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The Economics Department and Omicron Delta Epsilon congratulate **Kevin Klassen**, winner of the *2019 Dwight D. Eisenhower Society / R.M. Hoffman Family Memorial Prize in Economics*. The Eisenhower/Hoffman Prize is awarded to the economics student writing the best quantitative paper or project with public policy implications.

The Economics Department and Omicron Delta Epsilon congratulate **Kevin Klassen,** winner of the *2019 Best Thesis Award*.

The Economics Department and Omicron Delta Epsilon congratulate **Tyler Mann**, winner of the *2019 James Boyed Hartzell Memorial Award*, awarded to one student with junior standing possessing excellent scholarship in the social sciences.

The Economics Department and Omicron Delta Epsilon congratulate **Tyler Mann and Alex Xie** for being selected as a *2019 Kolbe Fellow*.

The Economics Department and Omicron Delta Epsilon congratulates **Luyang Chen**, winner of the 2019 *Dr. and Mrs. William F. Railing Fellowship for Faculty-Student Research in Economics*.

The Economics Department and Omicron Delta Epsilon congratulates **Luca Menicali**, winner of the *2019 John Edgar Baublitz Pi Lambda Sigma Award*.

The Economics Department and Omicron Delta Epsilon congratulate **Olivia Fischer** and **Christian ansinger** for their induction into Phi Beta Kappa. Phi Beta Kappa celebrates and advocates excellence in the liberal arts and sciences. Its campus chapters invite for induction the most outstanding arts and sciences students at America's leading colleges and universities.

The Economics Department and Omicron Delta Epsilon congratulate the following students for their achievements in the 2018-2019 academic year:

Economics Graduation Banner Carriers:

BA: Colleen Campbell
BS: Kevin Klassen

2019 Economics Honors Graduate:

Colleen Campbell
Madison Fox
Jack Gardner
Kevin Klassen
Luca Menicali
Elizabeth Miller
Polina Rozhkova
Haley Skinner
Alex Xie

Omicron Delta Epsilon would also like to thank our outgoing officers, **Emily Keyser** and **Katrina Niedziela**.

CONTENTS

Are Price-Earnings Ratios Mean Reverting? An Empirical Study

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Abstract

Mean reversion in stock prices is a highly studied area in the financial literature with controversial findings. While some economists have found evidence of mean reverting processes in stock prices, many argue in favor of the Efficient Market Hypothesis which states stock prices are random walk processes. This paper seeks to add to the literature on mean reversion but testing for evidence in price-earnings ratios rather than stock prices. The study employs a robust regression model controlling for company-specific and general market factors that influence price-earnings ratio deviations. After correcting for heteroskedasticity, serial correlation, and unit root processes, the results indicate mean reverting behavior does exist in US equities from 2008-2017 and mean reversion in price-earnings ratios may occur more quickly than mean reversion of stock prices. The outcome of this paper also implies some level of endogeneity in the Three-Factor-Model proposed by Fama and French (1992).

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I. Introduction

Whether stock prices and ratios can be described as random walk or mean reverting processes is highly controversial within the financial literature. Mean reversion refers to a tendency of asset prices or ratios to return to a trend path. This paper sets out to examine whether the price-earnings (P/E) ratios of US companies have transitory components and thus exhibit mean reverting behavior. Fama and French (1988) and Poterba and Summers (1987) are among the first to provide direct empirical evidence that mean reversion occurs in US stock prices over long horizons. At the same time, other economists are critical of their results. Richardson and Stock (1989) and Richardson (1993) report that correcting for small sample bias may reverse the results found by Fama and French and Poterba and Summers mentioned above. Moreover, Kim et al. (1991) argue that mean reversion is a pre-World War II phenomenan and current stock prices exhibit mean averting behavior.

The question of whether stock price-earnings contain transitory components poised in this paper is important for financial practice and theory. For example, consider technical analysis of stock price movements. If stock price-earnings ratios contain large transitory components, then observing a stock with a P/E ratio statistically far from its mean may establish a trend that could be traded technically. The notion of stock price trends is harshly rejected by many economists who argue in favor of the Efficient Market Hypothesis (EMH), which states that share prices reflect all information about a security, including information derived from fundamental and technical analysis. Therefore, it is theoretically impossible to consistently produce risk-adjusted excess returns, or alpha, and only inside information can result in outsized risk-adjusted returns.

This paper can also be used to evaluate the claims made by Keynes in his book *The General Theory of Employment, Interest and Money* (1936) where he states, "all sorts of considerations enter into market valuation which are in no way relevant to the prospective yield." Poterba and Summers (1987) state that "if divergences between the market and fundamental value of a stock exist, but at beyond some limit are eliminated by speculative forces, then stock prices exhibit mean reversion." Thus, if Keynes' claim is true and the psychology of speculators can cause the market valuation of stocks to diverge from their fundamental values, evidence of mean reversion in P/E ratios should exist.

Lastly, the results of this paper could have interesting implications on the Three-Factor-Model proposed by Fama and French (1992). To expand on the traditional Capital Asset Pricing Model (CAPM), Fama and French suggest stock returns are explained by size and valuation factors in addition to market risk. The valuation factor they employ is related to book-to-market value of a stock, which is highly correlated to the price-earnings ratio. If P/E ratios are mean reverting processes, there may be endogeneity in their valuation factor that is not properly accounted for. A more in-depth discussion of these implications is located in the Theory and Methodology section.

This study fits in an extensively researched section of the financial literature but seeks to test for mean reverting behavior in stock price-earnings ratios rather than stock prices and utilizes a slightly different methodology than those used by economists such as Fama and French (1988). I utilize quarterly stock and sector data gathered from Bloomberg. The sample period ranges from 2008 to 2017. The outcome variable of interest is the distance of the current P/E ratio from its trailing five-year average and the explanatory variable of interest is its lagged value. This is a similar model used to test for mean reversion in stock prices by Balvers et al

(2000), but I introduce several more controls to achieve more accurate estimators. Moreover, much of the previous literature employs variance ratio tests and standard unit root tests for mean reversion. However, econometric studies by Campbell and Perron (1991), Cochran's (1991) and DeJong et al. (1992) indicate that standard unit roots tests have very low power against local stationary alternatives in small samples. Further, Zhen (2010) argue that panel data can be used to generate more accurate unit root estimation. In this paper, I employ a linear regression model using panel data from S&P 500 companies to test for mean reverting processes in price-earnings ratios.

While most of the previous literature examine stock price mean reversion, these results can be misleading. Stock price movements occur for a wide variety of reasons, many of which are either difficult or impossible to isolate. So, it will be difficult to isolate a reversion coefficient due to potential endogeneity from many unobserved variables. The price-earnings ratio of a company has well-grounded determinants, including expected growth, consistency of dividends, company size, and extent of analyst converge, to name a few. Including these variables as controls in a regression will allow me to get a more accurate and unbiased estimation of the presence of mean reverting behavior.

The estimators of interest used in this paper are likely subject to several statistical biases due to the nature of the data. Issues that I found to be present through the use of rigorous econometric testing are heteroskedasticity, serial correlation and unit roots. The paper addresses them by employing heteroskedastic-robust standard errors while differencing and detrending each variable. There is also likely to be survivorship bias and small sample bias present in this analysis. I address the former by using both time-series panels and pooled panels but fail to address the latter due to limited time and resources. Regression results from both datasets support the mean reverting hypothesis, showing evidence of mean reverting processes in US company price-earnings ratios from 2008-2017.

The remainder of the paper is organized as follows. Section II will discuss the previous literature on stock mean reversion and the relationship between price-earnings ratios and stock returns. Section III will describe the theory behind my model and define the methodology used to achieve unbiased estimators of my coefficients. Further, Section IV will review the data used to address the research question. Finally, Section V will examine the results of the regression output and will be followed by a comprehensive conclusion for this paper.

II. Literature Review

Most of the existing literature relating to this topic simply employs unit root and stationarity tests to detect mean reversion in stock prices. There is also controversy over the existence of mean reverting behavior in financial assets. Many economists argue in favor of the EMH which, as mentioned in the introduction, asserts that all asset prices follow a random walk and thus, do not exhibit mean reverting behavior. Some economists have found evidence of mean reverting behavior through the use of variance ratio tests, but others believe correcting for biases negates their findings.

This paper focuses on mean reverting behavior in price-earnings ratios, which has not been widely studied in the financial literature. However, P/E ratios have been researched extensively on their relation to excess returns in equity markets and as a determinant of equity prices. Basu (1977) conducts an empirical study to test whether P/E ratios are related to investment performance in common stocks. He does so by creating five diversified portfolios, each with different portfolio P/E ratios. The results indicate lower P/E stocks are underpriced relative to the market and tend to experience the highest unexplained excess returns. A study by

Gill et al. (2012) finds that price-earnings ratios explain a significant portion of the variation in equity share prices in the United States.

There have been ample studies into stock price mean reversion with conflicting results. A study by Poterba and Summers (1987) aims to test whether transitory components account for a large fraction of the variance in common stock returns using variance ratio tests. Using data on firms form the United States and 17 other countries over the period 1926 – 1985, the authors find positive autocorrelation in stock returns over short horizons and negative autocorrelation over long horizons. They also report that transitory components in stock prices account for more than half of the variance in monthly returns. They conclude mean reversion does occur in stock prices and it is likely due to slowly-decaying "price fads" that cause stock prices to deviate from fundamental value. Fama and French (1988) provide further evidence of transitory stock price components in a study focusing on the relationship between dividend yield and stock returns. They find that the power of dividend yields to forecast stock returns increases with the return horizon and concluded this is likely due to time-varying expected returns generating temporary components of prices. Another study by Fama and French (1988) investigates the permanent and transitory components of stock prices during 1926 – 1985. They consider a time series dataset and employ variance ratio tests similar to those used by Poterba and Summers (1987). Their findings indicate a slowly mean-reverting component of stock prices tends to induce negative autocorrelation in returns.

More recent studies also indicate mean reverting behavior in stock prices. Mukherji (2011) uses a powerful nonparametric block bootstrap method and fresh data to examine the unresolved issue of mean reversion in stock returns. The results show that both large and small company stocks experienced significant mean reversion in returns for periods of 1 through 5 years during 1926–1966. In 1967–2007, there was significant mean reversion in 5 year returns of large company stocks, and 1, 4, and 5 year returns of small company stocks. The findings indicate that, although mean reversion in stock returns has weakened in recent decades, it persists, particularly for small company stocks. Another study uses panel data from national stock market indices of 18 countries from 1969 to 1996 (Balvers et al. 2000). They find strong evidence of mean reversion in relative stock index prices and a significantly positive speed of mean reversion with a half-life of three to three and a half years. According to their findings, investment strategies that fully exploit mean reversion across national indexes outperform buy-and-hold strategies.

Other publications reject the possibility of mean reverting behavior and argue in favor of the Efficient Market Hypothesis. Kim et al. (1991) compare stock return data before and after World War II. Using randomization tests to calculate significance levels under the null hypothesis that returns are distributed independently of their ordering in time, they find that mean reverting behavior is an entirely pre-war phenomena and current stock prices exhibit mean averting behavior. They interpret these results as evidence of a fundamental change in the stock return process and conjecture that it may be due to the resolution of the uncertainties of the 1930s and 1940s. A paper by Zhu (2010) asserts that conventional unit-root tests have weak power against stationary alternatives. His study uses unit-root tests in panel data to re-examine the time-series properties of the stock prices as unit root tests on panel data appear to have increased power of unit root tests. The results cannot reject the random-walk hypothesis for G-7 country stock-price indices. Richardson and Stock (1989) and Richardson (1993) develop an asymptotic distribution theory for statistics involving multiyear returns and correct for the small sample bias that they believe was present in previous mean reversion analyses. Their alternative theory provides substantially better approximations to the relevant finite-sample distributions used in conventional financial theory. It also leads to empirical inferences much less at odds with the hypothesis of no mean reversion and they claim their results may negate those found by Poterba and Summers (1987) and Fama and French (1988).

III. Theory and Methodology

A typical formulation of a stochastic process for an asset displaying mean reversion to a simple moving average, in this case in the asset's P/E ratio, is as follows:

$$\left|ln\left(\frac{P/E_t^i}{\overline{P/E_t^i}}\right)\right| = \pi^i + \lambda^i\left\{\left|ln\left(\frac{P/E_{t-1}^i}{\overline{P/E_{t-1}^i}}\right)\right|\right\} + \varepsilon_t^i, \quad (1)$$

where P/E_t^i is the price-earnings ratio of company i at time t, $\overline{P/E_t^i}$ is the trend price-earnings ratio of company i at time t, π^i is a constant, and ε_t^i is a stationary shock term with an unconditional mean of zero. The parameter λ^i measures the impact of increasing the distance of the previous P/E ratio from trend P/E ratio in the previous period on the distance of the current P/E ratio from trend P/E ratio in the current period. To accept the alternative hypothesis that mean reverting behavior exists in P/E ratios, λ^i must be statistically significant and $0 < \lambda^i < 1$. If $0 < \lambda^i < 1$, deviations in P/E ratio from the trend are reversed as t increases which, by definition, is mean reversion.

However, there is likely to be serial correlation as the model proposed is an autoregressive process of order one. Therefore, first differencing will be applied to equation (1) to yield the following:

$$\left|ln\left(\frac{P/E_t^i}{\overline{P/E_t^i}}\right)\right| - \left|ln\left(\frac{P/E_{t-1}^i}{\overline{P/E_{t-1}^i}}\right)\right| = \tau^i + \delta^i\left\{\left|ln\left(\frac{P/E_{t-1}^i}{\overline{P/E_{t-1}^i}}\right)\right| - \left|ln\left(\frac{P/E_{t-2}^i}{\overline{P/E_{t-2}^i}}\right)\right|\right\} + \Delta\varepsilon_t^i, \quad (2)$$

which can be written more simply as:

$$\Delta\left|ln\left(\frac{P/E_t^i}{\overline{P/E_t^i}}\right)\right| = \tau^i + \delta^i\left\{\Delta\left|ln\left(\frac{P/E_{t-1}^i}{\overline{P/E_{t-1}^i}}\right)\right|\right\} + \Delta\varepsilon_t^i. \tag{3}$$

The interpretation of δ^i is slightly different than in equation (1). In this case, the δ^i measures the speed of reversion between t – 1 and t. $\Delta\left|ln\left(\frac{P/E_{t-1}^i}{\overline{P/E_{t-1}^i}}\right)\right|$ represents the change in the distance of the observed P/E ratio for company i from the trend P/E ratio for company i from t – 2 to t – 1. If $\Delta\left|ln\left(\frac{P/E_{t-1}^i}{\overline{P/E_{t-1}^i}}\right)\right|$ has a positive value, that means the P/E ratio for company i diverged from the trend P/E ratio during the period between t – 2 to t – 1. Therefore, to accept the alternative hypothesis that mean reverting behavior exists in P/E ratios, δ^i must yield a statistically significant and negative result. An intuitive interpretation of this model is given that the P/E ratio of company i diverged from its trend value over the previous period, the P/E ratio should converge towards its trend value over the current period if mean reverting behavior exists.

To estimate equations (1) and (3), I will employ the following econometric models:

$$abs\_diff_{it} = \beta_0 + \beta_1 abs\_diff_{it-1} + \beta_i \boldsymbol{X}_{it} + e_{it}, \tag{4}$$

$$\Delta abs\_diff_{it} = \theta_0 + \theta_1 \Delta abs\_diff_{it-1} + \theta_i \Delta\boldsymbol{X}_{it} + \Delta e_{it}, \tag{5}$$

where "abs_diff_{it}" is the distance of company i's current P/E ratio in the current quarter from its 20-period simple moving average as a percentage. In the context of this paper, the 20 period simple moving average is equal to the trailing 5-year average P/E ratio for company i at time t. "abs_diff_{it-1}" is the one period lagged value of "abs_diff_{it}". "$\boldsymbol{X}_{it}$" is a vector representing the set of control variables used, which includes *pe_ratio*, *pe_ratio2*, *sector_delta*, *eps_growth*, *lvolume*, and *lmarket_cap*. Full descriptions of those variables can be found on Table A in the Appendix and are discussed further in the Data Section. The variable *pe_ratio* is used to control for companies that trade at unusually high P/E ratios; *pe_ratio2* is the squared value of *pe_ratio,* which is used to control for the decrease in marginal effect of increasing *pe_ratio* by one when the value of *pe_ratio* gets very large; *sector_delta* is used to control for business cycle changes where certain sectors tend to trade at higher or lower P/E ratios; *eps_growth* is a key determinant of P/E ratio as suggested by financial theory since companies that having accelerating earnings growth can often sustain expanding P/E ratios for extended periods of time; *lvolume* is used as a proxy for shock factors that may cause P/E ratios to deviate from their trend value since trading volume tends to increase when investor sentiment is highly positive or highly negative; *lmarket_cap* is used to control for the size of the company since larger companies tend to have more analysts covering their stock, so there is more information available for investors to consider when making an investment decision. Therefore, I would expect larger companies to trade closer to their trend values. The coefficient of interest for equations (4) and (5) are β_1 and θ_1, respectively, and the sign and significance of these coefficients will indicate whether mean reverting behavior is exhibited.

Due to the nature of the data, there are several econometric issues that will need to be addressed to get unbiased estimators. The four most important issues that this paper addresses are heteroskedasticity, survivorship bias, serial correlation, and unit roots. Heteroskedasticity is likely to exist in financial time series data, as indicated by the prior literature. Survivorship bias is likely present in the time series panel data used in this paper and is discussed further in the Data section of this paper.

Similar to many other financial time series datasets, the one used in this paper is likely to be serial correlated. One of the most important predictors of company *i*'s P/E ratio this quarter is the P/E ratio from the previous quarter. Specifically,

$$P/E_{it} = \xi + \phi P/E_{it-1} + \varepsilon_{it},$$

(6)

where ϕ is a statistically significant coefficient different from zero. This is likely an issue for most of the variables employed in my study. In addition, the similar issue of unit roots is likely to arise where ϕ = 1 or is close to 1. Unit root processes occur when the stochastic process that determines the variable of interest is non-stationary and often appears in financial time series datasets.

The presence of these econometric issues is tested for and discussed in further detail in the Results section of this paper. The econometric technique that allows me to correct for heteroskedasticity is using heteroskedastic-robust standard errors. Survivorship bias is minimized through the use of a second pooled dataset but is not completely eliminated. To control for serial correlation and unit roots, differencing and detrending are applied to the model.

While it was not the original intent of the present study, the results yielded could have interesting implications for the three-factor model proposed by Fama and French (1992). Consider the Capital Asset Pricing Model (CAPM) shown in equation (7), which is used to determine a theoretically appropriate required rate of return of an asset to make decisions about adding assets to a well-diversified portfolio:

$$r_i = r_f + \beta_1(r_m - r_f) + \alpha_i + e_i. \tag{7}$$

Fama and French expand on the CAPM by including two more factors believed to explain the variation in required return of an asset. Market risk is still the primary determinant, but also included is a company size factor (*SMB*) and a company value factor (*HML*):

$$r_i = r_f + \beta_1(r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \alpha_i + e_i \tag{8}$$

Their results indicate that small companies tend to outperform large companies, and companies with high book-to-market ratios tend to outperform companies with low book-to-market ratios. The book-to-market ratio of a company is defined as the inverse of the price-to-book ratio, so higher book-to-market ratios indicate higher values. They found similar results from other value ratios; companies with lower price-earnings ratios tend to outperform companies with higher price-earnings ratios. The value factor they propose is of interest since the mean-reverting behavior of this factor is the focus of my study. If P/E ratios exhibit mean reverting behavior, there may be a mean reverting function that goes unmodeled in their three-factor specification. Thus, the value factor they propose may be endogenous, which would lead to bias in the estimation of β_3 in equation (8).

IV. Data

The datasets used in this paper were pulled from a Bloomberg Terminal and every variable is measured quarterly from the first quarter of 2008 to the last quarter of 2017. One dataset is organized in time-series panels where the same companies are followed from 2008Q1 to 2017Q4. The 50 companies used were randomly selected from the set of companies that have remained in the S&P500 from 2008Q1 to 2017Q4. This is likely to cause survivorship bias because companies that remain in the S&P500 for 10 years are likely high-quality companies. To address this issue, I use a second dataset where 50 companies are randomly selected for every observed year. The companies selected in the second dataset must have remained in the S&P500 for the entire year observed. This is meant to minimize survivorship bias and provide a robustness check for the results yielded by the time series panels. While the time series dataset only follows 50 companies, the pooled dataset follows 307 total companies and allows for the companies observed to have released shares to the public after 2008. The same variables were gathered from both datasets.

