Gree Gosnell, Robert Metcalfe and John A List

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Greer K. Gosnell
John A. List
Robert Metcalfe

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ABSTRACT

Understanding motivations in the workplace remains of utmost import as economies around the world rely on increases in labor productivity to foster sustainable economic growth. This study makes use of a unique opportunity to “look under the hood” of an organization that critically relies on worker effort and performance. By partnering with Virgin Atlantic Airways on a field experiment that includes over 40,000 unique flights covering an eight-month period, we explore how information and incentives affect captains’ performance. Making use of more than 110,000 captain-level observations, we find that our set of treatments—which include performance information, personal targets, and prosocial incentives—induces captains to improve efficiency in all three key flight areas: pre-flight, in-flight, and post-flight. We estimate that our treatments saved between 266,000-704,000 kg of fuel for the airline over the eight-month experimental period. These savings led to between 838,000-2.22 million kg of CO2 abated at a marginal abatement cost of negative $250 per ton of CO2 (i.e. a $250 savings per ton abated) over the eight-month experimental period. Methodologically, our approach highlights the potential usefulness of moving beyond an experimental design that focuses on short-run substitution effects, and it also suggests a new way to combat firm-level externalities: target workers rather than the firm as a whole.

Greer K. Gosnell
London School of Economics
and Political Science
g.gosnell@lse.ac.uk

John A. List
Department of Economics
University of Chicago
1126 East 59th
Chicago, IL 60637
and NBER
jlist@uchicago.edu

Robert Metcalfe
University of Chicago
Saieh Hall for Economics
5757 S. University Avenue
Chicago IL, 60637
rdmetc@gmail.com

1 Introduction

Many scientists believe that global climate change represents the most pervasive externality of our time (Stern, 2006). Perhaps one of the lowest-hanging fruits in combating climate change is to design firm-level incentive schemes for workers to engage in green behaviors. We are not aware of any studies that have explored incentive aspects within the workplace that pertain to sustainability, whether it is shifting work hours to less energy-intensive times of the day or incenting employees to use fewer resources per unit of output. Given the Environmental Protection Agency estimate that 21 percent of carbon emissions in the United States are from firms (U.S. Enviromental Protection Agency, 2015), there is undoubtedly much to gain. Indeed, when resource use is linked to production costs (as is almost always the case), mitigating the externality has the potential to foster increased profits, providing distinct possibilities of a win-win scenario.

Consider the transportation sector, and in particular air transportation of humans and cargo. The airline industry is a significant contributor to human welfare, with over three billion passengers per year and 35% of the value of world trade transported by air (Federal Aviation Administration, 2015). However, the global aviation industry is directly responsible for significant health costs among vulnerable population groups (Schlenker and Walker, 2015).[1] Moreover, excessive fuel use in the industry affects profits—fuel represents an average 33% of operating costs (Air Transport Action Group, 2014)—and poses a severe risk to the global environment. Emissions from the air transport sector currently account for 3.5-5% of global radiative forcing and 2-3% of global carbon dioxide emissions (Penner et al., 1999; Lee et al., 2009; Burkhardt and Kärcher, 2011), deeming the industry a significant force in climate change discussions.[2] Technology adoption and market-based instruments continue to appear on the industry's agenda as primary means to reach its dual goals of carbon neutral growth by 2020 and halving greenhouse gas emissions from 2005 levels by 2050 (see International Civil Aviation Organization, 2013). Yet, despite large potential to reduce fuel burn from eliminating operational inefficiencies (Green, 2009; Singh and Sharma, 2015), almost

[1] Schlenker and Walker (2015) focus on the effects of network delays in the east coast of the United States on congestion at large airports in California to assess health effects from daily variation in air pollution. These effects are presumed to be generalizable across large airports globally and are a consequence of the aviation industry as a whole.

[2] Past research has shown that the airline industry has also not fully internalized social costs associated with crashes (Borenstein and Zimmerman, 1988). Here we highlight yet another means by which the social cost of the industry is not incorporated into its decision calculus. Nonetheless, demand for air travel is forecasted to increase over the next two decades and, as a result, airline emissions will likely trend upwards (Borenstein, 2011).

no research has been undertaken to understand the potential for cost and emissions savings from changes in the behavior of transport personnel. In fact, we do not know of any research, more generally, on the optimal incentive structure for employees to engage in conservation activities in the workplace.

Our study takes a strong initial step toward such an understanding by partnering with *Virgin Atlantic Airways* (VAA) on a field experiment. We observe over 40,000 unique flights over a 27-month period for the entire population of captains eligible to fly both before and during the experiment.[3] In the aviation industry, airline captains maintain a considerable amount of autonomy when it comes to fuel and flight decisions.[4] We capitalize on recent technological developments that capture detailed flight-level data to measure captains' fuel efficiency across three distinct phases—pre-flight, in-flight, and post-flight.[5] Our pre-flight measure (denoted *Fuel Load*) assesses the accuracy with which captains implement final adjustments to aircraft fuel load given all relevant factors (e.g., weather and aircraft weight). Our in-flight measure (denoted *Efficient Flight*) assesses how fuel-efficiently the captain operates the aircraft between takeoff and landing. Our post-flight measure (denoted *Efficient Taxi*) provides information on how fuel-efficiently the captain operates the aircraft once on the ground.

