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An Integration of a Currency Portfolio Project to Teach International Finance

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ABSTRACT

We explore the integration of a currency portfolio project for teaching an international finance course using the simulated trading platform OANDA. The application of this platform enables students, the instructor, and the School of Business to benefit from this experiential learning method. Under the expectation of incorporating the real FX trading platform into the class, finance students gain hands-on real business world currency trading experiences while the instructor assists students in achieving qualified learning outcomes. The creation of a practical currency project is also meaningful for the School of Business to meet the AACSB requirements and maintain credential standards.

Introduction

Adapting new technology that has been widely used by investment practitioners into the classroom is among the many innovative efforts to make finance education relevant. Among these efforts, Li and Wang (2017) explore how to incorporate the Bloomberg Professional System in teaching corporate finance subjects. Lei and Li (2012) establish how the Bloomberg works in an investment/portfolio management class, and, Coe et al. (2007) demonstrate how the Bloomberg system helps in developing a market microstructure and trading course. However, there is little discussion about how similar trading systems can be useful in an international finance class. In this paper, we propose an experiential learning method for the upper-level undergraduate finance students or graduate students, and discuss how to integrate a practical currency-trading project using OANDA to teach key international finance topics. We believe that this project helps students better understand the foreign exchange markets and improve their quantitative and qualitative analysis skills.

OANDA is a simulated trading platform that offers real-time leveraged trading, hedging, and data services on foreign exchange (Forex or FX) markets. It can be accessed directly from its website www.oanda.com. OANDA is free for students to open a demo account and trade FX on laptops or download this platform for use in a mobile system. The free demo account is particularly beneficial for schools that have tight budget controls or students that have limited financial means. Use of OANDA can also be extended to other advanced-level business courses, such as a portfolio management course that covers portfolios with alternative asset classes, or student activities including investment competitions and student-managed investment funds.

The application of OANDA in international finance courses enables instructors and students to use real-world trading information to achieve high-quality learning outcomes. It can help students develop real FX market trading skills and experiences and can improve students' analytical and critical thinking skills and aptitudes for using information technology. These goals are allied with the Association to Advance Collegiate Schools of Business's (AACSB) standards and learning goals (AACSB International 2018).

The rest of the paper is organized as follows. In the next section, we review the literature. The third section provides details of the currency research and trading project using the OANDA platform, including the pedagogical benefits this project can bring. The fourth section concludes the article.

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Literature Review

Finance instructors have long recognized the importance of internationalizing the business and finance curriculum. Although different business programs may have dissimilar preferences in the coverage of international finance components, how FX markets work and how to manage exchange rate risks are essential topics that must be included in the design of an international finance course (Desai 2006; Manuel and Shooshtari 1996).

To improve student understanding regarding the dynamics in the financial markets, many instructors use simulations. Simulations as a form of active learning help students to apply and therefore to better understand the definitions and concepts from textbooks. Butler and Kwok (1994) designed a foreign exchange market simulation game to involve students in the operation of the market and help students gain a "hands on feel." Marshall (2004) uses an in-class simulation to teach triangular and covered interest arbitrage and help students identify and then make decisions on how to act on arbitrage opportunities in FX markets. Not satisfied with the pencil and paper system in Butler and Kwok (1994), Chou and Liu (2013) developed a web-based trading system to replicate electronic brokerage FX markets, where students could create a trading strategy and set the "market" price. However, while these endeavors help to improve student understanding about FX markets, they are mainly simplified systems that do not allow students to grasp the complexity and depth of financial markets.

Among the effort of using real market data and environment to explain international economics and finance subjects, Holowczak (2007) introduces Excel modeling based on real-time data from Reuters to examine key concepts such as forward rates, bid/ask spreads, and triangular arbitrage. However, the high subscription costs may make Bloomberg or Reuters services unaffordable for many business schools and students. Therefore, systems such as OANDA is attractive to finance instructors as a free alternative trading system that employs real-time data and real market settings. Seiver (2013) addresses the application of OANDA in international business finance courses and discusses the pedagogical benefits of using the OANDA platform. Nevertheless, his research targets a group of general business students and lacks detailed technical instruction for students and faculty on conducting actual FX trading.

In this article, we guide instructors through the process of conducting an OANDA currency portfolio project in an international finance course. We believe our paper contributes to the literature in several significant ways: first, our simulation project functions on a readily available free online trading system that does not require expensive data subscriptions. This allows faculty and students with various levels of budgets to engage in productive experiential learning. Second, we provide a detailed introduction on how to integrate OANDA in classrooms and address the challenges that instructors and students may face in the adaption of this project. This project is suitable for a more advanced group of students, but it can also be easily modified for an introductory level class. In addition, we outline several pedagogical benefits from this experiential learning exercise for business school students.

Currency Trading Project

At many universities, international finance is a required course for junior or senior finance majors. Main topics covered in the course include the foreign exchange market, determination of exchange rates, international banking, international capital markets, international investments, and international corporate finance. The general learning goals include improving students' skills in critical thinking, problem solving, decision-making, teamwork, and the use of technology.

Students taking our international finance course are required to work in groups and complete an OANDA-based project. The specific learning goals for the project are to get students to gain a deeper understanding of the foreign exchange market, currency quotes, communication systems, and currency forecasting techniques discussed in the international finance textbook by Bekaert and Hodrick (2012). The analytical and trading skills students learn from this project can also benefit their understanding and practicing in other financial markets such as the stock or bond markets. The written report of the project counts for 20% of students' grades. A sample of the project instructions is provided in Appendix A.

Pedagogical Benefits

For the purpose of maximizing pedagogical benefits, we designed the project to meet the following learning goals:

Learning Goal 1: Improve students' analytical and problem-solving skills.

With the real-market exchange rate quotes and news on the FX market provided by the OANDA platform, students observe and analyze exchange rate movement patterns in the computer lab or on their own electronic devices. They are then faced with real-life questions such as "Why does the dollar rise by 24% over the euro in one year?," "What causes the graph of the USD/ZAR to look like a bow in April?," or "How much leverage should I use to maximize the portfolio returns?." Attempts to answer these questions lead students to apply theories and principles about exchange rate determination.

Learning Goal 2: Improve students' decision-making skills.

Experiential learning is a great way for students to understand the real business world. OANDA provides the demo account for students to trade in FX markets without having to use real money, while still enabling them to gain the same trading experiences. In this project, students have to make decisions on the currency pairs they want to trade and how to trade them. They have to justify their decisions with in-depth analysis and judgment.

Learning Goal 3: Improve students' skills in using finance technology.

According to a recent article on from Reuters (Irrera 2017), financial technology, or "fintech," can help students' careers and many leading business schools design their curricula to embrace trends in finance technology. Compared to a traditional pencil-and-pen approach, integrating OANDA into the classroom helps students gain familiarity with the latest finance technology, including the trading platforms and access to information and data.

In this currency portfolio project, students are required to apply the data analysis tool in Excel to conduct descriptive and regression analysis using historical data downloaded from OANDA. Students also practice the Solver function to find optimal weights of the currency portfolio.

Learning Goal 4: Improve students' business writing and communication skills.

Students are required to submit a written report to summarize their analysis, decisions, and trading performance. Grades are based on the quality of their writing and effective collaboration with other students in the group. Therefore, this is an excellent opportunity for students to practice their business and professional writing skills.

Analysis before Placing an Order

To start, students are instructed to open a demo account on OANDA. The demo account is free and gives students full access to trading and $100,000 of virtual currency in US dollars. In the demo account, students create a currency portfolio by choosing different currency pairs in the FX market. We recommend students start tracking the movements of several major currency pairs, such as USD/CAD, USD/JPY, and GBP/USD, and then apply quantitative and qualitative methods to select which currency pairs they want to add to their portfolios.

Both fundamental and technical analyses are required in this project. For the fundamental analysis, students should consider the impact of many factors such as government policies, interest rates, inflation rates, and employment rates on the movements of exchange rates. To search for news relative to the fundamental analysis at OANDA, students can filter the search criteria under Dow Jones and MarketPulse. For example, if instructors wants students to search the news regarding the movements of Canadian dollars, they can guide students to click the button "NEWS" in the FX trading practice frame and then type the word "CAD." Students are able to find news about the movement of Canadian dollars in this way. The search results are shown in Figure 1. Thus, instructors can show students news releases on Dow Jones or MarketPulse and discuss how the macroeconomic data or news can affect the movements of exchange rate. An alternative way to access news is to choose the buttons "OANDA MarketPulse" and "Economic Analysis" in the FX-trade practice frame. OANDA also provides direct analysis resources through MarketPulse and Economic Analysis to show the macroeconomic analysis including the investment opinions from other leading financial media.

For the fundamental analysis part, the instructor can ask students to address the following questions in their reports:

1. From a perspective of the global market, what is the phase of the economic cycle for the current economic situation and how does it perform?

2. Do the political or technological factors impact the FX market? If yes, how?

3. Is the unemployment rate, inflation rate, or interest rate causing a change in the currency movement patterns?

Figure 1. Checking News at OANDA
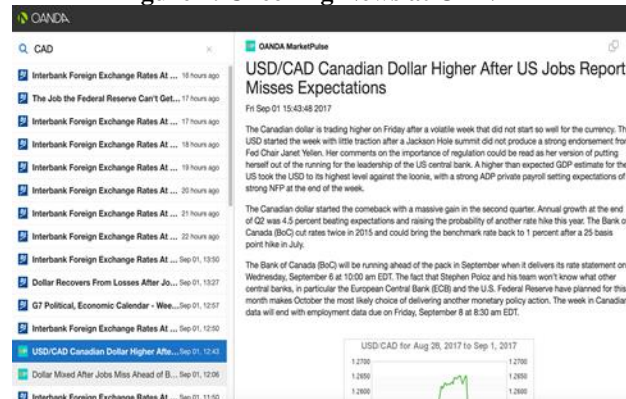
The technical or quantitative analysis allows students to use chartism, filter rules, regression analysis, or non-linear analysis to identify investment opportunities (Bekaert and Hodrick 2012). In this project, students are able to apply the knowledge to generate the charts of selected currency pairs, create the correlation matrix, and then construct a regression model to show the currency portfolio performance. The lower right side in Figure 2 presents the chart of FX rates in five days for the tendency movements of currency pairs. Instructors can guide students through these different types of charts to discuss how the support or resistance levels appear and how the moving-average line can be interpreted as a buy, sell, or hold signal.

Figure 2. Main Page of FX Trade Platform
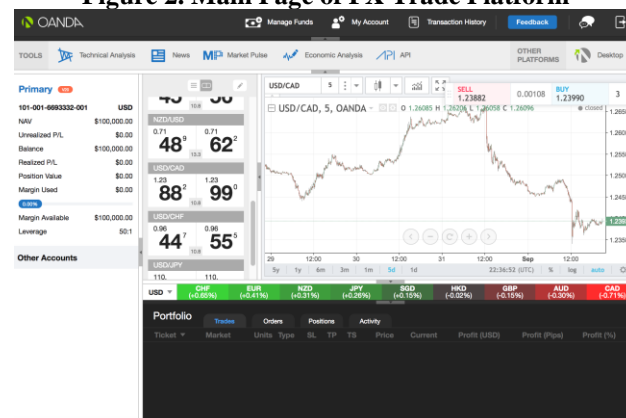
After downloading the historical FX rates into spreadsheets, students can conduct the correlation and regression analyses to link the exchange rate changes to the macroeconomic data of inflation rate or interest rate differentials. Students also can use the technical analysis resource at OANDA for analyzing and discussing how the potential trading opportunity measures against past performance. Therefore, with the application of the fundamental and technical analyses, students are able to use their own judgment to predict the movements of exchange rates.

For the technical analysis part, the instructor can ask students to address the following questions in their reports:

1. How do the charts of currency pairs in your portfolio look? Can you identify the support level and resistance level from the charts?

2. What does the correlation matrix tell you about the relationship among currency pairs?

3. Do you think that the performance of the currency portfolio could be improved by selecting the different currency pairs?

Instructors can require students to generate the pool of currency pairs based on the statistical correlations among these sets. Lower correlations among currency pairs indicate diversification potential. The currency portfolio, just like a bond or equity portfolio, needs to diversify investment risk. Students can select more than one currency pair in the project so they can learn how portfolio theory applies in the currency market. They should analyze the correlation matrix and then select the less correlated currency pairs in the portfolio. The positive value in their expected portfolio return interprets the trading profits and the negative return means a trading loss.

Placing Orders

Instructors can show students how FX traders use live quotes to conduct currency trading. OANDA updates real-time FX bid-ask quotes every five seconds. Students can check the quote panel or quote list on the FX trading platform. This project requires student use the buy and hold investment strategy. In consideration of other investment strategies, students can also customize the panel or list for their portfolio. Figure 3 shows that the currency pairs can be moved or added from the pool on the left side to the quote list on the right side. The customized quote panel or list is shown on the main page of the trading platform after a brief period. It is a convenient way for students to track the rates of currency pairs.

Figure 3. Customizing Quotes List
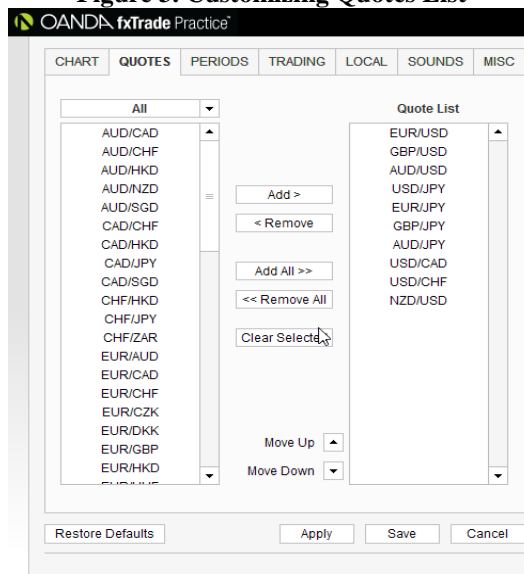
Each group is asked to use the 100,000 units of virtual funds to trade on the OANDA platform. Figure 4 shows the window on OANDA that students can access to place buy or sell orders. With this window, the instructor can explain trading terminology such as market order, limit order, and stop loss order. It presents the current market quote executed when the student submitted the order. Limit orders are only executed when the market rate reaches a specified price in the future. Furthermore, instructors can guide students to use Stop Loss and Take Profit functions in the buy and sell window. The open position could be cancelled by these opposite trading instructions on the system. Students may set the maximum loss they can afford and then set the Stop Loss level to avoid further unfavorable movements. A Stop Loss function protects students from potential loss. These functions help students reduce the loss if a price moves in an unfavorable direction.

Instructors can also discuss the risk of using leverage. When students place an order, they can use the leverage from 1:10 to 1:50. This provides an opportunity for them to understand the idea that higher leverage can enhance gains, but it also represents more risk for the investment. The instructor should give students clear guidelines about what type of order they are allowed to place. For our project, students can place either a market order or a limit order, and they make decisions on predicting the short-term movements of currency

Figure 4. Placing Orders
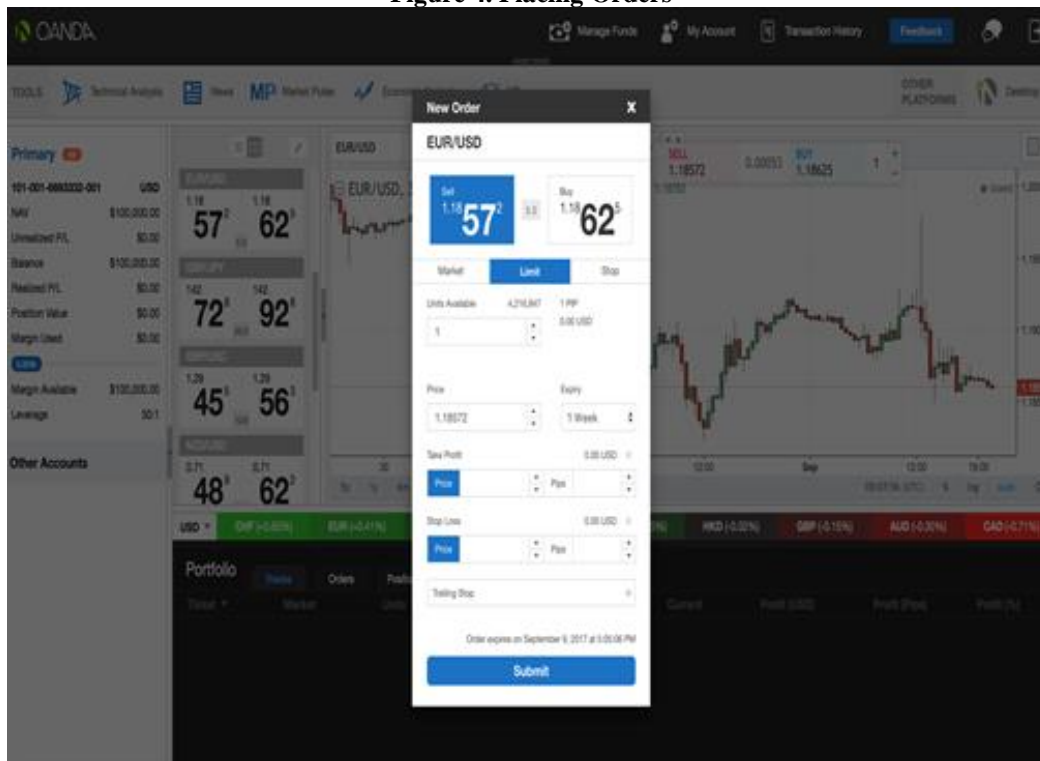
pairs. In addition, they decide about the amount of the leverage that can be applied in their investment on the basis of their own risk preference.

Tracking Orders

Instructors can let students place a buy or sell order and then hold it for several days or weeks before closing the position. The account summary on the main page of the FX trading platform shows the overall investment performance. Figure 5 shows the account summary on the cellphone-trading platform. Unrealized Profit and Loss (P&L) indicates the gains or losses for open positions and Realized P&L shows the gains or losses for closed positions that actually affect the account balance. Students can also track the type of order placed, current market quote, and profit in dollar or percentage terms, and adjust or rebalance their portfolios.

Figure 5. Account Performance

Wrapping up the Project

Following the trading procedure of this currency project, students must submit a written report to summarize their trading performance. In the report, they should describe the quantitative and qualitative analyses they conducted and how these analyses helped make investment decisions. They should also explain the models used in their analyses, including the assumptions and conclusions made in applying the models. Students can summarize trading results and explain any difference between expected results and actual profits or losses.

In this project, in order to inspire students to enhance portfolio efficiency, we give students bonus points if they earn a positive return on their portfolios. In addition, to encourage student communication and collaboration within their groups, the grade is partially based on peer evaluation from group members.

Anecdotal evidence shows that this project improves students' skills in critical analysis and research, and it provides opportunities for students to improve their business communication skills. A group of students' works was selected for presentation in our university's Undergraduate Research Symposium. Both reviewers and audience members of the symposium highly commended the research these students demonstrated. Appendix B shows additional evidence, including student comments, on what they came to understand from the currency project.

Conclusion

In this article, we present a currency-trading project incorporating the OANDA simulation platform that provides a direct trading experience for students in international finance classes. In conducting this kind of experimental currency-trading project, students learn to analyze the currency market, place a selected type of trading order, and track portfolio performance.

This currency-trading project helps finance instructors and students achieve teaching and learning outcomes using a user-friendly platform that is very popular among finance professionals. Those outcomes meet the AACSB's standards and goals, including the integration of the academic and professional engagement and the application of knowledge, information technology, and analytical thinking. Schools of business should benefit from these achievements in their applications for maintenance of AACSB accreditation.

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APPENDIX A. SAMPLE CURRENCY PORTFOLIO PROJECT

International Finance, OANDA Project
Spring 2015

The final project is group work. The purpose of the project is to enhance student understanding and practical trading skills in the currency market using knowledge learned in the class. Students are going to build a currency portfolio using the OANDA.

This project is worth 60 total points.
Please follow the instructions below.
1. Generate an OANDA demo account to create your portfolio.
2. Select three of the major currency pairs for your portfolio.
3. Collect the raw data and relative information from OANDA.
4. For historical exchange rate data, the size of the dataset should be greater than 30 observations.
5. Use a "buy hold" investment strategy: place the orders on or before March 25, 11:00am, sell these orders on or after May 4, 11:00am and hold the positions between March 25, 11:00am and May 4, 11:00am, 2015.
6. Use Excel to conduct the data analysis (draw a graph to identify the trend movement of exchange rates and use the data analysis table under ADDIN function to run the correlation matrix and general data descriptive).
7. Write an OANDA report using both qualitative and quantitative research methods.
8. Use the equal weighted average method in your portfolio.
9. You are required to use both Excel and Word to present this currency project.
10. Write an essay for this project in Word of no less than five pages (APA format required).

Grading Criteria:

Quantitative analysis	20 points
Qualitative analysis	20 points
Introduction and Conclusion	10 points
Fill out the form of the peer evaluation group work	10 points
Total	60 points
Bonus: open for groups gaining positive portfolio returns	10 points

Submit the completed project to Dropbox by May 15, 11:00am, 2015.

APPENDIX B. SAMPLE STUDENTS' REPORTS

- The goal for our currency portfolio project was to enhance our understanding of trading skills and the currency market. We built a portfolio that we believed would take advantage of currencies with excellent market returns and good correlations. We were able to do this through many different analysis work and the historical data from OANDA.
- From researching the financial news and analysts' reports at OANDA, we can see that in the last year, the US Dollar is up 23.88% over the Euro, it's up 11.45% over the British Pound, and it's up 17.60% over the Japanese Yen. The dollar is rising recently due to a relatively strong U.S. economy, improving trade balance, improving budget deficit, and higher interest rates relative to developed alternatives.
- Through doing research on OANDA, we found related information that stated that the best foreign currencies to invest in were foreign currencies with higher interest rates than the domestic currency you currently had. Our portfolio consisted of the USD/CAD, USD/JPY, and the CHF/JPY currency pairs. We had an expected return of 12.48% and a Sharpe ratio of 1.26.
- I presented the spreadsheet work from this project to the employer during an interview, and they were very impressed.

Color-Coding Variables in Time Value of Money Instruction

Daria Newfeld[1]

ABSTRACT

This study examines whether or not color-coding the variables involved in time value of money (TVM) calculations can improve student-learning outcomes. Students with little to no previous instruction in TVM were divided into two groups. One group received instruction with variables (PV, FV, PMT, n & r) appearing in different colors. The other group received identical instruction but with all variables appearing in black font. The results of the end of study quiz scores show some support for the hypothesis that color-coding had a positive effect on student performance.

Introduction

Time value of money (TVM) calculations are the basis for evaluating capital investment decisions and debt instruments as well as planning for key future expenditures such as retirement and educational costs, so student understanding of this concept is vital. Instruction in TVM analysis can employ mathematical equations, PV and FV tables, financial calculators and spreadsheet programs like Excel. This paper examines whether color-coding the variables utilized in TVM calculations can improve students' understanding of and ability to accurately compute TVM calculations. While this particular study used financial calculators as the vehicle for calculation, the practice of color-coding the variables can easily be adapted to any of the other methods. Study participants were divided into two groups. One group received instruction with: future value (FV) in red, present value (PV) in brown, interest rate (r) in green, payments (PMT) in purple and number of compounding periods (n) in blue. The other group received identical instruction but with all variables appearing in black font. The effect of color-coding on student performance will be evaluated based on post-test scores.

Pedagogy of TVM

Over the years several pedagogical papers have been written to help professors tackle this topic in a meaningful way. Some have focused on the use of formulas vs. tables vs. calculators; for instance, Dempsey (2003) found that students who were taught using the formulas performed significantly better than those who were taught using tables. More recently, Eschenbach and Lewis (2011) advocated the use of financial calculators as opposed to tables (which have been the traditional method of instruction in engineering economy classes) for more complex calculations. The authors noted that calculators require the same conceptual understanding to "match factors to cash flows." Others have developed methods to augment formula based instruction. Eddy and Swanson (1996) suggested that one should avoid mentioning interest rates or introducing the PV and FV formulas or calculations until the students have established an intuitive conceptual framework of the time value of money. Jalbert (2002) advocates the use of a flowchart based instruction to assist students in determining the appropriate problem solving methodology. More recent research has focused on the use of spreadsheet software to provide a holistic view of TVM; for instance, Mangiero et al. (2010) propose that TVM should be introduced using a dynamic Excel presentation of retirement annuity analysis and capital structure decisions to highlight the sensitivity of the solutions to changes in the parameters. Along these lines, several papers have focused on using a retirement problem to

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illustrate the concept of TVM. Evans (2004) created a case study focusing on the use of a financial calculator. Stuebs (2011) developed a problem focused on Excel and Arellano et al. (2012) presented a retirement model in an Excel template that extended the analysis to include the percentage of income that should be saved rather than focusing on a fixed amount of savings per year. And yet, despite these efforts, students still struggle with this concept. Bianco et al. (2010) surveyed a large number of students enrolled in junior and senior level finance and accounting courses to determine whether the number of courses taken involving TVM or the method of instruction employed affected their ability to solve TVM problems. They found no significant differences based on either of these criteria. This finding indicates the need for additional research in TVM pedagogy.

Pedagogical Use of Color-Coding

Recent research in instructional methodology has shown that color-coding can aid student learning. Color-coding should theoretically be an effective pedagogy for TVM instruction because it has been shown to be an effective aid to help students integrate information from multiple sources. As Toney et al. (2013) explains, when presented with multiple sources of information (i.e. the components of a mathematical equation and their relationship to a graph, table or calculator functions) students face the difficult task of directing their attention to each individual source of information, encoding them separately then storing them in working memory long enough for a meaningful connection to be made. Irrespective of the dominant methodology employed (formulas, tables, calculators or spreadsheets), TVM calculations require students to integrate information from multiple sources. Students must identify the variables given as well as the variable they are being asked to calculate and then evaluate how to use their preferred methodology to perform the actual calculation. For more complex problems such as the retirement problem, students must also locate multiple cash flows along a timeline and determine whether or how to augment these cash flows to arrive at a final solution.

Pashler et al. (2007) finds that color can be used to simplify the workload of a student's working memory, thus making it easier to represent and strategize the material more effectively. Two recent pedagogical papers have evaluated the validity of this claim in a manner similar to this study. Misanchuk and Schwier (1995) studied student learning in a high school geometry class utilizing computerized instruction delivered with one of three types of display: monochromatic, color, and a color display with consistent color cues. They found that the students who viewed the instruction with consistent color cues scored higher on the post-test than the other groups. Similarly, Reisslein et al. (2014) examined whether color-coding of the variables used to denote electrical qualities could improve student understanding of circuit analysis. Their sample consisted of two groups of high school students. One group was shown all variables in black font, while the other group was shown voltage in blue, current in red and resistance in black. The authors found that the students who received color coded instruction scored significantly higher on the end of study test. Little to no research has been done on color-coding with TVM. Newfeld (2012) examined the effectiveness of a modified version of the Jalbert (2002) flow chart augmented with color-coding to assist dyslexic students in a small case study, but the color-coding was limited to red and green arrows within the chart and highlighting the appropriate strategy. Still, the results did indicate that the method was beneficial for dyslexic students. This study expands not only the degree of color-coding employed but also the subject pool.

Methodology

Design and Participants

Study participants were recruited from students enrolled in pre-requisite courses for the introductory finance course at a small midwestern university. Pre-requisite courses were selected to ensure that the subjects had little to no prior exposure to TVM. Requests for participation were sent to the four professors teaching those prerequisites during the semester of study. Three of the four responded and agreed to allow their students to be recruited. The resulting sample pool consisted of 140 students enrolled in five separate classes. The pool was then evenly divided into two groups, namely the black font group and the color-coded group. The subjects then received invitations to participate in the study on Canvas, the online learning management system used at the university. A variety of inducements was used to encourage participation: one class offered to drop the lowest quiz for any student who completed the study, another offered extra credit to any student who completed the study and two classes were offered pizza if 70% of the class completed the study by a given date. Sixty-five students accepted the invitation to enroll in the black font group, 58 from the color- coded group. Of those 27, or 41.54%, completed the study from the black font group and 29, or 50%, completed the study from the color-coded group.

Instructional Material

To insure consistency of content and delivery, both groups received instruction via an online learning module administered through Canvas, the online learning management system utilized on campus. The Canvas module consisted of a welcome screen introducing the study, an informed consent document, a link to an online financial calculator[2], a 30-minute instructional video and a four question multiple choice quiz.

The instructional video was produced using Camtasia Studio 8. It included a PowerPoint presentation as well as calculations using the online financial calculator. The instructional videos were identical aside from the color-coding. Following a basic introduction to the concept of compound interest and the use of the calculator, the instruction was broken down into four parts: present value, future value, uneven cash flows, and annuities. Two examples were shown for each topic. Each example consisted of a question followed by two bullet point prompts, "What variables am I given?" and "What variable am I being asked to solve for?". In the first example in each set, the answers to both of these were shown. The instructional video broke down the question, identified these variables and discussed the problem-solving process referencing these prompts. Then, the calculation was shown using the online financial calculator and the answer was discussed. The second example allowed students a chance to practice identifying the variables and performing the calculations on their own before being shown the answers. Students were encouraged to pause the video as needed to facilitate this process. For the uneven cash flow segment the timeline was shown along with the question in the first example, and in the slide immediately following the question in the second. To more accurately approximate an in-class lesson, both the uneven cash flow and annuity segments included present value and future value calculations.

All the variables in the black font group were displayed in black font in all segments of the presentation. In the color-coded group, the variables were shown as follows: future value (FV) in red, present value (PV) in brown, interest rate (r) in green, payments (PMT) in purple, and number of compounding periods (n) in blue. These colors were introduced at the beginning of the lesson. Although the online financial calculator used doesn't have a color option, the students were shown a screenshot of the calculator with the colors overlaid prior to its use in any calculations. The variables, corresponding text and calculator, in the first example were shown with these color codes applied. The second example showed only the prompts with color-coding to allow the students a chance to identify the variables on their own before the coding is applied in the following slide. The process is illustrated below.

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[2] http://www.zenwealth.com/businessfinanceonline/TVM/TVMCalculator.html

The four question multiple choice quiz at the end of the study was entirely in black font. The scoring was done by Canvas.

Results

The final sample consisted of 27 subjects in the black font group and 29 in the color-coded group. The average subject took 46.36 minutes to complete the study, 12.55 minutes of which were spent on the quiz. The color-coded group on average, spent less time on the study site, completed the quiz more quickly and scored higher on the quiz than the black font group. The descriptive statistics are reported in Table 1.

Table 1: Desciptive Statistics

	Black Font Group (N=27)		Color-Coded Group (N=29)	
	Mean	Standard Deviation	Mean	Standard Deviation
Time on Site	48.815	15.249	44.069	16.981
Time on Quiz	13.444	6.097	11.724	4.052
Number Correct	2	1.414	2.621	1.374

Single factor ANOVA analysis showed no statistically signifigant differences between the two groups in either the number correct, time spent on the study site or time spent on the quiz. The P-values are reported in Table 2.

Table 2: Single Factor ANOVA

Time on Quiz	0.216
Number correct	0.102
Time on site	0.277

Six OLS models were run to examine the impact of the determinants of quiz score. The full model included the following variables: Color-code, Time on Quiz, Time on Site and interaction terms between color-code and Time on Quiz and Site. Color-Code is an instrumental variable that took the value of 1 if the subject was in the color-code group and 0 if the subject was in the black-font group. Both Time on Quiz and Time on Site were measured in minutes. As Models 4-6 show, color-coding has a statistically signifigant positive impact on quiz performance even after controlling for time spent on the quiz and time on the study site; however, once the interactive effects are examined, color-code was no longer statistically signifigant.

Table 3: OLS Anlaysis
Dependent variable: Quiz Score

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Color-Code	0.595	0.988	0.534	1.000	0.986	0.951
	(0.40)	(0.11)	(0.45)	(0.00)**	(0.00)**	(0.00)**
Time on Quiz	0.139	0.101	0.112	0.102	0.212	
	(0.00)**	(0.00)**	(0.00)**	(0.04)**	(0.00)**	
Time on Site	0.026	0.043	0.035	0.043		0.069
	(0.1941)	(0.00)**	(0.04)*	(0.00)**		(0.00)**
Interaction (CC & Time on Quiz)	-0.0766	0.0009				
	(0.3514)	(0.9842)				
Interaction (CC & Time on Site)	0.029		0.010			
	(0.247)		(0.489)			
Adj R-Sqr	0.6925	0.6903	0.6932	0.6962	0.6188	0.6557

P-values are shown in parentheses **Statistically signifigant at the 99% level, * Statistically signifigant at the 95% level

Summary and Conclusions

This study examined whether or not color-coding the variables utilized in TVM calculations could improve students' understanding of and ability to accurately compute TVM calculations. Subjects were divided into two groups, a color-coded group and a black font group. Each group received instruction via a 30-minute instructional video posted on Canvas then completed a four question multiple choice quiz. The color-coded group, on average, spent less time on the study site, completed the quiz more quickly and scored higher on the quiz than the black font group. In addition, OLS results show that color-coding had a statistically signifigant positive impact on on quiz performance even after controling for time spent on the quiz and time on the study site. These results suggest that color-coding the variables utilized in TVM calculations is a pedagogical technique that professors may want to incorporate into their TVM instruction.

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Resolving Conflicts in Capital Budgeting for Mutually Exclusive Projects with Time Disparity Differences: Two Comments

David Eagle[1]

ABSTRACT

McGowan (2013, this journal) claims that when two mutually exclusive projects have a single crossover rate in their NPV profiles, which project the firm should choose depends on whether the reinvestment rate is greater than or less than the crossover rate. He also claims that the firm's reinvestment rate should exceed the cost of capital on average because the firm would accept only positive NPV projects. This paper's computer spreadsheet uses McGowan's own examples to demonstrate McGowan's first claim to be false. This paper also challenges McGowan's second claim based on some real-options literature that resolves the Cost-of-Capital Paradox.

Introduction

In "Resolving Conflicts in Capital Budgeting for Mutually Exclusive Projects with Time Disparity Differences," McGowan (2013) correctly notes that the existence of a crossover rate between two projects is relevant to the existence of a conflict between NPV and IRR. He also correctly shows how to determine the crossover rate by looking at the IRR of the cash flows that are the differences between the cash flows of each project. However, McGowan makes two claims that I question. First, he claims that which project the firm should invest in depends on whether the reinvestment rate is less than or greater than the crossover rate. The second section of this paper uses McGowan's own examples to show that, when the firm reinvests in *independent* projects, the reinvestment rate is irrelevant to the decision of which project to undertake.

McGowan's second claim is that "the company will never invest at a rate below the NPV so that the average future reinvestment rate will be above the rate assumed by the NPV" (McGowan 2013, p. 1). McGowan's argument relates to the Cost-of-Capital Paradox, which has been resolved in the real-options literature. The third section explains that resolution and applies it to the reinvestment rate. Although I am unable to say that McGowan's second statement is false, section 3 explains why I am uncomfortable with this statement in light of the resolution to the Cost-of-Capital Paradox.