The outcome variable of interest is the absolute value of the percentage difference between the current price-earnings ratio and the trend price-earnings ratio. The main explanatory variable is lagged value of the outcome variable. The variables for the value of the P/E ratio and the P/E ratio squared as controls for companies that trade at unconventional P/E ratios. I include the squared term since as a company's P/E ratio gets very large, increasing the value by 1 will not have as large an effect on the percentage difference from its trend. I use the trailing 20-period simple moving average as a proxy for the trend value, which is used to calculate the outcome and explanatory variables. I use the change in P/E ratio of each sector as for the business cycle, as mentioned in the Theory and Methodology section. Finally, the earnings-per-share growth, log of market cap and log of per-period volume act as controls for the determinants of a company's P/E ratio.

V. Results

The empirical results from the different models tested both indicate mean reverting behavior in P/E ratios. However, as discussed in the Theory and Methodology section, the interpretations are slightly different. The simple AR(1) OLS regression is displayed in Tables I. The estimated coefficient on *abs_diff_1* is positive, between 0 and 1, and statistically significant at the 99% confidence level, which indicates mean reverting behavior is present in P/E ratios between 2008 and 2017. Increasing the distance of a company's current P/E from the company's historical P/E in the previous period by 1% is estimated to increase the difference in the current period by 0.7381%. The estimated coefficients from the simple OLS regression on the remaining variables are consistent with my expectations.

As mentioned earlier, to control for possible survivorship bias and as a robustness check, I run the same regression using a pooled panel dataset. The results of the simple OLS model are confirmed by the pooled regression, estimating very similar coefficients with the only one change in significance levels coming from *sector_delta*. The coefficient on *sector_delta* also changed signs, but the pooled regression was inconclusive with a t-statistic of 1.25.

As with many financial datasets, the datasets I use likely suffer from heteroskedasticity in the error terms. To test for the presence of heteroskedasticity, I run Breusch-Pagan's test for heteroskedasticity and the results for both datasets can be seen on Table E. As expected, both the time series panels and pooled panels suffer from heteroskedasticity. Therefore, I will continue my analysis using heteroskedastic-robust standard errors.

There is likely some time-constant, firm or sector specific unobserved factors lying in the error term that may contribute to the distance of a firm's P/E ratio from its historical average in both the time series panel and pooled panel regressions. Specifically,

$$abs\_diff_{it} = \beta_0 + \beta_1 abs\_diff_{it-1} + \beta_i \boldsymbol{X}_{it} + a_i + u_{it}, \tag{9}$$

where a_i represents the unobserved, time-constant factors and $e_{it} = a_i + u_{it}$. There are two methods primarily used to address this issue, demeaning and first differencing. First differencing can also be used to correct for serial correlation while demeaning cannot correct this issue by itself. I discussed the theoretical possibility of serial correlation within the datasets used in the Theory and Methodology section. After running the simple OLS, I find further evidence of serial correlation since the R^2 values from both time-series panels and pooled panels seems to be quite high relative to the R^2 values achieved by other papers in the financial literature. To confirm the presence of serial correlation in my dataset, I estimate the impact of the lagged values of each variable on the current period's value along with the impact of the lagged residuals gathered from a regression of each variable on the time trend. The results are displayed in Table F and Table G, respectively, and indicate that every variable suffers from serial correlation. One difference to note between the time-series and pooled datasets was the serial correlation was of significantly less magnitude in the pooled regression. This is likely because different companies were used every year and I would not expect variable x of company i in year t to be serially correlated to variable x of company j in year t+1. Nonetheless, there is evidence of serial correlation in both datasets, so I opt to apply differencing to each variable rather than demeaning. I also detrend each variable as detrending can also be used to address this type of bias.

To detrend, I regress each variable on the time trend t and gathered the residuals. More specifically, to detrend variable x_{it}, I estimate the model:

$$x_{it} = \alpha_0 + \alpha_1 t + e_{it}, \tag{10}$$

where $e_{it} = \ddot{x}_{it}$, which is the portion of the variation in x_{it} not explained by the time trend. Every variable is replaced with its detrended counterpart, so the model can now be written as:

$$abs\ddot{\_d}\imath ff_{it} = \beta_0 + \beta_1 abs\ddot{\_d}\imath ff_{it-1} + \beta_i \ddot{\boldsymbol{X}}_{it} + e_{it}, \tag{11}$$

where the accent over each variable indicates that is has been detrended. Next, I apply first differencing to each variable for i firms and proceed to estimate the following regression:

$$\Delta abs\ddot{\_d}\imath ff_{it} = \beta_0 + \beta_1 \Delta abs\ddot{\_d}\imath ff_{it-1} + \beta_i \Delta \ddot{\boldsymbol{X}}_{it} + \Delta u_{it.} \tag{12}$$

Notice that the time-constant unobserved factors a_i drops out, so I am left with serially uncorrelated and exogenous variables.

Furthermore, an issue that often arises when dealing with financial time series data is non-stationarity and random walks. These issues are known to be present if a variable follows a unit root process. More specifically, variable x_{it} follows a random walk with a drift, a special type of unit root process, when

$$x_{it} = \mu_0 + \rho_i x_{it-1} + e_{it}, \tag{13}$$

where ρ_i is not statistically different from one. Moreover, since I am estimating an AR(1) model, it is also important to see that the absolute value of ρ_i for every x_{it} is less than one to ensure I have a weakly dependent, stable AR(1) process. To test for the presence of unit roots, I run a modified form of the Augmented Dickey-Fuller test for panel data. I employ a Levin-Lin-Chu unit test, which involved fitting an augmented Dickey-Fuller regression for each panel (Balvers et al, 2000). One critical assumption that must hold for this test to yield accurate results is a common autoregressive parameter for all panels. This means that the test does not allow for the possibility that some panels contain unit roots while others do not. The results can be seen in Table H and indicate that only two variables do not display unit root processes in the time-series panels, and only one variable does not display a unit root process in the pooled. Conveniently, if a variable has a unit root process, the first difference of the variable is stationary. Differencing was already applied to correct for serial correlation, so I can continue my analysis using the model specified in equation (12).

The results of the first differenced and detrended model confirm the findings of the simple OLS model.

Variable	Simple OLS *Absolute Difference*	Detrended and Differenced (Robust SE) *Absolute Difference*
First Lag of Absolute Difference	0.7381*** (0.1333)	-0.1270*** (0.0339)
P/E Ratio	0.0037*** (0.0004)	0.0143*** (0.0014)
P/E Ratio^2	-3.00e-06*** (4.87e-07)	-0.00001*** (1.70e-06)
Sector P/E Ratio Delta	0.0001** (0.00005)	0.00005* (0.00003)
EPS Growth Trailing 1 Year	-9.99e-07 (6.63e-06)	2.54e-08 (1.67e-06)
Log of Volume	0.0191*** (0.0050)	0.0595*** (0.0195)
Log of Market Cap	-0.0133*** (0.0050)	-0.3025*** (0.0511)
Constant	-0.2997	4.74e-06
R^2	0.7206	0.4319
Observations	2,000	1,950

Note: (***) denotes statistical significance at the 99% confidence level, (**) denotes statistical significance at 95% confidence level, (*) denotes statistical significance at 90% confidence level

As discussed in the Theory and Methodology section, the interpretation of this regression is slightly different from the simple OLS model. The sign on the coefficient for *abs_diff_1* flipped from positive to negative while remaining statistically significant at the 99% confidence level, as expected if mean reverting behavior exists. It is estimated that a 1% increase in the distance of a company's current P/E from the company's historical P/E over the previous period is estimated to decrease the difference over the current period by 0.1270%. Therefore, the difference between the current P/E ratio and the trend will approach 0 over time, which is consistent with mean reverting behavior. Again, this model estimates how a change in the distance of the current P/E ratio from the trend over the period $t-2$ through $t-1$ affects the change in the distance over the period $t-1$ through t. It is not surprising to see that the level of R^2 dropped rather significantly between the simple and robust regressions from 0.7206 to 0.4319. This is likely due to detrending the second equation, since the time trend probably accounted for a large portion of the R^2 in the simple model.

Similar results were yielded from the pooled regression.

Variable	**Simple OLS** *abs_diff*	**Detrended and Differenced (Robust SE)** *abs_diff*
First Lag of Absolute Difference (*abs_diff_1*)	0.7391*** (0.0157)	-0.2748*** (0.0644)
P/E Ratio (*pe_ratio*)	0.0015*** (0.0002)	0.0092*** (0.0032)
P/E Ratio^2 (*pe_ratio2*)	-1.42e-06*** (3.48e-07)	-0.00002*** (7.18e-06)
Sector P/E Ratio Delta (*sector_delta)*	-0.0001 (0.00008)	-0.00005 (0.00008)
EPS Growth Trailing 1 Year (*eps_growth*)	-3.38e-08 (4.33e-06)	1.13e-06 (2.52e-06)
Log of Volume (*lvolume*)	0.0271*** (0.0043)	0.0346 (0.0223)
Log of Market Cap (*lmarket_cap*)	-0.0254*** (0.0044)	-0.3025*** (0.0739)
Constant	-0.4157	0.0006
R^2	0.7206	0.4319
Observations	2,000	1,550

Note: (***) denotes statistical significance at the 99% confidence level, (**) denotes statistical significance at 95% confidence level, (*) denotes statistical significance at 90% confidence level

As in the time series panel regression, the coefficient for *abs_diff_1* is negative while remaining statistically significant at the 99% confidence level. The magnitude of the effect is actually larger in the pooled regression, as a 1% increase in the distance of a company's current P/E from the company's historical P/E in the previous period decreases the difference in the current period by 0.2748%, as opposed to 0.1270% in the time series. This may be the most interesting result because I would have expected the effect to be lower in the pooled regression due to the lower variance of the data. About 25% of the observations needed to be dropped in the first differenced model since the companies observed changes every year and it would not make sense to difference the data from two different companies. Further, previous research suggests that mean reversion takes several years (Balvers et al, 2000 and Poterba and Summers, 1987). If that is the case, it would be unlikely to observe mean reversion within the year-long sample period collected for each company. Thus, it is possible that the results yielded from this paper contradict those of previous studies that support mean reversion. It may also be that P/E mean reversion happens faster than price mean reversion, which was the primary topic of study in previous works. Additionally, it may be that companies that released shares to the public after 2008 display more mean reverting tendencies. Only companies that were in the S&P500 from 2008 to 2017 were used in the first set of regressions, while new companies were selected every year for the second.

Another difference between the simple and robust regressions to note is the increased magnitude of the coefficient on *lmarket_cap*. After correcting for the biases mentioned above, the magnitude coefficient increases 25 and 15-fold for the time series and pooled regressions, respectively. A 1% increase in the market cap of a company is estimated to decrease the distance of the company's current P/E from the company's historical P/E in the current period by 0.3025% in both the time series and pooled regressions. This result is consistent with financial theory since larger companies are often highly covered by investment analysts, so there are higher quantities of analysis on the company, so its price should act more efficiently and not deviate as far from fundamental value.

A final detail to point out is the constant terms from both regressions. In the simple OLS regression for both time series panels and pooled panels, the constant term was quite far from 0. Holding all the employed variables constant, I would expect the difference between a company's current P/E and its historical P/E to be relatively close to 0, assuming markets are mostly efficient. The constant term yielded by the robust regression for both the time series panels and pooled panels were consistent with this hypothesis, further indicating that the biases discussed earlier were corrected for in the robust regression.

One issue that was not addressed but could be corrected for with further research is small sample bias. While the results of the differenced and detrended model imply that P/E ratios exhibit mean reverting behavior, small sample bias may be affecting the coefficients since only 10 years of data on 50 companies were collected. Richardson and Stock (1989) and Richardson (1993) report that correcting for small-sample bias problems may reverse the Fama and French (1988a) and Poterba and Summers (1988) results. Both Fama and French's and Poterba and Summers' results provided the foundation for price mean-reversion investment strategies when they were published. If correcting for small sample bias reverses their results, it is possible the same can happen to my results. However, I will point out that both studies employed variance ratio tests for mean reversion, which were not used in this paper.

VI. Conclusion

In this paper, an attempt was made to empirically determine whether price-earnings ratios exhibit mean reverting behavior. The research conducted falls in the section of economic literature on the Efficient Market Hypothesis; specifically, it aims to test the alternative hypothesis of mean reverting processes in price-earnings ratios of a stock against that of a random walk process. Previous literature on the topic rely on variance ratio tests and conventional unit root tests using time series data to detect mean reversion. However, some economists have found these tests to have little power against the stationary alternative and panel data can be used to increase their power. This paper contributes a robust linear model using panel data from US equites to achieve the a more accurate test for mean reversion. Further, the paper directly addresses and corrects for heteroskedasticity, serial correlation and unit roots which attempting to minimize survivorship bias.

The results provide evidence of mean reverting processes in the price-earnings ratios of US equities and appear to be robust to presence of survivorship bias. Previous works that found evidence of stock price mean reversion state that mean reversion typically takes between three to three and a half years to occur (Balvers et al, 2000). The output of this empirical study, however, suggest price-earnings ratio mean reversion may occur much faster. Moreover, endogeneity in the Fama and French Three-Factor-Model may be an important consequence of this paper, but further research should aim to test this hypothesis directly. In addition, future studies should attempt to correct for small-sample bias and increase the sample period to acquire more consistent and unbiased estimators.

Appendix

Table A – Variable Descriptions

Variable Name	Description
pe_ratio	Company's P/E ratio in the current period
pe_ratio2	$(pe\_ratio)^2$
hist_pe	Company's trailing 5 year average P/E ratio
ldiff_hist	ln(*pe_ratio*) – ln(*hist_pe*). Shows how far company's current P/E ratio is away from its 5 year average P/E ratio as a percentage.
abs_diff	Absolute value of *ldiff_hist*
abs_diff_1	1 period lag of *abs_diff*
sector_delta	Change in average sector PE ratio from the last period to the current period
eps_growth	Trailing 1 year earnings-per-share growth
lmarket_cap	Log of the company's market capitalization in the current period
lvolume	Log of the number of company shares traded in the current period

Table B – Summary Statistics from Time Series Panel Data

Variable	Observations	Mean	Std. Dev.	Min.	Max.
abs_diff	2,000	0.385	0.443	0.00014	3.540
pe_ratio	2,000	22.996	53.134	1.73	781.60
pe_ratio2	2,000	3,350.62	38,984.87	3.01	610,904.8
hist_pe	2,000	19.748	17.431	6.13	172.07
sector_delta	2,000	.1922	115.01	-1,526.18	1,524.38
eps_growth	2,000	9.686	805.19	-31,900	5,100
volume	2,000	4.19e+08	5.78e+08	4,124,512	6.40e+09
lvolume	2,000	19.306	1.028	15.232	22.579
market_cap	2,000	51.539	79.737	0.608	729.29
lmarket_cap	2,000	3.225451	1.145	-0.498	6.592

Table C – Summary Statistics from Pooled Panel Data

Variable	Observations	Mean	Std. Dev.	Min.	Max.
abs_diff	2,000	0.2216	0.3066	0.00018	2.657
pe_ratio	2,000	24.46	44.227	0.942	759.44
pe_ratio2	2,000	2,553.4	26,750.64	0.888	576,749.1
hist_pe	2,000	23.69	49.705	2.983	1016.435
sector_delta	2,000	0.503	53.821	-598.87	815.71
eps_growth	2,000	9.178	996.76	-39,770.69	9,300
volume	2,000	4.10e+08	1.26e+09	20,260	2.99e+10
lvolume	2,000	19.086	1.116	9.916	24.294
market_cap	2,000	34.575	59.858	0.028	729.29
lmarket_cap	2,000	2.837	1.141	-3.309	6.592

Table D – Ramsey RESET Test from Time Series Panels

Models	F-Statistic	p-value
Without P/E Ratio^2	114.13	0.0000***
With P/E Ratio^2	2.08	0.1028
R^2	0.7146	0.7198

Note: (***) denotes statistical significance at the 99% confidence level

Table E – Breusch-Pagan Test for Heteroskedasticity

Time Series Panel		**Pooled Panel**	
chi2(1)	*p-value*	*chi2(1)*	*p-value*
1931.21	0.0000***	2413.97	0.0000***

Note: (***) denotes statistical significance at the 99% confidence level

Table F – Serial Correlation (First Lag)

Variable	Time Series Panel: Coefficient on first lag	Time Series Panel: Adjusted R^2	Pooled Panel: Coefficient on first lag	Pooled Panel: Adjusted R^2
abs_diff	0.8300***	0.6864	0.7952***	0.5899
pe_ratio	0.8862***	0.7813	0.2885***	0.0791
pe_ratio2	0.8828***	0.7791	0.3403***	0.1142
sector_delta	-0.5221***	0.2577	-0.0756***	0.0044
eps_growth	0.0964***	0.0088	0.1793***	0.0048
lvolume	0.9739***	0.9412	0.0719***	0.0044
lmarket_cap	0.9918***	0.9812	0.1573***	0.0237

Note: (***) denotes statistical significance at the 99% confidence level

Table G – Serial Correlation (Lagged Residuals)

Variable	Time Series Panel: Coefficient on lagged residual from time trend regression	Time Series Panel: Adjusted R^2	Pooled Panel: Coefficient on lagged residual from time trend regression	Pooled Panel: Adjusted R^2
abs_diff	0.8291***	0.6847	0.1529***	0.0208
pe_ratio	0.8845***	0.7778	0.2741***	0.0710
pe_ratio2	0.8822***	0.7774	0.3355***	0.1111
sector_delta	-0.5225***	0.2581	-0.0757***	0.0044
eps_growth	0.0940***	0.0083	0.1786***	0.0048
lvolume	0.9703***	0.9380	0.0583**	0.0026
lmarket_cap	0.9881***	0.9801	0.0832***	0.0061

Note: (***) denotes statistical significance at the 99% confidence level, (**) denotes statistical significance at 95% confidence level

Table H – Levin-Lin-Chu Test for Panel Unit Roots

Variable	Time Series Panel (*p-value*)	Pooled Panel (*p-value*)
abs_diff	0.1769	0.7422
pe_ratio	0.5973	0.9997
pe_ratio2	0.0009***	0.9353
sector_delta	0.0001***	0.0000***
eps_growth	0.9984	0.9993
lvolume	0.9025	0.9932
lmarket_cap	0.8749	0.9671

Note: (***) denotes statistical significance at the 99% confidence level

Table I – Regression Output from Time Series Panels

Variable	**Simple OLS** *abs_diff*	**Detrended and Differenced (Robust SE)** *abs_diff*
First Lag of Absolute Difference (*abs_diff_1*)	0.7381*** (0.1333)	-0.1270*** (0.0339)
P/E Ratio (*pe_ratio*)	0.0037*** (0.0004)	0.0143*** (0.0014)
P/E Ratio^2 (*pe_ratio2*)	-3.00e-06*** (4.87e-07)	-0.00001*** (1.70e-06)
Sector P/E Ratio Delta (*sector_delta)*	0.0001** (0.00005)	0.00005* (0.00003)
EPS Growth Trailing 1 Year (*eps_growth)*	-9.99e-07 (6.63e-06)	2.54e-08 (1.67e-06)
Log of Volume (*lvolume)*	0.0191*** (0.0050)	0.0595*** (0.0195)
Log of Market Cap (*lmarket_cap)*	-0.0133*** (0.0050)	-0.3025*** (0.0511)
Constant	-0.2997	4.74e-06
R^2	0.7206	0.4319
Observations	2,000	1,950

Note: (***) denotes statistical significance at the 99% confidence level, (**) denotes statistical significance at 95% confidence level, (*) denotes statistical significance at 90% confidence level

Table J – Regression Output from Pooled Panels

Variable	**Simple OLS** *abs_diff*	**Detrended and Differenced (Robust SE)** *abs_diff*
First Lag of Absolute Difference (*abs_diff_1*)	0.7391*** (0.0157)	-0.2748*** (0.0644)
P/E Ratio (*pe_ratio*)	0.0015*** (0.0002)	0.0092*** (0.0032)
P/E Ratio^2 (*pe_ratio2*)	-1.42e-06*** (3.48e-07)	-0.00002*** (7.18e-06)
Sector P/E Ratio Delta (*sector_delta)*	-0.0001 (0.00008)	-0.00005 (0.00008)
EPS Growth Trailing 1 Year (*eps_growth*)	-3.38e-08 (4.33e-06)	1.13e-06 (2.52e-06)
Log of Volume (*lvolume*)	0.0271*** (0.0043)	0.0346 (0.0223)
Log of Market Cap (*lmarket_cap*)	-0.0254*** (0.0044)	-0.3025*** (0.0739)
Constant	-0.4157	0.0006

R^2	0.7206	0.4319
Observations	2,000	1,550

Note: (***) denotes statistical significance at the 99% confidence level, (**) denotes statistical significance at 95% confidence level, (*) denotes statistical significance at 90% confidence level

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Allocating in the Presence of Dominance: A Mean-Variance Portfolio Choice Economic Experiment

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Abstract:
I conduct a mean-variance portfolio choice economic experiment to evaluate how individuals' portfolio choices deviate from what modern portfolio theory considers optimal. The experimental framework is comprised of three treatments. In each treatment the portfolio selection task involves choosing between two risky assets with zero correlation among their payoffs and one risk free asset. Participants are tasked with completing thirty choice rounds in which they must allocate a constant experimental capital amount to the available asset options after which they are shown period-by-period state-realizations. I utilize the definition of dominance as described in Neugebauer (2004), and Baltussen and Post (2011), that states an asset is dominant if it is attractive in isolation – the asset with the higher Sharpe-ratio. The risky asset, A or B, that is dominant, and the return characteristics of the dominant asset vary over treatments 1, 2, and 3. I find that, relative to theoretically optimal allocation, subjects disproportionately allocate their experimental capital to asset A, the asset with higher expected return and variance, in all treatments, and forgo the benefits to diversification that asset B provides. In order to analyze subjects' allocation decisions across treatments, I utilize Robust OLS and Fixed Effects regression frameworks.

