

JOURNAL OF THE ACADEMY OF BUSINESS EDUCATION

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CONTENTS

FALL 2024

- 1 **Venture Capital Fund Portfolios: A Qualitative, Mean-Variance Model**
by Manuel Tarrazo
- 35 **What Sections of Courses Fill Up First? Investigating Class Selection by
Business Students** by Mikhail Kouliavtsev
- 55 **Hoops and Health Care Fraud: The Defrauding of the NBPA Health Plan**
by Jake Lechner, Matthew Heard, Tyler Custis, and
Phillip Adam
- 68 **Gender Diversity Dividends and Divisions: Student Team Strategic
Decision-Making, Team Performance, and Corporate Social
Responsibility** by Wendy Cook, Theresa Wilson, and
William Provaznik
- 89 **True Applications of Economics from the Business World**
by Stefani Milovanska-Farrington, Jeremy Bess, and
Patrick Luce
- 114 **Academic Performance in Standardized Testing: The Mediation Role of
Big-5 Conscientiousness in the Relationship between Core
Self-Evaluation and ETS Test Scores** by Lisa A. Schwartz and
Michael T. Geier

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Venture Capital Fund Portfolios: A Qualitative, Mean-Variance Model

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In this study, we introduce a correlation-based version of Markowitz's mean-variance model, which can be used for qualitative analysis. The application of the model was very successful in the two contexts we chose (1- and 3-hour presentations and classroom time) and to each of the audiences selected (undergraduate and venture capital practitioners in the United States and graduate students in France). The model liberates traditional mean-variance from its historical data-needing corset and replaces it with expert knowledge. In addition, the model is designed to be used in concentrated portfolios, which may enable investors to reduce risk by enhancing information.

Keywords: Portfolio analysis, Mean-Variance, Correlation, Qualitative Analysis, Venture Capital, Early Stage Investing, Silicon Valley, Entrepreneurship, Start-ups, Entrepreneurship, Investments, Venture Capital, Qualitative Mean-Variance Model

Disciplines of Interest: Business Finance, Economics

"An investor, like the venture capitalist selecting ventures in which to invest, faces a sorting problem (distinguishing good investments from bad)." [Barry, 1994, p. 10]

"As long as no quantitative measure is available, qualitative description is important." [Morgenstern, 1951, p. 283]

"To suppose that safety-first consists in having a small gamble in a large number of different [companies] where I have no information to reach a good judgment, as compared with a substantial stake in a company where one's information is adequate, strikes me as a travesty of investment policy." [Keynes, 1934]

INTRODUCTION AND LITERATURE REVIEW

This study makes three contributions. First, it develops a correlation-based analogue to the mean-variance portfolio-selection model (i.e., Markowitz,

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1952). Second, it introduces the modifications required to permit a qualitative interpretation of the previous model. Third, it presents two promising applications of the model: 1) venture capital project selection; and 2) qualitative analysis of portfolio positions.

Our contributions originated in our previous research on theoretical and applied mean-variance analysis, both in educational and actual investing contexts. Conversations with venture capitalists from the San Francisco Bay Area motivated this specific study. Some of the early conversations took place during the *Silicon Valley Venture Capital Symposium* series, where some of the preliminary developments were first presented [Tarrazo, 2014b]. Venture capital companies run private partnerships where senior partners actually get involved in the management of these companies in which the fund invests. This involvement creates resource (managerial) constraints that add to the financial constraints (i.e., limited funds to be invested in a few of the many possible projects submitted to the fund). Selectivity, therefore, becomes the first critical feature of their investing effort. Other investors, especially households, cannot “spray and pray” their funds or managerial time and talent over many investments.

First, venture capitalists’ most interesting projects all refer to new ventures and, in the most innovative cases, new products and markets. Therefore, and second, they rarely have any historical information that can be used as numerical support, much less any information based on repetition (resampling), such as that suitable to statistical analysis. As a third critical feature, each project is fully forward-looking, which means projections and expectations are never able to capture all relevant factors and possible contingent states.

Enter portfolio theory: Markowitz’s [1952] version of mean-variance analysis took the finance world by storm and motivated many other important developments in the areas of optimization, money demand, inventory analysis, and financial markets equilibrium. The enhanced understanding of risk and return advanced by this model facilitated the development of mutual funds, which offer diversification at reasonable management cost. However, the current situation concerning portfolio optimization is paradoxical. On the one hand, both practitioners and theorists have concerns regarding mean-variance analyses. Doran and Wright [2010], for instance, note little use of it by finance professors. On the other hand, it has made itself essential in situations such as illiquid investments, natural resource allocations, inventories, pharmaceutical R&D, certain military applications, local government decision-making, and many others (see the recent survey by Salo, Keisler, and Morton [2011]).

The possible current impasse with mean-variance optimization in finance is easy to explain. The original specification was very straightforward but later became loaded with so many features that it became difficult to 1) see what the model was doing and 2) see any connections between security characteristics and optimal portfolio weights. This overburdening was done for commercial reasons to develop new product variations to attract funding and, for

academic reasons, to produce variations of both theoretical and practical interest. The result was to overwhelm the original model. Very tellingly for our purposes, the original specification never favored taking positions in a large number of securities. In addition, it reduces the number of holdings during financial crises [Tarrazo, 2018]. However, users have been shown to have very strong preconceived notions of what the output of the model should be. This preference holds particularly true with respect to the number of optimal securities, and "... frustrated by the seemingly unreasonable solutions that portfolio optimizations would produce, ... [users] abandoned the technology or relinquished most of its benefits by applying so many constraints that the solution was largely predetermined" [Jones, Lim, and Zangari, 2007, p. 24]. It is very interesting to note that, in its original specification, Markowitz's model aimed to help (any type of) investors in their sorting problem alluded to in our prefatory quote: distinguishing good from bad investments.

Another interesting situation concerns qualitative analysis. Despite the preeminence of quantitative analysis in the past century, particularly with respect to analytical and operational methods in economics, researchers continue to struggle to incorporate every type of information into decision-making. Hayek [(1974) 1989] stressed the serious problems caused by neglecting information simply because it was not readily quantifiable. Uzawa [1960] proved that even ordinal rankings could suffice to support a rational demand theory. Strategic analysis is eminently qualitative in Mintzberg's [1978] influential approach.

Currently, there is strong interest in decision-making models, methodologies, and techniques that can integrate quantitative and qualitative information (i.e., hybrid models; see the survey by Smith and Winterfeldt [2004] and the effort in mapping attributes and choices in Hogarth and Karelia [2005]). In a way, the use of heuristics (rules of thumb), in assessing commercial success in early stage ventures by Åstebro and Elhedhli [2006], is a sorting procedure equivalent to a portfolio-selection model. The young methodology of fuzzy sets, initiated by Zadeh [1965], offers additional methods to implement approximate reasoning in situations characterized by imprecision and vagueness and in the analysis of time-critical processes such as those in venture capital projects. Tarrazo [1997, 1999] employed the algebra of fuzzy sets (relational possibilistic modeling equations) to formulate a variety of qualitative portfolio analysis. Tarrazo [2008b] can be read as a survey of the available methodologies that can bridge words and numbers.

Our steps to develop a qualitative reformulation of the mean-variance model are as follows: 1) simplify the original model to its bare essentials; 2) focus on a few investing choices; 3) establish a qualitative, correlation-based analogue (hereafter, QC); and 4) see if its applications are helpful.

We have experimentally applied the QC model to entrepreneurial projects and start-ups as well as to established firms. We have done so in three contexts: 1) entrepreneurial courses in the United States and abroad (Master in Strategy and Entrepreneurship, University of Paris II, France); 2) the 2013

Silicon Valley Research Symposium, where we introduced the model to a select group of venture capital professionals; and 3) established firms in the context of the aforementioned program in France [Tarrazo, 2014b].

Our research offered unexpected rewards. Some of these were academic in nature. For example, statisticians in physical and social sciences have put a great deal of effort into strengthening the signals extractable from various types of information. The relationship between first moments (about the origin, the mean) and second moments (about the mean, variance) has been the focus of a great deal of research. This relationship is known as the performance ratio in portfolio theory, as well as signal-to-noise ratios, μ_i/σ_i , in other contexts. This research produced insights concerning regression analysis that culminated in the modern path analysis. It has been shown that the very same ratio— r_i/σ_i , individual security return-to-standard deviation—is the key to portfolio optimization. Therefore, it must also be at least one of the keys to selecting qualitatively successful projects. In addition, the methods we will present lend themselves to be synthesized in some operational heuristics. (Note: μ_i denotes the expected mean return but, in practice, the historical average return, r_i , is used.)

Another unexpected reward originated in the versatility of the QC model. In its qualitative context, there may be a way to link the normally static optimization to project and portfolio time horizons or time windows. This approach might be useful in the case of venture capitalists, who often think on k-multiples of the capital put at risk, and time windows or preestablished horizons. In addition, one can observe a convergence or integration between what the QC model does and the findings of recent contributions to entrepreneurship on the one hand and the way venture capitalists invest and the current developments in portfolio analysis on the other. Our qualitative methods may prove to be useful in new modalities of investing such as crowdfunding and (group) angel investing. Perhaps the common thread of what qualitative analysis offers is a clarification of diversification that, until now, has been confined to a realm in which it was never sufficiently defined neither at the theoretical nor at the application level, to the point that some investors (Peter Lynch, no less) refer to it as “diworsification.”

The first section of the study focuses on the mean-variance model and its reformulation in the qualitative correlation-based model. The second section describes the preliminary applications of the model, and the third evaluates and pursues some of the unexpected leads offered by the model. In this study, we focus on the development and initial applications to best help those educators and professionals who may be interested in applying the qualitative portfolio model themselves and who may want to also add and try their own variations.

The material presented in this work is interdisciplinary and covers several important areas of research: 1) investments in general and portfolio analysis in particular; 2) applied statistics in investing; and 3) actual investing in both

mature, publicly traded stocks, and start-ups. The work presented is also multi-purpose (used in the classroom and in presentations). Finally, it has an applied intention. These characteristics present many challenges to both the author and the reader, not the least of which is finding a set of references with the same properties. An early set of 70 references aimed at satisfying those readers with knowledge and experience in areas 1, 2, and 3 above. This early set was primarily concerned with studies providing solid foundations of the exercise presented. To those early references, we added another five with the intention to connect the exercise to recent research and to future work as well:

- Scherer [2013] notes that small portfolios may not necessarily be undiversified.
- Lassance [2022] shows that mean-variance theory provides reasonable numbers in the presence of non-Gaussian returns.
- Zweig [2022], writing in the context of mutual and exchange traded funds, illustrates why “bigger is not better.”
- Rose [2014] pioneers applying portfolio theory to angel investing, to which he dedicates an entire chapter.
- Lo and Foerster [2022], after reviewing major investment theories, suggest that optimal portfolios may be unique to each individual investor’s situation, characteristics, and experiences. We present here a view that is fully compatible with the work.

QUANTITATIVE AND QUALITATIVE MEAN-VARIANCE ANALYSIS

Our task in this section is to present mean-variance analysis in the most suitable way for its reformulation as a qualitative model and show why it should be of interest to venture capital and other investors in start-ups. Perhaps the most straightforward way to do so is to return to its origins: Markowitz [1952] provided the necessary information, in the most appealing manner (charts and logical explanations), to attract different types of professionals to portfolio analysis. Markowitz [1959] did have sufficient space to carefully demonstrate and explain how he transferred his investment intuitions into the framework of mean-variance analysis.

The following references offer a good basis for understanding mean-variance analysis. Constantinides and Malliaris’s [1995] work is more than a well-crafted survey. It not only integrates the various strands of portfolio theory (circa 1995) but also specifically stresses that investors’ preferences are already implicit in portfolio optimization, and, therefore, one does not need to add yet another function into the mix [op. cit., p. 4]. Steinbach [2001] offers a very comprehensive survey that, despite its mathematical nature, strives to enhance the theoretical and applied reach of mean-variance models. He initiates his

study by first getting rid of what he refers to as “inessential generality”—that is, all those bells and whistles a mathematician has no patience for because they interfere with the model without adding anything (e.g., inequalities when they are not needed). Steinbach [2001] also helps to distinguish what difficulties originate in the model and what difficulties are due to the complex environment in which the model is used (e.g., monetary instability, international effects, hard-to-anticipate policies). Rubinstein [2002] celebrates the fifty-year anniversary of Markowitz’s [1952] contribution. A review of Rubinstein [2006] is essential to comprehend the role played by portfolio theory in the modern edifice of finance.

As we have noted earlier, it is true that Markowitz [1952], despite his extraordinary accomplishments, left some important issues unspecified even while opening many doors to be explored later on. However, it seems that every time something was added to the basic model (utility theory, optimization variants, market issues, advanced statistics, advanced mathematics, and so forth), other sources of complications were implicated.

Mean-Variance Portfolio Optimization

Let us introduce the easiest formulation of mean-variance analysis. We may call it the “algebraic approach” because it uses linear algebra; for example, it is used in solving a set of simultaneous equations. If readers even vaguely remember solving equations from high school, they should have no problem acquiring a considerable, practical understanding of mean-variance analysis and how it can relate to investing in start-ups.

Let’s use a list for clarity and conciseness.

1. Investors want to make money from their invested capital. Their progress is measured by the returns periodically calculated on market prices (usually as the natural log of price relatives, $r_t = \ln(p_t/p_{t-1})$). Investors also care about risk, which is approximated by the dispersion of returns around their expected target (i.e., their variance). Another fundamental aspect of portfolio theory is that it was conceived, and is understood, in terms of expectations.
2. The traditional mean-variance portfolio model is based on historical analysis. Therefore, we need data. Mean-variance analyses do not provide much guidance concerning how many securities are needed to get started or about the number of return observations to collect for each security, the type of frequency, and the closing values. These are important issues, and only recently has there been an authoritative pronouncement in the literature with respect to them. Fabozzi, Gupta, and Markowitz [2000] acknowledge that, with respect to the items above, “the truth is that there is no right answer because we are dealing with

the world of uncertainty” [Fabozzi, Gupta, and Markowitz, 2000, p. 10]. However, they suggest a reasonable protocol we have always used (namely, monthly returns and the five-year sample period; op. cit., p. 9). It is standard to calculate returns using closing prices, adjusted for dividends and splits.

3. Next, we calculate returns and statistical indicators: sample average, variance, and covariance terms. That is, let R represent an n -by- m matrix of returns (n observations, m variables) and b a vector of average returns. Let A represent the variance-covariance matrix for the return matrix R . The function to be optimized is the following: $F(A, b, x) = -1/2x'A x + x'b$, where x' signifies the transpose of vector x . Differentiating with respect to the vector of optimal proportions x and equating the result to zero (first-order conditions), we obtain a very familiar simultaneous equation system, $A x = b$, with solutions $x = A^{-1} b$. Customarily, the vector of average returns is represented as r ; therefore, let $b = r$. The optimal portfolio weights are calculated by rebalancing the x^* so that the sum adds up to one: $w_i^* = x_i / \sum(x_i)$, where w_i and x_i are the characteristic elements in the m -by-one vectors w and x . Then, we can easily calculate portfolio numbers: portfolio return, $r_p = w'b$; portfolio variance, $\text{var}_p = w'A w$. This approach is known as the algebraic approach to portfolio optimization simply because it relies on linear algebra. The top panel in Table 1 shows both the variance-covariance table (risk of each security with itself (i.e., its variance, σ_i^2) and in relation to other securities (i.e., covariance, σ_{ij}^2). We also have the vector of average returns on the right-hand side.

Now we get to the mathematical part of the optimization, and our account will be easier to follow if we take a look at Table 1, which summarizes some of the key aspects of mean-variance optimizations. It resembles a Rosetta Stone in that it includes all insights needed to learn the secrets of portfolio optimization.

4. Within the algebraic context, concepts, variables and notation are kept very straightforward. One can start by simply solving the $A x = b$ system. The results are shown on the left-hand side in Panel 2 (Table 1). The x solution variables have two issues that must be taken care of: 1) They do not add up to one [$\sum(x) = 6.8324$]. Therefore, we must normalize them; we divide each term by that sum, and we have portfolio weights adding to 1. Each of these weights represents our position in each security. For example, 0.10 would mean that we have invested 10% of our initial wealth into that security. Still, we have yet another issue: Some values for x are negative. For some time, according to textbooks, we would understand that those negative numbers would imply borrowing securities one does not own and selling them (i.e., short selling). However, in practice, those weights are not acceptable. Also, 2) they are

Table 1. Mean-Variance Optimization

Panel 1: Variance-Covariance matrix (A), and returns vector (b):							
	MCD	IBM	HPQ	KO	PFE	GE	Returns
MCD	0.0023372	0.000917	0.001509	0.001356	0.001494	0.002187	0.016911
IBM	0.0009172	0.003591	0.002336	0.001217	0.000315	0.002359	0.009801
HPQ	0.0015089	0.002336	0.004872	0.001488	0.001697	0.003797	0.010851
KO	0.0013561	0.001217	0.001488	0.00241	0.001117	0.002856	0.005473
PFE	0.0014941	0.000315	0.001697	0.001117	0.004184	0.003008	−0.00709
GE	0.0021867	0.002359	0.003797	0.002856	0.003008	0.010211	−0.01148
Panel 2: Optimal results, $Ax=b$, $x \times = A^{-1}b$, $w_i = x_i/\text{sum}(x_i)$							
	Short Sales ($w_i < 0$) Allowed Ranking			No Short Sales ($w_i > 0$)			
	x	w	ri/C'i =	ri/stdi	xi	wi	ri/C'i =
MCD	11.2375	1.6447	6.8324	0.349792	6.8510	0.8749	7.830387
IBM	0.8333	0.1220	6.8324	0.163552	0.9794	0.1251	7.830387
HPQ	2.4870	0.3640	6.8324	0.155465			
KO	−0.0027	−0.0004	6.8324	0.111483			
PFE	−4.3600	−0.6381	6.8324	−0.1096			
GE	−3.3627	−0.4922	6.8324	−0.11358			
Sum	6.8324	1.0000			7.8304	1.0000	
Panel 3: Alternative sequential approaches to find the optimal, no short sales ($w_i > 0$), portfolio							
	Basis Reduction (BR)			Selective Basis Addition (SBA)			
	Opt 1	Opt 2	Opt 3	Opt 1	Opt 2	Opt 3	
MCD	1.644735	0.910016	0.874922	0.874922	0.910016	1.2470115	
IBM	0.121958	0.166776	0.125078	0.125078	0.166776	0.2480148	
HPQ	0.364006	−0.07679			−0.07679		
KO	−0.0004					−0.495026	
PFE	−0.63813						
GE	−0.49216						
Sum	1	1	1	1	1	1	
rp	0.043129	0.01619	0.016021	0.016021	0.01619	0.0208092	
pvar	0.006312	0.002072	0.002046	0.002046	0.002072	0.0030403	
pstd	0.079451	0.045517	0.045233	0.045233	0.045517	0.0551393	
rp/pstd	0.542843	0.355695	0.354195	0.354195	0.355695	0.377394	
rp/pvar	6.832443	7.814468	7.830387	7.830387	7.814468	6.8443796	

Data: Securities selected from the Dow-Jones Industrial Average, 6/1/2010–5/31/2005 (see Table 3).

unrealistic: Imagine buying 1,123% of your wealth in MCD by short selling 336.27% of your wealth in GE, among other equally fantastic trades. In addition, the optimization does not reflect short-selling constraints (e.g., leverage, liquidity, broker interest paid/earned) and does not obey Federal Reserve regulations. In other words, those weights are not useful at all. Fortunately, getting rid of them is very easy to do within the algebraic approach. For example, one can run the first optimization and eliminate those variables that produce negative x 's. It usually takes between two to four steps to get to the "all positive" solution. This is done in the left-hand side of panel three (basis reduction). First, we take off the data for KO, PFE, and GE by removing the corresponding columns and rows from A and b , respectively, and optimize again. We see that HPQ's weight, which was positive, is now negative. This shows some securities are only worthwhile to purchase because of the financing brought in by short selling (negative weights). Remove that financing and those securities cannot carry their own weight. Now we remove the data for HPQ and solve the remaining equations again. We arrive at an optimal, two-security portfolio ($k = 2$), with 87.49% allocated to MCD and 12.50% to IBM. Instead of the peeling-off method (basis reduction), we could have tried a "selective basis addition" method, whereby we start with the two securities with the highest performance ratios (r_i/σ_i) and continue adding in one security at a time. The security would be kept if the weight is positive; otherwise, it would be discarded. The optimization is complete when we run out of securities with positive returns. Note that the $rp/pvar$ for the optimal two-security portfolio (7.83) is larger than that of the first portfolio (6.83).

Historically, getting rid of those negative weights has been made a very complicated affair, even when Martin [1955] suggested the straightforward way to do it, as we have described in the previous paragraph. However, as Tarrazo [2014a] illustrates, at every step of the search, the more complex option—nonlinear programming, quadratic programming, and Lagrange multiplier—was chosen over the most direct one, to the detriment of understanding how the model works. As it turns out, the simplest way to optimize a portfolio had been there all along because the underlying equation is quadratic. Martin [1955] suggests running the "peeling-off" basis reduction method. Tarrazo [2009] introduced the selected basis addition using a graph theory rationale. Jobson and Korkie [1983] show that mean-variance portfolios could be calculated with an "atypical" regression, where a constant (a column of ones will do) takes the place of the regression and the regression is run without an intercept (see also Britten-Jones, 1999). In sum, there are many ways to optimize a portfolio without using mathematical programming [Tarrazo, 2014a].

5. Insights and other technical details: The first insight is that individual return-to-risk ranking (r_i/σ_i) rules the optimization. Note that MCD and IBM are the top two securities in terms of the aforementioned ratio (more on that later). The second insight concerns the effect of the sign of

average returns on the optimization. We can state that positive returns are a mathematically and economically necessary condition for a security to be included in the optimal portfolio but not sufficient [Tarrazo, 2009, 2008a]. We see that the cases of HP and KO, despite having positive average returns, are not included in the optimizations. The “necessary” part of the assertion can be explained (and proved) in at least three ways:

- a. Using finance logic, the marginal return-to-risk benefit from each security (marginal return/marginal variance) must be positive in the optimal portfolio, $r_p > 0$; otherwise, the investor should not invest. The marginal return for a security is its own return, and the marginal variance can be computed by premultiplying optimal weights by the transpose of the variance-covariance matrix. The marginal covariance is positive for any security in the optimal portfolio, so $r_p > 0$ requires $r_i > 0$ as well.
- b. Because of linearity, that optimal ratio is shared both at the portfolio and security levels. The marginal return-to-marginal risk ($r_i/C'i$) is shown in the rightmost column following the optimization. The value for each security equals 7.8304, which coincides with the value at the portfolio level, $r_p/varp = 7.8304$.
- c. Inspecting the logic of the simplex algorithm at play in the optimization, it always selects the positive “signals” offered by positive returns. Also, when the individual return is negative, its inclusion would lower the objective function. Therefore, it is not selected. Our third insight is that the best optimized result should come from giving the optimizer a good choice set. In other words, out of an initial set of “m” securities, we may have to discard some to hold the optimal set of “k” securities ($k < m$). Mean-variance offers no guidance on this one, other than preselecting securities with positive average returns.

With respect to sufficiency, a security with positive returns will be included in the optimal portfolio when its inclusion increases the return-to-risk ratio of the portfolio.

6. Three other important technical details are as follows: First, due to the positive definiteness of A , the portfolio calculated above exists (A is invertible) and is unique. This portfolio is known as the “tangent portfolio.” It has important properties: First, it offers a higher return-to-risk within all efficient portfolios, those for which one cannot find a higher return without incurring higher risks. Second, the tangent portfolio embodies arbitrage relationships, which can be thought of as “efficiency” relationships at the level of the securities of the portfolio (and out of the portfolio in a market context). This property can be traced back to the linear arbitrage rule that tells us that the summation of weights in the portfolio (w_p)

equals 1, $w_p = \text{sum}(w_i) = 1$, which, in turn, causes $w_p r_p = 1 r_p = r_p = \text{sum}(w_i \times r_i)$. In other words, the return on the portfolio is the weighted average of individual returns because the optimization takes care of arbitrage opportunities (see Jarrow, 1988, p. 24). Third, the tangent portfolio is the best-linear-unbiased estimator.

And now we can highlight some aspects of the mean-variance of particular interest for the venture capital case.

- a. First, it can be shown that the security with the highest return will always be included in the optimization [Samuelson, 1967].
- b. Second, as we have noted earlier, if a tangent portfolio has positive returns (otherwise, it is not worth investing in), a security's positive return is a necessary, but not sufficient, condition for its inclusion in the optimal portfolio, as illustrated by the HPQ and KO cases in Table 1. Some people focus on the so-called minimum variance (MV) portfolio that some say disregards individual security returns (optimizes C only). This focus is not interesting at all to venture capitalists because they are after returns, and the individual quality of the securities in a portfolio (as measured by the r_i/σ_i ratio) deteriorates markedly as we travel downward from the tangent toward the MV portfolio. One must wonder whether the MV portfolio is worthwhile for any practical purpose.
- c. Third, the signal-to-noise, μ_i/σ_i , ratio rules the show. The best portfolio is that with the highest $r_p/p\text{var}$ (or $r_p/p\text{std}$). As expected, the individual signal-to-noise ratios have a lot to do with that value. We propose that covariance effects cannot be trusted to produce a high-yield portfolio even in the best possible conditions. The power of the individual signal-to-noise or performance ratios can be surmised in various ways: 1) If all the covariances are zero, $x_i = r_i/\sigma_i^2$, and $w_i = (r_i/\sigma_i^2)/\text{sum}(x_i)$, as usual. In other words, without a covariance effect, the individual r_i/σ_i is all that matters; and 2) the variance-covariance matrix A is positive definite, which means it has a "weighty" main diagonal (the left-corner to right-bottom diagonal of variances). This means individual variances tend to have a greater influence on optimization than the covariances do (off-diagonal elements). In fact, as noted earlier, the positive definiteness ensures A is invertible and, therefore, that $Ax = r$ has a unique solution; and 3) the ranking of optimal weights (w_i) is always close to the ranking by individual r_i/σ_i ratios, as even the brief example in Table 1 illustrates (note how the ranking of performance ratios anticipates the ranking of optimal weights). In sum, the ratio r_i/σ_i can be used as a heuristic to set up a ranking of investments, and one would not be (qualitatively) too far off the mark by proceeding in that way.
- d. Fourth, what is the role of diversification and how strong are its effects on optimal weights? Figure 1 shows eight mean-variance optimizations for some companies located in the San Francisco Bay Area, each with

ten initial securities and five years of monthly returns (January 31, 2010–March 31, 2015). As you may note, securities are first selected according to their individual performance ratios (r_i/σ_i). After that, covariance effects have their turn. However, they may modify only some of the ranking established by individual performance ratios, as in all cases on the left-hand side (i.e., similar to rearranging the existing chairs in a dining room). In some other cases, other securities are brought in (new chairs), but they rarely alter the positions significantly, as all the right-hand side cases illustrate. Mean-variance seems to prefer the strongest individual performance ratios, especially when those performers are uncorrelated with others (e.g., AAPL, WCN); PG&E and NFLX were other companies offering good diversification effects for this data sample. Yep! The chairs analogy brings to mind the saying about “rearranging the deck-chairs on the Titanic”: diversification will not do much for a bad portfolio.

