Essays in Experimental Economics and Applied Econometrics

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DEDICATION

Above all, thanks be to God for this opportunity and the strength to see it through. This work is dedicated to my loving and supportive wife, Justyna Brown, and wonderful children Benjamin and Daniel. Without them, this journey would not have been possible. Special thanks to my mentors and advisors that took interest in me and in my work and dedicated countless hours of their time to see me succeed.

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ABSTRACT

This dissertation presents one essay that utilizes an experiment and two essays that use observational data to causally examine important economic questions. In the first essay, I describe a laboratory experiment with human participants designed to test key theoretical predictions related to the effects of using public and secret reserve prices in independent private value, first-price sealed bid auctions. The results support theoretical predictions related to bidding in public reserve auctions and predicted revenue differences between public and secret reserve auctions. Predictions regarding buyer bidding in secret reserve auctions, and that public and secret reserves generate higher revenue than no reserve auctions, is not supported by the data.

The second essay investigates the relationship between air quality and human endurance and strength. I utilize a database of physical fitness scores from members of the United States Air Force and merge this with particulate matter measures from the Environmental Protection Agency. I exploit daily variation in particulate matter and the random assignment of members to work locations to identify a causal effect of particulate matter on member run times, push-ups, and crunches. I find that particulate matter exposure results in significant decreases in push-up and crunch repetitions and increases run times. Furthermore, I find that the physical fitness test failure rate increases with exposure to high particulate matter concentrations.

The third essay, a joint project with Celeste K. Carruthers (University of Tennessee, Knoxville), Michael Koefed and Aaron Phipps (United States Military Academy), and Jenna Webb Kramer (RAND Corporation), estimates the causal effects of providing free community college on military enlistments and aptitude. To identify these relationships we employ a two-

way fixed effects model and exploit the staggered rollout of the Tennessee Promise scholarship program, which is a last-dollar aid program that became available to graduating high school seniors in a subset of Tennessee counties in 2009 and by 2015 was implemented statewide. Our quantitative analysis complements the findings of Dr. Kramer's qualitative analysis and shows that Tennessee promise led to a significant decrease in military enlistments. We also find that Tennessee Promise motivated more technically adapt persons to enlist.

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Chapter 1

Reservation Prices in First Price Sealed Bid Auctions: An Experimental Approach

Abstract

This study uses an experiment with human participants to investigate the effects of using reservation prices, a minimum price that a seller is willing to accept to exchange a good, on bidder behavior and seller revenue in auctions. The experimental design varies whether groups of two or four potential buyers bid in auctions characterized by no reservation price, a public reservation price that is known prior to bidding, or a secret reservation price that is unknown when bidding. Consistent with theory, results from the experiment indicate that bids increase with the number of bidders and bidder valuations. The theoretical predictions about bidding in public versus no reserve bids hold while predictions related to expected revenues do not. Predictions concerning secret vs no reserve bids are not supported while the predicted trend in secret versus no reserve revenues holds, albeit at different ranges than predicted. Predictions concerning secret versus public revenues tend to hold in two-person auctions while the trend holds in four-person auctions at different-than-predicted ranges. The experiment identifies patterns of behavior that are not predicted by theory. Bidders tend to overbid the risk-neutral Nash equilibrium by a large margin, and a measure of risk preferences does not explain variation in bidding or revenue outcomes for any auction format. It is likely that non-monetary preferences like a joy of winning, independent of participant risk, are driving up bids.

1.1 Introduction

Auctions are popular marketplaces that bring potential buyers and sellers together to facilitate trade. Online auction houses such as eBay, eBid, Sotheby's and many others host millions of auctions daily. eBay alone hosts nearly 192 million live auctions at any given time (Babu, 2021). Over 20,600 businesses conduct traditional auctions across the United States with a market size of over $7 billion (IBISWorld, 2021). In most auctions, the objective of the seller is to maximize revenue. One potential tool at the seller's discretion to influence revenue is a reserve price, which is a minimum amount that must be bid for a transaction to take place. Such a reserve can either be "public" in the sense that buyers know this amount prior to bidding, or "secret" in that it is only revealed after bidding has completed. In either case, reserve prices can guard sellers from unexpected low sales prices. Moreover, a seller may strategically set the reserve in an attempt to generate additional revenue. For instance, even in a setting where the seller's minimum acceptable price would naturally be met, a relatively high public reserve price may motivate buyers to bid closer to their true valuation. Secret reserve prices can likewise be strategically set, and uncertainty over the actual reserve may motivate higher bids. In this paper, I use a theory-driven, induced-value laboratory experiment involving first-price sealed bid auctions to compare bids and revenue across no reserve, public reserve, and secret reserve auction mechanisms.

The seminal theory of reserve price auctions was developed by Riley and Samuelson (1981). Assuming a first-price auction with independent private values (IPV) and risk-neutral bidders, they show that setting an optimal public reserve that is higher than the true valuation (i.e., salvage value of the item sold) of the seller generates higher revenue relative to an auction

with no reserve price. For buyers with valuations higher than the reserve, the public reserve motivates higher bids. The revenue advantage of the public reserve decreases with the number of bidders.

Levin and Smith (1996) relax the IPV assumption in first price auctions and demonstrate in common value auctions that the optimal public reserve price converges to the seller's true value as the number of bidders increases. If the seller's true value is zero, this implies a no reserve auction. They also show that in second price auctions, regardless of whether values are correlated, reserve prices that exceed the seller's true value are only effective in generating additional revenue if the reserve falls between the second highest value and highest value. As the number of bidders increase, the difference between the second highest and highest value becomes infinitely small. In the limit, this renders reserve prices exceeding the seller's true value innocuous at best but potentially harmful to the seller.

Elyakime et al. (1994) is the first important paper to explore the theoretical implications of secret reserve prices. Assuming the same IPV, risk-neutral bidder framework of Riley and Samuelson (1981), and assuming that the seller's value is drawn from the same distribution as the bidders, they show that secret reserves generate more revenue than no reserve auctions and the optimal reserve is the seller's true value. Intuitively, it is never optimal for a seller to set a reserve higher than the true value as this only serves to increase the probability that the reserve is not met. If a no sale should occur, the seller is guaranteed the salvage value of the item and is protected from occurring a loss. Importantly, the authors also show that a public reserve weakly dominates a secret reserve in terms of expected revenue. Since secret reservation prices are so prolific in real world auctions, other theory papers have relaxed the assumptions of IPV, risk

neutrality, and endogenous entry to show that secret reserves can be strategically dominant over public reserves.[1]

The theoretical work on reserve auctions has motivated a limited number of empirical studies. Reiley (2006) uses a field experiment with online auctions involving cards from Magic: The Gathering to test Riley and Samuelson's (1981) public reserve auction theory. Reiley finds that as reservation prices increase, the number of bidders decrease and that the seller revenue increased conditional on a sale. He also finds that bidders generally behaved strategically when facing reserve values. Unconditional revenue decreases, however, inconsistent with theory. As Reiley acknowledges, bidder private values could not be controlled, market demands for certain cards likely differ across auctions, and values for different cards may be correlated due to the nature of desired sets within a collection. He concludes that it would be beneficial to test the theory in a laboratory setting.

Katkar and Reiley (2007) conduct a field experiment involving the sale of 50 identical pairs of Pokémon cards on eBay. One half of the pairs are sold with trivially low starting bids and a secret reserve price, while 50 are sold with nontrivial starting bids as the public reserve price. They find that secret reservation prices significantly decrease both the probability of a sale as well as the revenue generated when a sale occurs. They also find that the number of bidders is higher for secret reserve auctions. The authors acknowledge, however, that Pokémon cards are a specific niche market that may not generalize to other markets. Further, eBay auctions associated with a "reserve price" tends to signal items are "expensive", which in turn may limit generalizability. It is also important to note that eBay auctions are better characterized as second-

[1] See Vincent (1995), Li and Tan (2017), and Jiao (2011)

price auctions with continuous bidding. Unlike a sealed bid auction, a bidder receives real-time information as to whether the reserve price has been met and can adjust bids in accordance.

While the above-mentioned field experiments are most closely related to the present study, there are other papers that provide insight on the effects of reserve prices. Valsan and Sproule (2008) show that secret reserve prices in abstract art auctions tend to yield overestimations of the "low" value of art compared to auctions with no reserve price, therefore shrinking the pre-auction value window provided to bidders. They also show that secret reserve prices tend to result in a sale price closer to the "low" valuation rather than the "high" valuation due to the smaller value window.

Hendricks, Porter, and Spady (1989) examine Outer Continental Shelf Drainage auctions and how government public reserve prices impact bidder behavior. Consistent with their theoretical model, they find that uninformed buyers bid less frequently than informed buyers. Further, when uninformed buyers do bid, they submit high rather than low bids. This implies that random reserve prices deter uninformed buyers whereas informed buyers are confident to submit bids so long as the expected payoff is still positive despite the reserve price. Their model indicates that reserve prices have strong effects on bidder behavior in asymmetric information auctions and that bidding strategies are driven more by the information possessed by the bidder than the reserve price per se. The authors conclude that their research does not investigate the optimal reserve price strategy and is not generalizable to IPV or secret reserve auctions.

Sujarittanonta and Viriyavipart (2020) examined public reserve prices in experiments as a mechanism to combat bidder collusion. . While the authors find that a seller reserve price decreases collusion and shifts the surplus back to the seller, they do not investigate the seller

reserve price as a mechanism to maximize seller revenue or influence the bid function outside the scope of bidder collusion. Their findings indicate that buyer bid functions are affected through the mitigation of collusion in auctions where collusion occurs, however they do not focus on reserve prices as a strategy to elicit higher bids and maximize seller revenue in general.

To my knowledge, no experiment has been conducted to investigate the predictions of reserve prices on bidder behavior and seller revenue in a controlled, laboratory setting. In this study, I investigate public, secret, and no reserve auctions while varying the number of bidders, and the reserve prices. The laboratory experiment allows for the control of private values and eliminates threats to identification such as asymmetric information and correlations between sold items. I find that public reserve auction bids tend to be higher than bids in no reserve auctions conditional on a bidder's value meeting the reserve. The probability of no sale scenarios renders the expected revenue lower in public reserve auctions, however. I also find that no significant difference exists in the estimated secret and no reserve auction bid functions despite the unambiguous theoretical prediction that those in reserve auctions submit higher bids. Over a range of actual reserve prices, I find that secret reserves can generate more revenue than no reserve auctions. In the case of public reserve auctions, the realized probability of a no sale effectively eliminates any strategic benefit that a public reserve auction has over a no reserve auction in terms of expected revenue.

1.2 Theoretical Framework

To gain insight on incentives in the experiment, and to motivate testable hypotheses, this section summarizes the standard theory results as they pertain to a setting where a seller has one unit of a good to sell through a first price sealed-bid auction. There are N potential risk-neutral

buyers, and the seller either has no reserve price, a reserve price that is publicly known, or a reserve price that is unknown prior to bidding. Let v_i denote the monetary value to bidder i, where v_i is independently drawn from a distribution with density f and cumulative distribution function F.

1.2.1 No Reserve Auction (NR)

In a setting where the seller has no reserve price, and values are drawn from a uniform distribution, Vickrey (1961) shows that the Bayesian Nash equilibrium bid function is

(1) $$b_{\mathrm{NR}}(v_i) = \frac{N-1}{N} v_i$$

A buyer shades her bid in a way that depends on the number of bidders, with the bid converging to her valuation as the number of bidders increases. As the bid increases with value, revenue to the seller in a particular auction is equal to the bid submitted by the buyer with the highest value. In the special case where values are drawn from a uniform distribution on the unit interval, expected revenue for the seller is:

(2) $$\mathrm{E}[R_{\mathrm{NR}}] = \frac{N-1}{N+1}$$

1.2.2 Public Reserve Auction (PR)

Riley and Samuelson (1981) demonstrate that the seller can obtain additional revenue, in expectation, by optimally including a public reserve price. This reserve price is known to buyers prior to bidding, and the highest bid must meet or exceed this reserve price for the transaction to take place. Following Riley (2006), and denoting the reserve price as *r,* the Bayesian Nash equilibrium and expected revenue are:

(3) $$b(v_i, r) = \begin{cases} v_i - \frac{1}{F(v_i)^{N-1}} \int_r^{v_i} F(u)^{N-1} du, & v_i \geq r \\ 0, & v_i < r \end{cases}$$

(4) $\mathrm{E}[R(r)] = \int_r^{\infty} b(v;r) * N * F(v)^{N-1} f(v) dv = N * \int_r^{\infty} [vF'(v) + F(v) - 1] f(v)^{N-1} dv$

Assuming bidder valuations are distributed according to a uniform distribution $U(0,1)$, in which case $0 \leq r \leq 1$, the resulting bid and expected revenue functions are as follows:

(5) $b_{PR}(v_i; r) = \begin{cases} \frac{N-1}{N} v_i + \frac{r^N}{N v^{N-1}}, & v \geq r \\ 0, & v < r \end{cases}$

(6) $E[R_{PR}(r)] = \frac{N-1}{N+1} + \left(1 - \frac{2N}{N+1} r\right) r^N$

Following from (5), when the reserve price equals zero, the optimal bid is $\frac{N-1}{N} v_i$. This coincides with the result for the no reserve auction (1). When the buyer's valuation is at least as high as the reserve price, the reserve price motivates a higher bid. The equilibrium bid is (weakly) increasing in the reserve price.

With $r = 0$, the expected revenue is $\frac{N-1}{N+1}$, which again coincides with the no reserve result. In general, including a reserve price represents a tradeoff for the seller. On one hand, increasing the reserve motivates higher bids. On the other, the probability a sale is made decreases with the reserve price. A public reserve price increases expected revenue, relative to the case of no reserve, if $r < \frac{N+1}{2N}$. In this framework, $r = 1/2$ maximizes expected revenue for any value of N. As the number of bidders increases the additional revenue decreases, approaching 0 in the limit as $N \to \infty$.

1.2.3 Secret Reserve Auction (SR)

The seller may instead use a reserve price but decide not to disclose this amount prior to bidding. With a secret reserve, buyer expectations of the reserve price are an important

determinant of bids. When the seller's secret reserve is known to buyers to be drawn from the cumulative distribution G, Elyakime *et al.* (1994) show that the Bayesian Nash equilibrium is:

(7) $$b(v) = v - \frac{\int_0^v F(x)^{N-1} G(b(x))dx}{F(v)^{N-1} G(b(v))}$$

In the special case explored in the experiment, it is common knowledge that the seller's reserve price is drawn from the same distribution as the buyer valuations, i.e., $G = F$ With the assumption that buyer and seller valuations are independent draws from the uniform distribution on the unit interval, it follows that $F(x) = x$ and $G(b(x)) = b(x)$, and (7) simplifies to:

(8) $$b(v) = v - \frac{\int_0^v x^{N-1} b(x)dx}{v^{N-1} b(v)}$$

The following bid function is a solution to (8):

(9) $$b_{SR}(v_i) = \frac{N}{N+1} v_i,$$

which is equivalent to the equilibrium bid function for a no reserve auction, but as if there were instead $N + 1$ bidders. From the bidders' perspective, the seller acts as another potential buyer that submits their own bid and buys the item back for themselves if the potential buyers do not achieve or exceed the seller's bid (McFadden 2002).

Unlike public reserve auctions, the actual revenue from the secret reserve auction increases as the reserve price drawn decreases. This is intuitive as the equilibrium bids are not a function of the actual reserve price drawn.

To calculate expected revenue, conditional on a particular threshold, let Y denote the maximum bid among all bidders, i.e., $Y = max(v_1, \dots, v_N)$. Let H denote the CDF of the distribution of the maximum value. As bidder distributions are independently and identically

distributed, $H = F^N$. With the distributional assumption $F = U(0,1)$, $F(x) = x$, and $H(x) = x^N$. The associated pdf of Y is $h(x) = x^{N-1}N$.

With the equilibrium bid function (9) and assumed value distribution, the highest possible bid is $\frac{N}{N+1}$. Any threshold drawn above this value therefore yields zero revenue. Otherwise, the reserve will be met if $\frac{N}{N+1}Y \geq r$, which implies that $Y \geq \frac{r(N+1)}{N}$. Expected revenue is then:

$$(10) \quad \mathrm{E}\left[R_{SR}(r) \mid r \leq \frac{N}{N+1}\right] = \int_{\frac{r(N+1)}{N}}^{1} b(x)h(x)dx = \left(\frac{N}{N+1}\right)^2 \cdot \left(1 - \left[\frac{r(N+1)}{N}\right]^{N+1}\right)$$

1.2.4 Risk Aversion

Previous experiments have generated strong evidence that bidders in first price auctions often bid higher than the equilibrium predictions under risk neutrality. To account for this, Cox et. al (1982a, 1982b, 1983a, 1983b, 1984,1985a, 1985b, 1987, 1988) propose that risk aversion, in particular constant relative risk aversion, could potentially explain bidding behavior. Li and Tan (2017) attribute bids higher than risk-neutral predictions to an aversion of losing. Li and Tan show that as a bidder's degree of absolute risk aversion increases, their degree of aversion to losing also increases. Because of this, bidders that exhibit risk-averse behavior are expected to bid closer to their valuation given an unknown reserve value.

1.2.5 Theoretical Predictions

The theoretical framework yields a series of predictions that can be readily tested using a controlled experiment that varies the auction mechanism (no reserve, public reserve, secret reserve) and number of bidders. The following hypotheses follow directly from the theory, under the assumption of risk-neutral bidders:

Hypothesis 1. Conditional on valuations exceeding the reserve price, public reserve auctions generate weakly higher bids than a no reserve auction.

Hypothesis 2. Bids are higher in secret reserve auctions relative to no reserve auctions.

Hypothesis 3. Bids increase with the number of potential buyers.

Hypothesis 4. When $r < \frac{N+1}{2N}$, public reserve auctions generate higher revenue than no reserve auctions. Otherwise, no reserve auctions generate higher revenue.

Hypothesis 5. When $r < \frac{N^{\frac{N-1}{N+1}}}{N+1}$, secret reserve auctions generate higher revenue than no reserve auctions. Otherwise, no reserve auctions generate higher revenue.

Hypothesis 6. When $r > 0.32$ (N=2) or $r > 0.43$ (N=4), public reserve auctions generate higher revenue than secret reserve auctions. Otherwise, secret reserve auctions generate higher revenue.

Hypothesis 7. Revenue increases with the number of bidders.

Given evidence that risk aversion may be an important behavioral driver in experimental auctions, I include two additional hypotheses:

Hypothesis 8. Bids increase with risk aversion.

Hypothesis 9. Revenue increases with risk aversion.

Hypotheses (1) to (3), and (7) directly follow from the theoretical framework. Comparisons referenced in Hypotheses (4) to (6) depend on the reserve price and the number of bidders. When comparing revenue from no reserve and reserve auctions, there is a tradeoff between the probability of making a sale and the revenue generated from a sale. This tradeoff favors reserve auctions when the reserve price is sufficiently low, but the gain in additional revenue is not enough to offset the low chance of making a sell as the reserve becomes large.

Equating (2) and (5), and solving for r, reveals that expected revenue from no reserve and public reserve auctions is equal when $r = \frac{N+1}{2N}$. Reserve prices above this amount yields higher revenue for no reserve auctions. Equating (2) and (10) reveals similar logic in secret reserve auctions, where the reserve price needs to be $r < \frac{N^{\frac{N-1}{N+1}}}{N+1}$ to generate higher revenue.

Comparing revenue for the two reserve auctions is more complicated, as revenue for both mechanisms depend on N and r. Intuitively, as bids conditional on exceeding the reserve are higher for the public reserve, revenue conditional on a sale will be higher for the public reserve. However, the higher bids mean that the chance of a sale decreases for the public reserve, and as such there will be a critical value of r at which expected revenue becomes higher for the secret reserve. While it is challenging to obtain an analytical solution for the critical threshold value for r (holding N fixed), using simulations reveals a threshold of 0.32 in auctions with two bidders and 0.43 in auctions with four bidders.

1.3 Experimental Design

There are six experimental treatments defined by the fist-price auction mechanism (no reserve, public reserve, secret reserve) and the number of bidders (two or four). The auction mechanism is varied across sessions as a between-participant treatment, whereas the number of bidders (auction size) is varied within-participant. Players within a session first engage in 25 independent auctions (decision rounds) of a given auction size, and then switch to the other auction size for the remainder of the experiment. The order of the two- and four-person auctions varies across sessions.

For each auction, a participant receives as her private valuation an independent draw from the uniform distribution with supports of 0 to 100.[2] Values are redrawn prior to each round. Players within an auction submit bids simultaneously, without knowledge of the actual valuation(s) or bid(s) of the other player(s). In the no reserve auction, there is no reserve price and so the highest bidder wins the auction and receives as earnings the difference between her bid and her induced value. Any unsuccessful bidder earns zero for the round. In public reserve auctions, bidders know the reserve prior to bidding. If the highest bid meets or exceeds the reserve, the bidder wins the auction and earns the difference between her bid and value. Otherwise, there is no winner, and all bidders earn zero. For consistency with the secret reserve auction, and to facilitate comparisons with the other auction mechanisms, players are informed that the reserve price is randomly drawn from the $U[0, 100]$ distribution.[3] In theory, knowing the underlying distribution should not alter equilibrium bids. While those with values less than the reserve should, in theory, bid zero in the auction, bids from these players are not restricted in any way.

With the secret reserve auction, players know there is a reserve price, and that this reserve is a randomly drawn value from the $U[0, 100]$ distribution. However, this reserve is not announced prior to bidding. Earnings are determined in a manner consistent with the public reserve.

[2] In the theoretical framework, for convenience we assume $U[0,1]$ distributions. Given the properties of uniform distributions, the various predictions from the theory can be multiplied by 100 and applied to the experiment data.
[3] The first three sessions of reserve auctions drew the reserve from a uniform distribution from 19 to 59.

1.3.1 Experimental Procedures

Between June 2021 and June 2022, 307 students participated in the auction experiment. 20 of these participants participated in a pilot experiment which was used to conduct a detailed power analysis and determine the final format of all remaining auctions. Participants were drawn from two large pools of students at the University of Tennessee and Appalachian State University registered as potential participants in economics experiments. In total, 16 experiment sessions were conducted. This includes five sessions of no reserve auctions, five with public reserve auctions, and six with secret reserve auctions. The number of participants in a session range from 12 to 28 with an average of 20 per session. Sessions lasted approximately 70 minutes and individual earnings for the session averaged $24.42. Participants were allowed to attend only one session of the experiment. Table 1-1[4] provides a summary of treatment and participant descriptive statistics.

The experiment is programmed with the software z-Tree (Fischbacher, 2007), and implemented using z-Tree Unleashed (Duch et al., 2020). The experiments are conducted online, with individual participants engaging remotely through Internet browsers. This administration mode was motivated by the COVID-19 pandemic, and procedures otherwise are intended to resemble a traditional lab experiment.

The typical session proceeds as follows. Prior to the session, registered participants are emailed with experiment instructions and a Zoom link. The Zoom session provides a mechanism for experiment moderators to interact with participants. Participants join the Zoom session, and their registration and student status are verified prior to the start of the experiment. All

[4] All tables are in the appendix

instructions are read by the same experimenter for all sessions, which are also displayed in Zoom via a screen share.

Participants first go through a risk elicitation procedure, then proceed to the auction experiment, and finally complete a questionnaire. The risk elicitation procedure uses a multiple price list (MPL), similar to Holt and Laury (2002). For each scenario in the MPL, participants either select a sure payoff of $2 or a lottery that pays $4 or $0 with known probabilities, and only the probabilities vary across scenarios. Upon completion of the risk elicitation, but before the questionnaire, one scenario is selected at random to be implemented for real. Each scenario has an equal chance of being selected, and participants are encouraged to treat each decision independently.

After the auction experiment instructions are read, but prior to bidding, participants answer a set of quiz questions to help gauge and motivate comprehension of instructions and are paid 50 cents for each correct answer. In the auction experiment, participants know their group size, and are otherwise aware of the underlying value and, when applicable, reserve price distributions. After each decision round, participants are shown a results screen that displays their bid, whether they won the auction, and their profit for that round. No other information is provided. Participants can earn money in each auction round. Earnings are denominated in Experimental Currency Units (ECUs) and exchanged into US$ at a rate of $1 per 15 ECUs at the end of the session.

Upon completion of the auction experiment, participants complete a short questionnaire. The questionnaire collects demographic information such as age, gender, employment

information, grade point average, prior participation in economics experiments, and participation in naturally occurring auctions such as those conducted through eBay.

Overall earnings for the session are equal to a show-up fee, and earnings from the risk elicitation exercise, auction quiz questions, and the auction experiment. The show-up fee is $5 in no reserve auction sessions, and $10 for sessions with a reserve auction. The differential show-up fees are intended to help equate earnings, which are predicted to differ across auctions. Payment is made using Amazon gift cards.

1.3.2 Power Analysis

I conducted a paid pilot experiment with 20 participants involving no reserve auctions to help determine reasonable sample sizes. During the pilot, participants bid in groups of two for 14 rounds and groups of five for 35 rounds. Aside from the number of rounds and the fact that participants bid in groups of 5, the procedures followed those described in section 1.3.1. In my power calculations, I assume that the estimated between and within-participant variations are larger in no reserve auctions than reserve auctions since no additional constraints are theoretically levied on the bid functions. Because of this, using a no reserve auction yields the most conservative estimate in calculating power. Consistent with the actual data analysis, I assume that tests are based on linear regressions with standard errors clustered at the participant level. For reserve auctions, I assume that a no sale scenario will occur 20% of the time when considering revenue. Given these assumptions, I settled on sample sizes of about 80 for each auction type. In four-person auctions, this allows me to detect a minimum effect of 3.44 units between no reserve and reserve auction revenues, 3.56 units between the two reserve auction revenues, and 4.65 units when testing for differences in bids across all auction formats. In two-

person auctions, I can detect a minimum effect of 3.06 units between no reserve and reserve auction revenues, 3.22 units between the two reserve auction revenues, and 3.74 units regarding bids across all auction formats. All power calculations assume 80% power and a 5% significance level.

1.4 Data and Estimating Equations

1.4.1 Data

Table 1-1 summarizes the data collected across all sessions. In total, 287 students participated across 15 sessions. The number of people in a session varies between 12 and 28. The average age of participants is about 21 and over 59% are female. Over 79% of all participants participated in prior economics experiment. The average bid in no reserve auctions is 38.5 in groups of two and 42.9 in groups of four. In public and secret reserve auctions, these figures are 51.2 and 55.0, and 40.5 and 44.2 respectively. Average revenue in no reserve auctions is 52.4 for groups of two and 71.2 for groups of four. In public and secret reserve auctions, revenues are 43.1 and 59.1, and 34.5 and 57.4 respectively. It is worth noting that average revenues in public and secret reserve auctions account for zero revenues earned in no sale auctions in Table 1-1, i.e., what is reported is unconditional revenue.

1.4.2 Analysis of Bids and Revenues

The econometric specifications are closely tied to the theoretical framework. In the case of a no reserve auction (equation (1)) or a secret reserve auction (9), conditional on the number of bidders, theory suggests that the bid is a linear function of induced value:

(11) $Bid_{it} = \alpha + \beta Value_{it} + \varepsilon_{it}$,

where the dependent variable is the bid of participant i in auction (decision period) t, v_{it} denotes the bidder's induced value, and ε_{it} is a mean-zero error term. I assume that the error term is potentially heteroskedastic, and that bids from the same person are correlated across auctions.