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Introduction:

Standard theories of finance assume humans are computational, rationally minded actors. Sharpe's (1964) research on portfolio allocation, embodied in the CAPM, shows that rational investors should choose a portfolio based on risk weighted return. Empirical evaluation of Sharpe's model is complicated by the uncertainty associated with the return and variance of real-world assets. The purpose of this paper is to evaluate Sharpe's model in an experimental setting where return characteristics can be tightly controlled.

Specifically, I examine how human decision-making deviates from optimality in a portfolio choice environment. Further, it is important to study the environment in which humans are prone to making sub-optimal choices and to exploit the behavioral fallacies humans exhibit while making investment choices. I add to the current body of literature by studying subjects' ability to properly diversify when a dominant asset is in their set of available asset options. Results from the three treatments showcase how subjects' allocation in relation to optimality is affected by changes in the position[1] of a dominant asset. Moreover, this analysis provides further evidence alongside a growing body of behavioral literature that showcases that humans are not the hyper rational actors that neoclassical economic theory describes.

It is important to distinguish the laboratory environment from a naturally occurring environment. In reality it is often impossible to observe data on a single subject over time, and it is often difficult to observe the returns an investor received on an investment choice as well as how the investor reacts to that return. Further, empirical studies of portfolio choice may analyze the decisions of investors at a firm or corporation level and, as a result, fail to measure the preferences of any individual investor but rather measure the choices that result from the action of many individuals with differing preferences (Kroll, Levy, Rapoport. 1988). The experimental laboratory creates an environment where it is possible to examine the behavioral biases humans exhibit while investing. Laboratory environments are described as simplistic or unrealistic as they cannot account for the number of factors that affect individuals'

[1] Position changes over the three portfolio choice treatments as the dominant asset changes from asset A to asset B.

investment choices in a naturally occurring setting, but some important benefits of the laboratory setting are described here: 1.) The ability to observe how an investor reacts to the return on an investment choice creates the opportunity to observe whether subjects exhibit decision making biases in an investment decision environment. 2.) Asset return distributions can be constructed to match the assumptions of underlying portfolio models. 3.) The estimation of investor risk preferences is made possible by observing a subject's choices over time along with how their wealth changes over time. Further, estimating subjects' degree of risk aversion is a necessary component in understanding their asset allocation choices.

The next section reviews previous authors' study of portfolio choice and decision-making behavior as well as differences in experimental framework across studies. Section III presents the mean-variance model, Section IV covers the experimental design and what the portfolio choice environment allows me to analyze that is relevant to understanding human behavior. Data from the experimental sessions are discussed in Section V. Section VI includes discussion on the econometric techniques employed in order to analyze allocation choices across treatments, and Section VII concludes.

II

Literature Review:

Prior research relevant to this study has examined behavioral biases including overconfidence, ambiguity aversion, and sequential dependencies (Kroll et al. 1988). The research I present compares decisions against the normative theory of mean-variance analysis that describes the behavior an investor should follow while allocating capital among asset options (Fabozzi, Markowitz, Kolm, and Gupta, 2013). Portfolio theory provides a means to quantify the expected return and risk on a portfolio and introduces the ability to combine assets with varying risk and return characteristics in order to create a portfolio with a level of expected return corresponding to the individual assets within a portfolio but with a significantly lower amount of risk (Fabozzi et al. 2013).

Decision making under risk and uncertainty has been studied by several authors. Kahneman and Tversky (1979) criticize the ability of the Expected Utility Theory to describe decision making under risk and present an alternative choice theory, called Prospect Theory. They analyze subjects' responses to choice-problems regarding risky outcomes defined by probability. Results support the following deviations from Expected Utility Theory: 1.) People overweight outcomes with certainty relative to probable events (certainty effect). 2.) Subjects value changes in wealth rather the final outcome. 3.) Marginal utility of loss is greater in magnitude than the marginal utility of an increase in wealth.

The experimental design I present benefits from the work of Kroll et al. (1988). They design a portfolio selection task that involves subjects choosing between two risky assets with uncorrelated returns. In their design, subjects also have the option to borrow and lend at a risk-free rate of 3%. Ackert et al. (2015) analyze subject responses in a mean-variance context but differ from the experimental design of Kroll et al. (1988) and the experiments I present as the two risky assets in their experiment have perfectly negatively correlated payoffs. The mean-variance framework I implement differs from their 1988 study in that subjects have the option to allocate their capital endowment between the two risky asset options and the risk-free asset option whereas the framework of Kroll et al. (1988) requires that subjects allocate capital between one of the two risky assets with the option to utilize the risk-free borrowing and lending. Neugebauer (2004) and Baltussen and Post (2011) find that participants tend to disproportionally allocate to risky assets that are attractive in isolation but ignore dominated assets that offer a lower expected return but are attractive from a portfolio diversification perspective. The experimental design I implement involves three treatments, and the position of the dominant asset in the experimental portfolio varies across the three treatments. Further, the design I implement does not allow for borrowing or lending. The specific design characteristics for each treatment are discussed in detail in Section IV.

The objective of Kroll et al. (1988) and Ackert et al. (2015) is similar to the research I present in that these studies seek to identify the factors that compel individuals to hold inefficient portfolios and how subjects allocate capital between risky and riskless assets. Kroll et al. (1988) specify their goal to determine if the asset return distributions have the predicted effect on capital allocation. Further, they test whether initial capital size affects portfolio selection by conducting different experimental sessions with different initial amounts of wealth, and they analyze the effect of the ability to borrow and lend on allocation to the risky asset. The experimental findings of Kroll et al., (1988) study show that about 26% of all portfolios are mean-variance inefficient. Further, they observe a high number of switches in asset allocation choices between the two risky assets – a finding unsupportive of the mean-variance model. Their results also indicate that subjects exhibit sequential dependencies and that subjects' choices, with regard to optimality, do not improve as they make more allocation decisions. Ackert et al. (2015) find participants fail to properly balance risk and reward in their portfolios and that participants hold optimal portfolios when their payout is contingent on a single period and knowledge of payouts is unavailable until the end of the period. Additionally, they find the lack of feedback on allocation outcomes eliminates the behavioral bias resulting from misunderstanding of randomness.

Overestimating how closely one's decisions resemble the optimal choice is a violation of standard finance theory documented in experimental literature known as overconfidence. Dittrich et al. (2001) take an experimental approach to test overconfidence in investment decisions by allowing participants the ability to choose an alternative investment choice in place of their own. Their findings provide evidence to support the fact that overconfidence increases with deviation from optimal choices as well as task complexity and decreases with uncertainty. In a six-year study on the diversification choices of 60,000 individual investors at a large U.S. brokerage firm, Goetzmann and Kumar (2008) find that under-diversification among individual investors is related to investment choices characterized by trend-following behavior and over-confidence. In order to accurately draw these conclusions, they measure the covariance structure of investors' portfolios and analyze diversification in terms of holding more than one security as well as the presence of imperfectly correlated stocks in investors' portfolios. Empirical studies of individual portfolio choices in naturally occurring environments support results in the experimental setting in that investors fail to properly diversify (Ackert et al. 2015).

The experimental environment provides an opportunity to observe ambiguity aversion as the probability of an event occurring in a natural environment is rarely known. Charness and Gneezy (2010) analyze how portfolio choice depends on three behavioral phenomena: ambiguity aversion, the illusion of control, and myopic loss aversion. They find that when experiment participants are asked to pay to decrease ambiguity, increase control, or obtain more frequent feedback on investment choices, participants' investment choices do not change as a result of the level of ambiguity, preference for control is nonexistent, and that participants were willing to pay to have more frequent opportunities to change their investment choices. Ahn et al. (2007) analyze ambiguity aversion using data from a portfolio choice experiment. In their experimental design, subjects allocate their endowment between three assets and each asset produces an equal payout in one of three possible states. One asset payout occurs with a known probability, the other two occur with unknown probability. Their findings show that subjects exhibit considerable heterogeneity in ambiguity aversion. Ahn et al. (2007) fail to reject the null hypothesis of the Subjective Expected Utility theory for the majority of their experiment participants. Now, it is relevant to discuss the framework of the mean-variance model and outline its assumptions.

III

Mean Variance Model:[2]

$$R_t = \sum_{i=1}^{I} w_i r_i \tag{1}$$

The mean-variance framework assumes that investors are risk averse and desire to maximize the expected utility of wealth. Equation (1) describes the total return, R, over a time period, t, from individual assets, i, with individual returns, r, and weights, w. The mean-variance portfolio choice model provides a solution to the investor's problem. The model is constructed to create the optimal balance of risk and reward, measured by expected return and variance (or standard deviation) associated to the random normal distribution specific to each asset option. Further, the MV model assumes that one capital allocation choice is preferable over another if the expected return of the allocation is greater and its variance lower.

$$E_A w \geq E_B w \tag{2}$$

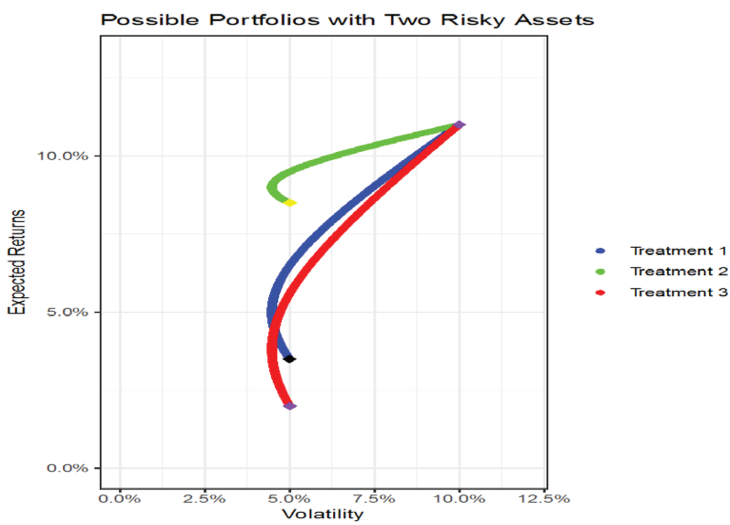
$$Var_A(w) \leq Var_B(w) \tag{3}$$

Equations (2) and (3) describes these preferences where $E_A w$ and $E_B w$ are the expected excess returns on the allocations A and B, respectively, and $Var_A w$ and $Var_B w$ are the variances corresponding to each allocation.

[2] Discussion of the mean variance model in this section follows that of Kroll, Levy, Rapoport. (1988)

Portfolio theory underlying the mean-variance portfolio choice experiment involves the study of the capital allocation line and the opportunity set of risky assets. The opportunity set of risky assets shows all combinations of portfolio expected return and standard deviation constructed from available assets. In the case of Figure I, the opportunity sets of risky assets A and B for treatments 1, 2, and 3 are shown. Portfolio theory suggests the optimal portfolio choice is the point along the opportunity set of risky assets where risk adjusted return is maximized. The tangency point that produces the highest slope on each of these opportunity sets denotes the optimal portfolio and is the point at which the Sharpe ratio of the two-asset portfolio is maximized.

Figure I: The Opportunity Set of Risky Assets



[3]

In order to solve the investor's problem of maximizing expected utility from wealth, portfolio theory provides a solution for the weights of the two risky assets in the optimal risky portfolio. The weights[4] of the risky assets are calculated in equation (4).

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$$w_A = \frac{E(R_A)\sigma^2{}_B - E(R_B)Cov(R_A,R_B)}{E(R_A)\sigma^2{}_B + E(R_B)\sigma^2{}_A - [E(R_A)+E(R_B)]Cov(R_A,R_B)} \tag{4}$$

$$w_B = 1 - w_A$$

IV
Experimental Design:

Participants receive a set of instructions (see Appendix) describing the nature of the capital allocation problem and are made aware of the risk and reward characteristics of the asset options and experiment payoff structure. In treatments one, two, and three, subjects are tasked with completing a series of 30 choice rounds during which they allocate their working-capital among two risky assets, option A and option B, as well as the risk-free asset, option C, which carries a fixed return value of 1%. In treatment 1, option A has an expected gross return value of 11% and a standard deviation of 10%, option B has an expected gross return of 3.5% and a standard deviation of 5%. In treatment 2, the risk-reward characteristics of options A and C remain unchanged, but option B now carries an expected gross return of 8.5% and a standard deviation of 5%. In treatment 3, the return characteristics for options A and C again remain unchanged, but option B carries an expected gross return of 2% and a standard deviation of 5%. As mentioned earlier, the payoffs of the two risky asset options are uncorrelated in all three treatments. Inputting these asset return characteristics into equation (4) allows me to see the optimal allocation weights for option A and B across the three treatments. In treatment 1, options A and B are equally attractive from a portfolio diversification perspective and portfolio theory suggests participants should allocate their capital to these risky assets in equal proportion. In treatment 2, asset B is dominant, and portfolio theory suggests participants should allocate 25% of the capital they will invest in risky assets to option A and 75% to option B. In treatment 3, the dominant asset is option A. Portfolio theory suggests participants should allocate 71.4% of the capital to be allocated to risky assets to option A and 28.6% to option B. These optimal allocation proportions are reiterated in Section VI.

This portfolio choice experiment is administered through Z-Tree (Zurich Toolbox for Readymade Economic Experiments) software[5]. After reviewing instructions and payoff structure, subjects click through a series of screens that display random-normal computer-generated draws specific to the risk-reward characteristics of asset options A and B in each treatment. I do this in order to provide subjects with a baseline understanding of random-normal draws and to enforce the fact that with higher expected return comes higher risk. Upon completion of these 'draw' screens, subjects continue to the capital allocation choice problem. Participants have access to 50 experimental dollars (ED) in working capital at the beginning of every choice round over all three treatments. Participants then enter the amount of experimental capital they choose to allocate to each asset, knowing the total allocation amount between the asset options must be equal to the available working capital of 50 ED. After option allocation amounts are specified, the computer-generated draw specific to the random normal distribution of each asset option is applied to each asset allocation. Any returns, positive or negative, are applied to the subjects total ED account. At the end of each choice round, subjects have the opportunity to observe their updated account, the draw (percent return) they received on option A and option B, as well as the return on their allocation to each asset option.

Upon completion of the 30 choice rounds, subjects are then instructed to complete the Holt-Laury (2002) questionnaire that tasks participants with choosing a series of paired lottery choices. In this questionnaire, subjects choose between options A and B (different than risky assets A and B) ten times. Each option carries with it the probability for low payout as well as the probability for high payout. As subjects make their decisions, they are aware that only one of their choices will be selected at random to determine their earnings from the questionnaire. The expected payouts on options A and B change over the ten paired decisions. As a result, measuring the point at which subjects switch from choosing option A to option B provides a measure of subject risk preference. Upon completion of the treatment, subjects'

[5] Fischbacher, Urs. "z-Tree: Zurich toolbox for ready-made economic experiments." *Experimental economics* 10, no. 2 (2007): 171-178.

total experimental dollar account, the returns they receive from their working capital allocation, is converted to U.S.D. at a rate of 4ED:1U.S.D.

V

Data:

The data set generated from 48 subjects over all treatments produces 1,440 observations over the course of thirty choice rounds. Data is recorded in the Z-Tree experimental toolbox (Fischbacher, 2007) on each subject over the course of their thirty decision rounds and the Holt-Laury (2002) questionnaire. I seek to observe how subjects' capital allocations deviates from optimal allocation proportions according to the mean-variance portfolio framework. I measure the amount subjects allocate to the two risky assets, option A and option B, as well as subjects' allocations to the risk-free asset, option C. The computer-generated draws corresponding to the random-normal distribution specific to each asset option are also recorded.

Although a subject is not required to allocate experimental capital to each risky asset during a decision round, the return received on each asset option is presented to subjects. The return on the allocation to an asset provides subjects with a means to easily understand how their allocation choice affect their total ED account. It is important for participants to see how their working capital changes across periods due to the fact that participants may have some expectation with regard to the return they believe they should receive over the course of thirty choice rounds. The presence of this expectation may cause participants to alter their allocation among the two risky assets and risk-free asset such that their portfolio in a given round takes on more or less risk in order to achieve a desired benchmark return. Measuring these variables and providing subjects the opportunity to observe the outcomes of their decision upon completion of a choice round increases subjects understanding of the risk reward characteristics specific to each asset option and how volatility in asset returns impacts working capital.

The number of times a subject chose option B, the risky choice of the two options, in the Holt-Laury (2002) questionnaire is recorded as a measure of risk preference. However, some experiment subjects exhibit behavior that implies misunderstanding of paired choice problem in that they choose option A some number of times, choose option B, and then switch back choice A. I measure the number of times a participant chose A as their last selection of this option, and subtract this amount from ten, the total number of choices, to calculate the number of times they chose risky option B.

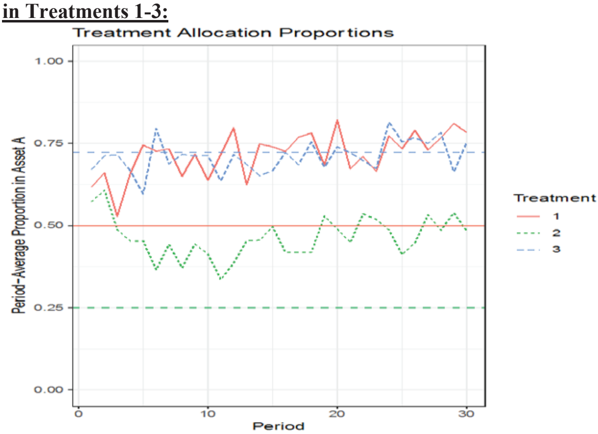
VI
Results:

This section provides analysis on subjects' asset allocation choice over the three treatments in this framework. Table I shows optimal allocation amounts by treatment. Figure II displays the average proportion of risky asset capital that subjects allocated to asset A. Table II provides Z-scores on the average proportion of ED that subjects allocated to asset A by treatment, and Table III provides Z-scores over specific periods in order to investigate learning and end-game effects.

Table I: Optimal portfolio weights by treatment:

Treatment	1(%)	2(%)	3(%)
Weight A*	0.5	25	71.4
Weight B*	0.5	75	28.6

Figure II Average Proportion Allocated to Asset A in Relation to Optimality Over Choice Rounds in Treatments 1-3:



The proportion of capital allocated to asset A is computed as: $\frac{(Capital\ Allocated\ to\ option\ A)}{(Working\ Capital - Capital\ Allocated\ to\ option\ C)}$.