- e. Fifth, portfolio optimizations favor small numbers of stocks, even for the MV portfolio. “When the chips are down” (i.e., “times of crisis”), the portfolio tries to maintain the highest return-to-risk by reducing the number of securities [Tarrazo, 2018]. As Jagannathan and Ma [2003] observe, “A striking feature of MV portfolios constructed to the restriction that portfolio weights should be nonnegative is that investment is spread over only a few stocks. The MV portfolio of a 500-stock universe has between 24 and 40 stocks, depending on which covariance matrix estimator was used” [op. cit., p. 1677]. Table 2 shows three different tangent portfolios for companies included in the Dow-Jones Industrial Average of thirty stocks. Note the dates: one overlapping the 2000 dot.com bubble, another in the 2003–2008 presumed good-weather sailing, and the other in the aftermath of the subprime-originated crisis. Mean-variance selects very few stocks: two out of 30 in the oldest and newest optimizations. Despite the apparently numerous non zeros in the middle optimization, one can observe that four stocks make up 58.33% of the investing and eight about 90% of all optimal investing. There seems to be both a search for signal strength in the optimizations and a “winner takes all” effect.
- f. Sixth and final, quantitative mean-variance optimizations may not be very accurate, especially if they involve a large number of securities [Sengupta and Sfeir, 1985]. The lack of accuracy can be severe even in relatively small sets of variables, such as those for the Dow-Jones 30 stock average. For instance, in the optimization for the 2003–2008 period, the determinant of the variance–covariance matrix has thirty-four zeros before the first significant decimal and a condition number of 24.86: a veritable numerical tragedy. In econometrics, this problem afflicting regression matrices has been recognized for some time (multicollinearity). It is easy to appreciate the severity of the accuracy problem

Figure 1. Mean-Variance Optimization of Small Portfolios

ticker	ri/stdi	Case # 4	ticker	wi*
MCK	0.403579		WCN	27.93%
INTU	0.352168		MCK	19.60%
WCN	0.324509		CLX	17.15%
CLX	0.322128		EXPO	16.23%
GILD	0.316248		INTUIT	9.73%
EXPO	0.313732		GILD	9.35%
WFC	0.206738		rp	0.017094
GOOGL	0.158931		stdp	0.028145
CVX	0.151725		rp/stdp	0.607349
SCHW	0.114099			

ticker	ri/stdi	Case # 5	ticker	wi*
ROST	0.406425		WCN	38.17%
AAPL	0.326821		ROST	29.75%
WCN	0.324509		AAPL	17.61%
WFC	0.206738		PCG	11.80%
ADBE	0.17337		GOOGL	2.66%
GOOGL	0.158931		rp	0.017324
PCG	0.152027		stdp	0.032027
GPS	0.138264		rp/stdp	0.54093
INTC	0.136592			
ORCL	0.132936			

ticker	ri/stdi	Case # 6	ticker	wi*
MCK	0.403579		CLX	34.04%
V	0.330625		MCK	32.96%
CLX	0.322128		V	23.02%
CRM	0.241211		CRM	9.98%
RHI	0.181243			
ADBE	0.17337		rp	0.017336
CVX	0.151725		stdp	0.03293
INFA	0.077483		rp/stdp	0.526438
NVDA	0.03536			
NKTR	-0.03914			

ticker	ri/stdi	Case # 8	ticker	wi*
AAPL	0.326821		AAPL	41.90%
GILD	0.316248		GILD	26.03%
YHOO	0.222769		YHOO	21.03%
WFC	0.206738		IGATE	5.71%
IGATE	0.19562		NFLX	5.33%
GOOGL	0.158931		rp	0.022316
NFLX	0.142374		stdp	0.049899
GPS	0.138264		rp/stdp	0.447237
INTC	0.136592			
NVDA	0.03536			

ticker	ri/stdi	Case # 10	ticker	wi*
INTU	0.352168		INTU	50.51%
AAPL	0.326821		AAPL	36.10%
CRM	0.241211		EA	10.07%
EA	0.189738		CRM	3.33%
ADBE	0.17337			
GOOGL	0.158931		rp	0.01993
ORCL	0.132936		stdp	0.042919
TRMB	0.104412		rp/stdp	0.464375
BIO	0.076412			
DLB	-0.06208			

ticker	ri/stdi	Case #1	ticker	wi*
AAPL	0.326821		AAPL	41.97%
WFC	0.206738		PCG	30.03%
EBAY	0.183991		EBAY	15.95%
ADBE	0.17337		ADBE	6.31%
GOOGL	0.158931		WFC	5.08%
PCG	0.152027		SNDK	0.65%
CVX	0.151725		rp	0.015158
INTC	0.136592		stdp	0.038298
ORCL	0.132936		rp/stdp	0.395789
SNDK	0.094353			

when regressions are used to build portfolios (see Britten-Jones, 1999; Rekenhtaler, 1999).

Now we are ready to build a qualitative analog of the mean-variance model.

Qualitative Mean-Variance Analysis

In this section, we have to complete two tasks: first, to present the correlation-based specification of the mean-variance mode; and, second, to enable it to carry qualitative interpretations. This is done in each of the following subsections.

Table 2. Mean-Variance Optimization: Dow-Jones Industrial Average

	6/1/2010-5/31/2005			4/1/2008-3/31/2003			11/3/2003-12/01/1998		
	Ticker	Sorted ri/stdi	NSS Tangent	Ticker	Sorted ri/stdi	NSS Tangent	Ticker	Sorted ri/stdi	NSS Tangent
1	MCD	0.349792	0.874922	MCD	0.422509	0.203917	MMM	0.261209	0.820107
2	IBM	0.163552	0.125078	UTX	0.379721	0.084	C	0.154224	0.160004
3	HPQ	0.155465		CVX	0.37362	0.116184	CAT	0.106454	0
4	KO	0.111483		XOM	0.32892	0.011961	UTX	0.096706	0
5	TRV	0.105293		CAT	0.322833	0.086492	AA	0.095815	0
6	CVX	0.09833		BA	0.317197	0.112493	AXP	0.074469	0
7	UTX	0.095426		HPQ	0.287006	0	WMT	0.068275	0.002498
8	PG	0.084841		T	0.256979	0.048972	JNJ	0.063278	0
9	T	0.077528		PG	0.241008	0.02235	XOM	0.055344	0
10	MRK	0.072305		KO	0.210102	0	BA	0.038652	0
11	DIS	0.067789		JPM	0.204281	0.055069	MO	0.036374	0
12	MMM	0.058056		DIS	0.190007	0	PG	0.031413	0.017391
13	CAT	0.051682		GE	0.17703	0	HPQ	0.020182	0
14	JPM	0.030403		AXP	0.146239	0	INTC	0.014146	0
15	WMT	0.029817		JNJ	0.135872	0.150697	IBM	0.002148	0
16	XOM	0.029685		BAC	0.131659	0.01768	IP	-0.00982	
17	VZ	0.026016		AA	0.129226	0	GE	-0.01169	
18	CSCO	0.022831		IBM	0.122984	0	HD	-0.01277	
19	JNJ	0.016389		MMM	0.116577	0	DD	-0.02044	
20	KFT	0.014402		DD	0.095524	0	GM	-0.02099	
21	BA	0.011325		VZ	0.083618	0	MSFT	-0.0364	
22	MSFT	0.001698		MSFT	0.082953	0	HON	-0.03644	

Table 2. Continued

	6/1/2010-5/31/2005				4/1/2008-3/31/2003				11/3/2003-12/01/1998			
	Ticker	Sorted ri/stdi	NSS Tangent	Ticker	Sorted ri/stdi	NSS Tangent	Ticker	Sorted ri/stdi	NSS Tangent			
23	DD	-0.00291		INTC	0.050069	0	JPM	-0.03657				
24	AXP	-0.00955		HD	0.032792	0	DIS	-0.03945				
25	INTC	-0.03481		WMT	0.009282	0.090185	KO	-0.06381				
26	HD	-0.04247		MRK	-0.03431	0	MCD	-0.06783				
27	BAC	-0.08715		AIG	-0.04532	0	MRK	-0.08187				
28	AA	-0.09757		GM	-0.05196	0	SBC	-0.10922				
29	PFE	-0.1096		PFE	-0.06166	0	EK	-0.12969				
30	GE	-0.11358		C	-0.08424	0	T	-0.26613				
monthly	rp		0.016021			0.014226			0.016352			
	pvar		0.002046			0.000575			0.003744			
	pstd		0.045233			0.023975			0.061189			
	rp/pstd		0.354195			0.593362			0.267228			
	rp/pvar		7.830387			24.74924			4.367219			
yearly												
	rp		19.23%			17.07%			19.62%			
	pvar		0.024553			0.006898			0.04493			
	pstd		15.67%			8.31%			21.20%			
	rp/pstd		1.226968			2.055466			0.925704			
	rp/pvar		7.830387			24.74924			4.367219			

Table 2. Continued

	6/1/2010-5/31/2005				4/1/2008-3/31/2003				11/3/2003-12/01/1998		
	Ticker	Sorted ri/stdi	NSS Tangent		Ticker	Sorted ri/stdi	NSS Tangent		Ticker	Sorted ri/stdi	NSS Tangent
mdeterm		1.38E-82	7.55E-06			-2.44E-85	1.80E-34			9.31E-71	1.06E-09
emax = norm (k)		0.1072	0.0041			0.0242	0.0087			0.108146	0.01127
emin		0.000165	0.001864			5.16E-05	0.00035			0.000401	0.002958
cond(k) = emax/ emin		651.6525	2.1991			469.2584	24.8673			269.7937	3.809661

A Correlation-Based Specification of Mean-Covariance Analysis

Tarrazo [2013] developed a qualitative, *correlation*-based, instead of *covariance*-based, mean-variance model while studying the effects of alternative variable transformations in regression analysis. (Note: covariance $[\sigma_{ij}]$ is the general term used to describe second-order, pair-wise interactions between statistical variables, x_i and x_j . variance refers to the covariance of a variable with itself $[\sigma_i^2]$; and correlation is the standardized covariance, $\rho_{ij} = \sigma_{ij}/\sigma_i \sigma_j$, where the standard deviations of each variable appear in the denominator. That is why the correlation coefficient ranges from -1 to $+1$, which makes it very suitable for qualitative uses.)

Table 3 shows the correlation specification of mean-variance models on the left-hand side and the mean variance on the right-hand side. Although the transformations approach to correlation may ring a bell for those professionals with a statistical background, the procedures in Elton, Gruber, Brown, and Goetzmann [2010] may be similarly familiar to those without. During the 1960s, two very insightful and prolific professors at New York University, Edwin Elton and Martin Gruber, teamed up with Manfred Padberg. As one of the main contributors to some parts of modern optimization (e.g., integer, polyhedral theory, large scale), they concentrated on the key items at work in portfolio optimizations and developed a tablelike, parsimonious procedure to obtain optimal weights. Their procedure was an alternative to mathematical programming, which was still a welcome development at the time. More important, the research provided many investment insights. One of these was related to correlation, a tablelike procedure to optimize portfolios using mean-variance in which all securities had the same correlation coefficient (a positive 50 percent). Subsequent research has proved that such an assumption may have not been fully accurate, regardless of whether it helps a great deal in understanding observed mean-variance results, especially with respect to showing why only a few securities are selected and the modest role of diversification. That is also why the correlation matrix has coefficients of 0.5 out of the main diagonal. In practice, covariances and correlations are mostly positive and can be quite large.

As we see in Table 3, dividing each variable by its standard deviation produces the two objects we need to calculate optimal portfolio weights: the correlation matrix and the vector of standardized means (r_i/σ_i). Solving the simultaneous equations system as before yields the intermediate variables x_i , which must each be divided by their respective standard deviation and rebalanced to produce optimal portfolio weights (i.e., 52.43 percent = $1.94/3.71$). As shown in Table 1, two of the weights are negative, which means those securities are not good to buy; thus, a position would be taken on them only because of the financing they may provide via short-selling. We removed those securities from the original matrix and vector and reoptimized. The results appear at the bottom of the table.

Table 3. Correlation-Based, Mean-Variance Optimizations

Panel 1: Initial data set [Elton, Gruber, Brown, and Goetzman (2010), p. 194]											
Correlation Table					ri/StdI	Variance-Covariance Table					ri
1	0.5	0.5	0.5	0.5	8	9	3	6	9	3	24
0.5	1	0.5	0.5	0.5	7	3	4	4	6	2	14
0.5	0.5	1	0.5	0.5	6	6	4	16	12	4	24
0.5	0.5	0.5	1	0.5	5	9	6	12	36	6	30
0.5	0.5	0.5	0.5	1	4.5	3	2	4	6	4	9
	xi	xi/stdi	wi*						xi	wi*	
1	5.83	1.94	52.43%						1	1.94	52.43%
2	3.83	1.92	51.69%						2	1.92	51.69%
3	1.83	0.46	12.36%						3	0.46	12.36%
4	-0.17	-0.03	-0.75%						4	-0.03	-0.75%
5	-1.17	-0.58	-15.73%						5	-0.58	-15.73%
	10.17	3.71	100.00%						3.71	100.00%	
Panel 2: No short sales allowed (wi>0) results											
Correlation Table, C			ri/StdI	Variance-Covariance Table, A							ri
1	0.5	0.5	8	9	3	6					24
0.5	1	0.5	7	3	4	4					14
0.5	0.5	1	6	6	4	16					24
	xi	xi/stdi	wi*		vi	wi*					
1	5.50	1.83	46.32%	1	1.83	46.32%					
2	3.50	1.75	44.21%	2	1.75	44.21%					
3	1.50	0.38	9.47%	3	0.38	9.47%					
	10.50	3.96	100.00%		3.96	100.00%					
					rp	19.58					
					varp	4.95					
					stdp	2.22					
					rp/pvar	3.96					
					rp/pstd	8.80					
	$r'C^{-1}r$	77.50			$r'A^{-1}r$	77.50					
	$\text{sqrt}(r'C^{-1}r)$	8.80			$\text{sqrt}(r'A^{-1}r)$	8.80					

In addition to the optimal weights, additional information is worth noting. Let us look at the values for x_i , originating the optimal weights. Their summation (3.96) happens to be the value of the portfolio return-to-variance ratio (3.96). The optimal weights simply scale the contribution (r_i/σ_i^2) of each

variable to the portfolio ($rp/varp$); that is, $46.32 \text{ percent} = 1.83/3.96$ is simply the proportion (1.83) in the total sum of effects (3.96). Mathematically, there is a vector traveling through the linear space (a plane) defined by the matrices. This means that we can “see through” the weights and into the two main structures at play. In fact, by calculating $r'A^{-1}r$, and taking its square root, we obtain the portfolio return-to-standard deviation ratio (8.80), independently of whether we use the “variance–covariance, average returns” (bottom right) or the “correlation matrix, standardized average returns” (bottom left).

The correlation is not, in general, enough to define dependence between variables, except in the case of multivariate normal distributions. One way to justify mean-variance analysis is to assume returns are distributed normally. The correlation matrices used in portfolio analysis are positive definite, such as variance–covariance matrices. This means the determinant is not equal to zero; equivalently, the matrix is invertible, and a solution to the simultaneous equation system exists and is unique. Tarrazo [2013] contains an appendix showing the analytical equivalency between variance-covariance and correlation-based portfolio optimizations.

Our next step is to provide a qualitative interpretation of the correlations-based optimization, which is very easy.

Qualitative Interpretation

We need to keep in mind three types of variables:

- **Returns:** A qualitative interpretation of returns is straightforward. A project with an expected annualized return of 18% for the project time window is preferable to a project offering 9%. We may not be able to say the 18% project is twice as good as the 9% one, but it does look much, much better.
- **Standard deviations:** Variances and covariances are difficult to understand because they exist on a scale that uses the square of the variables. A return of 0.0125 may be associated with a variance of 0.001875, which says very little. However, if we annualized them (multiplying by 12), expressed them in percentage form, and substituted the variance for the standard deviation, we get a return of 15 percent and a standard deviation of 15 percent. That is something to which we can relate. Now, two devices become very handy: One of them is natural language (i.e., plain English). When we say that “next year we can earn \$100,000 dollars, give or take \$15,000” or “anywhere between \$85,000 and \$115,000,” we are actually using a primitive (instinctive) understanding of standard deviation. The second is the familiarity with the normal distribution (i.e., Gaussian curve). We have all learned that adding and subtracting one, two, or three standard deviations from/to the expected value covers 68 percent, 95 percent, and 99.7 percent of the probable happenings, respectively. In sum, we will be

using annualized percentage returns and standard deviation in our qualitative, correlation-based model.

- **Correlations:** Numerically, correlations are easy to interpret as they have a percentage value (e.g., 50 percent), bounded to plus or minus 100 percent, for perfectly identical movements or perfectly contrary ones. Theoretically, anticipating numerical correlations is a more difficult challenge than anticipating expected returns (means) and risk indicators (standard deviations). Fortunately, Grether [1974] proves that correlations can be used qualitatively. What is needed is a sign indicating the relationship does not change with respect to any order-preserving transformation. Grether [1974] provides the conditions for this to happen for two cases: cardinal-ordinal variable (e.g., suicide rates and the profession's prestige) and two ordinal-variables (marital adjustment and separations outlook; see also Grether, 1976). It is not a coincidence that the examples come from sociology because researchers in that area of endeavor have to make enormous efforts: first, to prepare qualitative information for evaluation and then to integrate qualitative information with numerical data.

Now that we have developed a qualitative version of the mean-variance model, we must initiate the process of its deployment.

USING THE QUALITATIVE MEAN-VARIANCE MODEL

In the previous sections, we studied the mean-variance model from its early introduction up until the most recent research. Most of the research has focused on large scale applications (from several dozens to thousands of variables). The justification to do so was statistical theory, explicitly or implicitly noted in each application: sampling, requiring over thirty observations for averages and close to 100 for variances; and the approximation of random variables and their groupings to normality (central limit theorem), over thirty independently distributed variables. However, mean-variance analysis has been welcomed for its conceptual contributions in the understanding of risk management, both at the security grouping (diversification) and larger, asset-grouping levels (hedging). Furthermore, even the very first contributions by Markowitz [1959, 1952] unveiled a most intriguing possibility: mean-variance analysis could be applied to small portfolios. Investors would certainly like to know what approach could contribute to security selection, but small portfolios were the best to learn about mean-variance and closely observe its logical and numerical power. Small portfolios gained acceptance over time in what has become known as the "limited diversification" approach. Small portfolios are the ones invariably used in pedagogical contexts and textbook illustrations. Our development of a qualitative version of Markowitz's model permits the user yet another higher level of scrutiny about

what the model does, as well as the closest examination and assessment of the value of the statistical inputs and operations. These characteristics indicated the advantage of applying the model in the following settings:

- 1) Students: a) undergraduate and b) graduate
- a) Practitioners: a) large portfolios users and b) small portfolios users

Our work in developing a qualitative mean-variance model (QMV), to complement and better learn the quantitative version (MV), has been very positive from a pedagogical angle. We have learned to present statistics in a very practical manner conceptually, and it has facilitated learning about numerical detail (e.g., those regarding sampling) and some statistical theories.

The QMV model provides a new choice to portfolio users: the ability to determine statistical inputs themselves by, for example, modifying historical estimates to account for structural change; or the ability to use the statistical concepts even in those cases where there is no valid history (e.g., start-ups, venture capital).

Ever since we developed the QVM, we have presented the model to three separate audiences: undergraduate students (e.g., entrepreneurship, senior undergraduates in the United States, classroom presentation), professionals (e.g., 21 venture capital investors, San Francisco Bay Area/Silicon Valley), and graduate students (e.g., entrepreneurship and strategy, extended classroom presentation, University of Paris 2, Panthéon-Assas, France), who carried out the application of the model to large publicly owned companies from the French CAC-40 market index. We will provide a very succinct account of these experiences to provide some minimal guidance to potential users of the model.

This is what we found in our early applications of the model.

With respect to pedagogy and work with students, we observed that the qualitative presentation of the model does help in providing a practical means to make investment decisions by learning concepts in a nonmathematical, non-theoretical way. This is illustrated in Table 4. One setting is that of an office manager trying to warm up a cubicle-arranged office space. Individual, primary “heat” effects (r_i/σ_i) are given by the heaters themselves, but there are also secondary effects (positive and negative correlations) in heat spilling over unintended areas or being wasted by proximity to doors, windows, and open areas. (Engineers apply portfolio concepts to the thermal management of buildings.) Another setting consists of one in which two students are sharing their grades with their parents. The same grade point average but with a different grade dispersion is likely to reveal sensitivity to risk (the C grade) as well as to opportunity (the lonely A grade). The third setting is from graph theory. The following concerns a group of three students: In one case, they are all positively correlated (each will do what the others do); in the other case, one of

them may: 1) do what another student does, 2) do exactly the contrary of what another student does, or 3) do as they please. The counterintuitive insight here is that there is diversification in the second group, and this diversification will ensure that the job (finishing the assigned group homework) will be carried out. If the first group decided to work on the homework, they would probably excel, but they may decide to skip their homework and go to the beach instead.

While working with graduate students, we tried two formats: 1) We tried to see if the exercise could be enhanced if we encouraged students to work in groups to produce their own expected returns and correlations between firms; and 2) We attempted to see if they could justify/explain/trade against historical data concerning major, publicly traded firms. The first format employed an accessible source of data on well-known student competition, shown at the following websites: <http://www.hbs.edu/newventurecompetition/winners-and-success-stories/Pages/winners.aspx> and http://www.mit100k.org/launch/2013_semi_finalists/.

First and foremost, the exercise stressed the value of concise and clear information when learning about what the business does and the potential advantages and weakness of the venture, something also learned in “elevators pitches.” Of course, formulating specific values for expected yearly returns and correlations takes the effort to another level of sophistication and difficulty.

Second, we noticed how quickly combinatorial complexity makes itself felt in the design of the exercise. The mechanics of the presentation are critical. We planned to ask the audience, by groups, to give us their estimates of returns, “give-or-take” tolerance (e.g., spreads, standard deviations), and correlations, for which we should also budget some discussion time. Clearly, the time needed depends on the number of inputs required in the problem, which, in turn, is related to the dimension (number of projects). This number of inputs equals $[(n \times n) - n]/2$ correlations, n returns, and n standard deviations. For example,


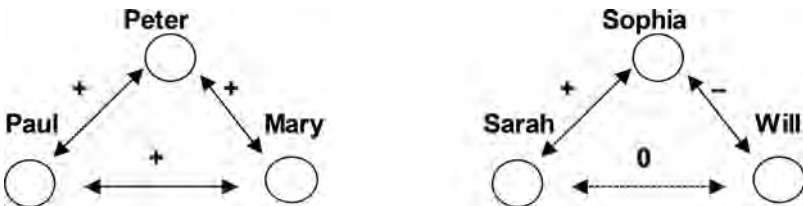
$$n = 3, 3 \text{ corr's} + 3 \text{ r's} + 3 \text{ std's} = 9 \text{ estimates}$$

$$n = 4, 6 \text{ corr's} + 4 \text{ r's} + 4 \text{ std's} = 14 \text{ estimates}$$

$$n = 5, 10 \text{ corr's} + 5 \text{ rs} + 5 \text{ std's} = 20 \text{ estimates}$$

Although returns and ranges are easy and intuitive to ascertain, correlations may require some more time. A four-case scenario may work best to manage time and, very importantly, to improve the power of correlations to determine whether optimal weights increase significantly in low-dimensional cases.

Table 4. Correlation-Based, Mean-Variance Optimizations

Heaters in a cubicle-organized office space		
		
• Your children come home with these grades; what is your reaction?		
	James	Stella
Course 1	B	A
Course 2	B	B
Course 3	B	C
GPA	3.0	3.0
• Group homework: which group would be best at getting some project done? (“+” and “-” mean “like” and “dislike,” respectively)		
		
• The way diversification works and does not work		
◦ Diversification is not stuffing your sleeping bag with all sorts of snakes hoping only the nonvenomous ones will bite you.		
◦ It is neither the only way to manage risk nor necessarily the most effective (better information, hedging with cash).		
◦ Diversification was never meant to carry dead weight.		

Third, regarding our work with graduate students at the University of Paris II (Panthéon-Assas, Group Sorbonne), we had two interesting findings: 1) Trying to explain historical returns from major companies (e.g., CAC-40, similar to the DJIA-30) is not an easy job, and 2) Correlation effects cannot even be considered. However, forming three or four security portfolios with very well-known firms (e.g., Carrefour, Airbus, Sanofi, Orange) does generate interesting conversations, especially because, with the QMV, one can consider correlations and become able to at least understand, if not fully explain, security selection in small portfolios (see Figure 1).

Our experience with venture capitalists was very different: First, they were at best patient with the pedagogical value of the model but never really bought that their portfolios could be formed using statistical inputs with a model that may appear to be too restrictive, with very few firms from which to choose. They seemed to favor more equal weights across the choices. All users quickly noticed these interesting issues:

- Percentages for expected returns should be quite high for early-stage ventures, not only because of the risk but also because of the relatively short time-planning windows.
- A higher expected return should go with a higher “give-or-take” (standard deviation) value, because higher risk would also command a higher return.
- When the differences in individual effects (σ_i) are smaller, the effects of alternative correlation inputs are larger.

The following section focuses on evaluating the potential advantages offered by the QVM in start-ups contexts.

QUALITATIVE MEAN-VARIANCE IN START-UPS CONTEXTS: BEYOND PEDAGOGY

With respect to the entrepreneurial/venture capital context, as we noted in the introduction, the objective of our research was to provide a way to help venture capitalists tackle some of the difficult issues in their line of business. One of those issues concerns the optimal number of investments in the venture capital (VC) portfolio. There are also related decisions (e.g., pure-plays, exit strategies) that may be best analyzed in the context of a portfolio of holdings. At the current state of the art, we may not expect a single model to provide all the answers for of the reasons mentioned by Morgenstern [1963, p. 42]: “It is therefore certain that the description of the system cannot give an ‘accurate’ picture, both for reasons of what is being described as well as by what means this is being done.” In other words, one model cannot suffice because 1) we cannot include all the relevant elements and 2) all models are limited by their constitutive elements (calculus, algebra, continuous, discrete, and so forth).

What we can do is see if our approach points us in the right direction. Qualitative analysis is justified by the situation itself. As noted in the introduction, everything is forward looking in the VC situation. Historical information either does not exist or is of very limited usefulness, and the relevant information and knowledge is of varying natures: quantitative, qualitative, and hybrid. A careful reading of the literature suggests advancing methods along the line of portfolio theory:

- a) By concentrating on realized risk-adjusted returns: “Sufficient returns at acceptable risk: Put simply, the challenge is to earn a consistently superior return on investments in inherently risky business ventures” [Zider, 1998, p. 133]. In addition, “An important indicator of the success of venture capital, therefore, is the realized rate of return in relationship to the riskiness of investments in venture capital funds: Have venture capitalists provided returns adequate to compensate for the risk incurred?” [Barry, 1994, p. 6].
- b) By clarifying correlations and their effect on investing positions and outcomes: “What we do not know—understanding risk and return. To ignore the true correlation may lead to incorrect investments decisions. Not to think about the risk and reward profile of venture capital is thus fraught with potential dangers” [Gompers and Lerner, 2001, pp. 162–163], which in turn leads to a better comprehension of the whole deal in one’s head:
- c) “If you cannot do the math in your head, it is probably not a venture deal” [Berlin, 1998, p. 20].
- d) Using expert knowledge: “What sets the qualitative approach apart from the quantitative is its primary reliance upon the investor’s own informed judgment and other sources of investment counsel, rather than mathematical algorithms or software programs, to establish initial positions weightings and then alter them at judicious intervals” [Darst, 2008, p. 32].

It was also reassuring for us to find components of mean-variance analysis already in the venture capital literature, such as the following:

- “[Venture capitalists] strive to expand the number of portfolio firms until the contribution of the marginal start-up to profits is zero” [Kanniainen and Keuschnigg, 2003, p. 528].
- “The efficient size of a VC portfolio balances a trade-off between diversifying risks with the dilution of value-added advice, among other things” [Cumming, 2006, p. 1084].
- Bernile, Cumming, and Lyandres [2007] use game theory to show the plausible optimality of certain VC-entrepreneur situations, which they also

contrast with real data. There is some connection as portfolio theory can be understood as a “game against nature.”

The heading of this section could very well be the title of a much-needed and likely extensive academic study requiring much more space than we can allocate in one section. We have already indicated how the QMV points us in the right direction for further research. Interesting readers may welcome the following four items.

The first one is about the special relationship between returns to investment and time. Calculating expected returns is always problematic, but it is even more so in early stage investing, where three elements converge: venture success, degree of the success, and time horizon when the events unfold. It is very interesting that, in venture capital, the results are often reported not in realized returns but in multiples of the amount initially invested (see, e.g., the yearbooks of the National Venture Capital Association or those of the European Private Equity and Venture Capital Association). In expected terms, expressing outcomes in dollars helps with a certain nonlinearity deformation imposed by returns scaling: For example, ask anyone if they would like to see their investment double from \$10 million to \$20 million in a few years. The answer should be an enthusiastic “yes.” However, although the net earnings do not change (\$10 million), the annualized compound returns fluctuate from 100 percent (if earned one year after the initial investment) to a “paltry” (for venture capitalists, given the risks) 14.87 percent if the time horizon is five years and 10.41 percent for a holding period of ten years (using the rule of 70, it takes approximately ten years, 70/10, to double your money). Coincidentally, a venture capital fund duration is typically ten years.