The Irrelevance of the Reinvestment Rate

Exhibit 1 shows a computer spreadsheet containing McGowan's own example of mutually exclusive projects A and B. Exhibit A1 in the appendix shows the formulas for this spreadsheet.[2]

In addition to McGowan's assumptions, other explicit assumptions concerning the reinvestment opportunities, are made in the spreadsheet in Exhibit 1. First, the spreadsheet assumes the firm would invest in *independent* projects C, D, and E at times 1, 2, and 3, respectively. The spreadsheet assumes an initial cost for each project so that that cost would be able to absorb the intermediate net cash inflow from either project

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[2] The website http://employeeweb.ewu.edu/deagle/Links/SpreadsheetCommentsOnMcGowan.xlsx contains downloadable versions of the spreadsheets used in this paper.

A or project B.[3] All three of these projects have an initial cost and only one future net incremental cash inflow that occurs at time 4. These cash flows at time 4 depend on the reinvestment rate as seen in the formulas in Exhibit A1.

Exhibit 1. Computer Spreadsheet of McGowan's Example with Reinvestment in Independent Projects

	B	C	D	E	F	G	H	I	J
2	rrr=	8%	8%		8%	8%		8%	8%
3		Mutually Exclusive			reinvestment rate =		8.00%	combined CFs	
4		Projects			Independent Projects			Accept A:	Accept B:
5	time	A	B	A-B	Project C	Project D	Project E	A, C, D, E	B, C, D, E
6	0	$(25,000)	$(25,000)	$ -				$(25,000)	$ (25,000)
7	1	$ 18,000	$ 2,000	$ 16,000	$(20,000)			$ (2,000)	$ (18,000)
8	2	$ 8,000	$ 3,000	$ 5,000		$(11,000)		$ (3,000)	$ (8,000)
9	3	$ 4,000	$ 4,000	$ -			$(8,000)	$ (4,000)	$ (4,000)
10	4	$ 2,000	$ 30,000	$(28,000)	$ 25,194	$ 12,830	$ 8,640	$ 48,665	$ 76,665
11									
12	NPV	$ 3,171	$ 4,650	$ (7,000)	$ 3,081	$ 815	$ 640	$ 3,171	$ 4,650
13	IRR	16.38%	13.38%	10.94%	25.97%	16.64%	8.00%	10.90%	10.91%
14									
15				crossover rate		NPV(B, C, D, E)-NPV(A, C, D, E)=			$1,479.33

Because projects C, D, and E are independent of projects A and B, if the firm undertakes project A rather than project B, it will then be undertaking projects A, C, D, and E. Column I of the spreadsheet combines the cash flows for these four projects. On the other hand, if the firm undertakes project B and not project A, then it will be undertaking projects B, C, D, and E. Column J of the spreadsheet combines the cash flows for these four projects. Cell I12 gives the combined NPV for projects A, C, D, and E, whereas cell J12 gives the combined NPV for projects B, C, D, and E. Cell J15 shows the difference between the NPV(B, C, D, and E) and the NPV(A, C, D, and E). The firm should undertake project B if this difference in cell J15 is positive and should undertake project A if this difference is negative.

First, consider the situation where the reinvestment rate is 8%, which is less than the 10.94% crossover rate. As Exhibit 1 shows, in this case, the NPV(B, C, D, and E) = $4650.09, which is greater than the NPV(A, C, D, and E) = $3,170.77. The difference is $1,479.33 in favor of project B. McGowan (2013, p. 3) states, "If the anticipated reinvestment rate is below 10.9393%, the financial decision maker should choose project B." McGowan's statement is correct in this case, but next let us consider a reinvestment rate greater than the cost of capital.

Exhibit 2 changes the reinvestment rate to 13%, which is greater than the 10.94% crossover rate. In this case the NPV(B, C, D and E) = $8,530.46 and the NPV(A, C, D, and E) = $7,051.14. The difference is still $1,479.33 in favor of project B. McGowan (2013, p. 3) states, "[I]f the future cash flows are reinvested at a rate above 10.9393%, then the financial decision maker should choose project A." Exhibit 2 shows that statement to be false.

The reinvestment rate is the return on projects C, D, and E. Because the firm undertakes these independent projects regardless of whether the firm undertakes project A or project B, both the NPV(B, C, D, and E) and the NPV(A, C, D, and E) increase by the same amount. Hence, the difference in the combined NPV remains the same.

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[3] The actual way the spreadsheet determined these initial costs for projects C, D, and E was to sum the intermediate net cash inflows of projects A and B for times 1, 2, and 3, respectively. An alternative would have been to set these initial costs equal to the maximum of the net cash inflows of A and B; however, had I done the latter the initial costs of C, D, and E would have exactly equaled the intermediate net cash inflows for either A or B for times 1, 2, and 3. I chose the former procedure over the latter to avoid any confusion this equality would have caused.

Exhibit 2. McGowan's Example with a Reinvestment Rate of 13%

	B	C	D	E	F	G	H	I	J
2	rrr=	8%	8%		8%	8%		8%	8%
3		Mutually Exclusive			reinvestment rate =		13.00%	combined CFs	
4		Projects			Independent Projects			Accept A:	Accept B:
5	time	A	B	A-B	Project C	Project D	Project E	A, C, D, E	B, C, D, E
6	0	$(25,000)	$(25,000)	$ -				$(25,000)	$ (25,000)
7	1	$ 18,000	$ 2,000	$ 16,000	$(20,000)			$ (2,000)	$ (18,000)
8	2	$ 8,000	$ 3,000	$ 5,000		$(11,000)		$ (3,000)	$ (8,000)
9	3	$ 4,000	$ 4,000	$ -			$(8,000)	$ (4,000)	$ (4,000)
10	4	$ 2,000	$ 30,000	$(28,000)	$ 28,858	$ 14,046	$ 9,040	$ 53,944	$ 81,944
11									
12	NPV	$ 3,171	$ 4,650	$ (7,000)	$ 6,223	$ 1,857	$ 1,040	$ 7,051	$ 8,530
13	IRR	16.38%	13.38%	10.94%	44.29%	27.69%	13.00%	14.18%	13.20%
14									
15				crossover rate		NPV(B, C, D, E)-NPV(A, C, D, E)=			$1,479.33

We must conclude that the reinvestment rate is irrelevant for the difference between these two terminal values, irrelevant for the difference between NPV(B, C, D, and E) and NPV(A, C, D, and E), and irrelevant for the financial decision-maker's choice between projects B and A.

The key to our results is the assumption that the firm "reinvests" into projects independent of both A and B. The firm will undertake these independent projects regardless of whether the firm undertakes project A or B. Because the firm invests in these independent projects regardless of whether it undertakes A or B, the return on these independent projects (the reinvestment rate) is irrelevant to the decision of which project to undertake.

The only way McGowan and other supporters of the reinvestment assumptions can try to salvage their conclusions is to argue that the firm reinvests in dependent projects. For example, suppose the firm would reinvest the intermediate cash inflows of project A into project X, which the firm would undertake only if the firm has undertaken project A. Also, assume that firm would invest the intermediate cash inflows of project B into project Y, which the firm will undertake only if project B is undertaken. If this is the thinking that McGowan was following, then the real problem is that the analyst did not fully determine all the incremental cash flows for projects A and B. If project X depends on project A, then the analyst should have included the incremental net cash inflows for project X in project A's incremental net cash inflows. Similarly, if project Y depends on project B, then the analyst should have included the incremental net cash inflows for project Y in project B's incremental net cash inflows.

What I said in the above paragraph is not new thinking. Keane (1979) says the same thing, except that he refers to the dependent projects as "satellite" projects. Keef and Roush (2001) cite and agree with Keane. Eagle et al. (2008) also conclude that the reinvestment rate is irrelevant when investing in independent projects. Brealey et al. (2008, p. 127, footnote 6) make one of the most forceful statements that the reinvestment rate is irrelevant: "It is often suggested that the choice between the net present value rule and the internal rate of return rule should depend on the probable reinvestment rate. This is wrong. The prospective return on another independent investment should never be allowed to influence the investment decision." Two articles in this journal have also argued against the relevance of the reinvestment rate: Johnston et al. (2002) and Hatem et al. (2013).

In summary, if the analyst has fully identified all the incremental net cash inflows for projects A and B, then the firm will reinvest the intermediate net cash inflows of these projects into independent projects. The return on these independent projects, which is the reinvestment rate for projects A and B, would then be irrelevant for the choice between A and B.

The Cost-of-Capital Paradox and the Reinvestment Rate

McGowan argued that the average expected reinvestment rate should be greater than the cost of capital because the firm would accept only projects that have expected returns greater than the cost of capital. I agree with McGowan that the firm would accept only projects that have returns greater than the cost of capital. However, I am uncomfortable with his conclusion that the reinvestment rate exceeds the cost of capital. This comment explains why.

McGowan's argument relates to what we call the "Cost-of-Capital Paradox" (see textbox). Eagle et al. (2010) used a mathematically based, stochastic, general competitive equilibrium model to resolve this paradox. In this comment, I explain their resolution on a more intuitive and conceptual level. I also relate this resolution to the relationship between the expected reinvestment rate and the cost of capital.

> ### *The Cost of Capital Paradox:*
> For a particular level of risk, we should use a hurdle rate equal to the average return on firms having that same level of risk. Yet, if all these firms used that same hurdle rate and only accepted projects with positive NPVs, then should not the firm's average returns *exceed* this hurdle rate? If so, then that contradicts my statement that the hurdle rate equals the average return on these firms.

Assume at time 1, one year from now, the firm will encounter project X, which the firm will then decide whether to undertake. At time 0, both the firm and the investors of the firm are aware that project X will be forthcoming. The possibility of undertaking this project is a real option. If the project's NPV turns out to be positive a year from now, then this option will be in the money and the firm should invest in the project. However, if the project's NPV turns out to be negative a year from now, then this option will be out of the money and the firm should not invest in the project.

As long as the possibility exists that NPV will be positive, then this real option's value at time 0 will be positive. If investors know about the possibility of this project, their valuation of the firm at time 0 should include the value of this option.

Exhibit 3 shows a spreadsheet of an example illustrating how the return on the firm's value will equal the cost of capital even though the firm will accept project X only if project X's NPV is positive. Below are our assumptions:

i.   The cost of capital is 8%.
ii.   The value of the firm at time 1 will equal $90 if the firm does not undertake project X.
iii. Project X's NPV at time 1 will either be a positive $20 and a negative $20 with equal likelihood.

Exhibit A2 in the appendix shows the formulas for the spreadsheet in Exhibit 3.

If the NPV = +$20 at time 1, the value of the firm will be $110, which equals the $90 value of the firm without the project plus this $20 NPV. On the other hand, if the NPV = -$20, then the firm will not undertake the project, and the value of the firm will be $90. The value added to the firm is therefore $20 if NPV = +$20 and zero if NPV = -$20. The expected value added of project X is $10 = 0.5 (20) + 0.5 (0)). The present value of this value added is $9.26 = $10/(1+8%). The $9.26 is the value of the real option of undertaking this project.

The expected value of the firm at time 1 will be $100 = 0.5 (110) + 0.5 (90). The value of the firm at time 0 equals the present value of this expected firm's value. Hence, the value of the firm at time 0 equals $92.59 = $100/(1+8%). The $92.59 value of the firm today can be broken down into the value of the option of undertaking the project ($9.26) plus $83.33, which is the value of firm without the possibility of undertaking the project. This $83.33 = $90/(1+8%), which is the present value of the value of the firm at time 1 without the project.[4]

The return from time 0 to time 1 on the firm's value is positive 18.80% (= 110/92.59-1) if the real option ends up being in the money and the firm undertakes the project. However, that return will be -2.80% (= (90/92.59-1) if the real option ends up being out of money and the firm does not undertake the project. The expected value of this return is 8% = 0.5 (18.80%) + 0.5 (-2.80%).

This example illustrates how a firm could accept only projects with positive NPVs yet the cost of capital would still be the expected return on the firm's value. There are two important issues here:

1. There is a distinction between the return on the firm's value and the return on projects.

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[4] We are not considering the $90 to be risk free. Rather we are holding everything else constant as we focus on only the NPV of project A changing. The "everything else" that we are holding constant include risky factors that cause that $90 to have the same level of risk as the project A.

Exhibit 3. Example of an 8% Cost of Capital and an 8% Expected Return on the Firm Even Though the Firm Accepts This Project Only if the Project's NPV > 0

	B	C	D	E	F	G
2	value of firm at time 1 w/o project =				$90	
3	cost of capital =				8.00%	
4						
5		prob.	NPV	value added	V_1	return
6	in the money	0.5	$20	$20	$110	18.80%
7	out of the money	0.5	($20)	$0	$90	-2.80%
8						
9	expected values			$ 10.00	$100	8.00%
10						
11	PV(expected values) =			$ 9.26	$ 92.59	
12						
13	value of the option at time 0 =			$ 9.26		
14	PV(value of firm w/o project) =			$ 83.33		
15	PV(value of firm w/ project) =			$ 92.59		

2. To determine the expected return on the firm's value correctly, one needs to consider the return both when the firm rejects the project and when the firm accepts the project.

It is true that if one averages the return over only those projects that the firm accepts, that average return will exceed the cost of capital. However, in this example, there is only a 50% probability that that will happen. The other 50% probability arises when the real option ends up being out of the money and the firm chooses not to exercise the option. When the real option turns out to be running out of the money, the firm loses the original value of the option, which results in a negative return.

Most establishments are in business to take advantage of opportunities. For retail ventures, the opportunities arise from people coming into the store or restaurant. For construction companies, the opportunities arise from people contacting them to try to work out a deal to construct a home, building, factory, highway, or whatever needs to be constructed.

Another word for opportunities is *options*. Firms are in business to take advantage of the real options that come their way. Firms have some setup costs for becoming a firm and for being positioned to attract these opportunities or options. In a competitive equilibrium, where the economic profit is bid down to zero, the setup costs for becoming a firm and positioning the firm to attract these opportunities or options should equal the value of these real options. The discount rate used to compute these real options should be the firm's equilibrium cost of capital based on its level of risk.

If we look at the firm from the beginning in a competitive environment, investing in the firm is to be viewed as a project. The expected return on the overall firm in a competitive equilibrium should equal its cost of capital, even though when the time comes to exercise the real options, the firm will exercise only the real options that are in the money.

In summary, it would be a mistake to argue that the firm's return on projects will exceed the cost of capital when we include the firm's being in existence as one of those projects. When we look at all the projects the firm undertakes, including the project of creating the firm itself, in a competitive equilibrium, the average return on those projects should equal the firm's cost of capital.

Now, let us focus on the potential projects available for reinvestment. It makes me uncomfortable to assert that the expected reinvestment rate should exceed the cost of capital, given our understanding of the Cost-of-Capital Paradox. Focusing only on reinvestment projects the firm would accept ignores the loss of the real options' value when these reinvestment projects have negative NPVs. It also does not take into account the on-going "project" of being a firm ready to take advantage of its real options.

Normally, one should determine how the reinvestment rate compares with the cost of capital in the context in which the reinvestment rate is relevant. However, the previous section shows that the reinvestment rate is irrelevant. Having no relevant context, one cannot say McGovern's statement is false; instead, I just state that I am uncomfortable with his statement given the resolution to the Cost-of-Capital Paradox provided by Eagle et al. (2010).

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APPENDIX

Exhibit A1. Formulas for Computer Spreadsheet in Exhibit 1

	B	C	D	E	F	G	H	I	J
2	rrr=	8%	8%		8%	8%		8%	8%
3		Mutually Exclusive			reinvestment rate =		8.00%	combined CFs	
4		Projects			Independent Projects			Accept A:	Accept B:
5	time	A	B	A-B	Project C	Project D	Project E	A, C, D, E	B, C, D, E
6	0	$(25,000)	$(25,000)	$ -				$(25,000)	$ (25,000)
7	1	$ 18,000	$ 2,000	$ 16,000	$(20,000)			$ (2,000)	$ (18,000)
8	2	$ 8,000	$ 3,000	$ 5,000		$(11,000)		$ (3,000)	$ (8,000)
9	3	$ 4,000	$ 4,000	$ -			$(8,000)	$ (4,000)	$ (4,000)
10	4	$ 2,000	$ 30,000	$(28,000)	=-G8*(1+$H$3)^2			=C10+SUM($F10:$H10	
11					=-F7*(1+$H$3)^3		=-H9*(1+$H$3)^1		
12	NPV	=NPV(C2,C7:C10)+C6							
13	IRR	=IRR(C6:C10)							
14									
15				crossover rate		NPV(B, C, D, E)-NPV(A, C, D, E)=		=J12-I12	
	To complete the formulas for the spreadsheet, fill to the right from								
	cells C12:C13 to cells J12:J13. Also, copy cell I10 to J10.								

Exhibit A2. Formulas for Computer Spreadsheet in Exhibit 3

	B	C	D	E	F	G
2		value of firm at time 1 w/o project =			$90	
3		cost of capital =			8.00%	
4						
5			prob.	NPV	NPV	V1	return
6	in the money	0.5	$20	=MAX(D6,0)	=$F$2+E6	=F6/$E$15-1
7	out of the money	0.5	($20)	=MAX(D7,0)	=$F$2+E7	=F7/$E$15-1
8						
9		expected values		=SUMPRODUCT($C$6:$C$7,E6:E7)		
10						
11		PV(expected values)=		=E9/(1+$F3)	=F9/(1+$F3)	
12						
13		value of the option at time 0 =		=E11		
14		PV(value of firm w/o project) =		=F2/(1+F3)		
15		PV(value of firm w/ project) =		=F11		
	Note: Fill to the right from cell E11 to G11 to get the formulas for					
	cells F11 and G11.					

Note — column alignment in Exhibit A2 table: the header row 5 columns are prob. (C), NPV (D), NPV (E), V1 (F), return (G).

Personal Financial Management Sentiment and Financial Literacy Program Effectiveness

Inga Chira, Bret W. Scott, Amy Bourne, and Jenna Wiegand[1]

ABSTRACT

Prior literature demonstrates that, despite a rise in financial literacy programs (FLP), their effectiveness is unsubstantial. We posit that an individual's sentiment towards personal financial management (PFM) is a potential mediating factor of FLP effectiveness. Using survey methodology, we examine factors that influence college students' sentiment towards PFM. Students' expected future cash flows, as well as their extrinsically-perceived financial conservativeness, influence how much they worry about their personal finances. These results exist regardless of our subjects' degree of extant PFM knowledge or whether our subjects have taken a course in personal finance.

Introduction and Motivation

Many programs have been created to provide financial literacy to children, young adults, and college students. Recently, the effectiveness of such programs has been called into question (e.g., Mandell and Klein 2009; Fernandes et. al 2014). Yet, while criticism over financial literacy program (FLP) effectiveness has primarily focused on flaws over curriculum design, delivery, and assessment (see Figure 1), mediating factors such as students' confidence and concern over their personal financial management (PFM), have been overlooked as potential determinants of FLP effectiveness (see Figure 2). Factors such as collegiate endeavors are likely to not only moderate students' confidence over their PFM, but also influence the overall effectiveness of FLPs (see Figure 3). Without considering students' sentiment towards PFM, or the determinants thereof, any direct assessment of FLP quality based on students' *ex post* personal financial decision efficacy may be incomplete. Our study examines factors that likely influence students' confidence and concern over their PFM, a necessary step in determining FLP effectiveness.

Fernandes et al. (2014, p. 1864) conduct a meta-analysis of 168 papers on financial education and conclude that "financial education interventions have statistically significant but miniscule effects... [explaining] about 0.1% of the variance in downstream financial behaviors...." This finding indicates that, despite the growth in supply and demand of financial literacy education, the effectiveness of FLPs is unsubstantial. Furthermore, Mandell and Klein (2007) argue that high school students who are not motivated to understand and retain financial literacy information do not benefit from those courses by way of sound personal financial decision-making. This suggests that individuals' sentiment towards PFM plays a dominant role in sound personal financial decision-making, and this may explain the lackluster impact of FLPs found in prior literature. We seek to identify the factors that influence individuals' sentiment toward PFM, as well as the potential determinants of these factors. Understanding these PFM sentiment factors enables us to not only identify potential barriers to FLP effectiveness, but also understand how to overcome those barriers so that FLPs can have a more meaningful impact on individuals' personal financial decision-making processes.

The difficulty in measuring the effectiveness of a FLP is due, in part, to inconsistency in how success or failure of such a program is defined. Prior studies examine individuals' relative level of debt (e.g., the amount of credit card debt) or objective financial knowledge (i.e., answers on financial literacy quizzes) to measure the effectiveness of FLPs (for example, see Chen and Volpe 2002). However, quantitative measures like

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these may not be *directly* influenced by individuals' financial literacy training. For instance, individuals' level of debt or personal finance competency could be influenced by their attitude about money in general.[2]
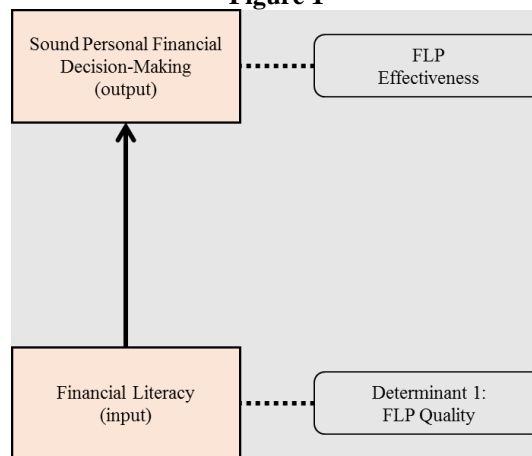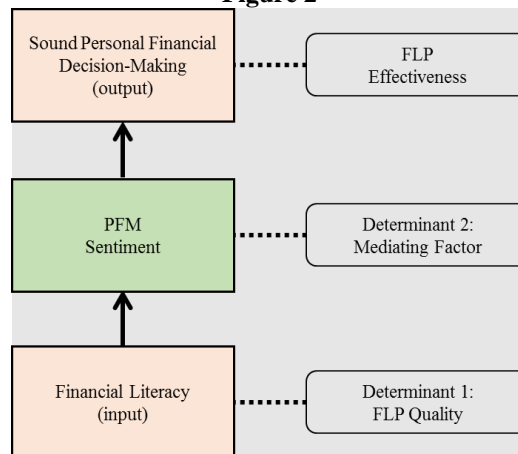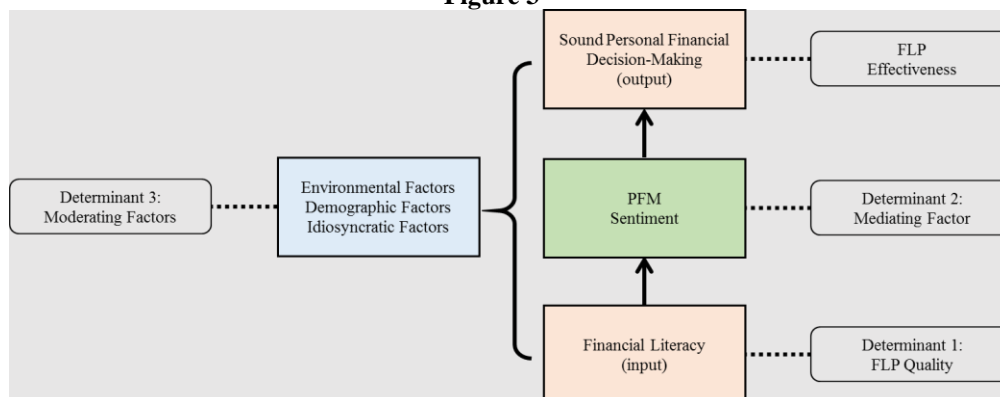
Figure 1

Figure 2

Figure 3

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[2] A college student who expects to obtain a higher salary after graduation, relative to her peers, may likely seek more student loan debt relative to her peers. Thus, student loan debt is not necessarily correlated with that individual's degree of financial literacy.

This is not to say that financial literacy education plays a subordinate role in sound financial decision-making. Rather, it is more plausible that an FLP influences an individual's personal financial decision-making *indirectly* by first influencing that individual's degree of self-confidence over personal financial decisions.[3] The extent to which self-confidence over personal finance is a mediating factor that determines FLP effectiveness has yet to be examined. The purpose of our study is to examine the impact of self-confidence on FLP effectiveness.

In baseline models, we find that college students' expected future salary has no significant influence on their concern over PFM. However, in higher-level interaction models, we find some evidence that college students' degree of PFM concern decreases with higher expected future salary levels. Also, this negative association become more pronounced if college students view themselves as financially conservative or if college students have extant knowledge about PFM. We also find strong evidence that college students' degree of PFM concern increases with greater expected future debt obligations, and this positive association increases with greater extant knowledge about PFM. Taken together, these findings suggest that expected future cash flows influence college students' degree of worry about their PFM.

In all model specifications, student financial conservativeness is positively associated with the degree of PFM concern. We find some evidence that this positive association is attenuated if students have completed a PFM course. These findings suggest that, on average, greater financial conservativeness is associated with greater concern over one's PFM.

When examining determinants of college students' degree of PFM confidence, we find strong evidence across all model specifications that higher expected future salary is associated with greater PFM confidence. We also find that greater expected future debt obligations are associated with lower PFM confidence. That is, college students feel less prepared to handle their personal finances when they have higher levels of debt relative to their peers. However, when PFM concern (i.e. college students' degree of worry over their PFM) is included as an independent variable, the association between PFM concern and PFM confidence is significantly negative, and the negative association between expected future debt obligations and PFM confidence disappears. This suggests that college students' degree of PFM preparedness is not a function of expected cash outflow, but rather how much they already worry about their personal finances.

We find evidence that greater financial conservativeness among college students is associated with greater PFM confidence. However, this association is only consistently significant across all model specifications for extrinsically-perceived specifications of conservativeness, suggesting that a college student's degree of PFM confidence is a function of how financially conservative *other* people perceive them to be, and not how financially conservative they perceive themselves to be.

In higher-level interaction models that include PFM concern as an independent variable, we still find no association between expected future debt obligations and PFM confidence. However, we do find evidence that greater expected future debt obligations reduced PFM confidence as college students become more financially conservative (both intrinsically and extrinsically). Conversely, this indicates that, financially conservative college students feel less prepared to manage their personal finances as their expected future debt obligations increase. We also find evidence that college students with relatively high levels of expected future debt feel less prepared to manage their personal finances when they possess relatively greater extant knowledge of PFM.

While our focus of the study is on the determinants of PFM sentiment, we control for whether our subjects have taken a personal finance course. In all model specifications we find that college students who have taken a course in personal finance have a lower degree of PFM concern and a higher degree of PFM confidence. Yet, regardless of whether students have taken courses in personal finance, our evidence indicates that students' expected future cash flows and degree of financial conservatism also influence their PFM sentiment. Thus, this study contributes to extant literature by demonstrating that both individuals' prior exposure to personal finance education as well as their general sentiment towards managing their personal finances play an important role in determining FLP effectiveness.

The remainder of the paper is organized as follows: Hypotheses are presented in section 2, methodology and data are described in section 3, results are presented section 4, and implications and conclusions are discussed in section 5.

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[3] For example, by completing FLPs, individuals may become aware that they can pay for college using student loans, a source of funding that they were not previously aware. As a result, these individuals may incur student loan debt because FLP training made them aware of that source of funding.

Hypotheses Development

Students' Concern over Money

The landscape of borrowing and saving has significantly changed over the last 20 years. Since the early 1980s, the U.S. personal saving rate has declined to historically low levels, while U.S. household borrowing has increased substantially over the past decade (McCully 2011). Chao and Schor (1998) offer "easy credit" access as one possible explanation for this trend. While credit may have become more accessible, prior literature suggests that the use of credit itself perpetuates one's indebtedness. Roberts and Jones (2001) find greater compulsive buying behavior as individuals increase the use of their credit cards. Additionally, Norvilitis et al. (2003) find that individuals with a liberal attitude about credit are more likely to have higher levels of debt, and that this relation becomes stronger as they become more indebted. Taken together, this line of research suggests that the use of debt perpetuates more indebtedness.

As individuals' indebtedness increases, so does their level of financial stress, or concern over their ability to meet financial commitments. Prior literature finds that financial stress negatively impacts people's self-esteem and strength in marital relationships (Freeman et al. 1993). Prior studies that view credit card indebtedness as a form of financial stress demonstrate that higher credit card balances among college students are associated with poor diet, exercise, and course performance (Ross et al. 2006). Hayhoe et al. (2000) examine financial stress, both related and unrelated to credit card debt, and find that as financial stress increases, students are more likely to pay only the minimum credit card balance due, thereby increasing their debt over time. The authors also find that increases in financial stress increase the likelihood of students writing bad checks, which also increased indebtedness over time.[4] Finally, the authors also examine the effect of college students' financial stress on their PFM sentiment. They find that, as their financial stress increases, college students' are less likely to feel good about managing their personal finances. Grable and Joo (2006) examine the effects of individuals' outstanding credit card debt on their feelings of financial stress in general. Controlling for race, gender, and other demographic factors, they find that high credit card debt is associated with greater financial stress. Taken together, these studies indicate that one's indebtedness plays a dominant role in individuals' lives both personally and financially.

While prior studies examine the effect of existing debt on PFM sentiment and decision-making, we examine the effect of expected debt (or *ex ante* debt) on PFM sentiment of debt. Controlling for demographic factors and extant PFM knowledge, we hypothesize that the extent to which college students currently worry about money is influenced by their by their expected future income generating potential, expected future debt obligations, and perceived fiscal conservativeness.. Specifically, we posit the following hypotheses:

> *H1a: College students' expected future salaries influence their degree of financial concern.*

> *H1b: College students' expected future debt obligations influence their degree of financial concern.*

> *H1c: College students' intrinsically-perceived conservativeness influences their degree of financial concern.*

> *H1d: College students' extrinsically-perceived conservativeness influences their degree of financial concern.*

Students' Confidence over Managing Their Finances

Joo and Grable (2004) find financial stress decreases with improved PFM decision making, thus providing support for FLPs. Grable and Joo (2006) further explore the stress factors of college students showing that credit card debt is positively related to financial stress. Similarly, Lim et al. (2014) show student debt is a leading cause of stress and that, in general, it ranks as the second largest stressor amongst college students. One-third of the respondents report that finances are traumatic or very difficult to handle. Additionally, National Survey of Student Engagement (2012) indicates that three in five freshman students worry about

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[4] A bad check necessarily suggests increased indebtedness. The failure to make a proper payment for goods or services received indicates that an outstanding financial obligation remains, regardless of the intended recipient of the payment.

paying for school and having enough money for regular expenses. The study also shows that four of the top five stressors identified by currently enrolled students were related to personal finance. Sages et al. (2013) also find that anxiety is heightened with increases in spending, credit card debt, and lack of financial knowledge and that higher anxiety correlates with negative financial behavior.

Prior studies also show that gender and age affect PFM. Henry et al. (2001) point to differences in financial behaviors between men and women. Although the authors do not address individuals' concern or worry over personal finances, they show that men and women manage their money differently. For example, women are more likely to have a budget compared to men. In an international study, Akben-Selcuk (2015) finds a significant difference between male and female students when it comes to budgeting; male students seem to be less prone to budget their personal finances. Interestingly, when examining the impact of prior finance related courses, the author finds no impact on budgeting behavior in participants' responses. Kettley et al. (2008) investigate the gender responses to financial situations concluding that although there are few gender differences in students' actual financial situation, women perceive themselves to be under greater pressure compared to men. Women worry more about their finances and express lower levels of well-being while "men express a more complacent financial attitude." In a recent survey conducted among adults, the Certified Financial Planner (CFP) board found that young respondents and women are most likely to have financial stress; 89% of women and 91% of younger adults are stressed about their finances, especially their everyday expenses (CFP Board 2015).

Given the various effects of environmental and demographic factors on sound personal financial decision-making and their influence on individuals' self-confidence over their personal finances, we hypothesize that an individual's degree of worry over personal finances are related to an overall attitude towards money, as well as expectations about future financial well-being. These expectations relate to both future income (salary expectations after graduation) and future debt (student loan expectations at graduation), as well as the philosophy or the degree of conservatism students feel about their finances.

Another aspect of personal financial self-confidence we examine is the degree that individuals feel they are prepared to handle their personal finances. To this extent, we study the factors that influence students' perception of preparedness to manage money and finances after graduation. There is little in the way of research that examines how prepared college students feel they are to manage their own finances after graduation. A 2001 Market Research Harris poll conducted on behalf of Key Bank shows about 50% of college seniors felt they were very uneducated about investments and financial planning and that collegiate class standing affects how prepared students feel to handle their personal finances. This study also finds that one-third of college upperclassmen reported feeling as financially unprepared as freshmen, while only one in five reported being "very well prepared" to manage their money on campus (*One-Third of College Upperclassmen Admit Being Financially Unprepared as Freshmen, 2006)*. The study, however, did not investigate how prepared the upperclassmen felt as they were ready to graduate (Fraczek 2014).

Prior research has examined other factors that influence how equipped students feel to manage their own finances. Chen and Volpe (2002) found that opinions differ by gender. Specifically, they find that about 60% of men consider themselves more knowledgeable about personal finances than women. Previous exposure to personal financial education also increases perceptions of preparedness. In a few studies assessing the impact of a high school financial planning curriculum, evaluators found that of 4,107 teens nationally, 40% reported greater confidence in money management after program completion (Danes et al. 1999; Peng et al. 2007). Likewise, Shim et al. (2010) found that students' level of previous financial education played a role in their perceived behavioral control over financial matters, or feelings of preparedness. Additionally, Akben-Selcuk (2015) finds that students who have positive attitudes towards money and budgeting tend to be more financially responsible, save more, and budget better.

A study on perceived competency in financial matters – which focuses on teachers and their perceived ability to teach financial literacy – finds that female teachers feel less prepared to teach students about personal finances as those teachers with less experience or knowledge about financial education (Way and Holden 2009). This study also finds that teachers' feelings of preparedness differ by discipline; social studies and math teachers are less likely to report a perceived lack of competency to teach more financially technical topics than teachers in other disciplines. Moreover, math teachers express greater confidence in their ability to teach about saving and investments relative to teachers in other disciplines, which is likely due to the mathematical nature of the topic itself (e.g. compound interest). Overall, this study indicates that an individuals' formal educational training influences their perceived ability to teach personal finance education topics. That being said, it is reasonable to suspect that one's perceived ability to teach personal financial education also transfers to the perceived preparedness to manage one's own personal finances. If so, then

college students' choice of major not only influences their perceived ability to teach personal finance education, but also influences their own perceived ability to manage their personal finances.

Controlling for demographic factors and extant PFM knowledge, we expect that the degree of confidence that college students possess in managing their personal finances in the future is influenced by their current concern over money as well as their expected future income generating potential, expected future debt obligations and perceived fiscal conservativeness. We explore the link between the perception of financial preparedness and other individual-specific characteristics: financial philosophy, financial worry, expectations of future income, and expected future debt. Specifically, we posit the following hypotheses:

H2a: College students' degree of current financial concern influences their confidence over managing their personal finances in the future.

H2b: College students' expected future salaries influence their confidence over managing their personal finances in the future.

H2c: College students' expected future debt obligations influence their confidence over managing their personal finances in the future.

H2d: College students' intrinsically-perceived conservativeness influences their confidence over managing their personal finances in the future.

H2e: College students' extrinsically-perceived conservativeness influences their confidence over managing their personal finances in the future.

Methodology and Data

The Student Survey

An online survey (available upon request) was administered to students at Oregon State University during the winter 2015 term. A total of 1,052 responses were collected. A breakdown of the respondents by class standing is presented in Table 1. The survey included categories for freshmen to seniors, as well as a category for others (e.g., non-degree, short-term exchange student). The final sample consists of a relatively even distribution between the four academic standings with 29.47% freshmen, 22.34% sophomores, 17.59% juniors and 20.72% seniors. 5.89% are represented by the other category and 3.99% of responded chose not to answer this question.

