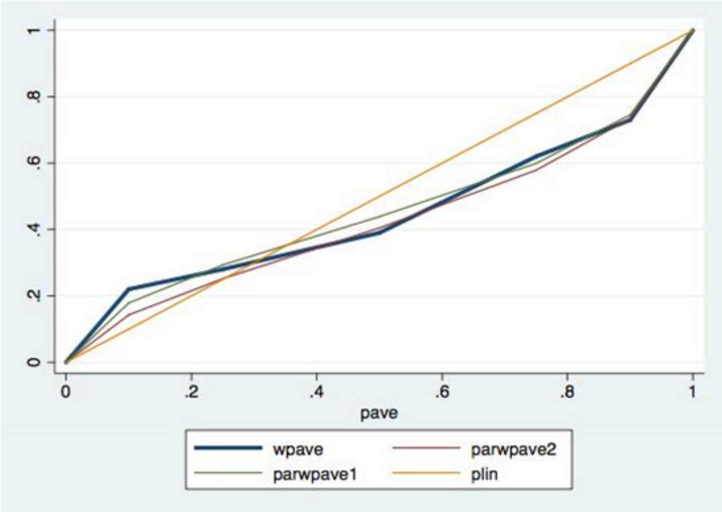
** nonparmed - refers to the non-parametric plotting of median indifference values. par2med- refers to the plotting of the derived median parametric curve per parametric specification 2*



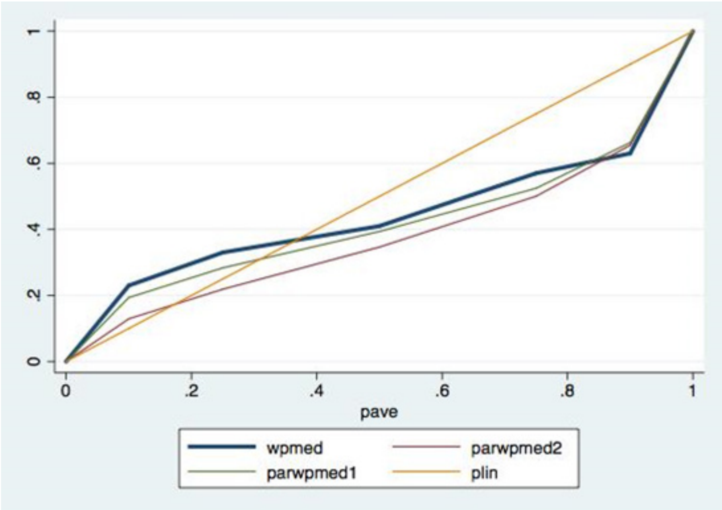
Graph 2.11: Parametric Weighted Probability Function Plot (Ave) – Gains
** pave - refers to objective probability; wpave - refers to the non-parametric plotting of mean weighted probability values; parwpave1 - refers to the plotting of the derived mean probability weighting curve per the 1-parameter specification; parwpave2 - refers to the plotting of the derived mean probability weighting curve per the 2-parameter specification*



Graph 2.12: Parametric Weighted Probability Function Plot (Med) – Gains
** pave - refers to objective probability; wpave - refers to the non-parametric plotting of mean weighted probability values; parwpave1 - refers to the plotting of the derived mean probability weighting curve per the 1-parameter specification; parwpave2 - refers to the plotting of the derived mean probability weighting curve per the 2-parameter specification*



Graph 2.13: Parametric Weighted Probability Function Plot (Ave) – Losses
** pave - refers to objective probability; wpave - refers to the non-parametric plotting of mean weighted probability values; parwpave1 - refers to the plotting of the derived mean probability weighting curve per the 1-parameter specification; parwpave2 - refers to the plotting of the derived mean probability weighting curve per the 2-parameter specification*



Graph 2.14: Parametric Weighted Probability Function Plot (Med) – Losses
** pave - refers to objective probability; wpave - refers to the non-parametric plotting of mean weighted probability values; parwpave1 - refers to the plotting of the derived mean probability weighting curve per the 1-parameter specification; parwpave2 - refers to the plotting of the derived mean probability weighting curve per the 2-parameter specification*

Who Wants to Find a Lover Online and Why? A Study of The Determinants of Online Dating Usage and The Effect of First-Time Meeting Venue on Relationship Outcomes

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ECON 499

A. REFERENCES

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B. APPENDICES

a. Tables

TABLE 1. SUMMARY OF DEMOGRAPHICS AND ONLINE SOCIABILITY OF SAMPLE ONLINE DATERS (PRESENTED BY PERCENTAGES)

	(1)	(2)
Variable	Use an OD site/app	Total sample population
General Information		
Population	223	2,252
Total responses	1,898	2,252
% of "yes" users out of total responses	11.7	n/a
% of "yes" users out of total sample population	9.9	n/a
Physical Attributes		
Gender composition		
Male	51.6	45.7
Female	48.4	54.3
Age composition		
Individuals with age data	98.7	97.3
18 to 20 years	4.6	4.8
21 to 35 years	35.5	20.6

36 to 55 years	35.9	30.8
Over 56	24.1	43.8
Race composition		
Individuals with race data	97.3	97.2
White	76.0	78.0
Black or African-American	13.8	13.1
Asian or Pacific Islander	1.4	2.1
Mixed race	4.6	2.8
Native American/American Indian	0.5	1.6
Other (specify)	3.2	2.0
Don't know	0.5	0.4
Geographic Location		
Census region		
Northeast	13.0	16.7
Midwest	22.0	23.1
South	40.8	38.6
West	24.2	21.6
Community composition		
Rural	11.2	20.0
Suburban	46.6	46.1
Urban	42.2	33.9
Assets and Human Capital		
Educational attainment		
Individuals with education data	100.0	99.1
Less than high school	5.4	7.5
High school or some college	39.0	44.3
College degree	39.0	32.2
Postgraduate degree	16.6	14.6
Don't know	0.0	0.5

Household Income		
Individuals with income data	92.4	86.7
Less than $20,000	13.9	15.6
$20,000 to under $40,000	19.7	18.6
$40,000 to under $100,000	41.7	31.5
$100,000 or more	12.6	15.8
Don't know	4.5	5.3
Employment status		
Individuals with employment data	100.0	99.5
Employed	73.1	53.0
Have own business/ self-employed	0.9	2.2
Non-employed	25.6	44.0
Other	0.5	0.3
Mating History and Preference		
Marital status		
Individuals with marital status data	100.0	98.5
Married or cohabited	28.7	54.6
Divorced, or Separated, or Widowed, AND non-single	7.6	3.8
Divorced, or Separated, or Widowed, AND single	26.9	20.6
Never been married, AND non-single	10.3	5.6
Never been married, AND single	26.5	13.9
Parental status		
Individuals with parental status data	100.0	99.5
Parent	26.5	25.0
Not a parent	73.5	74.5
Sexual orientation		

Individuals with sexual orientation data	98.7	95.7
Heterosexual or straight	87.4	90.6
Gay or lesbian	4.9	1.6
Bisexual	4.9	1.9
Other	0.5	0.2
Don't know	0.9	1.4
Behaivioural Online Sociability		
Involvement in certain online activities[1]	95.5	70.9
Involvement in virtual communication[2]	95.1	77.5
Attention to self's digital profile[3]	77.1	48.5
Attention to interested persons' digital profiles[4]	69.1	26.7
Location sharing[5]	32.7	19.8
Flirting online	60.1	17.4
Dating initiative[6]	52.0	17.0
Maintenance of long-distance relationship by virtual aid	28.7	6.6
Perceptual Onlnie Sociability		
	81.0	56.0
Online dating is a good way to meet people	17.7	37.4
	1.4	6.6
	70.4	48.7
Online dating allows people to find a better match for themselves because they can get to know a lot more people	25.6	41.6
	2.7	8.1
	12.7	23.3
People who use online dating sites are desperate	85.9	70.5
	1.4	6.3

	27.8	30.1
Online dating keeps people from settling down because they always have options for people to date	70.0	58.5
	2.2	10.7

Source: The data is from a national telephone survey conducted by Princeton Survey Research Associates Inter-national for the Pew Research Center's Internet & American Life Project from April 17th to May 19th in 2013.
1 Involvement in certain online activities = use online banking, or use a social networking site, or download or listen to Podcasts, or use Twitter, or use Reddit.
2 Involvement in virtual communication = send or receive email, or use cellphone to send or receive text mes-sages or participate in a video call or video chat.
3 Attention to own online profile = use a search engine or other websites to look up own name or information.
4 Attention to interested persons' online profiles = use the internet or a social networking site to search for in-formation about someone whom the respondent dated or had a relationship within in the past, or are currently dating or are about to meet for a first date, or are interested in dating; or 'follow' or 'friend' someone online be-cause the respondent's friends suggest the respondent might want to date that person.
5 Location sharing = Set up social networking accounts so that location is automatically included on posts, or ever include location in posts on social networking sites, or use cellphone to 'check-in' or share location.
6 Dating initiative = Use the internet or email or a social networking site to ask someone out on a date, or use a cellphone to ask someone out on a date by calling or texting.
7 Statistics of each opinion is presented in the following order: "Agree", "Disagree", "Don't know".