The second item refers to the analysis of returns. The steep nonlinearity of the early return calculations cannot be avoided as long as we use standard time-value-of-money rules. However, the qualitative mean-variance model offers an interesting surprise. The qualitative model admits a time scaling or return. When the user inputs an expected return for a project (r_i), it implies a time window that is not specified (one year, the whole gestation period for the project, the time to exit, etc.). A time indicator of multiplying by k (e.g., $k = 2$ for doubling) can be calculated by $t_i = \ln(k)/\ln(1+r_i)$. Then, one can replace r_i by $(1/t_i)$ in the right-hand side vector and obtain risk-adjusted time estimates. According to the extant research concerning qualitative correlation analysis, one can change the scale as long as the change does not affect the signs; obviously, further research on how the scale change affects optimal weights should be carried out. This is an unexpected research outcome that merits further research. One can see some resonance with the payback method of project evaluation analysis and with Peter Lynch’s “ten-baggers” (yes, $k = 10$) in his *One Up on Wall Street* [Lynch, 2000, p. 32]. Venture capitalists similarly look for “5×–10×” (i.e., five to ten times the initial investment) in their best investments, actually expecting to earn 100× in some of them.

The third item is the convergence in investment analysis methods in regular and early stage investing cases:

- a) Examination of brokerage records and surveys (e.g., Federal Reserve Board Survey of Consumer Finances) has shown evidence of the apparently normal practice of investing in a few securities by some investors, which includes private equity and VC as well: “investment in private equity is highly concentrated” [Denis, 2004, p. 322]. Venture capitalists also invest in small portfolios of less than twenty positions. The observed, presumably “nondiversified” behavior of a venture capitalist may be explained by specialization, stages of growth, or exit strategies [Knill, 2009]. This practice is the subject of intense research. In the case of stock investors, contrary to what would be expected according to the textbook understanding of diversification (i.e., that one needs many stocks to be able to diversify), these nondiversified investors do well (see Ivkovic, Sialm, and Weisbenner, 2008; Polkovnichenko, 2005; and references therein). In other words, although an argument can be made that some investors may not be doing “the textbook-right thing,” they may still do acceptably well on the return compartment. Take a look, for example, at the historical returns in the ten security portfolios in Figure 1: Multiply the monthly return by 12 to obtain the yearly returns and behold the powers of limited diversification; they fluctuate from 18.19% (Case #1, lower right) to 26.78% (Case #8, above Case #1).
- b) Our research reinforces some findings in the literature with respect to investing in a few stocks (also referred to as concentrated portfolios). Mao [1970] initiated research on the critical variables acting in portfolio optimization and in the performance ratios (r_i/σ_i , for mean-variance; b_i 's for the market-based model), which led to the procedures by Elton, Gruber, and Padberg, as noted (see Elton et al., 2010). In this study, we showed the strength of performance ratios in determining optimal weights in qualitative terms as well. At the same time, research was initiated in the so-called “limited diversification” [Jacob, 1974; Brennan, 1975]. Goldman [1979] presents research on investing in a few stocks, which he described with the revolutionary title of “Anti-Diversification or Optimal Programmes for Infrequently Revised Portfolios.” He shows why and how a few securities will always determine the fate of a small portfolio, which has also been echoed by Lynch [2000]: “... Venture capital depends on outliers ... eliminating the top 10% of investments resulted in an average return of -0.28% . In other words, venture capital success is highly dependent on finding a few outstanding investments, and diversification is vital” [Barry, 1994, p. 6].
- c) Research on small portfolios was considered “fringe” at best when it was being developed. This situation started to change, however, when heavy-duty theoretical contributions on alternative market hypotheses started to

appear. In these research contributions, investors hold concentrated positions (possibly not fully diversified) without harm to markets or to themselves. In Merton's [1987] model, for example, investors (price-takers, small) apply the Markowitz-Tobin mean-variance analysis to a subset of securities they know something about, and each subset differs across investors, which yields interesting hypotheses concerning information effects. Merton's model "provides no explicit recognition of institutional investors" [op. cit., p. 505]. Grossman and Stiglitz [1980] stress the cost of information and the traders who try to become better informed. The information-costly transactions limit the number of active markets at any given point. Levy [1978] studied market functioning when investors cannot invest in more than a few risky assets. More recently, Zivney and Hoban [2001] noted that investing in individual securities is equivalent to not only holding each stock but also the option of selling each individual security. This is a right that one does not have when holding a mutual or exchanged traded fund.

- d) One can observe a convergence between theory and practice at the level of household and small investors as well (see, e.g., Das, Markowitz, Scheid, and Statman, 2011; Chavra, 2004). The concept of diversification is very old, even older than portfolio theory. The reader may be surprised by how "modern" Loeb's [1935] comments on diversification sound in light of the optimizations in Figure 1. The type of diversification in Markowitz [1952, 1959] is one way to enhance portfolios, and we must keep in mind that portfolio theory in general, and mean-variance optimization in particular, still holds some secrets. One only has to peruse its earliest contributions and be left to wonder why Markowitz [1959] selected securities having all positive returns and used yearly data (instead of monthly) or why Roy [1952] focused on prices (dollar values) and not on returns.

Our final point could motivate by itself further research concerning the number of investments in situations where the investor may face various types of restrictions (number of investments available, lack of information, reduced investing budgets, pressures in the timeliness of returns, and so on). One may get started by explaining what happens in something often heard in start-up investing: "We lost money in most deals, but we made money overall."

We can diligently proceed by defining some numbers: Total losses (TL) = number of losing deals (L) \times average loss per deal (LA), and Total wins (TW) = number of winning deals (W) \times average win per deal (WA).

In the break-even case $= TW - TL = 0$, but "We made money overall" implies that $TW + TL > 0$, or $TW > TL$. Therefore, $W \times WA > L \times LA$, which means that the number of wins times the average win was larger than the number of losses times the average loss. It seems we have explained what happens, but by concentrating only on numbers and averages, we have missed

critical information that the QMV-minding observer may have wanted to pay attention to: the composition of winners and losers and the sequencing of projects. An example will be helpful:

Suppose the history of funds made with various projects is as follows:

- Winner projects ($W = 4$): 500, 100, 400, 200. Sum: 1,200. Average win (AW): 300.
- Loser projects ($L = 6$): -200, -200, -100, -100, -100, -100, -100. Sum: -800, Average loss (AL): -133.33.

The explanation deduced earlier ($W \times WA > L \times LA$) of course works well: $4 \times 300 = 1,200 > 6 \times 133.33$; therefore, ... success! We lost money in most deals, but we made money overall. However, to understand what really happened and perhaps enhance our management by planning, we may further study both the composition of the outcomes (4 wins to 6 losses) and their sequencing. Correlation may help understand the composition. As one anonymous referee of a previous draft pointedly noted, it may help, for example, if there are geographical effects in the distribution of outcomes. Yes! Groups of start-ups from Silicon Valley may register different correlations with respect to those within and to those outside the group. The same referee recommended incorporating a formula for the calculation of correlations. The correlation being discussed is based on qualitative reasonings. An investing board could set a protocol to calculate such an indicator. The main idea is to go beyond historical statistical associations, which fortunately is also recommended in discussions of diversification; companies in the same industry could respond similarly when facing the same economic situation. Companies selling similar products/services could also Table high degrees of correlations. Another idea is to study how the sequencing of wins and losses may help manage what may come next. Laplace's rule of succession tries to do that. It says that the chances of having the next outcome to be a win can be calculated as follows: $(W + 1)/(W + L + 2)$, which would be $(4 + 1)/(10 + 2) = 5/12$, or a 41.66 percent chance in the previous example.

CONCLUSION

In this study, we developed a correlation-based analogue to the mean-variance portfolio-selection model. We also introduced the necessary modification to permit a qualitative interpretation and use of the model. We then applied the model to a venture capital project selection and large company stocks.

Like any other type of investor, venture capitalists and early-stage investors face a sorting problem. However, they lack historical information varying in nature: Some of it is quantitative (e.g., comparison with previous start-ups), some is eminently qualitative, and some is hybrid.

The qualitative version of mean-variance analysis we have presented matches the perceived needs expressed in the literature and in direct exchanges

with venture capital investors. In some cases, these needs are even formulated in terms of the elements of the model itself (e.g., need to concentrate on realized, risk-adjusted returns, do not to ignore correlations). In other cases, the qualitative model provides a way to incorporate practice into the model analysis (e.g., in using investing multiples and time indicators to complement return expectations). In all cases, according to venture capitalists, it was critical to be able to comprehend the whole deal easily “in one’s head.” By relying primarily on expert knowledge, the qualitative model we have presented is one of the few tools that may provide some aid in that difficult task. Beyond its applications to early-stage investing, the qualitative version of the mean-variance model liberates the original specification from its historical data structure and opens up its horizons. In both early-stage and established firms, heuristics can be easily extracted from it.

As the reader may have noted, analyzing the adequacy of the mean-variance model took much effort and space. However, this thorough analysis allowed us to build its qualitative addition on solid foundations. Mean-variance still seems to guard some secrets, and one of its least-known aspects concerns investing in a few projects, which happens to be the usual case in VC. The good news in this case is that having few projects facilitates risk control by enhancing the information available.

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What Sections of Courses Fill Up First? Investigating Class Selection by Business Students

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This paper analyzes decisions made by undergraduate business students at the time of enrollment with respect to sections they select, using data from a comprehensive regional state university in Texas. The study employs data on student evaluations of teaching (SET), grade distributions, and class- and instructor-level measures to assess factors impacting students' class choices. Controlling for class schedule, the study finds that instructor reputation is a significant predictor of the relative popularity of that instructor's classes during registration: sections taught by faculty with higher SET ratings and higher average grades assigned tend to fill up faster.

Keywords: Higher Education, Class Demand, Student Evaluation of Teaching

Disciplines of Interest: Economics, Education

INTRODUCTION

College students in the United States have a multitude of decisions to make each term when it comes to class registration. Depending on the particular major or specialization selected, there is often at least some degree of flexibility in how one completes the required curriculum: which specific courses a student takes and in what order. Of course, some sequencing is typically predetermined because some courses act as prerequisites for other courses and therefore must be completed first; also, within a given major, there is usually some choice of elective courses available to a student. Nevertheless, even once these decisions are made, there are still others: Which section do I enroll in? With what instructor? At what time? Meeting once, two, or three times per week?

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This paper attempts to estimate student preferences over sections of required business courses at time of registration for the subsequent term. There is some evidence—previous research, anecdotal support, direct observation—that, on average, students tend to prefer classes with certain scheduling characteristics, *ceteris paribus*: late morning to early afternoon and twice rather than three times per week. In addition, there is widespread belief and understanding among both students and faculty that students consider instructor reputation when selecting classes. The mere existence of online services such as Koofers, MyEdu, Rate My Professor, and others strongly suggests that students seek out and use available information on other students' impressions of classes and instructors teaching them, past grades assigned in those classes, the perceived amount of work a class requires, and so on. Some of the websites contain other information on instructors, such as ratings of their physical appearance. This type of information regarding appearance is troublesome and has potentially serious implications for bias against some groups, which has been documented in the literature (see, for example, Baldwin and Blattner [2003], Centra [2003], D'Apollonia and Abrami [1997], Otto, Sanford, and Ross [2008], and Wagner, Rieger, and Voorvelt [2016]) but is outside the scope of our research.

Given access to daily class registration data and the ability to control for various instructor- and class-level characteristics, we are interested in estimating the extent to which popularity of some class sections depends on who is teaching and when. Specifically, we use data from 1) student evaluations of teaching (SET) surveys and 2) past grade distributions to measure instructors' popularity relative to other options available to students, and we estimate the extent to which that translates into stronger demand for classes taught by these instructors.

We find, as we expected, that students prefer classes scheduled in the middle of the day (for example, at eleven o'clock in the morning and before two o'clock in the afternoon) to those at eight o'clock in the morning or late in the evening. Controlling for time of day, students (weakly) prefer classes that meet fewer times per week, but with a caveat that we discuss later in the paper. Most importantly, conditional on specific course, instructors with higher than average SET ratings and those who assign higher average grades see their classes fill up significantly faster than others. On the other hand, instructor gender, experience, and contract status (tenured, tenure-track, or part-time) do not seem to be significant factors.

PREVIOUS RESEARCH

Although many studies have examined student evaluations of instruction in higher education (for example, see McPherson, Jewell, and Kim [2009], Sevier [1983], and Love and Kotchen [2010]; Benton, Cashin, and Kansas [2012] is a

good summary of the literature) and, separately, a large literature exists on how students make choices with respect to selecting colleges to attend, majors to pursue, and courses in which to enroll [Wilhelm [2004], Davison and Price [2009], and Tipoe [2013] are three recent examples), there haven't been many attempts to link evaluations to course choices. Perhaps the closest study to this one, both in spirit and the approach, is Brown and Kosovich [2015], who used data from the same institution to assess how students choose between sections of core (i.e., general education) courses. Unlike the present study, they used data from Rate My Professor for instructor ratings along such dimensions as helpfulness, clarity, easiness, and "hotness."¹ As in this paper, they used percentage of class capacity that is filled on days one, two, and three of registration to measure how popular a given class is. Their findings were that students do appear to rely on publicly available information on instructors to inform their enrollment decisions: instructors rated higher and those rated as "easier" saw their sections fill up more quickly. They also find that students prefer classes scheduled in the middle of the day to those scheduled late.

This study used the same basic approach but improves on that employed by Brown and Kosovich in several important ways. First, it focused on courses taken by business majors only, rather than core courses, which are taken by every student at this institution. This focus keeps the variability in student body composition to a minimum and allows us to concentrate on external factors affecting enrollment decisions.² Second, the study used nine years of data, which allows us to develop long-term measures of instructor popularity from their historical SET ratings and past average grades. Obviously, it also results in a larger sample. Third, student registration behavior can be observed at more points—i.e., on every day of the registration period of each of the semesters in the sample. In this analysis, each of the first three days, the ends of weeks one and two, and the last day were used. Fourth, official SET data and official grade distributions for each instructor in the data was used. Fifth, it was possible to more finely control for additional class and instructor effects; in particular, instructors' tenure status, experience, and gender and class schedule details, such as exact time of day, number of days per week the class meets, and whether it's delivered online, were observed.

Wilhelm [2004] is a study that asks fundamentally the same questions this study asked: Do instructor evaluations and grading leniency influence student selection of courses to take? However, unlike the study reported in this paper, that study did not use data on actual observed student behavior and rather relied on a type of survey, where students were asked to make a series of choices, each time between two hypothetical courses identified by various characteristics: instructor's evaluations, course workload, course's worth/usefulness, and grading leniency. Students were found to be twice as likely to say they would choose a course where the instructor was rated "excellent" as opposed to average; they also were found to be willing to engage in a trade-off of

greater workload for greater anticipated usefulness of the course. These results are interesting, and particularly relevant because the target audience were business majors at a regional university, not dissimilar to Stephen F. Austin State University (SFA). On the other hand, using data on actual student registration behavior is a superior approach.

In a study of some courses in business, computer science, and engineering at several elite universities (UC Berkeley, Harvard, and Rice), Tipoe [2013] found no relationship between instructor ratings on Rate My Professor and course enrollment. However, that study looks only at the final enrollment numbers and as, discussed below, this may not always reveal the true demand for classes during the registration period. Also, the unique characteristics of students attending highly selective universities probably play a role in how sensitive they are to instructor reputation.

BACKGROUND AND DATA INFORMATION

The data come used in this study from the college of business at SFA), which is a comprehensive, regionally accredited, public university located in east Texas. The university had a total enrollment of about 13,000 students during the sample period, the majority of whom were undergraduates (though SFA offers many master's and three doctoral degrees). The college of business houses the typical business majors (e.g., accounting, finance, management, marketing, etc.) as well as a few unique programs in sports business, business communication and corporate education, and banking. All majors lead to a bachelor of business administration (BBA) degree and therefore include a common set of business courses, which is what was used in this analysis. There are currently approximately 1,800 students enrolled as business majors, but that number fluctuated somewhat over the period covered by this data. Data from all required business core classes (the so-called *business foundation*) taught at SFA between Fall 2010 and Spring 2018 were used.

The business foundation courses were chosen for a number of reasons. First, in every semester, we are guaranteed to have multiple sections of each course, taught by multiple instructors, thus ensuring that there is some variation within each term and each course. Second, this choice of courses keeps the characteristics of the student population rather consistent as these are the required courses that must be taken by all business majors. The business foundation consists of 14 courses, of which 13 were used for the analysis:³

1. Principles of Financial Accounting
2. Principles of Management Accounting
3. Principles of Macroeconomics
4. Principles of Microeconomics
5. Business Communication

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6. Business, Ethics, and Society
 7. Management Principles
 8. Principles of Marketing
 9. Introduction to Financial Management
 10. Applied Statistics
 11. Operations Management
 12. Business Law
 13. Business Policy and Strategy

This study combined information from four unique datasets. For enrollment information, there were data on daily registrations for each section during the enrollment period. For fall semesters, registration for classes begins around April 15; for spring semesters, the start is in early November. In each case, registration remains open through the first week of the semester. Class capacities—the maximum number of seats in a given section—were also observed. Class capacities vary across courses and, to a lesser extent, within a course across class sections. Course-level variation is primarily based on pedagogy, with upper-level courses generally smaller than lower-level courses. Section-level variation is often dictated by classroom capacity, though sometimes instructor preferences also play a role. For example, two sections of a course in finance may be taught by two finance faculty members, one of whom employs primarily standard lectures and has a larger class, and the other engages students in classroom activities and experiments and therefore has a smaller, more manageable group. These class caps are not constant. Often, department administrators manipulate class capacities to manage enrollment of students across sections; other times, the desired capacity is set in the beginning of the registration process but is increased subsequently up to, say, the physical capacity of the classroom, to accommodate late-registering students.

Class capacities at SFA are small by public university standards, particularly for lower-level courses, such as principles of economics: micro and macro principles are typically capped at 60–65 students (but can be up to 75 if scheduled in a large enough classroom); all other classes have capacities ranging from 25 to 45 students. Online capacities are similar to those of face-to-face classes.

The second dataset is the universe of all student responses to the SET surveys during the period. The process of collecting student evaluations of teaching is described in more detail below because it is quite different from that used at many other institutions.

The third dataset contains complete grade distributions for each class section in the first dataset. This information was used to construct *InstructorGPA*—an overall mean grade assigned by the given instructor in all courses and all sections taught—as a measure of relative grading leniency (or perceived “easiness” from the students’ perspective).⁴

The fourth and final dataset contains information on classes and instructors teaching them. For classes, the study observed days and times of class meetings, whether the class is online, whether it is taught in fall or spring semester, and total class enrollment.⁵ For instructors, this study considered gender, years of experience teaching at the current institution (based on hire date), and contract status—tenured, tenure-track, or non-tenure-track—as well as tenure date, if applicable.

Given its uniqueness, a more thorough description of student evaluation of teaching process is in order. At SFA, SET surveys are administered electronically and outside of class. In other words, during a specified three-week period (for a Spring semester, for example, roughly from April 15 through May 5), surveys become available to students in the university's data management system (Banner). Students enrolled in each course receive an initial notification e-mail on the day surveys open as well as a reminder e-mail every Monday during the evaluation period and a final e-mail on the day surveys close. In addition, they receive a notification on the "Home Tab" of the front page of the university portal when they first log in. It is important to note that students are invited and encouraged to complete the SET survey but are not required to do so; there is no bonus or prize for choosing to fill it out and no penalty for not doing it.

The survey form did not remain constant over the review period. The college of business introduced an added set of questions in 2011 to gather information on availability of faculty during office hours, accuracy of syllabi, and clarity of directions on assignments, as well as prompts such as "My instructor treats me with respect" and others. In addition, individual departments could add or modify some of these new questions for certain courses, including business foundation courses. The only five questions that are common to every class evaluated during the sample period are the university-mandated survey questions:

1. My instructor displays a clear understanding of course topics.
2. My instructor presents information effectively.
3. My instructor encourages questions and expression of ideas.
4. My instructor is actively helpful when students have problems.
5. Grades are assigned fairly and impartially.

Students are asked to react to each statement by choosing their level of agreement on a five-point scale: Strongly Agree (5), Agree (4), Neither Agree nor Disagree (3), Disagree (2), Strongly Disagree (1) or Not Observed. They can also add written comments on many, though not all, of the questions on the survey. We use the composite score – simple average of the five questions.

This study aggregated the individual (anonymous) student responses to instructor level; in other words, it averaged across class sections and courses, using class sizes as weights to arrive at *InstructorSET*—the mean overall SET rating received by a given instructor in all classes taught. Similarly to the

calculation of *InstructorGPA* above, this study used data from all semesters in the construction of *InstructorSET*.

ESTIMATION APPROACH AND RESULTS

Following Brown and Kosovich [2015], a similar theoretical framework of students' enrollment choices was adopted. Although there is not a strict order in which business foundation courses must be completed, there are some rules. For example, Principles of Financial Accounting is a prerequisite for the Introduction to Financial Management, and all other courses must be completed before enrolling in the capstone course (Business Policy and Strategy). Given a limited number of alternatives (sections of required courses in a given term), a student chooses the option that maximizes their utility. The utility a student obtains from registering for a course can be thought of as a function of course attributes, such as expected class workload, expected grade, class scheduling attributes, and so on. Gathering information on course attributes can be costly, and the hypothesis is that students will select the option that gives them the most net benefit taking into account all of the class characteristics. For example, a student may register for a class at a nonpreferred time if it is taught by an instructor known to assign a lighter workload or known to assign higher average grades.

It is worth examining how the two measures of instructor popularity are related. Students appear to prefer to enroll in classes with instructors known to assign on average higher grades, but those instructors may also be the ones with higher-than-average SET ratings.⁶

Table 1 displays by-course correlation (ρ) between *InstructorSET* and *InstructorGPA*, ordered from highest to lowest. Note that the correlations are all positive, though there is some variation. Estimated ρ is lowest for economics courses, followed by the strategy course and the course on business environment and ethics, but is otherwise near or above 0.5 everywhere else. Therefore, there is at least some reason to suspect that instructor grading is positively associated with course evaluations. There is no apparent convincing explanation for why economics courses have the lowest observed correlation, whereas marketing has the highest, but one possibility is that business students tend to take economics relatively early and other courses, including marketing, later in their studies. It may be that what this study shows in the estimation results below—students showing strong preference for instructors with higher ratings who also assign higher grades—simply does not happen as much earlier in the students' progression through their degrees.

Although this is not particularly germane to our study, it may be interesting to investigate how an individual's SET rating changes over their teaching career. In the study sample, for most instructors the observed ratings remain

Table 1. Correlation Between Average Instructor Grade and SET Rating

Course	$\hat{\rho}$ of <i>InstructorGPA</i> with <i>InstructorSET</i>	No. of Sections	No. of Instructors
Principles of Marketing	0.94	71	4
Business Communication	0.85	244	18
Principles of Finance	0.80	68	4
Applied Statistics	0.63	61	7
Principles of Management	0.53	92	15
Operations Management	0.51	68	7
Business Law	0.49	66	6
Financial Accounting	0.49	86	18
Managerial Accounting	0.42	70	12
Business, Ethics, and Society	0.26	76	7
Business Policy and Strategy	0.26	89	7
Principles of Macroeconomics	0.16	79	10
Principles of Microeconomics	0.13	85	5
Total	0.35	826	91

fairly constant. In the appendix (Figure 4, Appendix C), there is an example plot of SET ratings for every instructor of accounting in the data; only one individual has a substantial decline in their evaluation scores over time.

For the estimation approach, enrollment in every class in the sample on each of the following registration days appears: day 1, day 2, day 3, day 7, day 14, and the last day. The dependent variable in all cases is the “fill rate”: proportion of current class capacity that is filled at the end of the registration day. The choice of registration days merits some explanation. During the first week of each registration period, groups of students can begin registering at seven o’clock in the morning on each day in staggered fashion: on Monday, seniors (those with 90+ earned credit hours) have access to registration; on Tuesday, then they are joined by juniors (60+ hours), and so on. In other words, although day 1 can reveal some immediate differences in class popularity, for at least some classes, the full potential demand is not realized until several days later. The study attempted to capture both of these effects. Day 7 is effectively the end of the first full week of registration; day 14—the end of two full weeks, whereas the last day gives us a measure of final enrollment demand. Descriptive statistics of all variables used are shown in Table 2.

It is also interesting to take a look at the distributions of *InstructorGPA* and *InstructorSET*. Figures 1 and 2, respectively, display these. It is worth noting that although *InstructorGPA* has a nearly symmetrical distribution with a

Table 2. Descriptive Statistics

<i>Dependent Variables</i>				
Variable	Mean	Std. Dev	Min	Max
day1	0.110	0.116	0.013	1.033
day2	0.184	0.175	0.013	1.050
day3	0.282	0.227	0.015	1.050
day7	0.509	0.274	0.015	1.143
day14	0.586	0.274	0.015	1.150
lastday	0.925	0.206	0.037	1.400
<i>Independent Variables</i>				
InstructorSET	4.387	0.333	3.360	4.850
InstructorGPA	2.520	0.434	1.440	3.576
tenured	0.470	0.499	0	1
InstructorExp	13.327	10.913	0	44
NumPerWeek	1.760	0.921	0	3
online	0.186	0.389	0	1
eight	0.063	0.244	0	1
nine-ish	0.174	0.379	0	1
eleven	0.168	0.374	0	1
late	0.099	0.299	0	1

single mode of about 2.5, *InstructorSET* has a distribution that is heavily right-skewed: most observed ratings are between 4 and 5, and the most frequently observed values are between 4.5 and 5.

Figure 3 shows how the fill rate changes over the course of the registration period. Note that the observed fill rates sometimes exceed one, particularly on the last day, reflecting that some classes have more students enrolled than the stated capacity.

Results of the study estimations are in Table 3. The dependent variable was the observed fill rate at the end of each day, and course fixed effects were used to control for course-specific characteristics. The dummy *tenured* was set to one if the instructor teaching that particular class was tenured as of that semester; *InstructorMale* was set to one for male instructors; *InstructorExp* measures years of teaching at SFA; *NumPerWeek* was the number of scheduled weekly class meetings, and *online* identified those classes taught online. For the time-of-day dummies, *eight* was used to identify classes starting at eight o'clock in the morning, *nine-ish* for those at 9:00 or 9:30 AM.; *eleven* for classes at eleven o'clock in the morning, and *late* for anything after four o'clock in the afternoon. The reference category are early afternoon classes—those between noon and 2:30 PM.

Figure 1. Distribution of *InstructorGPA*

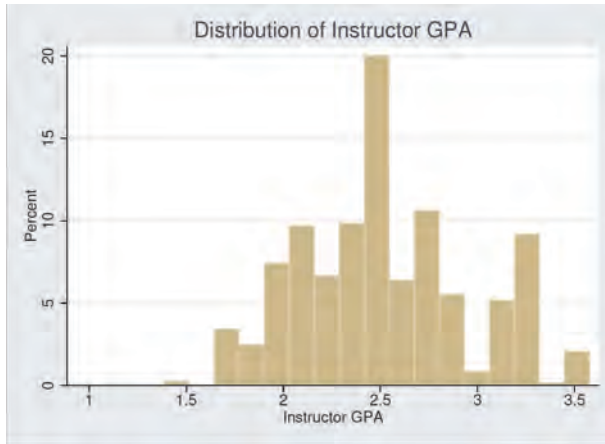
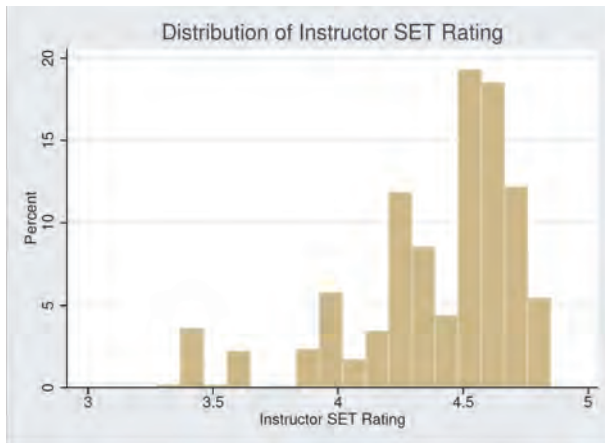


Figure 2. Distribution of *InstructorSET*



The two measures of instructor popularity, *InstructorSET* and *InstructorGPA*, both have significant positive effects throughout the estimations, suggesting that those instructors with reputations of having higher evaluation scores and being easier graders tend to have classes that fill more quickly. Both effects seem to reach their peaks on day 7 and day 14, where a one-point increase in rating leads to an approximately ten percent greater fill, and one-letter-grade increase in average instructor-assigned grade is associated with twelve to thirteen percent greater fill.