Table II: Proportion of risky asset capital allocated to option A in all choice rounds.

Treatment	Periods 1-30: Average Proportion Allocated to Option A.	Z-Score (Optimal Hypothesis)
1	0.7185	19.14838
2	0.4662	25.26242
3	0.7189	-0.5591691

In order to investigate the effects of learning as well as the effects of nearing the end of the 30 choice-rounds, I compute the proportion of risky asset capital participants allocated to option A in periods 1-10, and periods 11-20 to investigate the effects of learning, and then compute the proportion allocated to option A in periods 1-25, and periods 26-30 to investigate end-game effects. I do this under the hypothesis that the proportion allocated to option A is equal to the mean-variance optimal solution as well as the hypothesis that the proportion is equal to the average proportion allocated to option A across the three treatments.

Table III: Investigating Learning and End-Game Effects Across Treatments.

Treatment 1	Average Proportion Allocated to Option A.	Z-Score (Optimal Hypothesis)	Z-Score (Treatment Average Hypothesis)	Treatment 2	Average Proportion Allocated to Option A.	Z-Score (Optimal Hypothesis)	Z-Score (Treatment Average Hypothesis)	Treatment 3	Average Proportion Allocated to Option A.	Z-Score (Optimal Hypothesis)	Z-Score (Treatment Average Hypothesis)
Periods 1-10 (Learning)	0.6670457	8.451919	-3.111447	Periods 1-10 (Learning)	0.4609639	14.23203	-0.1168133	Periods 1-10 (Learning)	0.6984624	-1.616564	-0.702652
Periods 11-20 (Learning)	0.7404305	12.16493	1.462858	Periods 11-20 (Learning)	0.4399363	12.81347	-1.186512	Periods 11-20 (Learning)	0.6935194	-1.929463	-1.006257
Periods 1-25 (End-Game Effects)	0.7051714	16.41371	-1.162058	Periods 1-25 (End-Game Effects)	0.4700052	22.01661	-0.551331	Periods 1-25 (End-Game Effects)	0.7188648	-2.075855	-0.6450944
Periods 26-30 (End-Game Effects)	0.7759155	9.871451	2.59844	Periods 26-30 (End-Game Effects)	0.4975323	11.80798	1.232814	Periods 26-30 (End-Game Effects)	0.7431151	0.8556082	1.442475

In treatment 1, where optimal allocation is defined as placing an equal proportion of ED in option A and B, I see that subjects allocated a higher proportion of their experimental capital to option A in rounds 11-20 than they did in rounds 1-10. To calculate the Z-statistics in Table III, under the optimal hypothesis, I conduct a proportional Z-test on the average proportion of capital subjects allocate to option A out of the total capital they allocate to risky assets against the mean-variance optimal solution. Further, I conduct a Z-test on the average proportion of capital that subjects allocated to option A in the specific rounds noted above against the average proportion that subjects allocated to option A over all choice rounds. As these allocation proportions are significantly different, according to the Z-statistics above, from the optimal allocation hypothesis as well as the treatment average allocation hypothesis, this provides evidence that subjects allocation choices take on more risk as the treatment progresses. With regard to end-game effects, a similar relationship holds. Participants allocate a significantly higher proportion of their capital to asset A in periods 26-30 than in periods 1-25. This shows that participants take on significantly more risk in their allocation decisions towards the end of treatment 1.

In treatment 2, where option B is the dominant asset in the portfolio, I observe that participants allocate a lesser proportion of their risky asset capital to asset A in periods 11-20 than in periods 1-10; however, these allocation proportions are significantly higher than the optimal proportion of 25% of risky asset capital in option A. For end-game effects, similar to treatment 1, subjects allocate a higher proportion of their risky asset capital to option A in rounds 26-30 than in rounds 1-25. Again, these allocation proportions are significantly higher than the optimal allocation proportion to option A and suggest that participants make take on disproportionate amounts of risk in their final allocation decisions. In treatment 2, observing Z-scores under the treatment average hypothesis, I see that in rounds 1-10 and rounds 1-25, participants average proportion allocated to option A is not statistically different, but in the final choice rounds of 26-30, participants do allocate a significantly higher proportion of their experimental capital to option A.

In treatment 3, asset A is dominant, and I observe that participants allocate significantly less than the optimal proportion of 71.4% of their risky asset capital to asset A in periods 1-10 and 11-20. In periods 11-20, subjects showcase greater deviation from optimality as they allocate a lower proportion to option A than they do in periods 1-10. In periods 1-25, subjects' allocation decisions are not significantly different from the optimal as well as the treatment hypothesis, and in periods 26-30, unlike treatments 2 and 3, subjects do not take on higher risk and allocate significantly more risky-asset capital to asset A.

I observe the average allocation proportions in treatments 1 and 3 are similar across choice rounds. A possible explanation behind this result is that participants observe the simple fact that option A carries a higher marginal return characteristic than asset B. While option A still carries a higher marginal return than option B in treatment 2, the difference is not as large. Such similar proportional allocations support the fact that participants allocation choices do not resemble the mean-variance solution but may provide evidence that a driving factor in how subjects weight their portfolios is the marginal return characteristics of their available asset options.

Econometric Results:

To further analyze subject decision making, I implement robust OLS and Fixed Effects by subject and period model specifications. The dependent variable in each model is the amount allocated to option A in the current period. In both model specifications, I include as controls the total experimental dollar account, the return received on the allocation to option A in the last period, a binary variable equal to one if the return on the allocation to option A was negative in the last period, the return received on the allocation to option B in the last period, a binary variable equal to one if the return on the allocation to option B was negative in the last period, a binary variable equal to one if the subject allocated to option A in the last period, a binary variable equal to one if the subject lost money in the last period, and include period and interactions of period with treatment as additional controls. In the robust OLS model specification, I also control for the number of times a subject chose option B in the Holt-Laury (2002) questionnaire as a measure of risk preference.

Robust OLS:

$$Amount\ Allocated\ to\ A_t = \beta_0 + \beta_1 Experimental\ Dollar\ Account_t + \beta_2 Return\ A_{\ t-1} + C_3 Return\ A\ Negative_{t-1} + \beta_4 Return\ \mathrm{B}_{t-1} + C_5 Return\ B\ Negative_{t-1} + C_6 Allocate\ to\ A_{t-1} + \beta_7 Risky\ HL_t + C_8 LostMoney_{t-1} + \beta_9 Period_t + C_{10} Treatment + a_t$$

Fixed Effects:

$$Amount\ Allocated\ to\ A_{it} = \beta_0 + \beta_1 Experimental\ Dollar\ Account_{it} + \beta_2 Return\ A_{\ it-1} + C_3 Return\ A\ Negative_{it-1} + \beta_4 Return\ \mathrm{B}_{it-1} + C_5 Return\ B\ Negative_{it-1} + C_6 Allocate\ to\ A_{it-1} + C_7 Lost\ Money_{it-1} + \beta_8 Period_{it} + a_{it}$$

Table IV: Summary Statistics:

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Period	1,440	15.50	8.658	1	30
Subject	1,440	24.50	13.86	1	48
Draw on Asset A	1,440	0.107	0.0993	-0.154	0.419
Return on Asset A	1,440	2.951	3.568	-7.034	20.97
Draw on Asset B	1,440	0.0455	0.0603	-0.149	0.264
Return on Asset B	1,440	0.836	1.566	-7.129	11.75
Total Experimental Dollars	1,440	59.32	40.99	-1.850	242.1
Amount Allocated to Asset A	1,440	27.35	16.18	0	50
Amount Allocated to Asset B	1,440	14.91	13.85	0	50
(0-1) Subject Lost Money (Lag 1)	1,440	0.103	0.304	0	1
Risky Choices HL	1,440	4.250	2.195	0	10
Number of subjects	48	48	48	48	48

Table V: Coefficient estimates and their significance for each model specification:

Dependent Variable: ED Allocated to Asset A

VARIABLES	(1) Robust OLS	(2) Fixed Effects
Total Experimental Dollars	0.340***	0.0861**
	(0.0169)	(0.0328)
Return on Asset A (Lag 1)	0.412***	0.0298
	(0.134)	(0.142)
(0-1) Return on Asset A Negative (Lag 1)	3.940***	2.285
	(1.392)	(1.366)
Return on Asset B (Lag 1)	-1.551***	-0.396
	(0.284)	(0.257)
(0-1) Return on Asset B Negative (Lag 1)	-3.771***	-1.158
	(0.986)	(0.909)
(0-1) Allocated to Asset A (Lag 1)	9.309***	2.947
	(2.004)	(2.896)
Risky Choices HL	0.321**	
	(0.143)	
(0-1) Subject Lost ED (Lag 1)	0.967	-0.323
	(1.640)	(1.497)
Period	-1.100***	-0.104
	(0.0718)	(0.133)
(0-1) Treatment 2	-1.347	
	(0.845)	
(0-1) Treatment 3	-10.84***	
	(0.867)	
Constant	18.02***	21.15***
	(2.218)	(2.791)
Observations	1,439	1,439
R-squared	0.447	0.2567
Number of subject		48
Subject FE		YES
Period FE		YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Discussion of Regression Results (all treatments):

The coefficient estimate on subjects total ED account is positive and statistically significant at the 95% level in both model specifications and suggests that as participants progress through choice rounds and derive positive returns from their capital allocation, they allocate a significantly higher amount of their working capital to option A. The coefficient estimate on the return the subject received on their allocation to option A in the last period is positive and highly statistically significant in the robust OLS model, but is positive and statistically insignificant in the Fixed Effects model specification. The positive sign on this coefficient estimate suggests presence of sequential dependency. The coefficient estimate on the binary variable, equal to one if the subject received a negative return on their allocation to option A in the last period, is positive and highly statistically significant under the robust OLS model and positive and insignificant under the Fixed Effects model specification. The positive sign on this coefficient estimate suggests that subjects increase their allocation to option A after receiving a negative return on the prior period. This result suggests subjects may desire an asset with a higher return characteristic in order to counteract their loss. The coefficient estimate on the return on option B in the last period is negative and statistically significant under the robust OLS model and is negative and insignificant under the Fixed Effects specification. The sign of this estimate is in line with expectations as it is reasonable to assume that subjects would allocate less of their working capital to option A, and more to asset B, if B received a higher return in the last period. The coefficient estimate on the binary variable, equal to one if the subject received a negative return on their allocation to option B in the last period, is negative and statistically significant under the robust OLS model and negative and insignificant under the fixed effects model. I observe that the magnitude of this coefficient estimate is practically high, but is not in line with our hypothesis as I expect a negative return on option B in the last period would cause subjects to increase their allocation to option A in the current period. The coefficient estimate on the binary variable, equal to one if the subject allocated to option A last period, is positive and statistically significant in the robust OLS model and positive and insignificant under the Fixed Effects model. This aligns with our hypothesis as I expect this variable captures a subjects propensity to allocate working capital to option A. The coefficient estimate on the number of risky choices a subject made in the Holt-Laury (2002) questionnaire is positive and statistically significant in the robust OLS model. This is in line with expectations as I expect that subject who chose the riskier choice more often are more likely to allocate a greater proportion of their working capital to the more volatile asset option with prospect for higher return. Period controls in the robust OLS model specification are negative and statistically significant and are negative and statistically insignificant under the Fixed Effects specification. This showcases participants decrease the amount of working capital they allocate to option A as the treatment progresses. This result is out of line with our expectations as I observe, for treatment specific results, that participants increase the proportion of risky asset capital allocated to option A as they move on in choice rounds.

VII
Discussion of Results and Conclusion:

In the three treatments I implement in this experimental framework, the risk-reward characteristics of the asset options that I choose create clear differences in the optimal allocation proportions across treatments. In treatments 1 and 3, it is important to note that asset A has a higher expected return (11%) than its standard deviation (10%) whereas asset B has an expected return of (3.5%, 2%) and standard deviation (5%, 5%) in treatments 1 and 3, respectively. The simple fact that asset A has higher a higher expected return than standard deviation, while asset B does not, likely contributes to this disproportionate allocation.

In treatment 2 asset B now has a higher expected return than standard deviation. Asset A carries the same risk-reward characteristics, but asset B now has an expected return value of (8.5%) and standard deviation of (5%). In treatment two I see subjects allocate a nearly equal proportion of their experimental capital to each asset option; however, their choices are significantly different from the optimal allocation proportions according to the mean-variance solution. This raises the question, in the experimental environment, do subjects benefit from taking on a high amount of risk in their capital allocation? No participants experience bankruptcy in this experimental framework due to the fact that subjects have 50

ED to allocate every period and only hold the returns from their allocation. The risk reward characteristics of the risky assets are such that it is extremely unlikely that a subject would experience continual negative draws on an allocation. As a result, this may push subjects to take on risk in the experimental environment.

Limitations to the study I present include the small number of subjects that participated in this series of portfolio choice treatments. Of 48 total subjects, 16 subjects participated in one of the three experimental treatments. Certainly, increasing the number of participants would improve the robustness of the results I present. Further, it is important to note that the 48 participants are 18-22-year-old Gettysburg College students. While I control for the risk preferences of subjects through the Holt-Laury (2002) questionnaire, it is likely the risk preferences of 18-22-year-old college students do not resemble that of, for instance, those who are closer to retirement age, which may decrease the external validity of the results I present. Finally, in the future it would be beneficial to test for the presence of an 'A-effect' in the treatment I present. It is plausible that as subject observe the risky assets in the treatments are named assets A and B, they may believe asset A is inherently better. This could easily be examined by switching the asset return characteristics of the two risky assets over the three treatments and observing whether subjects exhibit similar behavior in each case.

I emphasize the benefit of the laboratory environment in that it provides a controlled setting to observe choice behavior. Further study of human decision-making behavior is crucial in order to understand the factors which cause humans to exhibit behavioral biases. Better understanding of where humans are prone to behavioral bias is relevant when considering the actions of investors in capital markets as well as individuals' ability to properly structure their assets to achieve greater financial stability. Moreover, the breadth of evidence that suggests humans do not allocate their asset optimally advocates for better solutions to diversification, or, better access to diversification in order to solve the investors problem. The dominant asset framework in this study provides additional insight as to why there is higher volatility at the aggregate market level that results from the disproportionate amount of risk investors take on in their investment decisions.

Appendix

Experiment On-Screen Instructions:

Outline of Experimental Framework: "This is an experiment in decision making. Your payoff will depend partly on your choices and partly on chance. Please pay careful attention to these instructions. The experiment should be completed in approximately an hour and a half. During the decision-making portion of the experiment, you will be working with 'experimental dollars' (ED) that will be converted to U.S. dollars upon completion of the experiment at a ratio of 4ED = 1$ US. At the end of the experiment, you will be paid privately and in cash your earnings plus a $7-dollar participation fee."

Payoff Instructions:

"The experiment will consist of thirty decision making rounds. In each round you will choose how to allocate 50ED between three asset options. Two of the asset options will have different risk reward characteristics. The other risk-free asset option will allow you to gain a 1% return on the capital allocated to this asset and exposes you to no risk of losing experimental dollars. In each choice period, you will see three boxes labeled A, B, and C. In each choice round, you must allocate all of your 50ED among these asset options."

Choice Round Instructions:

"To choose an option, use the mouse to click on the box corresponding to each portfolio or cash option. Then, type in the experimental dollar amount you would like to allocate to each option. You must allocate all of your 50 ED in each period. In other words, the sum of the amount you place in each option must be equal to 50ED. An onscreen message will appear if your allocation amounts do not sum to 50 ED.

Your payoff in each round is determined by your allocation of experimental dollars to each option. The three options have the following risk reward characteristics:

Option	Average Return	Standard Deviation of Return
A	11%	10%
B	8.5%	5%
C	1%	0%

At the end of the choice round, the computer will draw, from the random-normal distribution specific to each option, a return value for your allocation. Any returns, positive or negative, will be added to your total experimental dollars, and then you will move on to the next decision round. In the next decision round, you will have access to the same 50 experimental dollars that you had at the start of the treatment, and the resulting gain or loss from your allocation decision will be added to your total experimental dollars. This process will be repeated for a total of thirty decision rounds. At the end of the thirty rounds, you are asked to complete a brief questionnaire, and then you will be called out individually and paid in private. Your payment will be the $7 participation fee plus your total experimental dollars converted into real dollars at a rate of: 4ED = 1USD."

<u>Example Decision Round:</u>

"Here is an example of a decision round: 'You begin the experiment with 3$ in experimental dollars and allocate one experimental dollar to each option. For option A, the computer would draw a return from a distribution with an expected return value of eleven percent and standard deviation of ten percent. This return would be applied to the 1$, and the return amount would be allocated to your total experimental dollar account. For option B, the computer would draw a return from a distribution with an expected return value of eight and a half percent and standard deviation of five percent. This return value would again be applied to the $1, and the return amount would be allocated to your total experimental dollar account. The dollar allocated to option C would receive the guaranteed return of one percent and this capital would be allocated to your total experimental dollar account. In the next choice round, you would have access to the same $3 in experimental dollars to allocate among the available asset options. '

You will notice that the asset options have different expected returns. Note also that the asset options with higher expected returns have higher standard deviations-this means they also have an increased chance of negative returns or outsized positive returns.

In the following screens, you will observe a series of 'draws' that display the return on a $1ED allocation to each asset option, as in the above example."

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Blockchain Technology - China's Bid to High Long-Run Growth

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Abstract

Despite having the second largest economy at $13 trillion, China has only recently surpassed the World Bank's definition of the 'middle-income range' which is a gross national income per capita between $1,000 to $12,000 (constant 2011 international $). This is a noteworthy accomplishment since many other developing nations have fallen victim to economic stagnation within this range leading to the term "middle-income trap". This paper will argue that one of the ways in which China escaped the middle-income trap and will continue to grow its economic influence is through the support of blockchain technology. Research and development, early technological adoption and business climate all play a role in explaining how the Chinese public and private sector have used blockchain technology to encourage economic growth. While there are many questions and misconceptions about blockchain technology and its place in China, this paper seeks only to answer a select few.

1. – Introduction

"The first generation of the digital revolution brought us the Internet of information. The second generation — powered by blockchain technology — is bringing us the Internet of value: a new platform to reshape the world of business and transform the old order of human affairs for the better" said influential author Don Tapscott (Guarda 2016). As outlandish as that claim may sound, with a total cryptocurrency market capitalization of $270,638,328,602 as of August 2018 and a 24hr trade volume of $14,378,130,110, Mr. Tapscott might be right (Cryptocurrency 2018). There are already over 1700 cryptocurrencies and 12372 digital markets and these statistics don't even fully capture the extent to which blockchain technology has and will continue to change the world. This paper seeks to shed light on the development of blockchain technology in China and its long run economic impact on the nation but first, a brief overview of the technology itself.

Blockchain technology is a digital database structure with the potential to revolutionize the processes and capabilities of countless industries. This innovative technology has immense value for a wide array of applications because it can increase speed, transparency, and immutability of transactions while minimizing costs. Blockchain technology is most famous for being the underpinning of decentralized cryptocurrencies such as Bitcoin and Ethereum which have become an increasingly hot topic for their ability to operate outside of the oversight of third-party entities, increasing individual sovereignty and network trust. However, this type of digital database has also shown promise in a myriad of other industries, including traditional financial activities, supply chain management, energy efficiency, social impact initiatives and digital identities. For any industry or activity that could be improved by having an immutable record of transactions with the potential for a high level of transparency, blockchain technology is a powerful mechanism for future growth and development.

1.1 – Nodes, Ledgers and Consensus

While blockchains differ greatly depending on their purpose, there are some commonalities that give them their unifying backbone. A mastery of its mechanisms is not necessary to enjoy the benefits (just as with driving a car or using the internet) but having a basic understanding of blockchain will be useful in recognizing promising investment opportunities, corporate implementation strategies, and furthering the global adoption of this technology. At its most fundamental level, there are three crucial components of any blockchain: nodes, ledgers and consensus.

Nodes are the individual network users who communicate with others to maintain an agreed upon chain of data. In the popular context of cryptocurrencies, nodes are the users that buy, sell, trade, and sometimes mine the digital assets “constructed to function as a medium of exchange, premised on the technology of cryptography” (Chohan 2017).