Table 1: Distribution of Sample (N=1,052)

Class Standing	Count	Percentage of Sample
Freshman	310	29.5
Sophomore	235	22.3
Junior	185	17.6
Senior	218	20.7
Non-degree, exchange student, etc.	62	5.9
No data	42	4.0

The questions asked were grouped into the following categories: (1) related to actual financial behavior, (2) related to perceptions of money management, philosophy, and behavior, (3) measuring objective financial knowledge, (4) measuring subjective/perceived financial knowledge, and (5) expectations of financial well-being at and after graduation. We also collected demographic information and information about prior courses in economics and finance that students took in high school. The questions were compiled from various financial literacy and money attitudes surveys and also included questions that related to respondents' specific demographic. All variables are defined in Table 2.

<div align="center">**Table 2: Variable Definitions**</div>

VARIABLES	Definition[5]
WORRY	Respondents' degree of concern over money. Five categories, where 1 = never, 2 = a little, 3 = sometimes, 4 = often, and 5 = nearly all the time.
PREPARED	Respondents' sense of preparedness to manage money after graduation. Scale from 1 to 10, where 1 = not ready and 10 = extremely ready.
EXP_SAL	Respondents' expected gross salary after graduation. Four categories, where 1 = less than $30,000, 2 = between $30,000 and $39,999, 3 = between $40,000 and $49,999, and 4 = $50,000 or more.
EXP_LOANS	Respondents' expected amount student loans at graduation. Seven categories, where 1 = nothing, 2 = less than $5,000, 3 = between $5,000 to $9,999, 4 = between $10,000 to $19,999, 5 = between $20,000 to $29,999, 6 = between $30,000 to $49,000, and 7 = $50,000 or more.
FRESH	Indicator variable equal to 1 if the respondent is a freshman, and 0 otherwise.
SENIOR	Indicator variable equal to 1 if the respondent is a senior, and 0 otherwise.
GENDER	Indicator variable equal to 1 if the respondent is male and, 0 if female.
ENGINEER	Indicator variable equal to 1 if the respondent is majoring in engineering, and 0 otherwise.
NURS_SCI	Indicator variable equal to 1 if the respondent is majoring in nursing or science, and 0 otherwise.
BUS_ECON	Indicator variable equal to 1 if the respondent is majoring in business or economics, and 0 otherwise.
KNOWL	Measures respondents' objective knowledge of personal finance. Derived from a six-question quiz designed to assess a respondent's knowledge of personal finance, where a score of zero indicates the respondent did not answer any of the questions correctly, and a score of 6 indicates the respondent answered all 6 questions correctly.
CONS_PHIL	Indicator variable equal to 1 if the respondent perceives himself/herself to be financially conservative, and 0 otherwise.
OTH_CONS	Indicator variable equal to 1 if the respondent believes other people perceive him/her to be financially conservative, and 0 otherwise.
PER_FINC	Indicator variable equal to 1 if the respondent took a personal finance course (or part of a personal finance course) in high school, and 0 otherwise.
ECON	Indicator variable equal to 1 if the respondent took an economics course (or part of an economics course) in high school, and 0 otherwise.

Dependent and Independent Variables

The OLS regression models that test our first set of hypotheses (H1a through H1b) examine factors affecting students' worries about financial matters (*WORRY*). For these models, our primary variables of interest are respondents' subjective perceptions of financial conservativeness (*CONS_PHIL* and *OTH_CONS*) and expected financial position after graduation (*EXP_SAL* and *EXP_LOANS*). We control for other correlated factors such as respondents' objective knowledge of financial literacy (*KNOWL*) and prior financial literacy education (e.g. *PER_FIN*). Additionally, we control for demographic information such as gender (*GENDER*), class standing (e.g. *SENIOR*), and college major (e.g. *ENGINEER*).

To test our second set of hypotheses (H2a through H2e), we examine the factors that assess students' sense of preparedness over managing their personal finances after graduation. The OLS regression model used to test H2a includes *WORRY* as a determinant of *PREPARED*, while the OLS regression models testing H2b through H2e are similar to those testing H1athrough H1d, respectively.

Table 3 presents the descriptive statistics of the variables included in the analysis. The mean score on variable *PREPARED* (6.863) suggests that respondents feel relatively more prepared than unprepared.

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[5] Refer to questions 19, 24, and 28 for the exact questions used to develop the variables.

Regarding how often respondents worry about their finances, the mean score on variable *WORRY* (3.086) indicates that respondents worry about money "sometimes." Interestingly, approximately 71% of respondents perceive themselves to be financially conservative with money (*CONS_PHIL*), yet only 59% of respondents think that others perceive them as financially conservative with money (*OTH_CONS*). The mean score on variable *EXP_SAL* (3.051) indicates that respondents, on average, expect to make between $40,000 and $49,999 after they graduate while expecting to have between $5,000 and $9,999 in student loan debt (*EXP_LOANS*). Approximately 52% of the sample is comprised of males (*GENDER*), and about 63% of the sample is comprised of students majoring in business and/or economics (*BUS_ECON*). While 60% of the respondents had some type of economics education in high school (*ECON*), only 37% had exposure to personal finance topics (*PER_FINC*). The Pearson correlation matrix (not included) between all variables shows that none of the variables are highly correlated.

Table 3: Descriptive Statistics

VARIABLES	N	Mean	Std. Dev.	Minimum	Maximum
PREPARED	1,022	6.863	2.101	1	10
WORRY	1,050	3.086	1.086	1	5
CONS_PHIL	1,046	0.705	0.456	0	1
OTH_CONS	1,040	0.585	0.493	0	1
EXP_SAL	1,045	3.051	0.967	1	4
EXP_LOANS	1,044	3.152	2.104	1	7
KNOWL	1,052	4.775	1.326	0	6
PER_FINC	1,052	0.365	0.482	0	1
ECON	1,052	0.609	0.488	0	1
FRESH	1,052	0.295	0.456	0	1
SENIOR	1,052	0.207	0.406	0	1
GENDER	1,052	0.518	0.500	0	1
ENGINEER	1,052	0.106	0.309	0	1
NURS_SCI	1,052	0.125	0.331	0	1
BUS_ECON	1,052	0.629	0.483	0	1

Results

Hypothesis 1: Money Worries

Table 4 examines the factors which cause students to worry about money (*WORRY*). Across all three models, the variable *EXP_SAL* is not significant, indicating that students' expected future salary does not cause current concerns over money. However, the coefficient on *EXP_LOANS* is positive and significant ($p<0.01$) across all three models indicating that students with relatively high expected student loan debt are more worried about money than those with relatively low expected student loan debt.

Next, the coefficient on *CONS_PHIL* is positive and significant in model 1, indicating that students who perceive themselves as being financially conservative are more worried about money than students who do not perceive themselves as being financially conservative. Additionally, the coefficient on *OTH_CONS* is positive and significant ($p<0.01$) in model 2, indicating that students who are viewed by their peers as being financially conservative are more worried about money than students who are not viewed by their peers as being financially conservative. Model 3 indicates that students' concerns over money are affected by both intrinsic and extrinsic perceptions of financial conservativeness.

Taken together, the results in Table 4 indicate that financial stress among US students is influenced by both expectation and perception. While students' worry about money more as their expected debt obligation increases, their concerns over money also increase if they perceive themselves as being financially conservative or if they believe others perceive them as being financially conservative.[6]

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[6] We also ran three additional models to determine if the observed effects in model 3 of Table 4 interacted with each other. The first model included an interaction variable (*EXP_SAL* × *CONS_PHIL*), the second model included an interaction variable (*EXP_SAL* × *OTH_CONS*), and the third model included an interaction variable (CONS_PHIL × OTH_PHIL). None of these variables were significant in the models run, suggesting that the effects of expectation and perception shown in model 3 of Table 4 are independent.

TABLE 4: Factors Affecting Students' Concern about Money (*WORRY*)

VARIABLES	Model 1	Model 2	Model 3
Constant	2.552***	2.516***	2.454***
	(0.000)	(0.000)	(0.000)
EXP_SAL	-0.028	-0.036	-0.027
	(0.397)	(0.277)	(0.412)
EXP_LOANS	0.170***	0.165***	0.166***
	(0.000)	(0.000)	(0.000)
CONS_PHIL	0.254***		0.179**
	(0.000)		(0.012)
OTH_CONS		0.332***	0.295***
		(0.000)	(0.000)
KNOWL	0.054**	0.063***	0.048**
	(0.030)	(0.009)	(0.049)
PER_FINC	-0.157**	-0.128**	-0.141**
	(0.016)	(0.047)	(0.029)
ECON	-0.009	0.013	-0.019
	(0.891)	(0.844)	(0.763)
FRESH	-0.038	-0.029	-0.039
	(0.634)	(0.715)	(0.623)
SENIOR	0.056	0.041	0.049
	(0.488)	(0.612)	(0.543)
GENDER	-0.272***	-0.286***	-0.287***
	(0.000)	(0.000)	(0.000)
ENGINEER	-0.074	-0.075	-0.063
	(0.570)	(0.558)	(0.626)
NURS_SCI	0.058	0.072	0.078
	(0.632)	(0.548)	(0.512)
BUS_ECON	-0.232**	-0.219**	-0.204**
	(0.016)	(0.023)	(0.034)
Observations	1,032	1,037	1,024
Adj-R2	0.170	0.160	0.190

Parentheses contain p-values. Significance is denoted by *** p<0.01, ** p<0.05, and * p<0.10.

From Table 4, we also find a number of control variables are associated with financial stress. The coefficients on *GENDER* is negative and significant (p<0.01) across all three models, indicating that students who are male are less worried about money than students who are female. These results are consistent with prior findings by Henry et al. (2001), Akben-Selcuk (2015), and Kettley et al. (2008).

The coefficients on *BUS_ECON* across all three models in Table 4 are negative and significant (p<0.05), indicating that students who are business majors are less worried about money than those who major in arts, humanities, or other disciplines. These results are reinforced by the negative and significant coefficients on *PER_FINC* (p<0.05) across all three models, which suggests that students who took a personal finance class in high school are less worried about money than those who took no such class.[7] Taken together, these results suggest that students who know (or believe they know) more about personal finance relative to their peers are less worried about money.

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[7] It is worth noting that none of the coefficients for variable *ECON* are significant across all three models. This suggests that personal finance courses and economics courses are not substitutes for one another as they pertain to mitigating students' current financial concerns.

Hypothesis 2: Financial Self-Confidence

Table 5 examines which factors affect how prepared students feel to manage their own finances in college (*PREPARED*). The coefficient on *EXP_SAL* is positive and significant (p<0.01) across all three models, indicating that students who have a relatively high expected starting salary feel more prepared to handle their personal finances after graduation than students with a relatively low expected starting salary. Additionally, the coefficient for *EXP_LOANS* is negative and significant (p<0.05) across all three models indicating that students with lower expected debt obligations feel more prepared to handle their personal finances after graduation. Taken together, these results suggest a positive relationship between post-graduation financial optimism and financial preparedness. That is, students who expect a higher salary and less debt after graduation are more confident in their ability to manage their personal finances.

TABLE 5: Factors Affecting Students' Sense of Financial Preparedness (*PREPARED*)

VARIABLES	Model 1	Model 2	Model 3
Constant	5.000***	4.901***	4.814***
	(0.000)	(0.000)	(0.000)
EXP_SAL	0.293***	0.301***	0.306***
	(0.000)	(0.000)	(0.000)
EXP_LOANS	-0.059**	-0.079***	-0.075**
	(0.047)	(0.008)	(0.012)
CONS_PHIL	0.301**		0.158
	(0.033)		(0.274)
OTH_CONS		0.620***	0.573***
		(0.000)	(0.000)
KNOWL	0.122**	0.104**	0.099**
	(0.014)	(0.034)	(0.047)
PER_FINC	0.330**	0.360***	0.351***
	(0.012)	(0.006)	(0.007)
ECON	-0.002	0.015	0.006
	(0.988)	(0.907)	(0.962)
FRESH	-0.922***	-0.872***	-0.879***
	(0.000)	(0.000)	(0.000)
SENIOR	0.506***	0.490***	0.490***
	(0.002)	(0.002)	(0.003)
GENDER	0.490***	0.467***	0.473***
	(0.000)	(0.000)	(0.000)
ENGINEER	0.367	0.374	0.382
	(0.160)	(0.149)	(0.140)
NURS_SCI	0.031	0.090	0.094
	(0.899)	(0.711)	(0.697)
BUS_ECON	0.166	0.250	0.256
	(0.393)	(0.199)	(0.188)
Observations	1,004	1,000	996
Adj-R2	0.122	0.138	0.137

Parentheses contain p-values. Significance is denoted by *** p<0.01, ** p<0.05, and * p<0.10.

In model 1 of Table 5, the coefficient for *CONS_PHIL* is positive and significant (p<0.05). This suggests that students' sense of financial preparedness increases with their perception of personal financial conservativeness. Similarly, the positive and significant coefficient for *OTH_CONS* (p<0.01) in model 2 suggests that students' sense of financial preparedness increases with their peers' perception of their personal financial conservativeness. However, when the effect of both variables are examined in model 3, only the coefficient for *OTH_CONS* remains positively significant (p<0.01). This suggests that extrinsically perceived

financial conservativeness has a greater effect on a student's financial preparedness than intrinsically perceived financial conservativeness.

Table 6 examines which factors, including financial concern (*WORRY*), affect how prepared students feel to manage their own finances after graduation (*PREPARED*). The coefficient on *WORRY* across all three models is negative and significant (p<0.05) indicating that the more worried students are over their personal finances, the less prepared they feel to manage their personal finances after graduation. It is worth noting that this negative relationship exists in spite of students feeling more prepared to handle their personal finances given that they have taken a personal finance class (*PER_FINC*, p<0.05).[8] Taken together, these findings suggest that, while personal finance courses increase students' sense of financial preparedness, this positive effect is counteracted by those students' degree of financial worry.

The effects of perceived financial conservativeness in Table 6 are similar to those in Table 5. That is, when examined separately, there is a positive effect of intrinsically perceived financial conservativeness (*CONS_PHIL*) and extrinsically perceived financial conservativeness (*OTH_CONS*) on students' sense of financial preparedness. However, when examined together, model 3 indicates that only extrinsically perceived financial conservativeness affects students' sense of financial preparedness.

In both Tables 5 and 6, the coefficient on *FRESH* is negative and significant (p<0.01) while the coefficient on *SENIOR* is positive and significant (p<0.01). These effects suggest that students who are freshmen (seniors) feel less (more) prepared to handle their personal finances in college than sophomores or juniors. Likely, the effect of time on the certainty of future outcomes explains these diverging relationships. However, there are a multitude of other contributing factors, especially the knowledge students acquire on PFM topics, whether inside or outside the classroom.

The coefficients on *KNOWL* and *PER_FINC* are positive and significant (p<0.05) in both Tables 5 and 6. This indicates that students who are relatively more knowledgeable about personal finance and students who had a personal finance class in high school feel more prepared to handle their personal finances after college than those students who are relatively less knowledgeable about personal finance. The coefficient on *GENDER* is positive and significant (p<0.01) in Table 5, indicating that students who are male feel more prepared to handle their personal finances in college than students who are female. Interestingly, the coefficient on *GENDER* remains positive and significant (p<0.05) when controlling for *WORRY*, *KNOWL*, and *PER_FINC* (see Table 6). That is, regardless of students' financial concerns, financial knowledge, or financial education, male students are more confident in their financial preparedness than female students.

Conclusion and Implications

Our study points to the fact that on average, as financial conservativeness increases, the concern over personal financial management also increases. Further investigation shows that it is the perceived conservativeness from the outside, and not the self-perception of one's degree of financial conservativeness that drives our findings. In other words, college students' degree of PFM confidence is a function of how financially conservative *other* people perceive them to be, and not how financial conservative they perceive themselves to be.

Additionally, regardless of the model and specification, we show that higher expectations about post-graduation salaries are associated with greater personal financial management confidence. We also find that college students feel less prepared to handle their personal finances when they have higher levels of debt relative to their peers. Taken together, the results suggest that college students' degree of PFM preparedness is not a function of expected cash outflow, but rather how much they already worry about their personal finances.

We believe these findings have implications not only on how FLP effectiveness is measured, but also how FLPs are developed, modified, and administered in the future. One of the biggest takeaways from our findings is that in order to improve their effectiveness, personal finance courses can be redesigned to include in their curriculum less technical components along with knowledge-based components. Specifically, introducing psychology focused training/conversations about personal finances in financial education courses would increase the effectiveness of finance education by making college students more receptive to what is

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[8] In a separate test, we included the interaction of *WORRY* and *PER_FINC* in model 1 of Table 5 to determine if both effects were additive. The coefficient on the coefficient for *WORRY* × *PER_FINC* was not significant, suggesting the effects shown in model 1 of Table 5.

being taught in those courses. Our study finds that discussing and addressing the students' worries around personal finance topics could have a significant impact on how well college students retain finance education.

TABLE 6: Factors Affecting Students' Sense of Financial Preparedness (*PREPARED*), Including Financial Concern (*WORRY*)

VARIABLES	Model 1	Model 2	Model 3
Constant	5.490***	5.458***	5.379***
	(0.000)	(0.000)	(0.000)
WORRY	-0.191***	-0.220***	-0.229***
	(0.002)	(0.000)	(0.000)
EXP_SAL	0.283***	0.288***	0.294***
	(0.000)	(0.000)	(0.000)
EXP_LOANS	-0.027	-0.044	-0.038
	(0.388)	(0.163)	(0.224)
CONS_PHIL	0.350**		0.198
	(0.013)		(0.171)
OTH_CONS		0.694***	0.642***
		(0.000)	(0.000)
KNOWL	0.134***	0.120**	0.113**
	(0.007)	(0.014)	(0.024)
PER_FINC	0.301**	0.333**	0.319**
	(0.022)	(0.011)	(0.015)
ECON	0.006	0.023	0.013
	(0.963)	(0.857)	(0.922)
FRESH	-0.929***	-0.883***	-0.891***
	(0.000)	(0.000)	(0.000)
SENIOR	0.520***	0.502***	0.505***
	(0.001)	(0.002)	(0.002)
GENDER	0.444***	0.409***	0.413***
	(0.001)	(0.002)	(0.002)
ENGINEER	0.342	0.346	0.356
	(0.189)	(0.179)	(0.167)
NURS_SCI	0.045	0.110	0.117
	(0.852)	(0.647)	(0.627)
BUS_ECON	0.114	0.191	0.200
	(0.558)	(0.324)	(0.305)
Observations	1,002	998	994
Adj-R2	0.129	0.149	0.148

Parentheses contain p-values. Significance is denoted by *** $p<0.01$, ** $p<0.05$, and * $p<0.10$.

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Implementing Recorded Lectures: Education Production Function Analysis in Economics Online Courses

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ABSTRACT

Instructor created recorded lectures were introduced to two principles of macroeconomics and two principles of microeconomics online courses to improve student outcomes. Using the education production function, both time spent and access were modeled using a first difference regression and generalized method of moments estimator. Data for this study, covering nine weeks for each course, were collected from the course management system, book publisher, and college registrar. Results show that more time spent in the course management system and book publisher's homework system lead to increased grades while accessing recorded lectures had mixed results.

Introduction

The use of supplemental material to stimulate interest in lectures and improve student outcomes has long been a staple of face-to-face instruction. Technology has advanced societal patterns and established a broad reach within academia; however, this impact on academia, e.g., asynchronous online courses with an abundance of supplemental material, posits implementation and utilization concerns. Are students receiving enough material to supplement their needs and succeed in the course? Do students have the technical competency and sufficient time to use the material, process its content, and apply the information in a manner sufficient to increase positive outcomes? The number of students who engaged in online education in the United States grew by 26%—or nearly 200,000 students—from 2012 to 2014. Public institutions commanded the largest portion of online education students, with 72.7% of all undergraduate and 38.7% of all graduate-level students (Allen et al. 2016). Therefore, the ability to facilitate instruction and address implementation and utilization concerns may become increasingly important for student success.

Learning management system (LMS) advancements and publishers' digital learning platforms (MindTap, Connect, Smartwork, etc.) have continually evolved and now routinely include practice exercises, test banks, case studies, and videos, all directed towards improving student outcomes. Additional videos posted online to facilitate lecture to the asynchronous student include, but are not limited to, YouTube or publicly available videos such as those from the Khan Academy. These videos may provide a greater benefit to students as they are not subject to coordination issues, and they have the ability to re-watch lectures (Chen and Lin 2012). By moving to this generalized instructional delivery method, students may be able to increase their knowledge retention and grades.

To address course- and program-specific student learning objectives, some instructors have recorded lectures to supplement available ancillary materials. The use (or non-use) of an instructor's course-specific recorded lectures poses some unique questions and concerns regarding the breadth and rigor of a course when multiple sections of a course are taught by different instructors. To address these concerns, our department of economics has been using somewhat homogenous online principles of economics courses that are designed to mirror traditional course offerings, enhance student learning, and preclude students from taking a specific

section to find an easy "A." This has allowed us to monitor changes in how students perform by section and term, and determine what areas of study prove to be the most difficult for students.

Beginning in the fall of 2016, our department of economics introduced a new tool to address the issue of breadth and depth in supplemental material. One instructor created recorded lectures, available in all sections and to all students, for principles of macroeconomics and microeconomics courses. The idea was to simulate the face-to-face instruction of the traditional classroom and address areas of study found to be the most difficult for students. The recorded lectures were designed to complement the book and supplemental material already housed in the courses and improve student performance (Gulley and Jackson 2016). Having one instructor create the videos eliminated any differences that might arise from teaching styles of other instructors. If video based instruction is effective as a tool, then a positive association in grades should arise.

An education production function (EPF) can capture student performance with student inputs. To build upon the existing EPF literature, which are typically a two-time period models, this paper employs panel data across multiple sections of two courses. Further, a first difference model is used to estimate the EPF. The rest of the paper proceeds as follows: In the next section, we provide a literature review of the economics of education, online education, and instructor resources used in courses, we then describe the data used in this paper, followed by the empirical strategy. Results are then presented and concluding remarks are made.

From the Classroom to the Virtual Classroom

Economists have been studying student outcomes for decades (for example, see Allgood et al. 2015 and the references therein) to ascertain the determining factors that aid students in passing courses or doing well on exams. As distance education, and in particular online courses became more popular, economists shifted focus to factors that influenced how well students did online versus those in face-to-face courses (Coates et al. 2004; Howsen and Lile 2008; Gratton-Lavoie and Stanley 2009; Figlio et al. 2013; Xu and Jaggars 2013).

The ability to succeed in an online course has been studied by many economists and non-economists alike. Familiar student determinants of success move fluidly between traditional face-to-face courses and the online environment. A student's GPA (Cavanaugh and Jacquemin 2015), GPA and ACT percentile ranking (Brown and Liedholm 2002), term selection (Gratton-Lavoie and Stanley 2009), number of previous online courses, and age (Wojciechowski and Palmer 2005) influence future outcomes. Online students' grades are also determined to be partially dependent on age, ethnic background, and higher education experience (Koch 2006; Borg and Stranahan 2002). Perhaps more inherent to the online student is the ability to self-regulate and be accountable (Driscoll et al. 2012), as student-teacher interaction is more likely to be asynchronous.

Some recent research has focused on those students who were diligent in their studies as opposed to procrastinating students and the outcomes achieved in the course (Masui et al. 2014; You 2015). In addition, engaging in a greater amount of time on task, e.g., study time, utilization of supplemental material, viewing videos, practice quizzes, etc. led to more positive outcomes (Damianov et al. 2009; Calafiore and Damianov 2011; Bonesronning and Opstad 2012). Study time, an integral component of time on task, was shown to be causal determinant of academic performance (Andrietti and Velasco 2015). This is particularly important in a compressed term of eight weeks as course material is introduced at a faster pace.

Analysis of student outcomes was determined using an EPF (Manahan 1983). Even though this research used standardized courses to mirror traditional courses, we were not able to use the effect of attendance to study outcomes since attendance, measured as online student participation, varies across the week's scheduled work (Arulampalam et al. 2008). An alternate approach to quantifying attendance in an EPF for online classes would be the analysis of unobservable factors correlated with attendance, e.g., ability, effort, and motivation (Stanca 2006). Intuitively, the relationship between student effort and performance would seem to be intrinsically linked, but this linkage is subject to analysis with additional research merited (Krohn and O'Connor 2005).

Given the asynchronous environment and reduction in interaction of online learning, introduction of some type of video lecture or videoconference may help improve student outcomes and satisfaction. Rose (2009) found that utilizing instructional videos in an online setting was viewed positively by students. Ladyshewsky (2013) noted increased presence led to improved student satisfaction. Guo et al. (2014) found that breaking up longer lectures into shorter videos was more engaging for students. Shotwell and Apigian (2015) report students benefited by having online video tutorials. Lastly, Chen and Lin (2012) used lecture capture technology to determine if students who viewed the lecture capture videos after a class and before an exam could improve their exam score in an intermediate microeconomics course. They found a small and positive

impact on grades. It is worth noting in the Chen and Lin study that students, who attended traditional brick-and-mortar institutions and used the online video lectures in conjunction with class attendance, performed better than those who only attended class.

The preponderance of available literature addressing videos as an enhancement to online learning focuses on their use as a supplement to instructional deliveries in a traditional brick-and-mortar institution. To add to the existing literature, this paper focused exclusively on asynchronous delivery to students taking introductory macroeconomics and microeconomics courses, and how the use of these supplemental instructor generated videos impacted student outcomes.

Data

Data for this paper come from the two-term fall semester of 2016, in which four principles of economics courses were taught between two instructors, one teaching two macroeconomics courses and one teaching two microeconomics courses. Instructors kept their sections homogeneous, so that there were no differences between the two terms. Each course taught online is subject to a nine-week term, with eight weeks of instruction followed by a final exam week. Thus, the term system compresses a sixteen-week course into eight weeks of instruction, which may warrant the use of recorded lectures. Course grading was assigned through a midterm, final examination, discussion board posts, and Aplia homework for each chapter covered in the course (see Table 1).

Table 1. Grade Distribution and Assignments for Macro- and Microeconomics

| Week | Macroeconomics | | | Microeconomics | | |
	Assignments	Total Assignments	Weight	Assignments	Total Assignments	Weight
1	HW, DB Posts, Entry Assign.	4	10.71%	HW, DB Posts, Entry Assign.	4	11.15%
2	HW, DB Post	4	10.71%	HW, DB Post	2	8.08%
3	HW	2	5.71%	HW	1	3.08%
4	HW, DB Post	3	10.71%	HW	2	6.15%
5	Midterm, HW	2	22.86%	HW, DB Post	3	11.15%
6	HW	2	5.71%	HW, Midterm	2	23.08%
7	HW, DB Post	3	10.71%	HW, DB Post	3	11.15%
8	HW	1	2.86%	HW	2	6.15%
9	Final Exam	1	20.00%	Final Exam	1	20.00%

Note: HW = Aplia homework, DB Posts = discussion board posts. Weight columns may not sum to 100% because of rounding.

Using the university's Blackboard page, students can access their section's information, the weekly learning modules supported by Aplia, and the instructor recorded lectures. Students can also access a multitude of supplemental tools to aid in their understanding of the material. These include: worked problems for each chapter, practice tests, flashcards, enhanced PowerPoint slides, as well as any learning material found in Aplia.

Recorded lectures, the only learning material not found in learning modules, are found in the "Recorded Lectures" tab below the "Learning Modules" tab. This tab contains more than 50 recorded lectures for each section. Each section has an entire set of chapters' recorded lectures that are each no more than fifteen minutes long. Each chapter has between 2-6 recorded lectures, with a final recorded lecture that walks students through additional examples.[2] Students are also made aware of what each video contains, so they do not have to search a video to find a particular concept.

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[2] All videos are hosted on a private YouTube channel, whereby students would need to login to Blackboard to view the videos. From there, students had the option of either watching the videos in Blackboard or linking out to YouTube. In our data collection process, we found that students were mostly linking out to YouTube. We suspect this was due to being able to access a larger screen as Blackboard was restrictive in allowing a full screen view. In addition, the minutes of viewing time seemed limited in Blackboard, even though access was high among many students. Yet, the YouTube analytics showed that students had been viewing thousands of minutes during the term.

Between the two courses (two sections of principles of macroeconomics and two sections of principles of microeconomics), there were a total of 134 students, with 84 coming from principles of microeconomics and 50 coming from principles of macroeconomics. Data were collected on each student each week by using Blackboard's analytics. This included the number of times the student accessed material (either the learning modules or recorded lectures), the total number of hours (minutes) the student spent in the section, and where available the number of hours (minutes) spent in each area of the section. Data for Aplia usage were provided by Cengage and matched to student data from Blackboard by section.[3] Lastly, these data were matched to administrative data to complete the data set. We ended with 1,206 total observations (756 from microeconomics and 450 from macroeconomics) spanning nine weeks.

One interest in this paper is how students spend their time and how that reflects upon their grades, given that online learning requires critical thinking and discipline in time management (Bratti and Staffolani 2013). Online learning is structured by a LMS and directed assignments; however, this student engagement delivery methodology (Chen et al. 2010) requires the student to develop and utilize autonomous learning skills (Robinson and Hullinger 2008). As indicated in Table 2, our students spent most of their time in the section during the weekend. Among the 50 students in macroeconomics, a total of 2,235.07 hours was spent in the course (an average of 44.70 hours per student or an average of 4.967 hours per week) with 47.75% of the total hours spent occurring on the weekend. For the 84 microeconomics students, a total of 3,432.88 hours was spent in the course (an average of 40.87 hours per student or an average of 4.54 hours per week) with 48.07% of the total hours spent occurring on the weekend.

Table 2. Total and Average Hours Spent by Students by Day

Day	Total Hours in Macroeconomics	Average Hours in Macroeconomics	Total Hours in Microeconomics	Average Hours in Microeconomics
Sunday	662.74	1.473	1120.70	1.482
Monday	172.00	0.382	289.60	0.383
Tuesday	205.60	0.457	331.89	0.439
Wednesday	280.23	0.623	359.52	0.476
Thursday	261.09	0.580	381.19	0.504
Friday	248.80	0.553	420.55	0.556
Saturday	404.61	0.899	529.43	0.700

A takeaway from Table 2 is that students tend to access online course material more frequently during the weekend days than other days of the week. This method may naturally arise, as the majority of our students are older, have full-time jobs, and are concurrently taking other courses.

Students were also surveyed in week nine of the section to ascertain how they spent their time and what they found to be difficult. Among the 84 students in microeconomics, 69 responded. Among the 50 students in macroeconomics, 34 responded. Most questions focused on what the students spent most of their time doing; however, two questions were of particular interest.

The first question of interest asked students to rank each week from least challenging to most challenging based only on the chapter material. We single out this question as it reveals how students may have spent their time based on the level of difficulty and how their grades were affected.

Figures 1 and 2 show (by term) the total hours spent each week, the perceived level of difficulty,[4] the weight of assignments, and the average grade. From the two figures, it can be seen that grades tend to fall over the course of the term. Students, across all sections and generally speaking, viewed week one to be the least challenging week. In microeconomics, students tended to view weeks seven and eight as the most challenging—this was their introduction into market structure. In macroeconomics, there was not as much of a consensus. Weeks five through seven were perceived to be the most challenging. Week nine did not have any responses as the survey was given during week nine, so that difficultly level is the average of all the other

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[3] We were diligent to separate out minutes spent in Blackboard and Aplia by section so that there was no double counting of access time for either.

[4] The level of difficulty is calculated by first determining which week had the most responses for least challenging, second least challenging, and so on. Next, these summations were constructed as percentages. Lastly, we subtracted them from 100. For example, week 1 in term 1 for microeconomics had 31 responses as least challenging out of 39 total responses or 79.49%. Subtracting this from 100 gives week 1's difficulty rating of 20.51%.

weeks. Total hours spent by week seemed to fluctuate based on the perceived difficulty and weight of assignments.

Figure 1. Total Hours per Student, Assignment Weight, Student Perceived Difficulty and Grade by Week in Microeconomics
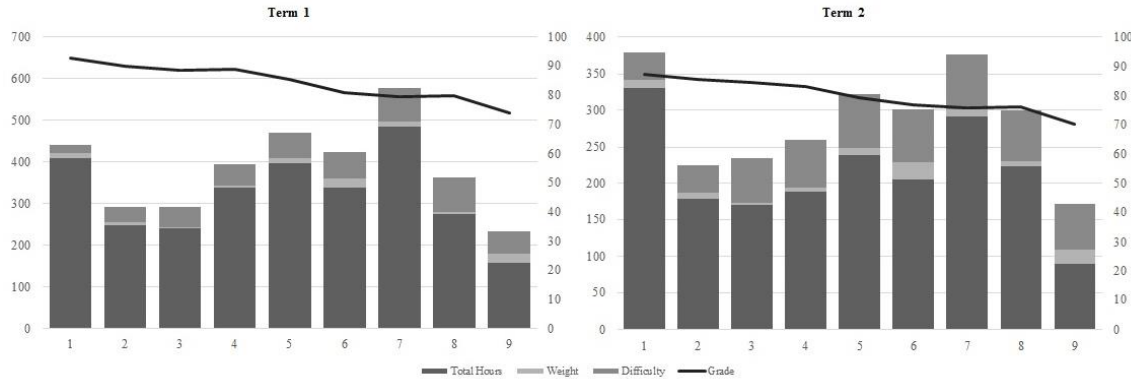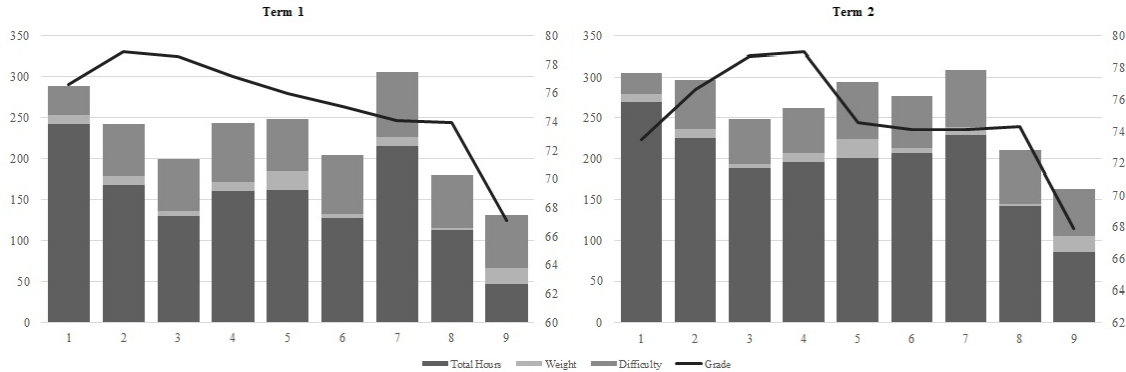

Figure 2. Total Hours per Student, Assignment Weight, Student Perceived Difficulty and Grade by Week in Macroeconomics

The second question of interest asked how students utilized their time. This question provides insight into how students are allocating their time across the available material, and, in particular, the recorded lectures. Of the 103 students who responded to the survey, 68.6% said they used the recorded lectures (75% from microeconomics and 55.9% from macroeconomics) with 25.5% of all respondents stating they used the recorded lectures more than any other resource.