As there is evidence of overbidding in the experimental auction literature, and some evidence that this may be a result of risk aversion, I extend the model to allow the estimated bid functions to vary by risk preferences. In the risk elicitation exercise conducted prior to the auction experiment, a risk-neutral person should select the certain payoff in the first 5 scenarios, whereas a risk-averse (risk-loving) player should select the certain payoff in six or more (four or fewer) scenarios. Following Evans, Vossler, and Flores (2009), I define the variable $Risk_i$ as the number of scenarios where the player selected the certain payoff minus five, and include this variable as an interaction with induced value in the regression model:

$$(12) \quad Bid_{it} = \alpha + \beta Value_{it} + \gamma_t(Risk_i * Value_{it}) + \varepsilon_{it}$$

When this risk measure (and hence the interaction) equals zero, the regression model remains consistent with the equilibrium bid function based on risk neutrality.

For the public reserve auctions, following (5) and further including the risk aversion term, suggests the regression specification:

$$(13) \quad Bid_{it} = \alpha + \beta Value_{it} + \delta_t\left(\frac{Reserve^N}{N*Value^{N-1}} * Public\right) + \gamma_t(Risk_i * Value_{it}) + \varepsilon_{it}$$

Unlike for the other auction mechanisms, this specification only applies to bidders with valuations that are at least as high as the posted reserve price.

In theory, for the no reserve auction the predicted revenue is equal to the bid from the person with the highest induced value. The same is true for the reserve auctions, but this is conditional on the highest induced value meeting or exceeding the actual reserve price. Thus, to

analyze actual revenue the regression functions provided above continue to apply, with the exception that there is at most one observation per auction, and the information related to induced value and risk preferences is tied to the person with the highest induced value for that auction.

For the public and secrete reserve cases, the estimated regression models can be used to calculate *unconditional* expected revenue for a given reserve price by multiplying the expected revenue conditional on a sale by the probability that a sale occurs. Based on the properties of the uniform distribution, it is straightforward to calculate the probability that a sale will occur based on a drawn reserve price and the maximum expected value draw in a group of N bidders as was demonstrated in equation (10).

1.5 Results

1.5.1 Bids

Tables 1-2 and 1-3 present the estimated bid functions,[5] which are estimated separately by auction type and the number of bidders. In accordance with theoretical expectations, the estimated intercept (α) is statistically zero in all cases, and the slope parameters (β and δ) are positive and statistically significant. The coefficient on the risk measure is statistically insignificant in all cases.

Hypotheses 1 predicts that conditional on valuations exceeding the reserve price, public reserve auctions generate weakly higher bids than a no reserve auction. Given the differences in

[5] The model was also ran with participant controls including age, gender, GPA, and previous experiment experience and controls for whether bidders started in groups of 2 or 4 and the number of the bidding period as a robustness check. The findings are robust to the additional controls. Tables 1-8 through 1-11 present the results with all controls.

the two bid functions, to do this I condition the comparison on buyer valuations and reserve prices. I assume the risk parameter is zero, although doing so has virtually no effect.[6] For no reserve auctions, I use an expected value for the buyer valuation of 50, which is the mean of the value distribution. For public reserve auctions, I differ the reserve price and calculate the corresponding expected valuation for the truncated bid space, since any value below the reserve cannot generate a qualified bid. I consider the two auctions to generate equivalent bids for a given reserve price if the predicted values are not different at the 10% significance level.

Focusing first on two-person auctions, for a reserve of 6 or less, bids are statistically different, and higher, for no reserve auctions. For a reserve of 7 to 14, the two auction formats are statistically equivalent. Once the reserve exceeds 14, however, public reserve auctions generate statistically different, and higher bids. In groups of four, the analysis reveals that no reserve auctions are predicted to generate higher bids than public reserve auctions if the reserve is less than or equal to 4. When the reserve is in the range of 5 to 12, the auctions are statistically equivalent. If the reserve is 13 or higher, bids submitted in public reserve auctions are predicted to be higher than bids submitted in no reserve auctions. Overall, with little qualification, the data support Hypothesis 1.

Hypothesis 2 predicts that secret reserve auctions will generate higher bids than no reserve auctions. Jointly testing for equality in the intercept and slope reveals that there is no statistical difference between bid functions for either two (p =0.17) or four-person (p =0.69) auctions. Therefore, the data strongly rejects Hypothesis 2. Instead, when participants face a secret reserve, they appear to behave as if the secret reserve is irrelevant.

[6] Indeed, the findings are robust whether risk is included in the model or not.

Hypothesis 3 predicts that bids increase with the number of bidders. This is predicted in all auction theory and is intuitive—as competition increases, bids must increase to beat the competition. While testing for differences across bid functions provides similar insights, for simplicity I instead test for differences in mean bids using simple t-test (with cluster-robust standard errors) based on the raw data. Table 1-4 summarizes the results. As predicted, bids increase in all auction types as the number of bidders in the auction increases.

Hypothesis 8 predicts that bids will increase with risk aversion. To test this, following Evans, Vossler, and Flores (2009), I constructed a measure of risk preferences by counting the number of safe choices that the participants picked in the lottery task before the auction experiment, excluding the choices between certain outcomes, and subtracted five. The resultant risk variable is equal to zero when participants are risk neutral, positive for risk aversion, and negative for risk seeking. Interacting this measure with induced value allows the slope of the bid function to vary by risk preferences. As evidenced by the results in Tables 1-2 and 1-3, the risk parameter (γ) reveals no significant change to the estimated bid functions in either two or four person auctions regardless of the auction type, there I reject Hypotheses 8. It is important to note that participants nevertheless still significantly overbid relative to the risk-neutral Nash equilibrium. Indeed, theory predicts that the slope for no reserve and secret reserve auctions are 0.5 and 0.67 for two-person auctions and 0.75 and 0.80 for four-person auctions. The regression results indicate the slopes are much higher.

1.5.2 Revenues

Tables 1-5 and 1-6 present the estimated revenue functions conditional on a sale based on the highest bid submitted in a group from the bidder with the highest value drawn within a group

as predicted by theory. The parameters of the estimated revenue functions are used to test Hypotheses 4, 5, 6, 7, and 9. It is important to note that the predictions concerning revenue across the different auction formats are conditional on a sale occurring in Tables 1-5 and 1-6. Therefore, the steps taken to test the revenue functions are identical to the steps taken when analyzing bids with the additional step of considering the probabilities of a no-sale result to estimate expected revenue.

Hypothesis 4 predicts that public reserve auctions will generate higher revenue than no reserve auctions when the reserve is less than 75 in two-person auctions and 63 in four-person auctions. To test this, I calculate the conditional revenue predicted by the model and multiply this by the probability of a sale to calculate expected revenue. This requires calculating the expected value of the highest value drawn in a group of bidders. While the no reserve auction can simply employ the highest draw formula[7] since all bidders will compete in the auction, public reserve auctions must take into consideration that bidder's will not compete if their drawn value is lower than the reserve. These probabilities are not difficult to calculate. For example, when the reserve is 75, there is a joint probability of 0.0625 that both participants draw a value that weakly exceeds the reserve. In this event, the highest expected value among these participants is 91.67. There is also a joint probability of 0.375 that only one of the bidders can clear the reserve with an expected value of 87.5 in this scenario. The remaining probability of 0.5625 is the probability that neither participant clears the reserve. Thus, the weighted expected highest value, conditional on a sale, is $\frac{0.0625*(91.67)+0.375*(87.5)}{1-0.5625} = 88.09$. Based on this expected high value and a reserve of 75, I estimate the conditional revenue through the estimated revenue

[7] The highest expected draw from a uniform distribution is N/(N+1)

function. This resultant conditional revenue is then multiplied by the probability that a sale occurs at a reserve of 75 which has already been established as $1 - 0.5625 = 0.4375$. The product is the estimated expected revenue. I then test whether this revenue is statistically different to the estimated no reserve revenue based on the no reserve highest expected value of 66.67. The same procedures are conducted for four person auctions revealing a high expected value of 83 when the reserve is 63 compared to a high expected value of 80 in no reserve auctions.

The data strongly rejects Hypothesis 4 revealing that no-reserve auctions dominate public reserve auctions at the predicted breakeven points with a p-value < 0.001 for both two and four person auctions. Lowering the reserve threshold mitigates the differences between the two auction types, however at no time does the estimated expected revenue of public reserve auctions ever exceed or become statistically equivalent to no reserve auctions. The evidence suggests that public reserve auctions are always inferior to no reserve auctions in generating expected revenue.

Hypothesis 5 predicts that secret reserve auctions will generate higher revenue than no reserve auctions when the reserve is less than 42 in two-person auctions and less than 46 in four-person auctions. I test this by evaluating the conditional revenue generated by secret reserve auctions multiplied by the statistical probability that a participant's bid will clear the reserve and comparing this revenue with the revenue generated in no reserve auctions. The expected high value in secret reserve auctions is equal to the expected high value in no reserve auctions as secret reserve auctions do not establish a minimum condition on whether bids can be submitted, only on whether the bids are accepted. To calculate the probability that no sale will occur, I calculate the joint probability that any participant competing in the auction can clear the reserve. This is simply the reserve divided by the product of the estimated value coefficient (β) to

calculate the required drawn value and using the properties of the uniform distribution to determine the probability that all participants draw a value less than this required value. Since the secret reserve intercept (α) is not statistically different than zero as per Tables 1-2 and 1-3, this intercept is not used to evaluate the required value.

Evaluating the estimating equation at a reserve of 42 predicts that secret reserve auctions generate less estimated expected revenue than no reserve auctions at this predicted breakeven point with a p-value < 0.001. However, the estimating equation predicts that expected revenue in secret reserve auctions is higher than no reserve auctions when the reserve is 17. From a reserve of 18 to 25, the two auction formats are statistically equivalent. At reserves greater than or equal to 26, no-reserve auctions are predicted to generate higher expected revenue than secret reserve auctions. In four person auctions, evaluating the estimating equation at a reserve of 46 with an expected high value of 80 and using the β from Table 1-6 predicts that secret reserve auctions generate significantly less revenue than no reserve auctions at this predicted breakeven point. Further analysis reveals that secret reserve auctions are never predicted to generate higher expected revenue than no reserve auctions at any level of reserve. At reserves less than 36, however, the estimating equation predicts that these two auction formats are statistically equivalent. Should the reserve increase beyond this, no reserve auctions are predicted to generate higher expected revenue than secret reserve auctions. In the strictest sense, I reject Hypothesis 5 as the evidence suggests that $r < \frac{N^{\frac{N-1}{N+1}}}{N+1}$ is not valid in defining the limit where secret reserve auctions predictably generate more expected revenue than no reserve auctions. It is worth noting that the evidence does suggest that secret reserve auctions should generate more revenue than no

reserve auctions if the reserve value is sufficiently low in two-person auctions, however this result could not be replicated when the number of bidders in the auction increases to four.

Hypothesis 6 predicts that public reserve auctions will generate higher revenue in expectation than secret reserve auctions when the reserve is greater than 32 and 43 in two and four-person auctions respectively. When the reserve drops below these levels, secret reserve auctions should generate more expected revenue. In order to test Hypothesis 6, I employ the methods of calculating the probability that each auction format will result in a sale as discussed in previous paragraphs. The estimated conditional revenues are then multiplied by these probabilities to calculate the predicted expected revenue of each auction type.

Evaluating the model at a reserve of 32 in two-person auctions reveals that public and secret reserve auctions are statistically equivalent when predicting expected revenue. When the reserve is increased to 34, public reserve auctions are predicted to generate more expected revenue.[8] The two auction formats are estimated to be statistically equivalent with reserves ranging from 28 – 33. Below a value of 28, secret reserve auctions predict expected revenues greater than public reserve auctions. Evaluating the four-person model at reserve of 43 reveals that secret reserve auctions are predicted to generate more revenue than public reserve auctions in contrast with the theoretical prediction. However, when the reserve is increased to 49, the two auction formats are statistically equivalent. For reserves below this threshold, secret reserve auctions are predicted to generate higher revenue than public reserve auctions at a reserve of 48. The two auction types are statistically equivalent when reserves range from 49 to 51. At reserves

[8] In these calculations, it is important to note that this is the first reserve value where the threshold is below 0.10. As you continue increasing or decreasing the reserve depending on the context of the analysis, p-values converge closer to 0.

exceeding 51, public reserve auctions are predicted to generate more revenue than secret reserve auctions.

In two-person auctions, the theoretical reserve breakeven points were extremely accurate when predicting the data. In four-person auctions, the breakeven point of 43 was not confirmed, however the true breakeven point was 49. Despite the small difference in these two values, the predicted behavior was accurate. For reserve values below the breakeven point, secret reserve auctions generate higher predicted revenue than public reserve auctions. For reserve values exceeding the breakeven point, public reserve auctions generate higher predicted revenue. The results of Hypothesis 6 are mixed. The evidence supports the trend that hypothesis 6 proposes and supports the assertion that the breakeven point between public and secret reserve auctions exists at a reserve of 32 in two-person auctions. While the trend is supported in four-person auctions, I reject the assertion that the auction types are equivalent at a reserve of 43.

Hypothesis 7 predicts that revenue increases in the number of bidders. Just as bids are predicted to increase when facing more competition, it follows that revenues must increase as well since revenues equal the maximum bid submitted. As predicted, revenues increase in all auction types as the number of bidders in the auction increases and I fail to reject Hypothesis 7. The introduction of a reserve price, whether public or secret, has no impact on this well-established principle. Table 1-7 summarizes the results.

Hypothesis 9 predicts that revenues increase with risk aversion. I reject Hypothesis 9 as the risk parameter (γ) in Tables 1-5 and 1-6 reveal no significant change to the estimated revenue function in either two or four person auctions regardless of the auction type.

1.6 Conclusion

While auctions are important exchange institutions, and the use of reservation prices by sellers is commonplace, there is surprisingly little research that examines the effects of reserve prices as a mechanism for generating higher bids and increasing seller revenue. This paper helps to fill this research gap through a theory-driven laboratory experiment that carefully compares no reserve, public reserve, and secret reserve auctions. The design further varies the number of bidders and realized reserve prices. The results provide insight on the performance of reserve auctions and the ability of standard theory models to explain patterns in the data.

Overall, the theoretical predictions governing bid functions were mixed. I confirmed the prediction that public reserve auctions generate higher bids than no reserve auctions conditional on a submitted bid. Furthermore, the predictions that bids and revenues increase in the number of bidders was also verified. I also confirm the predictions that secret reserve auctions generate more revenue than public reserve auctions at lower reserve prices and vice versa. I also confirmed that a breakeven point exists between the two auction formats. When participants bid in groups of two, the reserve thresholds largely held to theory. In groups of four, the reserve thresholds were slightly higher than predicted. Despite that, however, the theory accurately predicted that lower reserves tend to favor secret auctions whereas higher reserves tend to favor public auctions in terms of revenue generation.

I was not able to confirm the hypothesis that secret reserve auctions generate higher bids than no reserve auctions. Despite the additional competition that the seller adds to the auction with a reserve price unknown to the seller, the bid functions between no reserve and secret reserve auctions were not statistically different. I also could not confirm the predictions that

secret and public reserve auctions generate higher expected revenues than no reserve auctions with reserve prices below predicted thresholds. When zero revenue occurrences are factored into the expected revenue formula for the reserve auctions, public reserve expected revenue never exceeded the expected revenue in no reserve auctions regardless of the reserve price. This was true for all ranges of reserve prices regardless of auction size. I also could not confirm the theoretical breakeven point where secret and no reserve auctions are equal. Despite this, I was able to confirm that secret reserve auctions generate more expected revenue than no reserve auctions when the reserve is below 18 in two-person auctions. In four-person auctions, the two auction formats show no statistical difference in revenue generation with a reserve below 36, however no range of reserve prices exists where secret reserve auctions generate more revenue. Based on my findings, it is only strategic to employ a reserve price if the value to the seller is greater than zero, and the reserve should be set at the seller's true value to prevent a net loss. Note this conclusion only holds if the auction type is an independent private value first price auction without endogenous entry. Other auction formats are beyond the scope of this paper.

Finally, I do not find any evidence that risk aversion influences either bids or revenues, at least in the way predicted by the theory assessed in this model. It is possible that risk aversion is causing increased bids independent of bidder value. While the theory considered indicates a shift in the bid-value slope, it could be that risk aversion causes a bid increase that is exogeneous of the bidders drawn value. As it stands, however, bids and revenues were still greater than the predicted risk neutral Nash equilibrium, however the evidence does not suggest that risk was the cause of this through an increase in the bid-value slope.

I contend that the theoretical predictions concerning expected revenue could not be confirmed because of bids exceeding the Nash equilibrium. When theory predicts an increase in expected revenues, despite the probabilities of no sale scenarios, it assumes that participants in no reserve auctions are bidding at the Nash equilibrium. Since this is clearly not the case, the revenues generated in no reserve auctions are simply too high to overcome once zero revenues are factored into the expected revenue calculations. This deviation from theory is likely due to non-monetary incentives to the bidder such as the joy of winning. The data reveals that winners were often content with one or two units of earnings (worth about 7 or 14 cents) to secure a win. This occurred when participants did not face reserves close to their values and in no reserve auctions as well. Extending the theoretical model to incorporate non-monetary utility, may explain the deviations seen in the data. Since joy of winning is exogenous to auction type, I contend that a strong joy of winning results in higher bids even when a reserve is absent. If this be true, the theoretical benefits of reserve prices are overshadowed by the effects of non-monetary utility present in all three auction formats. Since joy of winning is also present in no reserve auctions, bids and revenues are too high relative to theory to overcome with the introduction of a reserve price that increases the probability of a no sale scenario.

An interesting extension to this experiment would entail second chance offers in secret reserve auctions. In real world auctions it is common for sellers to offer the item to the highest bidder if their secret reserve is not met[9]. In this scenario, the seller is allowed to bargain with the highest bidder to avoid a no sale. The current experiment does not allow for this option. Elyakime et al. (1997) considered a theoretical extension of their seminal 1994 paper which

[9] See Elyakime et al. (1997)

address this exact issue and motivates a follow-on experiment to assess this idea. It is possible that allowing a round of bargaining between the seller and the highest bidder could result in higher revenue extractions from secret auctions since no sale scenarios are potentially avoided.

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Appendices

Appendix A: Tables

Table 1-1: Session and Participant Statistics

Auction Type	Auction Size	Number of Participants	Bid Mean	Bid SD	Revenue Mean	Revenue SD
No Reserve	2	82	38.54	24.54	52.38	21.43
No Reserve	4	82	42.93	26.49	71.24	15.74
Public Reserve	2	99	51.23	21.41	41.35	30.79
Public Reserve	4	99	54.95	22.49	59.11	29.63
Secret Reserve	2	106	40.49	25.63	36.09	34.54
Secret Reserve	4	106	44.17	27.00	57.37	34.17
Participants		**Description**			**Mean**	**SD**
Age		Participant's age in years			21.22	2.18
Female		Ratio of females to males			0.60	0.49
Econ Courses		Number of economics courses taken by participants			2.38	3.88
Previous Experiment		Ratio of participants with previous experiment experience			0.78	0.41
Ratio w/ Previous Auction Exp		Ratio of participants that have bid in an auction (incl. eBay)			0.45	0.50
Ratio w/ GPA Greater than 3.0		Ratio of participants with a GPA over 3.0			0.81	0.40

Table 1-2: Estimated Bid Functions (2 Person Auctions)

Variable	Parameter	No Reserve	Secret Reserve	Public Reserve
Auction Type Intercept	α	-0.59	-0.33	1.64
		(0.42)	(0.39)	(1.02)
Value	β	0.80***	0.82***	0.67***
		(0.016)	(0.018)	(0.020)
$\frac{r^n}{n * v^{n-1}}$	δ			0.37***
				(0.06)
Value x Risk	γ	-0.001	0.008	-0.0001
		(0.007)	(0.007)	(0.006)
Observations	5,867			
R^2	0.952			

*Notes: *** p<.01, ** p<.05, * p<.1*

Table 1-3: Estimated Bid Functions (4 Person Auctions)

Variable	Parameter	No Reserve	Secret Reserve	Public Reserve
Auction Type Intercept	α	-0.36	-0.79	-0.16
		(0.47)	(0.26)	(1.15)
Value	β	0.88***	0.89***	0.80***
		(0.013)	(0.015)	(0.022)
$\frac{r^n}{n * v^{n-1}}$	δ			0.33*
				(0.18)
Value x Risk	γ	0.005	0.0001	0.003
		(0.004)	(0.006)	(0.01)
Observations	5,877			
R^2	0.966			

*Notes: *** p<.01, ** p<.05, * p<.10. Robust standard errors, clustered by participant, are reported in parentheses.*

Table 1-4: Hypothesis 3 Results

	Mean (*N=2*)	Mean (*N=4*)	Diff	Std. Err	*t* stat	*p* value
No Reserve	38.023	42.929	-4.906	0.771	-6.36	< 0.001
Public Reserve	51.23	54.952	-3.722	0.858	-4.34	< 0.001
Secret Reserve	40.492	44.174	-3.681	0.741	-4.97	< 0.001

Note: t-test, difference in means

Table 1-5: Estimated Revenue Functions (2 Person Auctions, Conditional on Sale)

Variable	Parameter	No Reserve	Secret Reserve	Public Reserve
Auction Type Intercept	α	0.000	3.17**	3.62***
		(0.85)	(1.46)	(1.07)
Value	β	0.81***	0.83***	0.68***
		(0.017)	(0.022)	(0.020)
$\frac{r^n}{n * v^{n-1}}$	δ			0.47***
				(0.04)
Value x Risk	γ	0.004	-0.0003	-0.003
		(0.006)	(0.006)	(0.006)
Observations	2,341			
R^2	0.979			

*Notes: *** p<.01, ** p<.05, * p<.1*

Table 1-6: Estimated Revenue Functions (4 Person Auctions, Conditional on Sale)

Variable	Parameter	No Reserve	Secret Reserve	Public Reserve
Auction Type Intercept	α	1.52	4.01**	4.26**
		(1.16)	(1.61)	(1.76)
Value	β	0.88***	0.86***	0.79***
		(0.018)	(0.022)	(0.025)
$\frac{r^n}{n * v^{n-1}}$	δ			0.66***
				(0.07)
Value x Risk	γ	-0.001	0.003	0.002
		(0.004)	(0.004)	(0.005)
Observations	1,289			
R^2	0.992			

*Notes: *** p<.01, ** p<.05, * p<.1*

Table 1-7: Hypothesis 7 Results

	Mean (N=2)	Mean (N=4)	Diff	Std. Err	*t* stat	*p* value
No Reserve	51.809	71.244	-19.436	1.058	-18.375	< 0.001
Public Reserve	41.549	59.31	-17.761	1.511	-11.755	< 0.001
Secret Reserve	36.327	57.46	-21.133	1.667	-12.675	< 0.001

Note: t-test, difference in means

Table 1-8: Estimated Bid Functions (2 Person Auctions, All Controls)

Variable	Parameter	All Auctions	No Reserve	Secret Reserve	Public Reserve
Auction Type Intercept	α		0.22	0.51	2.93
			(4.05)	(4.14)	(4.09)
Value	β		0.80***	0.82***	0.67***
			(0.016)	(0.017)	(0.020)
$\frac{r^n}{n * v^{n-1}}$	δ				0.36***
					(0.06)
Value x Risk	γ		0.002	0.007	-0.001
			(0.006)	(0.007)	(0.006)
Order (N=2 First)		-3.13***			
		(0.75)			
Bidding Period		0.08***			
		(0.02)			
Age		-0.22			
		(0.18)			
Female		0.36			
		(0.75)			
GPA		1.23***			
		(0.43)			
Employed		0.74			
		(0.84)			
Experiment Experience		-0.46			
		(0.91)			
Observations	5,867				
R^2	0.954				

*Notes: *** p<.01, ** p<.05, * p<.1*

Table 1-9: Estimated Bid Functions (4 Person Auctions, All Controls)

Variable	Parameter	All Auctions	No Reserve	Secret Reserve	Public Reserve
Auction Type Intercept	α		-1.31	-1.68	-1.19
			(3.67)	(3.59)	(3.74)
Value	β		0.88***	0.89***	0.80***
			(0.014)	(0.014)	(0.022)
$\frac{r^n}{n * v^{n-1}}$	δ				0.34***
					(0.18)
Value x Risk	γ		0.005	-0.0001	0.002
			(0.004)	(0.005)	(0.010)
Order (N=2 First)		0.44			
		(0.66)			
Bidding Period		0.13***			
		(0.02)			
Age		-0.19			
		(0.17)			
Female		-0.40			
		(0.69)			
GPA		0.78**			
		(0.34)			
Employed		0.97			
		(0.86)			
Experiment Experience		0.06			
		(0.82)			
Observations	5,877				
R^2	0.966				

*Notes: *** p<.01, ** p<.05, * p<.1*

Table 1-10: Estimated Revenue Functions (2 Person, Conditional on Sale, All Controls)

Variable	Parameter	All Auctions	No Reserve	Secret Reserve	Public Reserve
Auction Type Intercept	α		2.91	5.98	6.45
			(4.34)	(4.46)	(4.30)
Value	β		0.81***	0.83***	0.69***
			(0.018)	(0.023)	(0.020)
$\frac{r^n}{n * v^{n-1}}$	δ				0.47***
					(0.04)
Value x Risk	γ		0.005	-0.002	-0.003
			(0.006)	(0.006)	(0.006)
Order (N=2 First)		-2.55***			
		(0.81)			
Bidding Period		0.02			
		(0.03)			
Age		-0.18			
		(0.19)			
Female		0.84			
		(0.81)			
GPA		0.62			
		(0.48)			
Employed		0.22			
		(0.81)			
Experiment Experience		-0.93			
		(1.07)			
Observations	2,341				
R^2	0.979				

*Notes: *** p<.01, ** p<.05, * p<.1*

Table 1-11: Estimated Revenue Functions (4 Person, Conditional on Sale, All Controls)

Variable	Parameter	All Auctions	No Reserve	Secret Reserve	Public Reserve
Auction Type Intercept	α		-1.06	1.89	1.39
			(3.58)	(3.79)	(3.96)
Value	β		0.88***	0.86***	0.80***
			(0.018)	(0.022)	(0.024)
$\frac{r^n}{n * v^{n-1}}$	δ				0.66***
					(0.07)
Value x Risk	γ		-0.001	0.004	0.002
			(0.004)	(0.004)	(0.005)
Order (N=2 First)		0.91			
		(0.64)			
Bidding Period		0.13***			
		(0.03)			
Age		0.02			
		(0.14)			
Female		0.07			
		(0.66)			
GPA		0.11			
		(0.39)			
Employed		-0.78			
		(0.65)			
Experiment Experience		-0.25			
		(0.80)			
Observations	1,289				
R^2	0.992				

*Notes: *** p<.01, ** p<.05, * p<.1*

Appendix B: Experiment Instructions

Instructions for Lottery Experiment

Please refer to your computer screen while we read the instructions.