TABLE 2. SUMMARY OF RELEVANT DEMOGRAPHICS AND ONLINE SOCIABILITY OF DEEPER ONLINE DATERS (PRESENTED BY PERCENTAGES)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Pay to use an OD site/app	Ask others to help create or review OD profile	Go on a date with someone met through an OD site/app	Have a long term relationship or marriage through an OD site/app	Involve in deeper OD usage (i.e. involve in at least one of (1)-(4))	Total sample population
General Information						
Population	87	47	150	52	176	2,252
Total responses	223	223	223	223	223	2,252
% of "yes" users out of total responses	39.0	21.1	67.3	23.3	78.9	n/a

% of "yes" users out of total sample population	3.9	2.1	6.7	2.3	7.8	n/a
Physical Attributes						
Age composition						
Individuals with age data	97.7	97.9	98.7	98.1	98.9	97.3
18 to 20 years	1.2	10.6	4.0	3.9	4.0	4.8
21 to 35 years	26.4	34.0	34.7	30.8	33.5	20.6
36 to 55 years	39.1	36.2	35.3	30.8	36.9	30.8
Over 56	31.0	17.0	24.7	32.7	24.4	43.8
Geographic Location						
Community composition						
Rural	13.8	12.8	10.7	19.2	11.4	20.0
Suburban	49.4	48.9	48.0	46.2	47.2	46.1
Urban	36.8	38.3	41.3	34.6	41.5	33.9
Assets and Human Capital						
Household Income						
Individuals with income data	92.0	93.6	90.0	86.5	91.5	86.7
Less than $20,000	11.5	17.0	11.3	15.4	12.5	15.6
$20,000 to under $40,000	13.8	23.4	17.3	11.5	17.1	18.6
$40,000 to under $100,000	48.3	31.7	44.7	46.2	43.8	31.5
$100,000 or more	18.4	12.8	14.0	11.5	14.8	15.8
Don't know	8.1	8.5	2.7	1.9	3.4	5.3
Mating History and Preference						
Sexual orientation						

Individuals with sexual orientation data	99.0	100.0	99.3	98.1	99.4	95.7
Heterosexual or straight	93.1	89.4	88.7	86.5	88.6	90.6
Gay or lesbian	1.2	6.4	3.3	5.8	4.0	1.6
Bisexual	4.6	4.3	6.0	5.8	5.7	1.9
Other	0.0	0.0	0.7	0.0	0.6	0.2
Don't know	0.0	0.0	0.7	0.0	0.6	1.4
Behaivioural Online Sociability						
Involvement in certain online activities[1]	94.3	93.6	96.0	96.2	95.5	70.9
Involvement in virtual communication[2]	95.4	95.7	95.3	96.2	95.5	77.5
Attention to self's digital profile[3]	78.2	83.0	80.7	84.6	79.6	48.5
Attention to interested persons' digital profiles[4]	71.3	83.0	76.0	69.2	72.7	26.7
Location sharing[5]	31.0	42.6	33.3	23.1	31.3	19.8
Flirting online	57.5	72.3	67.3	73.1	65.3	17.4
Dating initiative[6]	47.1	61.7	62.0	65.4	57.4	17.0
Maintenance of long-distance relationship by virtual aid	27.6	31.9	32.0	32.7	30.1	6.6

Source: The data is from a national telephone survey conducted by Princeton Survey Research Associates International for the Pew Research Center's Internet & American Life Project from April 17th to May 19th in 2013
1Involvement in certain online activities = use online banking, or use a social networking site, or download or listen to Podcasts, or use Twitter, or use Reddit.
2Involvement in virtual communication = send or receive email, or use cellphone to send or receive text messages or participate in a video call or video chat.
3Attention to self's online profile = use a search engine or other websites to look up own name or information.
4Attention to interested persons' online profiles = use the internet or a social networking site to search for information about someone whom the respondent dated or had a relationship within in the past, or are currently dating or are about to meet for a first date, or are interested in dating; or 'follow' or 'friend' someone online because the respondent's friends suggest the respondent

might want to date that person.
5Location sharing = Set up social networking accounts so that location is automatically included on posts, or ever include location in posts on social networking sites, or use cellphone to 'check-in' or share location.
6Dating initiative = Use the internet or email or a social networking site to ask someone out on a date, or use a cellphone to ask someone out on a date by calling or texting.

Table 3. Summary of Quality of Life and Family of the Non-singles (Presented by Percentages)

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	*Excellent*	*Very good*	*Good*	*Fair*	*Poor*	*Total*
Panel A: First-time Meeting Venue of the Non-singles						
Partners met offline	20.4	28.4	34.7	12.8	3.7	95.6
Partners met online	27.0	25.4	27.0	15.9	4.8	4.5
Panel B: First-time Online Meeting Venue of the Non-singles						
Partners met through online dating sites	29.0	21.1	31.6	15.8	2.6	61.3
Partners met through some other way	25.0	29.2	20.8	16.7	8.3	38.7
Total non-single population	20.6	28.2	34.2	12.8	3.7	62.9

Source: The data is from a national telephone survey conducted by Princeton Survey Research Associates International for the Pew Research Center's Internet & American Life Project from April 17th to May 19th in 2013.
Notes: Only respondents who were currently non-single (i.e. married, living with a partner, in a committed romantic relationship) and with in-formation of first-time meeting venue are considered (N = 1,417) for Panel A and "Total non-single population". Only respondents who were cur-rently non-single and first met their partner online are considered (n = 62) for Panel B.

TABLE 4.1 AVERAGE MARGINAL EFFECTS OF DEMOGRAPHIC AND SOCIAL DETERMINANTS OF ONLINE DATING USAGE (DELTA-METHOD STANDARD ERRORS IN PARENTHESES)

Variables	(1)	(2)	(3)
Physical Attributes			
Gender *("Female" omitted)*			
Male	0.03**	0.04**	0.02
	(0.02)	(0.02)	(0.02)
Age *("Over 56 years" omitted)*			
18 to 20 years	0.07**	0.02	-0.12***
	(0.04)	(0.05)	(0.04)
21 to 35 years	0.15***	0.11***	-0.05*
	(0.02)	(0.03)	(0.03)
36 to 55 years	0.10***	0.09***	0.02

	(0.02)	(0.03)	(0.02)
Race ("White" omitted)			
Black or African-American	-0.01	-0.02	-0.00
	(0.02)	(0.03)	(0.02)
Asian or Pacific Islander	-0.10*	-0.13**	-0.01
	(0.06)	(0.07)	(0.06)
Mixed race	0.02	-0.03	-0.06*
	(0.04)	(0.05)	(0.04)
Native American/American Indian	-0.08	-0.03	-0.00
	(0.09)	(0.11)	(0.09)
Other (specify)	0.02	-0.02	0.02
	(0.04)	(0.05)	(0.05)
Don't know	-0.05	-0.06	-0.03
	(0.10)	(0.11)	(0.11)
Geographic Locations	No	Yes	Yes
Assets and Human Capital	No	Yes	Yes
Mating History and Preference	No	Yes	Yes
Behavioural Online Sociability	No	No	Yes
Perceptual Online Sociability	No	No	Yes
N	2143	1571	1530
Pseudo R-squared	0.052	0.149	0.351
Log pseudolikelihood	-705.190	-556.73	-411.67