Ledgers are the fluid copies of the network transactional history that nodes possess, and the ledgers are kept in the form of distributed chained blocks. Blocks are simply data structures that utilize cryptography to minimize digital size while increasing trustworthiness and transparency. Block structure varies but most blocks contain metadata, a pointer to the last chained block as well as a summary of the stored transactional history.

Consensus is an agreed upon processing system that allows nodes to assess and agree upon which newly created blocks are valid and worthy of being chained to personal ledgers. When all nodes agree, they are in a state of consensus and all records are final. As with block structure, the way in which networks achieve consensus varies but dividing blockchains into the subcategories of public chain, private chain, or a hybrid of the two does help to shed light on the topic.

1.2 – Public, Private and Consortium Blockchains

Public blockchains are the branch of blockchains that most people have heard about since this type includes the electronic cash system Bitcoin as well as the open-source operating system Ethereum. These networks have open membership, the potential for anonymity, no central authority and a consensus mechanism that all nodes can partake in. The two most popular consensus mechanisms for this branch of blockchain networks are Proof-of-Work (PoW) and Proof-of-Stake (PoS), a proposed alternative to PoW and its real-world shortcomings.

Private blockchains are another type of blockchain that have been gaining exposure as more firms and institutions speak of their potential. This centralized style has selective membership, known network users, a central block-creating process, and the ability to manipulate outsider visibility. This concept is in direct contrast with those who have turned to blockchain technology as way to avoid third party oversight but does still retain the cryptographic auditability function (Buterin 2015).

Consortium chains are a hybrid of the two previously mentioned blockchain styles, and this type brings together selective membership, visibility restriction capabilities, and node-driven consensus mechanisms. All three types of blockchains have their specific advantages and a mix of all three should be expected to be seen in the future as wider array of blockchain applications come into fruition.

1.3 – Blockchain and China

Blockchain technology has revealed itself to be highly disruptive digital database structure with the potential to redefine how information is stored, shared and protected in a plethora of applications. Through a combination of research and development, early technological adoption and business climate, China has positioned itself at the forefront of global blockchain application and innovation. Further supportive policy decisions will aid China in transitioning towards being a technological innovator which should help maintain strong economic growth (Zilibotti 2017). Using both neoclassical macroeconomic theory regarding long run growth and a modern macroeconomic theory relating a nation's growth rate to its proximity to the technological frontier, I will explain why policy decisions related to blockchain technology will help the nation maintain economic growth.

2. – Literature Review

After China's economic opening under Deng Xiaoping in 1978, the world's most populous nation has experienced unprecedented economic growth skyrocketing it to being the second largest economy in the world. Despite annual GDP per capita growth over 8% during the past few decades and 660 million people being lifted out poverty, Chinese income inequality has grown at an alarming rate, peaking with a Gini coefficient of 0.491 in 2008 (UNDP China 2016).

Increased FDI inflow, selective privatization, and the development of globally competitive production facilities for industrial inputs have been effective policy choices for China's historically impressive growth but this model has started to reveal its shortcomings. Using international evidence, three statistics related to China's economic status are red flags for the nation's future growth. As explained in Eichengreen, Barry, and others' 2012 paper "When Fast-Growing Economies Slow Down: International Evidence and Implications for China", a rapid-growing catch-up economy is likely to slow down if its "per capita incomes reach around US$ 17,000 in year-2005 constant international prices, … [or] the share of employment in manufacturing is 23 percent… [or] when income per capita in the late-developing country reaches 57 percent of that in the country that defines the technological frontier". All three of these indicators are true for China so for it to continue its strong economic growth despite these foreboding characteristics the government will have to change its approach towards economic growth. The high rate of growth generated from massive capital stock investments in the previous decades is no longer translating into the same increases in national output. This is a critical juncture for the Chinese economy with the choice of either transitioning towards more productive industries and becoming a technological innovator or following suit with many other emerging economies and fall victim to the middle-income trap.

There have been many studies that have investigated China's long-run economic growth trajectory and most agree on the necessity for China to turn to technology creation over adoption for strong continued growth. In his 2017 paper "Growing and Slowing Down like China", Fabrizio Zilibotti concluded that China's "high-growth trajectory then hinges on the transition from investment-driven to innovation-driven growth" as it approaches economic convergence with "developed" nations. Ha and others reached a similar conclusion in their 2009 paper "Optimal Structure of Technology Adoption and Creation: Basic versus Development Research in Relation to the Distance from the Technological Frontier" that as a nation's "distance to the technological frontier narrows, the growth effect of basic R&D increases [and] that the quality of tertiary education has a significant positive effect on the productivity of R&D".

This concept brought to light the positive relationship between innovation-driven growth and improvements to human capital stock. Luckstead and others explored this topic and concluded in their 2014 paper "China's catch-up to the US economy: decomposing TFP through investment-specific technology and human capital" that human capital "plays a central role in the decomposition of [Chinese] TFP" which goes hand in hand with Hongbin Li and other's conclusion in their 2017 paper "Human Capital and China's Future Growth" that there is "a clear positive correlation between income and education level of the sample countries for all five years of data". Shujie Yao and others empirically explored the results of Chinese policy on technological progress and human capital accumulation. One of the conclusions in their 2006 paper "Building a strong nation, how does China perform in science and technology" is that despite China's split approach of promoting domestic technology and attracting FDI and outside technology, "there is lack of evidence to prove that China has become one of the world's front runners in knowledge creation and innovations".

With all this in mind, if China aims to make blockchain technology the future of domestic technological innovation, policies to encourage research and innovation are critical. “As a late comer of industrialization, China is not able to create all the new technologies that are required to modernize its economy” (Yao 2006) which has explained its propensity for technological imitation. However, the literature agrees that this approach will not suffice for the sort of high level of economic growth that China aims to maintain. To continue to elude the infamous middle-income trap and achieve ‘developed’ nation status, China will need to lead the way on some technological fronts.

3. – Theory

3.1 – Total Factor Productivity

While there are many ways to interpret Chinese Communist Party’s (CCP) policies on blockchain technology. This paper will use the neoclassical Cobb-Douglas production function to consider China’s long-run economic growth by assessing the recent policy developments as changes to total factor productivity. Specifically, how supportive Chinese policies on blockchain technology have positioned China to continue to enjoy its trend of strong economic growth into the 21st century. It will be argued that recent Chinese policies related to blockchain technology have created great business and research conditions for innovation, increasing the technological growth rate which would put the Chinese economy on a more explosive economic trajectory.

The Cobb-Douglas production function defines an economy’s economic output (Y) as a function of labor (N), capital (K) and total factor productivity (A) as seen below:

$$Y = f(A,N,K) \qquad Y_t = A_t \cdot N_t \alpha \cdot K_t 1 - \square \quad (1)$$

[1]

[1] $|\square| < 1$ & □ and 1-α are output elasticities dependent on the economy’s state of technology

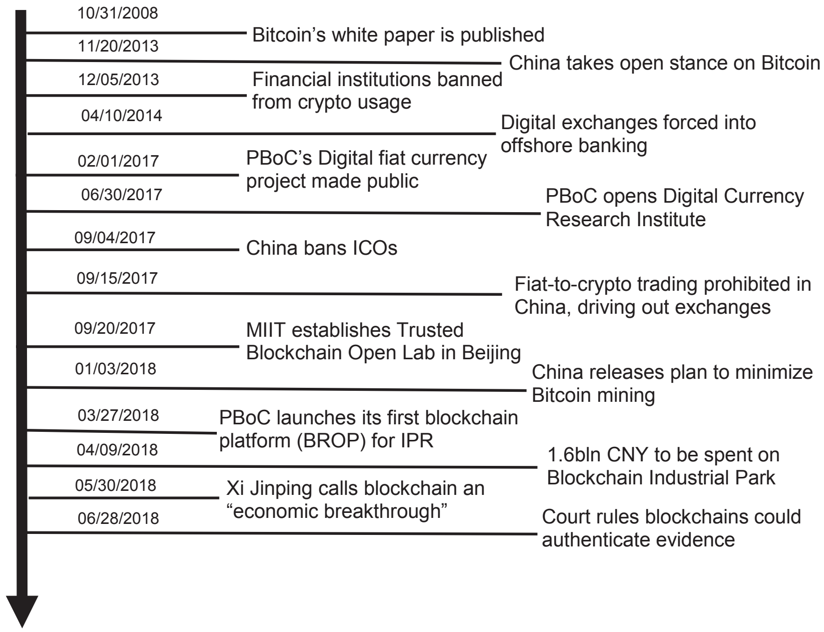
Manipulating this equation, two conclusions can be drawn. The first is that the balanced growth rate of output is proportional to the sum of the growth rate of labor and the growth rate of technology [$g_Y \sim g_A + g_N$]. The second conclusion is that balanced growth path for output per worker is proportional to the growth rate of technology [$g_y \sim g_A$] (see Technical Appendix). The undeniable role that the growth rate of technology plays in both total output and output per capita growth is critical to this paper's claim that recent Chinese policies supporting blockchain technology growth will be major factors in China's high growth in the future.

Total factor productivity (TFP) is commonly defined as the contributions to output that are outside of labor and capital inputs (Comin 2006). Considering the relatively expansive and open-ended nature of TFP, it is often considered the greatest contributor to economic growth. Three of the most academically discussed components of TFP are human capital, technology, and institutions which includes government policies.

3.2 – Innovation-led Growth vs. Investment-led Growth

In line with the theory developed in Acemoglu, Aghion, and Zilibotti (2006) (AAZ), this paper will cite policies and developments where China has opted for innovation-led growth over investment-led growth. Considering China's relative proximity to the technological frontier, aiming for this form of growth should lead to even greater long-run economic growth rates. Zilibotti et al. said, "when the economy is far from the technology frontier, the main growth engines are physical capital investments, the imitation of more productive foreign technologies, and the reallocation of resources from less to more productive activities" (Zilibotti 2017). However, once this economy has nearly capitalized on all the benefits capital accumulation, a new approach is necessary for continued growth. When "the economy has come closer to the technology frontier, it must switch on a new engine: innovation" (Zilibotti 2017). Failing to make progress towards innovation-led growth might explain why "many developing economies get thrown off their high-growth trajectories as they approach 25%–30% of the world technology frontier" (Zilibotti 2017). Providing the environment for innovative firms and ideas to flourish has the capability of sustaining a nation's growth to a degree that capital accumulation alone cannot.

4. – Policy Timeline [2]



(See Timeline Works Cited)

4.1 –Anti-Crypto Legislation

[2] PBoC: People's Bank of China | ICO: Initial coin offering

Despite China's support and adoption of blockchain technology, the CCP has not been as supportive of decentralized cryptocurrencies. China was one of the first nations to develop an affinity for Bitcoin and much of this was not with CCP's best interests in mind. As both a tool for speculation and circumventing strict capital controls, many Chinese citizens found Bitcoin as an appealing investment. After taking a relatively benign stance on Bitcoin a month prior, the Chinese Communist Party's first major restriction on the cryptocurrency came in December of 2013 and forbid financial institutions from trading the currency on the premise of its overly speculative nature. In April of 2014, the Party's next restrictive policy was driving crypto-to-crypto digital exchanges out of China by not allowing such companies to operate through the central banks.

After this price and trade-volume deflating legislation was enacted, China entered a period of minimal government intervention regarding blockchain technology and high digital asset demand despite the uncertain business climate. The business geography of the blockchain industry in China was primarily fintech companies in Beijing and Shanghai, mining operations in western provinces such as Xinjiang and Sichuan, and high-tech manufacturing occurring in Shenzhen.

2017 was an explosive year for the blockchain ecosystem. Not only were governments starting to give greater recognition to the technology's potential, but funding, adoption, and interest were reaching new peaks thanks to the popularization of initial coin offerings (ICOs). Initial coin offerings are much like initial public offerings of companies in the traditional finance space but specific to cryptocurrencies. To combat incidences of fraud, nefarious fundraising and financial manipulation, China banned initial coin offerings on September 4th, 2017. This decision was quickly followed up with a ban on fiat-to-crypto trading in China which further drove out domestic digital exchanges. These two policies are the most famous Chinese policies about blockchain technology but as the Timeline and Argument of this paper will explain, that does not tell the full story.

5. – Argument

5.1 – Research and Development

One approach the CCP has taken towards advancing the development of blockchain technology in China is through investing in specialized research in higher education institutions. In 1998, Project 985 was put into action. This government-funded project set out to establish “world-class universities” that would help push China into becoming a nation capable of producing new talent with the human capital to rival any other nation (China Education 2018). Of the 39 higher education institutions that received government funding under Project 985, 28 have newly established academic features associated with blockchain technology (Table 1).

Three nonacademic examples of China taking a more aggressive approach towards R&D include the People’s Bank of China opening the Digital Currency Research Institute in June of 2017, the Ministry of Industry and Information Technology (MIIT) establishing the Trusted Blockchain Open Lab in September of 2017, and the announcement of the Blockchain Industrial Park in Hangzhou and its 1.6 billion yuan in funding from both the private and public sector (Timeline). Yao Qian, director-general of the PBoC’s Digital Currency Research Institute said, “Conducting deep research on blockchain is the right thing for China to do to develop financial technology” (Xueqing 2018) a high value service industry that both the private and public sector seek to strengthen. Funding of this magnitude is a clear example of China making strides toward innovation-led growth.

5.2 – Early Technological Adoption

Despite the CCP's distaste for decentralized cryptocurrencies, China has been on the cutting edge of blockchain adoption for all variations of blockchains. A notable Chinese public blockchain is NEO, a community-driven blockchain project that "utilizes blockchain technology and digital identity to digitize assets and automate the management of digital assets using smart contracts" (NEO 2014). The NEO community's goal is to combine digital assets, digital identities, and smart contracts to create a smart economy. By not attempting to be a competitive currency in the Chinese economy, NEO has been able to live relatively harmoniously within China in ways that most other public blockchains have not.

The public sector's approach to blockchain technology has been through the implementation of private chains. The "Big Four State-owned banks – Bank of China, China Construction Bank, Industrial and Commercial Bank of China and Agricultural Bank of China- also use the technology on their projects, including poverty relief, international trade, home renting platform, e-commerce chain" (Zhang 2018). For example, the Bank of China is implementing a blockchain-based system to better manage the local poverty reduction fund in Tibet since the province has an unemployment rate four times greater than the national average (Wu 2018). This would not be achievable without the transparency and distributed nature of blockchain technology.

The People's Bank of China has made it clear that private chains are not the only form of blockchains that they see value in going forward. One of the most interesting announcements made by the PboC was in February 2017 when they announced their project to create a digital fiat currency utilizing "the core features of cryptocurrency and the existing monetary system" (Zhao PBoC 2018). Another example of the PBoC displaying its commitment to blockchain adoption was when the Hangzhou Blockchain Research Institute presented its Blockchain

Registry Open Platform (BROP) at the Global Financial Science and Technology Summit on March 2018. "The BROP is an open platform for developing independent intellectual property rights based on blockchain, according to its white paper (in Chinese). The platform will work with partners to make credible records of user identity, certificate data, and digital credentials for enterprise users. It plans to provide verifiable and supervised ownership registries and information on public services" (Borak 2018).

An interesting example of a consortium chain in China is MATRIX, the sole blockchain and AI solutions provider for the Party's One Belt One Road Initiative. MATRIX offers all types of blockchain solutions, not just consortium chains, and has a promising future since "The national government [has] put aside trillions to pour into belt and road projects and [has] recently invested $2.1 billion in an AI research park in Beijing"(cryptweeter 2018).

Perhaps the most progressive decision regarding blockchain adoption in China was a judicial decision made in June 2018. A court in China's Hangzhou city ruled that evidence authenticated with blockchain technology can be presented in legal disputes. This court set both a national and global precedent by stating that, "the usage of a third-party blockchain platform that is reliable without conflict of interests provides the legal ground for proving the intellectual infringement" (Blockchain 2018). The acceptance, acknowledgement and usage of blockchain technology by the China's government are promising signs of China aiming to position itself at the technological frontier.

5.3 – Business Climate

Another component of total factor productivity that China has been manipulating for its economic benefit are its institutions. Institutions include government policies, rules, and regulations. While there have been many disheartening institutional decisions made by the

Chinese government regarding blockchain applications including the ICO and fiat-to-crypto bans in September of 2017, the technology itself has seen tremendous government support.

In a more general sense, business conditions for blockchain startups were improved when after an inspection by the State Council, "25 provincial regions, 82 cities and 116 counties will be entitled to 24 incentive measures for their achievements in major policies in 2017, including supply-side reform and optimization of business environment" (China 2018). The official also noted that the 2018 innovation-led growth plans were mainly focused on "Beijing, Tianjin and Hebei province… advancing the incubation of cutting-edge technologies" (FTZs 2018).

After President Xi Jinping gave a rousing speech saying both that "a new generation of industrial revolution is substantially reshaping the global economic structure" and that "artificial intelligence, internet of things and blockchain [are] constantly making application breakthroughs" (Zhao Xi 2018) it was clear that the CCP wanted the world to know about its attitudes towards the next generation of technology. This powerful statement also was accompanied by the State Council's ordering of the "Guangdong Free-trade Zone to accelerate blockchain development and application" (Zhao Xi 2018) which further clarified the CCP's intentions for the technology.

Chinese blockchain industry growth has been astounding with the number of new blockchain companies in 2016 tripling those from 2015, "40% of all Chinese Blockchain startups [beginning] in 2017" and "68 equity financing initiatives for blockchain startups in the first quarter of 2018" alone (Zhao IT 2018). Policies of this nature have clearly done a tremendous job at providing funding, talent, and viable business opportunities for those seeking to expand the understanding and application of blockchain technology.

Patents are another tangible measure of human capital growth and innovation-friendly institutions. “More than half the world’s 406 blockchain-related patents in 2017 came from China” (Patent 2018) and this trend of dominance is growing. “China filed 225 and 59 patents in 2017 and 2016 respectively, while the US filed 91 and 21 in 2017 and 2016 and Australia took third place with 13 and 19 blockchain-related patents applications” (Patent 2018). In 2017, four of the ten global leaders in blockchain patent filings: Alibaba, Bubi Technologies, Hangzhou Fuzamei Technologies and Hangzhou Yunphant Network are Chinese firms (Table 2). Despite all that has occurred regarding cryptocurrency regulation, the policies surround research, adoption, and innovation have transformed China into the leading pioneer.

6. – Conclusion

The Chinese Communist Party’s approach towards blockchain technology has been confused thanks to a few restrictive regulations in past decade. The reality of the matter is that the Party is carrying a variety of plans to augment the implementation and development of blockchain technology within China.

Educational policies like Project 985 transformed Chinese higher education institutions into academic juggernauts, many of which have blockchain affiliated academic resources in the form of research institutes and key laboratories. Roughly half the world’s blockchain patents in 2017 came from China, demonstrating the nation’s edge in blockchain innovation. The establishment of the Digital Currency Research Institute in Beijing and the Blockchain Industrial Park in Hangzhou are two more examples of how the public and private sector are also contributing towards improving human capital related to blockchain technology.

The rate of technological progress is also increasing thanks to the government’s early adoption of the technology. All the major state-owned banks have implemented blockchain technology to some degree. Additionally, the acknowledgement of blockchain-based data being viable evidence in court means that the theoretical benefits of blockchain adoption are being realized in a tangible manner.

China's attempt to transition away from secondary industries like textiles and electronics manufacturing is directly in line with the AAZ theory that long run economic growth is best sustained by innovation-led growth over basic investment-led growth as a nation approaches the technological frontier. Blockchain technology has already shown its tremendous potential in the world of financial technologies, a high-value service-based industry that also assist in China's transition towards tertiary service industries. Beyond that, blockchain technology will elevate the economy because of its ability to improve efficiency levels for a plethora of other industries from supply chain to healthcare.

The significance of China's push towards blockchain adoption and innovation also connects to underlying economic challenges that China is facing today. In the financial realm, blockchain technology will improve transparency, efficiency and accessibility so the many millions of people in western China who are unbanked are likely to be given a whole new range of financial opportunities. State-owned banks are already working on poverty-relief efforts that incorporate the technology. With the capability to economically empower individuals who have been left behind by the traditional financial systems, this technology could not only strengthen China's economy in the major cities along the east coast but also be a tool to lift people out of poverty in the interior of China.

Research and development, early technological adoption and business climate relating to blockchain technology are all critical ways in which China is encouraging economic growth through blockchain technology.