We would like you to make a decision for each of 10 scenarios. Each scenario involves a choice between playing a lottery that pays either $4 or $0 according to specified chances (Option A) or receiving $2 for sure (Option B).

You will notice that the only differences across scenarios are the chances of receiving the high or low prize for the lottery. At the end of the today's session, ONE of the 10 scenarios will be selected at random and you will be paid according to your decision for this selected scenario ONLY. Each scenario has an equal chance of being selected.

Please consider your choice for each scenario carefully. Since you do not know which scenario will be played out, it is in your best interest to treat each scenario as if it will be the one used to determine your earnings.

Before making decisions, are there any questions?

Please proceed to entering decisions on your computer. Once you are ready to submit your decisions, please click the "Submit" button.

No Reserve Auction Experiment Instructions

In this experiment you will act as buyers of a fictitious commodity. There will be 50 trading periods. Buyers will be separated into different markets (groups), and in each market a single unit of the commodity will be put up for auction in every trading period.

Your task is to submit bids for the commodity along with the other buyers in your market. In each trading period you will be assigned a private **value** for the item. This indicates the value to you of holding the item at the end of the period.

All money amounts in the experiment will be in terms of Experimental Currency Units (ECUs).

Drawing monetary values

In each period, all bidders will be given a private value for the good being sold. The value represents the amount of money that the item is worth to you. These values are drawn randomly from the range 0 to 100, so that each (whole) number has an equal chance of being selected.

Values are drawn separately for each player, and new values are drawn for each period. The value you have in one auction has no impact on the value you will have in other auctions. While you will know your value prior to bidding, you will not know the value drawn for the other bidders in your market. **Your value has no impact on the value of others and their value has no impact on your value.** Each bidder's value is entirely independent and drawn randomly from the same 0 to 100 distribution.

The auction

The highest bidder in the market obtains the item and pays what they bid for the item. Earnings for the highest bidder are:

Earnings = (Private value) – (Bid)

Please know that if you win the auction, and your bid is higher than your private value, you will **lose** money.

All non-winning bidders will earn **zero** for the trading period.

After each trading period, the computer will display whether you won the auction and your earnings from that auction.

Market organization

Prior to each new trading period, buyers will be randomly placed into different markets. The

number of bidders in your market will vary at some point during the experiment, from either 2 or 4 bidders (including you). Please pay attention to the number of bidders in your market prior to placing a bid.

Given the number of experiment participants, and the randomization process, it is very unlikely that the other bidder(s) you compete with in one auction will be the same as in the prior auction.

Experiment earnings

Earnings for the experiment are equal to the sum of your earnings from all trading periods. This means that it will be important to consider each bid in each auction very carefully. This amount will be converted to dollars at a rate of 15 ECUs to $1. Please note that you have already earned $5 just for your participation today.

Public Reserve Auction Experiment Instructions

In this experiment you will act as buyers of a fictitious commodity. There will be 50 trading periods. Buyers will be separated into different markets (groups), and in each market a single unit of the commodity will be put up for auction in every trading period.

Your task is to submit bids for the commodity along with the other buyers in your market. In each trading period you will be assigned a private **value** for the item. This indicates the value to you of holding the item at the end of the period.

All money amounts in the experiment will be in terms of Experimental Currency Units (ECUs).

Drawing monetary values

In each period, all bidders will be given a private value for the good being sold. The value represents the amount of money that the item is worth to you. These values are drawn randomly from the range 0 to 100, so that each (whole) number has an equal chance of being selected.

Values are drawn separately for each player, and new values are drawn for each period. The value you have in one auction has no impact on the value you will have in other auctions. While you will know your value prior to bidding, you will not know the value drawn for the other bidders in your market. **Your value has no impact on the value of others and their value has no impact on your value.** Each bidder's value is entirely independent and drawn randomly from the same 0 to 100 distribution.

The auction

In each trading period, the fictitious seller will set a **minimum acceptable bid, called the "reserve price"**. You will know the reserve price prior to bidding. All bids below this value will be rejected. The highest bidder in the market, if their bid is equal to or higher than the reserve price, obtains the item and pays what they bid for the item. Earnings for the highest bidder are:

Earnings = (Private value) – (Bid)

Please know that if you win the auction, and your bid is higher than your private value, you will **lose** money.

All non-winning bidders will earn **zero** for the trading period.

After each trading period, the computer will display whether you won the auction and your earnings from that auction.

Market organization

Prior to each new trading period, buyers will be randomly placed into different markets. The number of bidders in your market will vary at some point during the experiment from either 2 to 4 bidders (including you). Please pay attention to the number of bidders in your market prior to placing a bid.

Given the number of experiment participants, and the randomization process, it is very unlikely that the other bidder(s) you compete with in one auction will be the same as in the prior auction.

Experiment earnings

Earnings for the experiment are equal to the sum of your earnings from all trading periods. This means that it will be important to consider each bid in each auction very carefully. This amount will be converted to dollars at a rate of 15 ECUs to $1. Please note that you have already earned $10 just for your participation today.

Secret Reserve Auction Experiment Instructions

In this experiment you will act as buyers of a fictitious commodity. There will be 50 trading periods. Buyers will be separated into different markets (groups), and in each market a single unit of the commodity will be put up for auction in every trading period.

Your task is to submit bids for the commodity along with the other buyers in your market. In each trading period you will be assigned a private **value** for the item. This indicates the value to you of holding the item at the end of the period.

All money amounts in the experiment will be in terms of Experimental Currency Units (ECUs).

Drawing monetary values

In each period, all bidders will be given a private value for the good being sold. The value represents the amount of money that the item is worth to you. These values are drawn randomly from the range 0 to 100, so that each (whole) number has an equal chance of being selected.

Values are drawn separately for each player, and new values are drawn for each period. The value you have in one auction has no impact on the value you will have in other auctions. While you will know your value prior to bidding, you will not know the value drawn for the other bidders in your

market. **Your value has no impact on the value of others and their value has no impact on your value.** Each bidder's value is entirely independent and drawn randomly from the same 0 to 100 distribution.

The auction

In each trading period, the fictitious seller will set a **minimum acceptable bid, called the "reserve price"**. This reserve price will be **unknown** to you. All bids below this value will be rejected.

The highest bidder in the market, if their bid is equal to or higher than the reserve price, obtains the item and pays what they bid for the item. Earnings for the highest bidder are:

Earnings = (Private value) – (Bid)

Please know that if you win the auction, and your bid is higher than your private value, you will **lose** money.

All non-winning bidders will earn **zero** for the trading period.

After each trading period, the computer will display whether you won the auction and your earnings from that auction.

Market organization

Prior to each new trading period, buyers will be randomly placed into different markets. The number of bidders in your market will vary at some point during the experiment from either 2 to 4 bidders (including you). Please pay attention to the number of bidders in your market prior to placing a bid.

Given the number of experiment participants, and the randomization process, it is very unlikely that the other bidder(s) you compete with in one auction will be the same as in the prior auction.

Experiment earnings

Earnings for the experiment are equal to the sum of your earnings from all trading periods. This means that it will be important to consider each bid in each auction very carefully. This amount will be converted to dollars at a rate of 15 ECUs to $1. Please note that you have already earned $10 just for your participation today.

Appendix C: Post Experiment Questionnaire

Part 1: About the Experiment

Please answer the following questions to the best of your knowledge. All information is completely anonymous and confidential. This page relates to your experience in today's experiment.

Have you previously participated in an economics experiment?

Yes; No

Please indicate your level of agreement with the following statement: "I understood well the instructions for the experiment"

1- Strongly Disagree; 2; 3; 4; 5- Strongly Agree

Please indicate your level of agreement with the following statement: "I was well compensated for my participation in this study"

1- Strongly Disagree; 2; 3; 4; 5- Strongly Agree

Part 2: About Yourself

In the next questions, please tell us something about you.

What is your age?

What sex were you assigned at birth, such as on an original birth certificate?

Male; Female

What is your major?

What is your classification for the current semester?

Freshman; Sophomore; Junior; Senior; Graduate student; Not a student

What is your student status for the current semester?

Full-time student; Part-time student (taking fewer than 12 hours / sem);

Not a student

How many economics courses have you taken at the university level? (include this semester)

How would you best describe your current employment situation?

Full-time employed outside of the university; Part-time employed outside of the university; Student only; Work at the university / Research assistantship

In what range is your GPA?

0 to 2.0; 2.1 to 2.5; 2.6 to 3.0; 3.1 to 3.5; 3.6 to 4.0

How often do you participate in auctions (i.e. eBay)?

Never; Rarely (less than once a year); Occasionally (1-2 in past 12 months); Sometimes (3-4 in past 12 months); Often (5+ in past 12 months)

Please use the space below to write any comments you may have about the experiment.

Chapter 2

"Dirty Air" Force Fitness Tests: Does Bad Air Quality Effect Strength and Endurance? Evidence from the United States Air Force

Abstract

I study the effects of air quality on human endurance and strength performance. Utilizing a dataset of physical fitness (PT) test scores of servicemen and women in the United States Air Force, I exploit the variation in particulate matter (PM) on the day of the tests to identify a causal relationship between increasing PM concentrations as measured by the Air Quality Index (AQI) and the degradation of member strength and endurance performance as measured by the time required to complete a 1.5-mile run, and pushup and crunch repetitions in 60 seconds. I find that at the highest level of exposure, PM increases the amount of time required to complete a 1.5-mile run by as much as 8.4 seconds, decreases the number of pushups and crunches performed in one-minute by 0.3 repetitions, and increases the PT test failure rate by as much as 3%.

2.1 Introduction

Numerous health studies indicate that air pollution has negative short-term and long-term health impacts on human health.[1] These health impacts may include reductions in physical performance and worker productivity, although there are surprisingly few empirical examinations of these links. According to the Bureau of Labor Statistics, over 60% of the Average American's workday requires physical activity other than sitting among all US jobs. Forty-five percent of all US jobs required medium strength or greater requiring frequent lifting up to 25 pounds (BLS, 2018). Therefore, the loss of physical productivity due to airborne particulate matter could aggregate to billions of dollars lost across a $20 trillion economy and impact the earnings and tenure of men and women that perform this type of work. This paper uses a database of physical fitness (PT) scores from members of the United States Air Force (USAF), and environmental and meteorological data from the Environmental Protection Agency (EPA), to gain a better understanding of how air quality impacts physical performance in a consequential setting.

Members of the United States Air Force submit to mandatory physical fitness tests at least once per year. While there are a handful of occupations that require physical fitness evaluations, active-duty military members are unique in that they are assigned and reassigned to different duty locations across the world, sometimes multiple times during their career. Although this process is not strictly random, base assignments are uncorrelated with both member physical

[1] See Rumana, Sharma, Beniwal, & Sharma (2014), Yamamoto, Phalkey, & Malik (2014), Zhang, Qian, & Zeng (2014), Brucker, Charão, Moro, Ferrari, Bubols, Sauer, et al. (2014), Biggeri, Bellini, & Terracini (2004), Vermaelen & Brusselle (2013), Kan, Chen, Zhao, London, Song, Chen, et al. (2010), Zhou, Cui, Yang, Han, Chen, Zhou, et al. (2014)

performance and location air quality. This randomization provides the opportunity to identify the causal effects of air quality on physical performance. By evaluating the physical performance of military members assigned to areas with differing particulate matter (PM) exposure based on location and the day of the test, this is the first large-scale study on the effects of air quality on non-athlete physical performance in a high stake setting.

According to the National Center for Health Statistics, data collected in 2015-2016 indicate that 39.8% of Americans over the age of 20 are obese according to the Body Mass Index (BMI) (FastStats, 2020). While few members of the Air Force may be classified as obese, the average military member is not a conditioned athlete. In fact, the average member has a BMI near or over 25 (26.2 for males, 24.2 for females), indicative of a person that is "overweight" for males and nearly "overweight" for females. While the distribution of physical fitness among members of the military differs from the general population, there is nevertheless considerable overlap. This allows us to explore the effects of air quality using a subpopulation that is more representative than what has been used in prior work.

Previous studies have found that air quality has an adverse impact on people in high-skilled, quality-focused occupations. In a study investigating the impacts of pollution on the performance of Major League Baseball umpires, Archsmith, Heyes, and Saberian (2018) find that small increases in carbon monoxide and $PM_{2.5}$ have significant effects on the accuracy of on-field decisions (i.e., calls). A mere 1 ppm increase in carbon monoxide yields an 11.5% increase in the chance an umpire makes an incorrect call and $PM_{2.5}$ increases as small as 10 micrograms per cubic meter results in a 3% increase in incorrect calls. The findings indicate the potential for errors and subsequent lost workforce productivity for occupations that require a

high degree of mental focus. While this study provides evidence that acute mental abilities can suffer with rising pollution, it does not provide evidence for effects of pollution on physical performance.

Chang *et al.* (2016) examines how the performance of fruit pickers is impacted by higher exposure to air pollutants. Using earnings as a proxy for effort, the authors show that higher exposure to $PM_{2.5}$ pollution on a given day decreases the effort exerted by the fruit pickers, resulting in less compensation. The results provide a glimpse of the impact of air pollution on adult physical performance; however, the lack of data on worker characteristics such as age, weight/height, and gender limits what I may learn about how air quality impacts different segments of the population. This paper aims, in part, to fill those gaps and extend this literature.

In related work, Lichter, Pestel, and Sommer (2017) examine the effect of air pollution on the productivity of German professional soccer players. Like my paper, they rely on the exogeneity of air quality on the scheduled event date since events are scheduled far in advance. Using the number of passes in a match as a proxy of productivity, the authors find that a 1% increase in air pollution reduces the total number of team passes by approximately 0.03%. A one standard-deviation increase in PM_{10} decreases pass accuracy by 0.2%, providing evidence of a connection between air quality and productivity. In a similar vein, Guo and Fu (2019) analyze data from over 300,000 marathon runners in China and find that exposure to PM has a negative impact on run times. Guo and Fu's study differs in that their findings focus on individual effort whereas passes and accuracy in soccer require a team dynamic. Both studies are similar in that they involve highly conditioned athletes.

This paper contributes to the current stream of literature by evaluating the impact of PM on physical performance by using a large dataset of non-athletes observed in a consequential setting. I find that poor air quality significantly decreases physical endurance resulting in additional time needed to complete a 1.5-mile run. I also find that physical strength decreases, resulting in less pushups and crunches in one minute. The effects of both endurance and strength degradation appear to increase as air quality gets worse. Finally, I see a strong and significant increase in the PT test failure rate for members that test during a period of very poor air quality. Even if the impacts of air pollution on performance are transitory, the aggregate effect of decreased performance likely has strong implications for the US economy. Furthermore, the evidence suggests an increased likelihood of adverse consequences for members of society that struggle to meet minimum physical standards should exposure to poor air quality increase.

2.2 Particulate Matter

I investigate air quality through the concentration of ground based PM. The EPA typically records PM concentrations in units on the Air Quality Index (AQI). This is the convention I use when discussing PM throughout this study. AQI transforms the concentration of PM, measured in micrograms per cubic meter, into a numerical scale that ranges from 0 – 500. The formula used for the conversion is publicly available via the EPA website.[2]

Particulate matter has been regulated in the United States under the Clean Air Act since 1971. Early regulation controlled for any suspended particle smaller than 100 microns in size, however in 1987 the EPA limited the regulation to any suspended particle 10 microns (PM_{10}) or

[2] See the EPAs *Technical Assistance Document for the Reporting of Daily Air Quality – the Air Quality Index (AQI)* published in September 2018. https://www.airnow.gov/sites/default/files/2020-05/aqi-technical-assistance-document-sept2018.pdf

smaller due to research revealing that only particles smaller than 10 microns diffuse past lung tissue. Further research indicates that particles smaller than 2.5 microns ($PM_{2.5}$) diffuse deeper into the lungs and seep into the bloodstream, which motivated further EPA regulations in 1997 to control for these smaller particles independently from PM_{10} (Chang et al. 2016).

Particulate matter occurs in the atmosphere by both natural and man-made causes. Natural events such as the wildfires in California and man-made pollution through the combustion of fossil fuels contribute to suspended particles in the air. The size of PM results in lengthy and far-reaching exposure since PM is dispersed by natural meteorological phenomena and the chemical properties of it are quite persistent, being affected by temperature and precipitation. Evidence suggests that, given the right wind speeds and temperatures, PM can disperse to areas over 150 kilometers from the source in significant concentrations (Uugwanga & Kgabi 2021). Further studies have shown that PM can diffuse into indoor facilities at rates of 70-100% making exposure to PM highly likely regardless of indoor or outdoor activity (Thatcher & Layton 1995). Indoor diffusion is especially relevant in highly ventilated areas such as an active gym where windows and doors are typically opened to prevent undesirable workout conditions.

A large body of literature investigates the health effects of PM on humans. The EPA released a two-volume study on PM that includes toxicology and epidemiology health studies on the effects of PM on human health which is publicly available for a detailed review (EPA 2004). The health effects of PM on human members are largely due to changes in pulmonary and cardiovascular functioning (Seaton et al. 1995 as cited in Cheng et al. 2016). Various health effects can include asthma and heart attacks, blood pressure changes, ear, nose throat, and lung

irritation, as well as headaches and other physiological symptoms (Dockery & Pope 2004, Pope 2000, Ghio, Kim, and Delvin 2000, Auchincloss et al. 2008).

2.3 Air Force Physical Fitness Test

For the years 2004 to 2014, the Air Force PT test was governed by Air Force Instruction (AFI) 36-2905. Under this regulation, all members of the United States Air Force are required to submit to a PT test at least annually. Depending on the score earned on the test, members are either tested once per year (if the aggregate score is greater than or equal to 90) or twice per year (if the aggregate score is between 75 and 89.9). Points are awarded on the test through four different categories which are summarized in Table 2-1.[3]

Members are required to achieve passing scores in all four categories and achieve an aggregate score of at least 75 to pass the test. AFI 36-2905 details the points earned by gender at various performance levels across the five different age groups of under 30, 30-39, 40-49, 50-59, and 60+. Age and gender point breakdowns from AFI 36-2905 are included in the Appendix.

PT tests are scheduled by each base's health and wellness center typically 30 days in advance. The tests are scheduled before air quality forecasts are available and are only rescheduled in the event of weather emergencies. On an as needed basis for deployments, temporary duty assignments, and permanent change of station orders, PT tests can be scheduled outside this 30-day window. Per AFI 36-2905, the PT test can be conducted indoors due to significant rainfall, freezing temperatures, or extreme temperatures based on the Wet Bulb Globe Temperature System. Barring these conditions, outdoor tests are standard.

[3] All tables and figures are located in the appendix

Members report to the testing facility at the scheduled appointment time and date and are evaluated in the following order: waist measurement, one-minute pushups followed by one-minute crunches or vice versa, and the 1.5-mile run. Depending on the size the testing cohort, the test is typically completed within 30-45 minutes. Because of the standardized nature of the examination and the point structure, it is possible to identify minimum run times needed to achieve the aggregate score of 75.

Based on the point structure of the test, each member is required to put forth at least a minimum level of effort regardless of fitness level. Further, a member's PT score sends a signal to their commander and front-line supervisor, which should induce even very high-performing members to try their best. Nevertheless, it is perhaps unrealistic to assume that all members put forth maximal effort on the examination, as members could pass and even achieve a score greater than 90 without maximal effort depending on individual fitness levels. Fortunately, this renders the examination akin to the behaviors of the general population that put forth at least minimal effort in their day-to-day activities as maximal effort is difficult to sustain.

Failing the PT test has adverse impacts. At a minimum, a failure results in a Letter of Counseling from the member's front-line supervisor, impacting the ability to compete for unit-level awards and potentially impacting the ability of the member to promote. Furthermore, failures presumptively result in enrollment in a reconditioning program that is fulfilled on the member's own time (i.e., outside of normal duty hours) and requires retesting within 90 days. Further failures result in additional corrective paperwork, typically a Letter of Reprimand (stronger than a Letter of Counseling) and the establishment of an Unfavorable Information File

that has significant adverse impacts on the member's future in the United States Air Force. Persistent failures ultimately result in the discharge of the member.

Before the test commences, members are required to sign paperwork indicating that they are medically fit to take the test. Any member that indicates they are medically unfit are directed to the Military Treatment Facility to be evaluated by a medical professional. Commanders then review the opinion of the medical professional and either reschedule the test or take appropriate action against the member for malingering. Malingering an offense punishable under Article 83 of the Uniformed Code of Military Justice (UCMJ), which justifies a non-judicial punishment (also known as an Article 15), or, at a minimum, a Letter of Reprimand and an automatic failure from the member's unit commander. Based on the consequences of the infraction, members are unlikely to refrain from the examination based on poor air quality.

2.4 Data

Over the course of 11 years, the United States Air Force compiled information on daily physical fitness tests into a single consolidated database. Testing typically did not occur on weekends or holidays. The daily samples consist of men and women in the Active Duty that were assigned to locations across the United States independent of athletic ability and location air quality. This resulted in a natural experiment involving 496,240 members observed one or more times over the course of 3,972 testing days, generating over 1.2 million data points.

I merged the PT test data with available daily county level meteorological and pollutant data. Particulate matter, temperature, and precipitation data from the EPA from counties where Air Force testing occurred was merged with the Air Force physical fitness data by date and county, when available. I pulled county elevations from the Area Health Resource Files, which

are publicly available from the U.S. Health Resources and Services Agency. Summary statistics for the daily PM AQI and daily temperatures are presented in Table 2-2.

The Air Force data contains aerobic performance measurements, pushups in one-minute, sit-ups in one-minute, abdominal circumference, height, weight, BMI, age, gender, test date, and the unit assignment of the member. About 81% of the observations in the dataset correspond to males and 19% females between the ages of 17 to 67. Race and other socio-economic data are not provided. To identify the city, county, and state of the testing sites, I matched the unique Unit Identifier Code (UIC) associated with each entry in the dataset to a UIC master document containing all the locations of each UIC.[4]

I winsorized the dataset to deal with potential data entry errors. For example, some entries correspond with run times and/or pushup and sit up repetitions that objectively exceed human capabilities. Since the data is recorded manually at each test, nonsensical entries are likely due to human error. Observations such as these are few and disregarded. Table 2-2 provides the summary statistics.

2.5 Econometric Specification and Identification Strategy

In line with the literature[5], I estimate both a linear specification where daily maximum PM enters the model in levels, and a non-linear specification that includes indicators for PM deciles to investigate the effect of PM concentrations on member performance. To identify the causal effect of PM on physical performance, I rely on the fact that PM is exogenous to the member on the day of the test. In general, members must schedule their PT test several weeks in

[4] UICs and UIC-Location document are controlled and not releasable. UIC information cannot be shared without proper authorization

[5] See Archsmith, Hayes, and Saberian (2018), Chang et al. (2016), Guo and Fu (2019)

advance of the test day. By policy, members do not have a choice; they must participate in the test unless medically exempted by a licensed medical professional. Furthermore, the members must test when they are ordered mollifying the threat of "seasonal choice". Because of this, PM levels can be treated as random and exogeneous to the testing members.

I regress member run times, pushup count, and crunch count on EPA daily $PM_{2.5}$ AQI readings absorbing member and date fixed effects while controlling for daily high and low temperature, high and low temperature squared, precipitation, elevation and member characteristics of age and abdominal circumference. Gender is differenced out with the member fixed effect. I estimate the effects of PM on member performance via the following model:

(1) $$performance_{ijt} = \rho_i + \delta_t + \beta_1 PM_{jt} + \beta_2 Prec_{jt} + \beta_3 \boldsymbol{Temp}_{jt} + \beta_4 Elev_j + \beta_5 \boldsymbol{X}_i + \varepsilon_{ijt}$$

where *i, j,* and *t* represent individual *i,* county *j,* and the test date *t.* The left hand side variable *performance* is the run time in seconds, pushup count, or crunch count, ρ is the member fixed effect, δ is the day-of-test fixed effect, *PM* is the daily maximum EPA measure *Prec* is the level of precipitation measured in millimeters, ***Temp*** is a vector of temperature and higher-order temperature controls in degrees Celsius, *Elev* is the officially recorded county elevation in feet above sea level, ***X*** is a vector of the member characteristics (age and abdominal circumference), and ε is a mean-zero error term. I also use the same two specifications to examine the effects of PM exposure on the failure rate, in which case the dependent variable equals 0 or 1 depending on whether individual *i* in county *j* on test date *t* failed the test. I employ the same model when investigating the nonlinear effects of PM. Under this framework, I replace the daily maximum EPA measure with the decile that corresponds to the daily maximum EPA measure.

By nature of the dataset being pooled cross-sectional data, I control for unobservables related to day-of-test through the inclusion of time fixed effects per Wooldridge (2010 pp. 146 - 147). I note that when time fixed effects are included, it is not further possible to include county fixed effects as doing so results in a fully saturated model. I consider a specification with county and month fixed effects among my robustness checks. I control for the approximate elevation of the test site to account for any effect elevation has on member performance. For all other location specific factors that are unobserved, I rely on the fact that members are assigned to different base locations in a manner that is orthogonal to both physical fitness ability and air quality.

2.6 Performance Results

2.6.1 Endurance

I begin my analysis by assessing whether member endurance responds to differing concentrations of PM. First, my linear specification estimates the constant marginal effect of an increase in the daily max PM AQI on member run times. The first column of Table 2-4 shows the marginal effect of PM AQI on member run times with only the member and date-of-test fixed effects. The second, third, and fourth column introduces weather, elevation, time variant member controls, respectively.

The results indicate a strong relationship in PM AQI and run times. In particular, each one-unit increase in the PM AQI increases run time by over $1/10^{th}$ of a second. The results are robust to environmental controls of temperature, precipitation, and elevation. Given the standard deviation of PM is 19.5 units, the models presented in columns 3 and 4 indicate that, on average, a one-standard deviation increase in PM AQI adds about 2.15 seconds to a member's run time.

While I investigate estimates on failure rates late in the paper, it is worth noting that the models suggests that over 3,200 tests would have resulted in a failure had those members been exposed to a one standard deviation increase in PM on the day of their test based on the fact that these tests were within two seconds of failure within the dataset

Considering the average run time given in Table 2-2 is 758.4 seconds, a one standard deviation increase in PM results in a 0.2% increase in member run times. The evidence suggests that increased particulate matter exposure has negative acute effects on members endurance, even when the task at hand lasts, on average, under 13 minutes.

Since the effects of PM may be non-linear, I consider the impact after binning AQI readings into deciles. With the first decile as the baseline, I examine the effect of PM AQI on member run times as members are exposed to different levels of PM after controlling for all effects in the model. The results are summarized in Figure 2-1. The results show a significant increase in the time required to run the 1.5-mile test as members are exposed to PM AQIs above the first decile. As air quality worsens, I find that the impact on run times increases, and reaches a peak effect of over 8 seconds when pollution extends to the ninth and tenth deciles. The results indicate that even relatively low levels of PM have serious consequences on acute endurance as evidenced by the significant jump in run times from the first to the second decile, getting increasingly stronger as the exposure level increases. To put this in perspective, I flagged the observations within each decile that could have been impacted by the additional required time and discovered that 8,827 tests, or 0.72% of the sample, likely failed the test due to exogeneous PM exposure.