A final point needs to be made. In three of the sections, more hours were spent in week one than any other week. However, across all sections, week one was viewed as the least challenging. This may have arisen since "Total Hours" measures time spent in Blackboard and Aplia as well as student acclimation in Blackboard and Aplia. Students spent more time in week one because they were becoming familiar with Blackboard, the course, and Aplia, not because they perceived that week's to be the most challenging.

Empirical Strategy

We begin our empirical strategy by specifying our model of student production,

$$G_{i,t} = X_{i,t}\beta + Z_i\gamma + \tau_t + \mu_{i,t} \quad i = 1, 2, \dots, n \qquad t = 1, 2, \dots, T \text{ (1)}$$

where $G_{i,t}$ is the grade of student i in time t. $X_{i,t}$ is a vector of variables that vary over time and include the number of minutes spent in Blackboard ($BBMin$), the number of minutes spent in Aplia ($ApliaMin$), the number of times the student accesses the current week's learning module ($LMAccess$), and the number of times the student accessed the current week's recorded lectures (RL).[5] Z_i is a vector of time invariant variables

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[5] We perform a robustness check on $BBMin$, $ApMin$, and RL by looking at alternative measures. $BBMin$ ($ApMIn$) measures the total minutes in Blackboard (Aplia) spent by student i per week; however, we may also view learning economics as a cumulative experience. So we alter $BBMin$ ($ApMin$) to be a running total of the number of minutes spent in Blackboard (Aplia). The new

that measure, presumably, the student's ability and other characteristics. For ability, we use the student's cumulative GPA up to the time of section enrollment. Other characteristics include whether the student has previously taken the same course (*MacroRetake*, *Microretake*), and the adjusted credits the student is currently taking (*AdjCred*). Adjusted credits measure the course load of the student. For example, if the student is taking 12 credit hours including one of the economics courses, then the student's adjusted credit hours are 9. As the online courses are on a term system (9 weeks), students are limited to a maximum of 10 credit hours per term, so it is possible for adjusted credits to be as high as 7 and as low as 0. $\boldsymbol{\tau}_t$ is a vector of time dummies measuring the course week. Lastly, $\mu_{i,t}$ is the idiosyncratic error term.

In (1), we assume strict exogeneity of the independent variables,

$$E[\mu_{i,t}|\boldsymbol{X}_{i,t}, \boldsymbol{Z}_i] = 0 \quad t = 1, 2, \dots, T \ (2)$$

and no unobserved heterogeneity (an assumption we relax later). Further, we assume that the variables in (1) are reasonable proxies for a student's ability and effort, such that they do not violate (2). Under this assumption, we estimate (1) with pooled OLS as this estimator will provide consistent and unbiased estimates. However, we still need an efficient estimator if the errors exhibit a non-constant variance. We, therefore, rely on a cluster robust variance matrix to provide the efficiency in the standard errors.

From the above strategy, we can obtain estimates that show how students' ability and effort influence their grades. However, if the variables we use in place of students' unobserved ability and effort fail to be reasonable measures, then we must seek additional ways to estimate our model. The above problem arises when the variables in (1) do not capture enough of the correlation between the unobserved heterogeneity and the appropriate regressors.

Before moving to the next strategy, we note that *LMAccess* and *RL* have the potential to measure student interest in the subject. In a given week, a student will access, at least once, the learning module for that week, because the learning module contains all the relevant information. During that time, the student sees the current week's objectives, assignments, and links to Aplia. At a minimum, the student only has to access the learning module once, and that is to link to Aplia or any other weighted assignment that is housed in the learning module. However, students who want to be more engaged in the subject matter may revisit the learning module numerous times to review any material. In addition, the recorded lectures are not housed in the learning modules. These are kept in a separate tab in the Blackboard section page. While students learn differently, continued access to these videos may imply that a student wishes to review the concept or is more interested in that particular topic. Given the above, we assume that these two measures do contain some information as to student interest.

Two approaches can be taken to exploit the within-student variation and address endogeneity concerns (when (2) is violated). First, we can use the fixed effects (FE) estimator, which absorbs the unobserved heterogeneity into dummy variables, essentially capturing all the relevant information that otherwise would not be directly measurable into a single variable. Or we can use the first difference (FD) estimator to difference out the unobserved heterogeneity. The drawback to both methods is the loss in time invariant variables. However, under the assumption of strict exogeneity, we obtain a consistent and unbiased estimator.

The choice between the FE and FD estimators comes down to efficiency. When T > 3, serial correlation becomes the issue for efficiency. The FE estimator is more efficient when there is no serial correlation in $\mu_{i,t}$ and the FD estimator is more efficient where there is serial correlation in $\mu_{i,t}$, since the differencing cancels the serial correlation out. Since T > 3 in our data, we test for serial correlation in the FD model and find that the lag of $\mu_{i,t}$ is insignificant meaning serial correlation is found in $\mu_{i,t}$. We, therefore, use the FD estimator given by Equation 3:

$$\Delta G_{i,t} = \Delta X_{i1,t}\beta_1 + \Delta X_{i2,t}\beta_2 + \Delta X_{i3,t}\beta_3 + \Delta X_{i4,t}\beta_4 + \boldsymbol{\tau}_t + \Delta\mu_{i,t} \ (3)$$

where $\Delta X_{i1,t}$ is the difference in minutes in Blackboard for student i in time t, $\Delta X_{i2,t}$ is the difference in minutes in Aplia for student i in time t, $\Delta X_{i3,t}$ is the difference in learning module access, and $\Delta X_{i4,t}$ is the difference in recorded lecture access. Time dummies, $\boldsymbol{\tau}_t$, are also included to control for differences in material and weight of assignments across each week.

While first differencing cancels out endogeneity that arises from unobserved heterogeneity, there is still another concern for endogeneity bias. First, there is the concern that the variables related to time spent in either Blackboard or Aplia, and the variables that replicate attendance (*LMAccess* and *RL*), may be influenced

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variables: *BBTot* and *ApTot* measure the cumulative number of minutes the student has spent in Blackboard or Aplia during the week. This may be viewed as a student drawing on past and current learning to help the current grade. *RL* is altered by using a dummy variable for whether or not the student accessed the material (*Access*).

by other factors. For example, time spent may be influenced by the number of announcements an instructor created for the given week, creating more or less interest in the particular subject matter. We test for this type of endogeneity bias by following the procedure outlined by (Wooldridge 2002, p. 285). The leads of each variable ($w_{i,t+1}$, which are a subset of variables from (3)) are added to the first difference models and are adjusted for heteroscedasticity and autocorrelation. If the leads are significant, then future values of these variables are correlated with past values of the dependent variable.

From the above, we can determine if we have met the condition imposed by (2). If strict exogeneity fails, we may use assumptions imposed by sequential exogeneity:

$$E\left(u_{it}|\boldsymbol{x}_{it},\boldsymbol{x}_{i,t-1},\ldots,\boldsymbol{x}_{i1},c_i\right) = 0 \quad t = 1, 2, \ldots, T \quad (4)$$

such that current and past values of $\boldsymbol{x}$ and c (the unobserved heterogeneity component) are uncorrelated with the error term, and, hence, past values of $\boldsymbol{x}_{it}$ do not affect the expected value of y_{it}. First differencing (1) eliminates c, and assuming (4) results in:

$$E(x'_{is}u_{it}) = 0 \quad s = 1, 2, \ldots, t \quad (5)$$

implying the following orthogonality conditions:

$$E(x'_{is}\Delta u_{it}) = 0 \quad s = 1, 2, \ldots, t-1 \quad (6)$$

such that, at time t, the regressor $x^O_{i,t-1}$ can be used as a potential instrument for Δx_{it}. Given that $x^O_{i,t-1}$ is uncorrelated with Δu_{it}, the estimated matrix meets the rank condition and pooled two-stage least squares (TSLS) can be used with $\Delta x_{i,t-1}$ (or the lag in x_i) as instruments for $\Delta x_{i,t}$, should such a need arise (Wooldridge 2002, p. 303).

Before concluding this section, we point out that the principles of macroeconomics and microeconomics courses are different, not only in subject matter but also in the course layout. For these reasons, we separate our results by students who took macroeconomics courses and those who took the microeconomics courses.

Results

Table 3 presents the summary statistics for the variables used in our models. Since some students did not access Blackboard or Aplia in a particular week, some minimum values are zero.

Table 3. Summary Statistics

Variable	Microeconomics (N = 756)			Macroeconomics (N = 450)		
	Mean	Min	Max	Mean	Min	Max
BBTot	1388.3710	0.0000	7174.3000	1645.1680	0.1167	7996.2830
ApTot	486.0770	0.0000	2584.4200	539.9061	0.0000	3096.5600
BBMin	273.3766	0.0000	1674.0500	301.6771	0.0000	1724.3670
ApliaMin	107.0320	0.0000	687.2800	112.4656	0.0000	659.2500
CumGPA	2.8207	0.0000	4.0000	2.7047	1.8680	3.9480
AdjCred	3.1905	0.0000	10.0000	2.9200	0.0000	9.0000
LMAccess	8.2659	0.0000	48.0000	8.9022	0.0000	52.0000
RL	1.3505	0.0000	84.0000	0.8156	0.0000	23.0000
Accessed	0.1984	0.0000	1.0000	0.1911	0.0000	1.0000
Work	0.6548	0.0000	1.0000	0.6400	0.0000	1.0000
MicroRetake	0.1905	0.0000	1.0000			
MacroRetake				0.1400	0.0000	1.0000
Announce	5.9563	1.0000	16.0000	8.5689	2.0000	23.0000

As a starting point, we present the pooled OLS results for the microeconomics courses for equation (2) in Table 4. Across all models, the Aplia variables are highly significant. Total cumulative time spent in Aplia (*ApTot*) shows that a 10% increase in minutes spent in Aplia adds about a 0.011 percentage point increase in the student's grade. Whereas a 10% increase in minutes spent in Aplia in the current week (*ApMin*) increases the student's grade by about 0.40 percentage point, time spent in Blackboard is only marginally significant

when considering time spent each week as opposed to cumulative time spent. Students receive about eight times less of an increase in their grade by spending one additional minute compared to the results from Aplia.

The student's prior ability, measured by *CumGPA*, is highly significant and shows a large positive effect across all models. For every one point higher the students' cumulative GPA, their grades are expected to increase between 11 and 12 points. This is an unsurprising result and one commonly found in the literature.

While the Model 1 and Model 2 results find that accessing the learning modules an additional time increases the student's grade by about 0.24 percentage points, viewing the recorded lectures had a negative effect on the student's grade. Possible reasons for this result are those who viewed the recorded lectures were not going to do well to begin with. On the other hand, the recorded lectures may not have been of any use to the students—or bad altogether—and viewing them detracted from more fruitful activities. Whatever the reasons may be for the negative impact of the recorded lectures, our proxies for student attendance show positive and negative effects, though never in the same model.

Table 4. Pooled OLS Regression Results for Microeconomics

	Model 1	Model 2	Model 3	Model 4
BBTot	0.0011	0.0009		
	(0.001)	(0.0010)		
ApTot	0.0108***	0.0112***		
	(0.0034)	(0.0033)		
BBmin			0.0056*	0.0046*
			(0.0028)	(0.0026)
ApMin			0.0399***	0.0412***
			(0.0095)	(0.0095)
TotalMin				
CumGPA	11.4061***	11.4777***	11.5874***	11.6735***
	(1.526)	(1.5189)	(1.4869)	(1.4801)
AdjCred	-0.7664	-0.7630	-0.7425	-0.7376
	(0.5596)	(0.5624)	(0.5577)	(0.5608)
LMAccess	0.2432**	0.2186**	0.1619	0.1432
	(0.1157)	(0.1105)	(0.1106)	(0.1077)
RL	-0.1753		-0.2000*	
	(0.1105)		(0.1145)	
Accessed		-0.9830		-0.9007
		(1.3561)		(1.3307)
Work	2.6707	2.5632	2.5871	2.4690
	(2.4125)	(2.4000)	(2.4347)	(2.4279)
MicroRetake	-3.5514	-3.5064	-3.8927	-3.8021
	(3.7759)	(3.7797)	(3.8128)	(3.8252)
Time effect	Yes	Yes	Yes	Yes
Constant	54.4215***	54.5745***	48.2291***	48.3166***
	(5.5256)	(5.5332)	(5.8287)	(5.8528)
Observations	756	756	756	756
R^2	0.4647	0.4631	0.4665	0.4642
F	25.80	26.28	27.3442	28.5305

Notes: Cluster robust standard errors in parentheses; Total 84 clusters; Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 5 reports the pooled OLS regression results for the macroeconomics courses. The results are similar to those found in Table 4; however, there are a few differences. Though the coefficients remain roughly the same, the variables measuring time spent in Aplia have reduced from the one percent level of significance to ten percent. Second, the variables measuring time spent in Blackboard are insignificant, and two are even negative. This is not completely unexpected, as the pooled OLS results are biased. Thirdly, *RL* is now positive and significant across the three models in which it is found.

Table 5. Pooled OLS Regression Results for Macroeconomics

	Model 1	Model 2	Model 3	Model 4
BBTot	0.0002	0.0002		
	(0.0013)	(0.0013)		
ApTot	0.0125*	0.0126*		
	(0.0069)	(0.0069)		
BBmin			-0.0012	-0.0004
			(0.0045)	(0.0044)
ApMin			0.0515**	0.0521**
			(0.0212)	(0.0210)
TotalMin				
CumGPA	15.8370***	15.7644***	16.8984***	16.7629***
	(4.9409)	(4.9458)	(4.4371)	(4.4265)
AdjCred	-0.9332	-0.9050	-0.9455	-0.9204
	(1.3205)	(1.3261)	(1.3205)	(1.3227)
LMAccess	0.2452	0.2701	0.2899	0.2929
	(0.1936)	(0.1891)	(0.2168)	(0.2108)
RL	0.8313**		0.7883*	
	(0.3840)		(0.4165)	
Accessed		3.0732		3.2649
		(3.0068)		(3.0328)
Work	-3.4348	-3.0721	-2.9550	-2.7082
	(4.2322)	(4.2784)	(4.1221)	(4.1969)
MacroRetake	3.9094	3.8732	4.4924	4.5053
	(5.0126)	(5.1018)	(4.7207)	(4.7958)
Time effect	Yes	Yes	Yes	Yes
Constant	28.8527**	28.4431**	18.7359	18.2984
	(13.2871)	(13.2954)	(11.6418)	(11.6961)
Observations	450	450	450	450
R^2	0.4348	0.4286	0.4372	0.4327
F	14.55	14.354	20.2039	20.6629

The positive and significant result for *RL* suggests that viewing the recorded lectures had a positive impact on the student's grade. In particular, viewing an additional recorded lecture increased the student's grade by 0.73 - 0.83 percentage points. However, the variable *Access* does not show a significant effect, which is different from the results found by Chen and Lin (2012). However, both suggest that recorded lectures (either the total number of times accessed or, as in Chen and Lin, accessing the recorded lectures) do increase student grades. Table 6 presents the results for the microeconomics sections and Table 7 presents the results for the macroeconomic sections. As the pooled OLS models suffer from unobserved heterogeneity and potential endogeneity bias, we turn our attention to the first difference models outlined by Equation (3) to address both microeconomics and macroeconomics.

The first two models in Table 6 show similarities to what was found from the first two models in Table 4. Spending time in Aplia is still positive and significant at the 5% level, leading to increases in a student's grade. Model 3 still shows the change in weekly time spent in Aplia is positive and highly significant, but Model 4 drops significance. Each model also shows that viewing recorded lectures is no longer negative. In most cases, spending more time in Aplia is more beneficial for the microeconomics student as compared to other activities the student could pursue.

In Table 7, we find that time spent in Aplia, either cumulatively or additionally, is still positive and significant, which matches the results found in Table 5. Further, accessing the learning modules additional times increases the student's grade. A notable change is the drop in significance for accessing recorded lectures. This results differs from Chen and Lin (2012) though it should be noted that their paper examined

Table 6. First Difference Regression (Microeconomics)

	Micro 1	Micro 2	Micro 3	Micro 4
ΔBBTot	0.0020*	0.0020**		
	(0.0010)	(0.0010)		
ΔApTot	0.0022**	0.0022**		
	(0.0011)	(0.0011)		
ΔBBMin			0.0014	0.0014
			(0.0009)	(0.0009)
ΔApMin			0.0122***	0.0123
			(0.0030)	(0.0030)
ΔLMAccess	0.0494	0.0459	0.0231	0.0199
	(0.0399)	(0.0403)	(0.0349)	(0.0351)
ΔRL	0.0076		0.0090	
	(0.0515)		(0.0545)	
ΔAccess		0.6338		0.6716
		(0.4941)		(0.5014)
Time Effects	Yes[†]	Yes[†]	Yes[†]	Yes[†]
Constant	-3.9808***	-3.9542***	-0.4675	-0.3508
	(1.0838)	(1.0887)	(1.0539)	(1.0641)
$w_{i,t+1}$	2.86 (0.0283)	2.48 (0.0504)	26.63 (0.0000)	72.62 (0.0000)
R^2	0.1485	0.1505	0.1742	0.1764
F	40.15	36.37	31.65	29.72

Notes: Cluster robust standard errors in parentheses; Sample total of 84 clusters; * $p<0.10$, ** $p<0.05$, *** $p<0.01$; F-test statistic given for $w_{i,t+1}$ and the corresponding p-values are in parentheses; [†] Indicates that some or all of the week dummies are significant. There are 672 observations in all four models.

Table 7. First Difference Regression (Macroeconomics)

	Macro 1	Macro 2	Macro 3	Macro 4
ΔBBTot	0.0005	0.0004		
	(0.0010)	(0.0009)		
ΔApTot	0.0113**	0.0115**		
	(0.0046)	(0.0046)		
ΔBBMin			0.0006	0.0005
			(0.0010)	(0.0010)
ΔApMin			0.0022**	0.0022**
			(0.0008)	(0.0008)
ΔLMAccess	0.0411	0.0387	0.0436*	0.0419*
	(0.0276)	(0.0274)	(0.0399)	(0.0248)
ΔRL	0.0509		0.0767	
	(0.1097)		(0.0994)	
ΔAccess		0.8359		0.8353
		(0.7905)		(0.7743)
Time Effects	Yes[†]	Yes[†]	Yes[†]	Yes[†]
Constant	-0.9946***	-0.9702***	-4.4315***	2.6860*
	(0.3207)	(0.3280)	(0.9544)	(1.4378)
$w_{i,t+1}$	18.96 (0.0008)	7.04 (0.1337)	0.32 (0.8623)	0.29 (0.8811)
R^2	0.2339	0.2368	0.1485	0.2217
F	21.39	21.60	40.15	27.80

Notes: Cluster robust standard errors in parentheses. 50 clusters in the sample. * $p<0.10$, ** $p<0.05$, *** $p<0.01$; F-test statistic given for $w_{i,t+1}$ and the corresponding p-values are in parentheses; [†] Indicates that some or all of the week dummies are significant. There are 400 observations in all four models.

intermediate microeconomics courses and used a fixed effects model. This result shows a positive effect; however, we mention again that data limitations from Blackboard and YouTube precluded us from being able to accurately determine how many minutes were watched by each student.

We test for strict exogeneity by including the leads of each variable suspected to be endogenous. These results are found in Tables 6 and 7 under the variable $w_{i,t+1}$, where the week dummy variables were removed to report the test statistic. An *F*-test for each model reveals that strict exogeneity holds for most macro models, except for Macro3. Micro1, Micro3, and Micro4 resoundingly reject the null of strict exogeneity at the 5% and 1% levels, respectively. Micro2 shows a weak rejection of strict exogeneity. As five of the eight models reject (or weakly reject) the null of strict exogeneity, we employ generalized method of moments (GMM) IV estimation to produce unbiased and consistent results.

Table 8 provides the estimates from the GMM IV estimation for the five models that rejected strict exogeneity. Each model was instrumented with two lags of the endogenous regressor(s)—*ApTot*, *ApMin*—and Micro 1 and Micro 2 were also instrumented with the difference in the number of announcements sent per week.[6] Instrument tests were conducted to determine the validity of the instruments. Across each model, the Kleibergen-Paap (K-P) rk LM statistic rejects underidentification suggesting that the instruments are correlated with the endogenous regressors. The K-P rk Wald *F* statistic is a test for weak identification and is akin to the Craig-Donald F statistic. However, the K-P rk Wald *F* is robust to heteroscedasticity and autocorrelation. Staiger and Stock (1997) suggest a "rule of thumb" of 10 on the test statistic to reject weak identification. Our last test for instruments is the Hansen *J* statistic. It reveals that the instruments used in Micro 1 and Macro 1 satisfy the overidentification restrictions and the instruments are uncorrelated with the error term. Results for Micro 2 are just significant at the 5% level and the instruments used ($ApTime_{t-1}$, $ApTime_{t-2}$, $\Delta Announce$) are correlated with the error term.

Our last test is one for endogeneity of the regressor in question. This test statistic is chi-square distributed and indicates whether the regressor can be treated as exogenous if it fails to reject the null. The suspected endogenous regressors ($\Delta ApTot$) in Micro 1 and Micro 2, do not reject the null of exogeneity, and can be treated as such. However, the suspected endogenous regressors ($\Delta ApMin$ and $\Delta ApTot$) in Micro 3, Micro 4 and Macro 1 reject the null of exogeneity at the 5% and 1% levels, respectively. These results are readily confirmed by comparing the test statistics for $w_{i,t+1}$ found in Tables 6 and 7.

As Micro 1 and Micro 2 do not reject their exogeneity test, we defer to their earlier models found in Table 6. Spending weekly time in Blackboard is now significant at the 5% level for the Micro 3 and Micro 4 models, with the parameter estimates being slightly greater than those found in Table 6. The change in weekly time spent in Aplia loses all significance from Micro 3 when compared to the results found in Table 6. The change in cumulative time spent maintains its significance level, but is reduced by 0.003. Lastly, we note the results from Macro 1 being interpreted with caution, as the K-P rk Wald *F* suggest that the model is weakly identified.

Discussion and Concluding Remarks

The objective of recorded lectures was to provide greater benefit to students. Was this benefit realized and were students able to increase their knowledge retention and grades by using this instructional delivery method? Estimates of student ability and effort were initially determined using pooled OLS, with the assumption that no unobserved heterogeneity existed while cluster robust variance matrix provided efficiency in standard errors. FE and FD estimators were used to address the possibility that variables used in place of students' unobserved ability and effort failed to be reasonable measures. Identified serial correlation necessitated the use of the FD estimator to cancel serial correlation. Endogeneity bias was addressed and found that future values of identified variables were correlated with dependent variable past values. Since many of our models, in particular the microeconomics data, rejected the null of strict exogeneity, GMM IV estimation was used to produce unbiased and consistent results.

For the education production function, time use, in its various measures, were found to have a positive and significant effect on the students' weekly grades. Time use measured by the Aplia access variables were highly significant in most models while time spent in Blackboard was significant only in select models. The results suggest that online students who spent more time in their LMS and in their homework management system increased their grades. These results held across most model specifications and estimation procedures. Among the second part of the education production function were the student's assumed attendance and interest in the section and course material. These variables, and their various measures, were found to only

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[6] Further testing on the suspected endogenous regressors revealed that time spent in Aplia was the culprit for endogeneity. We, therefore, use two lags of the corresponding Aplia variables as instruments.

be marginally significant in the principles of macroeconomics course. In particular, increasing access to the current week's learning module showed to improve the students' weekly grades.

Aside from measuring the education production function for online students, our main focus was to determine if recorded lectures did, indeed, promote a greater benefit to students by increasing their weekly grades. Our results show that using pooled OLS, increasing weekly recorded lecture access increases the weekly grade for principles of macroeconomics. However, using the FD and GMM-IV approach, increased access to the recorded lectures or merely accessing the recorded lectures showed no significant effect. Data limitations may be the chief concern as we were not able to obtain the number of minutes watched by each student—aside from those who did not access any of the recorded lectures—due to Blackboard not capturing the linking out to YouTube and YouTube aggregating the time across all viewers.

While we were met with the above limitations, we are confident that a more accurate measure of time spent watching recorded lectures will statistically show an increase in students' grades. Our convictions stem primarily from two sources: direct statements made to us by students who have used the videos and deemed them useful, and from the time use survey we administered. Additionally, improved LMS and digital learning tool data analytics will provide data to validate our premise.

Table 8. GMM IV Estimation

	Micro 1‡	Micro 2‡	Micro 3	Micro 4	Macro 1
ΔBBTot	0.0029	0.0029			0.0002
	(0.0008)***	(0.0008)***			(0.0010)
ΔApTot	0.0031	0.0030			0.0083
	(0.0018)*	(0.0018)*			(0.0036)**
ΔBBMin			0.0019	0.0019	
			(0.0008)**	(0.0008)**	
ΔApMin			0.0040	0.0041	
			(0.0047)	(0.0047)	
ΔLMAccess	0.0103	0.0093	0.0295	0.0261	0.0460
	(0.0228)	(0.0230)	(0.0339)	(0.0334)	(0.0295)
ΔRL	0.0170		0.0042		0.1146
	(0.0367)		(0.0481)		(0.0878)
ΔAccess		0.2490		0.6188	
		(0.4341)		(0.4523)	
Term	-0.3093	-0.3268	-0.2008	-0.1935	-0.7449
	(0.3424)	(0.3419)	(0.3733)	(0.3744)	(0.4452)*
Time Effects	Yes	Yes	Yes[†]	Yes[†]	Yes
Constant	-3.1803	-3.2802	-5.0974	-5.0690	2.0438
	(1.7487)*	(1.7565)***	(0.6674)***	(0.6690)***	(3.6787)
K-P rk LM stat[a]	19.50 (0.00)	19.08 (0.00)	54.87 (0.00)	55.12 (0.00)	5.27 (0.072)
K-P rk Wald F	10.51	10.45	248.034	248.39	3.82
Hansen J stat [a]	5.34 (0.069)	5.88 (0.0529)	-	-	0.84 (0.359)
C statistic [a]	0.25 (0.618)	0.243 (0.622)	-	-	0.84 (0.359)
Endog. Test[a] χ^2	0.48 (0.49)	0.425 (0.515)	4.87 (0.027)	4.96 (0.026)	6.60 (0.010)
Observations	588	588	672	672	400
Centered R^2	0.2190	0.2199	0.1606	0.1627	0.1737
F	25.17	25.00	21.86	21.32	12.54

Notes: Cluster robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The K-P rk LM stat is the Kleibergen-Paap rk LM statistics for underidentification. The K-P rk Wald F is the Kleibergen-Paap rk Wald F statistic for weak identification and is robust to heteroscedasticity and autocorrelation unlike the Cragg-Donal Wald F statistic. The Hansen J statistic is an overidentification test. The C statistic is a test for instrument exogeneity.
[†] Indicates that some of the week dummies are significant.
‡Numerous combinations of instruments (lagged difference, lagged levels, difference in announcements) were used, but none showed the suspected endogenous regressor to reject the null hypothesis of exogeneity. We, therefore, report one that contained the best rejections of weak identification.
[a] *p*-value in parentheses.
The Stata module ivreg2 was used for these estimates (Baum et al. 2010)

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Calculating a Portfolio's Beta

John Levendis and Mehmet F. Dicle[1]

ABSTRACT

We present an active-learning computer exercise where students pick stocks for a portfolio. Using their selection of stocks, two different portfolios are created: 1) a portfolio that never rebalances and 2) a portfolio that continuously rebalances. They then calculate the rates of return and betas for their individual stocks and for their portfolios. The students are then asked to draw conclusions about the benefits of diversification which are shown to apply regardless of the specific type of rebalancing in a diversified portfolio.

Introduction

Since the seminal work of Markowitz (1952) portfolio selection has occupied a central place in financial teaching. Portfolio management involves managing and balancing risk as well as return. In this respect, the risk is divided into idiosyncratic risk (corporate and diversifiable) and market risk (undiversifiable). Working in the 1960s, Treynor (1961), Sharpe (1964), Lintner (1965a, 1965b) and Mossin (1966) developed the capital asset pricing model (CAPM) relating individual asset returns to the overall market.[2]

Since the introduction of the CAPM, the beta (the market risk in CAPM estimation) is considered one of the fundamental building blocks of portfolio management. Finance students know it describes the correlation between the returns of a financial asset and the overall market. Fewer students know how to calculate it themselves. Far fewer students know how to calculate the beta for a hypothetical portfolio. Anyone can look up a stock's beta online. Such tools are available at Yahoo! Finance, Google Finance, and many other popular investing sites. But none of these websites allow someone to calculate the beta for an arbitrary portfolio, even though being able to do so has immense practical benefit.

In this active-learning computer exercise, we show how to use Stata to calculate a portfolio's rate of return and beta, and contrast those with the rates of return and betas of its component stocks. In this way, students can see for themselves the benefits of diversification. Our exercise also compares two portfolios: A) one that never rebalances and B) one that continuously rebalances. Never rebalancing portfolios (buy-and-hold) are more common among individual investors whereas continuously rebalanced portfolios are much more common for large institutional investors. Thus, our aim isn't to teach Stata per se, nor to explore portfolio rebalancing, but to show students how to use Stata to explore various themes regarding portfolio rebalancing. Since we will be showing students how to use Stata for a particular purpose, we present the Stata output as-is, so that it looks like what the students would see as they work through the examples below.

The current paper can be seen as a complement to the Excel-based exercise by Sumner et al. (2017) on portfolio optimization. In their paper and ours, students can vary their own stocks and portfolio weights to explore the concepts in greater detail. Sumner et al. limit their discussion to the variance-reducing benefit of diversification. We extend this to explore variance reduction under different portfolio rebalancing schemes.

The optimality of portfolio rebalancing has been analyzed in the financial literature extensively. While a simple buy-and-hold strategy is considered a mere benchmark, it is a common strategy among individual investors. On the other extreme, continuous rebalancing is used by many of the popular (and most important) indexes such as S&P500 and Dow Jones.[3] The specific ETFs that follow these indexes as a proxy, then, must

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[2] The seminal study by Fama and French (2004) provides a very important review of the CAPM literature.

[3] In terms of the continuous rebalancing, Ritter and Chopra (1989) show the significant difference between two different methods: portfolios that are equally weighted versus portfolios that are value weighted.

also use continuous rebalancing. Several studies have shown that investors rebalance--however frequently or infrequently--on various criteria such as volatility, calendar (i.e., rebalance every month, every quarter, etc.), or investment targets etc. (e.g., Donohue and Yip 2003).

The increased return or lower volatility realized on a well-diversified portfolio is the essence of portfolio theory. In terms of higher returns, Willenbrock (2011) argues that diversification is associated with rebalancing, and thereby earns its own returns. Similarly, Calvet et al. (2009) provide evidence that actively rebalanced portfolios lower the proportion of risk associated with an individual security within the portfolio.

The Task

Consider the following task:

Suppose that back in January of 2014 you bought shares in the five companies listed in Table 1. Create two portfolios: a never-rebalanced portfolio (referred to as *Portfolio A*) and a continuously rebalanced portfolio (*Portfolio B*). Portfolio A will have the number of shares constant (i.e., you buy shares and never buy more or sell any). Portfolio B will have the share of dollars invested per stock constant (i.e., continuously rebalancing to keep these value shares constant as daily prices change). Suppose further that you maintained these portfolios until June 25, 2017. Calculate the rate of return and beta for each stock. Contrast this with the rate of return and beta for both Portfolios A and B. What conclusions can we draw regarding the benefits of diversification and of rebalancing? Via this exercise, students will see that diversified portfolios reduce much of the risk while maintaining much of the profitability of their component stocks. This is seen to be the case regardless of the specific form of the portfolio: Whether the portfolio is unbalanced or continuously rebalanced, both portfolios reduce risk and maintain much of the reward.

Table 1: Portfolio Contents

Company	Symbol	Portfolio A Shares	Portfolio B Weight
Amazon	AMZN	1,000	12%
Apple	AAPL	2,000	4%
Facebook	FB	1,000	2%
Google	GOOG	5,000	81%
Microsoft	MSFT	1,000	1%
Total		10,000	100%

The Solution

First, we download the daily data for each stock and calculate their daily rates of return. Dicle and Levendis (2011) wrote a user written Stata command, `fetchyahooquotes`, that automates the process of downloading financial data. If the `fetchyahooquotes` command has not already been installed on your computer, you can download and install it by typing:

```
. net install http://researchbtn.com/stata/203/fetchyahooquotes.pkg, force
```

The `fetchyahooquotes` command also calculates the daily rates of return. In the interest of pedagogy, we will do this by hand. We begin by downloading the stock price data:

```
. fetchyahooquotes AMZN AAPL FB GOOG MSFT ^GSPC, freq(d) ///
    start(01jan2014) end(25jun2017)
. gen obs=_n
. tsset obs
```

and calculating the daily rates of return:

```
. generate ret_AMZN = 100*ln(adjclose_AMZN / L.adjclose_AMZN)
. generate ret_AAPL = 100*ln(adjclose_AAPL / L.adjclose_AAPL)
. generate ret_FB   = 100*ln(adjclose_FB / L.adjclose_FB)
```

```
. generate ret_GOOG = 100*ln(adjclose_GOOG / L.adjclose_GOOG)
. generate ret_MSFT = 100*ln(adjclose_MSFT / L.adjclose_MSFT)
. generate ret_SP500= 100*ln(adjclose_GSPC / L.adjclose_GSPC)
```

The average rate of return for each stock is given by the mean in Table 2, and is calculated using the Stata command:

```
. summarize ret*
```

Table 2: Summary Statistics on Individual Stock Returns

Variable	Obs	Mean	Std. Dev.	Min	Max
ret_AAPL	874	0.081	1.459	-8.330	7.879
ret_AMZN	874	0.106	1.901	-11.650	13.218
ret_FB	874	0.120	1.783	-7.187	14.429
ret_GOOG	874	0.066	1.426	-5.464	14.887
ret_MSFT	874	0.086	1.408	-9.710	9.941
ret_SP500	874	0.033	0.802	-4.021	3.829

The average daily rate of return for Apple was 0.081%; for the S&P it was 0.033%.

Next, we calculate the beta for each stock. A stock's beta is simply the coefficient from the following linear regression:

$$ret\_Y_t = alpha + beta* (ret\_SP500_t) + e_t \tag{1}$$

where *ret_Y* is the daily rate of return for stock Y, and *ret_SP500* is the daily rate of return of the S&P500, our proxy for the overall market. For example, we calculate the beta for Apple by estimating the following simple regression:

```
. reg ret_AAPL ret_SP500

      Source |       SS           df       MS      Number of obs   =       875
-------------+----------------------------------   F(1, 873)       =    416.22
       Model |  601.271527         1  601.271527   Prob > F        =    0.0000
    Residual |  1261.13803       873  1.44460256   R-squared       =    0.3228
-------------+----------------------------------   Adj R-squared   =    0.3221
       Total |  1862.40956       874  2.13090339   Root MSE        =    1.2019

------------------------------------------------------------------------------
    ret_AAPL |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   ret_SP500 |   1.034816   .0507227    20.40   0.000     .9352636    1.134369
       _cons |   .0443604    .040666     1.09   0.276    -.0354541    .1241749
------------------------------------------------------------------------------
```

The output above indicates that Apple's beta is 1.034. That is, its rate of return varies almost one-for-one with the S&P500's. A one percent increase in the S&P's rate of return is usually accompanied by an increase of 1.034% increase in Apple's rate of return. We can do this for each stock, one by one, or we can write a loop to automate much of the task:

```
foreach i in AAPL AMZN FB GOOG MSFT{
    regress ret_`i' ret_SP500
}
```

Either method gives the betas in Table 3.