Figure 3. Distribution of the Dependent Variable (Fill Rate)



Of particular note are instructor characteristics that do not seem to matter: years of experience, whether the instructor is tenured, and instructor's gender all have nonsignificant coefficients throughout the estimations. To an extent, this is reassuring: students do not display strong preferences for classes taught by, for example, one particular gender. On the other hand, it is entirely possible that some of this bias is captured in the SET ratings. With respect to tenure, it is possible—or even likely—that students do not know whether their instructor is tenured; they may not even know what tenure is.

Students appear to (weakly) prefer classes that meet fewer times per week, but this effect is only significant in one of the regressions (Day 3). It is possible that there is a nonlinear effect to weekly meetings: students prefer two days per week to three days per week (say, Tuesday/Thursday classes to Monday/Wednesday/Friday) but prefer two weekly meetings to one, which always means an evening class, and as mentioned below, those are not popular.

Classes taught online display no significant differences in registration patterns when compared with those taught in the standard face-to-face format. This finding likely reflects demand for online classes by distance students who have no choice but to enroll in online sections.

Table 3. Dependent Variable: Fill Rate (% of Class Capacity Filled); Course Fixed Effects

	Day 1	Day 2	Day 3	Day 7	Day 14	Last Day
InstructorSET	0.0389*** (2.98)	0.0475*** (2.63)	0.0804*** (3.53)	0.0991*** (3.29)	0.1069*** (3.50)	0.0698*** (2.93)
InstructorGPA	0.0247* (1.95)	0.0458*** (2.60)	0.0673*** (3.04)	0.1325*** (4.51)	0.1182*** (3.96)	0.0589*** (2.53)
tenured	0.00234 (0.22)	0.00253 (0.17)	-0.01206 (0.64)	0.01304 (0.52)	0.01645 (0.65)	-0.02620 (1.33)
InstructorExp	9.22×10^{-6}	-0.0003 (0.57)	1.01×10^{-5}	-0.00032 (0.36)	0.00002 (0.02)	-0.00095 (1.35)
InstructorMale	-0.00407 (0.43)	0.00322 (0.25)	0.01770 (1.07)	0.00894 (0.41)	0.00581 (0.26)	0.00220 (0.13)
NumPerWeek	0.00469 (0.59)	-0.00535 (0.49)	-0.0323** (2.35)	-0.01656 (0.91)	0.00137 (0.07)	-0.00771 (0.54)
online	0.01733 (0.96)	0.01328 (0.53)	-0.02963 (0.94)	-0.0757* (1.82)	-0.05016 (1.19)	0.02625 (0.80)
eight	-0.0248* (1.69)	-0.0577*** (2.84)	-0.0888*** (3.47)	-0.1897*** (5.61)	-0.2191*** (6.39)	-0.0637*** (2.37)
nine-ish	0.00048 (0.05)	-0.00396 (0.28)	-0.01915 (1.07)	-0.0693*** (2.92)	-0.0697*** (2.89)	-0.03096 (1.64)
eleven	0.0291*** (2.92)	0.0460*** (3.33)	0.0657*** (3.77)	0.0732*** (3.17)	0.0650*** (2.78)	0.02685 (1.47)
late	-0.0344*** (2.70)	-0.0511*** (2.89)	-0.1060*** (4.76)	-0.1909*** (6.47)	-0.1934*** (6.48)	-0.1153*** (4.94)
Cons	-0.1341** (2.32)	-0.13101 (1.64)	-0.1752* (1.74)	-0.19388 (1.46)	-0.15111 (1.12)	0.5192*** (4.92)
R ² (within) ^a	0.0431	0.0545	0.0903	0.1298	0.1311	0.0703
N	1,086	1,086	1,086	1,085	1,080	1,086

^aThis is the R² reported by Stata for the demeaned (or deviated) regression using group fixed effects.

Note: Significance is indicated with the traditional thresholds: * 0.1 level, ** 0.05 level, *** 0.01 level.

When it comes to other aspects of scheduling, approximately what was expected from student preferences was observed. Eight o'clock in the morning classes are the least popular, and this effect becomes more pronounced as the registration period continues. On days 7 and 14, classes taught at eight o'clock in the morning are about twenty percent less filled than classes taught in the afternoon. Similarly, late classes, defined as those scheduled at four o'clock in the afternoon and later, are not popular either. The most popular start time is eleven o'clock in the morning.

The overall preference rank ordering in terms of registration desirability is as follows:

1. 11:00 AM
2. Afternoon (12:00 PM–2:00 PM)
3. 9:00 AM and 9:30 AM
4. 8:00 AM and late-afternoon/evening classes⁷

Following a referee's suggestion, a version of our model was estimated with several measures interacted. Specifically, the approach taken was to interact each of the class-time variables with the SET rating of the instructor to check whether students tend to choose a class offered at a specific time *conditional* on the class being taught by a popular instructor. We also separately interact the two measures of popularity, *InstructorGPA* and *InstructorSET*. Table 4 (in Appendix A) reports these results, with the added interaction terms appearing last in the list of variables. See provided discussion in the appendix; here, note that the qualitative effects of the variables of interest remained the same with the addition of interaction terms: signs and significance of *InstructorSET* and *InstructorGPA* were unchanged, although the sizes of these effects were larger.

DISCUSSION AND CAVEATS

The study results indicate that there are distinct patterns in the class selection process by students during enrollment. Specifically, strong support for the previously found effects (by Brown and Kosovich [2015], for example) of instructor popularity and perceived “easiness” were found: students prefer classes taught by those with better past student evaluations and those who give out higher grades on average. This finding has implications for university administrators interested in actively managing enrollment in individual sections of classes, scheduling of classes, and even assignment of instructors to classes. In particular, there are often concerns that a particular section will not “make”—i.e., have enough students enroll to justify running the section—and administrators sometimes take preemptive steps to prevent scheduled sections from not making. One approach is to actively advise students to consider enrolling in these at-risk sections; another is active management of maximum

class capacities. For example, setting a maximum class capacity of an 11:00 AM section lower will make that class appear full to potential students and encourage them to enroll in the other available sections, which may be at a less popular time or with a less popular instructor. The capacity of the popular section can subsequently be increased, and this is often done incrementally as student demand for that section continues. In addition, in rare cases, a new section is added to the schedule while registration for classes is already ongoing. This circumstance is quite rare because it requires either hiring a new instructor late in the scheduling process or having an existing instructor teach the additional class (an “overload”)—both can be costly.

On the other hand, there are factors that necessitate scheduling classes at various times, on various days of the week, and taught in various modalities. Limited classroom space often means that classes must be scheduled on all five days of the week, even if it is apparent that both students and instructors prefer classes that meet twice a week (either Monday/Wednesday or Tuesday/Thursday).

A few important caveats are worth mentioning. First, information on SET ratings and grade distributions that the study included to measure instructor popularity is not technically public—i.e., the university does not actively publish these data or even make them easily accessible. On the other hand, there *are* publicly available online resources where one can get a good idea of students’ impressions of an instructor’s class, teaching approach, grading rules, etc., as well as past grade distributions; Rate My Professor, Koofers, and MyEDU are just some of the examples of online instructor review services available. In other words, an important assumption made in this study was that, despite not being made public, this information is available to students. There is some empirical support for this conjecture: using data from Berkeley, Harvard, and Rice, Tipoe [2013] found that there is a good deal of agreement between official teaching evaluations and feedback on RateMyProfessor.com.

In addition, given the medium size of the university—and an even smaller subset of student population majoring in business—it is reasonable to assume that students have the ability to find enough information about courses they are taking, for example, through personal contacts with other students or on social media. As an anonymous reviewer suggested, students who are part of a Greek community on campus often have a network where such information is actively shared. Although statistics on Greek involvement by business students are not available, about eleven percent of the overall student body at SFA belongs to a social fraternity or sorority. This percentage is somewhat lower than some of the nationally reported figures on college students’ Greek participation—one survey suggests that about sixteen to seventeen percent of U.S. undergraduates belong to a Greek organization—but these data are also hard to find.⁸

Second, the assumptions in this study were that students have at least some idea of which instructors have permanent appointments—and which of those are tenured—and place some degree of weight on this information. It is not

immediately obvious that students have this awareness or whether a typical student even understands what it means to have tenure. Indeed, this may be one reason contract status was not found to be a significant factor in students' choice of classes.

Third, the finding regarding the effect of the number of weekly meetings—slightly negative but largely insignificant—is likely mismeasured and possibly captures both the times-per-week and time-of-day effect. In other words, classes meeting once per week would be more popular but for the fact that they meet in the evenings, which is an unpopular time.

Fourth, there surely are other unobserved factors that are nevertheless important to students' enrollment decisions. For example, some instructors teach multiple courses within the set of the required business curriculum, and it is likely that prior experience with a given instructor affects the willingness of a student to register for another course taught by the same instructor. For example, both Principles of Micro- and Macroeconomics and Applied Statistics are taught by economists. Given data limitations, tracking individual students' registration choices over time was not possible.

CONCLUSION

College students face many choices when making their enrollment decisions every term. Even within a prescribed course of study, where courses must be taken in a particular order, there are still options from which to choose an optimal set of classes. As found in this study, instructor-level characteristics are important to these decisions, and students actively seek out classes taught by those known to assign higher grades and those who receive higher SET scores. In addition, scheduling factors are important. These findings confirm what many in higher education casually observe and know anecdotally: that early morning classes are less popular than midday classes, and students generally like to be in class fewer times per week.

The use of daily registration totals provided a way to study demand for class sections throughout the enrollment period rather than only at the end. This approach is particularly important because at many institutions, like SFA, administrators actively monitor enrollment in classes and often manipulate class capacities accordingly.

One possible logical direction in which this research can be extended in the future is to investigate whether different majors within the college of business (or even broadly, at the university) behave differently when choosing their classes. For example, do accounting students choose classes with easier graders for non-accounting courses? Also, what other student characteristics are important in explaining registration behavior? Do those with higher GPAs register earlier and therefore have more options available to them? Much of this will require more detailed individual-level data than are currently available.

NOTES

¹A well-known feature of the site RateMyProfessor.com, the so-called chili pepper, was removed in 2018.

²A discussant questioned this claim at a presentation, suggesting that lower variability in the sample cannot be an advantage because “more variability is always better.” However, this author maintains that focusing on a more uniform group of students is a net plus here: there are many unobservable elements among student characteristics, and narrowing the focus to a smaller set of majors mitigates the inability to measure these directly.

³The information technology course was dropped because it was changed significantly during the period covered by the data. Prior to 2012, the course was a basic introduction to PC computing; subsequently, it was replaced with a course with a heavy focus on the use of spreadsheets (e.g., Microsoft Excel).

⁴The study included data from all available semesters for each instructor in this calculation. An alternative approach would use only the latest semester or year of grades assigned; the drawback is that this may inadvertently capture an unusual semester: a particularly strong or weak draw of students, or some other aspect that makes that term unique.

⁵The study omitted all classes taught in summer sessions during the period.

⁶In a companion study, this author attempts to disentangle this (possibly causal) relationship between grading approaches and student evaluations. A working paper is available on request.

⁷As mentioned above, it is possible that the effect of late-scheduled classes is conflated with once-per-week classes.

⁸Gallup-Purdue Index, based on a 2014 survey of randomly selected 29,650 individuals with a bachelor’s degree or higher, representing all 50 states and Washington, DC. According to the survey, 5,137 respondents identified as belonging to a fraternity or sorority.

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APPENDIX A

The main estimated model was extended to include interacted terms: between time of day and SET and between instructor's overall GPA and their SET. The goal was to check whether there are any complex or nonlinear effects in how students reveal their preferences for classes. In particular, with respect to instructor's grading history and their student evaluations, the author strongly suspects that there is a connection, perhaps even a causal one. Although that lies beyond the scope of this paper, it is interesting to investigate whether students prefer not only classes taught by easier graders and those with better evaluation scores, but whether those factors interact with one another. The added interaction term was found to have a significant negative effect in three of the six regressions (though, in two, the significance is rather weak). In the Last Day regression, the effect was statistically significant at the one percent level, negative, and substantial in magnitude, which suggests that students "trade off" the two characteristics in their chosen instructor.

The time dummies interacted with SET rating do not seem to have significant effects with the exception of late afternoon classes, where the coefficients on the interaction terms are negative. The interpretation is that the SET rating has a moderating or dampening effect on the scheduling preference by students: students prefer late classes relative to the early-afternoon classes, but this effect is weaker when SET considerations are added to the mix.

Table 4. Dependent Variable: Fill Rate; Course Fixed Effects and Interactions

	Day 1	Day 2	Day 3	Day 7	Day 14	Last Day
InstructorSET	0.1638** (2.35)	0.2265** (2.31)	0.2314** (1.90)	0.1187 (0.74)	0.1246 (0.76)	0.3992*** (3.13)
InstructorGPA	0.2489** (2.09)	0.3519** (2.13)	0.3413 (1.64)	0.1554 (0.56)	0.1307 (0.47)	0.6631*** (3.04)
tenured	−0.00035 (0.03)	0.00004 (0.00)	−0.01414 (0.75)	0.01078 (0.43)	0.01533 (0.61)	−0.02908 (1.47)
InstructorExp	0.00002 (0.04)	−0.00039 (0.70)	0.00005 (0.08)	−0.00006 (0.06)	0.00026 (0.28)	−0.00109 (1.50)
InstructorMale	0.00087 (0.09)	0.00882 (0.65)	0.02347 (1.38)	0.01259 (0.56)	0.00975 (0.43)	0.01247 (0.70)
NumPerWeek	0.00083 (0.10)	−0.00955 (0.85)	−0.0391*** (2.77)	−0.02820 (1.51)	−0.01164 (0.62)	−0.01373 (0.93)
online	0.00657 (0.35)	0.00102 (0.04)	−0.04727 (1.46)	−0.1016** (2.37)	−0.0788* (1.82)	0.00740 (0.22)
eight	−0.2165 (0.25)	−0.3119 (0.88)	−0.8102* (1.82)	−1.0153* (1.73)	−1.2995** (2.19)	−0.9789** (2.10)
nine-ish	−0.01288 (0.10)	−0.00387 (0.02)	−0.07005 (0.30)	−0.14555 (0.47)	−0.24192 (0.77)	−0.09708 (0.40)
eleven	−0.1288 (1.01)	0.0484 (0.27)	−0.0837 (0.38)	−0.18970 (0.65)	0.01157 (0.04)	−0.04318 (0.19)
late	0.2087 (1.61)	0.1411 (0.79)	0.2551 (1.13)	0.7152** (2.40)	0.7636** (2.53)	−0.02909 (0.12)
eight × SET	0.0432 (0.75)	0.0573 (0.72)	0.1625 (1.62)	0.18542 (1.41)	0.2428* (1.82)	0.2065** (1.97)
nine-ish × SET	0.0028 (0.09)	−0.0003 (0.01)	0.0114 (0.21)	0.01792 (0.25)	0.04012 (0.56)	0.01421 (0.25)
eleven × SET	0.0358 (1.24)	−0.0009 (0.02)	0.0338 (0.67)	0.06014 (0.90)	0.01227 (0.18)	0.01516 (0.29)
late × SET	−0.0554* (1.88)	−0.0436 (1.06)	−0.0824 (1.60)	−0.2078*** (3.05)	−0.2196*** (3.19)	−0.01884 (0.35)
SET × GPA	−0.0518* (1.87)	−0.0712* (1.85)	−0.0632 (1.31)	−0.00343 (0.05)	−0.00093 (0.01)	−0.1408*** (2.78)
Cons	−0.6647** (2.25)	−0.8753** (2.14)	−0.8137 (1.58)	−0.27882 (0.41)	−0.22691 (0.33)	−0.87240 (1.62)
R ² (within)	0.0526	0.0589	0.0971	0.1422	0.1448	0.0798
N	1,086	1,086	1,086	1,086	1,086	1,086

APPENDIX B

Table 5 displays the student-major composition of classes taught at various times during the day. Timeslots are arranged chronologically and grouped into parts of day (early morning, late morning, etc.), whereas the top ten majors enrolled in each class are sorted alphabetically.

Table 5. Composition of Classes by Student Major

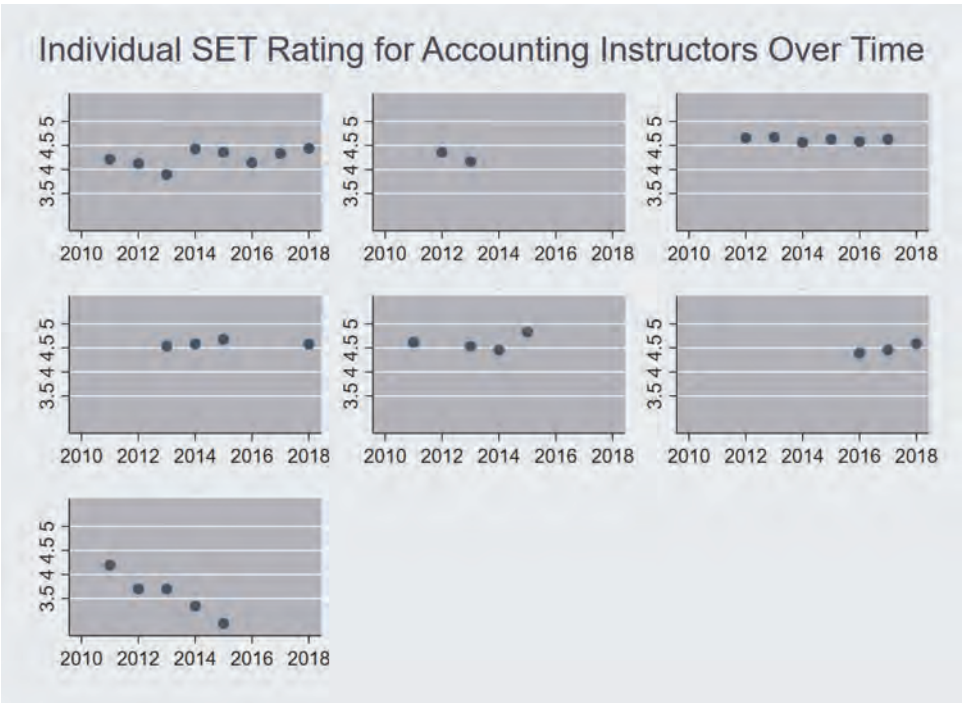
	Early Morning			Morning		Late Morning		Early Afternoon			Late Afternoon		Evening		
	8:00 AM	8:00 AM– 8:15 AM	9:00 AM	9:30 AM	10:00 AM– 10:45 AM	11:00 AM– 11:50 AM	11:00 AM– 12:15 PM	12:30 PM– 1:45 PM	1:00 PM– 2:15 PM	2:00 PM– 3:15 PM	2:30 PM– 3:45 PM	3:30 PM– 4:45 PM	4:00 PM– 5:15 PM	5:00 PM– 6:15 PM	6:45 PM– 9:15 PM
Majors															online
Accounting	0.15	0.15	0.14	0.19	0.12	0.11	0.17	0.14	0.17	0.18	0.17	0.21	0.19	0.20	0.28
Business Comm & Corporate Education	0.03	0.03	0.03	0.02	0.03	0.04	0.03	0.02	0.01	0.03	0.03	0.04	0.02	0.04	0.00
Business Economics	0.03	0.03	0.04	0.03	0.03	0.04	0.03	0.03	0.04	0.05	0.02	0.04	0.02	0.00	0.04
Finance	0.10	0.08	0.07	0.08	0.10	0.10	0.10	0.11	0.10	0.13	0.11	0.10	0.09	0.18	0.16
General Business	0.18	0.14	0.13	0.15	0.14	0.17	0.14	0.11	0.16	0.10	0.13	0.09	0.19	0.20	0.15
Human Resource Management	0.03	0.03	0.01	0.03	0.02	0.02	0.03	0.05	0.03	0.03	0.03	0.04	0.02	0.00	0.03
International Business	0.03	0.03	0.05	0.02	0.03	0.05	0.03	0.03	0.02	0.02	0.02	0.04	0.03	0.03	0.01
Management	0.14	0.08	0.11	0.13	0.11	0.02	0.13	0.14	0.09	0.12	0.11	0.10	0.13	0.07	0.11
Marketing	0.13	0.13	0.13	0.12	0.15	0.08	0.16	0.15	0.19	0.16	0.16	0.19	0.16	0.09	0.04
Sports Business	0.09	0.07	0.09	0.08	0.10	0.12	0.08	0.10	0.08	0.05	0.09	0.09	0.08	0.09	0.05

There is not much variation in the make-up of classes, although some slight patterns can be discerned. For example, marketing majors tend to have a slightly higher representation in afternoon classes, whereas accounting and general business majors have high shares of morning classes; accounting majors also make up large shares of evening classes, although that is simply an artifact of scheduling—there are relatively few evening classes overall.

APPENDIX C

Figure 4 below displays plots mean SET ratings for individual instructors in accounting—i.e., those teaching courses titled Principles of Financial Accounting and Principles of Management Accounting—over time. Each scatter plot corresponds to an instructor; the names have been suppressed. Only those with four or more semesters of teaching were kept for this purpose, and semester ratings were averaged to annual observations. In all but one case, the numeric ratings are not only fairly constant but also quite similar across individuals; we do not observe any clear pattern that can be indicative of a particular trend. The last plot corresponds to a faculty member late in their academic career.

Figure 4. SET Rating Over Time for Individual Accounting Instructors



Hoops and Health Care Fraud: The Defrauding of the NBPA Health Plan

Jake Leichner, Matthew Heard, Tyler Custis*, and Phillip Adam

This paper describes the alleged systematic fraud of the current/former NBA player health care plan. The authors created an instructional case based on this alleged scandal. This case provides students an understanding of business law concepts, including: (1) 18 U.S. Code §1347; (2) Identity Theft Penalty Enhancement Act; (3) Identity Theft and Assumption Deterrence Act; (4) Wire Fraud; and (5) ethical practices. This case details the scheme and enables the students to determine the correct sentencing for those involved. Student opinion surveys were also conducted, showing an outcome of engagement and an increase in knowledge.

Keywords: Health Care, Fraud, Conspiracy, National Basketball Association, 18 U.S. Code §1028A

Disciplines of Interest: Business Law and Ethics, Health Care Administration

INTRODUCTION

The U.S. Department of Justice (DOJ) Southern District Court of New York has charged Terrence Williams, the alleged ringleader, and 17 other NBA players for a scheme involving health insurance fraud. The indictment also charged multiple medical doctors, a California chiropractor, and a dentist who submitted false claims to the National Basketball Players Association (NBPA) plan. Williams faces charges of aggravated identity theft, conspiracy to commit health care fraud, and wire fraud. This indictment was carried out in the Southern District of New York. These health care claims ran a total of \$5 million, according to [DOJ, 2022]. Williams was indicted on October 7, 2021. He was put on a pretrial release until he threatened a witness in 2022, according to the DOJ. Williams threatened the witness via a text message, stating, “Me spitting in your face is exactly what you’ll see,” among other obscenities [DOJ, 2022].

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Background of Williams

Terrence Williams was born in Seattle, Washington, in 1987 and played for Rainier Beach High School, where he averaged 21.7 points in his senior year. During high school, he also played football as a wide receiver and free safety. Before his National Basketball Association (NBA) years, he played for the University of Louisville from 2005 to 2009. During his senior year, he was cocaptain of the team and averaged 12.5 points a game [Sports Reference, n.d.]. Williams helped lead his team to the No. 1 seed in the National Collegiate Athletic Association (NCAA) tournament and an Elite 8 appearance in his final year [Abrams, 2009]. He was also only the third player for Louisville to score a triple-double in the program's history; this, along with other achievements, led him into the NBA.

Williams was drafted 11th overall by the New Jersey Nets in 2009. He played for the team until 2012, when he signed a short-term contract with the Sacramento Kings. After a year-long hiatus from the NBA spent in China, he finished his NBA career in Boston with the Celtics.

Criminal History

On May 19, 2013, Williams was arrested for displaying a gun at the mother of his son during a visitation exchange with their 10-year-old child [ESPN Internet Ventures, 2013]. Williams claimed he showed it to the mother because he felt threatened by her and her boyfriend. Williams was later released after posting a bail of \$25,000. He was charged and investigated for second-degree domestic assault, but the King County officials did not press charges [Lintner, 2013].

Financial Difficulties

Many professional athletes have frequently mishandled their money. This mismanagement may have been why some of these former players allegedly committed the crimes described in the "Introduction" section. According to *Sports Illustrated* in 2009, "Within five years of retirement, an estimated 60 percent of former NBA players are broke" [Torre, 2009].

There are many examples of players who might not have planned their financial endeavors. Mike Tyson (boxing) and Allen Iverson (NBA) are two examples of this lack of planning. Mike Tyson at his peak of financial success was once worth \$400 million, yet before he even retired, in 2003 he declared bankruptcy due to mismanagement [Parker, 2022]. Allen Iverson is another example of a professional athlete who had some financial management troubles. He was unable to pay a jeweler \$860,000 in 2012, even after making over \$150 million in the NBA during his tenure [Parker, 2022].

Although the issue may potentially be attributed to financial mismanagement, for professional athletes, the window of opportunity for monetary gain is much smaller. This time constraint means that these athletes need to be smart financially during that period, usually around their early twenties. The financial decisions they make while competing are essential and will determine their future financial success.

RELEVANT BACKGROUND INFORMATION

Overview of Conspiracy

Conspiracy, according to the Legal Information Institute, is “an agreement between two or more people to commit an illegal act, along with an intent to achieve the agreement’s goal. Most U.S. jurisdictions also require an overt act toward furthering the agreement. An overt act is a statutory requirement, not a constitutional one” [Legal Information Institute, 2022].

Terrance Williams pleaded guilty to conspiracy charges due to his alleged actions to commit health care fraud with other former NBA players. They allegedly conspired to forge documents to wire money from the NBA health care plan. Conspiracy charges usually carry their separate penalty and have the ability to lead to derivative liability, meaning that even if the conspirator is not involved with a certain act in the scheme, they can still be charged for it [Legal Information Institute, 2022].

An Overview of Health Care Fraud

According to The National Health Care Anti-Fraud Association, health care fraud costs the United States about \$68 billion annually, or 3 percent (\$2.26 trillion) of total health care spending. According to Cigna, “Health care fraud is a crime. It’s committed when a dishonest provider or consumer intentionally submits, or causes someone else to submit, false or misleading information for use in determining the amount of health care benefits payable.” [Cigna Healthcare, n.d.]. There are a plethora of acts that are placed under the health care fraud umbrella. The act that Williams pled guilty to committing was filing claims for services that were not received. These fraudulent claims for medical and dental services were sent to the NBA health plan for reimbursement supposedly at the behest of the doctor and dentist. These services were never actually provided.

Health care fraud is covered in 18 U.S. Code § 1347, which states:

“Whoever knowingly and willfully executes, or attempts to execute, a scheme or artifice—

[1] to defraud any health care benefit program; or

[2] to obtain, by means of false or fraudulent pretenses, representations, or promises, any of the money or property owned by, or under the custody or control of, any health care benefit program, in connection with the delivery of or payment for health care

benefits, items, or services, shall be fined under this title or imprisoned not more than 10 years, or both.

If the violation results in serious bodily injury (as defined in section 1365 of this title), such person shall be fined under this title or imprisoned not more than 20 years, or both; and if the violation results in death, such person shall be fined under this title, or imprisoned for any term of years or for life, or both.”[Health Care Fraud, 2018].

An Overview of Aggravated Identity Theft, 18 U.S. Code § 1028A

According to Kristina Glithero, publishing in the *American Journal of Criminal Law*, “With the enactment of the ‘Identity Theft Penalty Enhancement Act,’ Congress created a new statutory crime: aggravated identity theft.” This crime includes a mandatory two-year sentence when the identity is found to belong to another person. It was also found by the Supreme Court in *Flores-Figueroa v. United States*, that for a person to be convicted of this crime, the defendant has to have the understanding that the identity belongs to another person [Glithero, 2009]. The text of 18 U.S. Code § 1028A states that “Whoever, during and in relation to any felony violation enumerated in subsection (c), knowingly transfers, possesses, or uses, without lawful authority, a means of identification of another person shall, in addition to the punishment provided for such felony, be sentenced to a term of imprisonment of 2 years.”