Source: The data is from a national telephone survey conducted by Princeton Survey Research Associates International for the Pew Research Center's Internet & American Life Project from April 17th to May 19th in 2013.
**Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.*

TABLE 4.2 AVERAGE MARGINAL EFFECTS OF DEMOGRAPHIC AND SOCIAL DETERMINANTS OF ONLINE DATING USAGE (DELTA-METHOD STANDARD ERRORS IN PARENTHESES)

Variables	(1)	(2)	(3)
Physical Attributes	No	Yes	Yes
Geographic Locations			
Census region *("South" omitted)*			
Northeast	-0.06***	-0.06**	-0.05**
	(0.02)	(0.03)	(0.02)
Midwest	-0.01	-0.04	-0.02
	(0.02)	(0.02)	(0.02)
West	-0.02	-0.02	-0.03
	(0.02)	(0.02)	(0.02)
Community type *("Suburban" omitted)*			
Rural	-0.06***	-0.06**	-0.04*
	(0.02)	(0.03)	(0.02)
Urban	0.02	0.03	0.03**
	(0.02)	(0.02)	(0.02)
Assets and Human Capital	No	Yes	Yes
Mating History and Preference	No	Yes	Yes
Behavioural Online Sociability	No	No	Yes
Perceptual Online Sociability	No	No	Yes
N	2252	1571	1530
Pseudo R-squared	0.017	0.149	0.351
Log pseudolikelihood	-758.32	-556.73	-411.67

Source: The data is from a national telephone survey conducted by Princeton Survey Research Asso-ciates International for the Pew Research Center's Internet & American Life Project from April 17th to May 19th in 2013.
**Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.*

TABLE 4.3 AVERAGE MARGINAL EFFECTS OF DEMOGRAPHIC AND SOCIAL DETERMINANTS OF ONLINE DATING USAGE (DELTA-METHOD STANDARD ERRORS IN PARENTHESES)

Variables	(1)	(2)	(3)
Physical Attributes	No	Yes	Yes
Geographic Locations	No	Yes	Yes
Assets and Human Capital			
Internet access			
Yes	0	0	0
	(omitted)	(omitted)	(omitted)
Education ("High school or some college" omitted)			
Less than high school	-0.01	-0.04	-0.04
	(0.04)	(0.04)	(0.03)
College degree	0.03	0.02	0.00
	(0.02)	(0.02)	(0.02)
Postgraduate degree	0.04	0.07**	0.03
	(0.03)	(0.03)	(0.03)
Don't know	0	0	0
	(omitted)	(omitted)	(omitted)
Household Income ("$40,000 to under $100,000" omitted)			
Less than $20,000	0.02	-0.02	-0.01
	(0.03)	(0.03)	(0.03)
$20,000 to under $40,000	0.01	-0.03	-0.02
	(0.03)	(0.03)	(0.02)
$100,000 or more	-0.09***	-0.06**	-0.06**
	(0.03)	(0.03)	(0.02)
Don't know	0.02	0.03	0.07*
	(0.05)	(0.04)	(0.04)
Employment status1 ("Employed" omitted)			
Have own business/ self-employed	-0.10	-0.11	-0.02

	(0.09)	(0.08)	(0.06)
Non-employed	-0.08***	-0.06***	-0.04*
	(0.02)	(0.02)	(0.02)
Other	0.05	0.12	0.11
	(0.14)	(0.13)	(0.08)
Mating History and Preference	No	Yes	Yes
Behavioural Online Sociability	No	No	Yes
Perceptual Online Sociability	No	No	Yes
N	1647	1571	1530
Pseudo R-squared	0.029	0.149	0.351
Log pseudolikelihood	-658.29	-556.73	-411.67

Source: The data is from a national telephone survey conducted by Princeton Survey Research Asso-ciates International for the Pew Research Center's Internet & American Life Project from April 17th to May 19th in 2013.
**Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.*
1Employed = "employed full-time or part-time"; Non-employed = "retired" or "not employed for pay" or "disabled" or "student."

TABLE 4.4 AVERAGE MARGINAL EFFECTS OF DEMOGRAPHIC AND SOCIAL DETERMINANTS OF ONLINE DATING USAGE (DELTA-METHOD STANDARD ERRORS IN PARENTHESES)

Variables	(1)	(2)	(3)
Physical Attributes	No	Yes	Yes
Geographic Locations	No	Yes	Yes
Assets and Human Capital	No	Yes	Yes
Mating History and Preference			
Relationship status ("Married or Cohabited" omitted)			
Divorced, or Separated, or Widowed, AND non-single	0.13***	0.14***	0.07**
	(0.03)	(0.04)	(0.04)
Divorced, or Separated, or Widowed, AND single	0.11***	0.20***	0.18***
	(0.02)	(0.03)	(0.02)

Never been married, AND non-single	0.13***	0.12***	0.04
	(0.03)	(0.04)	(0.03)
Never been married, AND single	0.13***	0.11***	0.14***
	(0.02)	(0.03)	(0.03)
Parental status			
Parent	0.03*	-0.01	-0.01
	(0.02)	(0.02)	(0.02)
Sexual orientation ("Heterosexual or straight" omitted)			
Gay or lesbian	0.14***	0.13**	0.06
	(0.05)	(0.06)	(0.04)
Bisexual	0.09**	0.11**	0.04
	(0.04)	(0.05)	(0.04)
Other	-0.01	0.03	0.05
	(0.11)	(0.15)	(0.07)
Don't know	-0.04	0.14*	0.19***
	(0.07)	(0.08)	(0.06)
Behavioural Online Sociability	No	No	Yes
Perceptual Online Sociability	No	No	Yes
N	2129	1571	1530
Pseudo R-squared	0.069	0.149	0.351
Log pseudolikelihood	-702.89	-556.73	-411.67

Source: The data is from a national telephone survey conducted by Princeton Survey Research Asso-ciates International for the Pew Research Center's Internet & American Life Project from April 17th to May 19th in 2013.
**Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.*

TABLE 4.5 AVERAGE MARGINAL EFFECTS OF DEMOGRAPHIC AND SOCIAL DETERMINANTS OF ONLINE DATING USAGE (DELTA-METHOD STANDARD ERRORS IN PARENTHESES)

Variables	(1)	(2)	(3)
Physical Attributes	No	No	Yes
Geographic Locations	No	No	Yes

Assets and Human Capital	No	No	Yes
Mating History and Preference	No	No	Yes
Behavioural Online Sociability			
Involvement in certain online activities[1]	0.08***	0.08***	0.09***
	(0.02)	(0.02)	(0.03)
Involvement in virtual communication[2]	0.01	0.01	0.02
	(0.02)	(0.02)	(0.03)
Attention to self's digital profile[3]	0.02	0.02	0.03
	(0.02)	(0.02)	(0.02)
Attention to interested persons' digital profiles[4]	0.04***	0.04**	0.05***
	(0.02)	(0.02)	(0.02)
Location sharing[5]	-0.00	-0.01	-0.02
	(0.02)	(0.02)	(0.02)
Flirting online	0.09***	0.08***	0.08***
	(0.02)	(0.02)	(0.02)
Dating initiative[6]	0.06***	0.06***	0.10***
	(0.02)	(0.02)	(0.02)
Maintenance of long-distance relationship by virtual aid	0.08***	0.07***	0.08***
	(0.02)	(0.02)	(0.02)
Perceptual Online Sociability	No	Yes	Yes
N	2252	2147	1530
Pseudo R-squared	0.255	0.262	0.351
Log pseudolikelihood	-575.02	-547.94	-411.67

Source: The data is from a national telephone survey conducted by Princeton Survey Research Asso-ciates International for the Pew Research Center's Internet & American Life Project from April 17th to May 19th in 2013.
**Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.*
1Involvement in certain online activities = use online banking, or use a social networking site, or download or listen to Podcasts, or use Twitter, or use Reddit.
2Involvement in virtual communication = send or receive email, or use cellphone to send or receive text messages or participate in a video call or video chat.
3Attention to self's online profile = use a search engine or other websites to look up own name or

in-formation.
4Attention to interested persons' online profiles = use the internet or a social networking site to search for information about someone whom the respondent dated or had a relationship within in the past, or are currently dating or are about to meet for a first date, or are interested in dating; or 'follow' or 'friend' someone online because the respondent's friends suggest the respondent might want to date that person.
5Location sharing = Set up social networking accounts so that location is automatically included on posts, or ever include location in posts on social networking sites, or use cellphone to 'check-in' or share location.
6Dating initiative = Use the internet or email or a social networking site to ask someone out on a date, or use a cellphone to ask someone out on a date by calling or texting.