2.6.2 Strength

I continue my analysis by studying the causal effect of PM AQI on pushups and crunches completed within 60 seconds, which are used by the Air Force as measures of strength. Table 2-5 presents the results based on the linear model specification. Models presented in columns 1 and 3 include all weather and elevation controls. Columns 2 and 4 add member characteristics to the model. The results reveal that both pushup and crunch performance decrease when members are exposed to higher PM AQI. For a one standard deviation increase in the PM AQI, the average number of pushups and crunches decrease by as much as 0.08 repetitions.

By policy, a partial pushup or crunch does not count as a repetition; for example, if members only get 90% up on their last pushup but can't complete the repetition, this pushup does not count. The data reveals that 2.96% of all recorded observations performed the minimum number of repetitions in either the pushup test or the crunch test indicating that any decrease in performance would have resulted in a test failure.

Applying the non-linear specification to push-ups reveals that overall pushup performance suffered significantly even at lower levels of PM exposure, as evidenced by the results in Figure 2-2. The average pushup count decreased by nearly 0.1 as members moved from the first to the second decile of PM concentration. When PM reaches the highest decile, the estimated average impact is a decrease of 0.3 repetitions. I flagged the observations in each decile above the first, where members failed the pushup test by one repetition. I identified 3,664 pushup failures, or 0.3% of all observations, where PM exposure likely contributed to the failure. It is important to note, however, that points are awarded for every pushup performed, and a decrease in a single repetition could lead to a failing aggregate test score.

Figure 2-3 indicates that crunch degradation follows a similar trend to pushups. When pollution increases from the first to the second decile, the average number of crunches performed in one minute decreases by 0.2. When pollution reaches the upper deciles, member performance degrades by 0.3 crunches on average. I flagged the observations in each decile above the first where members failed the crunch component by one repetition and identified 9,706 crunch failures, or 0.8% of all observations, where PM exposure likely contributed to failure.

2.6.3 Failure Rate Analysis

Within the dataset, 245,094 tests, or 20.0% of all observations, resulted in a failure. Recall that members can fail the test by failing an individual component or failing to earn an aggregate score of 75 points or higher. My goal in the following analysis is to identify how failure rates may have been impacted by PM pollution. As it stands, the Air Force does not consider air quality conditions when setting physical standards nor do they consider air quality when adjudicating appropriate action in the event of a failure. Understanding how PM affects the failure rate sheds light on whether physical performance standards, both in an outside the military, should be modified based on pollution levels.

I evaluate the change in the failure rate due to PM based on the non-linear specifications used previously. I code the dependent variable as 1 if the member failed their PT test and a 0 otherwise. Figure 2-4 shows the change in failure rate as members run their PT test while exposed to higher levels of PM. When comparing the failure rate against members that performed their PT test in the first decile, the data reveals a strong jump in the failure rate at the second decile of PM AQI. Even at this relatively low level of PM exposure, the failure rate

increases by 1.4%. The failure rate continues to increase across deciles, with failure rates 3% higher for the ninth and tenth deciles (relative to the first decile).

2.7 Robustness Checks

I perform three robustness checks to address potential concerns over interpreting my estimates of the effects of PM AQI on performance and failure rates as causal. WI consider an alternate fixed-effects model that employs county and month fixed effects as well as a standard OLS model with no fixed effects. I also investigate the results when evaluating the model on a separate data source that measures atmospheric PM via satellite. Table 2-6 displays the results of the comparative models.

2.7.1 Alternate Models

In order to absorb both time and county fixed effects, I must assume an alternative time specification than the day-of-test. As mentioned earlier, all PM variation is absorbed if I apply both a county and time fixed effect using the dates that the cross-sections were collected. For this cross-check, I employ a month fixed effect with the county fixed effect to ensure that I are still absorbing any seasonal effect on member performance while allowing us to control for county fixed effects without absorbing all the variation in the data. I add a gender dummy to this model as a member's gender is no longer differenced out. Naturally, I drop county elevation from the model as this is differenced out with the county fixed effect.

Under this model, PM exposure had a nearly identical effect on member runtimes. The effect on pushups and crunches is noticeably larger. The model indicated that failure rates increased to 5.6% higher in the upper decile versus the first decile; a larger effect than the primary model.

Next, I evaluate the model without any fixed effects. The standard OLS model indicates that the effect on member runtime is significantly stronger than the findings in the primary model. The effect on pushups and crunches isn't as dramatic. In this model specification, the failure rate surges to 8.7% higher in the upper decile than the first decile. While the results in this model boast strong, significant effects, the inability to control for invariant characteristics in either the member or location coupled with the model's inability to control for effects in the time dimension should raise caution.

2.7.2 Alternate PM Source

I test satellite PM data to test whether the model is robust to alternative data sets. Being ground-level PM data, the EPA dataset for PM is the most applicable data in my possession, however satellite readings of the atmosphere above the testing locations also provides an alternative source of PM data. While the concentrations may be different because the satellite data does not necessarily capture ground-level PM readings, there is high correlation between the two. Therefore, I test my model on atmospheric PM concentrations to determine whether the model is robust to different data collection methods. The results reflect the same conclusions that were drawn with the EPA dataset, however the model reports a smaller effect on member run times and pushups, though still significant. While the results cannot be compared as one-to-one since the EPA data presents PM in ground-level AQI and the satellite data presents atmospheric PM, the results both indicate significant and negative effects on both endurance and strength indicating that the primary model is robust to alternative data sources.

2.8 Conclusion

In this paper I investigate the effects of air pollution on human performance by analyzing physical fitness test data from members of the United States Air Force exposed to varying levels of PM. While previous research attempts to establish a causal effect of PM on human performance, the data has previously been limited to professional, collegiate, or marathon athletes or small sample sizes of niche labor markets. My paper is the first to exploit a large sample of non-athlete men and women that are required to submit to a standardized, high-stakes physical fitness test. I find a strong relationship between the degradation of physical performance and the worsening of air quality.

I first look at member endurance performance and how increasingly poor air quality affects the times on 1.5-mile runs. I discovered a strong linear relationship between the run times and PM AQI. Using specifications that allow for the effects of PM AGI to be non-linear, I find incrementally worse run times for members that test during days when PM levels reach higher deciles. I also analyzed the effect of poor air quality on strength performance as measured by the number of whole pushups and crunches performed in 60 seconds and found that increasing levels of PM decreased the average number of pushups and crunches performed by as much as 0.3 repetitions. The weight of the evidence suggests that thousands of servicemen and women every year face severe career consequences because of exogeneous PM exposure. What's more, the evidence shows that acute endurance and strength performance significantly decreases once individuals are exposed to relatively low levels of PM as evidenced by the strong decreases in performance from the first to second deciles of AQI. In the ninth and tenth deciles, acute

endurance performance suffered even larger decreases furthering the evidence that PM exposure carries high costs through lost performance across the aggregated economy.

I also explore how PM exposure leads to higher failure rates on the standardized test. The analysis indicates a strong and progressive increase in the failure rate as tests are conducted in higher concentrations of PM. In the Air Force, policy dictates that members cannot be discharged for one PT failure. In the general labor market, when employees are being evaluated daily, employees that otherwise perform on the margin of what is considered acceptable likely have no policy protections. Should the manager or supervisor deem that the employee is underperforming, it is highly likely that the employee could be dismissed with little recourse.

Given that the men and women of United States Air Force are not athletes and represent a large swath of the US population, it is not unreasonable to assume similar results would be found in the general population. Even if the acute results remain constant throughout the workday and do not progressively get worse, the effects that PM has on human performance could aggregate to billions of dollars lost across a $20+ trillion economy.

While I find a strong causal relationship between poor air quality and declining strength and endurance performance, this study is limited to relatively short durations of exercise. On average, the 1.5 mile run lasted about 12 minutes and 40 seconds and the strength tests, by design, last 60 seconds. How these effects continue to unfold as endurance and strength tasks get longer remains unanswered. It is quite possible that the effects begin to compound over time, however it is also possible that human physiology could adapt to the exogeneous shock and partially mitigate some of the effects. Further research should be conducted to investigate how

the relationship between poor air quality and performance evolves over the course of a standard workday.

Given these results and the potential negative impacts associated with decreasing performance, the USAF should seriously consider monitoring air quality on testing days. Based on the evidence found in this paper, adjustments to minimum allowed run times should be incorporated at every decile of PM measurement that corresponds to the findings in this paper. This solution is consistent with altitude adjustments in AFI 36-2905. Adjusting the push-up and crunch count would be as simple as decreasing the required number by one on days where the maximum PM falls within the second decile or higher. These simple adjustments could prevent unnecessary PT failures that affect thousands of servicemen and women as well as prevent the wasted time and resources required by commanders and front-line supervisors when a PT failure is likely caused by poor air quality that is unrelated to member fitness.

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Appendices

Appendix A: Tables

Table 2-1: USAF PT Test Components

Component	Possible Points
Waist Measurement[1]	20
Pushups in 1 Minute	10
Crunches in 1 Minute	10
1.5 Mile Run[2]	60

[1]Abdominal Circumference measured in inches rounded to the nearest ½ inch
[2]Measured in seconds

Table 2-2: Summary Statistics

Variable	Description	Mean	S.D.
PM AQI	Concentration of PM as measured by AQI	48.81	19.58
High Temp	Daily recorded high temperature, in ^{o}C	20.03	10.37
Low Temp	Daily recorded low temperature, in ^{o}C	8.18	10
Precipitation	Daily rainfall, in mm (bucket method)	2.4	5.57
Elevation	County elevation, feet above sea level	1,106.15	1,527.04
Waist	Abdominal Circumference measured in inches	33.05	3.47
Pushups	Number of repetitions performed in 60 seconds	47.29	13.44
Crunches	Number of repetitions performed in 60 seconds	49.17	9.74
Run	Time to complete 1.5-mile run (in seconds)	758.75	121.02
Height	Height in inches	69.11	3.56
Weight	Weight in pounds	176.15	30.42
BMI	Calculated as (703 * Weight)/Height^2	25.80	3.56
Age	Age in Years	29.86	8.87

Note: Descriptive statistics on winsorized data. Based on 110,503 unique location-day observations and 1,228,213 PT tests

Table 2-3: Linear Effects of PM AQI on Run Time (in seconds)

	(1) Run	(2) Run	(3) Run	(4) Run
PM AQI	0.07***	0.11***	0.11***	0.11***
	(0.00)	(0.00)	(0.00)	(0.00)
High Temp		-0.13**	-0.16***	-0.10**
		(0.05)	(0.05)	(0.05)
Low Temp		-0.06*	0.19***	0.17***
		(0.03)	(0.03)	(0.03)
(High Temp)^2		-0.013***	-0.014***	-0.014***
		(0.001)	(0.001)	(0.001)
(Low Temp)^2		-0.005***	-0.005***	-0.003**
		(0.001)	(0.001)	(0.001)
Precipitation		-0.021	-0.019	-0.02*
		(0.015)	(0.015)	(0.014)
Elevation			0.005***	0.006***
			(0.00010	(0.0001)
Age				0.70***
				(0.25)
Waist				12.18***
				(0.06)
Observations[1]	1,035,977	1,035,977	1,035,977	1,035,977
R^2	0.84	0.84	0.84	0.86
Weather	No	Yes	Yes	Yes
Elevation	No	No	Yes	Yes
Mem. Controls	No	No	No	Yes

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*
Mean Run Time = 758.75 seconds
[1]Regressions omitted 192,236 observations as singletons

Table 2-4: Linear Effect of PM AQI on Strength Measures

	Pushups		Crunches	
	(1)	(2)	(3)	(4)
	No Member Controls	*Member Controls*	*No Member Controls*	*Member Controls*
PM AQI	-0.004***	-0.004***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.000)	(0.000)
High Temp	0.019***	0.016***	0.007	0.004
	(0.006)	(0.006)	(0.005)	(0.005)
Low Temp	0.001	0.002	-0.003	-0.002
	(0.004)	(0.004)	(0.003)	(0.003)
$(\text{High Temp})^2$	-2.08×10^{-3}	-2.08×10^{-3}	-2.58×10^{-3}**	-2.58×10^{-3}**
	(1.48×10^{-3})	(1.46×10^{-3})	(1.30×10^{-3})	(1.30×10^{-3})
$(\text{Low Temp})^2$	4.88×10^{-6}	(-7.89×10^{-4})	5.16×10^{-3}***	(4.31×10^{-3})***
	(1.59×10^{-3})	(1.58×10^{-3})	(1.41×10^{-3})	(1.50×10^{-3})
Precipitation	-0.007***	-0.007***	-0.005***	-0.004***
	(0.002)	(0.002)	(0.002)	(0.001x)
Elevation	5.89×10^{-4}***	4.68×10^{-4}***	4.14×10^{-6}	-8.29×10^{-6}
	(1.57×10^{-4})	(1.55×10^{-4})	(1.35×10^{-4})	(1.33×10^{-4})
Age		-0.228***		-0.128***
		(0.029)		(0.025)
Waist		-0.626***		-0.642***
		(0.006)		(0.005)
Observations[1]	1,035,977	1,035,977	1,035,977	1,035,977
R^2	0.839	0.842	0.759	0.765
Weather	Yes	Yes	Yes	Yes
Elevation	Yes	Yes	Yes	Yes
Member Controls	No	Yes	No	Yes

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*
Mean push-ups = 47.29 repetitions
Mean crunches = 49.17 repetitions
[1]Regressions omitted 192,236 observations as singletons

Table 2-5: Comparative Models (Run Times)

	(1) *Member/Date FEs*	(2) *Location/Month FEs*	(3) *Member/Date Fes (Satellite Data)*	(4) *OLS, No FEs*
	Run	Run	Run	Run
PM AQI	0.11***	0.11***	0.05***	0.28***
	(0.00)	(0.01)	(0.01)	(0.00)
High Temp	-0.10**	-0.18***	-0.26***	0.69***
	(0.05)	(0.06)	(0.06)	(0.06)
Low Temp	0.17***	0.16***	0.18***	-0.20***
	(0.03)	(0.04)	(0.04)	(0.04)
Age	0.70***	2.06***	0.73***	2.29***
	(0.25)	(0.01)	(0.26)	(0.01)
Waist	12.18***	13.16***	12.17***	13.44***
	(0.06)	(0.04)	(0.06)	(0.04)
Female		189.53***		190.43***
		(0.28)		(0.29)
Observations[1] [2]	1,035,977	1,228,206	899,522	1,228,213
R^2	0.86	0.41	0.86	0.38

*Notes: Robust standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*
Mean Run Time = 758.75 seconds
[1]Observations are based on regressions after the exclusion of singleton observations.
[2]Satellite data cannot be collected when meteorological conditions prohibit resulting in less data

Table 2-6: Comparative Models (Pushups)

	(1) *Member/Date FEs*	(2) *Location/Month FEs*	(3) *Member/Date Fes (Satellite Data)*	(4) *OLS, No FEs*
	Pushups	Pushups	Pushups	Pushups
PM AQI	-0.004***	-0.011***	-0.001**	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
High Temp	0.016***	0.045***	0.016**	0.074***
	(0.006)	(0.006)	(0.007)	(0.006)
Low Temp	0.002	-0.015***	0.000	0.006*
	(0.004)	(0.004)	(0.004)	(0.004)
Age	-0.228***	-0.369***	-0.209***	-0.353***
	(0.029)	(0.001)	(0.031)	(0.001)
Waist	-0.626***	-0.807***	-0.609***	-0.803***
	(0.006)	(0.003)	(0.006)	(0.003)
Female		-23.354***		-23.372***
		(0.027)		(0.027)
Observations[1] [2]	1,035,977	1,228,206	899,522	1,228,213
R^2	0.86	0.41	0.86	0.38

*Notes: Robust standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*
Mean push-ups = 47.29 repetitions
[1]Observations are based on regressions after the exclusion of singleton observations.
[2]Satellite data cannot be collected when meteorological conditions prohibit resulting in less data

Table 2-7: Comparative Models (Crunches)

	(1) *Member/Date FEs*	(2) *Location/Month FEs*	(3) *Member/Date Fes (Satellite Data)*	(4) *OLS, No FEs*
	Crunches	Crunches	Crunches	Crunches
PM AQI	-0.003***	-0.017***	-0.003***	-0.015***
	(0.000)	(0.000)	(0.001)	(0.000)
High Temp	0.004	-0.002	-0.004	-0.007
	(0.005)	(0.005)	(0.006)	(0.005)
Low Temp	-0.002	-0.012***	-0.000	-0.007**
	(0.003)	(0.003)	(0.004)	(0.003)
Age	-0.128***	-0.343***	-0.113***	-0.344***
	(0.025)	(0.001)	(0.027)	(0.001)
Waist	-0.642***	-0.699***	-0.633***	-0.709***
	(0.005)	(0.003)	(0.006)	(0.003)
Female		-10.000***		-9.999***
		(0.023)		(0.023)
Observations[1] [2]	1,035,977	1,228,206	899,522	1,228,213
R^2	0.86	0.41	0.86	0.38

*Notes: Robust standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*
Mean crunches = 49.17 repetitions
[1]Observations are based on regressions after the exclusion of singleton observations.
[2]Satellite data cannot be collected when meteorological conditions prohibit resulting in less data

Appendix B: Figures

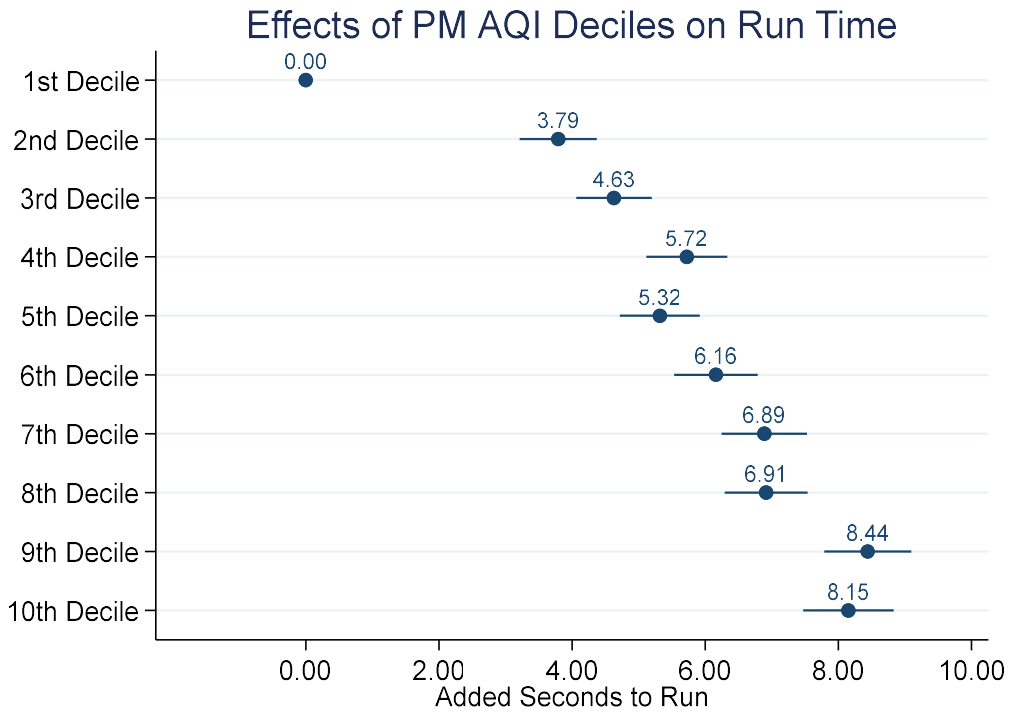


Figure 2-1: Effects of PM AQI Deciles on Run Time (95% Confidence Intervals)

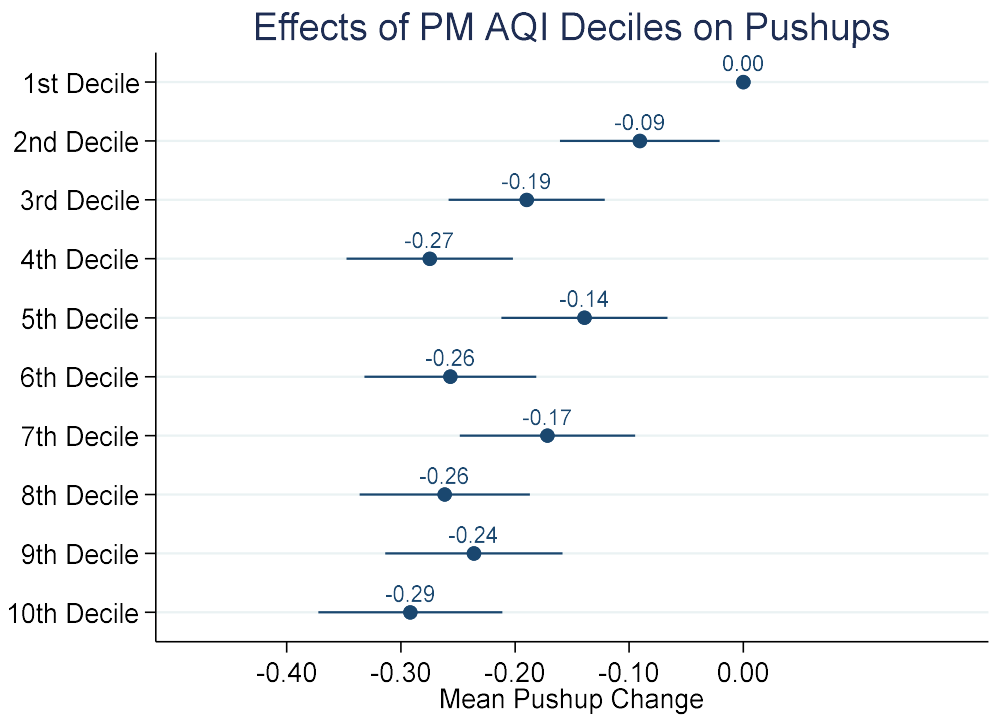


Figure 2-2: Mean Pushup Change by Decile PM (95% Confidence Intervals)

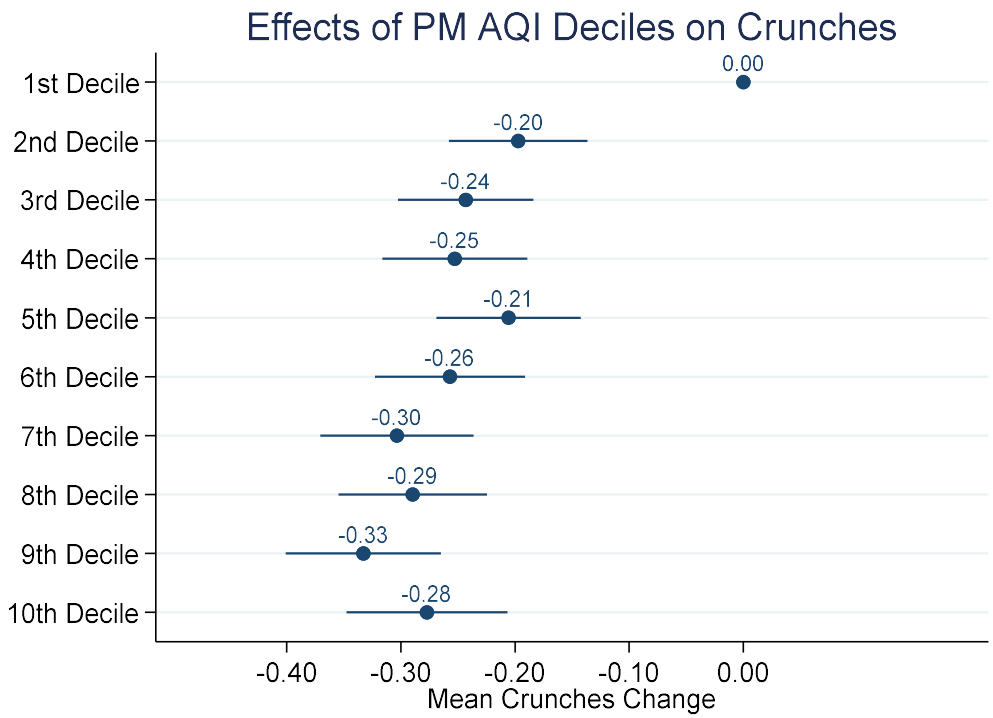


Figure 2-3: Mean Crunch Change by Decile PM (95% Confidence Intervals)

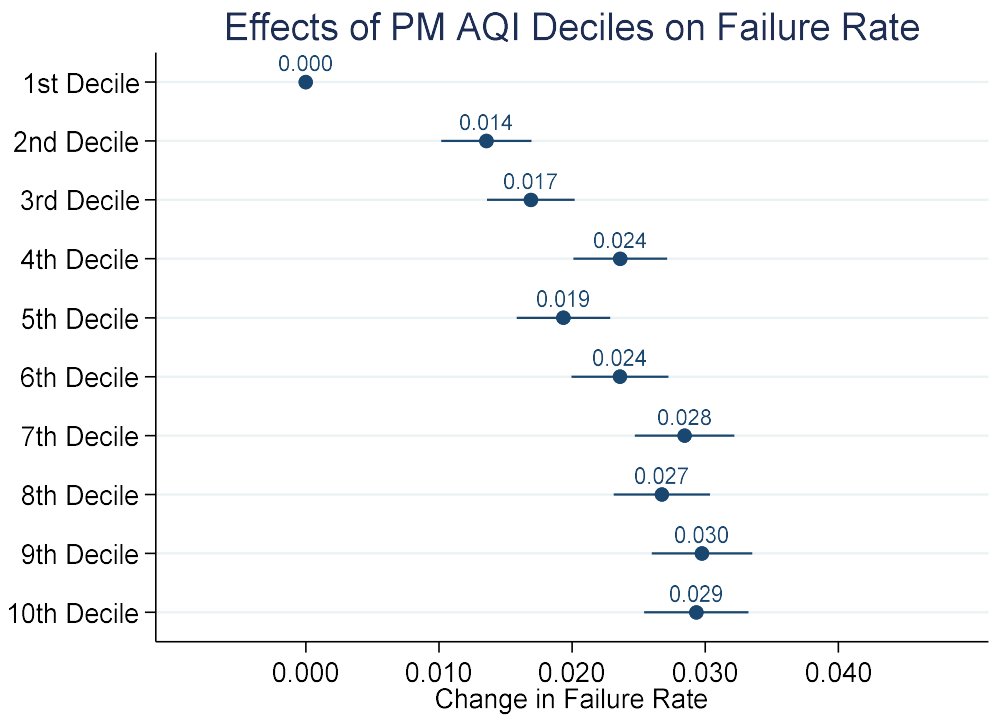


Figure 2-4: Effects of PM AQI Deciles on Failure Rate (95% Confidence Intervals)