In 2004 Congress created a second statute in addition to the original “Identity Theft and Assumption Deterrence Act” [Easter and DeVore, 2022], which created a harsher sentencing for specific federal crimes, such as wire, mail, and bank fraud [Congress.gov, 1998]. The difference between aggravated identity theft and identity theft is that aggravated identity theft is committed by stealing a person’s identity and then committing a specified crime with said identity. Aggravated identity theft carries a more severe sentencing due to the identity being linked with other federal crimes. Some examples of these federal crimes are any crime within Chapter 63 of the criminal code related to wire, mail, or bank fraud or 18 U.S.C. 664, which involves theft from employee benefit plans [Azhari LLC, 2021].

CASE DETAILS

NBA Health Plan

The NBA health care plan that Williams took advantage of provides benefits to eligible current and former players and their families. The plan was voted on unanimously by NBA owners and players’ unions in 2016 [Buckner, 2021]. According to an article published in the National Library of Medicine, “Despite its origins as a noncontact sport, basketball has evolved into an increasingly physical game in which contact is accepted and expected. Contemporary coaches

teach their players contact moves” [Drakos, Domb, Starkey, Callahan, and Allen, 2010]. This plan is focused on continuing these players’ health care support during their time playing in and retiring from the league.

The plan, defined under Title 18, U.S. Code, Section 24(b), as a “health care benefit program” has the means of providing extra coverage to current and former NBA players that qualify [DOJ (U.S. Department of Justice), 2019]. The plan allows for a health reimbursement account that reimburses certain medical expenses not covered by the player’s primary insurance imposed on the players or their families [DOJ (U.S. Department of Justice), 2019].

This plan was funded by NBA teams and generally requires three regular seasons worth of participation. An administrative manager oversees the day-to-day operations of the health plan, and all of the claims made by the NBA players must be overseen by this manager. During the timeline of Williams and his coconspirators’ crimes (2017–2021), there were two administrative managers.

Former Washington Bullets player Phil Chenier is worried about his benefits due to these fraud allegations. He stated, “It’s kind of disappointing because this was a plan we were all excited about” [Buckner, 2021]. Chenier was drafted fourth overall in 1971 by the Baltimore Bullets, and like many former older players he was grateful for the league passing this plan.

The Process

The conspiracy took place from at least 2017 to 2021. Williams helped lead the scheme by which NBA players and their family members submitted false claims to the NBA plan for reimbursement with the alleged help of a doctor, chiropractor, and dentist.

The first claim submitted by Williams was in or around November 2017, when he submitted a false claim for reimbursement of \$19,000 from a chiropractic office on Ventura Boulevard in California [DOJ (U.S. Department of Justice), 2019]. This claim was submitted with the help of the chiropractor, Patrick Khaziran, who was sentenced to thirty months in prison by a New York federal judge for his involvement [Uranga, 2023]. The plan paid for it in part with \$7,652.55. After this fraudulent claim and possibly some others, Williams started recruiting other players into the scheme.

According to Bloomberg.com, “Prosecutors said Williams recruited other participants of the plan and gave them false invoices provided by a dentist in California, a doctor in Washington state, and several non-medical professionals. Williams personally created fake letters of medical necessity that had grammatical errors, unusual formatting, and misspellings, according to court documents” [Dolmetsch, 2022]. Williams also provided fake invoices to help support the other alleged perpetrators of the conspiracy [DOJ, 2022]. Williams earned at least \$300,000 in kickback payments for planning these fraudulent claims.

Around May 28, 2019, an associate of Williams sent a template for a fake chiropractic office invoice that included items such as the date, invoice number, and services with a bill of \$15,000 [DOJ (U.S. Department of Justice), 2019]. This would be one of the many templates Williams would fill out and distribute to alleged partners of the scheme. The templates from the chiropractic office would generally include the same services, such as electrical stimulation, whirlpool, aquatic therapy, and therapeutic exercise. For some plans to be fulfilled, the administrative manager of the plan would require a letter of “medical necessity” to be provided from a licensed medical professional [DOJ (U.S. Department of Justice), 2019]. Some of these letters were unusual in the sense that they included many aforementioned grammatical errors.

In another occurrence of aggravated identity theft, Williams impersonated others in emails, such as when he pretended to be the NBA plan’s administrative manager. In one instance he used this email account to frighten a codefendant into continuing the conspiracy with him as well as pay him more kickback. In another instance he used his email account to frighten the doctor codefendant into sending him (Williams) “fines” or else he would be reported for the fraudulent invoices. Stating that his account “has the same processed invoice numbers as another claim for a different player,” these threats would net him \$346,000 [DOJ (U.S. Department of Justice), 2019].

The Ball is in Your Court - Case Questions

After all of the information you have read, answer the following questions:

Questions

- In your own words, define health care fraud and state whether you think Williams committed it according to your understanding of the crime.
- Who are the stakeholders in this situation?
- Williams defrauded a small fraction of the amount of money in this large insurance pool. Why is the law concerned with such an offense? If Williams fell on tough times, do you think what he did was right?
- Was Williams’ sentence fair? Why or why not?

Epilogue

Williams was sentenced to ten years in prison by United States District Federal Judge Valarie E. Caproni on August 3, 2023. Williams will also pay \$2.5 million for restitution as well as forfeit \$654,000 [Dolmetsch, 2022]. Williams pleaded guilty on August 26, 2022, “to defrauding the NBA players’ health and welfare benefit plan” [DOJ, 2022].

Student Evaluations

A mix of thirty-three health administration and business law students reviewed this case and answered the survey questions, some of which also left for additional comments. The students were in enrolled in an undergraduate course required for their respective major. A large majority of the sampled students were in the third or fourth year of their undergraduate college education. As evidenced by Figure 1, overall, the students found that the case was beneficial to their understanding of many of the topics discussed within it and would recommend it to their peers in upcoming years.

Figure 1. Student Evaluations
5 = Strongly Agree; 4 = Agree; 3 = Neutral; 2 = Disagree; 1 = Strongly Disagree

Item	Mean	Standard Deviation
1. Completing this NBA Healthcare Fraud case study helped me understand healthcare fraud, conspiracy, and all other charges.	4.66	0.48
2. Completing this NBA Healthcare Fraud case helped me understand the difference between identity theft and aggravated identity theft.	4.3	0.74
3. Completing this NBA Healthcare Fraud case study helped me understand ways fraud can be accomplished.	4.27	0.76
4. This case study was appropriate for a 300-level business course.	4.55	0.83
5. Analyzing this case was beneficial to my understanding of this course and its topics.	4.58	0.71
6. I would recommend this case to be a part of future business law and healthcare administration classes.	4.58	0.61

A business law course student stated, “Studying this case provided a valuable opportunity to bridge knowledge from our classroom content with real-world application. The case’s relevance illuminated the complexity of legal principles, which has fostered a deeper understanding of critical thinking. Engaging with this case enhanced my understanding of the law and its practical implications, contributing significantly to my overall learning experience.”

In addition, a health care administration student expressed, “This case highlights the significant legal consequences that both organizations and individuals can face as a result of engaging in unethical or illegal healthcare practices. As a prospective healthcare administrator, I am committed to upholding and respecting all laws, while ensuring that I, along with my organization, consistently adhere to the highest ethical standards.”

TEACHING STRATEGY AND CASE IMPLEMENTATION GUIDANCE

Introduction

Terrance Williams helped develop a conspiracy to steal millions of dollars from the NBA. This conspiracy not only affected the league and the program but also took funding away from players who were trying to use the health plan legally. Through this case study we get to view the conspiracy to commit health care fraud and other offenses that Williams and associates committed.

There are three parts to this study. First, there is the background on the case consisting of information on Williams, relevant information behind the legal charges, and the process by which the fraud was committed. Second, there are questions regarding the case study as well as an epilogue stating the sentencing Williams received. Third, the answers to the end-of-case study questions can be provided on request to the corresponding author.

Relevant Research

Understanding the legal process, especially regarding health care fraud, wire fraud, and conspiracy is very important to gaining a base-level understanding of legal issues in a business or health care environment. This study helps to create an understanding of ethical reasoning among students. Business students and majors tend to create a perception in the public of being unethical. This perception can be backed up by research from Linda Lau and James Huag [2011], who compared ethical tolerance between business and non-business majors. They stated, “Business students tend to have the lowest ethical standards and therefore a higher tolerance for cheating than the non-business students.” Therefore, it is necessary for business students to gain a better understanding of ethical and legal principles.

Another study showing the implications of not teaching students ethics of business and their practices was completed by Guillermina Tormo-Carbó and

Elies Seguí-Mas from the University of Valencia in Spain. They sampled 551 management students from a Spanish university. They concluded that “Our results suggest that business ethics/CSR courses increase awareness of the importance of ethics in (i) business courses, (ii) recognizing accounting ethical implications, and [iii] workplace decisions” [Tormo-Carbó, Seguí-Mas, and Oltra, 2018].

Learning Objectives

The following are learning objectives that are possible by assigning this case study to business law and health care administration students:

- Development of understanding of insurance fraud, aggravated identity theft, and conspiracy
- Understanding of criminal conduct and its red flags
- Ethical reasoning
- Understanding of health care and criminal procedures.

Intended Audience

This case study was audited and implemented in health care administration and business law classes at a medium-sized university in the Midwest. These undergraduate classes primarily consist of business school majors. The business law class is required for all business majors, whereas those who audited in the health care administration classes chose the class by declaring their major/minor.

Implementation Suggestions

Students were offered extra credit in the courses to review and audit this case study. They did this on an individual basis and were given a due date one to two weeks after the announcement. Instructors can choose to ask all of the questions or tailor the questions based on the other topics discussed in class. We recommend that ethics questions be brought up in both business law and health care administration classes. Health care fraud questions are brought up in the health care administration courses. It is important to decide the questions that should be asked in the course, although many of the questions are broad enough to be brought up in both courses. In both of our studies, we asked all of the questions; however, a professor could feel inclined to choose from the particular questions at their discretion due to the type of class they are teaching. The Student Grading Rubric in Figure 2 could also be used partially, or in its entirety based on which questions the instructor chose to ask the students.

Figure 2. Student Grading Rubric

Criteria	5 Points	3 Points	1 Point
Identification of the Main Problems/Issue	Identifies and demonstrates a complex understanding of all of the main issues/problems in the case study.	Identifies and demonstrates an understanding of most of the main issues/problems in the case study.	Identifies and demonstrates an understanding of some of the main issues/problems in the case study.
Identification and Understanding of Charges	Can identify and explain all of the charges described in the case study.	Can identify and explain most of the charges described in the case study.	Can identify and explain some of the charges described in the case study.
Connection to materials taught in class	Can effectively show and connect all materials taught in the course to those described in the case study.	Can show and connect most materials taught in the course to those described in the case study.	Can show and connect some materials taught in the course to those described in the case study.
Writing and Formatting	Demonstrates and utilizes all proper grammatical techniques where writing is required.	Demonstrates and utilizes most proper grammatical techniques where writing is required with some mistakes.	Demonstrates and utilizes some proper grammatical techniques where writing is required with numerous mistakes.

Total Points: 20

CONCLUSION

This innovative teaching tool validated its purpose with students by showing an average of 4.61 (agree to strongly agree) on the usefulness of this case study in their learning. Some quotations from the students regarding what they liked about the study were: “I found this case interesting and would like to know more about it” and “I really enjoyed reading this case and answering these questions. I think it allowed me to understand it more than maybe some of the other cases we read in class. It also allowed me to think on my own and have my own opinions that might differ from my classmates.” This case study is beneficial to a student’s education and understanding of health care fraud, judicial processes, and ethics.

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Gender Diversity Dividends and Divisions: Student Team Strategic Decision-Making, Team Performance, and Corporate Social Responsibility

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A growing body of research highlights the impact of gender diversity in student team strategic decision-making. Gender diversity, firm performance, and corporate social responsibility (CSR) choices were analyzed using student team decision data from a business simulation. Gender-diverse teams had the strongest financial performance, whereas all-male teams had the weakest. Contrary to previous self-report research, this study saw only weak support for student team gender diversity differences in CSR investments. The research suggests that gender diversity should be encouraged in student team composition.

Keywords: Strategy, Simulation, Gender Diversity

Disciplines of Interest: Management, Marketing, Finance, Supply Chain, Human Resource Management, Operations Management

INTRODUCTION

Gender diversity¹ and firm performance have been examined at the national, industry, firm, and team levels [Zhang, 2020]. Results on team gender diversity with various firm performance measures are mixed. Some gender-diverse teams have been found to innovate more effectively and efficiently [Xie, Zhou, Zong, and Lu, 2020], have improved information access and analysis [Fernando, Jain, and Tripathy, 2020], and achieve higher returns [Ferrary and Déo, 2023; Schwab, Werbel, Hofmann, and Henriques, 2016]. On the other hand, social identity theory, self-identity theory, and categorization-elaboration models are all connected to gender diversity group disruptive processes [Schwab et al., 2016]. Some empirical research suggests that lowered group

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cohesion and coordination in gender-diverse teams leads to less productivity and efficiency [Zhang, 2020].

At the same time, higher education has been responding to increased calls from business for students who are likely to be successful in our gender-diverse work environment. Given hiring trends of businesses towards leveraging benefits of a gender-diverse workforce, experience working with diverse teammates is an important piece of business student skill development. Business strategy courses, whether in functional areas (e.g., marketing, management, supply chain) or in general business capstone classes, often use teamwork in group projects or simulations to develop student teamwork, analysis, and decision-making skills. Yet, when students are allowed to endogenously choose groups, students prefer male-dominated groups [Fenoll and Zaccagni, 2022]. Even when students view diversity overall as a plus, they can be reluctant to participate in gender-diverse groups fearing the potential grade, time, and energy costs of lower social cohesion. “[C]onstant stress has become the new normal” for large numbers of college students [Hoyt, Cohen, Dull, Castro, and Yazdani, 2021, p. 272]. The preference for association with others sharing the same phenotypic traits is a natural impediment for the emergence of diverse groups on their own, particularly in highly uncertain contexts [Fu, Nowak, Christakis, and Fowler, 2012; Di Stefano, Scatà, La Corte, Liò, Catania, Guardo, and Pagano, 2015]. Whether student groups are self-selected, randomly generated, or assigned by the instructor, gender diversity in student teams may be perceived as a luxury that stressed students can ill afford.

In particular, differences in men and women’s views of the importance of corporate social responsibility (CSR) or ethical initiatives can be points of contention for groups having to make strategic team decisions. Findings on gender differences in CSR/ethical judgment have been equivocal [Forte, 2004; Izraeli and Jaffe, 2000; Marques and Azevedo-Pereira, 2009; Singhapakdi, Vitell, and Franke, 1999] or slightly favored women as the more ethical of the genders [Eweje and Brunton, 2010; Glover, Bumpus, Sharp, and Munchus, 2002; Herington and Weaven, 2008; Krambia-Kapardis and Zopiatis, 2008;]. One of the issues with this research is the widespread use of self-reported intentions as opposed to analysis of actual team decision-making. For example, social desirability appears to influence self-report findings. McCullough and Faught [2005] found that men might desire to simply appear, not be, more ethical than women. Several researchers have suggested that the self-reported instruments used in examining gender differences in ethical decision-making may be leading to the conflicting findings [Herington and Weaven, 2008; McCullough and Faught, 2005].

Business simulation games present an opportunity to gather data about actual student decision making with teams of varying gender diversity. Previous research on business simulation student team gender composition and decision-making is limited [Lamiraud and Vranceanu, 2018]. It has focused on

business performance and efficiency [Apesteguia, Azmat, and Iriberry, 2012; Lamiraud and Vranceanu, 2018], method of team assignment [Lamiraud and Vranceanu, 2018], and impact on CSR investments [Apesteguia et al., 2012]. Within these two studies, there were some indications of gender diversity impact on both firm performance and broad indices of CSR decisions.

This paper extends the previous business simulation research by doing a deeper dive into two main questions. First, does student team gender diversity have an impact on student strategic team performance when examined cumulatively and with a larger set of performance measures? Firm performance measures examined previously were stock price index [Apesteguia et al., 2012] and equity level, sales, and profit [Lamiraud and Vranceanu, 2018]. Apesteguia et al. [2012] used data from a first round of simulation decisions, whereas Lamiraud and Vranceanu, [2018] analyzed single round data from five and eight rounds of simulation performance. Our study adds additional firm performance measures and looks at cumulative team performance after ten rounds of decision-making. The second main question is, does student gender diversity have an impact on specific elements of CSR student strategic team decision-making? Apesteguia et al. [2012] examined only student team gender diversity investment decisions in broad indices. Our study looks at gender-diverse student team CSR investment choices with specific diversity, ethics training, and environmental initiatives.

LITERATURE REVIEW

Although literature on student team strategic decision-making is limited, theoretical differences in gender decision making are deeply rooted. Social role theory [Eagly, 1987] suggests that males and females are raised differently within society, and from their particular society or culture they learn which roles are appropriate for them. Under this theory, women typically develop to be more communal and men to be more agentic. These gender roles become part of an individual's identity, thus becoming not only descriptive and prescriptive for others, but also intuitive for the individual [Wood and Eagly, 2009].

Gender Diversity and Team Performance

Theoretically, gender diversity can have both positive and negative effects on team performance. From a resource-based view, gender diversity increases the range of employee skills, experiences, and knowledge that a team can draw on to be more creative, more productive, and better decision-makers [Zhang, 2020]. On the other hand, gender diversity can trigger dysfunctional processes. Homophily and the natural tendency for human collective action to base itself

on superficial similarities as a foundation of trust is a common tendency. Gender differences can form in-groups and out-groups that reduce communication and trust and can generate conflict [Schwab et al., 2016]. This tendency can lead to time-consuming and less-effective decision-making [Ferrary and Déo, 2023].

Past research has examined team gender diversity and firm performance at different levels. At an organizational level, managerial gender diversity has been shown to have an increasing positive firm performance effect after a critical mass of about 10–15 percent women until gender parity has been reached [Ferrary and Déo, 2023; Schwab et al., 2016]. With the limitation of relatively few majority female firms, there is some evidence to suggest that majority female firm performance would mirror that of majority male firm performance [Ferrary and Déo, 2023].

Most team studies have occurred with top management teams and corporate boards. Studies have found a positive relationship between gender diversity on corporate boards and firm financial performance [Campbell and Minguez-Vera, 2008; Carter et al., 2003; Erhardt, Werbel, and Shrader, 2003; Joecks, Pull, and Vetter, 2013; Fernando et al., 2020; Lückerath-Rovers, 2011; Mahadeo, Soobaroyen, and Hanuman, 2012; N. Smith, V. Smith, and Verner, 2006; Torchia, Calabro, and Huse, 2011]. Erhardt et al., [2003], for example, in a study of Fortune 1000 firms in the United States, found a positive relationship between gender diversity and return on assets (ROA) and return on investments (ROI). Campbell and Minguez-Vera [2008] also found a positive relationship between the ratio of women on corporate boards in Spain and firm financial performance. A few studies have not found a relationship with gender and financial performance [Miller and del Carmen Triana, 2009; Rose, 2007] or have uncovered a negative relationship [Adams and Ferreira, 2009; Shrader, Blackburn, and Iles, 1997].

Joecks et al. [2013] examined boards of directors using Kanter's [1977a, b] labels of differing levels of gender diversity as follows:

- *Uniform* – All share one visible characteristic like gender.
- *Skewed* – Mostly male with a few “token” females, where the majority dominates group processes and decisions.
- *Tilted* – Consisting of 20–40 percent women, where the minority are not necessarily seen as representing all their gender but are able to differentiate themselves based on skills and abilities.
- *Balanced* – 40–60 percent women where gender differences are less salient, and the knowledge, skills, and abilities of the group members are most important.

In their research, *Tilted* groups performed best, whereas the *Skewed* boards performed the worst. In particular, they found a curvilinear relationship between gender diversity and firm performance with the critical mass of board composition at 30 percent women directors [see also Torchia et al., 2011].

Gender diverse student team performance research is limited and also equivocal. Bacon, Stewart, and Stewart-Belle [1998] saw no effect of gender on student team performance. Similar to Joecks et al. [2013], Apesteguia et al. [2012] found that the best-performing student teams in a business simulation were composed of two men and one woman. On the other hand, Lamiraud and Vranceanu [2018] and Hoogendoorn, Oosterbeek, and Van Praag [2013] found that their best-performing business student teams were majority female. Curşeu et al. [2018] demonstrated a positive link between the proportion of women in student groups and group performance. Neumeyer and Santos [2020] found that entrepreneurship student teams with more women had better performance and better communication.

Hypothesis 1: Having women on a student management team will result in higher overall firm performance.

Gender Diversity and CSR Team Decisions

The research into attitudes around CSR shows either no difference between men and women or women showing more agreement with CSR survey items [see Boulouta, 2013]. In the strategic management and finance literature, research covering gender diversity on corporate boards and top management teams has found that women self-report a focus on CSR and ethics initiatives. Nath Holder-Webb, and Cohen [2013] found that women were more interested in obtaining future CSR information for the purpose of making investment decisions. In addition, women on corporate boards may be given committee assignments that are related to less essential functions of the business [Burgess and Tharenou, 2002], such as the public affairs committee or other CSR committees [Shrader et al., 1997; Williams, 2003], suggesting that women's interest in philanthropy may be a function of committee assignment rather than gender.

In the area of prosocial behavior, of which CSR and ethical behavior could be considered parts, there is evidence that both genders engage in prosocial behaviors in gender-stereotyped ways [Eagly, 2009]. As managers, women more than men engage in individualized consideration with subordinates, such as concentrating on developing and mentoring subordinates and attending to their individual needs [Eagly, Johannesen-Schmidt, and van Engen, 2003]. Gender identity theories suggest that women will engage in organizational citizenship behaviors that help others within the organization [Heilman and Chen, 2005], whereas men engage in organizational citizenship behaviors that assist the organization's functioning at a more macro level [Kidder and Parks, 2001]. Apesteguia et al. [2012] found that all-women business student teams invested significantly more in a broad social initiatives index than any other student team. This index represented overall student team investments in initiatives like having health plans or continuous learning plans for employees.

More specific self-report research indicates that women tend to favor firm investment in a wide array of CSR-related initiatives. Research suggests women desire more ethics training [Roberts, Green Hammond, Geppert, and Warner, 2004], they believe that codes of ethics are beneficial to the firm [Ibrahim, Angelidis, and Tomic, 2009], and they benefit more from ethics training [Ritter, 2006]. In their roles, female board members exhibit a greater intention toward charitable giving than do males [Ibrahim and Angelidis, 1994], and women are more likely to self-report donating to charity [Mesch, 2010]. Indeed, the higher the proportion of women on a corporate board, the more a company invests in charitable giving [Williams, 2003].

Earlier studies report that women are more likely than men to be concerned for the environment [Gkargkavouzi, Paraskevopoulos, and Matsiori, 2018], purchase environmentally friendly products [Gkargkavouzi et al., 2018], and desire to work for environmentally friendly firms [Murray and Ayoun, 2011]. Companies that hire more women show a stronger concern for climate change [Ciocirlan and Pettersson, 2012]. Research in business student teams is more equivocal. Apesteguia et al. [2012], using business simulations, found no relationship between gender and investment in an environmental initiatives index (e.g., using renewable raw materials or having safety and health compliant factories).

Hypothesis 2: Having women on a student management team will result in higher CSR investments.

METHOD

Participants

A total of 504 students from sections of a strategic management course participated in the Business Strategy Game [www.bsg-online.com] for course credit. Of the 504 students included in the data analysis, 268 (53 percent) were women, and there were 157 teams overall. Teams were randomly created using the team generator in the class's learning management system (LMS). Team gender distribution was such that thirty firms had no women on the management team (all men), thirty-two firms were 20–39 percent women (skewed/tilted), twenty-six firms had 40–59 percent women (balanced), thirty-five firms had 60–99 percent women (majority women), and thirty-four firms had only women. The simulation was a part of their business administration capstone coursework.

Simulation

This research was conducted during the delivery of a simulation in a strategic management capstone class. The simulation used was the Business Strategy

Game (version 1.15.17) [www.bsg-online.com; Thompson, Stappenbeck, Reidenbach, Thrasher, and Harms, 2023]. The simulation creates a competitive environment in which each company participating in the simulation exists within one industry during a ten-year period. Teams of students run their own athletic shoe company and make several decisions regarding global manufacturing, warehousing, marketing, distribution channels, and CSR initiatives. Students made annual decisions for the business once a week. Each decision deadline equals one year of business, and team members are provided with information on the industry and their competitors following each year's decisions. As is typical of strategic management simulations, student teams were responsible for all aspects of the business.

The students' simulation firms operated globally in up to twelve market segments, and they began at the end of the tenth year of business at the same, financially sound starting point. CSR choices included investing in recycled boxes, energy efficiencies for the production facilities, charitable contributions, ethics training, on-site cafeteria and childcare, improved lighting and ventilation, and a supplier code of conduct. Students were informed of the costs and benefits of each of the initiatives on the CSR decision screen. Teams were not required to invest in CSR.

The grade on the simulation results accounted for 30 percent of the grade in the class, and all course content was framed to facilitate performance in the simulation. The final, year 20, score on the simulation was used for the simulation grade. All scores at the end of the simulation were reggraded into roughly As, Bs, and Cs for each student who participated fully in the simulation (i.e., no missed decision rounds). Someone who earned a 60 in the simulation, for example, would receive a C– of 70 as the final score. Students were divided into teams of two to four managers and completed two practice decision rounds (years) prior to the beginning of the simulation. The practice rounds, once complete and debriefed, were deleted and the teams began the simulation again for their grade.

Student teams were instructed that their investors expected them to annually increase earnings per share and stock prices, maintain or increase return on equity, maintain or increase their credit rating, and achieve an image rating of 70 or better. The image rating was comprised of shoe quality in each of the geographic regions in which the game took place, the market share in each region, and CSR investments maintained over the previous four to five years. Simulation scores were based on how closely they met the investors' expectations and how well they performed in comparison with all the other companies in the industry. At the end of each decision round (year of business), the simulation calculated and provided the teams with all necessary financial performance information, their scores based on how well they did in comparison with other firms, and how well they did regarding investor expectations.

MEASUREMENTS

Energy efficiencies and charitable contributions were recorded as the dollar amount invested. Ethics training, recycled boxes, cafeteria and childcare, lighting and ventilation, and supplier code of conduct were all recorded as 0 = no or 1 = yes. Firm performance was recorded using the five performance indicators of the simulation for year 20: Earnings per share (EPS), return on equity (ROE), stock price, image rating, and credit rating. Credit rating in the simulation is indicated by a letter grade. To include it in the analysis, credit rating was transformed to a percentage such that A+ = 100, A = 95, A- = 93, B+ = 87, B = 95, B- = 83, C+ = 77, C = 75, C- = 73.

Each hypothesis was tested using Kanter's [1977a, b] diversity categories. Dichotomized variables for each category were created: men only (All men, 1 = *only men*, 0 = *all others*), 20–39 percent women (Skewed/Tilted, 1 = 20 percent–39 percent *women*, 0 = *all others*), 40–59 percent women (Balanced, 1 = 40–59 percent *women*, 0 = *all others*), 60–99 percent women (Majority women, 1 = 60–99 percent *women*, 0 = *all others*) on the team, and similar to Apesteguia et al. [2012], women only (All women, 1 = *only women*, 0 = *all others*) on the team.

All dependent variables were tested for curvilinear relationship with the independent variables, and none were found to exhibit curvilinearity. For the continuous outcome variables, ordinary least squares (OLS) regression was used because the data did not suffer from endogeneity. Data were tested for potential need of an instrumental variable (IV) regression [Stock and Watson, 2015] using three tests for endogeneity. These tests were: 1) Hausman's specification test, 2) the overidentifying restriction test, and 3) the weak instrument test through a macro, EndoS, installed in SPSS [Daryanto, 2020] using race as the instrument. The tests found that the external instrument was exogenous, which suggests that OLS results are more reliable than IV regression (Wooldridge, 2016). OLS regression was conducted with the number of team members entered in Block 1 and the independent variables in Block 2.