TABLE 4.6 AVERAGE MARGINAL EFFECTS OF DEMOGRAPHIC AND SOCIAL DETERMINANTS OF ONLINE DATING USAGE (DELTA-METHOD STANDARD ERRORS IN PARENTHESES)

Variables	(1)	(2)	(3)
Physical Attributes	No	No	Yes
Geographic Locations	No	No	Yes
Assets and Human Capital	No	No	Yes
Mating History and Preference	No	No	Yes
Behavioural Online Sociability	No	Yes	Yes
Perceptual Online Sociability[1]			
Online dating is a good way to meet people	0.07***	0.02	0.04*
	(0.02)	(0.02)	(0.02)
	-0.06	-0.04	-0.06
	(0.06)	(0.05)	(0.05)
Online dating allows people to find a better match for themselves because they can get to know a lot more people	0.03*	0.01	0.01
	(0.02)	(0.02)	(0.02)
	-0.02	-0.01	0.02
	(0.04)	(0.04)	(0.05)
People who use online dating sites are desperate	-0.05**	-0.03	-0.03
	(0.02)	(0.02)	(0.03)

	-0.09	-0.05	-0.01
	(0.07)	(0.04)	(0.05)
Online dating keeps people from settling down because they al-ways have options for people to date	-0.03	-0.01	-0.02
	(0.02)	(0.02)	(0.02)
	-0.09*	-0.02	-0.07
	(0.05)	(0.05)	(0.06)
N	2147	2147	1530
Pseudo R-squared	0.068	0.262	0.351
Log pseudolikelihood	-692.15	-547.94	-411.67

Source: The data is from a national telephone survey conducted by Princeton Survey Research Asso-ciates International for the Pew Research Center's Internet & American Life Project from April 17th to May 19th in 2013.

**Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.*
1Statistics of each opinion is presented in the following order: "Agree", "Don't know", as com-pared to the omitted group "Disagree".

TABLE 5. AVERAGE MARGINAL EFFECTS OF DEMOGRAPHIC AND SO-CIAL DETERMINANTS OF DEEPER ONLINE DATING USAGE (DELTA-METHOD STANDARD ERRORS IN PARENTHESES)

	(1)	(2)	(3)	(4)	(5)
Variable	Pay to use an OD site/ app	Ask others to help create or review OD profile	Go on a date with someone met through an OD site/app	Have a long-term relation-ship or marriage through an OD site/app	Involve in deeper OD usage (i.e. in-volve in at least one of (1)-(4))
Physical Attributes					
Age ("Over 56 years" omitted)					
18 to 20 years	-0.43**	0.24*	-0.03	-0.15	-0.00
	(0.21)	(0.14)	(0.17)	(0.16)	(0.17)
21 to 35 years	-0.23**	-0.06	-0.15	-0.13	-0.13
	(0.10)	(0.09)	(0.10)	(0.08)	(0.09)
36 to 55 years	-0.12	-0.04	-0.02	-0.15*	-0.01
	(0.10)	(0.09)	(0.09)	(0.08)	(0.09)

Geographic Location					
Community type ("Suburban" omitted)					
Rural	0.16	0.08	0.03	0.16	0.16*
	(0.12)	(0.10)	(0.10)	(0.10)	(0.09)
Urban	0.01	0.00	-0.05	-0.01	-0.03
	(0.08)	(0.07)	(0.07)	(0.07)	(0.06)
Assets and Human Capital					
Household Income ("$40,000 to under $100,000" omitted)					
Less than $20,000	-0.09	0.14	-0.10	0.02	-0.08
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
$20,000 to under $40,000	-0.08	0.01	-0.14*	-0.13	-0.16**
	(0.09)	(0.08)	(0.08)	(0.08)	(0.07)
$100,000 or more	0.15	-0.06	-0.04	-0.08	0.01
	(0.11)	(0.10)	(0.09)	(0.10)	(0.10)
Don't know	0	0.24*	-0.27*	-0.08	-0.19*
	(omitted)	(0.13)	(0.14)	(0.17)	(0.11)
Mating History and Preference					
Sexual orientation ("Heterosexual or straight" omitted)					
Gay or lesbian	-0.21	0.07	-0.16	0.08	-0.03
	(0.19)	(0.14)	(0.12)	(0.12)	(0.11)
Bisexual	0.04	-0.12	0.24*	-0.06	0.18
	(0.13)	(0.13)	(0.13)	(0.12)	(0.14)
Other	0	0	0	0	0
	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
Don't know	0	0	0.09	0	0.05

	(omitted)	(omitted)	(0.21)	(omitted)	(0.18)
Behaivioural Online Sociability					
Involvement in certain online activities[1]	-0.01	-0.20	-0.00	0.06	-0.18
	(0.16)	(0.18)	(0.17)	(0.19)	(0.17)
Attention to interested persons' digital profiles[2]	0.24***	0.11	0.19***	-0.02	0.11*
	(0.08)	(0.08)	(0.07)	(0.09)	(0.06)
Flirting online	-0.15*	0.03	0.08	0.19**	0.11*
	(0.08)	(0.07)	(0.07)	(0.08)	(0.06)
Dating initiative[3]	-0.12	0.13*	0.25***	0.08	0.17**
	(0.09)	(0.07)	(0.07)	(0.08)	(0.07)
Maintenance of long-distance relationship by virtual aid	-0.01	-0.10	-0.02	-0.02	-0.04
	(0.09)	(0.07)	(0.08)	(0.08)	(0.08)
N	190	199	201	199	201
Pseudo R-squared	0.126	0.100	0.203	0.097	0.184
Log pseudo-likelihood	-120.23	-108.48	-117.52	-109.62	-99.40

Source: The data is from a national telephone survey conducted by Princeton Survey Research Associates International for the Pew Research Center's Internet & American Life Project from April 17th to May 19th in 2013.
**Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.*
1Involvement in certain online activities = use online banking, or use a social networking site, or download or listen to Podcasts, or use Twitter, or use Reddit.
2Attention to interested persons' online profiles = use the internet or a social networking site to search for information about someone whom the respondent dated or had a relationship within in the past, or are currently dating or are about to meet for a first date, or are interested in dating; or 'follow' or 'friend' someone online because the respondent's friends suggest the respondent might want to date that person.
3Dating initiative = Use the internet or email or a social networking site to ask someone out on a date, or use a cellphone to ask someone out on a date by calling or texting.

TABLE 6. QUALITY OF LIFE AND FAMILY OF THE NON-SINGLES (ORDERED PROBIT)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(OLS)
Panel A: Meeting Venue as a Non-Determinant of Quality of Life and Family of the Non-singles							
Meeting venue ("Partners first met offline" omitted)							
Partners first met online	0.08	0.02	-0.01	0.05	0.10	0.07	0.06
	(0.18)	(0.17)	(0.17)	(0.18)	(0.18)	(0.19)	(0.17)
	[0.64]	[0.91]	[0.97]	[0.76]	[0.60]	[0.73]	[0.72]
Physical Attributes	No	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Locations	No	No	Yes	Yes	Yes	Yes	Yes
Assets and Human Capital	No	No	No	Yes	Yes	Yes	Yes
Mating History and Preference	No	No	No	No	Yes	Yes	Yes
Behavioural Online Sociability	No	No	No	No	No	Yes	Yes
Perceptual Online Sociability	No	No	No	No	No	Yes	Yes
N	1411	1355	1355	1196	1174	1140	1140
Pseudo R-squared (or R-squared for OLS)	0.000	0.013	0.016	0.056	0.062	0.071	0.188
Log pseudo-likelihood	-2120.03	-2023.04	-2017.47	-1737.56	-1697.06	-1631.35	n/a
Panel B: Online Meeting Venue as a Non-Determinant of Quality of Life and Family of the Non-singles							
Online meeting venue ("Through some other way" omitted)							
Through online dating sites	0.24	0.06	0.06	0.18	0.28	0.10	0.11