Appendix C: USAF Fitness Charts

Cardiorespiratory Endurance			Body Composition			Muscle Fitness			
Run Time (mins:secs)	Health Risk Category	Points	AC (inches)	Health Risk Category	Points	Push-ups (reps/min)	Points	Sit-ups (reps/min)	Points
≤ 9:12	Low-Risk	60.0	≤ 32.5	Low-Risk	20.0	≥ 67	10.0	≥ 58	10.0
9:13 - 9:34	Low-Risk	59.7	33.0	Low-Risk	20.0	62	9.5	55	9.5
9:35 - 9:45	Low-Risk	59.3	33.5	Low-Risk	20.0	61	9.4	54	9.4
9:46 - 9:58	Low-Risk	58.9	34.0	Low-Risk	20.0	60	9.3	53	9.2
9:59 - 10:10	Low-Risk	58.5	34.5	Low-Risk	20.0	59	9.2	52	9.0
10:11 - 10:23	Low-Risk	57.9	35.0	Low-Risk	20.0	58	9.1	51	8.8
10:24 - 10:37	Low-Risk	57.3	35.5	Moderate Risk	17.6	57	9.0	50	8.7
10:38 - 10:51	Low-Risk	56.6	36.0	Moderate Risk	17.0	56	8.9	49	8.5
10:52 - 11:06	Low-Risk	55.7	36.5	Moderate Risk	16.4	55	8.8	48	8.3
11:07 - 11:22	Low-Risk	54.8	37.0	Moderate Risk	15.8	54	8.8	47	8.0
11:23 - 11:38	Low-Risk	53.7	37.5 #	Moderate Risk	15.1	53	8.7	46 #	7.5
11:39 - 11:56	Low-Risk	52.4	38.0	Moderate Risk	14.4	52	8.6	45	7.0
11:57 - 12:14	Low-Risk	50.9	38.5	Moderate Risk	13.5	51	8.5	44	6.5
12:15 - 12:33	Low-Risk	49.2	39.0 *	Moderate Risk	12.6	50	8.4	43	6.3
12:34 - 12:53	Moderate Risk	47.2	39.5	High Risk	0	49	8.3	42 *	6.0
12:54 - 13:14 #	Moderate Risk	44.9	40.0	High Risk	0	48	8.1	41	0
13:15 - 13:36 *	Moderate Risk	42.3	40.5	High Risk	0	47	8.0	40	0
13:37 - 14:00	High Risk	0	41.0	High Risk	0	46	7.8	39	0
14:01 - 14:25	High Risk	0	41.5	High Risk	0	45	7.7	38	0
14:26 - 14:52	High Risk	0	42.0	High Risk	0	44 #	7.5	37	0
14:53 - 15:20	High Risk	0	42.5	High Risk	0	43	7.3	36	0
15:21 - 15:50	High Risk	0	43.0	High Risk	0	42	7.2	35	0
15:51 - 16:22	High Risk	0	≥ 43.5	High Risk	0	41	7.0	34	0
16:23 - 16:57	High Risk	0				40	6.8	33	0
≥ 16:58	High Risk	0				39	6.5	32	0
						38	6.3	31	0
NOTES:						37	6.0	30	0
Health Risk Category = low, moderate or high risk for current and future						36	5.8	≤ 29	0
cardiovascular disease, diabetes, certain cancers, and other health problems						35	5.5		
						34	5.3		
Passing Requirements - member ***must***: 1) meet minimum value in each of						33 *	5.0		
the four components, ***and*** 2) achieve a composite point total ≥ 75 points						32	0		
						31	0		
* Minimum Component Values						30	0		
Run time ≤ 13:36 mins:secs / Abd Circ ≤ 39.0 inches						29	0		
Push-ups ≥ 33 repetitions/one minute / Sit-ups ≥ 42 repetitions/one minute						28	0		
						27	0		
# Target Component Values						26	0		
Member should attain or surpass these to achieve ≥ 75.0 composite score						25	0		
						24	0		
Composite Score Categories						23	0		
Excellent ≥ 90.0 pts / Satisfactory = 75.0 - 89.9 / Unsatisfactory < 75.0						22	0		
						21	0		
						20	0		
						19	0		
						18	0		
						≤ 17	0		

Figure 2-5: Males Under 30 years of Age

Cardiorespiratory Endurance			Body Composition			Muscle Fitness			
Run Time (mins:secs)	Health Risk Category	Points	AC (inches)	Health Risk Category	Points	Push-ups (reps/min)	Points	Sit-ups (reps/min)	Points
≤ 9:34	Low-Risk	60.0	≤ 32.5	Low-Risk	20.0	≥ 57	10.0	≥ 54	10.0
9:35 - 9:58	Low-Risk	59.3	33.0	Low-Risk	20.0	52	9.5	51	9.5
9:59 - 10:10	Low-Risk	58.6	33.5	Low-Risk	20.0	51	9.4	50	9.4
10:11 - 10:23	Low-Risk	57.9	34.0	Low-Risk	20.0	50	9.3	49	9.2
10:24 - 10:37	Low-Risk	57.3	34.5	Low-Risk	20.0	49	9.2	48	9.0
10:38 - 10:51	Low-Risk	56.6	35.0	Low-Risk	20.0	48	9.2	47	8.8
10:52 - 11:06	Low-Risk	55.7	35.5	Moderate Risk	17.6	47	9.1	46	8.7
11:07 - 11:22	Low-Risk	54.8	36.0	Moderate Risk	17.0	46	9.0	45	8.5
11:23 - 11:38	Low-Risk	53.7	36.5	Moderate Risk	16.4	45	8.9	44	8.3
11:39 - 11:56	Low-Risk	52.4	37.0	Moderate Risk	15.8	44	8.8	43	8.0
11:57 - 12:14	Low-Risk	50.9	37.5 #	Moderate Risk	15.1	43	8.7	42 #	7.5
12:15 - 12:33	Low-Risk	49.2	38.0	Moderate Risk	14.4	42	8.6	41	7.0
12:34 - 12:53	Low-Risk	47.2	38.5	Moderate Risk	13.5	41	8.5	40	6.5
12:54 - 13:14 #	Moderate Risk	44.9	39.0 *	Moderate Risk	12.6	40	8.3	39 *	6.0
13:15 - 13:36	Moderate Risk	42.3	39.5	High Risk	0	39	8.0	38	0
13:37 - 14:00 *	Moderate Risk	39.3	40.0	High Risk	0	38	7.8	37	0
14:01 - 14:25	High Risk	0	40.5	High Risk	0	37	7.7	36	0
14:26 - 14:52	High Risk	0	41.0	High Risk	0	36 #	7.5	35	0
14:53 - 15:20	High Risk	0	41.5	High Risk	0	35	7.3	34	0
15:21 - 15:50	High Risk	0	42.0	High Risk	0	34	7.0	33	0
15:51 - 16:22	High Risk	0	42.5	High Risk	0	33	6.8	32	0
16:23 - 16:57	High Risk	0	43.0	High Risk	0	32	6.7	31	0
≥ 16:58	High Risk	0	≥ 43.5	High Risk	0	31	6.5	30	0
						30	6.0	29	0
NOTES:						29	5.5	28	0
Health Risk Category = low, moderate or high risk for current and future						28	5.3	27	0
cardiovascular disease, diabetes, certain cancers, and other health problems						27 *	5.0	26	0
						26	0	≤ 25	0
Passing Requirements - member ***must***: 1) meet minimum value in each of						25	0		
the four components, ***and*** 2) achieve a composite point total ≥ 75 points						24	0		
						23	0		
* Minimum Component Values						22	0		
Run time ≤ 14:00 mins:secs / Abd Circ ≤ 39.0 inches						21	0		
Push-ups ≥ 27 repetitions/one minute / Sit-ups ≥ 39 repetitions/one minute						20	0		
						19	0		
# Target Component Values						18	0		
Member should attain or surpass these to achieve ≥ 75.0 composite score						17	0		
						16	0		
Composite Score Categories						15	0		
Excellent ≥ 90.0 pts / Satisfactory = 75.0 - 89.9 / Unsatisfactory < 75.0						14	0		
						13	0		
						≤ 12	0		

Figure 2-6: Males 30-39 Years of Age

Cardiorespiratory Endurance			Body Composition			Muscle Fitness			
Run Time (mins:secs)	Health Risk Category	Points	AC (inches)	Health Risk Category	Points	Push-ups (reps/min)	Points	Sit-ups (reps/min)	Points
≤ 9:45	Low-Risk	60.0	≤ 32.5	Low-Risk	20.0	≥ 44	10.0	≥ 50	10.0
9:46 - 10:10	Low-Risk	59.8	33.0	Low-Risk	20.0	40	9.5	47	9.5
10:11 - 10:23	Low-Risk	59.5	33.5	Low-Risk	20.0	39	9.4	46	9.4
10:24 - 10:37	Low-Risk	59.1	34.0	Low-Risk	20.0	38	9.2	45	9.2
10:38 - 10:51	Low-Risk	58.7	34.5	Low-Risk	20.0	37	9.1	44	9.1
10:52 - 11:06	Low-Risk	58.3	35.0	Low-Risk	20.0	36	9.0	43	9.0
11:07 - 11:22	Low-Risk	57.7	35.5	Moderate Risk	17.6	35	8.8	42	8.8
11:23 - 11:38	Low-Risk	57.1	36.0	Moderate Risk	17.0	34	8.5	41	8.7
11:39 - 11:56	Low-Risk	56.3	36.5	Moderate Risk	16.4	33	8.4	40	8.5
11:57 - 12:14	Low-Risk	55.4	37.0	Moderate Risk	15.8	32	8.3	39	8.0
12:15 - 12:33	Low-Risk	54.3	37.5 #	Moderate Risk	15.1	31	8.1	38	7.8
12:34 - 12:53	Low-Risk	53.1	38.0	Moderate Risk	14.4	30	8.0	37 #	7.5
12:54 - 13:14	Low-Risk	51.5	38.5	Moderate Risk	13.5	29 #	7.5	36	7.0
13:15 - 13:36	Low-Risk	49.8	39.0 *	Moderate Risk	12.6	28	7.3	35	6.5
13:37 - 14:00	Moderate Risk	47.7	39.5	High Risk	0	27	7.2	34 *	6.0
14:01 - 14:25 #	Moderate Risk	45.2	40.0	High Risk	0	26	7.0	33	0
14:26 - 14:52 *	Moderate Risk	42.3	40.5	High Risk	0	25	6.5	32	0
14:53 - 15:20	High Risk	0	41.0	High Risk	0	24	6.0	31	0
15:21 - 15:50	High Risk	0	41.5	High Risk	0	23	5.8	30	0
15:51 - 16:22	High Risk	0	42.0	High Risk	0	22	5.5	29	0
16:23 - 16:57	High Risk	0	42.5	High Risk	0	21 *	5.0	28	0
16:58 - 17:34	High Risk	0	43.0	High Risk	0	20	0	27	0
17:35 - 18:14	High Risk	0	≥ 43.5	High Risk	0	19	0	26	0
≥ 18:15	High Risk	0				18	0	25	0
						17	0	24	0
NOTES:						16	0	23	0
Health Risk Category = low, moderate or high risk for current and future						15	0	22	0
cardiovascular disease, diabetes, certain cancers, and other health problems						14	0	≤ 21	0
						13	0		
Passing Requirements - member ***must***: 1) meet minimum value in each of						12	0		
the four components, ***and*** 2) achieve a composite point total ≥ 75 points						11	0		
						10	0		
* Minimum Component Values						9	0		
Run time ≤ 14:52 mins:secs / Abd Circ ≤ 39.0 inches						≤ 8	0		
Push-ups ≥ 21 repetitions/one minute / Sit-ups ≥ 34 repetitions/one minute									
# Target Component Values									
Member should attain or surpass these to achieve ≥ 75.0 composite score									
Composite Score Categories									
Excellent ≥ 90.0 pts / Satisfactory = 75.0 - 89.9 / Unsatisfactory < 75.0									

Figure 2-7: Males 40 – 49 Years of Age

Cardiorespiratory Endurance			Body Composition			Muscle Fitness			
Run Time (mins:secs)	Health Risk Category	Points	AC (inches)	Health Risk Category	Points	Push-ups (reps/min)	Points	Sit-ups (reps/min)	Points
≤ 10:37	Low-Risk	60.0	≤ 32.5	Low-Risk	20.0	≥ 44	10.0	≥ 46	10.0
10:38 - 11:06	Low-Risk	59.7	33.0	Low-Risk	20.0	39	9.5	43	9.5
11:07 - 11:22	Low-Risk	59.4	33.5	Low-Risk	20.0	38	9.4	42	9.4
11:23 - 11:38	Low-Risk	59.0	34.0	Low-Risk	20.0	37	9.4	41	9.2
11:39 - 11:56	Low-Risk	58.5	34.5	Low-Risk	20.0	36	9.3	40	9.1
11:57 - 12:14	Low-Risk	58.0	35.0	Low-Risk	20.0	35	9.3	39	9.0
12:15 - 12:33	Low-Risk	57.3	35.5	Moderate Risk	17.6	34	9.2	38	8.8
12:34 - 12:53	Low-Risk	56.5	36.0	Moderate Risk	17.0	33	9.2	37	8.7
12:54 - 13:14	Low-Risk	55.6	36.5	Moderate Risk	16.4	32	9.1	36	8.5
13:15 - 13:36	Low-Risk	54.5	37.0	Moderate Risk	15.8	31	9.1	35	8.0
13:37 - 14:00	Low-Risk	53.3	37.5 #	Moderate Risk	15.1	30	9.0	34	7.8
14:01 - 14:25	Low-Risk	51.8	38.0	Moderate Risk	14.4	29	8.8	33 #	7.5
14:26 - 14:52	Low-Risk	50.0	38.5	Moderate Risk	13.5	28	8.5	32	7.3
14:53 - 15:20	Moderate Risk	47.9	39.0 *	Moderate Risk	12.6	27	8.3	31	7.0
15:21 - 15:50 #	Moderate Risk	45.4	39.5	High Risk	0	26	8.2	30	6.5
15:51 - 16:22 *	Moderate Risk	42.4	40.0	High Risk	0	25	8.0	29	6.3
16:23 - 16:57	High Risk	0	40.5	High Risk	0	24 #	7.5	28 *	6.0
16:58 - 17:34	High Risk	0	41.0	High Risk	0	23	7.3	27	0
17:35 - 18:14	High Risk	0	41.5	High Risk	0	22	7.2	26	0
18:15 - 18:56	High Risk	0	42.0	High Risk	0	21	7.0	25	0
18:57 - 19:43	High Risk	0	42.5	High Risk	0	20	6.5	24	0
19:44 - 20:33	High Risk	0	43.0	High Risk	0	19	6.0	23	0
≥ 20:34	High Risk	0	≥ 43.5	High Risk	0	18	5.8	22	0
						17	5.5	21	0
NOTES:						16	5.3	20	0
Health Risk Category = low, moderate or high risk for current and future						15 *	5.0	19	0
cardiovascular disease, diabetes, certain cancers, and other health problems						14	0	18	0
						13	0	17	0
Passing Requirements - member ***must***: 1) meet minimum value in each of						12	0	16	0
the four components, ***and*** 2) achieve a composite point total ≥ 75 points						11	0	15	0
						10	0	≤ 14	0
* Minimum Component Values						9	0		
Run time ≤ 16:22 mins:secs / Abd Circ ≤ 39.0 inches						8	0		
Push-ups ≥ 15 repetitions/one minute / Sit-ups ≥ 28 repetitions/one minute						7	0		
						6	0		
# Target Component Values						≤ 5	0		
Member should attain or surpass these to achieve ≥ 75.0 composite score									
Composite Score Categories									
Excellent ≥ 90.0 pts / Satisfactory = 75.0 - 89.9 / Unsatisfactory < 75.0									

Figure 2-8: Males 50 – 59 Years of Age

Cardiorespiratory Endurance			Body Composition			Muscle Fitness			
Run Time (mins:secs)	Health Risk Category	Points	AC (inches)	Health Risk Category	Points	Push-ups (reps/min)	Points	Sit-ups (reps/min)	Points
≤ 11:22	Low-Risk	60.0	≤ 32.5	Low-Risk	20.0	≥ 30	10.0	≥ 42	10.0
11:23 - 11:56	Low-Risk	59.7	33.0	Low-Risk	20.0	28	9.5	39	9.5
11:57 - 12:14	Low-Risk	59.4	33.5	Low-Risk	20.0	27	9.3	38	9.4
12:15 - 12:33	Low-Risk	59.0	34.0	Low-Risk	20.0	26	9.0	37	9.2
12:34 - 12:53	Low-Risk	58.5	34.5	Low-Risk	20.0	25	8.8	36	9.1
12:54 - 13:14	Low-Risk	58.0	35.0	Low-Risk	20.0	24	8.5	35	9.0
13:15 - 13:36	Low-Risk	57.3	35.5	Moderate Risk	17.6	23	8.0	34	8.9
13:37 - 14:00	Low-Risk	56.5	36.0	Moderate Risk	17.0	22 #	7.5	33	8.8
14:01 - 14:25	Low-Risk	55.6	36.5	Moderate Risk	16.4	21	7.0	32	8.6
14:26 - 14:52	Low-Risk	54.5	37.0	Moderate Risk	15.8	20	6.5	31	8.5
14:53 - 15:20	Low-Risk	53.3	37.5 #	Moderate Risk	15.1	19	6.3	30	8.0
15:21 - 15:50	Low-Risk	51.8	38.0	Moderate Risk	14.4	18	6.0	29	7.8
15:51 - 16:22	Low-Risk	50.0	38.5	Moderate Risk	13.5	17	5.8	28 #	7.5
16:23 - 16:57	Moderate Risk	47.9	39.0 *	Moderate Risk	12.6	16	5.5	27	7.3
16:58 - 17:34 #	Moderate Risk	45.4	39.5	High Risk	0	15	5.3	26	7.0
17:35 - 18:14 *	Moderate Risk	42.4	40.0	High Risk	0	14 *	5.0	25	6.8
18:15 - 18:56	High Risk	0	40.5	High Risk	0	13	0	24	6.5
18:57 - 19:43	High Risk	0	41.0	High Risk	0	12	0	23	6.3
19:44 - 20:33	High Risk	0	41.5	High Risk	0	11	0	22 *	6.0
20:34 - 21:28	High Risk	0	42.0	High Risk	0	10	0	21	0
21:29 - 22:28	High Risk	0	42.5	High Risk	0	9	0	20	0
22:29 - 23:34	High Risk	0	43.0	High Risk	0	8	0	19	0
≥ 23:35	High Risk	0	≥ 43.5	High Risk	0	7	0	18	0
						6	0	17	0
NOTES:						5	0	16	0
Health Risk Category = low, moderate or high risk for current and future						4	0	15	0
cardiovascular disease, diabetes, certain cancers, and other health problems						≤ 3	0	14	0
								13	0
Passing Requirements - member ***must***: 1) meet minimum value in each of								12	0
the four components, ***and*** 2) achieve a composite point total ≥ 75 points								11	0
								10	0
* Minimum Component Values								≤ 9	0
Run time ≤ 18:14 mins:secs / Abd Circ ≤ 39.0 inches									
Push-ups ≥ 14 repetitions/one minute / Sit-ups ≥ 22 repetitions/one minute									
# Target Component Values									
Member should attain or surpass these to achieve ≥ 75.0 composite score									
Composite Score Categories									
Excellent ≥ 90.0 pts / Satisfactory = 75.0 - 89.9 / Unsatisfactory < 75.0									

Figure 2-9: Males 60+ Years of Age

Cardiorespiratory Endurance			Body Composition			Muscle Fitness			
Run Time (mins:secs)	Health Risk Category	Points	AC (inches)	Health Risk Category	Points	Push-ups (reps/min)	Points	Sit-ups (reps/min)	Points
≤ 10:23	Low-Risk	60.0	≤ 29.0	Low Risk	20.0	≥ 47	10.0	≥ 54	10.0
10:24 - 10:51	Low-Risk	59.9	29.5	Low Risk	20.0	42	9.5	51	9.5
10:52 - 11:06	Low-Risk	59.5	30.0	Low Risk	20.0	41	9.4	50	9.4
11:07 - 11:22	Low-Risk	59.2	30.5	Low Risk	20.0	40	9.3	49	9.0
11:23 - 11:38	Low-Risk	58.9	31.0	Low Risk	20.0	39	9.2	48	8.9
11:39 - 11:56	Low-Risk	58.6	31.5	Low Risk	20.0	38	9.1	47	8.8
11:57 - 12:14	Low-Risk	58.1	32.0	Moderate Risk	17.6	37	9.0	46	8.6
12:15 - 12:33	Low-Risk	57.6	32.5	Moderate Risk	17.1	36	8.9	45	8.5
12:34 - 12:53	Low-Risk	57.0	33.0	Moderate Risk	16.5	35	8.8	44	8.0
12:54 - 13:14	Low-Risk	56.2	33.5	Moderate Risk	15.9	34	8.6	43	7.8
13:15 - 13:36	Low-Risk	55.3	34.0 #	Moderate Risk	15.2	33	8.5	42 #	7.5
13:37 - 14:00	Low-Risk	54.2	34.5	Moderate Risk	14.5	32	8.4	41	7.0
14:01 - 14:25	Low-Risk	52.8	35.0	Moderate Risk	13.7	31	8.3	40	6.8
14:26 - 14:52	Low-Risk	51.2	35.5 *	Moderate Risk	12.8	30	8.2	39	6.5
14:53 - 15:20	Moderate Risk	49.3	36.0	High Risk	0	29	8.1	38 *	6.0
15:21 - 15:50 #	Moderate Risk	46.9	36.5	High Risk	0	28	8.0	37	0
15:51 - 16:22 *	Moderate Risk	44.1	37.0	High Risk	0	27 #	7.5	36	0
16:23 - 16:57	High Risk	0	37.5	High Risk	0	26	7.3	35	0
16:58 - 17:34	High Risk	0	38.0	High Risk	0	25	7.2	34	0
17:35 - 18:14	High Risk	0	38.5	High Risk	0	24	7.0	33	0
18:15 - 18:56	High Risk	0	39.0	High Risk	0	23	6.5	32	0
18:57 - 19:43	High Risk	0	39.5	High Risk	0	22	6.3	31	0
19:44 - 20:33	High Risk	0	≥ 40.0	High Risk	0	21	6.0	30	0
≥ 20:34	High Risk	0				20	5.8	29	0
						19	5.5	28	0
NOTES:						18 *	5.0	27	0
Health Risk Category = low, moderate or high risk for current and future						17	0	26	0
cardiovascular disease, diabetes, certain cancers, and other health problems						16	0	25	0
						15	0	24	0
Passing Requirements - member ***must***: 1) meet minimum value in each of						14	0	23	0
the four components, ***and*** 2) achieve a composite point total ≥ 75 points						13	0	≤ 22	0
						12	0		
* Minimum Component Values						11	0		
Run time ≤ 16:22 mins:secs / Abd Circ ≤ 35.5 inches						10	0		
Push-ups ≥ 18 repetitions/one minute / Sit-ups ≥ 38 repetitions/one minute						9	0		
						8	0		
# Target Component Values						≤ 7	0		
Member should attain or surpass these to achieve ≥ 75.0 composite score									
Composite Score Categories									
Excellent ≥ 90.0 pts / Satisfactory = 75.0 - 89.9 / Unsatisfactory < 75.0									

Figure 2-10: Females Under 30 Years of Age

Cardiorespiratory Endurance			Body Composition			Muscle Fitness			
Run Time (mins:secs)	Health Risk Category	Points	AC (inches)	Health Risk Category	Points	Push-ups (reps/min)	Points	Sit-ups (reps/min)	Points
≤ 10:51	Low-Risk	60.0	≤ 29.0	Low Risk	20.0	≥ 46	10.0	≥ 45	10.0
10:52 - 11:22	Low-Risk	59.5	29.5	Low Risk	20.0	40	9.5	42	9.5
11:23 - 11:38	Low-Risk	59.0	30.0	Low Risk	20.0	39	9.4	41	9.4
11:39 - 11:56	Low-Risk	58.6	30.5	Low Risk	20.0	38	9.3	40	9.0
11:57 - 12:14	Low-Risk	58.1	31.0	Low Risk	20.0	37	9.3	39	8.8
12:15 - 12:33	Low-Risk	57.6	31.5	Low Risk	20.0	36	9.2	38	8.5
12:34 - 12:53	Low-Risk	57.0	32.0	Moderate Risk	17.6	35	9.1	37	8.3
12:54 - 13:14	Low-Risk	56.2	32.5	Moderate Risk	17.1	34	9.1	36	8.2
13:15 - 13:36	Low-Risk	55.3	33.0	Moderate Risk	16.5	33	9.0	35	8.0
13:37 - 14:00	Low-Risk	54.2	33.5	Moderate Risk	15.9	32	8.9	34	7.8
14:01 - 14:25	Low-Risk	52.8	34.0 #	Moderate Risk	15.2	31	8.9	33 #	7.5
14:26 - 14:52	Low-Risk	51.2	34.5	Moderate Risk	14.5	30	8.8	32	7.0
14:53 - 15:20	Low-Risk	49.3	35.0	Moderate Risk	13.7	29	8.7	31	6.8
15:21 - 15:50 #	Moderate Risk	46.9	35.5 *	Moderate Risk	12.8	28	8.6	30	6.5
15:51 - 16:22	Moderate Risk	44.1	36.0	High Risk	0	27	8.6	29 *	6.0
16:23 - 16:57 *	Moderate Risk	40.8	36.5	High Risk	0	26	8.5	28	0
16:58 - 17:34	High Risk	0	37.0	High Risk	0	25	8.3	27	0
17:35 - 18:14	High Risk	0	37.5	High Risk	0	24	8.2	26	0
18:15 - 18:56	High Risk	0	38.0	High Risk	0	23	8.0	25	0
18:57 - 19:43	High Risk	0	38.5	High Risk	0	22	7.9	24	0
19:44 - 20:33	High Risk	0	39.0	High Risk	0	21	7.8	23	0
≥ 20:34	High Risk	0	39.5	High Risk	0	20	7.6	22	0
			≥ 40.0	High Risk	0	19 #	7.5	21	0
						18	7.0	20	0
NOTES:						17	6.8	19	0
Health Risk Category = low, moderate or high risk for current and future						16	6.5	18	0
cardiovascular disease, diabetes, certain cancers, and other health problems						15	6.0	17	0
						14 *	5.0	16	0
Passing Requirements - member ***must***: 1) meet minimum value in each of						13	0	15	0
the four components, ***and*** 2) achieve a composite point total ≥ 75 points						12	0	≤ 14	0
						11	0		
* Minimum Component Values						10	0		
Run time ≤ 16:57 mins:secs / Abd Circ ≤ 35.5 inches						9	0		
Push-ups ≥ 14 repetitions/one minute / Sit-ups ≥ 29 repetitions/one minute						8	0		
						7	0		
# Target Component Values						6	0		
Member should attain or surpass these to achieve ≥ 75.0 composite score						≤ 5	0		
Composite Score Categories									
Excellent ≥ 90.0 pts / Satisfactory = 75.0 - 89.9 / Unsatisfactory < 75.0									