For the dichotomous outcome variables of ethics training, on-site cafeteria and childcare, lighting and ventilation, recycled packaging, and supplier code of conduct, binary logistic regression was used because it is appropriate for dichotomous dependent variables [Peng, Lee, and Ingersoll, 2002]. Independent variables were entered as categorical variables such that 1 = all men, 2 = tilted, 3 = balanced, 4 = majority women, and 5 = all women.

RESULTS

Table 1 shows means, standard deviations, and correlations for study variables. The number of team members was significantly and positively correlated

Table 1. Means, Standard Deviations, and Correlations

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Number of team members	3.21	0.8	—																		
2. All Men	0.19	0.39	-.35**	—																	
3. 20–39% Women	0.2	0.4	0.09	-.25**	—																
4. 40–59% Women	0.17	0.37	.23**	-.22**	-.23**	—															
5. 60–99% Women	0.22	0.42	0.13	-.26**	-.27**	-.24**	—														
6. All Women	0.22	0.41	-0.08	-.26**	-.27**	-.23**	-.28**	—													
7. Gender Diverse Teams	0.71	0.46	.56**	-.76**	.33**	.29**	.31**	-.17*	—												
8. Recycled Packaging	0.43	0.5	0.08	-0.03	.14*	0	-0.09	-0.02	0.02	—											
9. Energy Efficiencies	195	214	-0.09	0.01	-0.12	-0.06	0.07	0.08	-0.04	.17*	—										
10. Charitable Contributions	2862	7173	0.11	-0.09	0.09	0.01	0.03	-0.04	0.09	.18*	0.13	—									
11. Ethics Training	0.76	0.43	-0.12	0	.17*	-0.08	-0.1	0	-0.06	.36**	.24**	.20**	—								
12. On-site Cafe and Childcare	0.92	0.27	-0.05	.15*	0.08	-0.01	-0.07	-0.13	-.19**	.20**	.16*	0.12	.24**	—							
13. Lighting and Ventilation	0.93	0.26	-0.09	.18**	.14*	-0.09	-0.09	-0.09	-.18**	.18*	.16*	0.12	.32**	.86**	—						
14. Supplier Code of Conduct	0.43	0.5	-0.04	-0.13	0.07	-0.01	-0.04	0.1	0.03	.49**	.19**	0.1	.36**	.20**	.18*	—					
15. EPS	11	9	0.12	-.28**	0.01	0.02	.13*	0.01	.23**	-.002	.22**	.14*	0.01	.14*	0.11	-0.02	—				
16. ROE	22	16	.24**	-.23**	0.04	0.02	0.07	0.1	.20**	-.004	0.09	.17*	-0.02	0.12	0.1	-0.01	.81**	—			
17. Stock Price	203	208	0.06	-.25**	0	0.02	0.11	0.09	.21**	-.001	.22**	0.13	0	0.11	0.08	-0.04	.97**	.75**	—		
18. Credit Rating	7.9	2.11	.17*	-.33**	0.03	0.09	0.09	0.11	.24**	0.1	0.04	0.11	0.14	-0.04	-0.04	0.06	.38**	.35**	.30**	—	
19. Image Rating	76	17	.15*	-.19**	0.11	0.09	0.07	-0.08	.19**	0.11	.24**	.18*	0.09	.37**	.34**	.14*	.70**	.53**	.68**	.25**	—

Note: * Correlation is significant at the .05 level (1-tailed).

** Correlation is significant at the .01 level (1-tailed).

with the outcome variables of image rating, $r(157) = .15$, $p\text{-value} = .03$; credit rating, $r(157) = .17$, $p\text{-value} = .02$; and ROE, $r(157) = .24$, $p\text{-value} = .001$, and as such, the number of team members was included in further analyses as a control variable for image rating, credit rating, and ROE. EPS, $r(157) = -.28$, $p\text{-value} < .001$; ROE, $r(157) = -.23$, $p\text{-value} = .00$; stock price, $r(157) = -.25$, $p\text{-value} < .001$; credit rating, $r(157) = -.33$, $p\text{-value} < .001$; and image rating, $r(157) = -.19$, $p\text{-value} = .01$ were significantly and negatively correlated with homogeneous teams consisting of men. Groups with gender diversity (tilted, balanced, and majority-women groups) correlated with EPS $r(157) = .23$, $p\text{-value} = .00$; ROE $r(157) = .20$, $p\text{-value} = .01$; stock price $r(157) = .21$, $p\text{-value} = .00$; credit rating $r(157) = .24$, $p\text{-value} = .00$; and image rating $r(157) = .19$, $p\text{-value} = .01$. Majority-women groups were significantly and positively correlated with EPS $r(157) = .13$, $p\text{-value} = .05$.

With regard to CSR investments, gender-diverse teams were negatively correlated with on-site cafeteria and childcare, $r(157) = -.19$, $p\text{-value} = .01$ and improved lighting and ventilation, $r(157) = -.18$, $p\text{-value} = .01$. On-site cafeteria and childcare $r(157) = .15$, $p\text{-value} = .04$ and improved lighting and ventilation $r(157) = .18$, $p\text{-value} = .01$ were significantly and positively correlated with all-men teams. Tilted teams were positively correlated with recycled packaging, $r(157) = .14$, $p\text{-value} = .04$; ethics training, $r(157) = .17$, $p\text{-value} = .02$; and lighting and ventilation, $r(157) = .14$, $p\text{-value} = .05$.

Hypothesis 1 states that having women on a team will result in better financial performance. This hypothesis was tested for EPS, ROE, stock price, credit rating, and image rating. (See Table 2.) Majority women teams had a significant positive relationship with EPS. There were no other significant relationships between the different ratios of women on a team and financial performance. There was a significant and negative relationship with teams that consisted of all men. To state it differently, in teams with even one woman, financial performance improved. Using a dichotomous variable 1 = at least one woman on the team/0 = no women on the team, it was found that women were significantly and positively related to EPS, $\beta = .27$, $t(156) = 3.21$, $p\text{-value} < .01$; ROE, $\beta = .17$, $t(156) = 2.07$, $p\text{-value} = .04$; stock price, $\beta = .26$, $t(156) = 3.14$, $p\text{-value} < .01$; and credit rating, $\beta = .31$, $t(156) = 3.82$, $p\text{-value} < .01$, thus supporting hypothesis 1. The main driver for this support was gender-diverse teams. Using a dichotomous variable 1 = gender diversity on the team/0 = no gender diversity, it was found that team gender diversity was significantly and positively related to EPS, $\beta = .23$, $t(156) = 4.29$, $p\text{-value} = .00$; stock price, $\beta = .21$, $t(156) = 95.44$, $p\text{-value} = .01$; and credit rating, $\beta = .21$, $t(156) = .96$, $p\text{-value} = .01$.

Hypothesis 2 stated that having women on a student management team will result in higher CSR investments. This hypothesis was tested for energy efficiencies, charitable contributions, recycled packaging, on-site cafeteria and childcare, lighting and ventilation, ethics training, and supplier code of conduct.

Table 2. OLS Regressions for Each Diversity Type

	All Men			Tilted			Balanced			Majority Women			All Women		
	B	SEB	b	B	SEB	b	B	SEB	b	B	SEB	b	B	SEB	b
EPS	-5.95	1.67	-.28**	.28	1.69	.01	.49	1.84	.02	2.72	1.63	.13*	1.97	1.65	.10
ROE ^a	-7.04	3.40	-.17*	.66	3.16	.02	-1.65	3.50	-.04	1.46	3.07	.04	4.82	3.06	.12
Stock Price	-132	41.08	-.25**	-1.53	41.41	.00	10.46	44.87	.02	55.45	39.83	.11	53.56	40.27	.11
Credit Rating ^a	-1.66	.43	-.31***	.09	.42	.02	.29	.46	.05	.36	.40	.07	.65	.40	.13
Image Rating ^a	-6.92	3.65	-.16*	4.29	3.37	.10	2.81	3.75	.06	1.91	3.29	.05	-2.65	3.31	-.06
Energy Efficiencies	-10.92	46.43	-.02	-57.29	42.34	-.11	-20.99	47.18	-.04	41.44	41.28	.08	37.97	41.52	.07
Charitable Contributions	-1,113.60	1,552.54	-.06	1,349.61	1,422.04	.08	-232.58	1,580.85	-.01	321.06	1,386.46	.02	-538.45	1,393.64	-.03

Note: *All Men* = only men; *Tilted* = 20–39 percent women; *Balanced* = 40–59 percent women; *Majority Women* = 60–99 percent women; *All women* = only women.

^aNumber of managers was included as a control for all regressions.

* p -value < .10. ** p -value < .05. *** p -value < .001.

Linear regression results are shown in Table 2, whereas binary logistic regression results are shown in Table 3. This hypothesis was weakly supported. Only tilted teams were found to show a significant positive relationship with CSR investments, namely recycled packaging and ethics training.

DISCUSSION

Results here add to a growing body of business simulation research that gender diversity benefits student team strategic firm performance. Our results add to this literature in two substantial ways. First, we show that student teams with at least one woman have significantly better financial performance across a wider array of financial performance measures, including ROE, stock price, EPS, and credit rating. Second, by examining cumulative results after ten rounds of decisions, we show the performance of diverse student teams is robust over a longer time frame.

Although there was a significant result positively linking majority female teams with EPS, this is the only significant firm performance result for teams including women, and although all-women teams do not show the negative associations with firm performance that all-men teams do, they are not adding significantly to most of the positive firm performance results of teams with at least one woman. Gender diverse teams are significantly and positively related to EPS, stock price, and credit rating. Our data show that it is gender-diverse teams that are the main driving force behind positive firm performance results.

The superior results for gender-diverse teams are consistent with Apesteguia et al. [2012] and Lamiraud and Vranceanu [2018]. In these investigations, the best-performing teams were diverse albeit on opposite sides of the gender parity divide. Our simulation team-level results are analogous to firm-level managerial gender diversity results by Ferrary and Déo [2023] and Schwab et al. [2016]. They theorized that heterogeneous groups could understand a broader range of customer needs and wants, allowing them able to be more effective in creating customer value. Well-functioning diverse teams may process information in new ways, be more creative, and have access to a wider range of human capital resources [Ferrary and Déo, 2023]. A firm's problem-solving ability is enhanced with collective, balanced decision-making, divergent thinking, and a broader knowledge base [Schwab et al., 2016]. Collective simulation results build a strong case that gender-diverse student teams should be encouraged where strategic decision-making for financial performance is key. Instructors can use these findings to motivate students to form gender-diverse teams on their own or feel comfortable in using gender diversity as a factor when assigning students to teams.

Our study's student team firm performance results differ from the earlier research in one significant way. All-men teams fared the worst on performance

Table 3. Binary Logistic Regression for All Diversity Types

Variable	All Men					Tilted					Balanced					Majority Women					All Women				
	b	SE b	Wald's χ^2	p	Odds Ratio (e^b)	b	SE b	Wald's χ^2	p	Odds Ratio (e^b)	b	SE b	Wald's χ^2	p	Odds Ratio (e^b)	b	SE b	Wald's χ^2	p	Odds Ratio (e^b)	b	SE b	Wald's χ^2	p	Odds Ratio (e^b)
Recycled Packaging	-.14	.41	.11	.74	.87	.69	.40	2.97	.09*	.76	-.02	.43	.00	.97	.98	-.45	.40	1.29	.26	.64	-.08	.39	.04	.84	.93
Ethics Training	.02	.48	.00	.97	1.02	1.28	.64	4.04	.04**	3.61	-.45	.47	.89	.35	.64	-.53	.43	1.53	.22	.59	.00	.46	.00	1.00	1.00
On-site Cafe and Childcare	19.01	7.463.65	.00	1.00	179,497.205	1.04	1.07	.95	.33	2.83	-.10	.81	.02	.90	.91	-.58	.65	.80	.37	.56	-.98	.62	2.48	.12	.38
Lighting and Ventilation	18.91	7.463.65	.00	1.00	163,029.571	18.91	7.463.65	.00	1.00	16,302.9571	-.79	.72	1.22	.27	.45	-.72	.66	1.20	.27	.49	-.72	.66	1.20	.27	.49
Code of Conduct	-.71	.44	2.61	.11	.50	.34	.40	.73	.39	1.40	-.50	.43	.01	.91	.95	-.18	.39	.20	.65	.84	.50	.39	1.62	.20	1.64

Note: * p -value < .10. ** p -value < .05.

measures in our study. In contrast, Apesteguia et al. [2012] and Lamiraud and Vranceanu [2018] found that all-men teams were among their better performing teams. They theorized that all-men teams' higher propensity for risk-taking behavior was driving these teams' superior performance. Because their data were collected from shorter periods of simulation performance, that propensity may be a contributor to the difference in results. Research has suggested that women have a strong interest in the long-term stability of the firm and may be more likely to invest sustainably [Apesteguia et al., 2012; Eagly et al., 2003]. It is possible that over longer rounds of simulation performance, an elevated tendency to risk-taking is not rewarded.

Another factor that explains these results may stem from female students' lowered simulation self-efficacy. Casile et al. [2021] reported that female students feel significantly less prepared and much less confident in their abilities to use simulations and make decisions in them. They found that female students were initially less motivated to participate in simulations, possibly because of simulations' competitive environment. This factor may mean that it takes longer for female team members to feel confident to compete fully in a simulation and engage in financially rewarding risk-taking behavior. Team performance measures taken from early decision rounds as in Apesteguia et al. [2012] or Lamiraud and Vranceanu [2018] may not accurately reflect team performance over time in gender-diverse and all-women teams.

When considering student team strategic decision-making in the domain of CSR and ethics, previous research, using largely self-report data, has suggested gender-diverse student teams might suffer from gender-based divisions [Schwab et al., 2016]. The only previous business simulation study that addressed this issue found significant gender differences for student team strategic decision-making on a broad social initiatives index but not for an environmental initiatives index [Apesteguia et al., 2012]. Our study examined relatively specific student team CSR, ethical, and environmental strategic decisions and found weak support for gender-based differences. Only two results were significant. Tilted teams were significantly related to recycled packaging and ethics training. There were no significant differences in investments in charitable contributions, on-site cafeteria and childcare, code of conduct, lighting and ventilation, or energy efficiencies.

One possible reason for this result is the difference in measurement. Our study collected actual decision data whereas most previous research was self-reported. Another possibility has to do with the simulation. In the real world, CSR initiatives can have direct and indirect impacts on many factors affecting firm performance, such as customer perception and value, corporate reputation, employee productivity and retention, etc. The nature of the simulation in this study motivates decisions based on financial calculations. The simulation encourages students to maximize EPS, ROE, stock price, image rating, and credit rating. Of those five targets, only image rating is directly related to CSR

initiatives, and it comprises multiple inputs. The link between investment in CSR initiatives and image rating may not have been clear for student teams, which in turn may have affected their CSR investment decisions. Another simulation feature that may have affected student CSR investment choices is how the simulation displayed projected outcomes from investment choices. All simulation investment decisions showed projected outcomes on firm performance measures. Students were told that the projections could be wrong, and they were not required to use this information in their decision-making. Still, it is possible that the projections and the course grade, which was impacted by their overall firm performance, drove financially motivated decisions. These two simulation features may have limited student consideration of CSR investments and overwhelmed gender-based CSR investment decisions.

When it comes to environmental initiative strategic decisions, ours is the second business simulation study to find very weak or no differences among gender-diverse student teams. The factors listed above can explain these results, but there are additional aspects of environmental initiatives that can contribute. Investment decisions in a simulation are not directly affecting the planet, so the unrealistic nature of a simulation may be causing this result. Previous research into gender differences in environmental concerns has found women to be more concerned with environmental issues when those issues are in their own community [Momsen, 2000]. Because this simulation has production facilities in different areas of the globe, perhaps women did not see a need to expend firm resources to protect the natural environment in places that were far away from their residence. Overall, although there is some limited support for gender diversity differences in student team strategic CSR investments, student team research to date would suggest that it is much less divisive than previous research would suggest.

LIMITATIONS

The study has some limitations. The most glaring limitation, like all of the previously cited research, is the use of a binary gender measurement. This literature stream is not the only one with this issue. Cameron and Stinson [2019] show that most articles in *Psychological Science* use a similar binary measurement. Although following historical measurement is certainly helpful in comparing results with previous studies, it fails to reflect the range of gender.

Second, the sample sizes for each of the tests were small, which likely influenced effect sizes. Effect sizes are typically small, however, in demographic research such as this [e.g. Torchia et al., 2011; Joecks et al., 2013].

Pro-diversity cultures and industries have been found to see the most positive firm performance effects from team gender diversity. Cultures that do not

value gender diversity tend to see much less of a positive effect from gender diversity [Zhang, 2020]. The effects seen in this paper may not generalize to cultures where gender diversity is not viewed positively.

Finally, most of the study's participants were nontraditional students who have worked or were working during their undergraduate education, and they were completing their final course before graduation. Although this factor may support the managerial generalizability of the findings, it may limit the generalizability of results to traditional college students.

FUTURE RESEARCH AND CONCLUSION

This investigation adds to the growing research of higher-performing business teams with a gender-diverse membership. This study provides vital evidence for the benefits of encouraging student team gender diversity, whether that is in instructor-assigned groups or student-selected ones. Our examination broadens and deepens the pedagogical literature demonstrating the superior strategic team decision-making and performance of gender-diverse student teams. An examination of the inner workings of these teams, especially given some research that suggests a critical mass of female team members aids in risk-taking decision-making for women [Lamiraud and Vranceanu, 2018] and increases team communication and cohesion [Neumeyer and Santos, 2020], would be a welcome addition to the literature.

One area of future study is in the emergence of varied forms of gender expression and how diverse teams that are not gender binary function. The theory on which this study was based provides little instruction in how individuals who are gender nonconforming or who are trans individuals may influence groups and teams.

Areas of expected extensive strategic decision gender divisiveness, namely CSR, environmental, and ethical issues, were shown to be much less divisive. This study adds to business simulation research that questions the extent of gender differences in the CSR, environmental, and ethical domains when it comes to actual student team strategic decision-making. Given that past research has largely been self-reports from firms' top management teams and simulation study subjects have been students without managerial experience, it would be interesting to see whether similar simulation results emerge when top management teams complete the simulation.

Instructors can be more confident that student team gender diversity performance benefits outweigh possible conflict about CSR, environmental, or ethical investment decisions. This analysis can be used by instructors to motivate students to be more accepting of gender-diverse student teams, whether those teams are endogenously or exogenously created.

ENDNOTE

1. The authors acknowledge that gender follows a nonbinary spectrum. The use of the term “gender diversity” in this work reflects the binary terminology for consistency with past research in the literature stream. See Eagly [1987] for background on the use of the binary, men/women gender distinction.

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True Applications of Economics from the Business World

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By understanding the underlying principles of economics and applying them effectively, businesses can enhance their strategic capabilities and improve their overall performance. However, despite the applications and insights that economics offers to the business world, students often find economics courses unattractive, perceiving them as challenging and inapplicable to the real world. In this paper, we address this issue by providing actual business scenarios that two of the authors have encountered during their careers in the consulting industry. The cases illustrate how existing companies, including a U.S.-based tire company and fast-food chains, apply economics daily. We present three teaching guides, each featuring a real-world business scenario. Given the interest of Gen Z in entrepreneurship and business, this paper provides an opportunity for educators to demonstrate business applications of foundation-level economics concepts in an engaging way that resonates with Gen Z and bridges the gap between business and economics. Incorporating real-world examples from a consultant perspective allows students to use the classroom as an opportunity to think like an economist while applying economic theory to the business world.

JEL codes: A20; A21

Keywords: Application, Business, Case Studies, Foundation Economics, Teaching Economics

Disciplines of Interest: Economics, Business, Entrepreneurship

INTRODUCTION

Despite the benefits of majoring in economics, a small proportion of students choose this area of study (Bayer and Rouse, 2016). This general lack of

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enthusiasm is unfortunate, given that the U.S. Bureau of Labor Statistics has predicted a 6 percent growth of the number of positions that will be available to economists between 2022 and 2032 (U.S. Bureau of Labor Statistics, 2024). Some of the main reasons for the inability of the major to attract students include the math requirement of higher-level economics courses that makes some of these classes forbidding for less mathematically savvy students, and the misconception that economics is abstract and disconnected from other disciplines. The latter necessitates the incorporation of real scenarios into the curriculum, particularly into foundation-level courses, where the main goal is to introduce students to basic concepts and their applications to the real world, and to create interest that will retain excellent students in the field, rather than focus on mathematical derivations.

Given that research suggests that 75 percent of the current generation of students would like to become entrepreneurs, 84 percent consider starting a small business a possible career path, and 93 percent of these individuals have taken steps to launch a business (Hummel 2023), it is important for students to understand the connection between business and economics and the applications and insights that economics offers in the business world.

Specifically, economics helps us understand how individuals and businesses make choices. For businesses, it provides valuable insights and analytical tools to help them navigate complex strategic interactions, make optimal decisions in terms of pricing, product development, production, hiring, marketing, market entry, and others, and achieve competitive advantages in dynamic environments. For example, businesses often apply game theory, a field in economics and a topic usually covered in introductory microeconomics courses, to analyze competitive situations and anticipate the actions of competitors to make strategic decisions; identify leverage points, understand their bargaining power, and negotiate optimal or favorable deals in situations where parties have conflicting interests; analyze pricing dynamics and determine optimal pricing strategies based on competitors' behavior, consumer preferences, and market conditions, including price wars, price discrimination, and value-based pricing; understand strategic interactions among different stakeholders to allocate resources (e.g., budgetary resources, production capacity, marketing efforts) efficiently to maximize overall performance; and assess potential risks and anticipate partner behavior to evaluate the costs and benefits of forming strategic partnerships with other firms and negotiate mutually beneficial agreements.

In this paper, we suggest incorporating business applications in the economics curriculum as an opportunity to engage students in the economics classroom and to create interest in economics by providing actual, real-company stories that resonate with a highly entrepreneurial and business-oriented generation of students. These true examples have been obtained from the experience in the consulting industry of two of the authors of this paper. To protect

client data, however, we do not disclose the true names of the businesses referenced in the cases discussed in this work.

Our goal is to facilitate the process of bridging the gap between economics and business by elaborating on three real-world scenarios from the business world that explicitly illustrate how existing businesses use economics to make optimal decisions on a daily basis. This paper builds on the work of Milovanska-Farrington and Mateer [2024a], who use the stories and business acumen of Gen Z entrepreneurs to illustrate foundational economic concepts. We extend this work by exploring actual scenarios where existing businesses had to apply economic thinking to evaluate options and make optimal decisions.

LITERATURE REVIEW

Even highly motivated students often find the material covered in introductory economics classes challenging. However, literature on the science of learning has documented that students' understanding of the material could improve if they can relate to it and find it engaging. Therefore, it is important to make the material relevant to the students and the real world [National Education Association 2023]. Concrete examples improve understanding [Weinstein, Sumeracki, and Caviglioli, 2018] and retention [Willingham 2021] of even abstract ideas. The importance of teaching with context, with concrete examples that resonate with the audience, to increase retention has been emphasized by Willingham [2021]. He explains that context creates meaning, meaning enhances students' thinking about the material, and the more they think about it, the more they will retain [Willingham, 2021]. Wooten, Al-Bahrani, Holder, and Patel, [2021] also highlight the importance of relevance in economics education and provide resources to facilitate the process of remaining current.

To create context and increase interest and engagement in introductory economics courses, prior literature has suggested incorporating examples from movies (e.g., Sexton 2006; Mateer, O'Roark, and Holder, 2016), music (e.g., Tinari and Khandke, 2000), television series (e.g., Hall 2005; Tierney et al. 2015; Ben Abdesslem and Picault, 2021), viral videos [Geerling, Mateer, and Picault, 2023a], and more recently, celebrities and influencers (e.g., DeWind, Geerling, Mateer, and Halfen, 2023; Milovanska-Farrington, Geerling, and Mateer, 2024b; Geerling, Mateer, and Wooten, 2023b). For example, Geerling et al. [2023a] provide teaching guides to help educators teach price controls using videos that went viral on social media. DeWind et al. [2023] and Milovanska-Farrington et al. [2024b] explain how the backstories and business acumen of Taylor Swift, MrBeast, and female influencers could be used to illustrate foundation economics concepts in a way that resonates with Gen Z. It

is also worth mentioning that in addition to the earned popularity, the celebrities featured in the previous two articles are also incredibly successful entrepreneurs.

This is of great importance, given that Gen Z is extremely entrepreneurial [Milovanska-Farrington and Mateer, 2024a]. Milovanska-Farrington and Mateer. [2024a] present teaching guides designed to teach foundation-level economic concepts using the stories and entrepreneurial spirit of three Gen Z entrepreneurs—Max Hayden, Mikaila Ulmer, and Alexandr Wang—who started their own businesses from very humble beginnings, but whose growth and gradual success provide real-world lessons that resonate with the students and foster Gen Z’s entrepreneurial spirit.

Given the current students’ interest in business ventures, connecting economics to business is likely to increase learners’ interest in both economics and business and improve understanding and retention by allowing students to make more connections [Milovanska-Farrington 2024]. Although business and economics are closely related fields, few classes “bridge the gap” between the two. McCaffrey [2016] offers books and essays that could help students understand the economics of entrepreneurial decisions. He provides insights about how economics could be incorporated into business and entrepreneurship courses. However, it is unfortunate that many introductory economics classes do not highlight enough the business applications of the covered material.

The goal of this paper is to fill this gap. Specifically, similar to the abovementioned pop-culture references, we use relatable topics to teach Gen Z relevant economics concepts. Although the work above relates to students’ interest in social media and pop culture, we focus on the business and entrepreneurial inclination of this generation of students. More important, similar to Milovanska-Farrington and Mateer [2024a], we develop teaching guides that could facilitate connecting introductory economics to business and entrepreneurship and incorporate real-life examples in the curriculum. However, instead of using the business stories of entrepreneurs, we offer business case studies that illustrate how businesses apply economics in their everyday decision-making.

Our true business-related case study approach allows educators to easily incorporate the business community situations in the classroom, which previous studies have documented as an effective way to relate theory and practice in business education [Hickman, Stoica, and Price, 2021]. Understanding some practical applications of economics in business decision-making by analyzing the *written* scenarios has benefits beyond the opportunity to connect economics to business and entrepreneurship. Specifically, Ebrahimi, Granitz, Kohli, and Nugroho, [2023] point out the importance of engaging Gen Z with “non-technology” and encouraging activities that improve students’ face-to-face social skills [Ebrahimi et al. 2023]. The latter is important because the current cohort of students needs to improve their social skills more than previous generations

[Schwieger and Ladwig, 2018]. Rohm, Stefl, and Ward, [2021] suggest using client-based business assignments as one way to help students prepare for their working careers through adequate development of such skills [Rohm et al. 2021]. Encouraging group discussion and analysis of the business scenarios presented in this article in the economics classroom serves to develop analytical, problem-solving, and much-needed social skills.

REAL-WORLD BUSINESS EXAMPLES IN THE CLASSROOM: TEACHING GUIDES

In this section, we present three business scenarios. Then, we provide a teaching guide for each of these cases. The guides contain descriptions of the business scenarios, related concepts, learning objectives, direct instructions that explain how the examples could be used in a classroom to lead a discussion and to illustrate economic concepts, and assessment questions. The questions could be used for discussion or as a form of summative assessment. Instructors are encouraged to modify the guides as they see fit for their courses.

Teaching Guide: U.S. Tire Industry

Concepts

Supply and demand model, Labor market, Costs, Production, Wages, Profit, Price elasticity of demand.

Business Scenario

- a) Background information about the tire industry in the United States.

During the COVID-19 pandemic, shutdowns levied production constraints that challenged the provision of goods and services to consumers (reduced the supply of goods and services). Demand also decreased. For the labor market, this was a period of massive layoffs, supported by higher levels of unemployment payments.

Then, after the COVID-19 pandemic, the U.S. tire industry experienced some of the highest levels of growth since the late 1970s [FRED, St. Louis Fed., 2024]. There were several reasons for the surge in demand, including pent-up consumer spending after a period of economic uncertainty, eagerness of the U.S. consumers to resume normal spending patterns after the pandemic that had been limiting their usual behaviors, and an injection of trillions of dollars of federal money. In addition, semiconductor shortages led to very low levels of new car inventory. Prices of new cars increased, which increased the demand for

used cars (substitutes for new cars), as well as the demand for repair and maintenance of existing vehicles, including tires (complements to used cars).