Table 3: CAPM Betas for Individual Stocks

Symbol	Beta
AAPL	1.035
AMZN	1.187
FB	1.232
GOOG	1.090
MSFT	1.168

Thus far we have calculated the rates of return and betas for each of our five stocks. How do these compare with our overall portfolio? We now construct variables describing the value of our hypothetical portfolio and its rate of return.

Portfolio A: Never rebalanced portfolio (where the number of shares is held constant). The value of Portfolio A consists of the value of each of its stocks, times the number of shares:

$$PortfolioA_t = (Price\ of\ Apple_t \times Shares\ of\ Apple)$$

$$+ (Price\ of\ Amazon_t \times Shares\ of\ Amazon) + \cdots \quad (2)$$

$$+ (Price\ of\ Microsoft_t \times Shares\ of\ Microsoft)$$

Since the number of shares does not change in a never-rebalanced portfolio, there is no subscript t in the equation above, and we can simply substitute the required number of shares from Table 1.

$$PortfolioA_t = (Price\ of\ Apple_t \times 2000) + (Price\ of\ Amazon_t \times 1000) + \cdots$$

$$\quad (3)$$

$$+ (Price\ of\ Microsoft_t \times 1000)$$

In Stata, we can generate a variable for the value of Portfolio A by typing:

```
. generate portfolio_A = (adjclose_AAPL*2000) + (adjclose_AMZN*1000) + ///
    (adjclose_FB*1000) + (adjclose_GOOG*5000) + (adjclose_MSFT*1000)
```

And the returns for Portfolio A are calculated by using the log-difference:

```
. generate ret_portfolio_A = 100*ln(portfolio_A / L.portfolio_A)
```

Portfolio B: Continuously rebalanced portfolio (where the dollar investment weight is held constant). The return in Portfolio B, under continuous rebalancing is:

$$Return_t = (Return\ on\ Apple_t \times Portfolio\ weight\ for\ Apple)$$

$$+ (Return\ on\ Amazon_t \times Portfolio\ weight\ for\ Amazon)$$

$$+ \cdots \quad (4)$$

$$+ (Return\ on\ Microsoft_t$$

$$\times Portfolio\ weight\ for\ Microsoft)$$

Substituting the portfolio weights from Table 1, we have

$$Return_t = (Return\ on\ Apple_t \times 0.04) + (Return\ on\ Amazon_t \times 0.12) + \cdots$$

$$\quad (5)$$

$$+ (Return\ on\ Microsoft_t \times 0.01)$$

In Stata, we type:

```
. generate ret_portfolio_B = (ret_AAPL*0.04) + (ret_AMZN*0.12) + (ret_FB*0.02) + ///
        (ret_GOOG*0.81) + (ret_MSFT*0.01)
```

Using these Stata calculations of each portfolio's daily return, we can compare the two portfolios' daily rate of return using the Stata command:

```
. summarize ret_portfolio_A ret_portfolio_B
```

Which gives the output as in Table 4:

Table 4: Summary Statistics of Portfolio Returns

Returns from	Obs	Mean	Std. Dev.	Min	Max
Portfolio A	874	.0724	1.338	-5.341	12.007
Portfolio B	874	.0716	1.351	-5.339	12.369

We can also calculate the monthly returns using:

```
. gen month = (year(date) * 100) + month(date)
. collapse (sum) ret_portfolio_A ret_portfolio_B, by(month)
. gen obs = _n
. twoway (line ret_portfolio_A obs), saving(A, replace)
. twoway (line ret_portfolio_B obs), saving(B, replace)
. gr combine A.gph B.gph
```

Which yields the graph in Figure 1.

Figure 1: Monthly returns
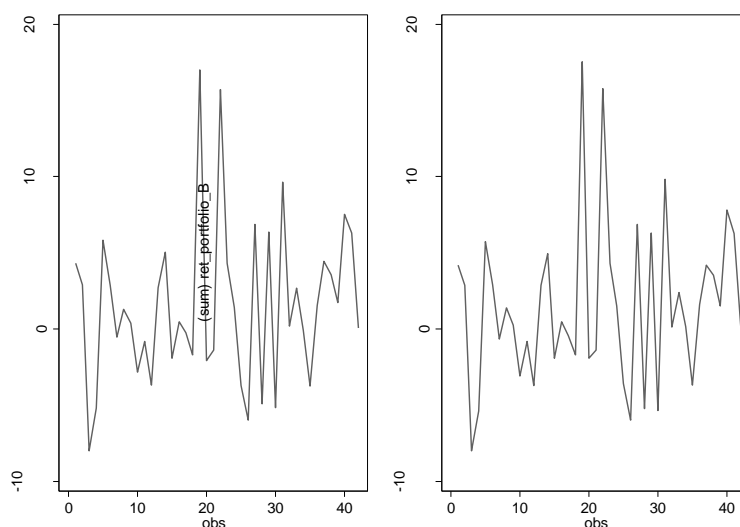
How profitable is each portfolio? The value of $1,000 invested in each portfolio would provide a handsome rate of return, which we can calculate using:

```
. collapse (sum) ret_portfolio_A ret_portfolio_B
. display 1000 * (1 + (ret_portfolio_A[1] / 100))
1622.8291

. display 1000 * (1 + (ret_portfolio_B[1] / 100))
1615.953
```

We can calculate each portfolio's beta by:

```
. regress ret_portfolio_A ret_SP500

      Source |       SS           df       MS      Number of obs   =       875
-------------+----------------------------------   F(1, 873)       =    677.93
       Model |  683.614952          1  683.614952  Prob > F        =    0.0000
    Residual |  880.321025        873  1.00838605  R-squared       =    0.4371
-------------+----------------------------------   Adj R-squared   =    0.4365
       Total |  1563.93598        874  1.78940043  Root MSE        =    1.0042

--------------------------------------------------------------------------------
  ret_portfo~A |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+------------------------------------------------------------------
    ret_SP500 |   1.103402   .0423781    26.04   0.000     1.020227    1.186577
        _cons |   .0351271   .0339759     1.03   0.301    -.0315568     .101811
--------------------------------------------------------------------------------


. reg ret_portfolio_B ret_SP500


      Source |       SS           df       MS      Number of obs   =       875
-------------+----------------------------------   F(1, 873)       =    654.31
       Model |  683.377762          1  683.377762  Prob > F        =    0.0000
    Residual |  911.779073        873  1.04442047  R-squared       =    0.4284
-------------+----------------------------------   Adj R-squared   =    0.4278
       Total |  1595.15683        874  1.82512224  Root MSE        =     1.022

--------------------------------------------------------------------------------
  ret_portfo~B |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+------------------------------------------------------------------
    ret_SP500 |    1.10321   .0431286    25.58   0.000     1.018562    1.187858
        _cons |   .0343475   .0345776     0.99   0.321    -.0335174    .1022125
--------------------------------------------------------------------------------
```

In Figure 2, we graph risk and return for the individual stocks as well as for both portfolios that we created for this assignment. Students are then asked to compare their risk-return profile with those of their classmates.

Figure 2: Risk vs. Return

58
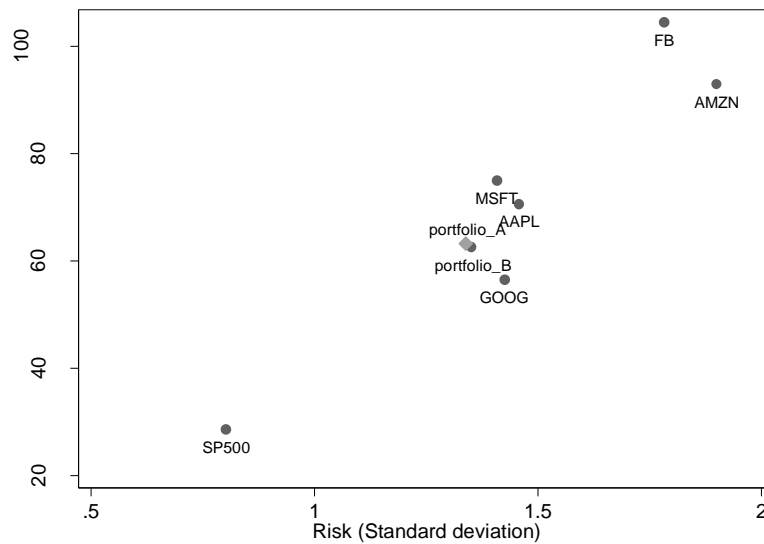
The Stata code to generate the graph is:

```
. reshape long ret_, i(date) j(symbol) string
. collapse (sd) sd=ret_ (sum) sum=ret_, by(symbol)
. label variable sd "Risk (Standard deviation)"
. label variable sum "Return (total percent return)"
. twoway (scatter sum sd if symbol~="portfolio_A", mlabel(symbol) mlabposition(6)) ///
         (scatter sum sd if symbol=="portfolio_A", mlabel(symbol) mlabposition(12)) ///
         , legend(off)
```

It should be mentioned that there is a cost to continuous rebalancing that we have not captured in this exercise. Specifically, we haven't modelled transactions costs. Continuous rebalancing requires many trades, each of which is costly, and which in aggregate may substantially decrease the effective rate of return. Modelling transactions costs, however, would take us too far afield from the main purpose of the paper, which is to show how Stata can be used to analyze the variance-reducing benefits of diversification.

Conclusion

We run this exercise in middle and upper level undergraduate finance classes. All students are asked to choose for themselves, and to track, a small number of stocks. Students then share their results, seeing how—regardless of the particular stocks chosen—-the overall conclusions still apply. Students also compare a portfolio that is never rebalanced to a portfolio that is continuously rebalanced. In this specific example, the two portfolios have very similar return and risk characteristics. The large amount of recurring transactions costs would naturally decrease the profitability of the continuously rebalanced portfolio. However, students also see that the variance-reducing property of diversified portfolios is maintained regardless of whether the portfolio is a buy-and-hold or continuously rebalanced portfolio. Students are then asked to compare their own risk-return profiles with those of their classmates. A few minutes discussion usually reveals that investing in a group of related stocks does not provide the same benefits of diversification as does investing in stocks across different industries.

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Teaching Model Selection with Time-Invariant Estimators

Adam Nowak and Yulia Chikish[1]

ABSTRACT

Teaching PhD-level theoretical econometrics course might be difficult if students lose the connection between the material presented in class and their own applied research. Even though there is a substantial literature on teaching undergraduate econometrics, to my knowledge there are no studies providing guidance for the graduate-level instructors. Aiming to begin to fill this gap in the literature, this paper provides an example of the approach I have undertaken in my classroom - presenting theoretical material as means necessary for solving applied problems students might encounter trying to estimate equations using some statistical software.

Introduction

Teaching a PhD-level econometrics course is a very intricate task - on the one hand, students should be able to grasp complicated theoretical concepts, on the other, they should always keep theoretical part in touch with its possible applications.[2] There are a number of studies focused on teaching undergraduate econometrics (see, for example, Becker and Greene 2001, Elder and Kennedy 2001, Kennedy 2001, Kennedy 2005, Johnson et al. 2012, Briand and Hill 2013, and O'Hara 2014) but to my knowledge, there are no papers on graduate econometric instruction. My paper begins to fill this void in the literature by explaining one of the approaches that can be adopted on PhD-level class based on my personal teaching experience.

In my 5 years as an assistant professor, I taught panel data and time series at the PhD level. Initially, I taught the course from a perspective of a theoretical econometrician. The early lectures focused on bias, consistency, and limiting distributions. Most students in the class were interested in applied work. More often than not, the questions I was asked during office hours were about problems that students encountered while trying to estimate regressions. I realized that students struggled translating theoretical material I taught into applications and I changed my approach to teaching the course. In particular, I began to lecture as if the students had shown up to office hours with data in hand but claim the statistical package has thrown an error. The example presented in this paper is but one example of this phenomenon: an error occurs when students are testing for gender inequality in wages.

Cross-Sectional Data

I usually begin the discussion about the least squares dummy variable (LSDV) model with introduction of a simple cross-sectional example. Suppose the student has cross-sectional data from the American Community Survey (ACS) that includes wages, gender, education, and employment industry for the year 2015. The student imports that data and regresses log wage, $w_n = \log(wage_n)$, on education and an indicator for women:

$$w_n = \alpha + \beta education_n + \gamma female_n + u_n$$
$$w = X\theta + u = [J_N, e, f](\alpha, \beta, \gamma)' + u \tag{1}$$

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[2] While co-authored, this article uses I instead of we since the majority is based on recollection from Adam Nowak's personal teaching experience.

In (1), J_N is a $N \times 1$ vector of 1s. The least-squares results, $\hat{\theta}_{LS} = [X'X]^{-1}X'w$, indicate each year of education increases log wages by 9% ($\hat{\beta} = 0.09$), and women earn 10% less than men, $\hat{\gamma} = -0.1$. Of course, the above model is too simple to be taken seriously. The student includes indicators for occupation and estimates for person n in industry i:

$$w_n = \alpha + \beta education_n + \gamma female_n + \psi_i + u_n$$
$$w = [X,Z](\theta',\psi)' + u \tag{2}$$

In (2), Z is a $N \times I$ matrix of indicator variables, z_{ni}, for each $i = 1, \dots, I$ industries, and ψ is the vector of industries. The model fits the data well as $R^2 = 0.9$, and the results now indicate $\hat{\gamma} = 0.05$.

Most statistical packages assume the researcher is interested in β or γ and normalize $\hat{\psi}$ either by dropping the first category or normalizing $\sum \hat{\psi}_i = 0$. Some normalization is required as the sum of the indicators across an individual is equal to 1, $\sum_i z_{ni} = 1$ in which case the $N \times 3 + I$ matrix $[X, Z]$ is not full column rank, $[X, Z]q = 0$ when $q' = (1,0,0, -J'_I)'$. In any event, the important takeaways are that 1) some normalization of ψ is required that 2) the student may or not be aware of. For the students who are more interested in using industry as a control, the normalization is not of great concern. However, this normalization will be of great concern when we discuss the LSDV model.

Using the Frisch-Waugh-Lovell Theorem, we can show that the estimates $\hat{\theta} = [X'M(Z)X]^{-1}X'M(Z)$ in (2) are identical to estimates when regressing industry-demeaned wages on industry-demeaned education and industry-demeaned gender. That is, the point estimates in (2) are identical to the point estimates from

$$w_n^* = \beta education_n^* + \gamma female_n^* + u_n^* \tag{3}$$

In (3) $w_n^* = w_n - \bar{w}_i$ and $\bar{w}_i$ is the average wage in industry i. As mentioned above, most economists view the industries as controls and are more interested in the return to education and gender differences.

In most situations described above, the normalization is innocuous. However, there do exist some situations where including controls are not feasible. For example, suppose women work in either industry 1 or industry 2. Furthermore, only women work in these two industries. Consider a short illustrative example with five individuals (Table 1).

Table 1: Cross Sectional Example

Individual	Education	Female	Industry 1	Industry 2	Industry 3
1	9	1	1	0	0
2	10	1	0	1	0
3	12	0	0	0	1
4	16	1	1	0	0
5	12	0	0	0	1

In this setup, the average value of $female_n$ is 1 in each of these industries and equal to 0 in the other industries (industry 3 in our example), $\overline{female}_1 = \overline{female}_2 = 1, \overline{female}_{3\leq i} = 0$, and $female_n^* = 0$, $\forall n = 0$. That is, the student is regressing demeaned wages on demeaned education and a vector of 0s. Table 1 makes the explanation even more intuitive. It allows students immediately see that there is no variation in gender within industries, and therefore it is impossible to estimate the effect of gender on wages while controlling for industry.

Panel Data

In the panel setup, the economist observes the same individual over time. The Panel Study of Income Dynamics (PSID) or Russian Longitudinal Monitoring Survey (RLMS) are the examples of such panel data sets. Of course, the benefit of the panel data is that the student can control for unobserved factors that do not change across time within individual. I begin with the introduction of the following hypothetical situation: a student tries to estimate gender wage gap using LSDV model, and statistical software does not show the coefficient for gender indicator. My goal is to make students realize why the error is occurring. We can write:

$$w_{it} = \alpha + \beta education_{it} + \gamma female_{it} + \mu_i + u_{it}$$
$$w = [X, P](\theta', \mu') + u = Z\psi' + u \tag{4}$$

In (4), the term μ_i captures any time-invariant properties of individual i such as ability and motivation and $u_{it} \sim IID(0, \delta_u^2)$. Using some simple algebra, we can confirm that if equation (4) holds, then the following equation must also hold:

$$\bar{w}_i = \alpha + \beta \overline{education}_i + \gamma \overline{female}_i + \mu_i + \bar{u}_i \tag{5}$$

where $\bar{w}_i = \sum_t w_{it}/T_i$, $\overline{education}_i = \sum_t education_{it}/T_i$, $\overline{female}_i = \sum_t female_{it}/T_i$ and $\bar{u}_i = \sum_t u_{it}/T_i$. Subtracting (5) from (4):

$$(w_i - \bar{w}_i) = \beta(education_{it} - \overline{education}_i) + \gamma(female_{it} - \overline{female}_i) + (u_{it} - \bar{u}_i) \tag{6}$$

For most statistical packages estimating fixed effects model amounts to performing ordinary least squares (OLS) estimation of equation (6). Because gender does not vary over time, the averaged over time indicator will equal to 1 for every woman and to 0 for every man in sample. Which, in turn, means that $(female_{it} - \overline{female}_i) = 0$ for both genders. So the student effectively regresses demeaned wages on demeaned education and a vector of zeros, and a package returns no coefficient on the gender indicator or an error message.

I can provide an even more intuitive example. Assume, for illustrative purposes, that our sample consists of three individuals and two time periods, so $N = 3$ and $T = 2$ (Table 2). We can see that the gender indicator vector is equal to the sum of μ_1 and μ_3, so matrix Z has less than a full rank in our example, and therefore cannot be inverted. To avoid this problem, some statistical software (e.g., Stata) does not include time-invariant variables in LSDV model by default.

Table 2: Example: Time-invariant Variable in LSDV Model

Individual	Year	Education	Female	$\mu 1$	$\mu 2$	$\mu 3$
1	1	12	1	1	0	0
1	2	12	1	1	0	0
2	1	14	0	0	1	0
2	2	15	0	0	1	0
3	1	9	1	0	0	1
3	2	10	1	0	0	1

After establishing the problem, students are usually interested in the possible practical ways of estimating the gender variable's coefficient. This presents a good opportunity to contrast LSDV model with pooled OLS and fixed effects (FE) models. It is worth noting that if the subject of interest is not the coefficient on the time-invariant variable itself, the variable could be excluded from the LSDV model. In our example, a student might be interested in estimating the return of a year of education in terms of wage. Excluding the female dummy will not bias the coefficient on the education variable because individual fixed effects already contain gender information.

For a short illustrative example, I use data from the RLMS for 2007 and 2008 containing information on individuals' wages, education, and gender.[3] The results of FE model estimation are presented in column 1 of Table 3. The method does not allow one to estimate the female indicator coefficient, but a student can estimate an unbiased coefficient on the education variable, which shows that each additional year of education increases an individual's wage on average by 7.4%.

If a student is interested in the coefficient on the gender dummy, one's first reaction is simply to drop the fixed effects from the model and estimate a pooled OLS model:

$$w_{it} = \alpha + \beta education_{it} + \gamma female_i + e_{it} \tag{7}$$

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[3] "Russia Longitudinal Monitoring Survey, RLMS-HSE," conducted by the National Research University Higher School of Economics and ZAO "Demoscope" together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS.

where $e_{it} = \mu_i + u_{it}$. $Corr(e_{it}, female_i) = 0$ and $Corr(e_{it}, education_{it}) = 0$ is required for $\hat{\gamma}_{OLS}$ and $\hat{\beta}_{OLS}$ to be unbiased. Even after assuming $Corr(u_{it}, \mu_i) = 0$, $Corr(u_{it}, female_i) = 0$ and $Corr(u_{it}, education_{it}) = 0$, fixed effects might still be correlated with gender and education variables. We assumed that μ_i contains unobserved ability and motivation. Education is positively correlated with both ability and motivation and, even though gender is uncorrelated with ability, $Corr(\mu_i, female_i) \neq 0$ because it might be correlated with motivation.

Table 3: Example: Simple Gender Wage Gap Equation

	FE	Pooled OLS	RE
	(1)	(2)	(3)
Education	0.0744***	0.0860***	0.0878***
	(0.0172)	(0.0030)	(0.0037)
Female		-0.4386***	-0.4373***
		(0.0163)	(0.0208)
Constant	7.9846***	8.0696***	8.0392***
	(0.2200)	(0.0387)	(0.0485)
Observations	12,483	12,483	12,483

Note: Parentheses contain standard errors. *** p<0.01, ** p<0.05

According to Cha and Weeden (2014) and Blau and Kahn (2017), women might be less prone to work overtime and would rather spend time with their families. Therefore, the coefficient on the gender variable estimated by a pooled OLS model might be biased downward (overstating the gender wage gap) while the coefficient on education might be biased upward (overstating the return on education). Column 2 of Table 3 presents the results from a pooled OLS model estimation. The estimated return on education is 8.6%, which compared with 7.4% in a FE model will provide a student some evidence of bias from pooled OLS.

After students realize that it is impossible to obtain the unbiased coefficient by using OLS if the independent variables are correlated with μ_i-s, the random effects (RE) model can be presented as a more appropriate strategy. It allows one to estimate gender differentials in wages and control for unobserved individual-specific terms. Now, in equation (1) we assume $\mu_i \sim IID(0, \sigma_\mu^2)$, $u_{it} \sim IID(0, \sigma_u^2)$, μ_i is independent of the u_{it} and both μ_i and u_{it} are independent from gender and education variables for all t and i.

After introducing the assumptions, students should be made aware that error covariance matrix $E[ee'] = \Sigma$ is now block diagonal. Therefore, the generalized least squares method should be used to correct standard errors, in which case $\hat{\theta}_{RE} = [X'\Sigma^{-1}X]^{-1}X'\Sigma^{-1}w$ (see, for example, Baltagi 2008 or Greene 2002).

Conclusion

Sometimes students in graduate classes are not particularly interested in theoretical aspects of econometrics courses because they cannot quite understand how the theory might enable them to advance their applied research. Sometimes they are interested in the material, but still struggle to connect the theory with practical problems they encounter. I suggest an alternative approach to teaching graduate-level econometrics courses by building theoretical content around some problems the students might come up against while running basic regressions typically found in field courses.

In particular, while teaching panel data methods I start with a hypothetical situation in which students get an error message from an econometrics software package when they are trying to estimate a LSDV model which includes time-invariant variables. The gender wage gap model is a perfect candidate for such a model - it is intuitively simple and it is very likely that students have encountered the model before. As if searching for the source of an error (the statistical package does not show a coefficient for gender dummy), I introduce the main assumptions of the model and their implications. After explaining to students why the error occurs, I contrast FE models with RE and pooled OLS models, as if searching for a practical way to estimate the coefficient on the time-invariant gender variable. I believe this approach benefits students' understanding of the theory, especially in more applied-oriented graduate classrooms.

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Excel Skills: Self-Assessment versus Reality

Don Cox, Delbert Goff, Chris McNeil, and Joe Walsh[1]

ABSTRACT

Expertise with Excel combined with business acumen is highly valued by many employers. In line with employer views, we find that students believe possessing a high level of spreadsheet skills is important. However, our results indicate that students exhibit overconfidence in their expertise, which equates to high-level beginner for our sample, and devote little time improving through self-study. We find that skill level overconfidence has a positive association with number of college courses completed that include spreadsheet coverage. Our results suggest a need to enhance student spreadsheet expertise and to evaluate the effectiveness of the curriculum in that regard.

Introduction

Potential employers of business school graduates commonly list Excel skills as a desired, if not a required qualification for many positions. As they prepare themselves for the job market, students would be well served to have an accurate perception of their own Excel skill level, including how their expertise compares to employer expectations. Student overconfidence in their Excel skills, where actual skill lags self-assessment, has a number of potential ramifications. Overconfidence would increase the likelihood that graduates will not possess sufficient expertise to efficiently perform expected job tasks. Prior to graduation, students would be less likely to realize that their skill level is sub-par relative to employer expectations and needs development. Initial job performance, an important factor for short-term career prospects, would suffer. Graduates would face greater on the job stress than they might have anticipated. Employers would have to devote more resources toward building the competency of new hires. For faculty, as well as students, overconfidence would suggest a need for more focused attention on building student spreadsheet expertise.

In this paper, we gauge the degree of importance students place on spreadsheet skills and compare student perceived skill with Excel to measured expertise using a sample of 470 undergraduate business students from three universities. We then examine factors that might impact the difference between self-rated and measured skill level. The results show that students tend to view Excel skills as important. When asked how important they believe spreadsheet skills will be in their first post-graduation job, 68% of responding students state very important or extremely important. In addition, the students are of the opinion that employers expect advanced expertise with Excel.

In terms of self-assessment, our sample students rated their own Excel skill level as intermediate, on average. Karsten and Roth (1998) and DuFrene et al. (2010) document similar self-assessment results. Compared to perceived employer expectations, 83% of our sample views their skill level as below employer expectations, with 68% falling 2 or more levels below employer expectations on a 10 point scale. This indicates that most of the students do not feel adequately prepared to perform at the level expected in their first post-graduation job.

Comparing self-assessed and actual skill, our results provide evidence of student overconfidence in their Excel expertise, consistent with the findings of Grant et al. (2009) and Csernoch and Biró (2013). Self-assessed skill level tends to exceed actual expertise. To measure actual spreadsheet skill level, we use results from a test composed of 17 questions evaluated by a panel of faculty experts. On average, our sample of students have a skill level of a high-level beginner. The overconfidence in skill level points to a need for

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faculty to work with students to build student spreadsheet expertise or to at least encourage students to more accurately self-assess their skill level.

Alternatively, we might expect students to act on their own to improve their expertise. As stated earlier, our results show that students perceive that employer expectations exceed student self-assessed skill level, so students have a motivation to act. Furthermore, students have ready access to ample online materials to develop spreadsheet expertise through self-study. However, we find that most students make little effort to improve via independent study. When asked to estimate how many hours they have spent exploring Excel on their own during the last 12 months, 64% of responding students indicate five hours or less and 24% indicate zero hours. In addition, we find that self-study hours have no statistically significant association with actual expertise, consistent with the view that most students do not focus their efforts on the appropriate aspects of Excel when engaging in self-study.

We employ cross-sectional regression analysis to examine potential factors that might impact the difference between self-rated expertise and measured skill level. Our results show that the number of college level courses completed that incorporate some Excel work is positively associated with overconfidence, a somewhat surprising result. Further analysis shows that number of college courses is positively associated with measured skill level, as we would hope, and self-assessed expertise as well. However, the association between number of college courses and self-assessed expertise is stronger. Thus, the course work for students in our sample appears to have a greater impact on student confidence than on student expertise. These results suggest a need to evaluate spreadsheet coverage in business curricula. For the three universities included in this study, spreadsheet coverage across courses tends to be unstructured, with little progression in level of difficulty. In such a setting, students are more likely to walk away with overconfidence in their Excel skills.

The cross-sectional regression results also show that grade point average (GPA) is negatively associated with overconfidence, while self-study hours has a positive association with overconfidence. Higher GPA students appear to possess a higher level of Excel skills but do not rate their expertise any higher than students with lower GPAs. Self-study hours tends to boost self-ratings but has no statistically significant association with measured skill level.

In summary, our results build on and add to the existing literature. Our results support the findings of Grant et al. (2009) and Csernoch and Biró (2013) that undergraduate business students tend to over-estimate their spreadsheet skills. In addition, we find that student overconfidence in spreadsheet skills is positively associated with the number of courses completed that include some Excel coverage and with hours of Excel self-study, noting that the curricula in place for our sample students is generally unstructured in its coverage of Excel across courses. These findings are new to the literature, to the best of our knowledge. We also document that students view Excel skills as important and tend to view employer expectations for Excel expertise as exceeding student self-rated skill level.

The remainder of our paper is structured as follows. The next section is a review of the literature and background for our study. We then discuss our data collection, sample, and results.

Literature Review and Background

A number of prior works note that it is important for undergraduate business students to develop spreadsheet skills. Holden and Womack (2000) propose that helping students develop spreadsheet modeling skills is the best way to prepare students for the business world. Payne and Tanner (2011) state that student job placement and job performance has a positive association with spreadsheet competency. Formby et al. (2017) document that approximately one-half of job postings for graduating business students reference Excel skills, and also find that an overwhelming majority of employers surveyed believe it is important for graduating students to possess good spreadsheet skills. Furthermore, spreadsheet assignments can enhance student knowledge of underlying course material, such as cash flow estimation and option pricing (e.g., Ghani and D'Mello 1993; Cagle et al. 2010; Wann 2015; and Sumner et al. 2017).

Additional studies provide evidence that undergraduate students possess subpar spreadsheet expertise. Wallace and Clariana (2005) find that college freshmen lack adequate Excel and other computer skills. The results of Grant et al. (2009), Hanson et al. (2012), and Csernoch and Biró (2013) indicate that students tend to over-estimate their Excel expertise. In all three studies, students tend to rate their spreadsheet skill level as intermediate or above (e.g., 3 on a 5 point scale). However, results from assessment tools indicate that the skill level of the sample students is materially below the intermediate level. Our results provide additional support for these earlier findings and show that overconfidence persists among college upperclassmen. The

Grant et al. (2009) and Csernoch and Biró (2013) samples are predominantly composed of college freshmen. College seniors make up Hanson et al.'s (2012) sample, but their sample is a relatively small 67.

Confidence in one's abilities has been shown to contribute to performance in academics (e.g., Morris and Bowling 1979; Pintrich and De Groot 1990; Bredthauer and Fendler 2016) and sports (Woodman and Hardy 2003). Prior research indicates that confident students are more likely to expend greater effort to accomplish a task (e.g., Fincham and Cain 1986; Paris and Oka 1986; Schunk 1985). Bandura (1993) and Seifert (2004) posit that overconfidence, however, can lead students to devote less time to studying than would otherwise be the case. A number of studies in fact find evidence that students tend to be overconfident in their academic abilities (e.g., Grimes 2002; Nowell and Alston 2007).

Our study's main contribution to the literature is the cross-sectional examination of factors that might contribute to student spreadsheet skill overconfidence, an examination that is lacking in prior studies of spreadsheet skills. We examine such factors as GPA, year of study, number of courses completed that include spreadsheet coverage, hours of self-study, and pre-graduation work exposure. We find that number of courses and hours of self-study are positively associated with overconfidence. For our sample, courses that include Excel work tend to include spreadsheet work that requires only lower level skills. Lower level work provides inadequate feedback on skill level, potentially leading to false confidence (Arkes 2001). Likewise, if the focus of student self-study is on lower level skills, hours of self-study could be associated with overconfidence.

Data Collection

Data is collected in three stages from undergraduate business students who are attending one of three colleges in the southeast and are enrolled in one of a set of classes made available to us by an instructor during the spring of 2017. The courses include introduction to accounting, introduction to finance, and two upper level finance courses. First, students were asked to rate their Excel skill level on a 10 point scale, with 1 for low-level beginner and 10 for expert. Appendix A contains our student self-assessment instrument. No definitions of the skill levels were provided to the students other than a descriptor for each level (e.g., high-level beginner for 3; mid-level intermediate for 5; and low-level advanced for 7). In this first stage, we also asked students their opinion about employers Excel skill level expectations for students graduating in their major. This first stage collection is conducted in the classroom and students were discouraged from discussing their selections during the process.

The second stage data collection consists of a quiz used to measure student expertise with Excel. The quiz was administered in-class and was proctored. Students were given some incentive to answer the questions to the best of their ability. The incentive varied by instructor administering the quiz. Student scores on 17 multiple choice questions serve as our measure of student skill level with Excel. The 17 questions are of varying levels of difficulty, as rated by a panel of eight faculty who have included substantial Excel work in their courses. Our faculty panel members also have significant interactions with industry professionals in different business fields and with the recruitment and job placement of students in business. Over time, these faculty members have developed what we believe to be a reasonable understanding of what many employers seek and expect with regard to Excel skills. This knowledge was the basis for developing the test questions we utilized; both in terms of the skills or knowledge being tested and the degrees of difficulty examined.

For our testing questions, the level of difficulty of the questions ranges from 2 (mid-level beginner) to 7 (low-level advanced). We do not include questions higher than a level 7 due to our need to have a quiz of reasonable length (limited class time and maintenance of student engagement), coupled with our expectation that few, if any, students would exceed that level of expertise. For our sample, the highest measured skill level is 5, in line with that expectation. If any student had scored 7, we would have adjusted our scaling for analysis purposes for all students to 1 through 6, plus 7 or greater.

We also include six easy filler questions (not scored for our skill measure) and intersperse the more and less difficult 17 scored questions within the quiz in order to maintain student engagement. The last filler question is question 21, which 98.9% of students answered correctly, indicating that the students remained engaged throughout the quiz. Appendix B shows our 23 quiz questions (17 scored plus 6 fillers), with level of difficulty added. A total of 470 students completed both stage one and two data collection.

We elected to utilize a written exam, rather than testing directly in Excel, for a couple of reasons. Doing so allowed us to greatly expand our sample size by using multiple course sections of business classes that did not meet in and/or have access to computer labs or testing facilities. In addition, faculty members involved

in this study have, over time, utilized both testing and assignments using Excel directly and in the form of written exams. Our experience indicates a high correlation between student performance working in Excel directly and responding to written exams related to Excel. In the third and final stage of data collection, we collect demographic information, opinions about Excel, and information about Excel usage. Information collected includes, for example, major, year of study, perceived importance of Excel in their first job, number of college level courses completed in which Excel was used, and hours spent learning Excel on their own. Completing the third stage survey was encouraged but voluntary for students. Of the 470 students who completed stage one and two data collection, 391 also provided stage three data.

Sample

Table 1 shows the count of students by college, year of study, and gender. The majority of students attend University/College A. Most of the students are juniors (55.2% of responding students) or seniors (27.1% of respondents). By gender, the majority of responding students are male (67.5%).

Table 1: Sample Description

School		A	B	C	Total		
	Count	354	76	40	470		
	%	75.3	16.2	8.5			
Year of Study		Freshman	Sophomore	Junior	Senior	missing	Total
	Count	7	62	216	106	79	470
	% of Total	1.5	13.2	46.0	22.6	16.8	
	% of non-missing	1.8	15.9	55.2	27.1		
Gender		Female	Male	missing	Total		
	Count	126	262	82	470		
	% of Total	26.8	55.7	17.4			
	% of non-missing	32.5	67.5				

Table 2 displays our sample by student major. Students can report more than one major. The most commonly reported major is finance at 32.4%, followed by marketing at 12.8%. The higher percentage rate of finance majors is due to sampling taking place in a combination of general business courses and upper level finance classes. None of the classes were on-line.