Figure 2-11: Females 30 – 39 Years of Age

Cardiorespiratory Endurance			Body Composition			Muscle Fitness			
Run Time (mins:secs)	Health Risk Category	Points	AC (inches)	Health Risk Category	Points	Push-ups (reps/min)	Points	Sit-ups (reps/min)	Points
≤ 11:22	Low-Risk	60.0	≤ 29.0	Low Risk	20.0	≥ 38	10.0	≥ 41	10.0
11:23 - 11:56	Low-Risk	59.9	29.5	Low Risk	20.0	33	9.5	38	9.5
11:57 - 12:14	Low-Risk	59.8	30.0	Low Risk	20.0	32	9.4	37	9.4
12:15 - 12:33	Low-Risk	59.6	30.5	Low Risk	20.0	31	9.2	36	9.2
12:34 - 12:53	Low-Risk	59.4	31.0	Low Risk	20.0	30	9.1	35	9.1
12:54 - 13:14	Low-Risk	59.1	31.5	Low Risk	20.0	29	9.0	34	9.0
13:15 - 13:36	Low-Risk	58.7	32.0	Moderate Risk	17.6	28	8.9	33	8.8
13:37 - 14:00	Low-Risk	58.2	32.5	Moderate Risk	17.1	27	8.8	32	8.5
14:01 - 14:25	Low-Risk	57.7	33.0	Moderate Risk	16.5	26	8.7	31	8.3
14:26 - 14:52	Low-Risk	56.9	33.5	Moderate Risk	15.9	25	8.6	30	8.2
14:53 - 15:20	Low-Risk	56.0	34.0 #	Moderate Risk	15.2	24	8.6	29	8.0
15:21 - 15:50	Low-Risk	54.8	34.5	Moderate Risk	14.5	23	8.5	28 #	7.5
15:51 - 16:22	Low-Risk	53.3	35.0	Moderate Risk	13.7	22	8.4	27	7.0
16:23 - 16:57	Moderate Risk	51.4	35.5 *	Moderate Risk	12.8	21	8.3	26	6.8
16:58 - 17:34	Moderate Risk	49.0	36.0	High Risk	0	20	8.2	25	6.4
17:35 - 18:14 *#	Moderate Risk	45.9	36.5	High Risk	0	19	8.1	24 *	6.0
18:15 - 18:56	High Risk	0	37.0	High Risk	0	18	8.0	23	0
18:57 - 19:43	High Risk	0	37.5	High Risk	0	17	7.8	22	0
19:44 - 20:33	High Risk	0	38.0	High Risk	0	16 #	7.5	21	0
20:34 - 21:28	High Risk	0	38.5	High Risk	0	15	7.0	20	0
21:29 - 22:28	High Risk	0	39.0	High Risk	0	14	6.5	19	0
≥ 22:29	High Risk	0	39.5	High Risk	0	13	6.0	18	0
			≥ 40.0	High Risk	0	12	5.5	17	0
						11 *	5.0	16	0
NOTES:						10	0	15	0
Health Risk Category = low, moderate or high risk for current and future						9	0	14	0
cardiovascular disease, diabetes, certain cancers, and other health problems						8	0	13	0
						7	0	12	0
Passing Requirements - member ***must***: 1) meet minimum value in each of						6	0	11	0
the four components, ***and*** 2) achieve a composite point total ≥ 75 points						5	0	10	0
						4	0	≤ 9	0
* Minimum Component Values						≤ 3	0		
Run time ≤ 18:14 mins:secs / Abd Circ ≤ 35.5 inches									
Push-ups ≥ 11 repetitions/one minute / Sit-ups ≥ 24 repetitions/one minute									
# Target Component Values									
Member should attain or surpass these to achieve ≥ 75.0 composite score									
Composite Score Categories									
Excellent ≥ 90.0 pts / Satisfactory = 75.0 - 89.9 / Unsatisfactory < 75.0									

Figure 2-12: Females 40 – 49 Years of Age

Cardiorespiratory Endurance			Body Composition			Muscle Fitness			
Run Time (mins:secs)	Health Risk Category	Points	AC (inches)	Health Risk Category	Points	Push-ups (reps/min)	Points	Sit-ups (reps/min)	Points
≤ 12:53	Low-Risk	60.0	≤ 29.0	Low Risk	20.0	≥ 35	10.0	≥ 32	10.0
12:54 - 13:36	Low-Risk	59.8	29.5	Low Risk	20.0	30	9.5	30	9.5
13:37 - 14:00	Low-Risk	59.6	30.0	Low Risk	20.0	29	9.4	29	9.0
14:01 - 14:25	Low-Risk	59.3	30.5	Low Risk	20.0	28	9.3	28	8.9
14:26 - 14:52	Low-Risk	58.9	31.0	Low Risk	20.0	27	9.2	27	8.8
14:53 - 15:20	Low-Risk	58.4	31.5	Low Risk	20.0	26	9.1	26	8.6
15:21 - 15:50	Low-Risk	57.7	32.0	Moderate Risk	17.6	25	9.0	25	8.5
15:51 - 16:22	Low-Risk	56.8	32.5	Moderate Risk	17.1	24	8.8	24	8.0
16:23 - 16:57	Low-Risk	55.6	33.0	Moderate Risk	16.5	23	8.7	23 #	7.5
16:58 - 17:34	Low-Risk	54.0	33.5	Moderate Risk	15.9	22	8.6	22	7.0
17:35 - 18:14	Low-Risk	51.9	34.0 #	Moderate Risk	15.2	21	8.6	21	6.5
18:15 - 18:56	Moderate Risk	49.2	34.5	Moderate Risk	14.5	20	8.5	20 *	6.0
18:57 - 19:43 *#	Moderate Risk	45.5	35.0	Moderate Risk	13.7	19	8.4	19	0
19:44 - 20:33	High Risk	0	35.5 *	Moderate Risk	12.8	18	8.3	18	0
20:34 - 21:28	High Risk	0	36.0	High Risk	0	17	8.2	17	0
21:29 - 22:28	High Risk	0	36.5	High Risk	0	16	8.1	16	0
22:29 - 23:34	High Risk	0	37.0	High Risk	0	15	8.0	15	0
≥ 23:35	High Risk	0	37.5	High Risk	0	14 #	7.5	14	0
			38.0	High Risk	0	13	7.0	13	0
			38.5	High Risk	0	12	6.5	12	0
			39.0	High Risk	0	11	6.0	11	0
			39.5	High Risk	0	10	5.5	10	0
			≥ 40.0	High Risk	0	9 *	5.0	9	0
						8	0	8	0
NOTES:						7	0	7	0
Health Risk Category = low, moderate or high risk for current and future						6	0	6	0
cardiovascular disease, diabetes, certain cancers, and other health problems						5	0	≤ 5	0
						4	0		
Passing Requirements - member ***must***: 1) meet minimum value in each of						3	0		
the four components, ***and*** 2) achieve a composite point total ≥ 75 points						≤2	0		
* Minimum Component Values									
Run time ≤ 19:43 mins:secs / Abd Circ ≤ 35.5 inches									
Push-ups ≥ 9 repetitions/one minute / Sit-ups ≥ 20 repetitions/one minute									
# Target Component Values									
Member should attain or surpass these to achieve ≥ 75.0 composite score									
Composite Score Categories									
Excellent ≥ 90.0 pts / Satisfactory = 75.0 - 89.9 / Unsatisfactory < 75.0									

Figure 2-13: Females 50 – 59 Years of Age

Cardiorespiratory Endurance			Body Composition			Muscle Fitness			
Run Time (mins:secs)	Health Risk Category	Points	AC (inches)	Health Risk Category	Points	Push-ups (reps/min)	Points	Sit-ups (reps/min)	Points
≤ 14:00	Low-Risk	60.0	≤ 29.0	Low Risk	20.0	≥ 21	10.0	≥ 31	10.0
14:01 - 14:52	Low-Risk	59.8	29.5	Low Risk	20.0	19	9.5	28	9.5
14:53 - 15:20	Low-Risk	59.5	30.0	Low Risk	20.0	18	9.4	27	9.4
15:21 - 15:50	Low-Risk	59.1	30.5	Low Risk	20.0	17	9.0	26	9.0
15:51 - 16:22	Low-Risk	58.6	31.0	Low Risk	20.0	16	8.8	25	8.9
16:23 - 16:57	Low-Risk	57.9	31.5	Low Risk	20.0	15	8.5	24	8.8
16:58 - 17:34	Low-Risk	57.0	32.0	Moderate Risk	17.6	14	8.0	23	8.7
17:35 - 18:14	Low-Risk	55.8	32.5	Moderate Risk	17.1	13 #	7.5	22	8.6
18:15 - 18:56	Low-Risk	54.2	33.0	Moderate Risk	16.5	12	7.0	21	8.5
18:57 - 19:43	Low-Risk	52.1	33.5	Moderate Risk	15.9	11	6.5	20	8.4
19:44 - 20:33	Moderate Risk	49.3	34.0 #	Moderate Risk	15.2	10	6.0	19	8.3
20:34 - 21:28 #	Moderate Risk	45.6	34.5	Moderate Risk	14.5	9	5.7	18	8.2
21:29 - 22:28 *	Moderate Risk	40.8	35.0	Moderate Risk	13.7	8	5.3	17	8.0
22:29 - 23:34	High Risk	0	35.5 *	Moderate Risk	12.8	7 *	5.0	16	7.8
23:35 - 24:46	High Risk	0	36.0	High Risk	0	6	0	15 #	7.5
24:47 - 26:06	High Risk	0	36.5	High Risk	0	5	0	14	7.3
≥ 26:07	High Risk	0	37.0	High Risk	0	4	0	13	7.0
			37.5	High Risk	0	3	0	12	6.5
			38.0	High Risk	0	2	0	11 *	6.0
			38.5	High Risk	0	≤1	0	10	0
			39.0	High Risk	0			9	0
			39.5	High Risk	0			8	0
			≥ 40.0	High Risk	0			7	0
								6	0
								5	0
								4	0
								3	0
								2	0
								≤ 1	0

NOTES:

Health Risk Category = low, moderate or high risk for current and future cardiovascular disease, diabetes, certain cancers, and other health problems

Passing Requirements - member ***must***: 1) meet minimum value in each of the four components, ***and*** 2) achieve a composite point total ≥ 75 points

* Minimum Component Values

Run time ≤ 22:28 mins:secs / Abd Circ ≤ 35.5 inches

Push-ups ≥ 7 repetitions/one minute / Sit-ups ≥ 11 repetitions/one minute

Target Component Values

Member should attain or surpass these to achieve ≥ 75.0 composite score

Composite Score Categories

Excellent ≥ 90.0 pts / Satisfactory = 75.0 - 89.9 / Unsatisfactory < 75.0

Figure 2-14: Females 60+ Years of Age

Chapter 3

Freedom Isn't Free, But College Is: Does Free Community College Impact Military Enlistments? Qualitative and Quantitative Evidence From Tennessee Promise

Abstract

State and local college Promise programs that offer non-merit based, free community college are growing in number and scope in the United States. A Promise program may lead some students to enroll in college directly after high school rather than receive education benefits through military service and the GI Bill. We find qualitative and quantitative evidence of this substitution in Tennessee, where last-dollar tuition-free community college has been available to every high school graduate since 2015. Through 19 focus groups involving 60 total participants, we gathered student accounts of the importance of financial aid in their decision to go to college, and the effect that Tennessee Promise had on their decision to enlist versus enroll. Quantitative analyses support these sentiments. Using 2006-2019 data on all new military enlistments and enlistee pre-enlistment aptitude test scores, and a quasi-experimental research design that exploits the staggered deployment of Tennessee Promise across counties, we find that the introduction of Tennessee Promise reduced a county's total enlistments by about 20%, and that the composition of successful enlistees shifted towards those who scored higher on automotive and mechanical sections of the Armed Services Vocational Aptitude Battery (ASVAB).

3.1 Introduction

As young adults near the end of compulsory secondary schooling in the U.S., they face a decision about what to do next. Broadly, the alternatives include what many states and school districts refer to as the "three Es": employment, enrollment, or enlistment (Pondiscio, 2019). These three pathways involve lifecycle costs and benefits that vary in terms of employment certainty of location, choice of career, and upfront investment. Serving in the military is a salient option, and the U.S. Department of Defense is the single largest employer of new high school graduates. Enlistment typically represents more certainty in short-term employment and financial security than the other two E's, at the expense of occupational choice. Going to work right out of high school offers more individual autonomy than military service, although many higher-paying occupations will be out of reach. Postsecondary enrollment can open the door to those occupations, but academic success in college is uncertain and requires years of direct costs and foregone earnings.

Service in the U.S. military offers a path to college that alleviates credit constraints, debt aversion, and imperfect information about benefits. Beginning in 1944, the Department of Defense has offered the GI Bill to veterans of the armed forces. The current version of the GI Bill, the Forever GI Bill, is available to service members and veterans who have completed 36 months of active service. The GI Bill covers tuition for public colleges and universities, up to $25,000 for private or nonprofit schools, as well as location-based living stipends.

While the GI Bill is generous, surveys indicate that the education incentive becomes less of a factor the more that an individual feels that they can pay for college. Among surveyed members that stated they could not pay for college at all, 86% indicated that the education

incentives were a main factor for military service. When individuals reported that they could pay for 1%-24% of their college expenses, joining the military for educational reasons dropped to 41% (Barr, 2016). A significant change in the relative price of postsecondary education should cause young adults to substitute away from military service through the classic rate-of-return channel when two years of college is covered by a Promise program, but also by weakening the value of postsecondary education benefits tied to military service. The "free college" benefit projected by the GI Bill now faces more competition from state and local Promise programs that also cover college tuition. Promise programs have much lighter preconditions than three years of military service, but Promise grants are typically less generous than the GI Bill, and they do not offer mortgage, healthcare, or other benefits that can follow military service.

We examine how the rollout of the Tennessee Promise free community college model, which began in one county and was eventually adopted by the state, affected student considerations toward military service as well as the volume and composition of new enlistments in Promise-eligible counties. Drawing on insights from 19 focus groups with 60 Tennessee Promise students, we find that students view military service as a significant source of financial aid for college, and that Tennessee Promise factored into some students' decision of whether to enlist or enroll in college immediately after high school. Drawing on administrative enlistment records for every branch of the U.S. military and a quasi-experimental research design, we find that new enlistments declined perhaps 20% when Tennessee Promise or one of its predecessors arrived in a county. The National Defense Authorization Act constrains the total military force nationwide, and this cap is managed through local recruiting quotas. It is possible that student sentiments about the enlistment-enrollment margin were not widespread enough to eliminate

excess supply of applications to enlist. We find that the composition of applicants and successful enlistees may have changed, however, favoring recruits who scored better on mechanical and automotive sections of the Armed Service Vocational Aptitude Battery (ASVAB).

3.2 Related Literature

Much of what we know about how students choose among the three Es has focused on factors that affect college enrollment. We know that reducing the direct cost of postsecondary enrollment through financial aid can raise the likelihood of going to college at all (Cornwell et al., 2006; Deming & Dynarski, 2010; Angrist et al., 2016; Hershbein et al., 2019), and that aid that targets specific institutions or sectors can shift enrollment choices in expected ways (van der Klaauw, 2002; Andrews et al., 2010; Cohodes & Goodman, 2014; Gurantz, 2019). We also know that students do not perfectly account for the cost of college or their choice set, in that more opaque financial aid awards have little to no effect on college enrollment (Carruthers & Welch, 2019), and efforts to provide better information or assist with financial aid applications meaningfully affect students' college choices (Bettinger et al., 2012; Barr & Castleman, 2017; Carrell & Sacerdote, 2017; Dynarski et al., 2021). On the margin, financial aid or access to better colleges can have a large and positive net effect on short-term and projected earnings (Hoekstra, 2009; Denning et al., 2019; Angrist et al., 2020; Smith et al., 2020), suggesting that students' postsecondary enrollment choices are not dictated by an optimal rate-of-return computation.

Since the end of World War II, the Department of Defense has used education benefits codified by various iterations of the GI Bill as a key tool to recruit and retain qualified personnel. Defense-funded grants for tuition and living expenses are conditioned on a period of service and were typically generous enough to evoke the compelling idea of "free college" that other public

and private funders have more recently adopted. Simon et al. (2010) and Warner (1990) both show that changes in the generosity of the Montgomery GI Bill correlated with changes in the number and quality of recruits. Kleykamp (2006) finds that among high school graduates, college aspirations were significantly related to the choice to enroll rather than work, but also to the choice to enlist rather than work.

The GI Bill has been effective as a recruitment tool, but also as a policy lever for increasing college enrollment and attainment. The combination of the WWII and the Korean War GI Bills increased college going and graduation rates among young men by around 15 to 20 percent (Stanley, 2003), although these estimates were concentrated among veterans from households with above median income. Looking across birth cohorts with different exposure to the WWII GI Bill, Bound and Turner (2002) found that military education benefits increased college enrollment for veterans compared to non-veterans. Turner & Bound (2003) found that the WWII GI Bill increased educational attainment for both black and white veterans outside the South, but the GI Bill had little effect on college going for black veterans inside the South. Angrist & Chen (2011) use draft lottery data from the Vietnam War to show that the GI Bill from that era increased post-secondary educational attainment amongst those who were drafted. The Post 9/11 GI Bill (PGIB) is the most recent iteration of military funded education benefits. Relative to its predecessor, the Montgomery GI Bill (MGIB), the PGIB was one of the largest expansions of college aid for veterans. The PGIB increased aid for tuition, added housing and living stipends, and made it possible for veterans to transfer unused benefits to a spouse or dependent (Kofoed, 2020). Barr (2015, 2019) shows that the PGIB increased veteran enrollment, particularly into four year colleges, and graduation.

It is increasingly clear that inadequate information or financial resources hinder some students' access to college, that financial aid or advising can help, and that GI Bill education benefits are one form of effective aid for students seeking postsecondary degrees. Enlisting in the military is a lengthy individual commitment, however, and we know very little about the margin between postsecondary enrollment and enlistment at the point where students are weighing the three Es. One reason is the lack of exogenous variation in financial aid generosity and access to individual-level enlistment data.

Most closely related to our research, Barr (2016) examines the effect of state merit aid on enlistment. He finds that when states initiated lottery-funded merit aid scholarships, the probability of military enlistment decreases by 0.6 percentage points (a six percent reduction relative to the baseline). We add to this by examining the effect of a broader financial aid campaign on aggregate enlistment volumes, relying on the expansion of Tennessee's "free community college" model from one county in 2009 to the entire state in 2015. Tennessee already had a merit aid program (the Tennessee HOPE scholarship) in place during this time, and state-funded Tennessee Promise and its privately funded predecessors were not tied to high school grades, SAT/ACT scores, or income requirements. The program's universal "free college" message accompanied efforts to improve the perceived value of college and ultimately raise postsecondary attainment among the state's workforce. This broad-based marketing of college *per se*, along with last-dollar support for tuition, may have resonated more than merit-based or need-based options among students who would have otherwise enlisted in pursuit of a military career or GI Bill education benefits. On the other hand, Tennessee Promise scholarships

were typically worth less than $1,000 per year, which is less than the value of Tennessee HOPE and an order of magnitude less than the benefits associated with the GI Bill.

3.3 Program and Policy Background

Knox Achieves, a privately funded nonprofit organization, pledged to pay community college tuition and fees for any Knox County high school graduate, beginning with the graduating class of 2008-2009. Any graduate from a Knox County public high school was eligible, regardless of grades, standardized test scores, or family income. This "place-based" criteria resembles other Promise programs such as Kalamazoo Promise (Bartik et al., 2019), Pittsburgh Promise (Page et al., 2019), and Say Yes to Education in Syracuse and Buffalo, New York (Sohn et al., 2017). In order to receive tuition benefits, Knox Achieves participants needed to meet with volunteer mentors, file a Free Application for Federal Student Aid (FAFSA), graduate high school, and enroll right away in a Tennessee community college. To maintain their tuition benefits after enrollment, students needed to enroll fulltime, earn at least a 2.0 grade point average (GPA), and continue to meet with volunteer mentors. Knox Achieves tuition benefits were "last dollar," meaning that the program covered any difference between a student's tuition bill and money provided by other grants and scholarships. About half of Knox Achieves students did not actually receive financial aid from the program, because they qualified for need-based federal Pell grants, merit-based Tennessee HOPE scholarships, and other grants that covered their tuition and fees. Even so, Carruthers and Fox (2016) show that eligibility for Knox Achieves significantly increased the likelihood of college enrollment.

After three years serving only Knox County residents, the program expanded under the name "tnAchieves," serving the 2011-2012 class in 23 counties, 26 counties for 2012-2013, and

27 counties for 2013-2014. In 2014, Governor Bill Haslam signed Tennessee Promise into law, adopting the tnAchieves model across all 95 counties in Tennessee. Figure 3-1 depicts this staggered rollout. [6]

Knox Achieves, tnAchieves, and Tennessee Promise benefits and requirements were very similar, and in the quantitative analysis, we treat them as equivalent and refer to them jointly as Promise, the Promise model, or the Promise program. There were, however, a few notable changes that may have made the statewide program more effective than the earlier private programs. Tennessee Promise broadened support to include private and homeschooled high school seniors. Funding for the grants changed following statewide expansion, shifting from private donors to the state's education lottery. With statewide Tennessee Promise, benefits could be used at public community and technical colleges as well as approved universities with associate degree programs (although, not necessarily to the last dollar of university tuition). tnAchieves's role changed as well, from managing all aspects of the program to that of a "partner organization" focusing on student interactions: advocating for the program to high school students, signing up interested participants, recruiting and matching mentors to students, managing cohort progress through applications and enrollment, and surveying students before and after they began college.

[6] All tables and figures are located in the appendix.

3.4 Qualitative Evidence

3.4.1 Qualitative Methods

To explore mechanisms underlying the enrollment-enlistment tradeoff under Promise, we draw on data collected during focus groups with first year Promise students at community and technical colleges across the state. A member of the research team facilitated nineteen 60-90-minute focus groups at 12 campuses of 10 public colleges (60 total participants) in March and April of 2018. This qualitative data collection was part of a broader effort to understand student experiences under Promise, and in particular, student perceptions of psychological contracts between themselves and sources of financial aid (Kramer, 2018). The research team member selected sites to cover a wide variety of campus experiences and geographies.

Focus groups took place at three technical colleges, six community colleges, and one four-year institution that serve students across all regions of the state. Table 3-1 in the appendix provides additional details on the students who participated in focus groups, as well as their colleges. Focus groups discussed college search, transition, and the first semester of enrollment. Most pertinent to this study are aspects of students' college search and decision to enroll.[7] All focus groups were audio recorded and transcribed verbatim. The research team member used an inductive, open coding approach in alignment with grounded theory techniques (Charmaz, 2006; Strauss & Corbin, 1990). As findings emerged through coding, the research team member explored the breadth and depth of enrollment decision themes within and across focus groups,

[7] See the Appendix for the semi-structured interview instrument.

taking an iterative approach to coding and writing analytic memos to capture themes and insights that arose from the data.

3.4.2 Results

Military enlistment questions were not an explicit part of the semi-structured interview instrument (excerpted in the Appendix), but nonetheless, the enlistment-enrollment margin emerged as an important part of student decisions about what to do after high school, and how to pay for college. First, consistent with the financial aid literature, students articulated the importance of financial considerations in their college enrollment decision. Many participants shared that they were at the margins of enrollment, weighing whether college was a practical fit for them; financial considerations were central in this calculation. This finding was consistent across participants, colleges, and geographic settings. Participants shared pertinent details about how their financial situations shaped their postsecondary decision-making under Promise. One technical college student shared that his family's financial challenges were offset by the generosity of the Promise scholarship:

> *Well, I mean, my dad was into clock repair and my mother was working insurance. Now she's trying not to pull her hair out over her job. And you know, [Promise offers] $2,000 for college. It was like, "Well, ain't no reason I shouldn't now," because financial shouldn't be too much of a problem [with the aid]…So, that's what influenced my decision.*

While a few participants shared that they would have been able to attend college without Promise, the vast majority articulated that it would have been difficult or impossible to attend without the tuition-free scholarship. One community college student put it plainly:

"I wouldn't have never been here if they didn't have it. But they do, and here I am."

Promise was not the only college aid that participants mentioned as being part of their enrollment decision-making. Participants also referenced the GI Bill, either by name or generally as a benefit to be earned through military service, and/or as an important resource for the pursuit of postsecondary training. One community college student captured this theme in her description of how her family leveraged both the GI Bill and Promise to provide opportunities for their children to attend postsecondary training:

> *"My parents…used the GI Bill for my sister…We kind of were struggling at that point. But, then with [Promise and other scholarships] that we looked into, we found a way to work it out [for me to attend." Participants shared the importance of these different forms of financial aid to pursuing postsecondary training.*

Promise, as a newer financial aid program, shifted students' and families' decision-making with regard to postsecondary opportunities. Focus group participants articulated that they directly weighed their initial inclination or plans to enlist in the military against the opportunity to pursue a college education tuition free under Promise. This experience was particularly prevalent among participants at community colleges. When pressed regarding the details they considered to make the enrollment-enlistment decision, participants articulated that financial considerations contributed to their initial inclinations to enlist. Specifically, participants referenced military tuition assistance as being a compelling benefit of enlistment. When asked about whether Promise shaped where they chose to go to college, one community college student stated:

I guess…because if I didn't have like a full ride, I probably would have enlisted. Because that's what my original plan was, enlist, and then like go to college while I'm in the service. But I think the Promise, or like the Pell Grant and everything, really helped me. It really helped show me that I can do this and it not like put me in a bunch of debt.

Participants across focus group settings articulated that they were uncertain about college enrollment and reluctant to take on student debt. This initially piqued their interest in enlistment and the GI Bill incentive, and ultimately made community college enrollment with the aid of Promise an appealing decision.

Focus group participants articulated that the amount of consideration towards enlistment was changed by the state of Tennessee's commitment to pay for college. Access to Promise allowed them to enroll in college directly rather than serve in the military prior to or concurrent with their pursuit of a college degree. Some admitted that this was perhaps a more challenging path for them to take. As articulated by one community college student:

"I was thinking about enlisting because of course that seems easier [than going to college first], but it's really just -- I learned early on you've just got to stay to it and it's going to suck, but in the end it's likely going to be worth the trouble. You know what I mean?"

Participants saw value in pursuing a college degree, even if they maintained an interest in ultimately joining the armed forces. Several participants who discussed enlistment during the decision-making process shared that they maintained an interest in serving in the armed forces. These individuals shared their belief that that by pursuing postsecondary training prior to joining the armed forces, they would be able to explore potential occupational areas of interest and, by

earning college credits and a degree, they might be able to enter the workforce with better pay or occupational choices.

3.5 Quantitative Evidence

3.5.1 Application, Enlistment, and ASVAB Data

We obtained de-identified 2006-2019 application, enlistment, and ASVAB records from the Defense Manpower Data Center (DMDC). We begin by focusing on enlistees under age 21 and aggregating these data to the county-year level to study the effect of free community college on total under-21 enlistments in a county as well as average ASVAB scores among new enlistees (overall and across ten subjects). We are able to identify every application and enlistment into the Department of Defense by branch as well as enlistments into the United States Coast Guard. The data include age, gender, race and ethnicity, date of enlistment, county, and each enlistees' ASVAB scores if the applicant was accepted into military service. We do not observe applicants or enlistees' socioeconomic background, high school, ACT/SAT scores, high school GPA, or other historical factors.