	(0.31)	(0.36)	(0.35)	(0.42)	(0.50)	(0.36)	(0.50)
	[0.43]	[0.87]	[0.87]	[0.67]	[0.58]	[0.79]	[0.83]
Physical Attributes	No	Yes	Yes	No	No	No	No
Geographic Locations	No	No	Yes	No	No	No	No
Assets and Human Capital	No	No	No	Yes	Yes	No	Yes
Mating History and Preference	No	No	No	No	Yes	No	Yes
Behavioural Online Sociability	No	No	No	No	No	Yes	No
Perceptual Online Sociability	No	No	No	No	No	Yes	No
N	62	62	62	57	56	62	56
Pseudo R-squared (or R-squared for OLS)	0.004	0.099	0.136	0.113	0.214	0.089	0.471
Log pseudo-likelihood	-111.53	-100.86	-96.79	-90.30	-78.41	-102.03	n/a

Source: The data is from a national telephone survey conducted by Princeton Survey Research Associates International for the Pew Research Center's Internet & American Life Project from April 17th to May 19th in 2013.
Notes: Robust standard errors are in parentheses; p-values are in squared brackets.

TABLE 7. RELATIONSHIP STABILITY OF THE NON-SINGLES

Variable	(1)	(2)	(3)	(4)	(5)
Panel A: Meeting Venue as a Non-Determinant of Quality of Life and Family of the Non-singles					
Meeting venue ("Partners first met offline" omitted)					
Partners first met online	-0.07**	-0.05	-0.04	-0.04	-0.04
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
	[0.03]	[0.15]	[0.21]	[0.25]	[0.28]
Physical Attributes	No	Yes	Yes	Yes	Yes

Geographic Locations	No	No	Yes	Yes	Yes
Assets and Human Capital	No	No	No	Yes	Yes
Mating History and Preference	No	No	No	No	Yes
Constant	0.32***	0.18***	0.18***	0.16***	0.18***
	(0.01)	(0.02)	(0.03)	(0.06)	(0.05)
N	525	507	507	469	462
R-squared	0.007	0.266	0.217	0.214	0.203

Panel B: Online Meeting Venue as a Non-Determinant of Quality of Life and Family of the Non-singles

Online meeting venue ("Through some other way" omitted)					
Through online dating sites	-0.13**	-0.09	-0.13**	-0.15*	-0.08
	(0.06)	(0.06)	(0.07)	(0.08)	(0.07)
	[0.04]	[0.14]	[0.05]	[0.06]	[0.28]
Physical Attributes	No	Yes	No	No	No
Geographic Locations	No	No	Yes	No	No
Assets and Human Capital	No	No	No	Yes	No
Mating History and Preference	No	No	No	No	Yes
Constant	0.33***	0.29***	0.32***	0.35*	0.29***
	(0.06)	(0.07)	(0.10)	(0.18)	(0.08)
N	50	50	50	45	49
R-squared	0.117	0.424	0.131	0.350	0.276

Source: The data is from a national telephone survey conducted by Princeton Survey Research Associates International for the Pew Research Center's Internet & American Life Project from April 17th to May 19th in 2013.
Notes: Robust standard errors are in parentheses; p-values are in squared brackets.
Stability index = (years been in the current relationship)/(age-16)
Relationships under a year and over 12 years are excluded for the validity of the comparison of interest. Reasons are: (1) relationships under a year are too short to evaluate the potential stability; (2) let's say online dating gained popularity roughly in 2001, then relationships longer than 2013-2001=12 years were formed before 2001 when the agents might not have the option of online dating, so those relationships are irrelevant for the comparison of relationship stability.

APPENDIX 1.1 VARIABLE ABSORPTION (DELTA-METHOD STANDARD ERRORS IN PARENTHESES)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Ivolve-ment in certain online activities	Involve-ment in virtual com-mu-nication	Attention to self's digital profile	Attention to in-ter-ested persons' digital profiles	Location sharing	Flirting online	Dating initiative	Mainte-nance of long-dis-tance re-lation-ship by virtual aid
Physical Attributes								
Gender ("Female" omitted)								
Male	0.00	0.03*	0.04	-0.03	-0.01	0.05***	0.10***	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
N	2252	2252	2252	2252	2252	2252	2252	2252
Pseudo R-squared	0.000	0.002	0.001	0.001	0.000	0.004	0.017	0.002
Log pseudolike-lihood	-1307	-1107.67	-1559.46	-1377.10	-1193.58	-1132.26	-1111.24	-613.13
Age ("Over 56 years" omitted)								
18 to 20 years	0.57***	0.45***	0.41***	0.54***	0.27***	0.40***	0.32***	0.17***
	(0.07)	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
21 to 35 years	0.40***	0.35***	0.31***	0.42***	0.24***	0.36***	0.38***	0.20***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
36 to 55 years	0.23***	0.25***	0.20***	0.24***	0.19***	0.19***	0.20***	0.11***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
N	2192	2192	2192	2192	2192	2192	2192	2192
Pseudo R-squared	0.157	0.203	0.056	0.137	0.053	0.140	0.138	0.134
Log pseudolike-lihood	-1074.46	-861.30	-1442.02	-1168.92	-1112.63	-966.63	-963.09	-526.47
Race ("White" omitted)								
Black or Afri-can-American	-0.02	0.01	0.01	0.05	-0.00	0.07**	-0.03	0.01

	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Asian or Pacific Islander	0.15*	0.29**	-0.06	0.04	0.15**	-0.01	-0.07	-0.00
	(0.09)	(0.12)	(0.08)	(0.07)	(0.06)	(0.07)	(0.07)	(0.04)
Mixed race	0.11*	0.08	0.06	0.11*	-0.04	0.09*	0.14***	0.07**
	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.03)
Native American/American Indian	-0.05	-0.02	-0.27***	-0.16	0.02	-0.02	-0.19**	0
	(0.08)	(0.07)	(0.09)	(0.11)	(0.06)	(0.07)	(0.08)	(omitted)
Other (specify)	0.02	-0.00	-0.04	-0.02	0.08	-0.05	-0.02	-0.10*
	(0.08)	(0.07)	(0.08)	(0.08)	(0.06)	(0.07)	(0.07)	(0.06)
Don't know	-0.00	0	-0.01	0.14	-0.03	0.15	-0.16	0
	(0.16)	(omitted)	(0.18)	(0.16)	(0.12)	(0.13)	(0.15)	(omitted)
N	2190	2181	2190	2190	2190	2190	2190	2145
Pseudo R-squared	0.005	0.009	0.005	0.005	0.005	0.007	0.010	0.011
Log pseudolikelihood	-1264.76	-1069.40	-1510.07	-1339.93	-1154.16	-1096.85	-1092.51	-590.50

Assets and Human Capital								
Education ("High school or some col-lege" omitted)								
Less than high school	-0.21***	-0.12***	-0.17***	-0.09*	-0.04	-0.05	-0.07*	-0.02
	(0.03)	(0.03)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)
College degree	0.14***	0.10***	0.17***	0.08***	0.03	0.03	0.03	0.05***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
Postgraduate degree	0.16***	0.16***	0.23***	0.04	0.01	-0.05	-0.03	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Don't know	-0.33**	-0.19*	-0.39*	0	-0.09	0	0	0
	(0.14)	(0.11)	(0.21)	(omitted)	(0.17)	(omitted)	(omitted)	(omitted)
N	2232	2232	2232	2220	2232	2220	2220	2220
Pseudo R-squared	0.059	0.041	0.043	0.010	0.002	0.005	0.005	0.017