Table 2: Sample by Major

Major	Frequency	Percent
Accounting	48	10.2
Actuary	14	3.0
CIS	20	4.3
Economics	13	2.8
Finance	152	32.4
Hospitality/Tourism	8	1.7
International Business	12	2.6
Management	53	11.3
Marketing	60	12.8
Mathematics	1	0.2
Other	36	7.7
Risk Management	36	7.7
Supply Chain	11	2.3
Undecided	5	1.1
Total majors reported	469	
Missing	79	

Results

Importance of Excel

Our results indicate that the majority of students in our sample view Excel expertise as important. When asked to rate how important Excel skills would be in their first job post-graduation, of the 391 students who responded, 67.8% answered very or extremely important, as shown in Table 3. Only 6.6% answered slightly important or not important. Additionally, when asked what level of Excel expertise do employers expect for students graduating in your major, 69.7% of the 469 responding students answer low-level advanced or above (i.e., 7 or greater on a 10 point scale). The average anticipated employer expectation equals 7.25. Less than 1% select beginner level skill. A summary of the responses showing the student view of employer expectations for Excel skills is presented in Table 4.

Table 3: Student View of Importance of Excel Skills

Importance of Excel	Frequency	Percentage
Extremely Important	114	29.2
Very Important	151	38.6
Moderately Important	94	24.0
Slightly Important	23	5.9
Not at all Important	3	0.8
No Opinion	6	1.5
Total	391	

Table 4: Excel Skills - Student View of Employer Expectations

Employer Expectations		Freq.	Perc.	Cumul. %
Beginner	1	1	0.21	0.21
	2	1	0.21	0.43
	3	2	0.43	0.85
Intermediate	4	9	1.92	2.77
	5	41	8.74	11.51
	6	67	14.29	25.80
Advanced	7	133	28.36	54.16
	8	107	22.81	76.97
	9	61	13.01	89.98
Expert	10	26	5.54	95.52
	unsure	21	4.48	100.00
	Total	469		
	Mean	7.25		
	Median	7.00		

Self-Rated and Measured Skill Level

Our results show that students tend to be overconfident about their Excel skills. Table 5 shows student self-rating of Excel expertise and their actual Excel skill level, as measured by their performance on our skill quiz. For the 470 students in our sample, the average self-rating equals 5.13, with 86.2% rating themselves as having low-level intermediate expertise or above (skill level of 4+) and only 13.8% as beginners. In contrast, the average skill level based on our test result is 3.14, with only 30.0% having low-level intermediate skill or above and 70.0% as beginners. The difference in the two averages is statistically significant (paired difference t-statistic of 27.76 with a p-value < 1%, not tabulated). In addition, self-rating exceeds measured skill level for 83.8% of the sample (result untabulated).

The results in Table 6 indicate that a similar level of overconfidence is exhibited across student years of study. Self-rated skill level exceeds measured expertise for each group of students: lower classmen (i.e., freshmen and sophomores), juniors, and seniors. Average *Self-Rating* jumps at the senior level, whereas *Test*

Rating tends to increase with years of study. The mean difference between *Self-Rating* and *Test Rating* is largest for seniors.

Table 5: Excel Skill Level - Self-Rating and Test Rating

Skill Level	Self-Rating				Test Rating			
	Level	Freq.	Perc.	Cumul. %	Level	Freq.	Perc.	Cumul. %
Beginner	1	7	1.49	1.49	1	17	3.62	3.62
	2	26	5.53	7.02	2	85	18.09	21.70
	3	32	6.81	13.83	3	227	48.30	70.00
Intermediate	4	77	16.38	30.21	4	95	20.21	90.21
	5	139	29.57	59.79	5	46	9.79	100.00
	6	106	22.55	82.34	6	0	0.00	100.00
Advanced	7	55	11.70	94.04	7+	0	0.00	100.00
	8	21	4.47	98.51				
	9	6	1.28	99.79				
Expert	10	1	0.21	100.00				
	Total	470			Total	470		
								Difference
	Mean	5.13			Mean	3.14		1.99***
	Median	5.00			Median	3.00		2.00***

*Notes: *** denotes statistical significance at the 1% level (two tailed test).*

Table 6: Self-Rating and Measured Excel Skills by Year of Study

	Lower Classmen		
	Mean	Median	N
Self-Rating	4.94	5.00	69
Test Rating	2.94	3.00	69
Difference	2.00***	2.00***	69

	Juniors		
	Mean	Median	N
Self-Rating	4.96	5.00	216
Test Rating	3.15	3.00	216
Difference	1.81***	2.00***	216

	Seniors		
	Mean	Median	N
Self-Rating	5.81	6.00	106
Test Rating	3.44	3.00	106
Difference	2.37***	2.00***	106

*Note: *** denotes statistical significance at the 1% level (two tailed test).*

Self-Study

Given the importance that most of the students in our sample place on Excel skills and that student self-rated expertise falls below anticipated employer expectations on average (5.13 compared to 7.25), we might expect that students would make a devoted effort to increase their Excel skill level on their own. Training materials, such as streaming videos and books, are readily available as well as being low cost or free. However, our results indicate that most students devote little time to enhancing Excel expertise on their own. As Table 7 shows, 76.4% of the 390 responding students spent 10 hours or less during the last year learning Excel through self-directed study, and 24.4% reported spending zero time. To the extent that employers expect students to have an intermediate to advanced Excel skill level, these findings point to a need that business school curriculum can address.

Table 7: Hours of Self-Study During the Last Twelve Months

Hours	Freq.	Perc.	Cumul. %
0	95	24.4	24.4
1	37	9.5	33.8
2	39	10.0	43.8
3	18	4.6	48.5
4	19	4.9	53.3
5	42	10.8	64.1
6-10	48	12.3	76.4
11-15	26	6.7	83.1
16-20	17	4.4	87.4
21-25	8	2.1	89.5
26-30	6	1.5	91.0
31-40	5	1.3	92.3
41-50	13	3.3	95.6
>50	17	4.4	100.0
Total	390		

Cross-Sectional Regression Analysis

In this section, we examine factors that may impact the difference between perceived and measured Excel skills using cross-sectional regression analysis. We define *OverCon* (short for overconfidence) as *Self-Rating* minus *Test Rating*, where *Test Rating* is our measure of actual skill level based on the student's performance on our 17 quiz questions. A better understanding of what factors tend to impact overconfidence could help us design steps that would better align student perceptions with reality. We regress *OverCon* on *GPA*, year of study, number of Excel related courses, and other factors. Since the factors may impact *OverCon* through *Self-Rating* or *Test Rating* or both (*OverCon* equals *Self-Rating* minus *Test Rating*), we also present regressions of *Self-Rating* and *Test Rating* alongside regressions of *OverCon*. In Table 8, *OverCon* is the dependent variable for columns (1) and (4), *Self-Rating* for columns (2) and (5), and *Test Rating* for columns (3) and (6). The regressions are estimated using ordinary least squares. T-statistics adjusted for hetereoskedasticity appear in parentheses below the coefficient estimates. The number of observations in our regressions range from 354 to 355 students. We present four different specifications of independent variables to better insure the robustness of our results and to minimize the possibility of confounding results that could be driven by including closely related independent variable in the same model (e.g., number of college courses (*CollegeCourses)* and number of Excel assignments (*Assignments))*.

In Table 8, we see that *GPA* has a negative association with *OverCon* (columns (1) and (4), significant at the 5% level) and that this association is driven by a positive association between *GPA* and *Test Rating* (columns (3) and (6)). In the *Self-Rating* regressions, the coefficient estimates for *GPA* are not statistically significant. The results indicate that higher GPA students tend to have lower overconfidence as these students tend to have better Excel skills, but do not rate themselves higher than their peers. It is also possible that higher GPA students tend to be better test takers. Doran et al. (1991) and Borde et al. (1991) document a positive association between GPA and performance. Similarly, *Finance* (value of 1 for students majoring in finance) and *OverCon* have a negative association, also driven by a positive association with *Test Rating*. In the *OverCon* regressions in columns (1) and (4), the coefficient estimate for *Finance* is significant at the 5% and 10% level respectively. In all regressions of *Test Rating*, *Finance* is positive and significant at the 1% level.

Relative to juniors, *LowerClassman* has a positive association with *OverCon*, controlling for other factors, as a result of a positive association with *Self-Rating* but no statistically significant association with *Test Rating*. Alternatively, *Gender* (indicator variable for female students), *Senior* (indicator variable for senior year of study), and indicator variables for *College B* and *College C* have no statistically significant association with *OverCon*. We continue to include these variables in our regressions as controls.

Table 8: Regressions of OverCon, Self-Rating and Test Rating

Dep. Var.	OverCon (1)	Self-Rating (2)	Test Rating (3)	OverCon (4)	Self-Rating (5)	Test Rating (6)
Constant	2.9290	3.7993	0.8703	3.1716	3.9162	0.7446
	(3.93)***	(5.62)***	(2.27)**	(3.85)***	(5.33)***	(1.72)*
CollegeCourses	0.1911	0.3764	0.1853	0.1995	0.3776	0.1780
	(3.00)***	(6.33)***	(5.47)***	(3.13)***	(6.32)***	(5.23)***
OwnHours	0.0188	0.0185	-0.0003	0.0197	0.0190	-0.0007
	(2.94)***	(2.92)***	(-0.07)	(3.05)***	(2.99)***	(-0.17)
GPA	-0.4834	0.0059	0.4894	-0.4513	0.0382	0.4895
	(-2.25)**	(0.03)	(4.42)***	(-2.11)**	(0.19)	(4.42)***
College B	-0.2655	0.2506	0.5161	-0.3259	0.2022	0.5281
	(-1.22)	(1.27)	(3.95)***	(-1.49)	(1.00)	(3.87)***
College C	-0.3873	-0.6657	-0.2784	-0.4320	-0.6802	-0.2482
	(-1.16)	(-2.20)**	(-1.54)	(-1.25)	(-2.18)**	(-1.36)
Gender	-0.2220	-0.3455	-0.1234	-0.2032	-0.3207	-0.1175
	(-1.27)	(-2.15)**	(-1.25)	(-1.15)	(-1.97)**	(-1.20)
Finance	-0.3452	-0.0137	0.3316	-0.3015	0.0174	0.3189
	(-2.08)**	(-0.09)	(3.34)***	(-1.74)*	(0.11)	(3.18)***
LowerClassman	0.5058	0.5113	0.0054	0.5104	0.5059	-0.0046
	(2.02)**	(2.25)**	(0.04)	(2.03)**	(2.19)**	(-0.04)
Senior	0.3027	0.3620	0.0594	0.3229	0.3673	0.0444
	(1.47)	(1.95)*	(0.49)	(1.56)	(1.98)**	(0.36)
MACuser				-0.0702	-0.1893	-0.1191
				(-0.43)	(-1.24)	(-1.28)
ParentUsage				-0.0005	-0.0184	-0.0179
				(-0.01)	(-0.32)	(-0.48)
Importance				-0.0745	-0.0217	0.0528
				(-0.83)	(-0.27)	(1.20)
N	355	355	355	354	354	354
R-squared	0.119	0.257	0.246	0.121	0.261	0.253

*Notes: *, **, *** denote statistical significance at the 10%, 5%, and 1% level (two tailed test).*

Somewhat surprisingly, our results show a positive association between *CollegeCourses* and *OverCon*, significant at the 1% level (columns (1) and (4) in Table 8). *CollegeCourses* equals the number of college level courses a student has completed that includes some Excel work. The variable ranges from 0 to 6, with 6 denoting 6 or more classes taken, as structured in our student survey instrument. The positive association between *CollegeCourses* and *OverCon* indicates that the more college courses taken that include Excel the greater a student's overconfidence in their spreadsheet expertise. This does not suggest that more college exposure to Excel is educationally detrimental, as higher levels of *CollegeCourses* are positively related to higher *Test Rating* (i.e., actual performance). However, the regressions of *Self-Rating* and *Test Rating*, show

that *CollegeCourses* is positively associated with both *Self-Rating* and *Test Rating*, but that the association with *Self-Rating* is greater. Our interpretation of these results is that incorporating Excel into coursework tends to improve student expertise with Excel as we would hope; however, for our sample at least, the Excel work tends to have an over-weighted impact on student confidence relative to skills acquired. We conjecture that this over-weighted impact on confidence is at least partially the result of unstructured coverage of Excel in the curriculum. If courses in the curriculum include a spattering of Excel here and there, with little progression in the level of difficulty of spreadsheet work and/or little coordination of Excel coverage across different faculty and courses, students may walk away with the misperception that they have high-level Excel skills. In order to better align student perceptions with reality, an implication for business school curriculum, based on our conjectures, is that Excel work should ideally progress in level of difficulty with the coursework. To do this effectively will most likely require faculty members to coordinate their teaching efforts related to Excel so that students get both depth and breadth of exposure, and reduce the likelihood of some topics being covered more than necessary while other Excel topics never get mentioned. For lower level spreadsheet assignments, faculty might also offer the caveat to students that the assignment only scratches the surface of what Excel can do.

Hours of Excel self-study (*OwnHours*) also has a positive association with *OverCon*, with coefficient estimates significant at the 1% level (columns (1) and (4) of Table 8). The positive association between *OwnHours* and *Self-Rating* (columns (2) and (5)) accounts for the positive association between *OwnHours* and *OverCon*. The regression results show no statistically significant association between *OwnHours* and measured skill level (*Test Rating*). These results indicate that, on average, student self-study of Excel builds student self-confidence but has little impact on Excel skill level. Thus, even when students devote time to self-study, there appears to be few benefits. One potential explanation is that student self-study tends to be focused on lower level Excel features. In our opinion, it is likely that most students do not have a good idea of what spreadsheet features they should focus on in order to effectively build their expertise with Excel.

We find no association between *OverCon* and *MACuser*, *ParentUsage*, or *Importance* (column (4) of Table 8). Nor do these factors have a statistically significant association with either *Self-Rating* or *Test Rating*. One might expect that MAC users would have a lower skill level with Excel, given the differences between MAC and pc Excel and that most instruction is provided in a pc Excel environment. Regarding *ParentUsage*, one might expect that students would have greater spreadsheets skills when their parents are heavier users of Excel. Regarding *Importance*, it would be reasonable to expect that students who place more importance on Excel expertise would have built up that expertise relative to other students. Our results do not support any of these expectations.

Table 9 contains additional regressions of *OverCon*, *Self-Rating*, and *Test Rating*. The first three specifications include *WorkHours* and *HSCourses*. *WorkHours* equals hours per week working in Excel on average in the student's pre-graduation job or internship in which the student used Excel the most. *HSCourses* is the number of high school level courses completed by the student which included some Excel usage. *HSCourses* can range from 0 to 6, with 6 indicating 6 or more. The results show that *WorkHours* is not statistically significant for any of our three dependent variables (columns (1) through (3)). In other words, pre-graduation work hours using Excel does not impact perceived or measured Excel skills for our sample, controlling for the other explanatory variables. We note that relatively few students indicate substantial usage of Excel in a job. Almost three-quarters indicate 0 weekly hours and 83% indicate 3 hours or less (untabulated). For those students using Excel at work, our results suggest that their pre-graduation work usage tends to focus on lower level features.

HSCourses has a positive association with both *OverCon* and *Self-Rating*, but no statistically significant association with *Test Rating*. Similar to *CollegeCourses*, *HSCourses* tend to boost perceived expertise but has a lesser impact on measured skill level as a college student (in this case, no impact). We expect that spreadsheet work at the high school level tends to focus on lower level Excel features. Based on our results, any differential benefits of having a high value for *HSCourses* disappears in college as all students (including those with low *HSCourses*) continuing working with Excel. However, the added focus on lower level Excel features provided by *HSCourses* manifests itself as greater perceived expertise.

Finally, in columns (4) thorough (6), we replace *CollegeCourses* with *Assignments*, which equals the approximate number of Excel assignments, quizzes or exams that a student has completed in their college course work. The results are similar to those for *CollegeCourses*. A greater value for *Assignments* is associated with a greater value for measured skill level (i.e., *Test Rating*); however, *Assignments*' association with *Self-Rating* is even stronger. As a result, *Assignments* has a positive and statistically significant association with *OverCon* (column (4) of Table 9).

Table 9: Additional Regressions of OverCon, Self-Rating and Test Rating

Dep. Var.	OverCon (1)	Self-Rating (2)	Test Rating (3)	OverCon (4)	Self-Rating (5)	Test Rating (6)
Constant	2.9702 (4.07)***	3.8318 (5.74)***	0.8616 (2.24)**	3.0846 (4.15)***	4.1201 (6.07)***	1.0355 (2.70)***
CollegeCourses	0.1334 (1.97)**	0.3271 (5.28)***	0.1937 (5.35)***			
OwnHours	0.0175 (2.76)***	0.0173 (2.78)***	-0.0002 (-0.04)	0.0187 (2.83)***	0.0184 (2.70)***	-0.0002 (-0.05)
GPA	-0.5349 (-2.56)**	-0.0366 (-0.19)	0.4984 (4.42)***	-0.4354 (-2.01)**	0.0989 (0.50)	0.5343 (4.76)***
College B	-0.1501 (-0.67)	0.3480 (1.75)*	0.4982 (3.71)***	-0.2281 (-1.08)	0.3308 (1.63)	0.5589 (4.17)***
College C	-0.3163 (-0.96)	-0.6059 (-2.01)**	-0.2896 (-1.60)	-0.2717 (-0.84)	-0.4364 (-1.40)	-0.1647 (-0.85)
Gender	-0.1493 (-0.85)	-0.2846 (-1.73)*	-0.1353 (-1.35)	-0.2275 (-1.30)	-0.3559 (-2.18)**	-0.1284 (-1.28)
Finance	-0.2670 (-1.57)	0.0515 (0.33)	0.3184 (3.12)***	-0.2609 (-1.63)	0.1551 (1.04)	0.4159 (4.10)***
LowerClassman	0.4790 (1.94)*	0.4893 (2.19)**	0.0104 (0.08)	0.3568 (1.44)	0.2183 (0.96)	-0.1385 (-1.06)
Senior	0.2864 (1.39)	0.3482 (1.87)*	0.0618 (0.50)	0.3580 (1.76)*	0.4722 (2.54)**	0.1142 (0.92)
HSCourses	0.1628 (2.58)**	0.1368 (2.24)**	-0.0261 (-0.71)			
WorkHours	0.0006 (0.04)	0.0018 (0.11)	0.0012 (0.11)			
Assignments				0.0097 (2.41)**	0.0186 (4.83)***	0.0089 (3.78)***
N	355	355	355	355	355	355
R-squared	0.135	0.269	0.247	0.106	0.206	0.212

*Notes: *, **, *** denote statistical significance at the 10%, 5%, and 1% level (two-tailed test).*

Conclusion

Our results indicate that students are of the opinion that possessing a high level of skill with Excel is important. However, for our sample at least, student skill level appears to fall below what many employers desire. Furthermore, the students exhibit overconfidence in their expertise and tend to devote little time to building their spreadsheet skills through self-study, and even when they undertake self-study their efforts are

not measurably effective at building skill. Overconfidence in Excel skills has a number of negative ramifications for both the student and their employer, including subpar job performance and added job stress.

Cross-sectional analysis indicates that overconfidence in skill level is positively associated with both self-study hours and number of college courses completed that include some Excel coverage. The results indicate no statistically significant association between self-study efforts and measured skill level. Thus, for most students, self-study in this setting is ineffectual at best. We expect that this result is due to student lack of understanding of what spreadsheet features to focus on in order to better upgrade their skill level.

The number of college courses with some Excel is positively associated with measured skill level for our sample, but the results show that number of courses has an over-weighted impact on perceived skill relative to measured skill level. We conjecture that this result is due to unstructured and/or uncoordinated coverage of spreadsheets within the curricula in place for our sample of students. That is, the curriculum includes a sprinkling of spreadsheet work here and there, with little progression in level of difficulty across courses. This unstructured approach increases the likelihood that students walk away believing that they have a higher level of expertise with spreadsheets than they possess.

Taken together, our results suggest steps need to be taken to improve student Excel skills. One potential step would be to reduce student overconfidence in their existing skill level. Doing so would hopefully better motivate students to improve their expertise. For example, one might require that students complete a skills test as a reality check and to provide more feedback about Excel capabilities that are associated with truly higher skill levels. To promote effectual self-study, a list of suggested materials could be provided to students. Another potential step would be to incorporate spreadsheet coverage within the curriculum in a manner that would better develop student spreadsheet skills, with a focus on the needs of employers. It might be the case that a single course or two serves as the primary vehicle to build student spreadsheet expertise. Ideally, in our opinion, intermediate and advanced skills would be reinforced across courses, in a coordinated manner by multiple faculty members, to promote retention and further knowledge development.

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APPENDIX A: Excel Skill Self-Rating Instrument

Please <u>rate your Excel Skill Level</u> on a scale of 1 to 10, by <u>circling</u> a selection below.

1	-	Beginner, Low Level
2	-	Beginner, Mid Level
3	-	Beginner, High Level
4	-	Intermediate, Low Level
5	-	Intermediate, Mid Level
6	-	Intermediate, High Level
7	-	Advanced, Low Level
8	-	Advanced, Mid Level
9	-	Advanced, High Level
10	-	Expert

In your opinion, what level of Excel skills do **employers** expect for students graduating in your major on average? <u>Circle</u> your selection below.

1	-	Beginner, Low Level
2	-	Beginner, Mid Level
3	-	Beginner, High Level
4	-	Intermediate, Low Level
5	-	Intermediate, Mid Level
6	-	Intermediate, High Level
7	-	Advanced, Low Level
8	-	Advanced, Mid Level
9	-	Advanced, High Level
10	-	Expert
??	-	No idea

APPENDIX B: Excel Skill Level Test

Excel Quiz   Your Name: _____

_____ 1.   (Level 2) The Excel function that adds up a set of numbers is
a. =add(d. =total(
b. =product(e. =tot(
c. =sum(

_____ 2.   (Level 3) The Excel function that computes the mean or average of a set of numbers is
a. =average(d. =mean(
b. =avg(e. =meanvalue(
c. =avgvalue(

_____ 3.   (Level 7) A software language whose code can interact with Excel (e.g., tell Excel do a number of things) is
a. Automation Computing Pro (ACP)   d. Visual Basic for Applications (VBA)
b. Microsoft Spreadsheet Protocol (MSP)   e. Performing Robotic Object (PRO)
c. Standard Excel Protocol (SEP)

_____ 4. (Easy/Filler) All calculations/formulas in Excel must
a. Begin with an ^.   d. Be written in ( ).
b. Begin with an =.   e. Begin with a number.
c. Be written in " ".

_____ 5. (Level 2) What is the shortcut key to <u>paste</u> to a cell or range?
a. Ctrl + c   d. Ctrl + r
b. Ctrl + b   e. Ctrl + v
c. Ctrl + p

_____ 6. (Level 7) What Excel tool would we most likely use to see how projected net income would vary with future
sales growth (e.g., display *net income* for each potential future *sales growth level* of 0%, 2%, 4%, 8%, etc . .
.), as part of a sensitivity analysis of net income to sales growth
a. Data Table   d. Pivot Table
b. Macro   e. Data Filter
c. Vlookup

_____ 7. (Level 3) =IF(is typed into a cell. To access the function dialog box (shows the function's arguments,
inputs) to assist us in completing the IF function, we would click on
a. ? (i.e., the question mark at the top of the screen)   d. *func* (located on the formula bar)
b. ✓ (i.e., the check mark on the formula bar)   e. *=fnc* (located on the formula bar)
c. *fx* (located on the formula bar)

_____ 8. (Level 4) The appropriate setup to make all cell references in the formula =D5*E7 <u>absolute cell references</u>
is
a. =fixed(D5*E7)   d. =lock(D5*E7)
b. =#D#5*#E#7   e. =$D$5*$E$7
c. =absolute(D5*E7)

_____ 9. (Easy/Filler) What is the shortcut key to <u>copy</u> a cell or range.
a. Ctrl + a   d. Ctrl + c
b. Ctrl + b   e. Ctrl + p
c. Ctrl + z

_____ 10. (Level 7) To enter an array formula in a cell, press
a. Ctrl + a   d. Ctrl + Enter + a
b. Ctrl + Enter   e. Ctrl + Shift + Enter
c. Ctrl + Shift + a

_____ 11. (Easy/Filler) In Excel, the mathematical operator to <u>multiply</u> two numbers together is . . .
a. the "^"   d. the "@"
b. the "#"   e. the "*"
c. the "+"

_____ 12. (Level 6) What Excel tool would we most likely use to <u>automate a repetitive task</u> in Excel (e.g., to record
key strokes and other actions to run again any time later at our command).
a. Echo   d. Repeat
b. Macro   e. TaskMgr
c. Pivot Table

_____ 13. (Level 5) A worksheet contains a projected income statement. What Excel tool could we use to find the
dollar amount of sales that results in net income = 0?
a. Value Finder   d. Target Value
b. Goal Seek   e. Objective Function
c. Formula Builder

_____ 14. (Easy/Filler) An example of a <u>cell address</u> is . . .
a. 3C   d. 5&D
b. BB   e. E*7
c. A5

_____ 15. (Level 4) A worksheet contains a large block of data (cells A1 through M5000). What Excel feature could
we use *so that column A and row 1 would always be visible* no matter how far right or how far down we
scrolled?

   a. Lock Sheet   d. Hold Frame
   b. View Headers   e. Freeze Panes
   c. Fix Window

_____ 16. (Level 3) When a cell displays ######, it means that . . .
a. there is an error in the calculation.
b. the cell is using Number Format.
c. the cell is not large enough to display the number.
d. this could only mean that someone has typed the text ######.
e. Excel is asking for a number to be entered into this cell.

_____ 17. (Level 4) What is the shortcut key to make a cell reference absolute (i.e., fixed, locked)?

   a. Ctrl + a; Command + a (*mac Excel*)   d. F4 (*pc Excel*); Command + t (*mac Excel*)
   b. Ctrl + g; Command + g (*mac Excel*)   e. F7 (*pc Excel*); Command + 7 (*mac Excel*)
   c. Ctrl + l; Command + 1 (*mac Excel*)

_____ 18. (Level 5) A worksheet contains data for a group of companies, one row for each company. Column A has
company name. Column B has price per share. Column C has P/E ratio (i.e., price per share divided by
earnings per share). Column D has return for the year. <u>What Excel tool could we use to display only those
companies with a return above 10% for the year.</u>

   a. Column Filter   d. Screen Filter
   b. Data Filter   e. Sheet Filter
   c. Row Filter

_____ 19. (Easy/Filler) An example of a <u>range address</u> is . . .

   a. B3-D5   d. B3|D5
   b. B3=D5   e. B3*D5
   c. B3:D5

_____ 20. (Level 5) What is the shortcut key to display the Format Cells dialog box (formatting selections for numbers,
alignment, font, border, fill, protection) ?

   a. Ctrl + d   (Command + d for mac Excel)   d. Ctrl + 1   (Command + 1 for mac Excel)
   b. Ctrl + m (Command + m for mac Excel)   e. Ctrl + 2   (Command + 2 for mac Excel)
   c. Ctrl + z   (Command + z for mac Excel)

_____ 21. (Easy/Filler) In Excel, what is the mathematical operator to raise a number to some power (e.g., 5^3)?

   a. the "^"   d. the "@"
   b. the "#"   e. the "*"
   c. the "+"

_____ 22. (Level 6) To prevent changes to all cells in a worksheet <u>except C5</u>, you should
a. select (i.e., highlight) all cells except C5, then "protect" the worksheet
b. select (i.e., highlight) all cells except C5, then "lock" the worksheet
c. "protect" all cells except C5, then "lock" the worksheet
d. "unlock" cell C5, then "protect" the worksheet
e. "unprotect" cell C5, then "lock" the worksheet

_____ 23. (Level 6) What is the appropriate Excel function to combine the text contents of two cells into a single cell?
E.g., B5 contains "Bill". C5 contains "Jones". Combine B5 and C5's contents into another cell as "Bill
Jones".

   a. =Amalgamate(d. =String(
   b. =Concatenate(e. =Text(
   c. =Combine(

Teaching Value at Risk Using Excel

Saurav Roychoudhury[1]

ABSTRACT

Value at Risk or VaR is the most widely used financial model for measuring risk in the financial industry. However, VaR concepts do not find a way into most undergraduate finance courses due to the relative difficulty in implementing them. This paper provides three different methods to estimate VaR using Microsoft Excel with increasing levels of complexity. In particular, this paper estimates VaR using the historical, Delta-Normal and Monte Carlo simulation methods with real-world financial market data. The paper shows techniques to calculate single asset and portfolio VaR and uses matrix algebra in Excel for estimating multi-asset portfolio VaR.

Introduction

In financial markets, exceeding the return on government bonds requires one to invest in riskier securities ranging from highly rated municipal bonds to the riskiest of derivatives. Putting funds at risk raises the possibility of investment loss. Financial loss matters as it impairs the ability to invest, save, consume, borrow, retire, and sustain our well-being. A personal investor could face bankruptcy, a financial trader who trades on margin could face financial ruin if she fails to "exit" her position beyond a limit, and an investment bank could have its equity wiped out if its assets drop below a certain amount. Using Value at Risk (VaR), it is possible to model, at least within a reasonable bound, the maximum potential loss in a given period (Das and Lynagh 1997). VaR is one of the most common measures of risk used by financial institutions and can be applied to just about any asset class. Another reason VaR is so appealing is that it can measure both individual risks — the amount of risk contained in a single trader's portfolio, for instance — and firm-wide risk, which it does by combining the VaRs of a given firm's trading desks and coming up with a net number. Risk managers use VaR to quantify their firm's risk positions to their board. In the late 1990s, as the use of derivatives was exploding, the Securities and Exchange Commission ruled that firms have to include a quantitative disclosure of market risks in their financial statements for the convenience of investors, and VaR became the main tool for doing so.

Despite VaR's popularity in the financial industry, it has not been part of standard undergraduate finance courses, primarily because of the difficulty in implementing it in a classroom setting. The finance industry uses proprietary software, costing thousands of dollars in annual license fees, that estimate the VaR of a portfolio. However, over the years, Microsoft Excel has developed into a powerful tool that can be used to do sophisticated calculations in finance (see Johnson and Stretcher 2013; Wann 2015; Boudreaux et al. 2016; Wann and Lamb 2016). The popularity of Excel in academia stems from its ability to offer students an engaging learning opportunity. Hess (2005) suggests that "hands on" use of spreadsheet modeling in class, improves understanding and retention of concepts. Finance faculty at most leading business schools advocate the use of Excel to prepare students for the workforce (see Bailey and Heck 2002 and Gitman and Vandenberg 2003 for faculty surveys on the use of Excel). Ghani and D'Mello (1993) find that after doing spreadsheet based finance assignments students report increased levels of self-competence and self-actualization.

This paper uses Excel to estimate VaR using three widely used methods. The paper also provides seven examples, six of which are worked out in Excel.[2] Students should be able to replicate the results and recreate

the different VaR formulations using real-world data from different asset classes. For Monte Carlo method, the paper uses a free Excel Add-in for simulation. For advanced students, the paper uses Matrix algebra in Excel to estimate VaR for a multi-asset portfolio.

Value at Risk

In its most general form, VaR estimates the worst loss over a time horizon with a given level of confidence. For example, if the VaR on a portfolio is $10 million at a one-week, 95% confidence level, then there is only a 5% chance that the portfolio value will drop by more than $10 million over any given week. Representing the losses (and gains) in the form of a distribution, VaR describes the quintile (shaded area in Figure 1) that separates the tail from the body of distribution. VaR can be measured either in percentage terms or dollar terms.

Figure 1: Value at Risk (VaR)
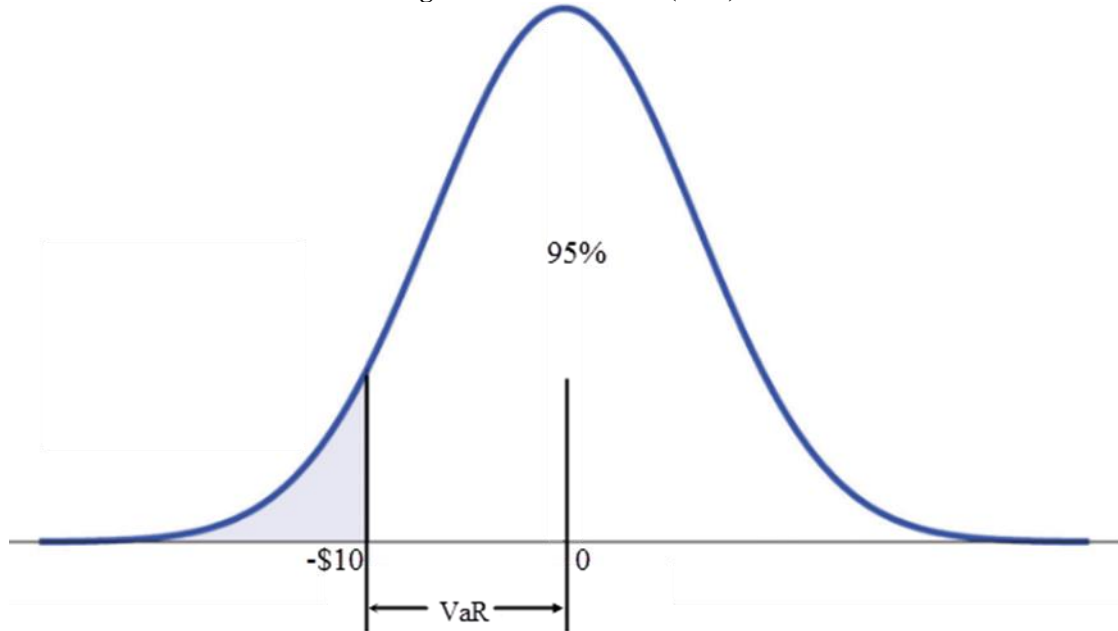
The generic VaR statistic is defined as a one-sided confidence interval on portfolio losses

$$Prob[\Delta P(\Delta t, \ \Delta \tilde{x}) > -VaR] = \ \alpha \qquad (1)$$

where $\Delta P(\Delta t, \ \Delta \tilde{x})$ is the change in the portfolio's market value, expressed as a function of the forecast horizon Δt and the vector changes in the random variable(s) $\Delta \tilde{x}$. The interpretation is that, over a specified number of trading days, the portfolio's value will decline by no more than VaR at α % of the time. The choice of α % depends on the risk tolerance of the investor, securities trader, fund manager, hedge fund, or bank. Typical values of α range from 1% to 10% and the forecast horizon Δt is usually a day, week, or month.

However, before we go any deeper, it is worthwhile to discuss how we measure investment returns. Rates of return are the building blocks of quantitative finance. A simple periodic rate of return, R_t, on any investment can be calculated by using the general formula

$$R_t = \frac{End\ of\ Period\ Investment\ value - Beginning\ of\ Period\ Investment\ Value}{Beginning\ of\ Period\ Investment\ Value}$$

$$R_t = \frac{End\ of\ Period\ Investment\ Value}{Beginning\ of\ Period\ Investment\ Value} - 1$$

Stock returns are one of the most widely used financial returns,[3] and when investors invest in company stock, they expect a return in the form of dividends and capital gains (losses).[4] The stock return in any period *t*, is simply the ratio of the sum of the dividends, D_t, plus the capital gains to the stock price at time *t-1*. Algebraically, the simple periodic return R_t is given as

$$R_t = \frac{P_t + D_t}{P_{t-1}} - 1 \tag{2}$$

If the periodic return is R_t and our initial investment is $1 then the end of period value or simple gross return is $1 \times (1 + R_t)$. In finance, it is often convenient to convert the periodic returns to continuous returns, as the statistical properties of continuous returns are more tractable. We can easily convert any periodic return to its continuously compounded form by taking the logarithm of 1 *plus* the periodic return. The continuously compounded return r_t is given by

$$r_t = ln(1 + R_t) = ln\left(1 + \frac{P_t}{P_{t-1}} - 1\right) = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3}$$

For example, if $R_t = 10\%$ the continuous return $r_t = ln(1.10) = 9.53\%$. It is easy to convert back from r_t to R_t. If the continuously compounded return for one year is 9.53%, the periodic return for the year will equal, $e^{0.093} - 1 = 10\%$.