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9. – Technical Appendix

The Cobb-Douglas production function Y = F(A, N, K) or $Y_t = A_t \cdot N_t \alpha \cdot K_t 1 - \alpha$ decomposes an economy's production (Y) as a function of labor (N), capital (K) and total factor productivity (A). α and 1-α are output elasticities. A critical assumption of this equation is that labor and capital display constant returns to scale together but diminishing returns to scale individually. With the assumptions in place, factors are in perfect competition and therefore receive only their marginal products:

Marginal product of capital: dY/dK = MPK | Marginal product of labor: dY/dN = MPN

A complete differentiation of the production function: $dY = F_A dA + F_N dN + F_K dK$

F_i is the partial derivative of factor i or the marginal product of that factor. This means it can also be written as $dY = F_A dA + MPNdN + MPKdK$

By dividing through by Y and converting factor changes into rates of growth the same equation can be expressed as: $dY/Y = (F_A A/Y)(dA/A)+(MPN*N/Y)(dN/N)+(MPK*K/Y)(dK/K)$

To simplify notation, growth rates can be denoted as $g_i = di/i$ representing percentage change of a given factor. $g_Y = (F_A A/Y)g_A + (MPN*N/Y)g_N + (MPK*K/Y)g_K$

(MPN*N/Y) and (MPK*K/Y) represent the share of income that goes to capital and labor respectively since factors receive their share based on their marginal product due to constant returns to scale and therefore perfect competition. This equation can further be simplified by replacing these two terms with α and 1- α. These terms can also be referred to output elasticities. $(F_A A/Y)$, the share of income dedicated to total factor productivity, is not as concrete of an output elasticity since total factor productivity is a multi-faceted variable. In this paper the growth rate of total factor productivity and the share of income given to total factor productivity are analogous enough to represent with the singular term g_A. The now simplified equation can be expressed as: $g_Y = g_A + \alpha g_N + (1- \alpha)g_K$

The two conclusions made in the theory section of this paper refer to the composition of variables on a balanced growth path, a macroeconomic condition that the Chinese economy has been trending towards. On a balanced growth path an economy's output and capital level grow in unison. With this in mind, g_Y and g_K can represented by the same term.

$$g_Y = g_A + \alpha g_N + (1- \alpha)g_K$$

[Substitute g_Y in for g_K]

$$g_Y = g_A + \alpha g_N + (1- \alpha)g_Y$$

$$\alpha g_Y = g_A + \alpha g_N$$

$$g_Y = (1/\alpha)g_A + g_N$$

$$g_Y - g_N = (1/\alpha)g_A$$

[Use division property of logarithms to combine g_y and g_N]

$$g_{(Y/N)} = (1/\alpha)g_A$$

$$g_y = (1/\alpha)g_A$$

The growth rates of output, capital, and labor can follow the properties of logarithms since the diminishing returns to either input individually creates an output growth path that would be comparable in shape that of that logarithmic function. Based on this model, total output's balanced growth path would also grow at a faster rate now that China has implemented policies that will increase the growth rate of technology. Output per capita, a popular proxy for standard of living, is an economic variable that's long run trajectory is often discussed. If the employment to population ratio is constant over time then output per capita would have a balanced growth path that mirrors output per worker. The employment to population ratio has been consistent over the last decade with a range of 0.88 of a percentage point. So as with the balanced growth path of output per worker, output per capita would grow at a faster rate now that China has implemented policies to accelerate the growth rate of technology.

10. – Appendix A

Table 1 – Blockchain-related Assets at Higher Education Institutions

Institution	**Key Feature**
Beijing Institute of Technology	Beijing Laboratory of Intelligent Information Technology
Beijing Normal University	Zhongguancun International Incubator
Beihang University	Key Laboratory of National Defense Science and Technology for Trusted Network Computing Technology
Central South University	Information Security and Big Data Research Institute
Chongqing University	Institute of Intelligent Computation and Information Security
Dalian University of Technology	Provincial Research Center for Internet of Things
Fudan University	National Demonstrative Experimental Computer Science Center
Harbin Institute of Technology	Research Center of Computer Network and Information Security Technology
Jilin University	Institute of Computer Science and Technology
Lanzhou University	MOE Engineering Research Center of Open Source Software and Real Time System
Nanjing University	Internet of Things Engineering (IOFTE) Center
Nankai University	Institute of Big Data Technology Research
Northeastern University	Key Laboratory of Big Data Management and Analytics
Peking University	Member university for affordable education DAO
Renmin University of China	Research Center of Data Warehouse and Business Intelligence
Shandong University	Key Laboratory of Cryptologic Technology and Information
Shanghai Jiaotong University	MOE Engineering Research Center of Network and Information Security
South China University of Technology	Guangdong Province Information Security Technology Engineering Research Center

Southeast University	Research Center of Future Network
Sun Yat-sen University	Information and Communication Technology Research Center
Tianjin University	Key Laboratory of Advanced Network Technology and Application
Tongji University	X Lab
Tsinghua University	Financial Technologies Lab
University of Electronic Science and Technology of China	IBM Mainframe Laboratory
University of Science and Technology of China	National High Performance Computing Center
Xiamen University	IoT and IT R&D Center
Zhejiang University	Zhejiang University Blockchain Research Center
East China Normal University	Shanghai Key Laboratory for Trustworthy Computing

Table 2 - 2017 Leaders in Blockchain Patent Filings

Rank	Name	Filings
1	Bank of America	45
2	EITC Holdings	42
3	CoinPlug	39
4	Alibaba	36
5	IBM	34
6	NChain Holdings	33
7	Bubi Technologies	30
8	Mastercard International	21
9	Hangzhou Fuzamei Technologies	19
10	Hangzhou Yunphant Network	18

The Effect of Fiscal Transparency on Output, Inflation, and Government Debt

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Abstract

This theoretical paper studies the issue of fiscal transparency, which we define as asymmetry of information between the households' perception of fiscal policy and the actual government balance sheet, in the context of a 24-hour news cycle. We model the economy using the New Keynesian three-equation model to study the effect of fiscal transparency on output, inflation, and especially government debt in order to draw conclusions that are relevant in the realm of policy-making in a sovereign debt crisis scenario. We find that a higher degree of fiscal transparency leads to greater levels of output and inflation as well as higher government debt.

1. Introduction

This paper theoretically analyzes how the government's transparency with regards to its fiscal position affects output, inflation, and especially public debt. We choose these three variables because they are mostly representative of the economy and they allow us to capture most of the effects of fiscal transparency on economic outcomes. Moreover, these three economic outcomes are the most present in the existing literature. This has to do with the notion that the effects of fiscal transparency on the real economy are mostly indirect, which means that choosing other outcomes, such as employment or the capital stock, may lead to far-fetched conclusions about their relationships.

Transparency in regard to all government activities is a cornerstone of a democratic society, as the people elected to public office have an obligation to keep their constituents informed to ensure that they are acting in their best interest. It is in fact not a coincidence that authoritarian regimes are known to give a distorted version of the truth, or even to outright lie, to their own citizens to make sure that they do not question the government's behavior. In the last two to three decades households have been able to retrieve important fiscal policy information from the media, thanks to the existence of a 24-hour news cycle, as the activities of governments in developed countries have been under a great degree of scrutiny. In particular, one of the topics which most news outlets spend a lot of time covering is government debt and fiscal policy. However, given the relatively infinite amount of channels through which individuals can obtain this information, they sometimes end up forming fiscal policy opinions that deviate from the government's actual fiscal position (Bernoth and Wolff, 2008). One of the greatest issues that arise with the existence of such a large number of news outlets has to do with how they each interpret an official government announcement, especially when it is not a transparent one. This issue has had the attention of global financial markets especially since the 2016 Presidential Election and the rise of the fake news phenomenon across most developed countries.

The principal issue that we investigate is how fiscal transparency (or lack thereof, referred to as fiscal opacy) affects market expectations of future fiscal policy. In particualr, we assume that both the government itself and media outlets make an announcement on the current status of fiscal policy which allows markets to form beliefs on future fiscal policy outcomes. Intuitively, if the media's announcement is close enough to the government's, then the government is being relatively transparent with regard to its fiscal position, and vice-versa otherwise, and is thus able to conduct expansionary fiscal policy and efficiently allocate money to meaningful projects. We hypothesize that fiscal opacy generates non-trivial uncertainties in the economy that cause households to act sub-optimally and expect a smaller fiscal stimulus then they otherwise would, therefore leading to lower income, inflation, and government revenue.

In this paper we model the economy using the New Keynesian 3-equation model to study the impact of this specific issue on output, inflation, and government debt. The vast majority of the papers that have been written are empirical ones, so this paper's contribution is to study a heavily-researched topic using a new theoretical approach. Our results from comparative statics analysis are consistent with our hypothesis and provide a theoretical backing for the existing quantitative findings. Specifically, they agree with the works of Galois and Wei (2002) and Teig (2006), Sargent and Wallace (1989), and Bastida et al. (2015) in that a lower degree of uncertainty on fiscal policy, generated by a relatively more transparent government, has beneficial effects across the economy: total output and inflation increase, thus suggesting positive economic outcomes, and government debt also increases, caused by the government's higher revenue and a greater degree of freedom to implement the fiscal stimuli that it intends to.

The remainder of the paper is as follows: in section 2 we place the topic of fiscal transparency in the existing economic literature; in section 3 we set up the theoretical model; in section 4 we solve the model and analyze the results by conducting comparative statistics; section 5 is the conclusion.

2. Literature Review

As we mentioned above, the existing literature abounds of studies on the effect of government transparency on economic outcomes. It is further divided into two separate categories, fiscal transparency and interest rate transparency. This theoretical paper fits inside the first. The literature, most of which is empirical, shows evidence that fiscal transparency is generally associated with a better economic outcomes, good governance, and more democratic (Fukda-Parr et al., 2011; Kopits and Craig, 1998). Furthermore, countries with low levels of fiscal transparency tend to be low-income, authoritarian regimes, and located in parts of the world with ongoing internal and international wars (Guillamon et al., 2011). The asymmetry of information generated by a non-transparent government causes a suboptimal outcomes because of wasteful and inefficient government spending (Persson et al., 1997). Heald (2003) is one of the few papers that claim that fiscal transparency is not always beneficial, arguing that an "overexposure" to government budgetary information may lead to some inefficiencies, political polarization, and high maintenance costs.

Since a lot of papers study the effect of fiscal transparency on output and inflation at the same time, we cover them simultaneously. Wehner and Renzio (2010) and Baldrich (2005) both find non-trivial positive relationships between fiscal transparency and GDP per capita. Similar works study the same relationship through a third outcome. Gelois and Wei (2002) find that lower fiscal opacity increases confidence in international investors, and therefore foreign direct investment, which leads to higher levels of GDP and inflation rates. Sargent and Wallace (1989) claim that fiscal transparency is closely tied to a well-functioning monetary authority. Especially in countries that adopt inflation targeting or that operate under high government debt, fiscal transparency is of fundamental importance: it puts pressure on interest rates and the money supply, and thus inflation levels. Teig (2006) finds a negative relationship between a transparent government and the level of corruption, as his result show statistically significant evidence to correlate corruption and output. Benito and Bastida (2009) study a sample of 41 countries, developed and developing ones, and find that higher fiscal transparency leads to higher voter turnouts and a decreased budget deficit, which then in turn translates into better economic outcomes, including output per capita. The empirical work of Montez and Lima (2018) shows a negative relationship between fiscal transparency and inflation, which they attribute to lower economic volatilities. They argue that the effect of inflation volatility on inflation expectations is stronger than the positive externalities of a more transparent government, thus resulting in an overall decrease in inflation. They find that this effect is stronger in developing countries and countries whose central bank adopts inflation targeting.

With regard to the effects of fiscal transparency on government debt, Bernoth and Goff (2008) empirically study the effects of creative accounting on interest rate spreads between bond yields in European countries; they find that a higher degree of fiscal transparency reduces risk premia, a result which they attribute to the relatively lower influence that a government announcement has on financial markets' beliefs regarding the current fiscal position. Wang et al. (2012) study the same relationship by mimicking the work of Duffie and Lando (2001), but they edit their asset density function with added positive bias; they find that low fiscal transparency, which they refer to as fiscal opacity, increase credit spreads non-linearly. Alt and Lassen (2006) study a cross-section off 19 countries in 1999 to study the impact of fiscal transparency on the government deficit; they show that fiscal transparency ensures better fiscal outcomes when the size of the debt is small enough, less than 1% of GDP, but they are unable to come to the same conclusion in countries that have large outstanding public debt.

In the existing economic literature numerous fiscal transparency papers study it quantitatively by exploiting the notion of creative accounting. Creative accounting is a government practice strategically implemented to lead individuals to form beliefs on fiscal policy that differ from its actual fiscal position. Von Hagen and Wolff (2006) show some European countries in the midst of a sovereign default crisis tend to utilize stock-flow adjustments, a form of creative accounting, to hide budget deficits. This phenomenon is particularly prevalent to circumvent the EU regulation named Stability and Growth Pact, whose very primary goal is to constrain government behavior. Milesi-Ferretti (2000) theoretically studies what types of environments lead governments to engage in creative accounting practices. She finds that when the publicly-available budget is not transparent to begin with governments are more likely to trade off a, costly, fiscal adjustment in favor or creative accounting. Unsurprisingly, Koen and van den Noord (2004) show that the more binding fiscal rules are the more likely a government is to adopt fiscal gimmicks.

Every paper mentioned above is an empirical one, whereas this paper takes a theoretical approach to study the effect of fiscal transparency on output, inflation, and government debt. To the author's best knowledge, there does not exist a study that analyzes these relationships using the New Keynesian 3-equation model. Hence, our most significant contribution is that we theoretically model fiscal transparency using the notion of creative accounting.

3. Model

We adopt the framework of the New Keynesian 3-equation model and analyze fiscal transparency in a similar fashion to how the existing literature models central bank transparency (Blinder, Ehrmann, Fratzscher, De Haan, Jansen, 2008; Poutineau, Sobczak, Vermandel, 2015). The model consists of three equations, each specifying the three variables of interest: output, inflation, and government debt.

We start off by introducing the notion of fiscal transparency. The works of Koen and van der Noord (2005), von Hagen and Wolff (2006), and Milesi-Ferretti (2000) show evidence to argue that governments regularly engage in creative accounting practices to booster their fiscal position and mislead financial markets. Once the government makes an official announcement regarding its fiscal position, we can write

$$F_t - F_t^{\text{official}} = CA_t \tag{1}$$

where $CA = c + \epsilon_c$. We assume that investors know c, the average usage of creative accounting, and that they *do not* know the true fiscal position of the government. F_t is the actual fiscal position and F_t^{official} is what the government says it is. Combining the two, we have

$$F_t - F_t^{\text{official}} = c + \epsilon_c \;\Rightarrow\; F_t^{\text{official}} + c = F_t - \epsilon \tag{2}$$

where ϵ is normally distributed with mean 0 and standard deviation ρ. Let $\widetilde{F}_t^{\text{official}} = F_t^{\text{official}} + c$. After the government makes an official announcement regarding its fiscal position, there is a second announcement, done by news outlets and other agencies that closely follow government activities. This is another estimate of F_t, which we denote by

$$F_t^{\text{other}} = F_t - \eta \tag{3}$$

where η is also normally distributed with mean equal to zero. Hence, households' true expectation of the government's fiscal position is given by

$$F_t^e = \frac{\rho\widetilde{F}^{\text{official}} + \omega F_t^{\text{other}}}{\rho + \omega} =$$

$$\frac{\rho\widetilde{F}^{\text{official}} + \omega\widetilde{F}^{\text{official}} + \omega F_t^{\text{other}} - \omega\widetilde{F}^{\text{official}}}{\rho + \omega} = \widetilde{F}^{\text{official}} + \frac{\omega}{\rho + \omega}(F_t^{\text{other}} - \widetilde{F}^{\text{official}}). \tag{4}$$

Let $\gamma = \frac{\omega}{\rho+\omega}$ and $m_t = F_t^{\text{other}} - \widetilde{F}^{\text{official}}$, so we have

$$F_t^e(m_t) = \widetilde{F}^{\text{official}} + \gamma m_t. \tag{5}$$

The parameter γ captures the level of precision of the news agencies' announcement with respect to government's announcement. Thus, $\gamma = 0$ means that news agencies do not lead financial markets to believe that the government's creative accounting practices are greater than it says they are; vice-versa, $\gamma = 1$ means that news outlet completely disregard the government's announcement and are able to completely sway the opinion of investors about creative accounting.

A more transparent government means that the value of m decreases, since the difference between the two fiscal policy announcement get small. Furthermore, we assume that the government intends to enact fiscal policy; this means that a higher level of fiscal transparency decreases the asymmetry of information and households behave optimally, thus gives the government more freedom and flexibility to allocate money optimally. Therefore, $F_t^e(m_t) < 0$. Below is a summary of the relationship between m and F_t^e:

- $m_t = 0 \Rightarrow F_t^e(m_t) = \widetilde{F}^{\text{official}}$
- $m_t \uparrow \Rightarrow F_t^e(m_t) \geq \widetilde{F}^{\text{official}}$
- $m_t \downarrow \Rightarrow F_t^e(m_t) \leq \widetilde{F}^{\text{official}}$.

As m_t decreases, the difference between F_t^{other} and $\tilde{F}^{\text{official}}$ decreases, therefore the government becomes more transparent with regards to fiscal policy. Intuitively, if the government's announcement is clear and concise, i.e. the government is transparent, the news media's announcement will closely resemble the one of the government and household will form belief on fiscal policy that are close enough to the government's true fiscal position. On the other hand, if the government is vague and not transparent, then news outlets will all have different interpretations in the second announcement and the public will form a wide range of opinions on fiscal policy.

The output equation is derived from the standard dynamic IS curve equation:

$$y_t = y_{t+1}^e - \frac{1}{\sigma}(r_t - \pi_{t+1}^e) - \alpha D_t. \tag{6}$$

This relationship arises from the intertemporal equilibrium condition of a representative household given its budget constraint (Poutineau et al., 2015). Specifically, the output gap in period t is a function of the expected output gap in period $t+1$ and the real interest rate $(r_t - \pi_{t+1}^e)$; σ is the risk-aversion parameter. Lastly, d_t is government debt in period t, so

$D_t = G_t - T_t$ (Mathieu and Sterdyniak, 2013). The coefficient α is negative because when D_t increases the government has to issue bonds to borrow money to repay its debt obligations. This corresponds to a leftward shift in the supply curve in the loanable funds model, which causes an increase in interest rates and a decrease in the price of the outstanding bonds. Therefore, the households that already owned government bonds will get a lower return than they otherwise would have, thereby decreasing public savings. Recalling the identity "total savings = total investment", we have an overall decrease in output.

We model inflation using a standard Phillips Curve equation:

$$\pi_t = \beta \pi^e_{t+1} + \kappa y_t. \tag{7}$$

This relationship arises from the aggregation of supply decisions by firms that operate under nomnal price stickiness (Poutineau et al., 2015). Specifically, inflation in period t is a function of expected inflation in period $t+1$ and the output gap in period t; β is the discount factor and κ represents the increase in inflation from a one-unit increase in the output gap.

We model government debt using the following equation:

$$D_t = D_{t-1}(1 + r_t - \pi_t) + \theta F^e_t(m_t). \tag{8}$$

Government debt in period t depends on government debt in period $t-1$, accounting for the real interest rate $(1+r_t-\pi_t)$, and the expected fiscal policy as a function of fiscal transparency. Recall that the quantity m_t is the difference between the government's announcement and the media's announcement.