It is important to understand the nature of the applications data when interpreting the results. We contacted local recruiting stations in the Knoxville area to determine what is considered an application and when that application would be officially logged by DMDC. We discovered that an application is not an enlistment contract and is not a binding agreement for the potential recruit to join the military if deemed qualified. There is little cost to potential recruits to initiate the process into the Armed Forces other than time. Applicants do not incur any obligations unless they sign a DD Form 4, the Enlistment/Reenlistment Document for the Armed Forces of the United States. As per the recruiting offices, the moment a potential recruit initiates

the process and provides their basic information, they are deemed an applicant and recorded in the system even if they discern out of the Armed Forces before they report to a Military Entrance and Processing Station (MEPS) to determine medical and AFQT qualification. According to a 2014 article published in the Washington Times, 80% of applicants do not enter the Armed Forces (Ernst, 2014). The applications data is therefore best interpreted as an indication of interest in the Armed Forces and does not precisely capture an actual intent to enlist. Since actual enlistments indicate full intent and purpose, the actual enlistment data is a much better indication of intent whereas the applications data is a better indicator of interest beyond contemplation.

We identify and remove counties outside of Tennessee that had their own local Promise programs during the 2006-2019 sample window, as identified by the Uphojn Institute database of local Promise initiative (Miller-Adams et al., 2017). We choose not to fold these out-of-state programs into our Promise treatment measure because their benefits and requirements in many cases are very different from the consistent last-dollar, broad-based model that evolved from Knox Achieves to tnAchieves to Tennessee Promise. We also choose not to leave these other programs in the control group since their effects may have been amplified or indirectly affected by what was happening in Tennessee. Results focus on the U.S. Southern region (16 states and Washington, D.C., as defined by the Bureau of Labor Statistics). The Appendix reports results for the eight-state Southeast region as well as the U.S. In the U.S. analysis we exclude California, New York, and Oregon from the sample because their statewide Promise programs are distinct from Tennessee's model and were introduced around the same time. Results reflect the impact of Tennessee's free community college model on student enlistment in the military,

but subject to local caps and quotas on new enlistees as well as the military's discretion in selecting recruits for service.

The ASVAB became the military's common selection and classification test in 1976 (Fischl et al., 1980). Today's ASVAB is a nationally normed test designed to screen recruits for aptitude and identify an individual's best occupational areas. Many high school students take the ASVAB for this latter career exploration purpose, although ASVAB data used in this study are limited to enlistees. The ASVAB was last normed through the Profile of American Youth (PAY97), in tandem with the National Longitudinal Survey of Youth (Moore et al., 2000).

The ASVAB is administered in a computer adaptive format for most recruits or in a longer pencil-and-paper format for recruits who do not live near a Military Entrance Processing Station. The test covers ten topics: General Science, Arithmetic Reasoning, Word Knowledge, Paragraph Comprehension, Numeric Operations, Coding Speed (for Navy recruits only), Automotive and Shop Information, Mathematics Knowledge, Electronics, and Mechanical Comprehension. Among these ten, scores for Arithmetic Reasoning, Mathematics Knowledge, Word Knowledge, and Paragraph Comprehension constitute the AFQT. Each branch has a minimum required AFQT score for enlistment. Word Knowledge tests vocabulary, and Paragraph Comprehension tests reading comprehension. The Arithmetic Reasoning section includes short mathematical word problems, whereas the Mathematical Knowledge section tests more formulaic high school-level math. When combined with the AFQT sections, the other parts of the ASVAB help to determine a recruit's best occupational areas. The General Science section tests life and physical science knowledge. The Numeric Operations section includes simple, two-number computations. For applicants to the Navy, Coding Speed tests how quickly and

accurately a recruit can retrieve information from a table. The Automotive and Shop Information section tests knowledge of automobile systems and tools. The Electronics Information section covers electricity, circuits, and associated formulas. Finally, the Mechanical Comprehension section tests mechanical principles and applied physics.

3.5.2 Estimation

We examine the effect of Tennessee's Promise model on military enlistment by assembling a panel of county-level enlistment and ASVAB data combined with county-by-year Promise availability (Figure 3-1) and then estimating the following:

$$y_{sct} = \nu_c + \lambda_t + \beta_1 Promise_{ct} + \boldsymbol{\beta_n X_{ct}} + \varepsilon_{sct} \quad (1)$$

where y_{sct} is number of enlistments in service *s,* in county *c*, and year *t,* ν_c and λ_t are county and year fixed effects, $Promise_{ct}$ is a binary treatment indicator equal to 1 when county *c* in year *t* is participating in a Promise program and is 0 otherwise, $\boldsymbol{X_{ct}}$ is a vector of time-varying county controls (population, median income, unemployment rate, and poverty rate), and ε_{sct} is the idiosyncratic error term. We compute robust standard errors that are clustered at the county level. We weight Equation (1) by county population.[8] When analyzing applications, we employ the same model, however y_{sct} becomes number of applications received instead of actual enlistments.

Similarly, we estimate the effect of Promise programs on the aptitude of military enlistees by estimating the following for the panel of average county-level ASVAB scores in each category, county-by-year Promise availability, and other time-varying county controls:

[8] A modified Breusch-Pagan test described by Solon et al. (2015) indicates that there is significant heteroskedasticity attributed to variation in county size.

$$a_{kct} = \nu_c + \lambda_t + \beta_1 Promise_{ct} + \boldsymbol{\beta_n X_{ct}} + \varepsilon_{kct} \quad (2)$$

Equation (2) differs from Equation (1) in that a_{kct} is the average ASVAB score in category *k* in county *c* in year *t.* Again, we allow for clustered errors at the county level, and we weight by county population.

As a two-way fixed effects estimation of a staggered-entry program, results are vulnerable to dynamic treatment effect heterogeneity, i.e., the possibility that early-entry counties like Knox may serve as bad controls for late-entry counties (Goodman-Bacon, 2021). In this application, we find that identification is dominated by comparisons between treated counties in Tennessee and counties that were not treated in the sample window. Specifically, a Nichols et al. (2019) decomposition shows that 99% of Equation (1) estimates for β_1 derive from two-by-two, difference-in-differences comparisons between Tennessee counties that were treated with Promise and untreated, out-of-state counties.

3.5.3 Enlistment and ASVAB results

Table 3-2 lists estimates from Equation (1), which estimates the effect of Promise availability on a county's number of new enlistees, by branch. We find that Promise is linked to 8.67 fewer enlistees summed across all branches, which is about 28% of the mean volume of new enlistees. This nearly 9-person drop is significant with over 95% confidence. Army, Navy, and Coast Guard enlistments fell by about 5, 3, and 0.62 respectively when Promise was introduced in a county, and all these estimates are statistically significant at the 95% level. Estimated effects are smaller and statistically insignificant for new enlistment into the Air Force and Marines. These findings are consistent with the hypothesis that enlistment and college enrollment are substitutes for high school graduates because a perceived decrease in the price of

college enrollment appears to be followed by a drop in the volume of new enlistees. Coefficients on other control variables suggest that growth in a county's median income is associated with a significantly lower volume of new enlistees, and that higher unemployment rates weakly or insignificantly increase enlistments.

ASVAB results from model (2) in Table 3-3 can give us a sense of how the composition of new enlistees changed after the introduction of Promise. Since the volume of accepted applicants decreased with free community college, we may see shifts in ASVAB performance that reflect differences in aptitude between students who chose college over the military because of Promise, and those whose decision to join the military was not swayed by Promise.

The results show that the average overall ASVAB score for new enlistees increased by 0.42 points, or 0.8% of the mean and 15.8% of the standard deviation, after Promise. The AFQT sections that determine eligibility to enlist changed very little. Scores for Arithmetic Reasoning declined by 0.41 points after Promise (13.8% of a standard deviation), while scores for Word Knowledge, Paragraph Comprehension, and Mathematical Knowledge increased by small and statistically insignificant amounts[9]. Arithmetic Reasoning subtests include short mathematical word problems, whereas Mathematical Knowledge subtests have high school-level problems that are more formulaic than applied. Post-Promise enlistees were slightly less adept at solving word problems and insignificantly different in formulaic math, possibly indicating a subtle shift toward more technical and more advanced math proficiency. Post-Promise enlistees were also stronger in Automotive and Shop subtests, by 0.38 points (8.7% of a standard deviation), coding, by 0.29 points (7.7% of a standard deviation), and they scored 3.38 points higher on the subtest

[9] Mathematical Knowledge and Paragraph Comprehension were significant at the 90% level

for Mechanical Comprehension (26.6% of a standard deviation). Altogether, ASVAB subject results suggest that among the students who found themselves on the margin between enlisting in the military or enrolling directly in college (and whose AFQT scores would have qualified them for the military), Promise encouraged less technically adept students to enroll in college. This could have resulted in enlistee cohorts that were relatively more knowledgeable about automotive and mechanical systems, similar to pre-Promise cohorts in terms of qualifying AFQT scores, and thus somewhat higher-scoring on the overall ASVAB.

Appendix tables 3-5 – 3-6 and 3-8 – 3-9 report Equation (1) and (2) results for the narrower Southeastern sample and the broader U.S. sample. Other states in the Southeast may be more similar to Tennessee in terms of postsecondary and labor counterfactuals after high school, whereas the U.S. sample may afford more degrees of freedom and more precise estimates. The sign, significance, and magnitude of the results are similar across different samples. Estimated enlistment declines are larger when we narrow our focus to the Southeast (Table 3-5) as well as when we broaden the sample to include states outside of the South (Table 3-8). ASVAB results for the Southeast and U.S. samples are consistent with what we report in Table 2, in that post-Promise new recruits are relatively stronger in Automotive and Mechanical knowledge and weaker in Arithmetic Reasoning.

Applications Results

Table 3-4 shows results from Equation (1) when the dependent variable is changed to investigate overall applications and applications by branch. We find that Promise has no significant effect on overall applications and no significant effect on the applications received in any branch, except the Marine Corps. Interestingly, we find that Promise led to a strong and

significant increase in the initial interest to join the Marine Corps with an average increase of 12.87 applicants per county (37.2% of a standard deviation) significant at the 95% confidence level. While the number of applicants increased, this did not yield any significant change to actual enlistments in the Marine Corps as evidenced by the null findings in the previous analysis.

Since applications do not necessarily reflect intent, it is possible that Promise caused graduating seniors to consider their options for college in ways that differ from previous cohorts that did not have Promise. This is alluded to in the qualitative analysis. If this is the case, it likely explains the increase in military interest, if only to garner more information on whether the education incentives provided by the Department of Defense present a net value greater than the benefits of Promise. Without deviating from the purpose of this paper, it is sufficient to acknowledge that the United States Marine Corps has spent over a century perfecting the image of the Marine as someone who is almost super-human—the elite fighter with no equal (Venable, 2019). Because of their marketing success, it is not unreasonable to see that significant changes in interest would be reflected in the Marine Corps application numbers.

Promise's overall null effect in enlistment applications coupled with the findings that actual enlistments decrease echoes the findings of the qualitative analysis. While interest in the Armed Forces as a means to pay for higher education is not decreased as a result of free community college, and actually appears to increase in the Marine Corps, would-be recruits appear to substitute military enlistment with Promise at a highly significant level. This finding indicates that, on the margin, young people still consider military membership but ultimately withdraw when Promise is available. Promise in and of itself does not offer a net benefit strong

enough to eliminate consideration of the Armed Forces, but the substitution effect is strong enough to prevent potential recruits from obligating themselves to military service.

Tables 3-4 and 3-10 report Equation (1) for applications in the Southeastern sample and the broader U.S. sample. The sign, significance, and magnitude of the results are similar across different samples. In all samples, Promise had no significant effect on applications overall, yet had a positive effect on Marine Corps applications, however this positive effect was only significant at the 90% confidence level in the Southeastern sample.

3.6 Conclusion

Our quantitative analysis suggests that the 2009-2015 expansion of last-dollar free community college from one county in Tennessee to the state reduced new military enlistments among under-21 individuals. Overall enlistments declined by about 8.67 recruits per county each year, which was largely accounted for by declines in Army and Navy recruits Our analysis of enlistees' average ASVAB scores suggests that the composition of enlistees, and perhaps applicants, changed when high school students were eligible for Promise. Enlistee aptitude shifted to favor mechanical and applied knowledge, perhaps because students with these skills were less interested in and less affected by tuition-free community college. We also find that Promise had no significant effect on overall applications to the Armed Forces, however applications to the Marine Corps increased significantly. This indicates that graduating high school seniors still consider military service for educational benefits but ultimately substitute Promise for service before joining the military. In ongoing quantitative work, we are studying effects of Promise on changes in the demographic profile of applicants and enlistees, as well as time-varying effects of Promise on enlistment and enlistee cohorts.

Qualitative data collection and analysis sheds light on the mechanisms working at the enrollment-enlistment tradeoff under Promise, as well as the salience of military versus state education grants. In focus groups with first-year Promise scholarship recipients at community and technical colleges across Tennessee, participants described the importance of access to resources to finance their college education in their decision-making processes. Students articulated a reluctance to take on student debt and a preference for grant aid or scholarships to finance their postsecondary education. Participants directly referenced the GI Bill as piquing their interest toward enlistment. However, for some students, access to Promise made college enrollment a more appealing decision. Focus group participants noted that their considerations regarding enlistment changed when Tennessee committed to pay for community or technical college, in line with the quantitative findings seen in application versus enlistment data. Access to Promise allowed them to enroll in college directly rather than serve in the military prior to or concurrent with their pursuit of a college degree.

While state funded community college is great for prospective students, these findings indicate that the Department of Defense cannot be content with "business as usual". This new source of competition for post-secondary education benefits threatens the greatest recruiting tool in America's all volunteer force. The Department of Defense needs to study this issue carefully and recalibrate their benefits package to maintain the comparative advantage that brings young adults into military service. Interestingly, the PGIB benefits are still far superior to what is offered in tnPromise in terms of monetary entitle and college choice, however the evidence indicates that many would be recruits are still substituting away from the PGIB benefits. This

may indicate that the solution is not “more money” as full tuition for four years plus a generous tax-free living stipend is not enough.

It is possible that direct monetary compensation in conjunction with the GI Bill could be enough to mitigate the loss of recruits, but the different military branches have often used “enlistment bonuses” to incentivize enlistment and it is unclear whether this is enough to prevent the decreases in enlistment due to Promise without further investigation. Whether the next-generation package of benefits includes more direct financial compensation or some other form of non-monetary compensation, it is clear that the Department of Defense cannot ignore the reality that society’s demand for state or federally funded college programs is direct competition to their most powerful recruiting over the last 75 years.

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Appendices

Appendix A: Analysis of All Ages

We extend the previous analysis to investigate the effect of Promise on enlistments, ASVAB, and applications regardless of age. While Promise directly affects traditional high-school aged cohorts with free community college or technical training, we believe that the overall effect on enlistments could be higher. Though the effect of Promise on the overall labor market is outside the scope of this paper, preliminary investigation revealed that the number of employed individuals in a county decreased with the Promise treatment. This phenomenon was significant at the 95% confidence level for both the Southern and broader U.S. regions and was imprecise yet negative in the Southeast region with a p-value of 0.12. While this phenomenon should be investigated more in further research, the decrease in the number of employed within a county indicated that Promise may have effects on enlistment through secondary causes as well. It is plausible that Promise creates opportunities in the local labor market when graduating seniors pursue college in lieu of employment. This is one of the fundamental trade-offs of the "three Es." As local employment opportunities become available, older adults not directly affected by Promise may choose to take employment in their local area versus enlisting in the Armed Forces—another fundamental trade-off of the "three Es." It is important to note that this secondary cause is purely speculative in nature.

When conducting the analysis on enlistments for all ages we find that Promise is linked to 19.50 fewer enlistees summed across all branches, which is about 44% of the mean volume of new enlistees. The overall magnitude is nearly double the effect when analyzing the enlistments of under 21's only and the ratio of the mean volume of new enlistees is over 1.5 times greater.

This nearly 20-person drop is significant with over 99% confidence. Army, Navy, and Coast Guard enlistments fell by about 6.5, 9.2, and 0.98 respectively when Promise was introduced in a county, with Navy statistically significant at 99% and Army and Coast Guard significant at 90%. Estimated effects remain statistically insignificant for new enlistment into the Air Force and Marine Corps. We previously demonstrated Promise's direct effect on military enlistment; however, these results indicate that Promise has a significant negative effect on military enlistments with age groups that do not qualify for the Promise scholarship. Since the older age groups gain nothing from Promise directly, there is likely an unintended secondary effect that is drawing older adults away from military enlistment. We speculate that this is likely the changes in the labor market, though we cannot know for certain without further analysis.

The effects on ASVAB scores are similar to the under 21 analysis, however results are weaker. The overall increase in ASVAB scores decreases from 0.42 to 0.18 though this is still significant at the 95% confidence level. The decrease in Arithmetic Reasoning is negligible, however changes in Coding scores and Paragraph Comprehension become null. While still significant, the increase in mechanical comprehension was reduced from 3.38 to 2.21. Considering that under 21's comprise the bulk of all enlistments, the evidence indicates that ASVAB composition changes are still being driven by the under 21 enlistees yet the effects are being mollified by the inclusion of older adults that do not benefit from free community college.

The results for applications are unchanged when looking at all ages. The changes in overall applications and applications to the Army, Air Force, Navy, and Coast Guard remain insignificant whereas applications to the Marine Corps increase at the 95% confidence level.

Results for enlistments, ASVAB, and applications are reported in tables 3-11 – 3-13 for the Southern Region, 3-14 – 3-16 for the Southeast, and 3-17 – 3-19 for the greater U.S.

Appendix B: Excerpted Semi-Structured Protocol for Student Focus Groups

Now we're going to roll back the clock even further. Think about yourself at this time last year, or even last fall. We're going to talk about the information you received and tasks you completed before going to college in order to get here.

1. Where did you get information about college while you were in high school?
2. What were the most helpful sources of information when [deciding whether or not to go to college / applying to college / applying for financial aid]?
3. Was there information or a resource that you didn't have access to that would've been helpful?
4. How do you determine which sources of information and support about college and career are trustworthy?
5. Thinking back to when you [applied to college/applied for financial aid/registered for coursework], how was the process similar to how you expected it would be? How was it different?
6. Were there requirements or things that surprised you as you were considering going to college during high school?

Appendix C: Tables

Table 3-1: Description of Focus Group Sample

Sector	Urbanicity	Enrollment	Total Participants	Race/Ethnicity	Gender
Public, 2-year	Suburb: Large	10,000 - 19,999	9	Black/African-American (1); White (8)	Female (6); Male (3)
Public, 2-year	Suburb: Large	5,000 - 9,999	7	Black/African-American (1); Hispanic (1); White (5)	Female (6); Male (1)
Public, 2-year	Rural: Fringe	5,000 - 9,999	2	White (2)	Female (1); Male (1)
Public, Technical	Rural: Fringe	0 - 999	9	White (9)	Female (2); Male (7)
Public, 2-year	City: Small	1,000 - 4,999	3	Black (3)	Female (1); Male (2)
Public, 2-year	City: Small	5,000 - 9,999	9	White (9)	Female (5); Male (4)
Public, Technical	City: Large	1,000 - 4,999	6	Black/African-American (3); White (3)	Female (4); Male (2)
Public, 2-year	City: Large	5,000 - 9,999	6	Black/African-American (3); White (3)	Female (5); Male (1)
Public, 4-year	City: Midsize	10,000 - 19,999	6	Black/African-American (5); White (1)	Female (5); Male (1)
Public, Technical	City: Large	1,000 - 4,999	3	White (3)	Female (1); Male (2)

Note: Institutional sector and urbanicity are derived from IPEDS 2016-2017. Two- and four-year college sizes are derived from IPEDS 2016-2017. Technical college size is derived from THEC 2017 Factbook.

Table 3-2: Estimated Effects of Free Community College on Enlistment

	(1) All New	(2) Army	(3) Navy	(4) AF	(5) Marines	(6) C. Guard
Achieves	-8.67**	-5.17**	-2.92**	-0.18	0.22	-0.62***
	(3.50)	(2.02)	(1.45)	(1.73)	(1.02)	(0.24)
ln(Pop)	230.37***	111.40***	55.41***	34.69***	27.29***	1.60
	(52.95)	(40.25)	(10.30)	(10.69)	(7.14)	(2.15)
ln(Med Inc)	-175.22	-113.11*	-35.37	-16.97	-13.79	4.02
	(107.79)	(62.18)	(23.50)	(12.48)	(12.05)	(2.53)
Unemp	8.40	5.10	1.79	0.73	0.71	0.07
	(6.70)	(3.58)	(1.35)	(0.73)	(0.96)	(0.18)
Poverty	-3.16	-1.87	-0.60	-0.45*	-0.30	0.05
	(2.57)	(1.43)	(0.59)	(0.27)	(0.35)	(0.05)
Intercept	-711.93	-63.05	-246.18	-205.19**	-137.10	-60.41
	(630.51)	(266.94)	(216.21)	(88.62)	(171.98)	(38.38)
Outcome mean	30.66	11.72	6.49	5.49	6.44	0.52
Outcome s.d.	(77.07)	(29.20)	(18.91)	(12.91)	(17.40)	(1.83)
Obs	18425	18425	18425	18425	18425	18425
R^2	0.98	0.96	0.97	0.96	0.98	0.81

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-3: Estimated Effects of Free Community College on ASVAB Scores

	(1) Overall	(2) GenSci	(3) Arith	(4) Word	(5) Para	(6) Num Ops	(7) Coding	(8) Auto	(9) Math	(10) Electronic	(11) Mech
Achieves	0.42***	0.00	-0.41***	0.03	0.12*	0.15	0.29**	0.38***	0.18*	0.08	3.38***
	(0.11)	(0.10)	(0.14)	(0.10)	(0.07)	(0.11)	(0.14)	(0.12)	(0.09)	(0.09)	(0.62)
ln(Pop)	-0.52	-0.06	0.48	-1.27***	-0.08	0.30	-0.60	-2.40***	-1.88***	-0.87***	1.15
	(0.34)	(0.47)	(0.36)	(0.34)	(0.27)	(0.34)	(0.47)	(0.39)	(0.34)	(0.29)	(1.54)
ln(Med Inc)	1.29***	0.70	1.02***	1.18***	0.12	0.73*	0.66	0.49	0.81*	0.81**	6.42***
	(0.34)	(0.48)	(0.38)	(0.37)	(0.37)	(0.38)	(0.43)	(0.46)	(0.45)	(0.35)	(1.47)
Unemp	0.01	-0.01	0.01	-0.01	0.01	0.04***	0.00	0.03*	-0.01	-0.00	0.08
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.06)
Poverty	-0.02**	-0.03**	-0.01	-0.00	0.00	0.01	-0.03**	-0.00	-0.01	-0.00	-0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)
Intercept	44.06***	46.71***	36.16***	53.95***	53.12***	43.08***	51.93***	71.41***	67.50***	54.07***	-37.30*
	(4.84)	(6.54)	(4.99)	(5.26)	(5.04)	(5.58)	(6.79)	(6.24)	(5.91)	(4.78)	(22.50)
Outcome mean	51.10	53.03	52.44	50.73	53.33	54.38	51.77	48.90	53.15	51.83	41.44
Outcome s.d.	(2.65)	(3.43)	(2.96)	(2.89)	(2.59)	(2.61)	(3.78)	(4.38)	(3.77)	(2.59)	(12.70)
Obs	17623	17623	17623	17623	17623	17623	17623	17623	17623	17623	17623
R^2	0.63	0.51	0.50	0.49	0.32	0.44	0.57	0.72	0.58	0.48	0.50

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-4: Estimated Effects of Free Community College on Applications

	(1) Overall Apps	(2) Army	(3) Navy	(4) AF	(5) Marines	(6) C. Guard
Achieves	37.36	14.54	8.20	0.47	12.87**	1.28
	(39.99)	(17.27)	(14.05)	(5.00)	(5.69)	(1.73)
ln(Pop)	-554.16	-249.42	-209.28	-9.98	-75.30	-10.18
	(391.35)	(174.83)	(165.90)	(12.50)	(47.88)	(10.13)
ln(Med Inc)	257.42*	43.52	109.26	33.15**	59.25*	12.25***
	(154.33)	(44.55)	(81.07)	(15.30)	(35.22)	(3.62)
Unemp	-3.18	0.67	-3.05	-0.07	-1.18	0.45
	(5.39)	(1.21)	(3.15)	(1.26)	(0.81)	(0.39)
Poverty	5.86	1.69	2.43	0.03	1.66*	0.04
	(3.70)	(1.07)	(1.70)	(0.43)	(0.88)	(0.13)
Intercept	4491.40	2805.09	1484.28	-155.95	358.44	-0.46
	(3391.97)	(1894.77)	(1249.17)	(244.29)	(379.13)	(116.89)
Outcome mean	89.47	44.06	16.11	14.06	13.64	1.60
Outcome s.d.	(202.02)	(92.62)	(46.94)	(31.72)	(34.52)	(5.57)
Obs	18879	18879	18879	18879	18879	18879
R^2	0.98	0.97	0.95	0.96	0.98	0.84

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-5: Estimated Effects of Free Community College on Enlistment (Southeast States)

	(1) All New	(2) Army	(3) Navy	(4) AF	(5) Marines	(6) C. Guard
Achieves	-11.54***	-6.46***	-2.55*	-0.34	-1.30	-0.89***
	(3.23)	(1.88)	(1.39)	(1.74)	(0.80)	(0.30)
ln(Pop)	226.97***	101.14***	51.69***	25.91***	41.37***	6.85**
	(37.72)	(19.77)	(9.94)	(8.60)	(7.41)	(2.67)
ln(Med Inc)	-48.62**	-49.47**	-9.84	3.31	2.06	5.31
	(20.76)	(19.95)	(7.57)	(4.27)	(7.44)	(3.56)
Unemp	1.53**	1.71***	0.23	0.19	-0.39	-0.20*
	(0.62)	(0.62)	(0.21)	(0.22)	(0.26)	(0.12)
Poverty	0.50	0.35	-0.00	-0.04	0.09	0.10*
	(0.54)	(0.23)	(0.20)	(0.11)	(0.15)	(0.06)
Intercept	-2109.28***	-658.42**	-492.65***	-326.95***	-493.97***	-137.28***
	(484.98)	(263.26)	(132.71)	(120.06)	(106.64)	(46.96)
Obs	9594	9594	9594	9594	9594	9594
R^2	0.98	0.95	0.94	0.92	0.96	0.80

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-6: Estimated Effects of Free Community College on ASVAB Scores (Southeast States)

	(1) Overall	(2) GenSci	(3) Arith	(4) Word	(5) Para	(6) Num Ops	(7) Coding	(8) Auto	(9) Math	(10) Electronic	(11) Mech
Achieves	0.56***	0.11	-0.29**	0.10	0.09	0.23**	0.45***	0.44***	0.20**	0.12	4.10***
	(0.11)	(0.11)	(0.14)	(0.11)	(0.08)	(0.11)	(0.15)	(0.12)	(0.09)	(0.09)	(0.63)
ln(Pop)	-0.87*	-1.68***	-0.58	-1.66***	0.08	0.04	-1.51**	-3.40***	-2.48***	-1.10***	3.56*
	(0.45)	(0.64)	(0.48)	(0.49)	(0.38)	(0.57)	(0.62)	(0.59)	(0.53)	(0.41)	(2.15)
ln(Med Inc)	0.75*	0.34	0.98**	0.66	0.45	0.58	-0.17	0.82	0.35	0.64	2.81
	(0.45)	(0.66)	(0.49)	(0.50)	(0.46)	(0.53)	(0.58)	(0.66)	(0.64)	(0.46)	(1.88)
Unemp	-0.01	-0.02	0.03*	-0.04*	0.00	0.07***	-0.02	-0.01	0.00	-0.02	-0.12
	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.09)
Poverty	-0.01	0.01	0.00	-0.00	-0.00	0.01	-0.01	-0.00	-0.01	-0.00	-0.08
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.05)
Intercept	53.93***	69.44***	48.79***	64.47***	47.83***	47.60***	71.66***	79.85***	79.09***	58.88***	-28.31
	(6.60)	(8.90)	(6.60)	(6.88)	(5.67)	(8.47)	(9.76)	(8.93)	(8.47)	(5.86)	(30.75)
Obs	9366	9366	9366	9366	9366	9366	9366	9366	9366	9366	9366
R^2	0.65	0.54	0.43	0.47	0.33	0.40	0.61	0.74	0.61	0.47	0.48

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-7: Estimated Effects of Free Community College on Applications (Southeast States)

	(1) Overall Apps	(2) Army	(3) Navy	(4) AF	(5) Marines	(6) C. Guard
Achieves	5.60	-3.08	-0.81	0.75	7.77*	0.96
	(27.24)	(10.13)	(8.85)	(5.21)	(4.53)	(1.67)
ln(Pop)	-84.36	18.46	-44.94	-41.02**	-13.87	-2.99
	(91.62)	(43.35)	(37.15)	(18.10)	(18.35)	(6.42)
ln(Med Inc)	123.22	-2.93	39.47	32.96	40.34	13.38**
	(98.63)	(45.94)	(37.88)	(22.57)	(32.26)	(5.46)
Unemp	-4.29	0.42	-2.08	-0.53	-1.39	-0.71**
	(3.14)	(1.63)	(1.37)	(0.62)	(0.93)	(0.29)
Poverty	-0.37	-0.17	-0.28	-0.05	-0.01	0.15
	(1.16)	(0.64)	(0.36)	(0.33)	(0.32)	(0.11)
Intercept	137.10	-4.71	218.62	211.20	-193.70	-94.31
	(1389.91)	(620.25)	(568.70)	(335.97)	(321.52)	(67.76)
Obs	9758	9758	9758	9758	9758	9758
R^2	0.97	0.96	0.92	0.91	0.94	0.88

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-8: Estimated Effect of Free Community College on Enlistment (U.S.)