Historically, an increase in demand is good news for businesses and tire sellers. However, businesses were not prepared for such a rapid rebound in demand after the industry had contracted significantly during the pandemic. Moreover, there were prolonged global supply-chain issues, following from the chaotic pandemic period and the struggle of many countries around the globe to fully recover from their pandemic responses. In response to the spike in demand, companies increased prices.

There were also massive shifts in the U.S. labor markets. U.S.-based companies found themselves facing high demand for goods and services coupled with global supply-chain issues and a shortage of workers. Job openings soared, compelling companies to increase wages to attract or retain employees. Higher wage offerings increased the costs of production to companies, and these costs were often passed onto consumers.

b) Specific business scenario

A U.S.-based tire company followed market trends by increasing prices by over 14 percent between 2022 and 2023 to eliminate the temporary shortage of tires that was occurring prior to the price adjustment.

When an opportunity came, it started to build up inventory while still increasing prices. However, blinded by the good market conditions, the company continued to increase supply and prices for too long.

Demand started to decrease. In addition, at the elevated prices, the company accumulated high levels of inventory (surplus of tires).

The tire company failed to adequately gauge demand. By mid-2023, the company faced a period of contraction. Sales team members attempted to stimulate demand by contacting car dealerships, retailers, and online stores, but their shelves were already fully stocked. Traditionally, excessive inventory increases companies' costs as warehouse space costs increase. To mitigate storage costs, companies often discount prices to stimulate consumers to buy (increase the quantity demanded). However, for this tire company, demand was declining, and profits were diminishing.

The tire company had experienced periods of slow demand and high inventories before, albeit not to the extent seen during the pandemic. Faced with limited options, they considered the following:

1. decreasing prices further to increase the quantity demanded
2. maintaining high prices to preserve profit margins at the risk of potentially losing market share.

Ultimately, the company realized that inventory levels were so high that even significant cost-cutting measures (that tend to increase supply and, therefore, decrease the price) were unlikely to decrease the price and increase the

quantity demanded sufficiently to eliminate the surplus of tires. The company also recognized that tire replacements are not frequent occurrences, so price adjustments might not significantly impact the quantity demanded.

Therefore, they chose the second approach above—that is, to maintain higher prices. They offered incentive programs to their top clients and also negotiated lower input costs from their suppliers by locking in long-term contracts. This strategy enabled them to maintain high profit margins despite seeing sales figures fall by over a half. They managed to retain existing staff and not shut down (i.e., produce) during this challenging time.

Learning Objectives

- Identify the effect of various events on the market for tires (shifts in supply, demand, or both)
- Construct a supply and demand graph to show the effects identified above
- Apply the supply and demand model to identify the effect of various events on the equilibrium price and quantity of tires
- Analyze the circumstances under which a shortage of tires occurs
- Analyze the circumstances under which a surplus of tires occurs
- Recognize the concept of elasticity in a real-world scenario
- Analyze the relationship between elasticity and a company's revenue.

Materials Needed

Whiteboard and markers, printed copies of the business scenario and the assessment questions (optional).

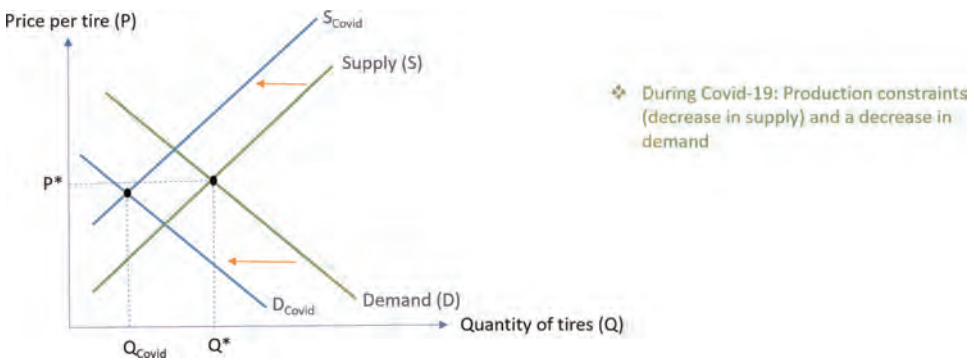
Note to Instructors

This scenario illustrates the supply and demand model and elasticity. Because elasticity is typically covered after the supply and demand model, we recommend that instructors use this case study after discussing elasticity. Although instructors are welcome to shorten or skip the supply and demand discussions suggested in the “Direct Instructions” section below or make them optional for students, literature has documented that spaced repetition improves students’ retention of the material (e.g., Carey 2014). Given that the supply-and-demand model is an essential topic in introductory economics courses, reviewing it after elasticity would be beneficial for the students. Furthermore, combining the concepts in a holistic approach allows students to make connections, which reduces the chance of forgetting, and is therefore positively related to retention. Literature refers to this approach as interleaved, or mixed, practice (e.g., Willingham 2021). Although instructors may adapt the suggested guide to fit their class time constraints, we encourage using as much of the case study as

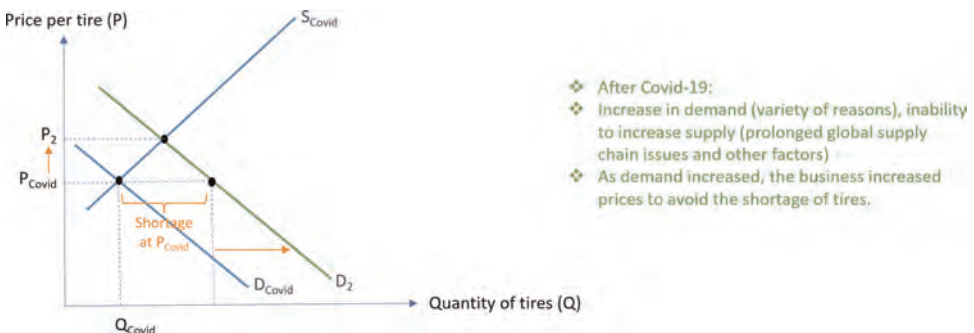
possible to ensure a comprehensive understanding of the business story, facilitate spaced repetition, and improve retention by connecting multiple topics.

Direct Instructions

- Distribute copies of the background information and the specific business scenario above. Provide the text only up to the sentence “Faced with limited options...” Give students 7–8 minutes to carefully read and understand all events that impacted the tire industry and the small business the scenario refers to. Ask them to take notes of these events (write and/or draw graphs).
- The following is a sample summary:
 - Tire industry:
 - During COVID-19: production constraints (decrease in supply) and a decrease in demand

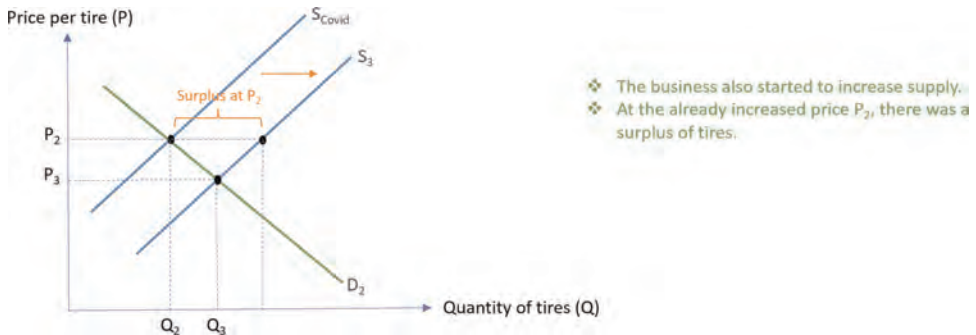


- After COVID-19: increase in demand (for a variety of reasons, available in the summary above), inability to increase supply (prolonged global supply chain issues and other factors)

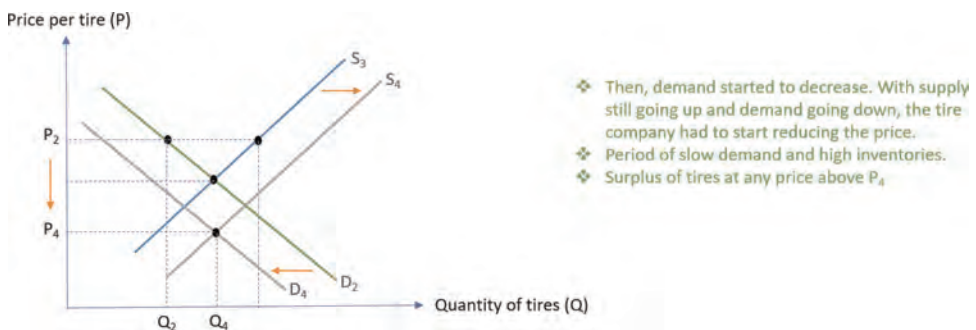


- Labor market: massive layoffs (decrease in labor demand) during COVID-19; job openings soared after COVID-19 (increase in labor demand)

- Result after COVID-19: increase in wages; increase in prices to P_2 on the graph above
- Specific small tire company:
 - As demand increased, the business increased prices (to P_2 on the graph above) to avoid the shortage of tires.
 - It also started to increase supply. At the already increased price, there was a surplus of tires.

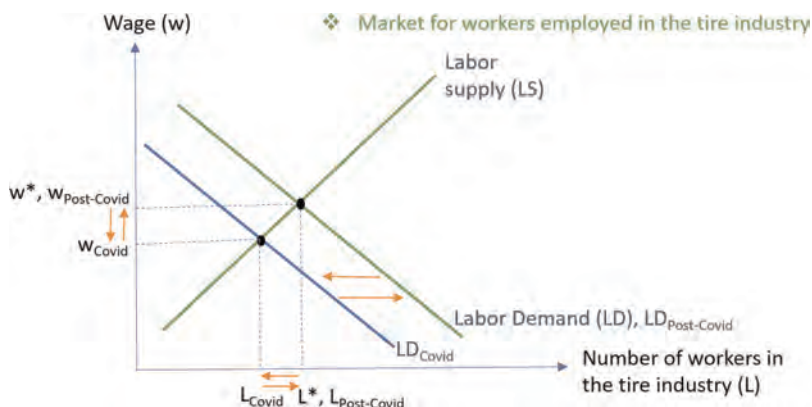


- Then, demand started to decrease. With supply going up and demand going down, the tire company had to start reducing the price.



- Period of slow demand and high inventories.
- The company considered two options: continue to decrease price or maintain higher price at the risk of losing market share (selected option).
- Draw a supply curve and a demand curve for the market for tires. Ask students to show the following effects that occurred in the market: (1) decrease in supply and decrease in demand; (2.1) increase in demand after COVID-19, and (2.2) a shortage of tires. The graphs students draw should look like the ones provided in the summary of the events above.
- Draw a supply curve and a demand curve for the market for workers employed in the tire industry. Ask students to show the following effects

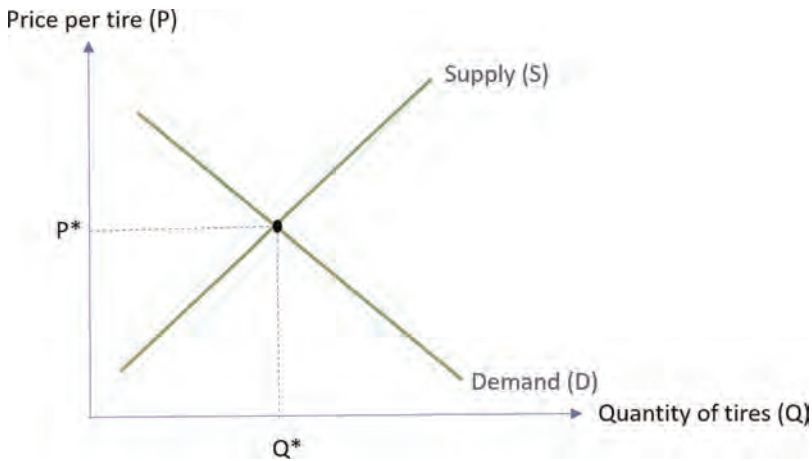
that occurred in this labor market: (1) decrease in labor demand during COVID-19; (2) increase in labor demand after COVID-19.



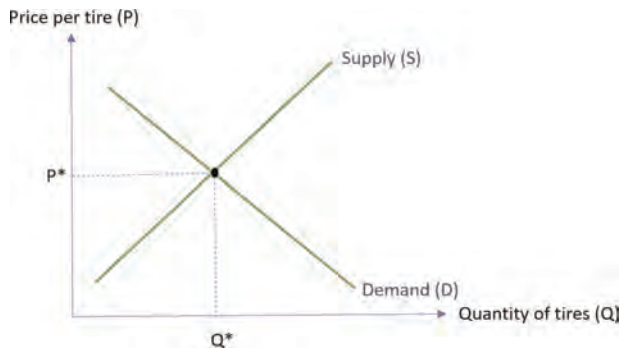
- Draw a supply curve and a demand curve for the tires of the small business under consideration. Focus on the events after COVID-19. Show all effects that occurred: (1.1) increase in demand, (1.2) a shortage of tires, (1.3) increase in tire prices; (2.1) increase in supply, (2.2) surplus of tires; (3) decrease in demand. The graphs should look like the ones provided in the summary of the events above.
- Given the situation of the tire business under consideration, ask students to imagine that they had to provide recommendations to the company about what to do. Ask them to brainstorm solutions in teams of four to six students.
- Then, tell students the two options that the company considered. A short discussion should follow.
- If the business chooses to decrease prices, would this change be associated with a movement along the demand curve for tires or a shift of the demand curve? This is a good opportunity to recall the difference between a shift versus a movement along the demand curve.
- Discuss the second option the company considered. Why could increasing and maintaining a higher price of tires potentially lead this business to holding a smaller share of the tire market? Relate this question to the concept of price elasticity of demand. Specifically, would a more relatively price elastic or inelastic demand imply a negative association between the price and the revenue of the company?
- Given that the company recognized that tire replacements are not frequent occurrences, and thus, changes in the price are unlikely to significantly affect the quantity demanded, did this business consider the demand for tires to be relatively price elastic or inelastic?
- Ask students to imagine that they would have to advise this tire company again. Which of the two potential options would they recommend and why?
- Tell students what the tire company chose and why. Allow students to comment if needed.

Assessment Questions

1. Which of the following factors was *not* a reason for the change in the demand for tires after the COVID-19 pandemic?
 - a. Pent-up consumer spending after a period of economic uncertainty.
 - b. Prolonged global supply issues.
 - c. Americans' eagerness to resume normal spending patterns after the pandemic.
 - d. An injection of trillions of dollars of federal money.
2. The following graph shows the supply and demand for tires in the United States. What was the effect of consumers' pent-up spending on the market for tires? At the initial price of tires, would there be a surplus or a shortage? Show this surplus/shortage on the graph below.



3. The following graph shows the supply and demand for the tires of a tire company in the United States. Consider a period when the company increased supply but simultaneously consumers slowed down demand. If the company set a price of tires between the initial and the new equilibrium price, would there be a shortage or a surplus of tires? Show the effect of the two events happening simultaneously and the surplus/shortage at the unadjusted price on the graph below.



4. If a tire company decides to maintain higher prices, its revenue would be higher as well if the demand for tires is:
 - a. Relatively price elastic.
 - b. Relatively price inelastic.
 - c. Unit elastic.
 - d. Perfectly elastic.

5. Consumers do not change tires very often, so price adjustments are unlikely to significantly impact the quantity demanded. This implies that the demand for tires is expected to be price:
 - a. Relatively elastic
 - b. Relatively inelastic
 - c. Unit elastic
 - d. Perfectly elastic.

Teaching Guide: Job Interviews

Concepts

Dominant strategy, Nash equilibrium (NE), Prisoner's dilemma.

Business Scenario

- a. Background information about a typical hiring process

In a hiring process, a lot of time is spent proving that a candidate is qualified. Candidates should spend significant time researching the company and the

job itself. It sounds obvious, but hiring managers want to see whether a candidate has done their research, because it is an easy and early clue that a candidate is taking the opportunity seriously, is thinking critically, and is coming with a go-getter attitude.

b. Specific business scenario

Imagine two job candidates, Alice and Bob, competing for the same position. Each of them has two strategies to choose from: preparing extensively or not preparing much. If both prepare well, they have an equal chance of getting the job. If one of them prepares well, while the other one does not, the one who has prepared gets the job, and the one who has not prepared well does not get the job. If neither of the candidates prepares well, nobody gets the job. The following is the payoff matrix:

		Bob	
		Prepares	Doesn't Prepare
Alice	Prepares	Alice has 50% chance of getting the job; Bob has 50% chance of getting the job (Alice and Bob have an equal chance)	Alice gets the job; Bob doesn't get the job
	Doesn't Prepare	Alice doesn't get the job; Bob gets the job	Alice doesn't get the job; Bob doesn't get the job

Learning Objectives

- Discuss job/internship interview strategies.
- Determine whether a player (job candidate) has a dominant strategy given a payoff matrix.
- Analyze a real-world example of a simultaneous-move game of complete information to determine the Nash equilibrium/equilibria of the game (if any).
- Recognize real-world examples of the Prisoner's dilemma.

Materials Needed

Whiteboard and markers, Printed copies of the business scenario and the assessment questions (optional).

Direct Instructions

- Begin by mentioning the potential benefits of this discussion for students, regardless of their major. In addition to offering a practical application of game theory, the scenario could improve students' job-search skills.

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- Ask students whether they have ever applied for a job or an internship. Have they prepared for a job/internship interview? Have they read any tips for preparation?
 - Share the following tips by distributing printed copies or showing on the screen. Have the students ever followed any of these suggestions? If yes, did the strategies help?

Before a job/internship interview, candidates should:

- Research the company, i.e., understand the mission, values, curriculum, staff, research opportunities, published work, and any recent developments or achievements of the company. Survey data suggest that 47 percent of recruiters would not hire a job candidate who has not researched the company prior to the interview¹.
- Be prepared to discuss their application (e.g., their academic background, achievements, interests, goals, etc.) and reflect on how their experiences align with what the company does and what unique qualities they bring to the table.
- Research the job description to be aware of the responsibilities and the opportunities, incorporate them in the conversation, and ask questions to the interviewer to show interest. According to surveys, 88 percent of recruiters share that preparation for a job interview is a key factor in the success of the candidate and “an informed candidate is a quality candidate”².
- Practice answering common interview questions concisely and confidently, e.g., “Tell me about yourself,” “Why do you want to work for the company,” and “What are your academic and career goals?”
- Prepare and ask the interviewer thoughtful questions to demonstrate interest and engagement. You can ask about specific aspects of the program, opportunities for research or internships, support services, etc.
- Follow an appropriate dress code and smile. According to survey data, 71 percent of interviewers would not hire candidates who are not dressed professionally³, and 40 percent of recruiters think that not smiling is enough to not hire a candidate⁴.
- Ask students to consider the typical scenario where there are two finalists competing for one position. They are both invited to an interview. Show

¹<https://www.twineemployment.com/uk/blog/8-surprising-statistics-about-interviews/>

²<https://www.inc.com/marcel-schwantes/this-is-no-1-trait-hiring-managers-want-most-according-to-research.html>

³<https://www.inc.com/wanda-thibodeaux/90-percent-of-interviewers-would-disqualify-a-job-candidate-for-this-1-reason.html>

⁴<https://www.twineemployment.com/uk/blog/8-surprising-statistics-about-interviews/>

students the payoff matrix presented in the summary above. Alternatively, you could ask them to create a payoff matrix that represents this scenario.

- Does each of the job candidates have a dominant strategy or not? If yes, what is it? Why? Does the game have a Nash equilibrium or not? Ask students to explain. Note: If Bob prepares for the interview, Alice is better off preparing as well, because she prefers to have a 50 percent chance of getting the job rather than no chance of getting it. If Bob does not prepare, Alice is better off preparing again, because she prefers to get the job rather than not getting it. Therefore, regardless of what strategy Bob chooses, Alice's best response is to prepare. This analysis implies that her dominant strategy is to prepare for the interview. Analogically, Bob's dominant strategy is to prepare as well. The game has one NE: (Alice prepares; Bob prepares). The strategies of the two candidates are best responses to each other, and nobody has an incentive to unilaterally change their strategy.

Assessment Questions

Consider the following game. Two job candidates are applying for a job. Research suggests that microcredentials (completed short programs of study) are beneficial to both employees and businesses [Gauthier 2020], so the job description mentions that preference will be given to candidates who have at least a microcredential in business analytics. The two job candidates are considering earning this microcredential. Suppose that there are no other candidates, the two applicants make a decision simultaneously, and their other skills, abilities, and education are comparable. The following is the payoff matrix:

		Candidate B	
		Earns a microcredential	Doesn't earn a microcredential
Candidate A	Earns a microcredential	Candidate A has 50% chance of getting the job; Candidate B has 50% chance of getting the job. (They have an equal chance.)	Candidate A gets the job; Candidate B doesn't get the job.
	Doesn't earn a microcredential	Candidate A doesn't get the job; Candidate B gets the job.	Candidate A has 50% chance of getting the job; Candidate B has 50% chance of getting the job. (They have an equal chance.)

Use the payoff matrix to answer questions 1 to 4.

1. Based on the payoff matrix above, what are the strategies Candidate A can choose from?
 - a. Get the job or not get the job.
 - b. Apply for the job or not apply for the job.
 - c. Earn a microcredential or not earn a microcredential.
 - d. Have a 50 percent chance of getting the job or have no chance of getting the job.
2. What is the dominant strategy of Candidate A (if any)?
 - a. Candidate A does not have a dominant strategy.
 - b. Earn a microcredential.
 - c. Does not earn a microcredential.
 - d. It cannot be determined based on the given payoff matrix.
3. What is the dominant strategy of Candidate B (if any)?
 - a. Candidate B does not have a dominant strategy.
 - b. Earn a microcredential.
 - c. Does not earn a microcredential.
 - d. It cannot be determined based on the given payoff matrix.
4. What is/are the NE of the game (if any)?
 - a. One NE: (Candidate A earns a microcredential; Candidate B earns a micro-credential).
 - b. One NE: (Candidate A doesn't earn a microcredential; Candidate B doesn't earn a microcredential).
 - c. The game does not have a NE.
 - d. Two NE: (Candidate A earns a microcredential; Candidate B earns a microcredential), and (Candidate A doesn't earn a microcredential; Candidate B doesn't earn a microcredential).

Teaching Guide: Pricing Pressures in a Restaurant Environment

Concepts

Profit, Revenue, Profit margin, Trade-off, Dominant strategy, Nash equilibrium (NE), Complements, Product differentiation, Monopolistic competition, Market structures, Price elasticity of demand.

Business Scenario

- a) Background information about competition and pricing wars in the fast-food industry

The fast-food industry has been historically characterized by intense competition and pricing wars. In the 2000s, major fast-food chains like McDonald's, Burger King, Wendy's, and Taco Bell engaged in aggressive pricing strategies to attract customers. These strategies often involved introducing value meals, combo deals, and discount promotions to increase foot traffic and sales.

One notable trend in the 2000s was the proliferation of dollar menus by fast-food chains. McDonald's, for example, introduced its Dollar Menu in the early 2000s, offering a selection of items priced at \$1 to attract budget-conscious consumers. Other chains followed, launching similar value menus and combo deals to remain competitive.

Intense competition among fast-food chains sometimes led to price wars, where rivals engaged in aggressive price-cutting and promotions to gain market share. Price wars could escalate as one chain lowers prices in response to a competitor's promotion, prompting further discounts and deals from other players in the market.

The pricing strategies of restaurants in the 2000s were also influenced by economic factors such as recessions, fluctuations in consumer spending, and rising food costs. During economic downturns, some restaurants introduced value-focused initiatives to retain customers and stimulate sales amid tighter budgets.

Overall, the 2000s were marked by intense competition and pricing dynamics in the restaurant industry, with fast-food chains leading the way in value-oriented strategies to attract and retain customers amid economic fluctuations and changing consumer preferences. The problem with this strategy was that all players began offering value pricing to keep or grow market share, which in turn can impact profits. No player wants to exit off the value offerings in fear that they will give their market share to their competitors, so a tight pricing environment emerges.

To move away from a tight pricing environment, restaurants had to focus more on (costly) marketing strategies to get their customers to rethink their value offering.

- b) Specific business scenario

Consider two fast-food chains: Chain A and Chain B. Each of them is considering two options: to offer discounts or not. The payoffs of the two chains depend on the choices made by both businesses.

		Chain B	
		Discount	Not discount
Chain A	Discount	Both chains attract more customers, but profit margins may decrease.	Chain A attracts more customers; Chain B loses customers.
	Not discount	Chain B attracts more customers; Chain A loses customers.	Both chains maintain current customer base.

Learning Objectives

- Analyze the characteristics of the fast-food industry to determine the market structure fast-food restaurants operate in.
- Discuss the importance of product differentiation in monopolistically competitive markets.
- Discuss various marketing strategies.;
- Understand the concept of a profit margin;
- Analyze businesses' decision of whether to offer discounts or not, given a payoff matrix that shows their profit margins when different combinations of strategies are chosen.
- Determine whether a business has a dominant strategy or not given a payoff matrix.
- Analyze a real-world example of a simultaneous-move game of complete information to determine the Nash equilibrium/equilibria of the game (if any).
- Recognize real-world examples of the Prisoner's dilemma.
- Recognize a real-world example of a barrier to entry.
- Compare the price elasticity of demand for given menu items between various customers.

Materials Needed

Whiteboard and markers, Printed copies of the business scenario and the assessment questions (optional)

Direct Instructions

- Ask students what they know about the fast-food industry, including the degree of competition, importance of product differentiation, etc.
- Explain or ask the students to read the background information about the fast-food industry provided above. Do *not* discuss the marketing strategies at this point.
- Ask students what is expected to happen to the economic profit of a fast-food restaurant in the long run. This question is an opportunity to discuss that if businesses make profits (losses) in the short run, fast food restaurants would have an incentive to enter (exit) the market. Entry (exit) would

continue until no more restaurants have an incentive to join (exit) the market, which is when the economic profits of all fast-food restaurants become zero. This discussion is also an opportunity to clarify the difference between an economic and accounting profit.

- Introduce the concept of profit margins. A profit margin is the percentage of the company's revenue that it keeps as a profit, i.e., $(\text{profit}/\text{revenue}) \times 100$. It is expressed in percentages. Ask students to guess what the typical net profit margin in the fast-food industry is. You can write the guesses on the board.
- The typical net profit margin of fast-food restaurants is in the range of 5 to 8 percent, but some bigger chains have a profit margin of up to 20 percent [FoodIndustry.com, 2021].
- Introduce the specific business scenario by showing and commenting on the payoff matrix above. Emphasize the trade-off between maintaining a business's customer base and the size of the profit margins.
- This is good time to explain that although game theory is typically associated with the strategic decision-making and behavior of oligopolies, it could be applied in a variety of scenarios not limited to oligopolies. Examples include pricing competitions, price leadership in monopolistic competition, decisions about product releases, decisions related to mergers and acquisitions, and so on. This scenario is an opportunity to illustrate the application of game theory in the context of monopolistic competition. This is possible when businesses strategically set prices taking into account market dynamics and rivals' potential actions.
- Consider the following numerical example of the business example above. The payoffs (in percentages) represent the profit margins of the two chains. The first payoff in each cell is that of Chain A, and the second payoff is that of Chain B. Suppose that this is a simultaneous-move game of complete information.