When we wish to emphasize the distinction between R_t and r_t, we shall refer to R_t as the simple return. The main advantage of continuously compounded returns, r_t, is the additive property. If we want to find multi-period continuously compounded returns, it is simply the sum of the continuously compounded one-period returns.[5]

Consider an investment of $1. Say in the first year the investment value rises to $2. The return, R_1 is 100%. In year 2, the investment falls back to $1, which will be a return of $R_2 = -50\%$ in the year 2. If we take the average of two-year returns, it gives an average annual return of 25% on this investment, even though our investment value is back to $100 (hence the return should have been 0%). But using continuously compounded returns resolves this problem. From equation (3), we can write

$$r_{t,2} = ln(1 + R_1).ln(1 + R_2)= ln(2).ln(-.5) = 0.693147 + (-0.693147) = 0\%$$

We will mostly use the continuously compounded returns to estimate VaR. There are three broad methods of estimating VaR, and there are numerous variations within each of these methods. VaR can be estimated by running hypothetical portfolios through historical data, computed analytically by making assumptions about return distribution and risks, or from Monte Carlo simulations. We illustrate the three methods in this section using three months of daily returns of Microsoft stock.[6]

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[3] The data on stock prices of publicly traded companies are freely available on popular financial websites like Yahoo! Finance, MSN money, and NASDAQ.com. The historical prices are automatically adjusted to account for dividends and stock splits.

[4] Some companies like Google Inc. have never paid a dividend. Investors buy non-dividend paying stocks because they tend to compensate investors with higher stock prices. Capital gains or losses from a stock at time *t* is the difference between the price at time *t* and price at time *t-1*; i.e., $(P_t - P_{t-1})$.

[5] Compounding, a multiplicative operation, is converted to an additive operation by taking logarithms.
$r_t(k) = ln(1 + R_t).ln(1 + R_{t-2}).ln(1 + R_{t-3})....ln(1 + R_{t-k+1}) = r_t + r_{t-1} + r_{t-2} + \cdots + r_{t-k+1}$

[6] For details on how to download stock price data from Yahoo and compute monthly stock returns, refer to Appendix A1. The daily returns of Microsoft stock are in the Excel file JEFE1.xslx which is available for download at bit.ly/JEFE001.

Method 1: Historical Simulation for One Risky Asset

Historical simulation represents the simplest way of estimating the VaR. It is a non-parametric approach which estimates the VaR of a portfolio by using actual historical returns data to create a hypothetical time series of returns. This method puts an equal weight to the time series data; that is, it treats the change in the portfolio from today to tomorrow as similar to what it was in the past. In its simplest form, VaR is calculated by looking at the percentiles of the data by ordering the return observations from largest to the smallest. For example, if a dataset has 100 daily time series observations, then the daily VaR at 5% will be the 5th lowest observation in the dataset.

Example 1
Calculate VaR at 1%, 5%, 10% and 15% for a 1-day horizon for Microsoft stock.

Solution
Step 1: We use three months of Microsoft stock returns to calculate the daily VaR.
Step 2: To find the value that corresponds to the appropriate VaR, Excel's PERCENTILE function returns the α percentile of values in an array. For example, if 5% is α percentile, then 95% of the values in the array would be greater than the value returned by the PERCENTILE function. The EXCEL syntax is =PERCENTILE($array, \alpha$). To create an array for Microsoft returns, see the Appendix A2 on "How to create an Array Name".
For calculating the daily VaR at 10% for Microsoft stock, we use =PERCENTILE($msft$, 10%). This returns -3.96%, which implies that based on the data there is a 95% confidence that the worst loss won't exceed -3.96%. In other words, only one out of twenty times would you expect Microsoft stock to fall by more than or equal to -3.96% in any given trading day. The detailed solution is provided in the "Historical" tab in the excel workbook.[7]

Note to Instructors
An exercise to demonstrate how the historical VaR depends on the choice of time period is to have the students select a turbulent period (say from September 2008 to March 2009) and compare it with a less turbulent period. The chosen security could be an Exchange Traded Fund (ETF) that mimics a stock market index (SPY for S&P 500 or DIA for Dow Jones) or sector-specific ETF's like XLF (financial sector).

The main advantage of historical VaR over the Delta-Normal and Monte Carlo methods presented below is there are no assumptions on the return distribution. This often makes historical value-at-risk easier to interpret and explain. However, the simple historical approach suffers from some obvious problems because it assumes that past prices are a good predictor of future prices and it uses single sample paths of prices to compute VaR which may not correctly reflect the future. This approach is unable to adjust to changing economic conditions and abrupt changes in parameter values. If the historical return observations do not include periods of high volatility, this method is likely to underestimate the VaR. In other words, the historical simulation method is heavily dependent on the time series of returns. A small number of historical scenarios would lead to lower statistical confidence in the VaR estimate.

Method 2: Delta-Normal VaR

The Case of One Risky Asset

Unlike the historical simulation method, the delta-normal VaR explicitly assumes a parametric distribution for the underlying observations. In its purest form, the delta-normal method assumes that the returns of the risky asset or portfolio follow a normal distribution. We define the VaR statistic as a one-sided confidence interval on portfolio losses, and the cutoff will be in the left tail of the returns distribution. In equation form, the VaR at significance level α is:

$$VaR_{\alpha\%} = \mu + Z_\alpha \sigma \tag{4}$$

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[7] The Excel file is available for download at bit.ly/JEFE001.

where μ and σ denote the mean and standard deviation of the distribution and Z_α represents the critical value α of the standard normal. In practice, the sample mean and standard deviation are used as approximations for population μ and σ.

Example 2

Calculate VaR at 1%, 5%, 10%, and 15% for a 1-day horizon for Microsoft stock using the delta-normal method.

Solution

Step 1: We use three months of Microsoft stock returns to calculate the mean μ and the standard deviation σ of daily returns.

Step 2: Calculate the Z_α value corresponding to the α. The NORMSINV returns the inverse of the standard normal cumulative distribution for probability (α) corresponding to the normal distribution with standard deviation σ. The Z_α value tells us how many standard deviations the α away is from the mean. For α= 5%, the Z_α value is -1.645 standard deviations to the left of the mean. Using equation (4), the VaR at 5% will be $[-0.36\% + (-1.645 \times 1.74\%) = -3.22\%]$ which implies that there is a 95% confidence that the worst daily return will not exceed -3.22%. The detailed solution is provided in "Delta Normal" tab in the excel workbook.[8]

Note to Instructors

Instead of a stock, students can use an ETF. Students can also use a longer period (like 3 years) to calculate the mean and standard deviations. Instead of estimating 1 day VaR, students can use weekly returns for 1 week VaR, and monthly returns for 1 month VaR.

The Case of Two Risky Assets

One of the primary objectives of creating a multi-asset portfolio is reducing or containing risk through diversification. The risk depends on the number of risky assets and how diverse the risky assets are. For example, an S&P index portfolio will typically have a lower portfolio risk than a portfolio of 10 randomly chosen stocks. Similarly, the more diverse the stocks in a portfolio (indicated by low or negative covariance between the assets), the more diversification benefits will be observed.

Portfolio standard deviation is the commonly used measure of risk of portfolio returns. To calculate a single asset standard deviation, we can simply use the Excel formula STDEVP. However, it is a bit more complicated for a portfolio.

Let us assume that there are only two risky assets, *A* and *B*, available for consideration in an investment portfolio. The expected portfolio return is given by

$$\mu_p = x_A\mu_A + x_B\mu_B \tag{5}$$

where μ_A and μ_B are the average returns and x_A and x_B are the respective portfolio weights of the two assets A and B.

We further assume that the portfolio weights should add up to 1 (i.e., $x_A + x_B = 1$) and that there are no short sales ($x_A, x_B \geq 0$). The portfolio variance is given by

$$\sigma_p^2 = x_A^2\sigma_A^2 + x_B^2\sigma_B^2 + 2\,Cov(A,B)x_Ax_B \tag{6}$$

and the standard deviation by

$$\sigma_p = \sqrt{x_A^2\sigma_A^2 + x_B^2\sigma_B^2 + 2\,Cov(A,B)x_Ax_B} \tag{7}$$

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[8] The file can be accessed at bit.ly/JEFE001.

We write the covariance between A and B as $Cov(A,B) = \rho_{AB}\,\sigma_A\sigma_B$ where ρ_{AB} is the correlation coefficient between assets A and B. The delta-normal VaR methodology follows the traditional approach of assuming a jointly normal distribution among all assets in the portfolio to compute VaR estimate analytically.

Example 3
Using the provided data, find the delta-normal VaR at 1%, 5%, 10%, and 15% for a two stock portfolio.[9]

Solution
Step 1: Find the portfolio return and standard deviation using equations (5) and (7).

Step 2: Find the Z values corresponding to 1%, 5%, 10% and 15% using NORMSINV(*probability*) function. For example, for α =1%, NORMSINV(.01) will return -2.33.

Step 3: Find the respective VaRs corresponding to 1%, 5%, 10%, and 15% using equation (4).

Note to Instructors
The students can be asked to create a two asset portfolio using a combination of two different stocks or a stock ETF and a bond ETF. The horizon can expanded from daily VaR to weekly or monthly VaR.

Log-Normal VaR

So far, we have based our analysis on the assumption that the return distribution is normal. The normal distribution is the most frequently used model to teach VaR. For any distribution, the mean and the standard deviation are the first two moments, the third moment measures the skewness (which measures both the direction and the magnitude of any asymmetry) and the fourth moment describes the kurtosis, which measures the fatness of the tails of the distribution. For a normal distribution, the kurtosis has a value of 3, and the skewness has a value of zero implying perfect symmetry. Sample estimates of skewness for US stock returns tend to be negative for stock indices but close to zero or positive for individual stocks. In general, real world investment returns are not precisely normally distributed, and they exhibit fat-tailed behavior, which means that extreme movements in portfolio return occur with a much larger probability than that predicted by a normal distribution. First, most financial assets like stocks have limited liability, so that the largest loss to an investor can never be less than -100%. However, since the normal distribution constitutes the entire real line, the lower bound of -100% violates normality. Second, if one-period returns are assumed to be normally distributed, then multi-period returns cannot also be normal as they are products of the single period returns. In the lognormal model, the natural logarithm of gross asset return is assumed to be normally distributed, which implies that single period gross simple return, R_t, is distributed as lognormal (i.e., $r_t = ln(1 + R_t)$). The lognormal distribution is skewed to the right. If gross returns are lognormally distributed, the gross returns cannot fall below negative 100 percent. These properties of the lognormal distribution make it a more realistic characterization of the behavior of market returns than the normal distribution.

It is simple to modify the delta-normal VaR to a lognormal VaR, as shown in equation (8):

$$VaR_{\alpha\%} = 1 - e^{\mu - Z_\alpha \sigma} \qquad (8)$$

Example 4
A $100 million portfolio has a continuously compounded annual return of 12% and a standard deviation of 20%, respectively. What is the 1 year lognormal VaR at 1%, 5%, and 10%?

Solution
Using equation (8):

Lognormal VaR(1%) = $1 - e^{0.12 - 2.33*0.20} = 0.292$
$= \$100 \times 0.292 = \$29.2$ million

Lognormal VaR(5%) = $1 - e^{0.12 - 1.65*0.20} = 0.1886$
$= \$100 \times 0.1886 = \$18.86$ million

Lognormal VaR(10%) = $1 - e^{0.12 - 1.28*0.20} = 0.1274$
$= \$100 \times 0.1274 = \$12.74$ million

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[9] The Excel workbook can be accessed at bit.ly/JEFE2.

Note to Instructors

A simple exercise would be to have the students compare the VaR derived from the delta normal method with the VaR estimated from the lognormal method.

Method 3: Monte Carlo Method

One of the most important characteristics of asset returns is their randomness. The return of Microsoft stock over the next day is unknown today and the best guess of tomorrow's price is today's price. A single point, like an average, may not be the best estimate for a group of data points. However, if we have thousands and thousands of points to consider, we greatly expand the horizon of possible outcomes. One way to do this is by generating random numbers to reveal possible outcomes in an uncertain environment and simultaneously attaching probabilities to each outcome. When we roll a die, we know that a 1, 2, 3, 4, 5, or 6 will come up (with a probability of 1/6), but we do not know which number will appear on any particular roll. That is randomness, and the random behavior in dice is similar to how Monte Carlo simulation works. This technique derived its name from the town of Monte Carlo in Monaco, where the primary casino attractions are games of chance such as roulette wheels, dice, and slot machines. One of the earliest applications of Monte Carlo simulation occurred in the late 1940s when scientists at the Manhattan Project at Los Alamos National Laboratory used the method to predict the range of possible nuclear fission results. Figure 2 illustrates the steps of Monte Carlo simulation.

Figure 2: Steps for Monte Carlo Simulation
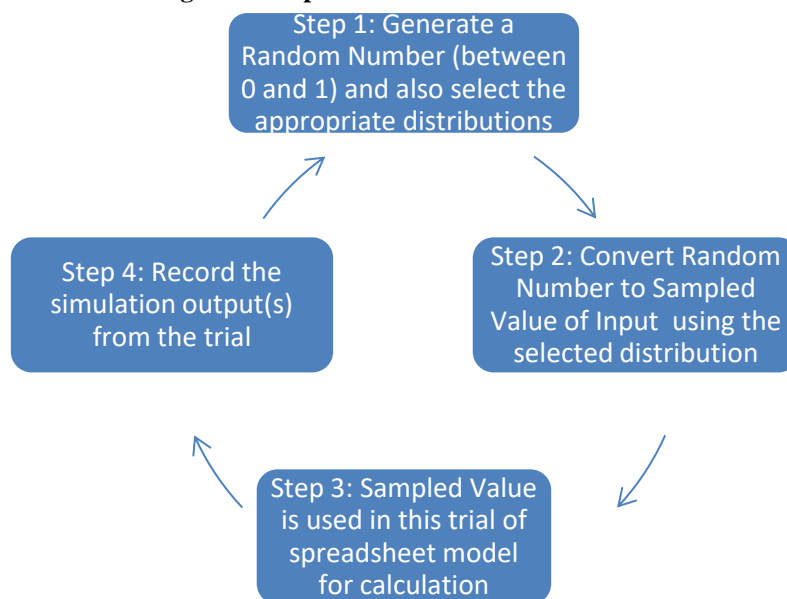
We can use Excel's $RAND()$ in step 1 to generate random numbers between 0 and 1. However, there is no way to record the results from the simulated trials as Excel will recalculate every time the Excel sheet is refreshed or used. There are commercial products like @Risk, Crystal Ball, and xlSim which allow us to run a simulation using Excel. University of Chicago economist Roger Myerson has developed an add-in called SIMTOOLS which can be used to conduct Monte-Carlo simulations in Excel. The add-in is freely available at his website. For instructions on SIMTOOLS refer to the Appendix A3. The following example uses the Monte Carlo method using the SIMTOOLS add-in.

The Case of One Risky Asset

Example 5

Calculate VaR at 1%, 5%, 10%, and 15% for a 1-day horizon for Microsoft stock using the Monte Carlo method.

Solution

Step 1: Select a specific distribution for Microsoft asset returns and estimate the parameters of that distribution. As a simple case, we use a normal distribution with parameters similar to the delta-normal method (mean = -0.36% and standard deviation= 1.74%). We use Excel's *RAND* () which generates an evenly distributed random real number between 0 and 1. Once the distribution has been selected, we use a pseudo-random number generator that will generate N hypothetical outcomes.

Step 2: To convert random numbers to sample values of the input we use Excel's NORMINV(*Probability, Mean, Standard Deviation*) function which returns the inverse of the normal cumulative distribution for the specified mean and standard deviation of the random probability value generated by RAND(). However, the mean values calculated will give a different output every time we refresh the worksheet.

Step 3: To store the results for each number of trials we use SIMTOOLS. For example, we want to create a table which will store results from 3000 trials. We start by selecting a "counter" column which will be the leftmost column for our simulation. In Figure 3 below, the counter column begins from SimTable in cell B7. The cell on the right (C7) would be the formula reference cell for the value we want to simulate (D5).

Figure 3: Using SimTools for the Monte Carlo Method
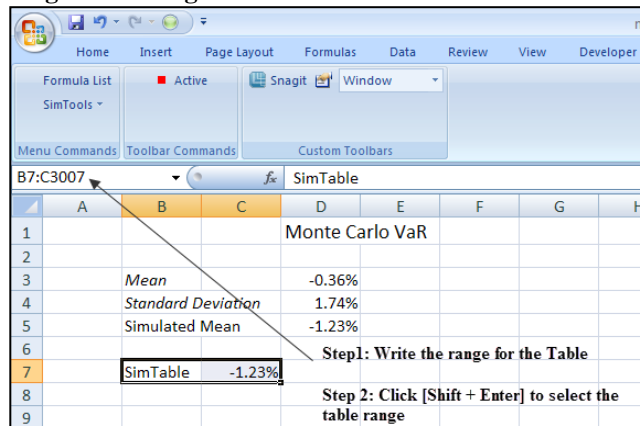
Once both cells (B7 and C7) are highlighted we type B7: C3007 on the name tab and press Shift + Enter to highlight the entire range. Once the column is highlighted, select *Simtools/Simulation table*. This action will populate the selected columns B8:C3007 with 3000 simulated results of MSFT daily stock returns. To find the 5% VaR, select the 5% percentile value using the PERCENTILE function (as in the historical simulation method). If there are 3000 observations, it will pick the 150th smallest observation. This gives a VaR value of -3.15%. Figure 4 shows the solution provided in the "Monte Carlo" tab in the Excel workbook.[10]

Figure 4: Creating a Simulation Results Table with SimTable

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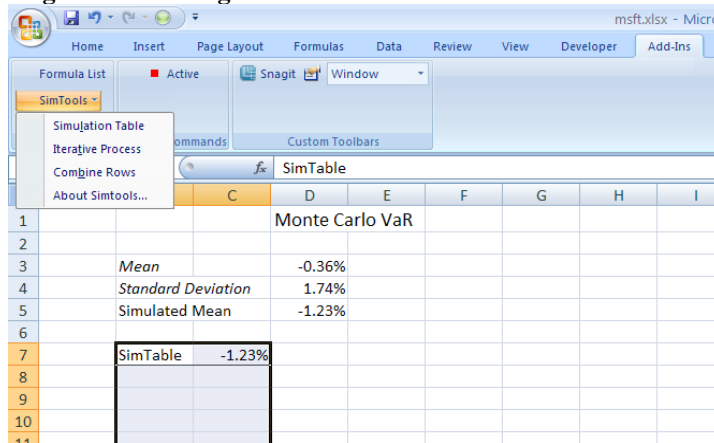
[10] The file is available for download at bit.ly/JEFE2.

Table 1 provides a comparison of the results of the three methods used to find the daily VaR for Microsoft stock returns.

Table 1: Comparison of Three Methods to Estimate Daily VaR

α	Delta Normal	Historical Simulation	Monte-Carlo Method
1%	-4.40%	-4.17%	-4.31%
5%	-3.22%	-3.96%	-3.15%
10%	-2.58%	-2.35%	-2.54%
15%	-2.16%	-1.89%	-2.17%

Note to Instructors

A comparison among the three methods could be the basis of a class project where the groups can choose to work on calculating VaR of an ETF. Allow the students to repeat these exercises for different asset classes and different time periods will improve understanding and enhance learning outcomes.

The Case of Two Risky Assets

Example 6

Find the VaR by Monte Carlo approach for the 2 stock portfolio using the data in the Excel Workbook.[11] Assume normally distributed returns.

Solution

We use the same basic framework as the delta-normal method. We assume the portfolio returns follow a normal distribution with an expected portfolio return of $\mu_P = 2.12\%$ and standard deviation of $\sigma_P = 8.41\%$.

Step 1: Generate random portfolio return by using Excel's $NORMINV(RAND(), \mu_P, \sigma_P)$

Step 2: Run 5000 iterations of step 1 using the SIMTOOLS to create a simtable.

Step 3: Find the respective cut-off points corresponding to the VaR of 1%,5%,10% & 15% using Excel's PERCENTILE function to come up with estimates of VaR.

The Case of Three Risky Assets

It is easy to modify the mean and standard deviation of a two-asset portfolio to a three asset portfolio (A, B, and C). We write the average portfolio return as

$$\mu_p = x_A \mu_A + x_B \mu_B + x_C \mu_C \tag{9}$$

with the condition that $x_A + x_B + x_C = 1$ and $x_A, x_B, x_C \geq 0$. Likewise, the portfolio standard deviation can be written as

$$\sigma_p = \sqrt{x_A^2 \sigma_A^2 + x_B^2 \sigma_B^2 + x_C^2 \sigma_C^2 + 2\,Cov(A,B)x_A x_B + 2\,Cov(B,C)x_B x_C + 2\,Cov(A,C)x_A x_C} \tag{10}$$

However, as the number of assets in a portfolio increases, the calculation of portfolio standard deviation becomes lengthy and complex. We can use Excel's matrix algebra functions like addition, subtraction, matrix multiplication, inverse, and transpose to solve this problem. The example below is based on three risky assets, but can be generalized to include any number of risky assets. The expected return, μ and portfolio weights X are both 1×3 column vectors.

$$\boldsymbol{\mu} = \begin{bmatrix} \mu_A \\ \mu_B \\ \mu_C \end{bmatrix} \quad \text{and} \quad \boldsymbol{X} = \begin{bmatrix} x_A \\ x_B \\ x_C \end{bmatrix}$$

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[11] The file can be accessed at bit.ly/JEFE2.

The matrix multiplication method gives the portfolio expected return

$$\mu_p = \mu'X \tag{11}$$

where μ' is the transpose of the vector μ. Equation (11) is the matrix algebra equivalent of equation (9) in the three asset case. For the portfolio variance (and standard deviation), we have to first define the variance-covariance matrix S, where $S = |\sigma_{ij}|$ (i is the row element, and j is the column element), $\sigma_{ij} = \sigma_i^2$ if $i = j$ (for example, $\sigma_{AA} = \sigma_A^2$), and $\sigma_{ij} = Cov(i,j)$ if $i \neq j$ (for example, $\sigma_{iAB} = Cov(A,B)$). For the three asset case, the variance-covariance matrix S is the following 3×3 matrix.

	Asset A	*Asset B*	*Asset C*
Asset A	σ_A^2		
Asset B	$Cov(A,B)$	σ_B^2	
Asset C	$Cov(A,C)$	$Cov(B,C)$	σ_C^2

The portfolio variance is therefore

$$\sigma_p^2 = X'S\,X \tag{12}$$

Example 7

Jill has a portfolio consisting of assets A, B, and C with expected returns of 17%, 6%, and 12% and standard deviations of 30%, 25%, and 45%, respectively. The three asset variance-covariance matrix is

	Asset A	*Asset B*	*Asset C*
Asset A	0.37		
Asset B	-0.07	0.1	
Asset C	0.05	-0.01	0.25

If $100,000 is Jill's initial investment, what is the maximum amount that Jill can lose in a year with VaR at 1%, 5%, 10%, and 15%? Use both the delta-normal and Monte Carlo methods.

Solution:

To implement the problem in Excel using Matrix algebra, we would need to define the data inputs into *arrays*, which are the basic building blocks of matrix algebra. Appendix A2 has a short description on how to create an array name.

As defined in the previous section, μ is a *1 x 3* column vector of mean returns of three stocks. We name this array as "**mu**." S represents a *1 x 3* column vector of the portfolio weights; the array is named "**s**," and finally $\Sigma = \left|\sigma_{ij}\right|$, represents the *3 x 3* variance-covariance matrix of the three asset returns, the rectangular array is named "**Sigma**".

We solve equations (11) and (12) to estimate the expected return and variance of Jill's portfolio. For matrix multiplication we use "MMULT()", and for transposing matrices, we use the "TRANSPOSE()" function. Equation (11) could be written in Excel as {=MMULT(TRANSPOSE(mu),X)} and equation (12) is {=SQRT(MMULT(MMULT(TRANSPOSE(X),S),X))}; see Figure 5.[12]

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[12] While executing a matrix algebra formula in Excel, remember to press CTRL + SHIFT + ENTER together. Simply pressing ENTER would give an error.

Figure 5: Using Matrix Operations in Excel for Three Risky Assets

	A	B	C	D	E	F	G	H	I	J
1				**Value at Risk for 3 risky Assets**						
2		Expected returns		Variance-Covariance Matrix				Portfolio Weights		
3	Asset 1	17%		0.37	-0.07	0.05		30%		w
4	Asset 2	6%	m	-0.07	0.10	-0.01	V	25%		
5	Asset 3	12%		0.05	-0.01	0.25		45%		
6										
7										
8	Mean Portfolio return	0.12			α	0.01		Level of VaR		
9	Portfolio Standard Deviation	0.3015			Cutoff	$ 41.85				
10	Initial investment	$100			Var at α%	$58.15				
11	Investment mean value	$ 112.00								
12	Stand. Dev. of Investment value	$ 30.15						=NORMINV(F8,B11,B1		
13										
14										
15					{=MMULT(TRANSPOSE(m),W)}					
16										
17				{=SQRT(MMULT(MMULT(TRANSPOSE(W),V),W))}						
18		z	α	VaR						
19		-2.33	1%	-58.1%						
20		-1.64	5%	-37.6%						
21		-1.28	10%	-26.6%						
22		-1.04	15%	-19.3%						
23										
24										

The detailed solution for the delta-normal and Monte Carlo methods is available in the Excel Workbook.[13] Once we obtain the portfolio expected return and standard deviation, we can use equation (4) to estimate the Delta-Normal VaR.

For Monte Carlo Method, we proceed the same way as the method for a single risky asset. We run 500 trials to simulate the portfolio values using portfolio expected return and standard deviation. We then use the Excel percentile functions to estimate the desired VaR statistics as shown in Figure 6.

Figure 6: Calculating VAR from SimTools Results

Percent Ranks	SimTable	-0.32	Portfolio Value				
42%	0	0.07	$ 6.59				
21%	0.002004	-0.13	$ (13.11)				
80%	0.004008	0.3772	$ 37.72	Using Vlookup			
11%	0.006012	-0.2556	$ (25.56)	$ (54.30) <----VaR at 1%			
91%	0.008016	0.50204	$ 50.20				
84%	0.01002	0.40782	$ 40.78	Monte Carlo VaR			
28%	0.012024	-0.0673	$ (6.73)				
8%	0.014028	-0.3015	$ (30.15)		α	VaR	
47%	0.016032	0.10493	$ 10.49		1%	$ (54.30)	
66%	0.018036	0.25635	$ 25.64		5%	$ (36.84)	Using Excel's
40%	0.02004	0.04053	$ 4.05		10%	$ (27.68)	Percentile functio
25%	0.022044	-0.1006	$ (10.06)		15%	$ (20.96)	
41%	0.024048	0.05346	$ 5.35				
4%	0.026052	-0.392	$ (39.20)				

Note to Instructors

For advanced undergraduate or graduate teaching this section on matrix algebra will be especially helpful. It is preferable to allow the students to work in groups to enhance the learning process in Excel as matrix implementation in Excel is not easy. Working in groups will also encourage students to improve their skills by learning from one another.

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[13] The Excel file is available for download at bit.ly/JEFE3.

Concluding Comments

This paper uses Microsoft Excel to implement VaR using real-world financial data. The VaR techniques used in this paper can serve as a readily usable teaching tool on how to model VaR in Excel. The teaching tools can be used in a standard "Introduction to Derivatives and Risk Management" course[14] or in a "Financial Markets and Institutions" course under the topic of risk management in financial institutions.[15] The paper can also be used as a stand-alone topic in a computational finance course. We have also used these VaR examples as part of a "Financial Modeling with Excel" course for MBA students. While the paper is designed primarily for teaching undergraduate students in finance, economics, and statistics, it can also cater to undergraduate students in mathematics, physics, and computer science who wish to take a course in computational finance.

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[14] For example, this paper could be used as a supplementary material to chapter 15 on Financial Risk Management Techniques and Applications in the "Introduction to Derivatives and Risk Management" text by Chance and Brooks (2012) or chapter 18 of Rene Stulz's (2002) 'Risk Management and Derivatives' textbook.

[15] With Chapter 23 of Mishkin and Eakins (2017) or a new topic between Chapter 19: Bank Management and Chapter 20: Bank Performance in Jeff Madura's (2011) textbook.

APPENDIX

A1: Downloading Stock Price Data and Calculating Daily Returns Using Excel

Step 1

Go to http://finance.yahoo.com and type in a company ticker (in our example, MSFT) or the company name in the 'Quote lookup.' This will bring up the summary page similar to the one shown below. To download historical stock price information, choose 'Historical Prices' to get Microsoft's price history.

Figure A1: Stock Summary Page on Yahoo! Finance

Step 2

Indicate the period and frequency for the data. We have chosen a three-month window from April 1 to July 1, 2010. Choose the 'Daily' option to download daily price data. If we scroll down the web page it gives us the option to download the data in the Excel spreadsheet format. Yahoo allows us to save the spreadsheet file as 'Table.csv' which is a comma separated value file and can be opened directly by Excel. Once the file is downloaded and opened in Excel, it is recommended to save it as a 'Microsoft Excel workbook' file as the Excel workbook file preserves any formulas we work on while the .csv file does not.

Figure A2: Saving the Historical Price Data to an Excel File
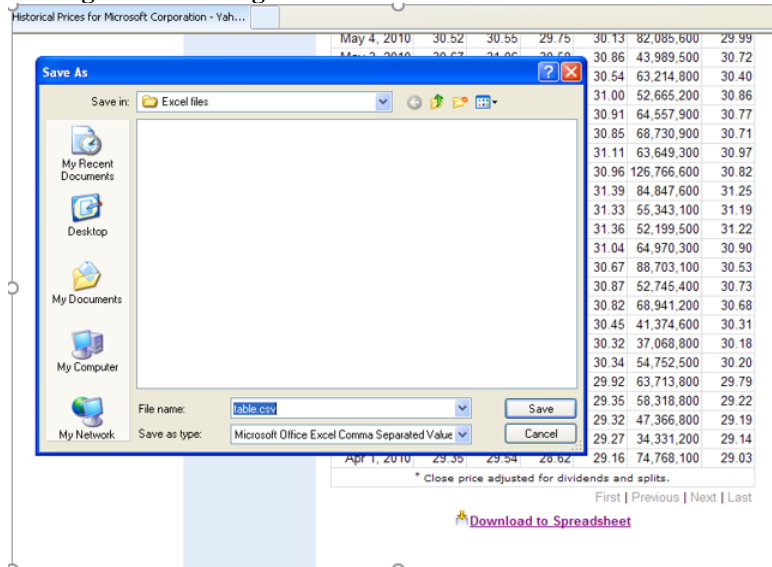
Step 3

To compute monthly returns we keep only the columns 'date' and 'Adj. Close.' The adjusted closing stock price in Yahoo accounts for any dividends and stock splits which may have occurred during our sample period. The date, presented in descending order, is sorted in ascending order to calculate returns. We use the Excel 'sort' function to sort the date in ascending order.

Figure A3: Formatting the Excel Sheet

Step 4:

The stock returns can be calculated using the formula for continuous periodic returns $r_t = Ln\left(P_t/P_{t-1}\right)$. In our example, Microsoft daily stock return corresponding to 4/5/2010 is given by typing the Excel formula "=LN$(B3/B2)$ " in cell C3. Here $P_t =$ Price on 4/5/2010 and $P_{t-1} =$ Price on 4/5/2010. Copying the formula from cell C3 to the end of your date range will give you the time series data on Microsoft stock returns.

Figure A4: Calculating Daily Returns

A2: How to Create an Array Name

It is convenient to *name* a series of data in a column or a row as an *array* in Excel. An array can be a single row (called a one-dimensional horizontal array), a column (a one-dimensional vertical array), or multiple rows and columns (a two-dimensional array). Instead of selecting the whole row or column we can use the *array name* in the formula. We can create the array name by selecting the data and right click to choose "Name a Range, " or you can highlight the data and then type the preferred name in the "Name Box" as shown below for Microsoft daily returns data (*array name=* MSFT).

Figure A5: Creating an Array in Excel

A3: How to Use Simtools

Simtools is an Excel add-in developed to conduct Monte-Carlo simulations in excel. Roger Myerson from the Economics department at the University of Chicago developed this add-in. The Simtools Excel add-in is available as free software.[16]

Normal Distribution

The most used Excel functions with Simtools are *RAND* and *NORMINV*. Every *RAND( )* takes a random value drawn from a **uniform distribution** on the interval between 0 and 1 such each variable is independent. RAND() draws new random values every time the spreadsheet gets recalculated. The NORMINV(*probability, mean, standard deviation*) function generates random variables that follow a normal distribution. By putting a *RAND(,)* value in the place of the *probability* parameter generates a normal random variable which has an approximately two-thirds chance of being within one standard deviation from the mean. For example, if we enter the formula =NORMINV(*RAND(),10,5*) into any cell, then its value becomes a normal random variable with mean 10 and standard deviation 5, and the variables lie between 5 and 15 about two-thirds of the time.

Lognormal Distribution

LNORMINV(probability, mean, standard deviation) returns the inverse cumulative distribution for a lognormal random variable, parameterized by its mean and standard deviation. So the formula =LNORMINV(*RAND(),10,5*) generates a lognormal random variable that has mean 10 and standard deviation 5. The value of a lognormal random variable can be any non-negative number.

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[16] Simtools can be downloaded at http://bit.ly/SIM2ul. The add-in needs to be saved in one of system directories. It can be either copied to "..…\Program Files\Microsoft Office\Office12\Library" directory or the "…..\Documents and Settings\….\Application Data\Microsoft\AddIns" directory or to the Excel MacroLibrary folder (in a Macintosh). We can then add Simtools in excel by the Tools>Add-Ins command, checking the SimulationTools box.

Developing the Journey Process: A Novel Approach to Teaching Undergraduate Economics

Neil Niman, Steven Furnagiev, Scott Lemos[1]

ABSTRACT

This paper introduces EconJourney as the pilot project for the newly developed 'journey process,' a novel approach to teaching undergraduate economics. This story-based approach incorporates key results from the education literature to develop a flexible and robust educational framework. The EconJourney pilot provides the means for teaching principles of economics by embedding course concepts and tools for effective learning within a semester-long creative writing experience.

Introduction

The 'journey process' is a writing-intensive, problem-based, self-regulated learning system designed to stimulate deep-learning. By affecting cognitive learning processes like skill acquisition and metacognition, the journey process is designed to do much more than impart discipline-based knowledge. Students engage in a semester-long writing experience that serves as a mechanism wherein they learn and link ideas together through the development of a coherent narrative. Concept learning and problem solving techniques are employed to create a self-regulated process designed to increase student motivation and learning. This paper presents EconJourney, the first pilot project utilizing the journey process, as an innovation for teaching Principles of Microeconomics.