	(1) All New	(2) Army	(3) Navy	(4) AF	(5) Marines	(6) C. Guard
Achieves	-16.32**	-5.82**	-8.36***	-0.73	-0.99	-0.42**
	(6.36)	(2.82)	(2.58)	(1.66)	(1.43)	(0.20)
ln(Pop)	279.34***	122.54***	78.38***	33.70***	44.02***	0.69
	(67.85)	(36.39)	(24.66)	(9.49)	(13.34)	(1.94)
ln(Med Inc)	-167.33**	-85.91**	-36.84**	-24.16***	-24.26*	3.84*
	(71.27)	(40.22)	(15.96)	(9.36)	(13.94)	(2.10)
Unemp	3.04	2.50	0.22	0.53	-0.26	0.06
	(3.61)	(1.78)	(0.97)	(0.38)	(0.79)	(0.11)
Poverty	-3.24*	-1.51	-0.94*	-0.32	-0.45	-0.02
	(1.89)	(0.99)	(0.57)	(0.20)	(0.31)	(0.04)
Intercept	-1381.29**	-491.29**	-502.69*	-116.90*	-223.21	-47.19
	(677.41)	(237.88)	(273.53)	(68.12)	(172.29)	(32.22)
Obs	38399	38399	38399	38399	38399	38399
R^2	0.98	0.97	0.96	0.97	0.98	0.81

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-9: Estimated Effects of Free Community College on ASVAB Scores (U.S.)

	(1) Overall	(2) GenSci	(3) Arith	(4) Word	(5) Para	(6) Num Ops	(7) Coding	(8) Auto	(9) Math	(10) Electronic	(11) Mech
Achieves	0.37***	0.15	-0.42***	0.06	0.12*	-0.16	0.35***	0.46***	0.27***	0.10	2.80***
	(0.09)	(0.09)	(0.13)	(0.09)	(0.07)	(0.11)	(0.12)	(0.11)	(0.09)	(0.08)	(0.61)
ln(Pop)	-0.75***	0.64*	0.50*	-1.03***	0.05	-1.28***	-0.24	-1.87***	-1.50***	-0.65***	-2.13
	(0.27)	(0.38)	(0.29)	(0.26)	(0.22)	(0.32)	(0.39)	(0.34)	(0.28)	(0.23)	(1.30)
ln(Med Inc)	1.39***	0.66**	1.52***	0.66**	0.24	1.32***	0.92**	1.03***	0.97***	0.52**	6.04***
	(0.27)	(0.33)	(0.31)	(0.27)	(0.25)	(0.39)	(0.38)	(0.35)	(0.32)	(0.24)	(1.26)
Unemp	0.02***	0.01	0.02**	-0.01	0.00	0.00	0.03**	0.04***	0.02	-0.01	0.13**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)
Poverty	-0.01*	-0.02**	0.00	-0.01	0.00	0.03***	-0.02	-0.00	-0.01	-0.01	-0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)
Intercept	46.21***	38.66***	30.48***	57.28***	50.35***	56.17***	44.99***	60.14***	61.75***	54.92***	7.35
	(3.88)	(5.12)	(4.41)	(3.95)	(3.67)	(5.14)	(5.55)	(4.99)	(4.47)	(3.51)	(19.12)
Obs	35521	35521	35521	35521	35521	35521	35521	35521	35521	35521	35521
R^2	0.62	0.51	0.43	0.48	0.28	0.40	0.58	0.75	0.61	0.46	0.50

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-10: Estimated Effects of Free Community College on Applications (U.S.)

	(1) Overall Apps	(2) Army	(3) Navy	(4) AF	(5) Marines	(6) C. Guard
Achieves	49.16	23.59	1.12	6.68	16.16***	1.61
	(38.23)	(16.10)	(11.93)	(6.40)	(5.60)	(1.64)
ln(Pop)	-645.23*	-306.54*	-185.36	-43.82*	-91.93**	-17.58*
	(335.32)	(161.64)	(134.42)	(26.53)	(44.09)	(9.01)
ln(Med Inc)	125.44	30.56	45.07	19.91	17.62	12.30**
	(111.18)	(49.13)	(54.81)	(16.82)	(26.72)	(5.71)
Unemp	-1.47	-0.87	-2.54	1.98	-0.36	0.32
	(4.25)	(1.54)	(1.82)	(1.78)	(0.63)	(0.31)
Poverty	4.28	1.63	1.43	0.22	1.09*	-0.10
	(3.49)	(1.71)	(1.05)	(0.66)	(0.66)	(0.10)
Intercept	7024.18**	3648.53**	1883.36*	385.68	1016.00***	90.60
	(3134.90)	(1686.95)	(1119.15)	(286.00)	(370.19)	(99.58)
Obs	39088	39088	39088	39088	39088	39088
R^2	0.98	0.97	0.96	0.95	0.98	0.84

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-11: Estimated Effect of Free Community College on Enlistment (Southern Census Region-All Ages)

	(1) All New	(2) Army	(3) Navy	(4) AF	(5) Marines	(6) C. Guard
Achieves	-19.50***	-6.52*	-9.20***	-2.15	-0.64	-0.98*
	(4.88)	(3.73)	(2.23)	(2.78)	(1.25)	(0.54)
ln(Pop)	222.55***	82.49***	66.58***	50.67***	19.58**	3.23
	(36.09)	(24.71)	(11.14)	(12.70)	(8.61)	(3.05)
ln(Med Inc)	-223.89*	-146.08**	-49.80*	-24.14	-8.83	4.95*
	(116.80)	(69.90)	(25.94)	(15.42)	(11.19)	(2.98)
Unemp	10.33	6.44	1.55	1.07	1.10	0.17
	(7.30)	(4.19)	(0.97)	(0.94)	(1.10)	(0.25)
Poverty	-3.41	-2.09	-0.67	-0.48	-0.25	0.08
	(2.69)	(1.57)	(0.58)	(0.31)	(0.35)	(0.08)
Intercept	3.20	692.26	-198.63	-309.58**	-92.03	-88.82**
	(989.75)	(561.91)	(243.09)	(124.98)	(186.98)	(40.85)
Obs	18879	18879	18879	18879	18879	18879
R^2	0.98	0.97	0.98	0.97	0.98	0.88

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-12: Estimated Effects of Free Community College on ASVAB Scores (Southern Census Region-All Ages)

	(1) Overall	(2) GenSci	(3) Arith	(4) Word	(5) Para	(6) Num Ops	(7) Coding	(8) Auto	(9) Math	(10) Electronic	(11) Mech
Achieves	0.18**	-0.13	-0.43***	-0.08	0.03	-0.01	0.07	0.18	-0.03	-0.03	2.21***
	(0.08)	(0.08)	(0.12)	(0.12)	(0.07)	(0.09)	(0.13)	(0.11)	(0.11)	(0.09)	(0.38)
ln(Pop)	-0.56*	-0.48	0.65*	-1.46***	-0.32	0.39	-0.91**	-2.74***	-1.81***	-1.09***	2.18**
	(0.30)	(0.43)	(0.34)	(0.35)	(0.25)	(0.29)	(0.39)	(0.37)	(0.34)	(0.31)	(1.09)
ln(Med Inc)	1.01***	0.59	0.81**	1.02***	0.08	0.53	0.58	0.37	0.75*	0.69*	4.67***
	(0.31)	(0.41)	(0.33)	(0.38)	(0.33)	(0.33)	(0.38)	(0.46)	(0.40)	(0.35)	(1.05)
Unemp	0.02**	-0.01	0.02*	-0.00	0.00	0.03**	0.01	0.05***	-0.01	-0.00	0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)
Poverty	-0.02**	-0.03**	-0.02*	-0.01	-0.00	0.01	-0.03**	-0.01	-0.01	-0.01	-0.09**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)
Intercept	48.57***	53.34***	37.00***	59.22***	57.21***	44.28***	57.69***	78.05***	67.97***	59.04***	-28.09*
	(4.56)	(5.92)	(4.67)	(5.71)	(4.66)	(5.30)	(6.33)	(5.99)	(5.61)	(5.20)	(16.19)
Obs	17969	17969	17969	17969	17969	17969	17969	17969	17969	17969	17969
R^2	0.67	0.57	0.57	0.56	0.41	0.54	0.63	0.77	0.64	0.56	0.51

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-13: Estimated Effects of Free Community College on Applications (Southern Census Region-All Ages)

	(1) Overall Apps	(2) Army	(3) Navy	(4) AF	(5) Marines	(6) C. Guard
Achieves	38.12	13.50	7.97	-1.23	15.44**	2.45
	(72.87)	(34.65)	(23.46)	(7.34)	(7.45)	(3.67)
ln(Pop)	-996.02	-522.77*	-329.37	-8.16	-114.99*	-20.73
	(612.90)	(305.04)	(235.43)	(14.89)	(60.53)	(16.84)
ln(Med Inc)	433.84*	123.92	177.82	31.56*	79.26*	21.29***
	(258.25)	(87.66)	(136.23)	(18.88)	(43.52)	(7.82)
Unemp	-6.14	-0.25	-5.57	0.26	-1.29	0.70
	(11.14)	(3.15)	(6.31)	(1.58)	(1.13)	(0.57)
Poverty	8.70	2.87	3.95	-0.07	1.84*	0.12
	(6.29)	(2.13)	(3.00)	(0.57)	(1.02)	(0.25)
Intercept	8252.97	5424.26*	2267.57	-119.47	644.19	36.43
	(5127.10)	(3111.73)	(1553.54)	(283.43)	(489.08)	(181.73)
Obs	18879	18879	18879	18879	18879	18879
R^2	0.97	0.96	0.95	0.97	0.98	0.86

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-14: Estimated Effect of Free Community College on Enlistment (Southeastern States-All Ages)

	(1) All New	(2) Army	(3) Navy	(4) AF	(5) Marines	(6) C. Guard
Achieves	-22.19***	-8.30**	-7.79***	-2.68	-1.89*	-1.52***
	(5.40)	(4.03)	(2.11)	(2.78)	(1.07)	(0.48)
ln(Pop)	258.24***	103.68***	60.04***	47.60***	36.03***	10.88***
	(40.39)	(20.09)	(10.55)	(13.91)	(8.67)	(3.35)
ln(Med Inc)	-85.04**	-70.44**	-25.19*	-1.63	6.40	5.82
	(36.70)	(30.54)	(13.60)	(7.12)	(9.34)	(4.29)
Unemp	2.74**	2.40**	0.40	0.51**	-0.38	-0.18
	(1.08)	(1.04)	(0.30)	(0.24)	(0.33)	(0.14)
Poverty	0.54	0.34	0.05	0.01	0.02	0.11*
	(0.63)	(0.28)	(0.22)	(0.16)	(0.16)	(0.07)
Intercept	-2027.00***	-430.61	-412.35**	-527.28***	-467.54***	-189.22***
	(590.80)	(334.64)	(177.14)	(179.95)	(125.75)	(57.51)
Obs	9758	9758	9758	9758	9758	9758
R^2	0.98	0.96	0.95	0.94	0.97	0.89

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-15: Estimated Effects of Free Community College on ASVAB Scores (Southeastern States-All Ages)

	(1) Overall	(2) GenSci	(3) Arith	(4) Word	(5) Para	(6) Num Ops	(7) Coding	(8) Auto	(9) Math	(10) Electronic	(11) Mech
Achieves	0.31***	0.01	-0.29**	0.00	0.02	0.05	0.24*	0.26**	0.04	0.02	2.70***
	(0.08)	(0.08)	(0.11)	(0.12)	(0.07)	(0.09)	(0.13)	(0.11)	(0.11)	(0.10)	(0.39)
ln(Pop)	-0.75*	-1.65***	-0.33	-1.50***	-0.15	0.05	-1.32**	-3.26***	-2.26***	-1.07**	4.00**
	(0.44)	(0.59)	(0.41)	(0.49)	(0.38)	(0.49)	(0.61)	(0.57)	(0.53)	(0.44)	(1.59)
ln(Med Inc)	0.51	0.26	0.71	0.47	0.18	0.71*	-0.23	0.30	0.28	0.40	1.97
	(0.42)	(0.55)	(0.43)	(0.52)	(0.41)	(0.43)	(0.54)	(0.62)	(0.56)	(0.46)	(1.38)
Unemp	-0.01	-0.03	0.02	-0.04**	-0.00	0.05***	-0.02	0.02	-0.01	-0.03	-0.03
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.07)
Poverty	-0.00	0.01	0.01	-0.01	-0.00	0.02**	0.00	0.00	0.00	-0.01	-0.06
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)
Intercept	55.98***	70.44***	49.38***	65.58***	54.02***	46.17***	70.85***	84.88***	77.72***	61.93***	-21.21
	(6.52)	(8.13)	(6.02)	(7.05)	(5.57)	(7.60)	(9.89)	(8.47)	(8.48)	(6.15)	(22.67)
Obs	9556	9556	9556	9556	9556	9556	9556	9556	9556	9556	9556
R^2	0.71	0.61	0.53	0.55	0.42	0.50	0.67	0.79	0.68	0.55	0.50

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-16: Estimated Effects of Free Community College on Applications (Southeastern States-All Ages)

	(1) Overall Apps	(2) Army	(3) Navy	(4) AF	(5) Marines	(6) C. Guard
Achieves	-4.16	-12.43	-3.43	-0.08	9.67	2.12
	(58.52)	(25.90)	(18.36)	(7.70)	(6.32)	(3.63)
ln(Pop)	-306.06	-92.81	-112.80	-47.93**	-40.58	-11.95
	(195.42)	(95.96)	(71.78)	(24.03)	(25.53)	(12.85)
ln(Med Inc)	226.17	45.18	59.34	37.17	59.41	25.06**
	(146.79)	(79.17)	(56.03)	(29.04)	(39.31)	(11.73)
Unemp	-8.74*	-1.08	-3.29*	-1.31	-1.83	-1.22**
	(4.77)	(2.36)	(1.98)	(0.93)	(1.25)	(0.58)
Poverty	-2.04	-1.42	-0.54	-0.05	-0.24	0.21
	(2.28)	(1.46)	(0.55)	(0.46)	(0.37)	(0.19)
Intercept	2002.68	978.27	888.07	290.66	-54.27	-100.05
	(2616.43)	(1235.60)	(986.10)	(459.60)	(388.16)	(143.55)
Obs	9758	9758	9758	9758	9758	9758
R^2	0.97	0.95	0.92	0.93	0.94	0.90

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-17: Estimated Effect of Free Community College on Enlistment (U.S.-All Ages)

	(1) All New	(2) Army	(3) Navy	(4) AF	(5) Marines	(6) C. Guard
Achieves	-17.95***	-3.05	-11.39***	-1.43	-1.31	-0.76
	(5.12)	(3.44)	(2.64)	(2.46)	(1.64)	(0.51)
ln(Pop)	256.01***	78.10***	85.70***	54.02***	37.90***	0.28
	(47.28)	(21.85)	(21.23)	(12.65)	(14.46)	(2.83)
ln(Med Inc)	-188.09**	-92.70**	-42.65**	-37.88***	-21.45	6.59**
	(78.86)	(46.94)	(17.07)	(12.79)	(14.73)	(3.05)
Unemp	4.52	3.55*	0.22	0.83*	-0.20	0.13
	(4.04)	(2.10)	(1.03)	(0.50)	(1.00)	(0.15)
Poverty	-3.18	-1.50	-0.88*	-0.39	-0.43	0.02
	(1.97)	(1.12)	(0.52)	(0.24)	(0.31)	(0.05)
Intercept	-792.14	162.89	-508.89**	-203.05**	-172.23	-70.87**
	(756.35)	(342.42)	(253.36)	(95.99)	(191.86)	(36.07)
Obs	39131	39131	39131	39131	39131	39131
R^2	0.99	0.98	0.98	0.97	0.98	0.87

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 3-18: Estimated Effects of Free Community College on ASVAB Scores (U.S.-All Ages)

	(1) Overall	(2) GenSci	(3) Arith	(4) Word	(5) Para	(6) Num Ops	(7) Coding	(8) Auto	(9) Math	(10) Electronic	(11) Mech
Achieves	0.15*	0.00	-0.46***	-0.03	0.03	-0.31***	0.12	0.29**	0.08	0.00	1.74***
	(0.08)	(0.08)	(0.12)	(0.12)	(0.06)	(0.09)	(0.13)	(0.11)	(0.11)	(0.09)	(0.40)
ln(Pop)	-0.63**	0.15	0.79***	-1.12***	-0.22	-0.82***	-0.58	-2.27***	-1.58***	-0.81***	0.18
	(0.25)	(0.35)	(0.27)	(0.28)	(0.20)	(0.29)	(0.36)	(0.36)	(0.29)	(0.24)	(0.95)
ln(Med Inc)	1.08***	0.66**	1.30***	0.64**	0.17	1.15***	0.67**	0.65*	0.89***	0.49**	4.16***
	(0.24)	(0.30)	(0.32)	(0.26)	(0.23)	(0.35)	(0.34)	(0.35)	(0.29)	(0.23)	(0.92)
Unemp	0.03***	0.01	0.04***	-0.00	0.00	-0.00	0.03***	0.07***	0.02**	0.00	0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)
Poverty	-0.01**	-0.03***	-0.00	-0.02***	-0.00	0.03***	-0.02*	-0.01	-0.01	-0.02**	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Intercept	48.97***	45.04***	30.01***	59.60***	55.20***	52.29***	52.80***	70.19***	64.23***	58.20***	2.12
	(3.66)	(4.63)	(4.35)	(4.13)	(3.52)	(4.75)	(5.07)	(4.98)	(4.33)	(3.79)	(13.85)
Obs	36249	36249	36249	36249	36249	36249	36249	36249	36249	36249	36249
R^2	0.66	0.58	0.50	0.55	0.38	0.49	0.63	0.78	0.67	0.53	0.49

*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

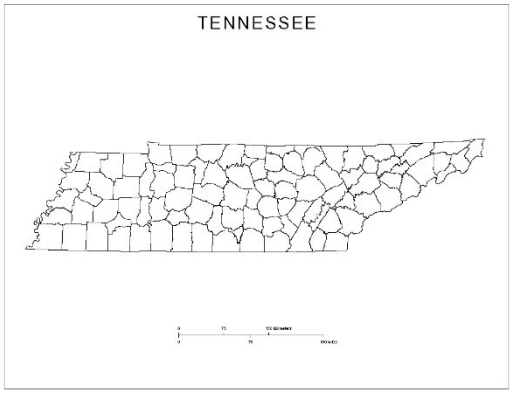
Table 3-19: Estimated Effects of Free Community College on Applications (U.S.-All Ages)

	(1) Overall Apps	(2) Army	(3) Navy	(4) AF	(5) Marines	(6) C. Guard
Achieves	67.79	36.89	1.26	7.51	19.45***	2.68
	(74.63)	(36.79)	(21.70)	(8.96)	(7.32)	(3.56)
ln(Pop)	-1283.32**	-748.72**	-316.59*	-46.32	-137.45**	-34.24**
	(561.98)	(322.30)	(189.37)	(29.45)	(56.93)	(15.11)
ln(Med Inc)	401.94*	229.96	102.34	14.96	33.38	21.30**
	(232.83)	(147.03)	(87.78)	(24.50)	(33.43)	(9.62)
Unemp	-0.99	-0.76	-3.42	3.13	-0.45	0.51
	(7.52)	(2.93)	(3.35)	(2.33)	(0.72)	(0.46)
Poverty	6.31	2.56	2.59	0.07	1.15	-0.06
	(5.90)	(3.24)	(1.90)	(0.80)	(0.78)	(0.19)
Intercept	12078.02**	7036.20**	2911.44**	508.25	1420.17***	201.95
	(4874.51)	(2915.41)	(1443.92)	(311.29)	(466.73)	(155.13)
Obs	39088	39088	39088	39088	39088	39088
R^2	0.97	0.96	0.96	0.96	0.98	0.86

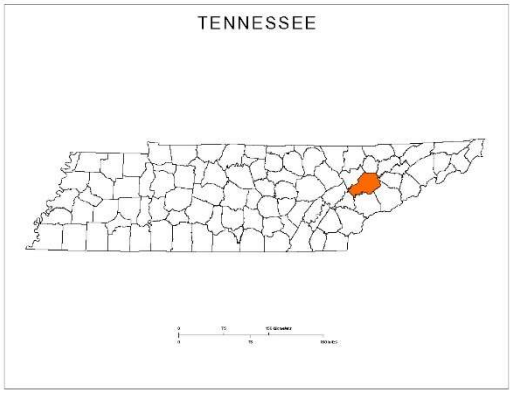
*Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Appendix D: Figures

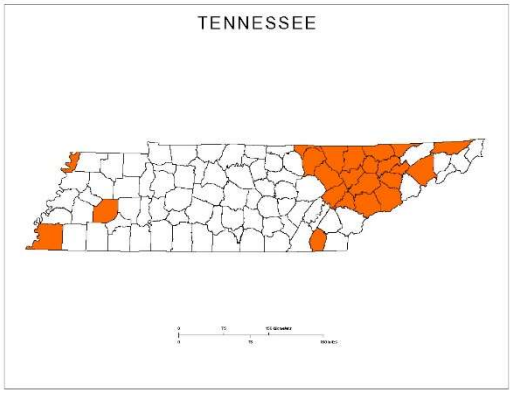
Classes of 2007 and 2008



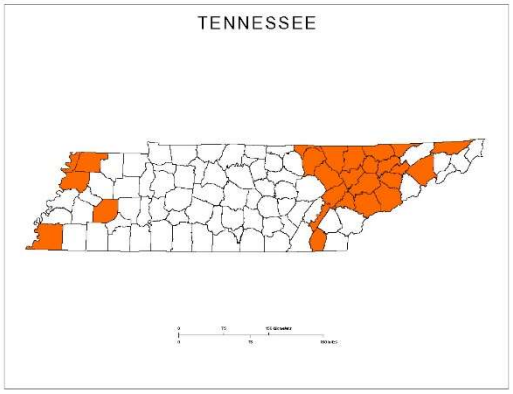
Classes of 2009, 2010, and 2011 (Knox Achieves)



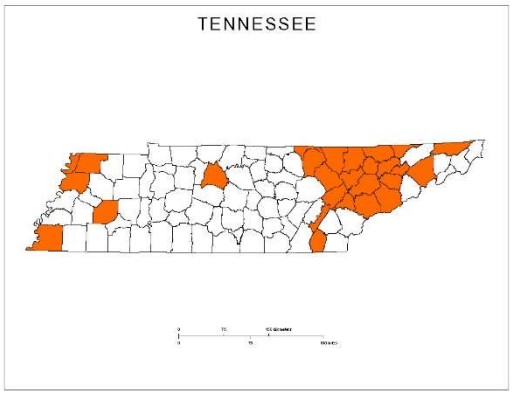
Class of 2012 (tnAchieves)



Class of 2013 (tnAchieves)



Class of 2014 (tnAchieves)



Class of 2015-2017 (Tennessee Promise)

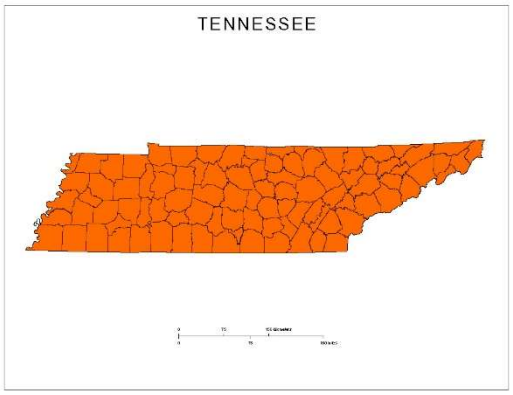


Figure 3-1: Expansion of the Promise Model from 2007-2015

Vita

Michael Brown was born in Boise, Idaho. He enlisted in the Idaho Air National Guard as an intelligence analyst in June 2004. In July 2007 he was accepted to the United States Air Force Academy Preparatory School followed by the United States Air Force Academy where he graduated with a Bachelor of Science in Economics with a minor in Philosophy in 2012. He received his commission as a second lieutenant in the United States Air Force in May 2012 as a finance officer. After a tour at Mountain Home Air Force Base, Idaho, Mike was accepted to the Air Force Institute of Technology where he earned his Master of Science degree in Government Cost Analysis in March 2017. Upon completion of his M.S. degree, Mike was stationed at Hansom Air Force Base, Massachusetts where he served as the Deputy Cost Chief in the E-3 Sentry system program office and Cost Chief of E-3 Foreign Military Sales. He deployed to Kabul, Afghanistan in 2018 – 2019 where he served as the Deputy Chief of Programs and Analysis for the Combined Security Transition Command – Afghanistan (CSTC-A). While deployed, he was selected by the United States Air Force to pursue a Ph.D. in Economics which he is fulfilling at the University of Tennessee, Knoxville. Mike's research interests include experimental and applied econometrics. Mike has been selected to fill a faculty position in the Government Cost Analysis program at the Air Force Institute of Technology.