		Chain B	
		Discounts	Does not discount
Chain A	Discounts	13%; 13%	18%; 8%
	Does not discount	8%; 18%	a%; b%

- Ask students to recall what a dominant strategy is and what a Nash equilibrium is.
- For what values of a and b would offering a discount be the dominant strategy for Chain A? What about Chain B? Note: The answer is $a < 18$ percent, and $b < 18$ percent.
- Suppose that $a = b = 15$ percent. The payoff matrix becomes:

		Chain B	
		Discounts	Does not discount
Chain A	Discounts	13%; 13%	18%; 8%
	Does not discount	8%; 18%	15%; 15%

- Does each of the two fast-food chains have a dominant strategy or not? If yes, what is it? Why? Does the game have a NE or not? If yes, what is it/are they? Why? Note: The answer is that both have a dominant strategy, and it is to offer discounts.
- In this example, does the NE imply that each of the chains would prioritize: (1) offering discounts to maintain its customer base while lowering its profit margins, or (2) not offering discounts and maintaining a higher price but losing some customers? Note: The game has one NE: (Chain A: Discounts; Chain B: Discounts). Both chains choose to offer discounts, so they are hoping to gain customers even if their profit margin decreases.
- Is the scenario above an example of the Prisoner's dilemma or not? Why (not)? Note: Yes, this is an example of the Prisoner's dilemma. Both chains choose to discount, whereas they could both be better-off not doing so. This is consistent with the tight pricing environment that the true background information provided in the summary refers to.
- Ask students to brainstorm strategies (other than offering discounts) that fast-food restaurants could adopt. Guide them to think about marketing strategies that could incentivize the customers to rethink restaurants' value offerings. Make a list of students' ideas on the board/screen.
- If students have listed any of the following marketing strategies, discuss why and how they allow restaurants to differentiate themselves from their competitors. If any are missing, add and discuss.
 - Many restaurants shifted their focus towards **offering value to customers** by emphasizing quality, service, ambiance, and overall dining experience rather than solely competing on price.
 - Restaurants have increasingly **differentiated themselves by offering unique menu items**, specialty dishes, and culinary experiences that set them apart from competitors. This focus on menu innovation allows restaurants to justify premium pricing based on the *perceived* value of their offerings.
 - **Segmentation and targeting:** Rather than trying to appeal to a broad audience with generic pricing strategies, many restaurants have adopted more targeted approaches. They segment their customer base and tailor pricing, promotions, and menu offerings to specific demographic groups or market segments. Note: Ask students how targeting a specific segment of the customer base relates to the concept of elasticity.

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- **Brand building and reputation:** Building a strong brand and reputation can help restaurants command higher prices and attract loyal customers. By investing in branding, marketing, and customer service, restaurants can create a perception of value that transcends price considerations. Note: Ask students why building a strong brand is important for businesses.
 - **Emphasis on local and sustainable sourcing:** Many restaurants have responded to consumer demand for sustainable and locally sourced ingredients. By highlighting their commitment to quality, freshness, and ethical sourcing practices, restaurants can justify higher prices and differentiate themselves from competitors.
 - **Focus on upselling and add-ons:** Rather than competing solely on base prices, restaurants focus on upselling additional items, add-ons, and premium offerings to enhance the overall dining experience and increase revenue per customer. Note: Ask students how the main meal they purchase and the additional items and add-ons are related (complements).
 - The adoption of **technology and data analytics** allows restaurants to better understand customer preferences, optimize pricing strategies, and personalize offers based on individual behavior and preferences.
 - Finally, is offering discounts associated with a movement along the demand curve for fast food or a shift of the demand curve? What about the aforementioned marketing strategies?

Assessment Questions

1. What market structure (monopoly, oligopoly, monopolistic competition, or perfect competition) do fast-food chains like McDonald's, Burger King, Wendy's, and Taco Bell operate in? Please justify your answer.
2. Offering specialty dishes and culinary experiences and investing in exceptional customer service help fast-food restaurants distinguish themselves from their rivals. What economic concept describes this attempt?
 - a. Incentive
 - b. Price ceiling
 - c. Product differentiation
 - d. Depreciation
3. Building a strong brand that the customers of a fast-food restaurant are willing to stay loyal to is a(n):
 - a. Barrier to entry
 - b. Opportunity cost
 - c. Competitive market
 - d. Price floor

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4. Which of the following customers of a fast-food restaurant is likely to have the most relatively price *inelastic* demand for a meal made of only fresh, organic vegetables?
 - a. A college professor with a Mediterranean background
 - b. A low-income family with two small children
 - c. A stay-at-home mother who believes that only brand-name products meet food high-quality standards
 - d. A health-conscious young professional concerned about the pesticide content of vegetables

 5. Consider two fast-food chains. They are simultaneously considering whether to offer discounts or not. The profit margins of each of the two chains depend on the decisions of both businesses. The payoff matrix is presented below. The payoffs represent the profit margins of the two chains. The first payoff in each cell is that of Chain A, and the second payoff is that of Chain B.

		Chain B	
		Discounts	Does not discount
Chain A	Discounts	13%; 13%	18%; 8%
	Does not discount	8%; 18%	11%; 11%

Does each of the two fast-food chains have a dominant strategy or not? If yes, what is it? Why? Does the game have a NE or not? If yes, what is it/are they? Why? Do your answers to the previous questions imply that each of the chains prioritizes: (1) offering discounts to maintain its customer base while lowering its profit margins, or (2) not offering discounts and maintaining a higher price but losing some customers? Is this game an example of the Prisoner's dilemma or not? Why?

CONCLUSION

Understanding and applying basic economic principles helps businesses improve their capabilities and performance. However, students in introductory economics classes often fail to understand how economics relates to the real world and other disciplines. Perhaps relatedly, they often find the class unattractive. To tackle these issues, given the interest of Gen Z in business and entrepreneurship, using business cases that provide examples and applications of foundation-level economic concepts and ideas is an excellent way to engage students and create interest in the subject. Therefore, this work, which builds

on previous contributions to economics education, is intended to help educators bridge the gap between introductory economics and business in their classroom. The teaching guides provided in the article offer a unique opportunity to explore real business scenarios that illustrate how existing businesses apply economics to make optimal decisions on a daily basis. Although we currently lack student data to assess the actual impact of using real business scenarios to teach economics—which could be seen as a limitation of this study—exploring these scenarios can still be beneficial to students in several ways. First, it could help them better understand basic economics by applying the material in a real-world context [National Education Association 2023]. Second, using real-world cases has been previously shown to actively engage students and develop their problem solving, analytical, and decision-making skills by establishing a framework for analysis⁵. Integrating real business examples in the curriculum provides context, which intensifies students' thinking, leading to greater retention of the material [Willingham 2021]. Third, the case approach offers a low- to no-cost alternative to the traditional classroom instruction. Finally, awareness of the applications of economics to the real world could motivate students to explore economics and its applications in the business world beyond the economics classroom. Future research could survey students who have been exposed to the scenarios suggested in this paper and examine the effect of the exposure to true business scenarios on students' perceptions about their understanding of the material, willingness to pursue further economics courses, and actual understanding of the material.

Declarations

Declaration of Anonymity

To respect anonymity, the authors declare that they have not disclosed any real names of people and companies in this work. Any similarities are accidental.

Declaration of Interest Statement

The authors declare no conflict of interest.

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⁵<https://www.bu.edu/ctl/resources/teaching-resources/using-case-studies-to-teach/#:~:text=A%20major%20advantage%20of%20teaching,qualitative%2C%20depending%20on%20the%20case>

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Academic Performance in Standardized Testing: The Mediation Role of Big-5 Conscientiousness in the Relationship between Core Self-Evaluation and ETS Test Scores

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This study examines the relationship between core self-evaluation, Big-5 conscientiousness, and Educational Testing Services (ETS) Field Test scores using a mediation model. The results suggest that conscientiousness mediates the relationship between core self-evaluation and ETS scores, with higher levels of both traits associated with lower test performance. Additionally, the study explores test scores by major, addressing a gap in the literature on standardized testing and personality traits, particularly the influence of core self-evaluation and conscientiousness on test outcomes.

Keywords: Standardized Testing, Core Self-Evaluation, Big-5 Conscientiousness

Disciplines of Interest: Higher Education, Psychology, Educational Testing and Measurement, Pedagogy, Business Education

INTRODUCTION

As accrediting agencies like AACSB and ACBSP began requiring more independent, objective measures of assessment, business schools turned to standardized exams like the *Educational Testing Services (ETS®) Field Test for the Bachelor's Degree in Business*. The tests are designed to measure business knowledge in different areas, including accounting, economics, management, quantitative business analysis, information systems, finance, marketing, legal and social environment, and international issues [ETS, 2023]. Test scores can indicate to the school whether they are meeting learning outcomes and can provide benchmarking to other comparable institutions.

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Standardized testing (i.e., instructions, environment, and grading are the same for everyone) is used for various reasons, one of them being an admission criterion. For instance, the law school admissions test (LSAT) scores are considered most important factor for law school admission [Greene, 2022]. As far as entry criterion for undergraduate programs, in recent years, the focus on standardized testing declined when colleges temporarily suspended SAT/ACT entrance requirements due to COVID-19 testing difficulties [Marcus, 2021]. Although some undergraduate institutions continue to move away from standardized tests [Nietzel, 2022], they still play a major role in entrance criteria for graduate programs. Another application of standardized testing, specifically the ETS, is to determine institutional effectiveness (e.g., AACSB and ACBSP requirements). In this case, the ETS is used as an assessment of knowledge. One concern of business schools is whether the ETS test is a more objective measure of knowledge than GPA. Allen and Bycio [1997], Bagamery, Lasik, and Nixon, [2005], Bycio and Allen [2007], Chowdhury and Wheeling [2003], and Iqbal [2020], found a strong relationship between grades and ETS test scores, which could indicate that the ETS test is not a better measurement than grades for assessment purposes. Further, Mason, Coleman, Steagall, Gallo, and Fabritius [2011] argue that the cost of the ETS test is not worth the added benefit. They find that a statistical model using GPA, SAT score, and demographic characteristics can predict the ETS test score, so the ETS test does not add additional value for accreditation purposes. Finally, some students may just be better at taking standardized tests in general. Allen and Bycio [1997], Bagamery et al. [2005], Mirchandani, Lynch, and Hamilton [2001], and Terry, Mills, and Sollosy [2003] found that students who do well on the SAT also do well on the ETS test.

Many studies have been done on the benefits and drawbacks of standardized testing. Traditional research focused on how factors such as gender, race, and socioeconomic background impact student performance on standardized testing [Connor and Vargyas, 1992; Medina, 1990; Rosser, 1989]. Other studies show that certain personality traits can have an effect on standardized test scores (e.g., Andersen, Gensowski, Ludeke, and John, 2020; Laidra, Pullmann, and Allik, 2007; Tetzner, Becker, and Brandt, 2020; Zhao and Seibert, 2006). There have been studies linking conscientiousness (a tendency to be persistent, organized, goal-directed, have self-control, and self-discipline) and academic performance (e.g., Vedel, 2014), and there have been studies establishing the positive relationship between core self-evaluation (a basic, fundamental appraisal of one's worthiness, effectiveness, and capability as a person) and conscientiousness (e.g., Bono and Judge, 2003). This study will evaluate a more comprehensive model of the indirect effect of core self-evaluation and conscientiousness on standardized testing performance. More specifically, it will investigate how core self-evaluation interacts with conscientiousness and influences ETS test scores.

Although this paper focuses on the ETS test, which is used for institutional effectiveness, the analysis may be extended to other types of standardized tests.

Understanding how the influence of individual factors such as core self-evaluation and personality is critical to evaluate the relevance of individual standardized test scores and how they are weighted in comparison with other factors whether used for determining institutional effectiveness or for an individual's entry criterion into higher education.

THEORETICAL FRAMEWORK AND HYPOTHESIS

Personality

The most common conceptualization of personality in research is the Big-5 model, which includes five personality traits: extraversion (or energy), agreeableness, conscientiousness, neuroticism (or emotional stability indicating the opposite), and openness (or intellect) [Zhao and Seibert, 2006]. Conscientiousness is referred to as the degree of organization, perseverance, hard effort, and motivation exhibited by a person in the pursuit of goal achievement. This concept has been seen as a sign of willpower or the capacity for hard work by certain researchers. Across all job kinds and occupations, it has proven to be the most reliable personality predictor of work performance. Conscientiousness is a broad personality trait that has three main components: achievement, motivation, and dependability.

Research on academic performance and personality traits has found some interesting relationships. Laidra et al. [2007], Andersen et al. [2020] and Tetzner et al. [2020] find a strong positive relationship between conscientiousness and grades. The meta-analysis by Vedel [2014] found that conscientiousness was the strongest predictor of GPA. Westphal, Vock, and Kretschmann [2021] found a positive relationship between conscientiousness and grades; however, a negative relationship exists with standardized test scores. Spengler, Lüdtke, Martin, and Brunner [2013] found that conscientiousness was more closely related to grades, whereas openness was more closely related to achievement test scores. Other personality traits such as agreeableness, extraversion, and neuroticism have not shown a strong correlation to academic performance.

Core Self-Evaluation

Core self-evaluation is referred to as the fundamental evaluation each person has developed about themselves [Bono and Judge, 2003]. Core self-evaluation is sometimes referred to as overall positive self-regard—or the extent to which people value themselves and feel proficient as individuals. Core self-evaluation consists of four characteristics. 1) self-esteem, which is the extent to which people see themselves as capable, successful, and worthy; 2) generalized self-efficacy, which is the sense of one's ability to perform capably across a variety of circumstances; 3) neuroticism, which is the tendency to have a negative outlook

and pessimistic approach to life; and 4) locus of control, which refers to a person's beliefs about the extent to which he or she can control his or her own experiences.

The four components are very similar, and the difference is subtle [Bono and Judge, 2003]. Therefore, the components create a single, powerful factor that lies at the core of personality. When people view themselves in a positive way, or when they possess high self-esteem, they also tend to feel capable of performing effectively across a variety of situations (generalized self-efficacy), they feel in control of their circumstances (locus of control), and they have a positive outlook about life (opposite of neuroticism).

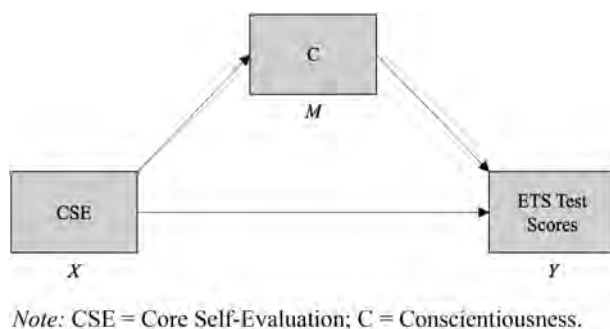
Core self-evaluation is a factor that may influence how students perform on the ETS exam indirectly, because core self-evaluation is related to personality [Bono and Judge, 2003]. It is well established in the literature that there is a positive relationship between core self-evaluation and conscientiousness. For example, Bono and Judge [2003] cite three studies that consistently show a positive relationship ($.24 < r < .37$).

The Present Study and Hypothesis

This study will continue the analysis into factors impacting ETS test scores by exploring the relationship between core self-evaluation, Big-5 conscientiousness, and ETS test scores. Based on the relationships between core self-evaluation and conscientiousness [Bono and Judge, 2003] and the relationship between conscientiousness and grades [Andersen et al., 2020; Laidra et al., 2007; Spengler et al., 2013; Tetzner et al., 2020; Vedel, 2014; Westphal, et al., 2021], we propose that core self-evaluation affects ETS test scores indirectly through conscientiousness. In other words, previous research suggests that core self-evaluation influences conscientiousness and that conscientiousness, in turn, influences ETS test scores. There is further indication of such relationships. H. Wang, Liu, Z. Wang, and T. Wang [2023] found that self-efficacy (generalized self-efficacy is part of core self-evaluation) mediated the relationship between Big-5 personality traits and students' academic achievements. Further, and more specifically, self-efficacy plays an intermediary role in the relationship between Big-5 conscientiousness and academic achievement [Di Giunta, Alessandri, Gerbino, Kanacri, Zuffiano, and Caprara 2013]. This study proposes a simple mediation, in which conscientiousness mediates the relationship between core self-evaluation and ETS test scores. A simple mediation model appears when the independent variable (X) affects a dependent variable (Y) through a mediator (M) [Hayes, 2013; Preacher and Hayes, 2004]. The mediation model is visualized in Figure 1.

Hypothesis: Big-5 conscientiousness ratings will mediate the relationship of the students' core self-evaluation ratings and students' ETS test scores.

Figure 1. Hypothesized Model Proposing the Mediation



METHOD

Sample

This investigation was a cross-sectional study using a convenience sample. The data were collected at a medium-sized, private university located in the southeastern United States between the spring semester 2019 and the spring semester 2021. Each semester had two sections of a capstone course, which involves the ETS test.

Participants

The total of 10 courses across the five semesters with two sections each had a total of 213 students. All 213 students completed the ETS test as a requirement for graduation. Two hundred and two surveys were returned (94.8 percent). The records were matched, leading to a final sample of $n = 202$. The student standings were 100 percent senior. The sample consisted of 56.4 percent males. The racial/ethnic backgrounds were as follows: 65.4 percent White, 11.3 percent Black or African American, 18.0 percent Hispanic or Latino, 0.8 percent Asian, and 4.5 percent Other.

Data Collection Procedure

As recommended by Hayes, Montoya, Preacher, Selig, Page-Gould, and Sharples [2016] for mediation analysis, the measurement was staggered in time. The data were collected in two stages. The Big-5 conscientiousness and core self-evaluation data were collected at the beginning of the semester (week one). The survey included an informed consent, the Big-5

conscientiousness and core self-evaluation survey items, and a demographics survey. The ETS test was administered in the second half of the semester. The order in which the measures were presented remained the same across all semesters and participants.

Measures

Core Self-Evaluation

Core self-evaluation was measured by using the core self-evaluation scale [Judge, Erez, Bono, and Thoresen, 2003], which has 12 items. Sample items are: “I am confident I get the success I deserve in life” or “I determine what will happen in my life.” The survey used a 5-point Likert agreement scale from 1 (*strongly disagree*) to 5 (*strongly agree*). Six of the 12 items were reverse coded. The responses to these 12 items were averaged to create an overall measure of core self-evaluation. The Cronbach’s alpha was .83.

Big-5 Conscientiousness

The measure used to assess conscientiousness was based on the Big-5 model short measure devised by Donnellan, Oswald, Baird, and Lucas, [2006] using the four out of twenty items that assess conscientiousness. Sample items are: “I get chores done right away” or “I like order.” The survey used a 5-point Likert accuracy scale from 1 (*very inaccurate*) to 5 (*very accurate*). Two of the four items were reverse coded. The responses to these four items were averaged to create an overall assessment of conscientiousness. The Cronbach’s alpha was .67. Donnellan et al.’s. [2006] Big-5 short measure had Cronbach alpha’s from .65 to .77. They stated that the “scales had acceptable reliability, especially in light of their reduced length” (p. 195). Therefore, the Cronbach’s alpha of .67 is acceptable for this study.

Analysis

The data analyses were conducted using *R* [R Development Core Team, 2022], including means, standard deviations, correlations, and reliability of the instruments. The hypotheses test for simple mediation was performed following the procedure outlined by Preacher and Hayes [2004] and Hayes [2013], using *R* with PROCESS (version 4.3). The bootstrapping approach was used to perform the test, thereby making no assumption about the distribution of indirect effect and providing confidence intervals for the estimate [Hayes, 2013].

Table 1. Means, Standard Deviations, Alpha Coefficients, and Intercorrelations

Variable	<i>M</i>	<i>SD</i>	1	2	3
1. CSE	3.95	.53	(.83)		
2. C	3.91	.68	.36***	(.67)	
3. ETS Test Scores	154	12.8	.04	−.20**	—

Notes: $n = 202$. CSE = Core Self-Evaluation; C = Conscientiousness; SD = Standard deviation. The values in italics represent Cronbach's alpha for the measures used. * p -value $< .05$.

** p -value $< .01$. *** p -value $< .001$.

RESULTS

Descriptive Statistics, Correlations, and Reliabilities

Table 1 displays the means, standard deviations, and correlations of the variables included in this study. Further, Cronbach alpha is shown for the Big-5 conscientiousness and core self-evaluation. Core self-evaluation showed a significant correlation with conscientiousness ($r = .36$, p -value $< .001$). Further, conscientiousness showed a significant correlation with ETS test scores ($r = -.20$, p -value $< .01$). Core self-evaluation was not associated with ETS test scores. All measures produced adequate estimates of reliability ($\alpha .67 - .83$).

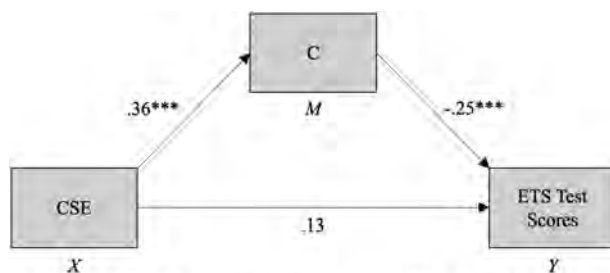
Hypothesis Testing: Core Self-Evaluation and ETS Test Scores and the Mediation of Conscientiousness

To examine whether conscientiousness mediated the relationship between core self-evaluation and ETS test scores, 10,000 resamples were used to estimate confidence intervals (CI) for the indirect effect [Hayes, 2013]. Results indicated that the standardized indirect effects of core self-evaluation on ETS test scores was $-.08$ (BootSE = $.04$). The 95 percent CI for the indirect effect excluded zero ($-.16$ to $-.03$), indicating that conscientiousness mediates the relationship between core self-evaluation and ETS test scores, therefore providing support for the hypothesis. Figure 2 shows further details of the mediation analysis.

Supplemental Analysis

Based on the general findings that higher levels of core self-evaluation leads to higher levels of conscientiousness, which then leads to lower ETS test scores, we explored ETS test scores by major. The analysis was for the four

Figure 2. Indirect Relationship between Core Self-Evaluation, Conscientiousness, and ETS Test Scores



Notes: $n = 202$. Bootstrap resample = 10,000. Confidence interval 95%. Values are standardized beta coefficients (* $p < .05$; ** $p < .01$; *** $p < .001$). The overall model was significant $F(2, 199) = 80.94, p = .004, R^2 = .05$. CSE = Core Self-Evaluation; C = Conscientiousness.

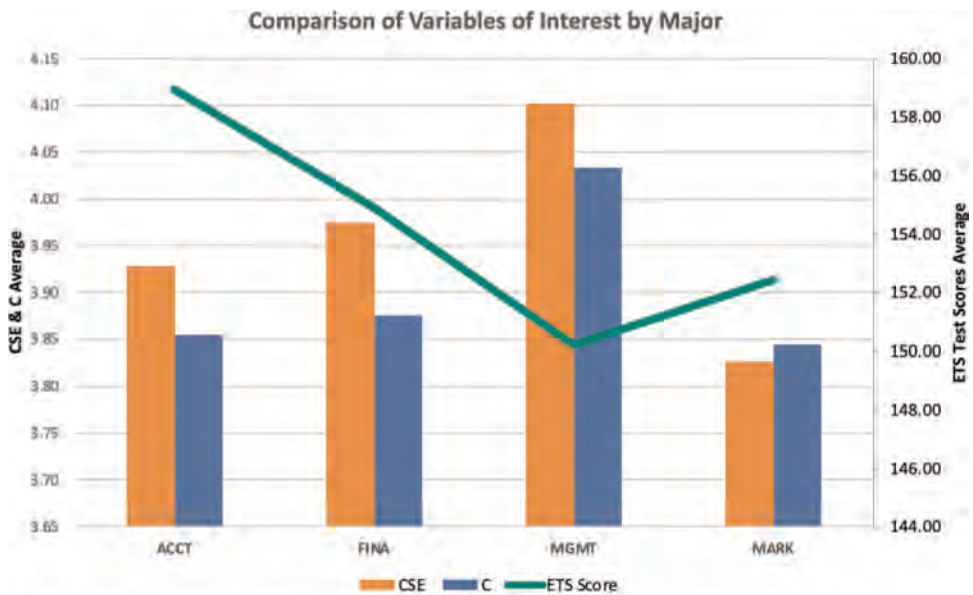
majors present in the school of business: accounting, finance, management, and marketing. Figure 3 shows the descriptive statistics.

The college major choice is not random; it is heavily influenced by parental background [Humburg, 2012]. Personality may also play a role. For example, Humburg [2012] found that extraversion increases the probability of choosing business, economics, or law in college. Therefore, personality may not be randomly distributed in a school of business because personality, in part, plays a role in college major choice. In this sample, management majors have both the highest core self-evaluation and conscientiousness. As expected, management majors also have the lowest ETS test scores.

DISCUSSION

Although generally, high core self-evaluation or high conscientiousness leads to positive outcomes, it seems that in standardized testing, such as the ETS, the combination of high core self-evaluation and high conscientiousness leads to negative outcomes. To the authors' knowledge, this is the first study to explore the indirect effects of core self-evaluation on academic performance (standardized testing). Results find that high levels of core self-evaluation leads to high levels of conscientiousness. This mediation affect may help explain the results in the previously mentioned paper of Westphal et al. [2021], who also found a positive relationship between conscientiousness and grades, yet a negative relationship with standardized test scores. Further, the supplemental analysis explored ETS test scores by major and demonstrated that the management

Figure 3. Means per Major



Notes: Accounting $n = 57$; Finance $n = 36$; Management $n = 53$; Marketing $n = 48$. ACCT = Accounting; FINA = Finance; MGMT = Management; MARK = Marketing.

major, which has the highest levels of core self-evaluation and conscientiousness, had the lowest ETS test scores across five semesters.

Implications

Standardized testing can be used for assessment of institutional effectiveness and benchmarking purposes, but it is not always a valid measure of student academic ability. This conclusion is supported by Terry et al. [2008], who found that the ETS test is mostly used for accreditation purposes (e.g., AACSB) and evidence of achieving specified learning goals. They further state that the dominant predictor of ETS test performance is the students' SAT or ACT score. Other factors are grades, quantitative courses, and gender. This study added another variable as a significant predictor: conscientiousness, which is a well-established measure of performance. Yet, this study shows conscientiousness can actually have a negative impact on standardized test scores. There is a need for benchmarking and comparative analysis across institutions, but it is questionable whether standardized testing is a suitable assessment of organizational effectiveness.

Shultz and Zedeck [2012] assessed personality via the Hogan Personality Inventory (adjustment, ambition, sociability, interpersonal sensitivity, prudence, inquisitive, and learning approach), finding that personality shows promising correlations with the twenty-six lawyering effectiveness factors they assessed. Prudence is the equivalent of conscientiousness, which correlated with eighteen of the twenty-six effectiveness factors. Hence, women have generally higher conscientiousness levels, which may be the reason they perform generally lower than men on the LSAT. However, higher levels of conscientiousness may be a desirable personality trait for a lawyer. This LSAT finding for women is evidence that standardized testing has shortcomings in accurately assessing students' abilities. The Shultz and Zedeck [2012] approach in determining job-related effectiveness factors and testing for these as an entry criterion may be an improved approach to developing selection criteria of students.

Limitations and Recommendation for Future Research

Our study uses a cross-sectional design, which does not allow for an assessment of impact, cause, and effect. The sample was recruited in the business school of one specific university. The sample was very homogeneous because it was 100 percent seniors. Hence, it may not extrapolate the findings to other settings, like other standardized tests. This approach has the advantage of holding institution factor constant, but researchers should replicate the findings in other institutions (e.g., high school and SAT testing) and using other types of standardized tests. Although the mediation model was significant, the variance explained was only 5 percent, indicating that other factors than core self-evaluation and conscientiousness play a role in academic performance on standardized tests.

Our study explored only business majors and the ETS. Future research should extend to other majors and other types of standardized testing. Although this study did not focus on gender, other research connects gender and conscientiousness. Verbree, Hornstra, Maas, and Wijngaards-de Meij [2023] found that females are generally more successful in higher education (i.e., more likely to graduate, obtain higher grades). They found that females are more conscientiousness than males and that conscientiousness fully mediated the gender gap in achievement. When looking at entrance testing, Kidder [2000] states that on the LSAT, one of the primary determinates for law school admissions, females perform worse than males; yet, Shultz and Zedeck [2012] found that although LSAT predicts law school grades, it does not relate to other forms of achievement in either academic or professional context.

Future research should focus more on gender differences and investigate whether females perform less well on standardized testing due to the generally higher conscientiousness [Kidder, 2000; Shultz and Zedeck, 2012]. More

comprehensive mediation models that include various factors, such as personality, gender, and race, are needed to fully understand student performance on standardized testing. Such understanding is important because the current emphasis on standardized testing may end up excluding highly conscientious people from academic pursuits.

Core self-evaluation offers various additional research questions. For example, Wang et al. [2023] explored self-efficacy, whereas core self-evaluation includes generalized self-efficacy. More research into academic self-efficacy, the specific belief that an individual can successfully complete academic tasks [Wang and Miao, 2012], may be interesting. Further, although the components of core self-evaluation are not individual dimensions [Bono and Judge, 2003], more research into these components should be considered. For example, self-esteem or locus of control are psychological constructs that could be explored in more detail. For instance, Wang and Miao [2012] explored the relationship of self-esteem and learning burnout and found a significant and negative relationship, which means, the higher the level of self-esteem of college students, the lower their level of learning burnout. Therefore, the relationship between self-esteem, Big-5 personality traits, and standardized testing ability could be interesting.

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