4. Results and Analysis

From equations (6) – (8), we total-differentiate each to get:

$$dy = dy - \frac{1}{\sigma} dr + \frac{1}{\sigma} d\pi - \alpha dD \tag{9}$$

$$d\pi = \beta d\pi + \kappa dy \tag{10}$$

$$dD = dD(1 + r - \pi) + D(dr - d\pi) + \theta F_m dm. \tag{11}$$

In this paper we are interested in the effect of fiscal transparency on output, inflation, and government debt: $\frac{dy}{dm}$, $\frac{d\pi}{dm}$, and $\frac{dD}{dF}$ respectively, in order to conduct comparative statics analysis. Furthermore, since we are interested in the independent effect of fiscal transparency, we set the change in interest rate equal to 0, that is $dr = 0$. By re-writing the system of equations above in matrix form we have

$$\begin{bmatrix} 0 & -\frac{1}{\sigma} & \alpha \\ -\kappa & 1-\beta & 0 \\ 0 & 0 & r-\pi \end{bmatrix} \begin{bmatrix} dy \\ d\pi \\ dD \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \theta F_m \partial m \end{bmatrix},$$

where the determinant is

$$\begin{vmatrix} 0 & -\frac{1}{\sigma} & \alpha \\ -\kappa & 1-\beta & 0 \\ 0 & 0 & r-\pi \end{vmatrix} = -\kappa d\alpha - \frac{1}{\sigma}\kappa(r-\pi) < 0,$$

provided that $r > \pi$. Note that this is a reasonable assumption, given current levels of inflation and interest rates.

Using Cramer's Rule, we have

$$\frac{dy}{dm} = \frac{\begin{vmatrix} 0 & -\frac{1}{\sigma} & \alpha \\ 0 & 1-\beta & 0 \\ \theta F_m & 0 & r-\pi \end{vmatrix}}{-\kappa d\alpha - \frac{1}{\sigma}\kappa(r-\pi)} = \frac{-\alpha(1-\beta)\theta F_m}{-\kappa d\alpha - \frac{1}{\sigma}\kappa(r-\pi)} \tag{12}$$

$$\frac{d\pi}{dm} = \frac{\begin{vmatrix} 0 & 0 & \alpha \\ -\kappa & 0 & 0 \\ 0 & \theta F_m & r-\pi \end{vmatrix}}{-\kappa d\alpha - \frac{1}{\sigma}\kappa(r-\pi)} = \frac{-\alpha F_m}{-d\alpha - \frac{1}{\sigma}(r-\pi)} \tag{13}$$

$$\frac{dD}{dm} = \frac{\begin{vmatrix} 0 & -\frac{1}{\sigma} & 0 \\ -\kappa & 1-\beta & 0 \\ 0 & d & \theta F_m \end{vmatrix}}{-\kappa d\alpha - \frac{1}{\sigma}\kappa(r-\pi)} = \frac{-\frac{1}{\sigma}F_m}{-d\alpha - \frac{1}{\sigma}(r-\pi)}. \tag{14}$$

From equation (12), recall that we assumed $F_t^e(m_t) < 0$. This implies that as fiscal transparency increases households are able to form accurate beliefs on the government fiscal position, which allows it to pass the expansionary policy measures that it desires, which corresponds to a larger fiscal stimulus, that is $F_m < 0$. Therefore, $\frac{dy}{dm} < 0$. This means that a decrease in m, which is an increase in fiscal transparency, leads to an increase in total output. While a direct relationship between the two variables is not immediately obvious, the source of this result is probably correlated to the positive externalities brought about by a more transparent government. This is in fact consistent with the findings of Galois and Wei (2002) and Teig (2006): a decrease in fiscal opacity most likely decreases the risk premium associated with financing projects, increases consumer confidence and political stability. Hameed (2006) also finds that fiscal transparency is positively correlated with fiscal discipline, which means that the government is able to efficiently allocate money to meaningful projects, thus stimulating economic activity. The aggregate effect is an increase in total output.

For the effect of fiscal transparency on inflation we have

$$\frac{d\pi}{dm} = \frac{-\alpha F_m}{-D\alpha - \frac{1}{\sigma}(r-\pi)}.$$

Similar to above, $F_m < 0$ implies that $\frac{d\pi}{dm}$ is also negative. Therefore, an increase in fiscal transparency leads to an increase in inflation as well. This relationship is perhaps even more indirect than the one with GDP, since it is so heavily influenced by expectations. When fiscal transparency increases, households expect that expansionary fiscal policy will stimulate economic activity which will likely help the economy grow, causing inflation to rise. One the one hand, this result partially agrees with Sargent and Wallace (1989), who argue that a higher degree of fiscal transparency increases the government trustworthiness and their ability to effectively stimulate economic activity which leads to an increase inflation. For reference, they also find that fiscal transparency eases the pressure on the central bank, especially when it operates under an inflation mandate, which means that it has an even broader impact on those countries. On the other hand, this result goes against the findings of Montez and Lima (2018) whose work shows that a higher degree of fiscal transparency lowers inflation rates and inflation volatility as well as that this effect is stronger in developing countries.

Finally, for the effect of fiscal transparency on government debt we have

$$\frac{dD}{dm} = \frac{-\frac{1}{\sigma}F_m}{-D\alpha - \frac{1}{\sigma}(r-\pi)}.$$

Similar to above, $F_m < 0$ implies that $\frac{dD}{dm}$ is also negative. An increase in fiscal transparency increases the credit ratings and the share of debt owned by foreign creditors, thus allowing the government to borrow more from the households than it otherwise would; this enhances the already-present fiscal policy regime, leading to greater government spending and higher levels of debt (Bastida et al., 2015; Kemoe and Zhan, 2018). This result goes against the findings of Alt and Lassen (2006) that show that the positive effect of fiscal transparency on output and revenue is greater than the fiscal burden caused by higher levels of spending; the net result is therefore a lower government debt.

As per Trinh (2017), "the job of monetary policy is one of managing expectations". One could thus draw a parallel between fiscal transparency and monetary policy transparency, especially in an economy in which households are able to obtain crucial macroeconomic information almost instantaneously, thanks to the 24-news cycle. Therefore, in terms of policy implication under a sovereign default crisis, our model shows that a higher degree of fiscal transparency increases output and therefore public revenue. Clear signs of fiscal transparency for the government are the equivalent of forward guidance behavior for the Federal Reserve. If the government is attempting to reassure and instill confidence in financial markets, implementing changes to the way in which it goes about relaying information about its finances can generate tangible benefits. For instance, publishing its fiscal position more frequently, including more detailed descriptions of its spending, or decreasing (if not completely eradicating) creative accounting practices are all possible routes to steer the economy in the right direction. Even though our model shows an increase in the government budget deficit, this is likely to only be temporary, as the economic growth and the positive externalities of a transparency are able to restore faith in creditors and households and steer the government onto the path of debt consolidation in the near future.

5. Conclusion

This paper investigates how fiscal transparency affects output, inflation, and government debt, with some emphasis on sovereign default scenarios. We find that less fiscal opacity creates a more favorable environment for the government to conduct expansionary fiscal policy, which leads to higher GDP, higher inflation, and higher government debt. All three effects are linked to the government's increased ability to borrow money in order to stimulate economic activity.

Significant limitations of these results lie in the numerous assumptions we imposed on a lot of our variables as well as in the fact that we modeled the economy with only three equations. We used the notion of creative accounting as a proxy for fiscal transparency, but there are several other ways to specify the same indicator. Furthermore, a lot of the rationalizations in our conclusions rely on the results already present in the existing literature, whose theoretical (and sometimes empirical) approach is entirely different; that is, we assumed that certain sectors of the economy, such as financial markets or households, behave the same way they do in prior research without actually modeling or specifying their incentive structure.

The topic of fiscal transparency is undoubtedly at the forefront of the economic literature, especially in an environment where the news cycle keeps us updated on current events every minute of every day. Future theoretical papers studying this issue should consider an environment which includes more agents with rigorous incentive structures and constraints, in order to cement the conclusions on solid ground. Moreover, since there does not exist a rigorous definition of fiscal transparency, further studies should consider modeling it using more than one indicator and minimize its inherent specification bias.

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Unsustainable Sustainability: Do Policies that Increase Environmental Quality Exacerbate Income Inequality?

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ABSTRACT

International pressure to meet climate and sustainability goals are mounting. Countries attempting to industrialize in the age of sustainability are tasked with industrializing using low-carbon practices. The transition to a "green" economy requires elimination of some jobs and skillsets that may upset social equality. This paper empirically examines the hypothesis that policies aimed at increased environmental performance promote increased income inequality in developing countries. Because existing literature firmly supports the hypothesis that lower income inequality leads to higher environmental performance, this paper develops a simultaneous equations model (SEM) to estimate the hypothesized endogenous relationship using two stage least squares (2SLS) estimation with an instrumental variable. While the instrumental variables employed were not per se valid, the 2SLS estimation results for the sample of developing countries reflects a positive and practically large, though statistically insignificant effect of air quality on income inequality.

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Honor Code: I affirm that I have upheld the highest principles of honesty and integrity in my academic work and have not witnessed a violation of the Honor Code.

I. INTRODUCTION

Economies around the globe are facing pressure to become more environmentally friendly in their economic activities. Since the 1970's, global agreements, protocols, and conventions have arisen with the goal of achieving collaborative solutions to mounting environmental strain. This pressure was intensified by the 2015 adoption of the United Nations' Sustainable Development Goals (SDGs), a comprehensive list of goals to continue global economic growth in environmentally, economically, and socially sustainable ways. However, despite the SDGs' concurrent goals of reduced inequality, inclusive economic growth, and environmental sustainability, the transition to sustainability necessarily involves shifting away from many traditional, stable carbon-intensive industries including industrial sectors, non-renewable energy, natural resource extraction, etc.

Both developed and developing countries are tasked with meeting such goals, whether through formal contract or economic and social pressures from other nations. I expect that developing countries might be disadvantaged in achieving the same goals as those who have achieved advanced levels of income and development. The development process historically relies on carbon-intensive industrialization activities as a fundamental driver of economic prosperity and growth. Such carbon-intensive industries also provide many low-skilled and labor-intensive jobs, such as mining and truck driving. Due to the large environmental impact of industrialization and subsequent goals to alter or diminish its environmental footprint, I expect that developing countries experience challenges and ramifications when attempting to meet these goals that developed countries do not.

The transition from manufacturing and resource-intensive (environmentally degrading) industries to an economy powered by more environmentally friendly, low-carbon industries will require education and training that is not yet present and less accessible to particular factions of the population. Poorer people who conventionally hold low-skilled, labor-intensive jobs and have less access to education and training will suffer disproportionately from this change. Thus, this research attempts to ask the question: do policies that increase environmental quality tend to increase income inequality? I hypothesize that decreased environmental degradation (that is, higher environmental quality) leads to increased income inequality in developing countries.

Section II of this paper will explore the conclusions of the existing literature surrounding this relationship. Section III will discuss the theory used to formulate the hypothesis and the methodology employed to test it. Section IV describes the data used for econometric testing. Section V discusses the results and Section VI will discuss overall conclusions, policy implications, and challenges for future research on this topic.

II. LITERATURE

The existing literature relevant to this hypothesis is broken up into two main bodies. First, that which acknowledges the relationship but hypothesizes causality such that income inequality affects environmental quality. Second, that which posits a relationship such that environmental quality affects income inequality. This paper contributes uniquely to the existing literature by proposing an empirical model to test the latter relationship.

i. INEQUALITY AFFECTS ENVIRONMENTAL PERFORMANCE

The Environmental Kuznets Curve (EKC) theory hypothesizes that as income per capita increases, environmental degradation increases up to a particular point in the development process (as illustrated by a threshold amount of income). After this threshold is reached, environmental degradation begins to fall again when economies shift to less resource-intensive growth strategies. Graphically, this demonstrates what has been described as an "inverted-U-shape" (Dinda, 2004; Grossman and Krueger 1991; Shafik and Bandyopadhyay, 1992; and Panayotou, 1999). Boyce (1994) expands EKC theories to include income inequality as a necessary determinant of environmental quality. He argues that when there is economic activity that is environmentally harmful, there are people who benefit from it ("winners") and people are harmed by it ("losers"). The winners, he posits, are those with some form of power over others. If these winners could theoretically compensate losers for environmentally damaging activities and still win, then it is efficient to continue with the degrading activity. Generally, he notes, winners will not compensate losers and will simply ignore externalities, thus the degrading activity will be pursued even when its net impact to society is negative (Boyce, 1994). Thus, higher levels of inequality in both power and wealth (which he essentially equates because those with greater wealth are generally more powerful) will incite greater environmental damage. He dubs this idea the "equality hypothesis." Torras and Boyce (1998) build off of Boyce (1994) by using empirical analysis to criticize EKC scholars which rely on income per capita as the chief explanatory variable. Echoing Boyce (1994), they find that more equitable income/power distributions will result in lower environmental degradation.

While these hypotheses are not directly comparable to my hypothesis, they are important and relevant. Unlike traditional EKC theorists, my hypothesis focuses on income inequality as opposed to income per capita. Furthermore, this paper treats environmental quality as the independent variable which affects income inequality, as opposed the literature which treats income as the independent which affects environmental quality. Nonetheless, this literature is useful to consider as it explains linkage between environmental performance and income inequality. Moreover, the EKC theory is helpful to my hypothesis because it suggests that after a certain point of economic development, the relationship between environmental degradation and income changes dramatically. Thus, this theory guides my expectation that for developed countries, environmental performance will have a negative if not neutral relationship with income inequality.

ii. ENVIRONMENTAL PERFORMANCE AFFECTS INEQUALITY

While previous theory indicates a link between the two variables, there is little existing research that supports this paper's hypothesis that greater environmental performance increases income inequality. Some authors and international organizations published reports discussing the theoretical causal relationship between environmental performance and income inequality, but nobody has formulated an empirical model to test it. This section will examine the existing theoretical reasoning for my hypothesis.

The OECD (2016) discusses expected economic challenges that accompany the transition to environmentally friendly economic activities, which are summarized in *Figure 1*. This lays a foundation for the discussion of a potential relationship working opposite the relationship already established in the literature. Dercon (2012) contributes to this theoretical foundation for the argument by explaining that the poor are disproportionately affected by such economic shifts. It is important to consider these economic implications from the poor both in situations where the poor act as consumers and where they act as producers, Dercon (2012) argues. In the consumption context, the poor typically spend a larger share of their income on energy and environmental goods like water and fuel. The poor also lack resources to adapt to environmental pressures. Therefore, shocks to the price of these goods due to policy changes and regulation to mitigate environmental degradation will most heinously affect the poor (Dercon, 2012: 11).

On the production side, too, the poor tend to suffer disproportionately. The United Nations Environment Programme (UNEP) produced a report in 2008 which discusses in depth the potential implications of the transition towards sustainable development. One noteworthy conclusion is that such economic change will be accompanied by be several changes to overall employment which will thus affect the poor as producers. With greater global focus on environmental performance, it is expected that some jobs will be created – such as the design, innovation, and manufacturing of new equipment such as abatement devices and monitors. Some jobs will be substituted or transformed – for example, those working in extraction of fossil fuels may instead be hired by renewable energy industries. Other positions will be completely eliminated, such as production of goods such as packaging materials which may be discouraged or banned for environmental reasons (UNEP, 2008). Not all low-skilled jobs will be eliminated, but as with any new venture, there will be a learning curve to many new processes.

Because curbing environmental damage implies diversion of resources and investment from "conventional growth-oriented opportunities," demand will drop for many exports (which tend to be resource-intensive) from low-income countries (Decron, 2012: 3, 8). The economic costs of transforming an economy into a green economy will be most felt by the developing world which hopes to achieve economic growth and mobility. Decron (2012) discusses the tight link between growth and poverty and points out that inhibited growth tends to inhibit poverty reduction. Therefore, he argues, "there will be distributional effects that do not necessarily imply Pareto improvements for everyone unless there are also (lump sum) transfers to compensate the losers… [which] rarely happens" (2012; 9). For example, it is common for the poor's income to rely on "environmental capital" (natural resources, animal products, etc.), thus making them most susceptible to income shocks due to environmental policy changes (Dercon, 2012: 12). Policy change or regulation that raises the cost of using environmental capital will incentivize a shift to production that relies less on environmental goods and more on other forms of capital (physical, human). The poor tend to face greater barriers to these alternative forms of capital (for example, transition to new technology may require skills or training that is costly to the poor but more accessible to the wealthy). "The key for the poor would be the low-skilled-labor intensity [of greener industries]," Dercon explains. "The expectation that industries need to find more energy efficient ways of production may lead to higher intensity in human and physical capital with sophisticated technologies, which are not necessarily labor intensive" (Dercon, 2012: 12). Dercon acknowledges that, due to lack of existing relevant research focused on developing countries, these conclusions are greatly conjecture. Nonetheless, the conclusions imply that, absent policy provisions to favor or compensate the poor, prioritization of environmental quality through emphasis on green economic activity will promote inequality.

Musyoki (2012) argues accordingly that green economic policies must involve measures aimed at poverty reduction and empowerment of minorities to avoid unequal economic growth. Some of the policies and stipulations he suggests include equal access to skill development, opportunities for livelihood diversification, and ensure affordable green energy to the poor (Musyoki, 2012: 4). Without such accommodating policies and provisions, the transition to a greener economy may have concentrated benefits which exacerbate societal inequalities (Cook et al., 2012; ADBI, 2013). There is a plausible concern for simultaneity such that environmental degradation may exacerbate inequality *in addition to* the well-documented belief that inequality affects environmental quality (UNRISD, 2012). For this reason, I anticipate that low-skilled labor may be more adversely affected than higher skilled labor, which may potentially create inequality. This paper builds upon existing literature by empirically testing this hypothesis.

IV. DATA

This research uses panel data covering a sample of 110 countries of varying income level/development status spanning the years 2007 to 2017. Where a few data were missing, I filled gaps with the variable mean. However, for datasets with no data for an individual country across all years, I left absent data as blank observations.

My dependent variable is income inequality (*ineq*), which I measure using the United Nations Development Programme (UNDP) Human Development Reports' measure of inequality in income (UNDP, Income Inequality, Inequality in income, 2018). This metric uses the Atkinson index to capture inequality in an income distribution based on household surveys. I chose this indicator over other conventional measures of inequality (such as the GINI coefficient, Palma coefficient, or quintile ratio) primarily due to data availability. While I considered attempting to create my own income distribution ratio, international datasets are not complete enough to sufficiently improve my model by offering data for a greater number of countries. This data unavailability ultimately creates an issue of small sample size which I will discuss in my conclusions and opportunities for further research.

This paper uses air quality (*aq*) as a proxy for environmental policy (and subsequently environmental quality) as measured as an indicator included in Yale University's Environmental Performance Index (EPI). The EPI scores and ranks individual country's performance on priority environmental issues. The index is constructed using data on several measures that fall under one of two main issue areas: environmental health and ecosystem vitality (Hsu et al., 2016

Environmental Performance Index, 2016). In this index, air quality is an indicator of environmental health that is comprised of several subcomponents. The first subcomponent is household air quality, defined as the percentage of the population using solid fuels as primary cooking fuel and Health Risk from PM2.5 (particulate matter that have a diameter of less than 2.5 micrometers) exposure. The second is air pollution defined as average exposure to PM2.5. The third subcomponent is air pollution exceedance, measured as the proportion of the population with exposure levels above World Health Organization thresholds. The fourth and final subcomponent is air pollution based on exposure to nitrogen dioxide.

The second instrumental variable explored in this paper, tree cover loss (*forest)*, is also sourced from EPI 2016 data. EPI measures this as tree cover loss in greater than 50% tree cover divided by 2000 levels. It is thus expressed as a rate of loss. *See Figure 3* for a more complete breakdown of other subindexes which compose the EPI and their relative size and relevance to the air quality index. EPI is a biennial project. Data is available using the 2018 index, but the index has evolved over time. Therefore, in order to create panel data using this index, I used the 2016 backcasted data, in which the developers of the data reevaluated the years 2007 to 2015 using the 2016 index. Using this backcasted data allows me to make valid comparisons across different years (Hsu et al., 2016 Environmental Performance Index, 2016).

Because I expect, as existing literature indicates, that political and economic institutions also have a strong influence on economic inequality, I control for political oppression using the variable *opp* to capture a rating of political freedom as calculated by Freedom House in their 2018 *Freedom in the World* report. Freedom House has produced this report annually since 1973, and therefore its data covers 195 countries and 14 territories for over 40 years. This variable represents a score between 0 and 4 for each of 10 indicators of political rights such that countries with a score of 0 have the smallest degree of freedom and those with a 4 have the greatest. The questions measure three categories of interest: electoral processes, political pluralism and participation, and the functioning of government. This score is then translated into a rating between 1 and 7 such that countries with a rating of 1 are quite free and "enjoy a wide range of political rights…candidates who are elected actually rule, political parties are competitive…and the interests of minority groups are well represented in politics and government" (Puddington & Dunham, 2019). Alternatively, countries rated 7 are quite unfree "because of sever government oppression...some are police states…[while others] suffer from extreme violence or rule by regional warlords" (Puddington & Dunham, 2019). Because, when included, an index of economic freedom (Fraser Institute's Economic Freedom index) is collinear with political oppression, I omit this economic freedom variable. Theoretically, it is fair to assume that generally, the two go hand in hand such that countries that are politically free are often more economically free and globally integrated. Thus I capture the effect of both political and economic institutions using the *opp* variable.