The journey process and its manifestation in EconJourney stems from ideas developed in Niman (2014). Loosely based on Joseph Campbell's "Hero's Journey" (Campbell 1968),[2] the journey process guides students through a 12-stage process in which students integrate course concepts into a cohesive narrative that allows the material to unfold in the context of a familiar story archetype. Each stage represents one chapter of the core curriculum for a standard Principles of Microeconomics course, and thus embeds each student's individual story within the broader narrative of the course curriculum. After four of the twelve stages have been completed, the student is asked to combine them into a coherent story line in the form of a chapter. The twelve stages contribute to three chapters and at the end of the semester students are required to ensure that their chapters line up and tell a complete story.

The journey process is designed to integrate additional pedagogical tools such as content summaries, writing prompts, concept maps, and iterative peer review. These tools are intended not just to improve the quality of writing but to also reinforce higher order learning goals within a self-regulated learning environment.

Students are guided through the story-making process by a series of steps. The first step involves reading a brief summary of key ideas from the chapter. The summaries are short paragraphs and anecdotal stories that replicate the "snackable content" students are familiar with through other forms of media, and which have been found to entice the reader's interest (Hopp and Gallicano 2016). The challenge begins with students reading a brief excerpt from a sample Hero's Journey-type story that runs through all twelve stages. The next step involves completing a short series of questions that are meant to help students identify how economics concepts have been integrated into the sample story. These multiple-choice questions are ungraded, but are required before gaining access to the new phase, and force students to think actively about the concepts before

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[2] See for example, http://www.thewritersjourney.com/hero's_journey.htm.

proceeding to their writing. Lastly, students are given a writing prompt and asked to compose a stage writing that consists of 250-300 words in which their character experiences a situation where they are influenced by, and asked to interact with, the primary concepts of that stage.

EconJourney has been developed using an online platform[3] that provides a centralized delivery for both students and faculty. It allows students to obtain journey-related materials and complete writing tasks in a single location. At the same time, it gives faculty an easy-to-use interface for grading and commenting on students' work. In its current form, students gain free access to the EconJourney site and course content at the beginning of the semester.

The objective of this paper is two-fold. First, we aim to introduce the reader to EconJourney and establish the concept as an effective tool for improving learning outcomes in Principles of Microeconomics. In doing so, we will highlight both the practical delivery of EconJourney as a course tool/assignment, as well as the pedagogical innovation it represents. Second, EconJourney addresses a critical deficiency in the delivery of the standard principles of economics curriculum: the average student needs to improve the efficacy of their writing, while the average economics faculty member struggles to assign writing given institutional and other teaching-related constraints. We will describe how the EconJourney platform and assignments were designed to maximize the benefits students receive from writing while minimizing the costs associated with incorporating writing into the curriculum. The overall goal of this paper is to provide a bridge for other faculty who would like to adopt the journey approach in their classroom.

The paper proceeds as follows: Section 2 develops the rationale for and pedagogical innovation embedded in the development of the journey process, Section 3 describes the specific EconJourney pilot project, and Section 4 discusses the results of a survey used to assess student perceptions of their EconJourney experience.

Developing the Journey Process

While an extensive literature exists with respect to the efficacy of writing within the learning process, and writing is increasingly being used to support learning in other fields (Graham et al. 2013), anecdotal evidence suggests economics faculty members seldom turn to writing assignments, especially at the principles level. EconJourney was developed to capitalize on the power of story, through writing, to creatively embed economics concepts in an engaging story. The role of writing in this setting is more than a tool used to supplement the learning process; instead, the learning process itself is embedded in the writing process as defined by the EconJourney assignments. Course concepts must be used to construct a story that both requires that a student develop a basic core competence with the subject matter *and* be able to apply the concepts in a way that creates a coherent storyline.

The 'Hero's Journey' Explained

The EconJourney story is a loose interpretation of the Hero's Journey archetype developed by Joseph Campbell—a universal pattern found in many familiar stories (Campbell 1968). This basic archetype can be found in well-known characters like Dorothy in the Wizard of Oz, Luke Skywalker from Star Wars, or Moses in the Old Testament. As a result, the concept of a hero and the triumph of good over evil has become a fundamental pillar supporting modern culture. As Daniel Kahneman (2011, p. 387) has remarked, "…we all care intensely for the narrative of our own life and very much want it to be a good story, with a decent hero." By adopting the role of the hero, students establish an identity within the context of the story. This identity is further developed in each stage of the journey wherein the hero encounters a problem, the problem leads to conflict, and the conflict creates some challenge that must be overcome.

Each student's journey process starts by choosing a theme and defining a character. In doing so students gain a sense of autonomy in defining their learning goals. Clearly defined goals are necessary for students to reflect upon and evaluate their performance (Schunk 2012). To unify the story and the course content, students are directed to choose a theme based in scarcity. Examples of themes chosen by past students relate to environmental concerns (insufficient amounts of clean water to drink, consequences of climate change, disposal of electronic waste), the role of government (lack of personal freedom, inequality, territorial disputes), and entrepreneurship (opening a vegetarian food truck, creating a new app, starting a sports analytics firm). Each story is then about a person who uses economics to overcome challenges.

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[3] See www.econjourney.com.

In the first chapter, existing conditions are assessed, a hero identified, solutions are not as obvious as they seem, and resolution can only be achieved with the pursuit of new knowledge. In the second chapter, the hero of the story must travel to a new place where life is substantially different and new experiences form the basis for fashioning a solution to the problem that set in motion the journey. The third chapter is one of revelation when mysteries are revealed, answers are discovered and the hero must decide how best they can become a force for good.

Promoting Narrative

EconJourney provides a bridge between deep-learning outcomes and content narrative. Students often move on from traditional principles of economics courses without having synthesized the larger course narrative. This leads not only to problems of understanding and retention, but stands in the way of creating an otherwise meaningful learning experience. The journey-related course content not only unfolds in the context of each students' creative writing exercise, including their individual and chapter level narratives, but students are encouraged to reflect upon the broader course narrative as they merge weekly stages into chapters and chapters into a complete story. Along the way they are provided feedback to check their understanding. These on-going narratives promote learning that alters behavior, intuition, and performance (Kopechek et al. 2016).

The journey process is predicated on the need to discover a solution to a problem that is so fundamental that the state of the world (as imagined) is contingent on the formulation of a solution. In constructing a coherent narrative, the student eventually discovers that the key to success rests on their ability to frame the problem of scarcity in a way where action can be taken and some form of resolution achieved. It is about synthesis: the discovery of patterns within patterns. This is where the burden on the imagination is the greatest, but also where the largest learning gains can be obtained. In the context of EconJourney, we promote `narrative with a purpose': an exercise that takes place with the development of a transformational story where a hero emerges; one capable of making an important contribution toward solving a problem of epic proportions. It is designed to empower students to believe that they can make a difference, or that the acquisition of knowledge gives them the power to develop their own individual talent and channel it to do something of significance.

EconJourney: the Journey Process Applied to Principles of Microeconomics

To better understand how EconJourney logistically unfolds over the course of a semester, this section lays out the key features as applied to various Principles of Microeconomics courses at the University of New Hampshire during the 2015-2017 school years.

Content and Schedule

Figure 1 maps out the content and schedule used in a pilot Principles of Microeconomics course. As explained above, each chapter is associated with four individual stage writings, each with their own instructor-generated content on the EconJourney site. As a means to supplement this content, a course text was chosen at the instructor's discretion.[4] Each stage was then mapped to a particular textbook chapter (or sections thereof), which captured the concepts as detailed on the EconJourney site. Note that EconJourney is not specific to any one particular textbook, and can be adapted to fit any variation in sequencing or depth offered by alternative textbooks.

In terms of scheduling, each stage is then associated with a week during the semester. Here we plan around a 15-week semester. For example, Stage 1 and content are discussed in class during Week 1 and the associated student-generated Stage 1 writing is due early the following week (after the student has been exposed to the material in the classroom setting). In week 5, the students are expected to take an in-class examination covering the material, as well as compose their Chapter 1 writing. These two assignments can be seen as complementary to each other, as each task requires repeat interaction with the material in differing contexts.

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[4] The text used for this particular course was *Principles of Microeconomics* by Greenlaw and Shapiro (2018), which is available for free via the OpenStax platform. The book can be accessed at https://openstax.org/details/principles-microeconomics.

Figure 1: EconJourney Content Map and Schedule for Principles of Microeconomics

Chapter	Stage	Topic	Readings	Concepts	Assignment
1	1	Introduction	1.1, 1.2, 1.3, 1.4	Scarcity, choice, opportunity cost	Worksheet #1
	2	Opportunity Cost	2.1, 2.2, 2.3	Specialization, comparative advantage, trade	Stage 1
	3	Demand & Supply	3.1, 3.2, 3.3, 3.4	Market, equilibrium, allocative efficiency	Stage 2
	4	Economic Efficiency	3.5, 3.6	Price controls, deadweight loss	Stage 3
		Exam 1 Review and Worksheet #2			Stage 4
		Exam 1			
2	5	Elasticity	5.1, 5.2, 5.3, 5.4, 5.5	Elasticity, total revenue	Chapter 1 Peer Review(1)
	6	Consumer Choice	6.1, 6.2, 6.3	Utility, budget constraint, marginal utility per dollar	Stage 5
	7	Production Theory	7.1, 7.2, 7.3, 7.4	Diminishing marginal product, average cost, fixed/variable costs	Stage 6
	8	Perfect Competition	8.1, 8.2, 8.3, 8.4, 8.5	Perfect competition, entry/exit, efficiency	Stage 7
		Exam 2 Review and Worksheet #3			Stage 8
		Exam 2			
3	9	Monopoly	9.1, 9.2, 9.3	Monopoly, barriers to entry, market power	Chapter 2 Peer Review(2)
	10	Monopolistic Competition	10.1, 10.2	Differentiated products, monopolistic competition, long-run inefficiency	Stage 9
	11	Oligopoly	10.3	Oligopoly, collusion, cooperative equilibrium	Stage 10
	12	Open content for instructor to choose			Stage 11
		Final Exam Review and Worksheet #4			Chapter 3 Worksheet #5 Peer Review
		Final Exam			Final Story

Finally, apart from exams and stage and chapter writings, students are also required to complete a series of interactive worksheets to aid them in constructing a coherent story through the semester. This gives the student time for theme and character development, something which may not be accomplished in a shortened classroom setting. Additionally, about 30 minutes of class time during the exam week can be set aside for Worksheets 2, 3, and 4, as the students are handing off their writings to an assigned peer in order to receive additional writing feedback and support.

Importantly, EconJourney serves as both a complement to and a substitute for extant economics curricula and course structures. In its full form, EconJourney offers instructors a tool that is capable of standing alone within a course structure. During the pilot trials at the University of New Hampshire, instructors used it (according to their preferences) both in lieu of more traditional assignments as well as along with them. It is also at the instructor's discretion to decide how much in-class time to spend on EconJourney. We have run several successful trials following the outline in Figure 1, suggesting that adopting EconJourney still leaves sufficient time for traditional economics curricula.

Instructor Generated 'Stage' Material

The journey process is first and foremost about learning course material in the context of writing a coherent and cohesive narrative. Thus each stage begins with an introduction to the three most important

concepts found in the companion material located in the course textbook. However, we recognize that despite their best efforts, students are not reading the textbooks produced by the major publishers (Burchfield and Sappington 2000; Clump et al. 2004; Sappington et al. 2002; Sikorski et al. 2002). Thus, to supplement the textbook, the EconJourney platform introduces the material in a substantially different form, appealing to the current paradigm of media consumption in the form of 'content snacking.' Snackable content, or ideas that are broken down into bitesize chunks, is becoming a ubiquitous means for gaining information, especially the web-based content students are familiar with. The effectiveness of snackable content for our purposes relies on its ability to gain the interest and attention of readers (Hopp and Gallicano 2016); it also lessens the barrier to entry that many students feel when it comes to reading textbooks.

Figure 2 demonstrates an example of `snackable content' as applied to the first chapter (`Stage' in EconJourney) in a Principles of Microeconomics course. The students are introduced to the foundational concept of scarcity in a digestible manner by not only seeing the textbook definition of the concept, but also by being exposed to it in a variety of contexts. The expectation is that by presenting the material in a more engaging manner that is similar to how they receive other news and information, students will be more inclined to read and think about the material.

Figure 2: Instructor-Generated Content from EconJourney Stage #1

Student Challenges

To encourage students to reflect on the opening passage found in each stage, students are presented with a challenge designed to have them think more carefully about the key concepts introduced. Rather than designing the challenges as an assessment mechanism, they are used as a teaching opportunity aimed at reinforcing concepts and demonstrating logical linkages. Each challenge contains two parts: (1) a set of traditional multiple choice questions aimed to reinforce the student's technical understanding of the material written within the context of the EJ story, and (2) a short set of multiple choice questions designed to make

the student identify stage-relevant economic concepts in the story that unfolds on the EconJourney site. The former includes questions of computation, graphing, and logic, whereas the latter include questions of interpretation and identification within context. Rather than thinking of the questions as a quiz, they are used instead to introduce what Bjork (1994) has referred to as "desirable difficulties." Testing the student's grasp of the material, even without feedback, has been found to increase retention more than additional study questions. (Roediger and Karpicke 2006).

The purpose of the challenges, however, extends far beyond that of a device designed to support the learning of a particular set of concepts. They were also written to show the student how a coherent narrative that follows the form of the Hero's Journey and spans all twelve stages can be crafted. In this way, the challenges become a social model (Zimmerman and Kitsantis 1997) designed to demonstrate how the concepts can be combined to create a story. They are in essence a story within a story capable of serving as a template for the construction of the student's own narrative.

In addition to facilitating the learning and writing process, the challenges are designed to reinforce both the idea of a growth mindset and create a situational prime designed to encourage students to think of themselves as the hero of their own story, which increases student self-efficacy. Self-efficacy relates to student perceptions of learning abilities, and strong self-efficacy improves self-regulated learning (Schunk and Pajares 2009). To empower students in a way that enables them to believe that they have the power to solve problems that extend beyond the confines of an individual course, they need to believe that they are capable of developing the skills and mastering the knowledge needed to make a difference; in other words, the formation of a growth mindset.

Dweck (2007) demonstrated that with a growth mindset students believed they can develop the capabilities needed to take on new challenges and succeed. In contrast, students with a fixed mindset are fearful of mistakes and have inferred that hard work merely suggests lower intelligence. Students who have developed a growth mindset are more likely to take on new challenges, believe that effort enhances ability, and confront and correct deficiencies (Yeager and Walton 2011). For example, one of the primary characteristics associated with heroism is a selfless willingness to help others. Nelson and Norton (2005) show how the concept of a superhero can be used as a subtle priming technique to encourage volunteerism. In their study, individuals were primed by having them think about a helpful category (e.g., superheroes) or an exemplar member of the community (e.g., Superman). Their goal was to determine if situational primes could cause people to think of themselves as being more helpful and cause them to predict more helpful behavior in the future. The results of their study suggest that heroism can be used successfully to promote selfless behavior, in both the short- and long-term.

Writing Prompts and Story Coach

Once the challenge for a particular stage has been completed, the student is asked to reflect on the concepts and incorporate them into their story. The ability to explain something to oneself has been shown to have a positive effect on learning outcomes (Chi et al. 1989) across a wide variety of environments (Chi et al. 1994; Pirolli and Recker 1994; Recker and Pirolli 1995; Wolfe and Goldman 2005) and instructional forms (Ainsworth and Loiziu 2003; Roscoe and Chi 2008; Trabasso and Magliano 1996). Self-explanation works by helping learners identify gaps and fill in missing information. It also helps students to repair and revise their understanding of instructional material that conflicts with their existing mental model (Chiu and Chi 2014).

In an effort to provide some structure to the writing process, prompts were designed to assist the student in thinking about how the previous content might be used in the development of a story of their own choosing. This is illustrated in Figure 3. Embedding prompts within an active learning environment has been shown to be an effective strategy for encouraging self-explanation (Bielaczyc et al. 1995; McNamara 2004; Renkl 1997; Griffin et al. 2008). Further, we developed an additional tool that students can leverage for self-explanation in the form of a "story coach." As shown in Figure 4, the story coach feature is designed to provide students with further guidance on constructing a storyline that progress through each individual chapter, as well as providing additional explanation in terms of how to utilize the economic concepts in the broader context of their story. To provide even more support, sample chapter writings from past users and instructors are made available, so students have access to further examples of the concepts at work. These stage prompts and story coach features serve as a form of guidance that encourages the student to reflect on what has been presented and to think about what it means in the broader context of their unfolding story.

Figure 3: EconJourney Stage 1 'Writing Prompt'

Though students have the option to develop a fictionalized story throughout the semester, they are also allowed to develop a personalized story, relating the economic concepts to events in their own life. By asking students to relate a concept to their own lives, the goal was to take advantage of the potential learning gains associated with personalization. The literature suggests that material that is personalized in a way that speaks directly to them can have a significant impact on the learning process (Mayer et al. 2004; Ginns et al. 2013). Our own research suggests that when students were given one of three treatments that delivered the same content in very different ways, the personalized version had the greatest impact on those students that were both unfamiliar with the material and have struggled with learning in the past.[5]

Self-Reflection and Peer Review

Self-reflection is an integral part of successful self-regulated learning, as is evident from its role in both behavior theory (Mace et al. 1989) and social cognitive theory (Zimmerman and Schunk 2004). EconJourney encourages self-reflection through a variety of feedback mechanisms including peer reviews and summary worksheet assignments.

As any good writing process is iterative in nature, it is increasingly important that students are exposed to the ideas of self-reflection and peer-review. We learned from early iterations of EconJourney that students often treat stage writings as one-and-done assignments in which they submit their writing on a specified due date, and do not view that writing again until it is time to construct the larger chapter writing. This suggests that without proper incentives, students will generate disparate stage writings, often out of the context of their larger story.

As a means to encourage students to be more proactive in connecting concepts across the semester, we have designed a series of five in-class worksheets designed to encourage self-reflection. As shown in

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[5] To access examples of student generated stories from the course, please use the following link: https://www.dropbox.com/sh/t44pi2sxtp1prnm/AAA1t5bHM3c0Vi2vaSGngn_Aa?dl=0

Appendix A1, the first `introductory' worksheet helps the student in developing the overarching theme for their story. It forces them to identify something that is scarce and the problems created by this issue of scarcity. Further, as a means to brainstorm ideas for future writings, it asks students to identify what could help to eliminate or worsen these problems. And finally, to assist in developing the student's main character, we ask the students to identify any special abilities (i.e., leadership), personality traits (i.e., optimistic, caring), and strengths/weaknesses (i.e., intelligent but shy) to provide the scaffolding for their unfolding story.

Figure 4: EconJourney Chapter 1 'Story Coach'

The next three worksheets in the series are designed to help the student construct their chapter writings using already-developed stage writings from prior weeks. Appendix A2 provides an example of these worksheets. Each encourages the student to view the major ideas contained in each stage as one logical progression. Further, it asks the student to think about creating effective transitions between stages, not only making their narrative more coherent, but also increasing their understanding of the logical connections between concepts.

The worksheets also serve as the foundation of the peer review process. The student is asked to fill in the worksheets with content from their own work. At the same time, they are paired with another student who provides their partner with a copy of their stage writing. They are then asked to fill out a similar worksheet using their partner's stage writing as the raw material (see Appendix A4a-A4c). Worksheets are then swapped and the student then has an opportunity to review the worksheet they filled out based on their work and the worksheet filled out by their review partner using their stage writing. The peer review process takes on three steps: (1) concept identification, (2) critical review comments and suggestions of substantive material, and (3) critical review comments and suggestions of organization.

This exercise serves two primary purposes. First, it exposes the student to the economic concepts in an entirely different context, thereby helping them to prepare for in-class examinations. In addition, the exercise allows the student to begin to understand how others perceive their writings. If the two worksheets are filled out with similar content, then the student has reason to believe the ideas in their writings are clear and coherent. If there are discrepancies between the two worksheets, this is an indicator that the student's ideas are not clear to others and potentially need revision.

The final worksheet in the series is designed to help the student construct their overall narrative based on their writings from earlier in the semester. As shown in Appendix A3, this final worksheet helps the student to visualize their story by sketching out a "plot line," in which the introduction to the story (Chapter 1) sets the stage for the larger narrative to unfold. Next, the students discuss their "rising action" in terms of story and character development (Chapter 2). Finally, the student is asked to describe how their crisis is resolved and the story will be brought to a successful conclusion.

Grading

Students find it challenging to adopt new strategies for learning in an information vacuum. Without some sense of how they are doing relative to a set of performance standards, they may engage in suboptimal behavior that could have easily been corrected. Feedback can also serve as a mechanism that reinforces positive behavior and serve as an important source of motivation. Success tends to build on success as individuals are encouraged to continue doing what leads to positive results. Meta-analyses investigating the power of feedback (Hattie and Timperley 2007; Kluger and DeNisi 1996; Shute 2008) give credence to the common aphorism that "feedback can double the rate of learning, and that feedback is among the top 10 influences on achievement" (Hattie and Yates 2014, p. 47).

Understanding that timely and substantive feedback is necessary in writing development, advanced undergraduate graders were used to grade stage and chapter writings. These graders used an instructor-generated rubric that was communicated to the students at the beginning of the semester for full transparency, which can be found in Appendix A5 and A6. Within the EconJourney site, these graders are able to access each student's writing and use a form to enter their assigned grades by rubric category (i.e., content, organization, etc.). Further, there is a comment box for entering additional comments on the student's writings. The students then have complete access to these grades and comments in their individual EconJourney account, allowing for feedback that is clear and easy to use when making corrections and updates to their story.

Results of Student Perception Survey

A survey of students' perceptions of EconJourney as a pedagogical platform was conducted at the end of the course. Specifically, students were asked to rate their perceptions of the readings, the challenge of writing, any change or improvement in writing abilities, the effectiveness of the peer review process, and the overall effectiveness of the EconJourney framework. These survey results herein represent a sample size of 274 respondents, and a more detailed list of the questions and responses can be found in Appendix section A7.

With regards to the choice of readings, half of the respondents (49.4%) preferred reading the material presented on the EconJourney site, whereas 26.0% of the students preferred reading the textbook. The remainder of respondents either didn't have a strong preference (23.4%) or indicated they didn't read either (1.3%). The preference for reading the material in EconJourney over the text can be attributed to the fact that students found the material on the site clear, engaging, and fun relative to the text.

With regards to perceptions over writings, information gathered on perceived challenges of writing showed that students found the most difficult aspect of the weekly writings to be tying the concepts together through the semester (32.4%) and developing a storyline (32.4%). On the other hand, 28.2% of students found the effective use of concepts as the most challenging part of writing and 7.0% found organization the most difficult aspect. Though the students faced these challenges, almost 60% of the students felt their writing at least somewhat improved throughout the semester. Further, in terms of the peer review process, feelings were mixed. Overall, 52.7% of students felt the peer review process improved writings through either peer-comments, self-reflection, or both, whereas 47.4% of students felt the process did not improve outcomes, or did not use it at all.

In terms of the design of EconJourney, a series of questions gathered information on application and connection of material throughout the semester. Here, 68.8% of students felt that writing about the concepts helped them think about how they were applied and 61.8% of students felt the weekly writings helped them connect ideas throughout the term. Further, 86.5% of students felt that writing a story using economic concepts provided a benefit, either by remembering them after the class ends (27.0%), making them more personally meaningful (23.0%), or helping in furthering comprehension (36.5%). Finally, 97.4% of students felt the approach taken through EconJourney was an effective tool for learning economics, representing an overwhelmingly positive reaction to the writing-intensive process.

Conclusion

One dramatic change associated with the rise of the internet is that everyone is becoming a teller of stories. At one time, storytelling was a specialized skill left to the creative artistry of those in Hollywood able to bring their vision to the screen, in the music performed in local bars or physical media, or the books penned by a select group of authors. Now everyone not only has access to the tools needed to create a story, but also to a seemingly unlimited distribution network capable of sharing that story across the globe. As a result, story has taken on a significance that has gone far beyond a means for entertainment or a method for disseminating knowledge.

While storytelling has always been a tool for sharing ideas and inspiring action, it has become even more important as the line between our online and offline identities has blurred to the point where the truth begins and ends in the stories we tell about ourselves through the use of social media. Yet these stories that we tell about ourselves help reinforce the confidence needed to take action, particularly when outcomes are uncertain.

As the boundaries between the real and the synthetic have blurred dramatically, the same may be true between the imagined and the real self. By having the student write a story with a character of their own creation who undertakes a hero's journey where they must learn important concepts in order to successfully overcome adversity to 'save the day,' it not only asks the student to take a lead role in the construction of the narrative, but it also has them creating a character that must take action in order to achieve success.

Just as their character must learn, the student does as well if they are to acquire the concepts essential for their story to advance and their character to develop an understanding of what is needed to solve the crisis and achieve victory. Thus, as their character undergoes a learning process as part of a constructed narrative, the student is actually experiencing a similar one. However, their experience is not a concrete one encountered in the real world, but instead is an imagined one.

The journey process uses a variety of learning theories to create a robust learning environment that mirrors the structure and skills required for success in an experiential journey. By walking students through a logical thought process, it assists them in building associations between what often appear to be a series of disconnected ideas. By having them apply these concepts within the context of a storyline of their design, they begin to see their applicability toward solving a problem that is meaningful to them. In turn, it empowers them to think about change and the power of narrative as both a thought process and a means of communicating ideas in an understandable and engaging way.

What a story-based approach to learning economic principles suggests is that rather than turning the educational process into something that is disconnected from a student's life, it can instead become just one more extension of those daily activities that leads them to consider who they are and how they fit within the broader social fabric. The stories we tell about ourselves help us to establish a sense of self that can serve as the foundation for acquiring the knowledge and skills that lead to personal success both in the here and now as well as into the future.

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APPENDIX

A1: EconJourney Worksheet #1

Developing a Theme

What is EconJourney?

"We often learn through the use of story and telling a good narrative is often the key to success. With EconJourney, you will construct a narrative and learn some economics in the process."

Identify Something that is Scarce:

What Problems are Created by this Issue of Scarcity?

What Could Eliminate these Problems?

Character Description

In the three boxes below, plan out your character. Think about things that make your character special, what they can use to overcome adversity, their personality, and strengths & weaknesses.
Be creative!

What Could Make them Worse?

Special Abilities:	Personality Traits:	Strengths & Weaknesses:
Ex: leadership	*Ex: optimistic, caring*	*Ex: intelligent but shy*

A2: EconJourney Worksheet #2

Chapter 1: Fundamental Problem – Modest Progress – Serious Crisis – Inadequate

The Journey consists of 3 chapters. They are connected as your character first recognizes that a problem exists, obtains the knowledge that will be needed to solve the problem, and then reaches the point where meaningful change can occur.

Fill in the boxes with your story (or a short summary). Although your details and storyline may differ from the outline on the previous page, the big picture is still the same. Make sure you've included at least one economic concept in each stage, the attributes you've earned to help build your character, and transitional sentences between stages to keep one, consistent story.

Stage 1 - Scarcity, Choice, Opportunity Cost

Transitional Sentence

Stage 2 - Specialization, Comparative Advantage, Trade

Transitional Sentence

Stage 4 - Price Controls, Price Ceiling, Inefficiency

Transitional Sentence

Stage 3 - Market, Equilibrium, Allocative Efficiency

A3: EconJourney Worksheet #5

Plot Line Sketch

Using your theme surrounding scarcity, start to plan your story. Don't worry about details yet – simply outline your ideas for your story. Start to get creative – the more abstract and interesting, the better!

Story Development

Keeping your scarce situation in mind, what is the main crisis that your character faces? Maybe your character has overcome smaller issues surrounding scarcity in the past, but now a bigger issue hits. Using your character description and traits previously outlined, how are they planning to deal with their situation?

Introduction

Introduce the problem your character has faced due to the issue of scarcity. How have they identified this problem in their life? Do they have any ideas on how they can overcome this problem or do they feel hopeless?

Conclusion

Did you character overcome the crisis? How did they do it and what do they plan to do in the future to avoid this from happening again? How has your character developed over the course of the story? Have they obtained any new abilities or recognized new weaknesses they plan to work on?

A4a: EconJourney Peer Review Worksheet

Read your partner's chapter over TWICE, then respond to the following questions. Your comments should be as specific and complete as possible. Your objective is to point out solvable problems to make their story better organized, smoother, and more focused. Comments should not be personally critical! Whether you agree or disagree with the writer's ideas or positions, your job is to see that they are expressed more clearly.

Identify the relevant economic concepts from Chapter 1. Include the concept, a brief definition, and where in the writing you found the concept (i.e. paragraph #, sentence #)

Concept	Definition & Location

A4b: EconJourney Peer Review Worksheet

What appears to be the main point/thesis of the chapter? Is it stated in such a way that you can tell clearly what the writer's big idea is?

Writer's Checklist:

Has it!   *Needs Work!*

Has it!	Needs Work!	
☐	☐	**Transitional Sentences**
☐	☐	**Identifiable Paragraphs**
☐	☐	**Ideas Relate and Flow Logically**
☐	☐	**No Run-On Sentences**
☐	☐	**Correct Grammar**
☐	☐	**No Spelling Errors**
☐	☐	**Consistent Story Line**
☐	☐	**Economic Terms Are Clearly Shown Without Needing to State Glossary Definitions**

What is the greatest strength of the chapter? (i.e. organization of points, very clear main ideas, good use of evidence, etc.)

ECONJOURNEY
linking game design with learning

What is the greatest weakness? How can the writer fix this problem?

A4c: EconJourney Peer Review Worksheet

Final Thoughts...

Are the paragraphs organized in a logical fashion? Are the introduction and the conclusion effective? Do you lose track of the organization of ideas at any time? Where and how?

Does the writing itself seem unclear, vague, too sparse, too wordy, too pompous? Grammar, spelling, or punctuation problems? Use this space to address any of these issues.

Are there any other problems or places needing improvement that you can identify? Use this space to give any extra suggestions, advice, or comments to help improve your partner's story.

A5: EconJourney Stage Grading Rubric

	1 Weak	2 Adequate	3 Strong	4 Exceptional
Content (i.e. Economics Ideas)	Unacceptable use of concepts; little or no comprehension	Acceptable use of concepts; limited comprehension	Good use of concepts; effective comprehension	Excellent use of concepts; excellent comprehension
Presentation (i.e. Organization)	Many spelling, grammar, and punctuation errors; sentence fragments; incorrect use of capitalization	Some spelling and grammar errors; acceptable structure through use of sentences and paragraphs	Minimal spelling and grammar errors; effective structure	Correct spelling, grammar, and punctuation; complete sentences

A6: EconJourney Chapter Grading Rubric

	1 Doesn't Meet Expectations	2 Partially Meets Expectations	3 Nearly Meets Expectations	4 Meets Expectations	5 Exceeds Expectations
Ideas/Economic Concepts	Does not demonstrate understanding of important concepts	Concepts underdeveloped, lack of supporting evidence	Writing is at times unclear or uncertain; some "fluff"	Ideas clearly explained and fully supported with evidence	Demonstrates rich understanding of concepts; ideas supported well; writing is both informative and engaging
Organization	Little or no evidence that writer is thinking about the text as a whole, e.g. thesis lacking or nonexistent; unclear how ideas relate; missing appropriate transitions; etc.	Ideas related, but explanations and evidence unclear or nonexistence; paragraph order questionable; weak transitions, conclusion, and or introduction.	At times unclear how sentences, ideas, or evidence relate to one another. Structural elements (introduction, thesis, closing) in need of improvement. Perhaps could have used one more revision.	Writing is focused. Sentences, ideas, and evidence all follow one another logically.	Evidence that writer has seriously considered all elements of structure from global (thesis, main points) to local (sentences connected).
Professional Presentation	Writer has paid little attention to how text looks: frequent typos/errors, missing name/date/title etc.; writer demonstrates little or no sense of how to write for a business audience; sentences full of "fluff"	Writing is at times vague, imprecise, and/or unclear; many typos/errors; writer has been careless about adhering to conventions (title, page numbers, etc.)	Language is clear, though writer does not seem to understand the audience for this assignment; writer did not fix easy-to-spot typos, neglected some conventions; one more revision would've made a big difference.	Sentences mostly free of excess words; writer has command of word choice and understands purpose and audience for this text; text is mostly error-free	Sentences are engaging and interesting; clear sense of purpose and audience; text free of errors; writer clearly has firm grasp of business writing conventions

A7. *Results of survey on student perceptions of EconJourney (n =274)*

1. If you could choose between the textbook and the readings in EconJourney, would you
    a. Prefer reading the textbook (26.0%)
    b. Prefer reading the material in EconJourney (49.4%)
    c. I don't have a strong preference (23.4%)
    d. It doesn't matter because I didn't read either. (1.3%)

2. Thinking about the material in your textbook and EconJourney, please rank EconJourney in relation to your textbook based on the following:

	Strongly Prefer Text	Weakly Prefer Text	Indifferent	Weakly Prefer EJ	Strongly Prefer EJ
Voice	7.0%	11.3%	21.1%	31.0%	29.6%
Clarity	5.6%	18.3%	21.1%	31.0%	23.9%
Brevity	7.0%	12.7%	29.6%	28.2%	22.5%
Engaging	8.5%	4.2%	14.1%	29.6%	43.7%
Fun	9.9%	8.5%	21.1%	28.2%	32.4%

3. What was the most challenging part of writing?
    a. Organization (7.0%)
    b. Using the concepts effectively (28.2%)
    c. Tying the concepts together (32.4%)
    d. Developing a storyline (32.4%)

4. Overall, do you feel that your writing abilities have improved throughout the semester?
    a. Much improvement (6.5%)
    b. Some improvement (51.9%)
    c. Not sure (20.8%)
    d. No improvement (20.8%)

5. The stages are designed to get you to think about the material and apply it in a way that is meaningful to you. Do you find that writing about the concepts prompts you to think more about how to use them?
    a. Yes, writing about the concepts helps me think about how they are applied (68.8%)
    b. I'm not quite sure if it helps (22.1%)
    c. I don't think applying the concepts is important (2.6%)
    d. I think memorizing the concepts is more important (6.5%)

6. Building on the last question with regard to stage writings, do you feel the weekly writings allowed you to more effectively connect ideas throughout the term?
    a. Yes, the weekly writings helped me to connect concepts and ideas across the term (61.8%)
    b. I'm not quite sure if it helped me connect ideas (25.0%)
    c. I don't think connecting the ideas is important (6.6%)
    d. No, the weekly stage writings made me more confused and thus unable to connect ideas at all (6.6%)

7. The peer review process was not only designed to have you critique another student's writings, but also to serve as a method of self-reflection on your own work. Do you feel the peer review was an effective tool at improving your own writing, either through peer's comments or your own self-reflection?
    a. Yes, improved my writing through both peer's comments and self-reflection (22.4%)
    b. Improved my writings only through peer's comments (9.2%)
    c. Improved comments only through self-reflection (21.1%)
    d. Did not improve writings (42.1%)
    e. Did not use the peer review process (5.3%)

8. Do you think that writing a story using economic concepts will
   a. Help you remember them after the class ends (27.0%)
   b. Makes them more meaningful to you (23.0%)
   c. Helped you understand them better (36.5%)
   d. It doesn't matter because you will probably forget them anyway (13.5%)

9. Do you think the approach you have taken this semester using EconJourney is an effective tool for learning economics?
   a. Very effective (35.1%)
   b. Somewhat effective (62.3%)
   c. Not sure (2.6%)
   d. Somewhat ineffective (0.0%)
   e. Ineffective (0.0%)