Log pseudo-likelihood	-1218.83	-1054.08	-1483.04	-1355.23	-1186.89	-1125.46	-1119.28	-601.49
Household Income ("$40,000 to un-der $100,000" omitted)								
Less than $20,000	-0.21***	-0.12***	-0.17***	-0.09*	-0.04	-0.05	-0.07*	-0.02
	(0.03)	(0.03)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)
$20,000 to under $40,000	0.14***	0.10***	0.17***	0.08***	0.03	0.03	0.03	0.05***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
$100,000 or more	0.16***	0.16***	0.23***	0.04	0.01	-0.05	-0.03	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Don't know	-0.33**	-0.19*	-0.39*	0	-0.09	0	0	0
	(0.14)	(0.11)	(0.21)	(omitted)	(0.17)	(omitted)	(omitted)	(omitted)
N	2232	2232	2232	2220	2232	2220	2220	2220
Pseudo R-squared	0.059	0.041	0.043	0.010	0.002	0.005	0.005	0.017
Log pseudo-likelihood	-1218.83	-1054.08	-1483.04	-1355.23	-1186.89	-1125.46	-1119.28	-601.49
Mating History and Preference								
Relation-ship status ("Married or Co-habited" omitted)								
DSW1, AND non-single	0.01	0.07	0.08	0.20***	0.07	0.17***	0.30***	0.09***
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)
DSW, AND single	-0.22***	-0.16***	-0.18***	-0.05	-0.06**	0.02	-0.08***	-0.03
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Never been married, AND non-single	0.21***	0.24***	0.16***	0.33***	0.13***	0.27***	0.30***	0.13***
	(0.05)	(0.06)	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)

Never been married, AND single	0.14***	0.09***	0.09***	0.21***	0.06**	0.18***	-0.01	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
N	2218	2218	2218	2218	2218	2218	2218	2218
Pseudo R-squared	0.074	0.067	0.025	0.062	0.015	0.065	0.102	0.068
Log pseudo-likelihood	-1190.63	-1014.94	-1500.99	-1281.57	-1161.51	-1053.40	-1009.15	-570.42
Sexual orientation ("Heterosexual or straight" omitted)								
Gay or lesbian	0.21***	0.35***	0.35***	0.32***	0.21***	0.30***	0.14**	0.03
	(0.08)	(0.10)	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)	(0.05)
Bisexual	0.09	0.07	0.14	0.26***	0.17***	0.27***	0.18***	0.09**
	(0.08)	(0.07)	(0.09)	(0.07)	(0.06)	(0.06)	(0.06)	(0.03)
Other	-0.59***	-0.07	0	-0.24	-0.13	-0.10	-0.10	0
	(0.19)	(0.15)	(omitted)	(0.21)	(0.18)	(0.17)	(0.17)	(omitted)
Don't know	-0.41***	-0.27***	-0.45***	-0.31**	-0.40***	0	-0.23*	-0.03
	(0.08)	(0.06)	(0.13)	(0.13)	(0.12)	(omitted)	(0.13)	(0.07)
N	2155	2155	2150	2155	2155	2123	2155	2150
Pseudo R-squared	0.024	0.019	0.015	0.019	0.016	0.024	0.011	0.006
Log pseudo-likelihood	-1199.28	-1019.81	-1473.30	-1316.38	-1137.98	-1073.66	-1092.89	-602.69

Source: The data is from a national telephone survey conducted by Princeton Survey Research Associates International for the Pew Research Cen-ter's Internet & American Life Project from April 17th to May 19th in 2013.
**Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.*
1DSW = Divorced, or Separated, or Widowed.

APPENDIX 1.2 VARIABLE ABSORPTION (DELTA-METHOD STANDARD ERRORS IN PARENTHESES)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Online dating is a good way to meet people - Agree	Online dating is a good way to meet people - Don't know	Online dating allows people to find a better match for themselves because they can get to know a lot more people - Agree	Online dating allows people to find a better match for themselves because they can get to know a lot more people - Don't know	People who use online dating sites are desperate - Agree	People who use online da-ting sites are desperate - Don't know	Online dating keeps people from settling down be-cause they always have op-tions for people to date - Agree	Online dating keeps people from settling down because they always have options for people to date - Don't know
Physical Attributes								
Gender ("Female" omitted)								
Male	0.10***	0.01	0.08***	0.00	0.01	0.06	0.08***	-0.00
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.09)	(0.02)	(0.01)
N	2213	2213	2216	2216	2212	2212	2208	2208
Pseudo R-squared	0.008	0.002	0.001	0.000	0.000	0.001	0.006	0.000
Log pseudolike-lihood	-1502.67	-515.14	-1531.65	-579.96	-1210.91	-483.76	-1399.12	-690.87
Age ("Over 56 years" omitted)								
18 to 20 years	0.16***	0	0.05	-0.09**	0.02	0	0.12**	-0.15***
	(0.05)	(omitted)	(0.06)	(0.04)	(0.05)	(omitted)	(0.05)	(0.05)
21 to 35 years	0.15***	-0.04**	0.11***	-0.06***	-0.06**	-0.07***	0.06**	-0.10***
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
36 to 55 years	0.10***	-0.02	0.07**	-0.03**	-0.04*	-0.04***	0.01	-0.04***
	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)
N	2159	2054	2160	2160	2157	2052	2154	2154
Pseudo R-squared	0.012	0.008	0.005	0.019	0.004	0.034	0.004	0.037
Log pseudolike-lihood	-1464.93	-485.87	-1499.54	-548.67	-1183.70	-428.81	-1378.69	-638.60
Race ("White" omitted)								

Black or African-American	-0.02	-0.01	-0.03	-0.04*	0.08***	-0.03	0.10***	-0.00
	(0.04)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
Asian or Pacific Islander	-0.11	0.03	-0.06	-0.00	0.05	0.02	0.15**	-0.02
	(0.08)	(0.04)	(0.08)	(0.04)	(0.07)	(0.03)	(0.07)	(0.04)
Mixed race	0.00	0.00	-0.07	-0.03	-0.05	0.00	0.09	-0.05
	(0.07)	(0.03)	(0.07)	(0.04)	(0.06)	(0.03)	(0.07)	(0.04)
Native American/American Indian	-0.14	-0.05	0.03	-0.05	0.02	0.00	0.16*	-0.12**
	(0.09)	(0.05)	(0.09)	(0.04)	(0.08)	(0.04)	(0.09)	(0.05)
Other (specify)	-0.13	0.04	-0.14*	-0.05	0.14**	-0.01	0.13*	-0.03
	(0.08)	(0.03)	(0.08)	(0.05)	(0.06)	(0.03)	(0.08)	(0.05)
Don't know	-0.21	0	-0.54***	0	0.39***	0.07	-0.02	0
	(0.18)	(omitted)	(0.16)	(omitted)	(0.13)	(0.06)	(0.17)	(omitted)
N	2153	2144	2157	2148	2156	2156	2148	2139
Pseudo R-squared	0.004	0.005	0.006	0.006	0.013	0.006	0.010	0.005
Log pseudolikelihood	-1464.12	-482.18	-1488.00	-549.72	-1163.18	-457.21	-1355.07	-652.22

Assets and Human Capital

Education ("High school or some col-lege" omitted)								
Less than high school	-0.03	-0.06**	0.02	-0.02	0.04	0.01	0.07*	-0.04
	(0.04)	(0.03)	(0.05)	(0.02)	(0.04)	(0.02)	(0.04)	(0.03)
College degree	0.10***	-0.02*	0.07**	-0.01	-0.10***	-0.02	-0.09***	-0.01
	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)
Postgraduate degree	0.12***	0.03*	0.02	0.01	-0.16***	-0.01	-0.19***	-0.00
	(0.04)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)
Don't know	-0.14	0.06	-0.15	0.10	-0.04	0.16***	-0.51***	0.15**
	(0.16)	(0.07)	(0.17)	(0.07)	(0.13)	(0.05)	(0.17)	(0.07)
N	2196	2196	2197	2197	2193	2193	2190	2190