I control for levels of education among a population as a potential determinant of income inequality. Education (*educ*) data is captured using mean years of education achieved by people age 25 and older in a population as recorded by the UNDP as part of the Human Development Reports. While I considered using literacy rates to gauge education (which would benefit this research by capturing both formal and informal education), lack of data availability dictated my use of mean years of schooling. I collected data on GDP per capita (*gdppc*) based on purchasing power parity measured in current international dollars from the World Bank (2018).

This paper also controls for the impact on inequality of reliance on agriculture relative to other industries like manufacturing which tend to drive down income inequality. Countries with higher employment in manufacturing are generally more equal because manufacturing generally offers a narrow range of relatively high earnings for modestly educated people (Long, Rasmussen, & Haworth, 1977). Contrarily, countries with a larger share of employment in agriculture will tend to be less equal. Thus, I control for this influence using *ag*, that is, the relative size of the agricultural sector. This variable takes the form of employment in agriculture as a percentage of total employment in an economy, as per the World Bank.

The control variable *ldc* is a binary variable such that *ldc* = 1 for less developed countries and *ldc* = 0 for developed. I used data from the World Bank on analytical classification history by country and the World Bank's 2018 standards for characterization of low- and middle-income countries as developing and high-income countries as developed. For years when a country was considered low- or lower-middle-income, I classified the country as "developing." If at some point it became high-income, as determined by the Bank, it would be reclassified as "developed."

The instrumental variable *cprecip* (change in precipitation between years) was calculated using data from the World Bank Group's Climate Change Knowledge Portal. The dataset was produced by the Climatic Research Unit (CRU) of University of East Anglia (UEA) and reformatted by the International Water Management Institute (IWMI). I collected the data initially as monthly averages of rainfall in millimeters, which I later converted to annual averages. This paper also experiments using tree cover loss (*forest*) as an instrumental variable. Because forests are an important subindicator of the EPI, I extracted the data from that dataset.

III. THEORY & METHODOLOGY

There is no universal understanding of what environmental policies and economic activities necessarily encourage higher environmental performance. Literature often refers to such activity as being “low-carbon,” “sustainable,” or “green.” More than a dozen published definitions of “green growth,” exist to date. The OECD synthesize some of these definitions in *Figure 2* which may be helpful for our practical understanding of what sustainable environmental policies might look like in practice. By adopting policies such as those discussed by the OECD (see *Figure 1*) and implied by the definition of low-carbon infrastructure discussed above, environmental quality will increase, though I expect at the cost of economic equality (as explained in the literature review). Alternatively, I expect that developed countries will not have a positive relationship between environmental quality and income inequality. The EKC theory indicates that after a certain point in the growth process (i.e. once a country is developed), environmental degradation sharply decreases. After a country is “developed,” the marginal impact of a policy to increase environmental quality will be smaller. By improving quality of life for the population (including the poor), perhaps they will have better health and even be able to achieve greater mobility. Therefore, it would make sense that developing countries would see a different relationship between environmental quality and income inequality than their developed counterparts.

To determine the proper estimation technique for my panel data model, I run the Hausman Specification Test which recommends a fixed effects estimation rather than random effects. This makes sense as the presence of unobserved country-fixed effects is more than likely. I run separate fixed effects estimations for a sample of developed countries and a sample of developing (or less developed) countries. Comparing normal standard errors to those which are robust reflects a difference, thus indicating the presence of heteroskedasticity. I also suspect autocorrelation may be present; thus I use the Wooldridge test for autocorrelation in panel data on both of these regressions. The tests indicate that both the regression of developing countries and that of developed countries contain autocorrelation. I therefore attempt to correct for autocorrelation and heteroskedasticity. Because my panel is of the "large N, small T" variety (that is, my data is comprised of a relatively large number of panels and a small number of time periods), I attempt to simultaneously correct for both using cluster-robust standard errors.

Existing literature argues that greater inequality negatively influences environmental quality, which I believe is a well-supported argument. I also contend that my hypothesis that environmental quality impacts income inequality holds merit. Thus, I suspect that these variables are endogenous and jointly determined. I begin with an OLS estimation (see Appendix *Table 3*) which does not yield efficient estimators, nor does it display a statistically significant relationship. This is to be expected, as it does not properly account for endogeneity. Thus, o estimate this relationship while properly accounting for endogeneity, I employ a simultaneous equations model (SEM) using an instrumental variable and two-staged least squares (2SLS) estimation.

(1) $$aq_t = \beta_0 + \beta_1 ineq_t + \beta_2 educ_t + \beta_3 gdppc_t + \beta_4 ag_t + \beta_5 opp_t + \beta_6\, cprecip_t + \beta_7\, ldc + u_t$$

(2) $$ineq_t = \propto_0 + \propto_1 aq_t + \propto_2 opp_t + \propto_3 educ_t + \propto_4 gdppp_{t-1} + \propto_5 gdppp^2{}_{t-1} + \propto_6 ag_t + \propto_7 ldc + \varepsilon_t$$

The first equation (1) represents the relationship between inequality and environmental performance with the causality that most of the existing literature supports, whereas the second (2) represents the relationship I hypothesize.

The selection of an appropriate instrument is challenging, as most factors that influence environmental issues also somehow affect income distributions. A valid instrument in this case is a variable which must be both correlated with my measure of environmental quality (air quality *aq*) and uncorrelated with inequality (*ineq*). I hypothesize that the change in precipitation (*cprecip*) affects air quality without directly influencing income inequality because precipitation washes out water-soluble pollutants and other particulate matter from air, thus improving air quality. By examining correlation coefficients, it is not clear that this instrument is strong. This instrument is a statistically significant determinant of income inequality for developing countries, as demonstrated by a p-value of 0.038 in the first-stage regression on the less developed sample. However, for the sample of developed countries, the instrument did not prove to be significant in first-stage regression results, thus calling its strength into question.

Due to the questionable nature of the strength of precipitation rates as an instrument, I also estimate the endogenous relationship using changes in tree cover (*forest*).

(3) $aq_t = \beta_0 + \beta_1 ineq_t + \beta_2 educ_t + \beta_3 gdppc_t + \beta_4 ag_t + \beta_5 opp_t + \beta_6\, cforest_t + \beta_7\, ldc + u_t$

(4) $ineq_t =$

$$\propto_0 + \propto_1 aq_t + \propto_2 opp_t + \propto_3 educ_t + \propto_4 gdppp_{t-1} + \propto_5 gdppp^2{}_{t-1} + \propto_6 ag_t + \propto_7 ldc + \varepsilon_t$$

Tree cover loss does not boast a very direct influence on income inequality. However, there is an argument to be made that deforestation has an effect on economic growth which may translate into an effect on income inequality. Referring back to previous discussion of the EKC, one could argue that deforestation (as a form of environmental degradation) increases with national income (as a country develops), until that country reaches an amount of income associated with being "developed," at which point environmental protection is less of a luxury and more of a normal good. After this threshold of national income, the deforestation would decline. Given the Kuznets Curve (the inverted U-shaped relationship between income inequality and income per capita), we know that income inequality also has this type of relationship with income per capita. Thus, there is likely some relationship (though perhaps indirect such that A leads to B leads to C) between deforestation and income inequality.

Nonetheless, this paper experiments with the *forest* instrument and compares it to the seemingly stronger instrument, *cprecip*. It is easy to understand how tree cover influences air quality, given that trees supply oxygen and absorb gaseous pollutants, thus facilitating a natural cleansing process of air (Nowak et al., 2014). The first-stage coefficient estimate on *forest* for the instrumental variable regression of less developed countries reflects statistical insignificance, while this estimate for the sample of developed countries was statistically significant. Unfortunately, like *cprecip*, it is not apparent based on correlations or first-stage regression results that *forest* is a strong instrument. Nonetheless, the inconclusive results and theory offer some support to its potential legitimacy.

V. RESULTS

Because I hypothesize endogeneity in income inequality and air quality, a linear fixed-effects estimation is unlikely to be the most efficient means of estimation. Thus, I defer to two-stage least squares estimation. First, I instrument using changes in precipitation rates (*cprecip*) as demonstrated below in columns (1) and (2) of *Table 1*.

Table 1: 2SLS Results (Dependent Variable = Income Inequality)

Variables	(1) **LDC** (*cprecip*)	(2) **Developed** (*cprecip*)	(4) **LDC** (*forest*)	(5) **Developed** (*forest*)
Air quality (*aq*)	2.242	3.752	-6.751	0.364
	(1.826)	(2.574)	(9.820)	(0.414)
Political oppression (*opp*)	2.448**	2.052	-1.058	-0.174
	(1.201)	(2.722)	(4.664)	(0.538)
Education (*educ*)	-1.360	1.581	-3.229	-0.525
	(3.155)	(2.978)	(4.093)	(0.919)
Size of agricultural sector (*ag*)	-0.0512	0.620	-0.0367	0.500*
	(0.161)	(0.481)	(0.409)	(0.302)
Lag GDP (*gdppp_1*)	-0.00791*	-0.00102	0.000238	-0.000578
	(0.00447)	(0.00126)	(0.0141)	(0.000444)
Lag GDP squared (*sqgdppp_1*)	3.73e-07*	1.07e-08	1.55e-07	6.62e-09*
	(2.12e-07)	(1.17e-08)	(5.53e-07)	(3.94e-09)
Year	1.009*	1.258	-0.745	0.302
	(0.572)	(0.893)	(2.215)	(0.199)
Constant	-2,139*	-2,813	2,016	-603.4
	(1,215)	(1,960)	(5,088)	(405.5)
N	378	433	378	435
Number of Countries	51	62	51	62

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In the two-stage estimation of the less developed sample (column 1), the coefficient on air quality suggests that a 1% increase in air quality increases income inequality by 2.242%. While this estimate's statistical insignificance does not indicate that air quality is especially important in determining income inequality in developing economies, the sign and magnitude otherwise support my hypothesis. Moreover, the estimate is practically large, and thus deserves consideration. The same two-staged regression on the sample of developed countries (column 2) reflects a positive relationship such that a 1% increase in air quality would increase income inequality by 3.75%. Similar to the developing regression, this coefficient is insignificant. The sign and magnitude of this relationship do not support my hypothesis and seem counterintuitive to EKC theory.

Given the apparent weakness of my instrument choice based on first stage statistical insignificance on *cprecip,* I conduct the same estimation using a different instrument: tree cover loss (*forest*), the results of which are reflected above in columns (3) and (4) of *Table 1.* This estimation contradicts the results of the previous estimation using *cprecip* as an instrument. Where before the coefficient on air quality for less developed countries was 2.242, it has now drastically changed in size and magnitude to -6.751. This would suggest that a 1% increase in air quality leads to a 6.751% decrease in income inequality in developing countries, which staunchly opposes my hypothesis. The coefficient on air quality in the sample of developed countries (column 4) suggests a small positive increase of 0.364%, which is nearly negligible. The magnitude counters my expectations, but the miniscule magnitude makes sense.

The drastic change in the coefficient estimate on my variable of interest, air quality, begs suspicion. Upon examining the coefficients on my controls, I find questionable estimates in the *forest* instrument regression. The coefficient estimate for political oppression (*opp*) for developing countries when instrumenting with precipitation rates shows a statistically significant and positive coefficient such that a 1 unit increase in the political rights rating (that is, a whole number increase on the 1-7 scale which demonstrates a *loss* of political freedom) increases income inequality by 2.448%. This result corresponds with intuition and theory which contend that less free societies tend to be more unequal. This estimate is statistically significant for developing countries. For developed countries, we see very similar magnitude and sign (which again makes sense), though the coefficient is now insignificant. When the *forest* instrument is employed (columns 3 and 4), we see a negative coefficient on *opp* for both developing and developed countries. This relationship follows neither intuition nor theory. Therefore, I am inclined to prefer the results from the regression which employs the precipitation rate *cprecip* as an instrument, though experimentation with other instrumental variables would surely benefit this research, as neither instrument employed in this paper is especially compelling.

VI. CONCLUSION

This paper sought to determine the nature of the relationship between environmental policies and income inequality in developing countries. This empirical study of the hypothesis that policies that increase environmental quality (as captured by air quality) increases income inequality in developing economies contributes uniquely to existing literature by formulating a simultaneous equations model to test this theory, where there had previously been no proposed empirical strategy.

Results from this SEM estimation offer some support for my hypothesis. Using the instrumental variable *cprecip,* I find a positive coefficient estimate on air quality indicative of a roughly 2.2% increase in income inequality as a result of a 1% increase in air quality in less developed countries. For the less developed sample, *cprecip* is a more valid and legitimate instrument than *forest*, and thus I consider this estimation to be most plausible. Therefore, if a policy were enacted strengthening air pollution standards thus resulting in an increase in air quality, we would expect income inequality to increase. This corroborates my hypothesis that, in developing countries, environmental policies increase income inequality. I recognize that the insignificance of the coefficient indicates that perhaps air quality is not a strong determinant of income inequality as I have estimated it. However, literature and theory support the probability that this causal relationship exists. Therefore, future work can improve upon my model and estimation techniques to hopefully find similar results with more reliable test statistics and significance levels.

The estimates for air quality's impact on income inequality in developed samples defies expectations that it would be unlikely to have a positive impact. In fact, in the estimation using the *cprecip* instrument (the instrument I ultimately prefer), this coefficient is notably larger than that in developing countries, indicating that air quality improvements lead to an even greater increase in income inequality in developed countries. Based on the EKC and the fact that developed countries are generally post-industrial and more likely to respond well to technology or skill changes than developing countries, this is a surprising result. Again, however, it is statistically insignificant, so it must be taken with a grain of salt.

A potential policy implication that may be drawn from this conclusion is that international organizations and sovereign governments alike must be weary of the consequences of "sustainable development" through pursuit of "low-carbon" or "green" infrastructure and industries. Meeting SDGs requires environmentally friendly activity that also promotes equality – which these results indicate is a challenge. All policies aimed at sustainable development ought to be accompanied by job training, skill-development programs, lump-sum transfers to compensate the poor, or other poverty reduction measures as discussed in the literature. However, due to the lack of statistical significance on these coefficients, these policy implications require further, more robust research and corroboration before these results could be truly useful and reliable for policy formulation.

Future research can improve this model in a number of ways. Firstly, as data in developing countries becomes more accessible, better variables (and proxies) will become available to more accurately measure the relationship at hand. As data collection continues to improve globally and more years of data become available, a longer time frame can be evaluated, which would improve upon this study which focuses on an effect over a relatively short time period. For example, my dependent variable, income inequality, was captured using data with many holes in it. Due to lack of availability, I was forced to use a measure of inequality that is uncommon and less ideal than a GINI coefficient or ratio of top income earners to bottom income earners in a distribution. A more typical measure of income inequality with more complete data may yield results that are easier to interpret and estimate. Moreover, lack of data on inequality dramatically reduced the sample size on which this analysis rests. Existing literature tends to work with much smaller sample sizes, such as individual countries or countries in a particular geographic region. Thus, I would recommend narrowing the sample size and ultimately the scope of the paper in accordance with these papers for more robust estimates with less gaps in data.

Future research might also involve experimenting with different instruments. On a theoretical level, finding a valid and strong instrument for this research is a challenge. That challenge is exacerbated by poor data availability for developing countries. Perhaps as data becomes more accessible, future researchers could experiment using participation in environmental agreements or environmental regulatory stringency could be experimented with as instrumental variables. Perhaps with more time, this research could have determined an identifying instrument for the simultaneous equations system that yields a statistically significant coefficient on the dependent variable of interest. Expansion of this research might also include a wider range of control variables. However, I caution that several control variables such as economic freedom, democracy, and manufacturing rates were dropped from this analysis due to collinearity. Collinearity is likely to be a problem in future research due to the inherent nature of inequality and its determinants being so closely intertwined with each other.

Researchers hoping to improve this study could also experiment with different models and estimation techniques. Perhaps to avoid the challenge of finding a stronger, valid instrument, a more experienced researcher could apply the generalized method of moments (GMM) or three-stage least squares (3SLS) to address endogeneity.

APPENDIX

Figure 1: Examples of Policy Challenges by Development Status (OECD, 2016)

Countries	Challenges	Policy options
Developed countries	• High greenhouse gas emission per capita • Lock-in into carbon intensive infrastructure	• R&D into technological innovation • Investment into low-carbon infrastructures • Pricing externality through market-based instruments
Developing Countries	• Industrialisation and increased energy and material consumption • Low energy efficiency • Weak legal enforcement	• Shifting away from carbon-intensive infrastructure and promoting energy and material-efficient technologies • Strengthening government capacity • Technology development, diffusion and transfer
Least developed countries	• High dependence on natural resources (both renewable and non-renewable) • Climate vulnerability • Lack of basic infrastructure (e.g. transport, energy and water) • Insufficient financial and technical capacity in government	• Avoiding open-access regime of natural resources • Increasing productivity of net resource use • Climate risk assessment of national policy, plans and programmes • Investment in infrastructure to support access to markets

Source: OECD, 2011b.

Figure 2: Defining Green Growth (OECD, 2016)

Box 5.1. **Defining Green Growth**

The concept of green growth has its origins in the Asia and Pacific Region. At the Fifth Ministerial Conference on Environment and Development (MCED) held in March 2005 in Seoul, 52 governments and other stakeholders from Asia and the Pacific agreed to move beyond the sustainable development rhetoric and pursue a path of "green growth". Today, at least 13 separate definitions for green growth have been identified in recent publications, including:

- **UNESCAP:** growth that emphasizes environmentally sustainable economic progress to foster low-carbon, socially inclusive development.
- **OECD:** fostering economic growth and development, while ensuring that natural assets continue to provide the resources and environmental services on which our well-being relies.
- **World Bank:** growth that is efficient in its use of natural resources, clean in that it minimizes pollution and environmental impacts, and resilient in that it accounts for natural hazards and the role of environmental management and natural capital in preventing physical disasters.
- **GGGI:** green growth is the new revolutionary development paradigm that sustains economic growth while at the same time ensuring climatic and environmental sustainability. It focuses on addressing the root causes of these challenges while ensuring the creation of the necessary channels for resource distribution and access to basic commodities for the impoverished.

Source: Green Growth Knowledge Platform; *https://sustainabledevelopment.un.org/index.php?menu=1447*.

Figure 3: EPI Breakdown (Hsu, A. et al., 2016)

Table 2: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
countryid	1,210	5.5	31.76	1	110
year	1,210	2012	3.16	2007	2017
ineq	813	23.67	10.80	4.4	68.3
aq	1,210	73.40	16.66	23.9	97.98
educ	1,210	8.32	3.23	1.3	14.1
opp	1,210	3.29	2.03	1	*polfree*
gdppc	1,210	17177.73	16645.82	613.73	75648.23
ag	1,210	29.10	25.13	0.17	91.56
ldc	1,210	.47	.50	0	1
cprecip	1,123	7.97e+11	2.29e+11	5.15e+07	1.92e+12
forest	1,210	29.75	20.60	0.69	89.26

Table 3: OLS Results (Dependent Variable = Income Inequality)

Variables	(1) LDC	(2) Developed
Air quality (*aq*)	0.111	0.00326
	(0.174)	(0.0733)
Political oppression (*opp*)	1.617	-0.413
	(1.055)	(0.512)
Education (*educ*)	-1.803	-0.759
	(2.985)	(0.925)
Size of agricultural sector (*ag*)	-0.0478	0.488
	(0.177)	(0.303)
Lag GDP (*gdppp_1*)	-0.00598	-0.000536
	(0.00502)	(0.000423)
Lag GDP squared (*sqgdppp_1*)	3.21e-07	6.22e-09*
	(2.42e-07)	(3.64e-09)
Year	0.593	0.205
	(0.532)	(0.194)
Constant	-1,155	-378.4
	(1,062)	(383.1)
N	378	435
R-squared	0.054	0.091
Number of Countries	51	62

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