Pseudo R-squared	0.009	0.017	0.003	0.004	0.020	0.015	0.020	0.005
Log pseudo-likelihood	-1490.53	-504.78	-1524.26	-566.18	-1177.47	-465.10	-1370.52	-677.95
Household Income ("$40,000 to un-der $100,000" omitted)								
Less than $20,000	-0.14***	-0.00	-0.14***	0.00	0.15***	0.01	0.07**	0.00
	(0.03)	(0.02)	(0.04)	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)
$20,000 to under $40,000	-0.04	-0.02	-0.08**	0.00	0.09***	0.00	0.09***	-0.01
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)
$100,000 or more	0.03	0.00	-0.04	0.01	-0.05	-0.03	-0.09**	-0.01
	(0.04)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)
Don't know	-0.23***	0.03	-0.22***	0.07***	0.07	0.09***	0.08	0.08***
	(0.05)	(0.02)	(0.05)	(0.02)	(0.04)	(0.02)	(0.05)	(0.02)
N	1927	1927	1933	1933	1930	1930	1929	1929
Pseudo R-squared	0.019	0.007	0.013	0.014	0.025	0.061	0.013	0.013
Log pseudo-likelihood	-1313.47	-420.87	-1357.37	-471.92	-1044.86	-363.23	-1247.73	-562.74
Mating History and Preference								
Relation-ship status ("Married or Co-habited" omitted)								
DSW1, AND non-single	0.01	-0.02	0.02	-0.01	0.12**	-0.03	0.20***	-0.03
	(0.06)	(0.03)	(0.06)	(0.03)	(0.05)	(0.03)	(0.06)	(0.04)
DSW, AND single	-0.08**	0.02*	-0.05	0.02	0.09***	0.04***	0.04	0.05***
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.02)
Never been married, AND non-single	0.12**	-0.03	0.14***	-0.07*	0.04	-0.09**	0.04	-0.07**

	(0.05)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.03)
Never been married, AND single	0.02	-0.05**	-0.02	-0.04**	0.04	-0.05***	0.08***	-0.03
	(0.03)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
N	2182	2182	2185	2185	2180	2180	2178	2178
Pseudo R-squared	0.006	0.018	0.005	0.015	0.008	0.045	0.009	0.020
Log pseudo-likelihood	-1483.17	-489.82	-1511.33	-554.78	-1184.50	-449.75	-138.67	-655.45
Sexual orientation ("Heterosexual or straight" omitted)								
Gay or lesbian	0.21**	-0.08*	0.28***	0	-0.19*	-0.06	-0.02	-0.05
	(0.10)	(0.05)	(0.09)	(omitted)	(0.10)	(0.04)	(0.09)	(0.05)
Bisexual	0.08	0	0.16*	0	-0.14*	-0.05	0.02	-0.11**
	(0.08)	(omitted)	(0.09)	(omitted)	(0.08)	(0.03)	(0.08)	(0.05)
Other	0.12	0	0.06	0.04	0.39**	0.07	0.11	0
	(0.29)	(omitted)	(0.27)	(0.08)	(0.18)	(0.07)	(0.25)	(omitted)
Don't know	-0.09	0.05	-0.19**	0.01	-0.05	0.07***	-0.18*	0.05
	(0.10)	(0.04)	(0.10)	(0.04)	(0.08)	(0.03)	(0.10)	(0.04)
N	2125	2079	2126	2049	2123	2123	2122	2118
Pseudo R-squared	0.003	0.005	0.007	0.000	0.006	0.014	0.002	0.005
Log pseudo-likelihood	-1447.75	-467.47	-1469.11	-526.89	-1155.50	-417.58	-1354.12	-646.05

Source: The data is from a national telephone survey conducted by Princeton Survey Research Associates International for the Pew Research Cen-ter's Internet & American Life Project from April 17th to May 19th in 2013.
**Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.*
1DSW = Divorced, or Separated, or Widowed.

Authors

TAYLOR R CUMING

ECONOMICS

Taylor grew up in Calgary before moving to Vancouver to pursue his Economics degree at UBC. Part of the graduating class of 2017, Taylor has been working as a transfer pricing analyst at KPMG in Vancouver since then. Taylor became interested in economics and the financial markets at a young age through observing his father's involvement in the stock market. Furthermore, he was inspired to select the 2008 US financial crisis as a research topic after witnessing the economic devastation of the US financial market's crash and hearing of Donald Trump's actions to repeal regulations put in place by Barack Obama in 2010, which aimed to prevent future financial crises by similar causes.

JACOB CUTTS

ECONOMICS
INTERNATIONAL RELATIONS

Jacob Cutts is a fourth year student in Economics and International Relations. He is in his final year of study at UBC, and intends to continue on to a Master's program in International Affairs. His interests lie at the intersection of international relations and economics, and he hopes to pursue a professional career that integrates both fields. He has a regional interest in the the United States, and is an avid follower of American politics. Having worked for both the Canadian and US Federal Governments, he is interested in cross-border economic relations. This led to his choice of topic for this paper, as it is one of the areas of continuous disagreement between otherwise close allies.

SARAYU KANTHETI

ECONOMICS

Sarayu's undergraduate studies involve a major in Economics with a minor in Commerce. This combination has given her a strong theoretical foundation in economic models, with an exposure to the workings of commerce through courses in corporate finance, accounting and marketing. She particularly enjoyed Econometrics, as it provided the tools to address socio-economic challenges. As a result, the focus of her research was to examine the relationship between access to healthcare and GDP growth in the long-run growth accounting model using panel data. In the future, Sarayu hopes to use her knowledge of economics as a foundation to work in investment banking and private equity.

NATASHA LAPONCE

ECONOMICS

Natasha Laponce completed her B.A. in 2017 with a major in Economics and a minor in Commerce. During her time at UBC she was involved with various internationally focused initiatives and worked at the Global Lounge as a Community Animator and Programming Committee Chair. In her final year she took her interest in global affairs abroad, studying at the Free University of Berlin and at the University of Edinburgh. Since graduating from UBC, Natasha has been working as an Accounting Associate at a financial tech company in Vancouver but will be heading to Ottawa this May to start a new position as Research Assistant with the Bank of Canada's Monetary Policy Report Division. In the future, Natasha plans to pursue a graduate degree in a policy-related field and continue to develop her burgeoning interests in food policy, public health, and fitness.

LINDSEY OGLIVIE

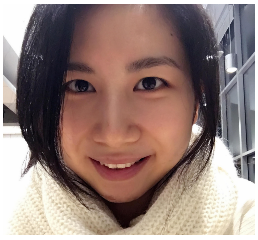
ECONOMICS

Lindsey is a graduating fifth year Economics student with a minor in Commerce. This summer she will be completing an internship in Brussels with the European Commission's Directorate-General for Education, Youth, Sport and Culture before entering full-time employment in the fall. In the future, she hopes to go back to school to attain an MBA or law degree. Lindsey's research was inspired by her international service learning trip to Uganda last summer, during which she learned that the country, which is relatively poor by global standards, has one of the best refugee policies in the world. This revelation made her question the far stricter refugee policies of relatively wealthy nations that are seemingly more capable of hosting refugees and lead her to research the effect of refugees on economic growth across countries. She hopes her findings improve the general understanding of the effect of refugees on host economies.

ANDREW SHIELDS

HONOURS ECONOMICS

Andrew Shields graduated from the UBC Honours Economics program in 2017 with a minor in Psychology. He is from Marin County, California and came up to UBC in search of better skiing and craft beer. He became interested in behavioural economics after being hired as a research assistant by his mentor and fellow ski sender, Chuck Howard, a PhD student at the Sauder School of Business. He has since started researching for Professor Dale Griffin and is examining the intersection between risk analysis and monetary and medical decision making. He has also worked at a consulting firm in San Francisco and has recently transitioned into a business development role at a data analyst start-up. In his spare time, he works on his tattoo removal start-up, and un-ironically drinks cold brew nitro coffees.



SIBYL XUEMIN SONG

HONOURS ECONOMICS

Sibyl Xuemin Song is an Economics student at Vancouver School of Economics (VSE) at the University of British Columbia (UBC), who holds a Bachelor of Arts degree in Economics with honours from UBC, and is currently working toward a Master of Arts degree in Economics at VSE. She worked as a research assistant with Professor Michael Peters at UBC on applied microeconomics, participated in the Bank of Canada Governor's Challenge as a member of UBC team, presented her honours thesis in the Canadian Economics Association 51th Annual Conference as one of the 11 selected undergraduate students across Canada, and won a Bank of Canada Student Award for best poster presentation. She got PhD admissions in economics from University of Toronto, Queen's University, and McGill University, and chose to pursue a PhD degree at the University of Toronto after graduation from the MA program at UBC.

IONA Team

EDITOR-IN-CHIEF

Bachelor of Arts *Double Major in Economics and Canadian Studies*

MARIAM NASSER

Mariam Nasser is currently in her fifth and final year of her undergraduate degree, with a double major in Economics and Canadian Studies. Having worked as both a Junior and Senior Editor for the IONA Journal of Economics, she has been with the journal since its inaugural year. Through her work with the journal, she hopes to again showcase new and unique economic research while highlighting its relevance to all the issues in today's world. Motivated by a strong interest in public economics and Canadian governmental policy, she hopes to pursue graduate school and work for the Government of Canada in the future.

MANAGING EDITOR

Bachelor of Arts *Major in Economics*

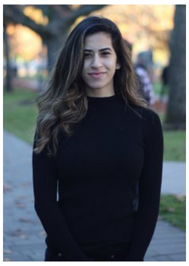
KAVYA DINESH

Kavya is a third year student pursuing a major in Economics and a minor in Sociology. Her primary interest is in welfare economics and understanding how different players in the economy benefit from various government policies. She plans on pursing a graduate degree in Economics or Business Administration after graduation.

Bachelor of Arts

Major in Economics

LINA ERAIKAT



Lina is a fourth year Economics major with a minor in International Relations. She has an interest in economic development and sustainability. Lina hopes to learn more about the role that education plays in economic development in developing societies. She joined the IONA Journal of Economics to learn more about theories of economic development and their application to the real world.

Bachelor of International Economics

Major in International Economics

LILY SUH

Lily is a second year student in the Bachelor of International Economics program. She has had experience with introductory graphic design, cover designs, and mural designs. Her passions lie in both art and economics. She is currently interested in trade policy and its effect on North America. She hopes to express the heavy topic of economics accurately through the use of semiotics and visual art.

Bachelor of International Economics

Major in International Economics

AURORA WANG

Aurora is a fourth year student in the Bachelor of International Economics program, with a minor in Psychology. Her interest resides within the field of international banking and development economics. She is interested in the development of economic policies that allow governments to regulate and monitor cryptocurrencies in the current economic environment.

SENIOR EDITORS

Bachelor of Arts *Combined Major in Economics and Mathematics*

SARA CORTES

Sara is in her third year of a combined a major in Economics and Mathematics, with a minor in International Relations. She has a keen interest in the global political economy, especially in the dynamics of economic growth and development. Her motivation for joining the IONA Journal of Economics is to further expand her knowledge of current economic affairs and join like-minded individuals. After her undergraduate degree, she hopes to pursue a Juris Doctor in Immigration Law.

Bachelor of Arts *Major in Economics*

SARAYU KANTHETI

Sarayu is a fourth year student majoring in Economics with a minor in Commerce. She is passionate about economics and the manner in which its concepts manifest themselves into business and financial markets. Her long-term objective is to use economics as a bridge between the financial world and the needs of people, especially in the development space. As a Senior Editor for the IONA Journal of Economics, she hopes to contribute to the important practice of information sharing and the synthesis of popular opinions.

Bachelor of Arts *Double Major in Honours Economics and International Relations*

PETER KI

Peter is a fifth year honours Economics and International Relations student who has a keen interest in development economics and social welfare. He is also passionate about the idea of entrepreneurship as a means of improving people's lives, whether in a micro or macro sense. After graduation, Peter plans to pursue an MA in International Affairs or an MPA with a heavier focus on economics.

Bachelor of Arts *Double Major in Economics and Political Science*

NICHOLAS MAI

Nicholas is a fourth year major in Economics and Political Science, with a minor in Food and Resource Economics. His primary interests are in trade economics, specifically how multilateral free trade agreements and trade blocs develop in a globalized economy. He is also interested in sustainable agriculture, aquaculture, and resource extraction. After graduation, Nicholas wants to pursue a graduate degree.

Bachelor of Arts *Combined Major in Economics and Political Science*

LAUREN SEIBT

Lauren is a fourth year student pursuing a combined major in Economics and Political Science and a minor in Commerce. With a primary interest in international development, Lauren is always searching for ways for the global economy to tend to the needs of those at the bottom as much as it helps those at the top. She is particularly interested in using tools of micro-finance to assist in the development of undeveloped and developing countries without the use of government intervention.

Bachelor of Arts *Major in Economics*

MINA SIDHU

Mina is a third year student pursuing a major in Economics and a minor in Commerce. With deep interests in financial and welfare economics, Mina is interested in learning about the applications of monetary and fiscal policy in a way that can improve the lives of the lower and middle class. She is also interested in the topic of economic advancement and its different paths in developing countries. Upon graduation, Mina hopes to work in central banking.

Bachelor of Arts — *Combined Major in Economics and Mathematics*

MIKAEL GASTER

Mikhael is a third year student pursuing a combined major in Economics and Mathematics. Mikhael was raised near Washington, D.C., where he witnessed inequality, poverty, and other social issues first-hand. He sees economics as a set of tools which can be used to quantify, understand, and correct the world's patterns and problems. Some specific areas of interest include inequality, development, and automation. After graduation, Mikhael hopes to pursue graduate studies and travel the world.

Bachelor of International Economics — *Major in International Economics*

RAGINI JAIN

Ragini is a second year student in the Bachelor of International Economics program, whose interest in economics stems from its countless applications into prevalent social issues. Growing up in India and Qatar, she found economics to be an important tool to explain and form solutions for the social injustices and problems regarding welfare and inequality that she witnessed regularly. She joined the IONA Journal of Economics to learn more about this field, as well as to learn more about writing and editing in an academic context.

Bachelor of International Economics — *Major in International Economics*

MATTHIAS LEUPRECHT

Matthias is a first year student in the Bachelor of International Economics program. He is studying economics to learn more about how the world works and to try and understand how economics can help solve some of the most pressing issues facing our world today. Matthias joined the IONA Journal of Economics to be exposed to the talented group of young economists at the Vancouver School of Economics who are conducting research that is shaping the issues of discussion for the 21st century. In the future, Matthias hopes to pursue a career in public policy.

Bachelor of International Economics

Major in International Economics

MANIKA MARWAH

Manika is a second year student in the Bachelor of International Economics program. Her interest in economics stems from a desire to understand the basis behind the functioning of our societies and world today. Her areas of interest are public policy and corporate finance. She joined the IONA Journal of Economics due to her interest in writing and research, as well as for the exposure to new ideas within her fields of interest.

Bachelor of International Economics

Major in International Economics

SARAH NEUBAER

Sarah is a fourth year student in the Bachelor of International Economics program. Sarah became interested in economics after living in countries like Nigeria and Brazil, where she realized how much inequality there is in the world. Sarah decided that she wanted to be a part of an effort to ensure a more equal playing field for all of humanity and that all their basic needs are met: essentially allocating resources efficiently. Therefore, Sarah is interested in developmental economics. In the future, she hopes to work for an NGO or do something in advocacy journalism.

Bachelor of International Economics

Major in International Economics

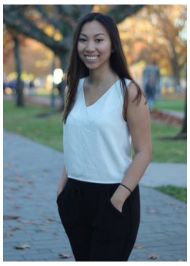
ASHINTYA SINGH

Ashintya is currently a second year student in the Bachelor of International Economics program. His primary interests are in the fields of international development and global politics. He became particularly fascinated by the two after studying them at LSE over the summer. He joined the IONA Journal of Economics because he enjoys reading and writing, especially about issues regarding economics. After graduation, he is planning on pursuing a Master's degree in International Development.

Bachelor of Arts

Major in Economics

CHRISTINE WU



Christine is a third year student majoring in Economics. After travelling to India on a service trip, she was compelled to turn to economics to understand the underlying issues of poverty. She is particularly interested in monetary policy and microeconomics. After graduation, Christine plans to pursue a Master's degree in Economics or Public Policy.

Sponsors

Vancouver School of Economics

The Vancouver School of Economics (VSE) is a part of the University of British Columbia, and it is one of the top 25 schools for Economics in the world. It offers a Bachelors in Economics and International Economics, in addition to it's Masters and Doctoral Programs.

Vancouver School of Economics Undergraduate Society

The Vancouver School of Economics Undergraduate Society (VSEUS) is a student run body that supports student initiatives in the field of Economics, at UBC. It represents the students of the Economics and International Economics departments within the governing bodies of UBC.

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