Our experiment explores the extent to which several experimental treatments—implemented from February 2014 through September 2014—influence captains' behaviors. The treatments are inspired by a simple principal-agent model wherein we attempt to influence the behaviors of VAA captains. Our theoretical model yields predictions on how the act of measurement itself might yield behavioral change, in the spirit of the Hawthorne effects

[3] The "captain"—as opposed to the "first officer"—is the pilot on the aircraft who makes command decisions and is ultimately responsible for the flight's safety. As a rule, captains are the most senior pilots in an airline (see Smith (2013) for insight into captains' roles and responsibilities). In the cockpit of a typical flight from New York to London, there would be one captain and one first officer on board who both engage (more or less equally) in aircraft operations, though the captain is ultimately responsible for all aspects of flight operation. A vast majority of airline captains survive rigorous job market competition to secure their jobs, investing thousands of hours of training (privately or elsewhere) before obtaining the opportunity to be considered for a flying career with a major airline. A handful of VAA captains who were on leave for personal reasons or were fulfilling duties outside of their usual obligations were excluded from the sample.

[4] There has been prior research on understanding the decision making of airline captains under risk, especially through weather conditions (see Gilbey and Hill, 2012; Hunter, 2002; Madhavan and Lacson, 2006; Walmsley and Gilbey, 2016; Wiggins et al., 2012).

[5] The Fuel Efficiency team within *Virgin Atlantic Airways* was responsible for identification of the fuel-efficient behaviors targeted in this study, which represent the outcomes of just a few of the many decisions that a captain engages with during a given flight.

described in Levitt and List (2011).[6] In addition, the model shows how performance information, personal targets, and prosocial incentives for reaching those targets can motivate behavioral change. As such, our experimental design revolves around understanding how the act of measurement and each of these three factors—information about recent fuel efficiency, information including target fuel usage, and prosocial incentives (a donation to the captain's chosen charity conditional on achieving the target efficiency)—affect captains' behaviors from pre-flight to post-flight. We are unaware of any previous research that tests the impacts of targets or prosocial incentives on worker productivity in such a high-stakes professional setting.

Making use of more than 110,000 observations of behavior across 335 captains, we find several interesting insights that have the potential to alter conventional approaches to motivate employee effort in the workplace and to both efficiently reduce operating costs and environmental waste. Perhaps most surprisingly, by simply informing the captains that we—i.e. the academic researchers and VAA Fuel Efficiency personnel overseeing the study—are measuring their behaviors on three dimensions, we are able to considerably reduce fuel inefficiency.[7] For example, captains significantly increased the implementation of Efficient Flight and Efficient Taxi by nearly 50 percent from the pre-experimental period. These behavioral changes generated more than 6.8 million kilograms of fuel saved for the airline over the eight-month experimental period (i.e. $5.37 million in fuel savings), which translated to

[6] Captains were assured on several occasions that their participation in the experiment held no implications or consequences for their salaries or career prospects. For instance, the initial letter sent to all (treatment and control) captains in January 2014 included the following statements (emphasis included): ***"This is not, in any way, shape or form, an attempt to set up a 'fuel league table', or any attempt at moving in the direction of a fuel league table.*** *It is an independent research project to see whether information provided in different ways affects individual decisions. All data gathered during this study will remain* ***anonymous*** *and* ***confidential...*** *Again, we would like to stress that Captains' anonymity will be maintained throughout the study; whilst somebody in Flight Ops Admin has to correlate which Captain gets which letter, Flight Operations Management will have no visibility of which Captain is in which Group, and who is doing what in response to which information. Information will be sent to all Captains in the active study groups. What you choose to do with that information is entirely up to you."*

[7] This pure monitoring effect aligns with agency theory (e.g., Alchian and Demsetz, 1972; Stiglitz, 1975), as well as with experimental results such as those in Boly (2011). These results are also related to the work of Hubbard (2000, 2003), who found that monitoring truckers' performance using GPS technology leads to improved performance for those workers where driver effort is important and where verifying drivers' actions to insurers is valuable. He estimates that such technology has increased capacity utilization by around 3% in the trucking industry. Company policies precluded the designation of an uninformed control group, so estimates of Hawthorne effects are based on before-and-after comparisons, as in Bandiera et al. (2007, 2009). Nonetheless, our results suggest that the data before the experiment was stationary and there was an upward trend once the experiment started (adjusting for seasonality). Importantly, since all information provided to captains in treatment groups is individual-specific, we are able to rule out contamination (i.e. spillover effects of information) as a possible contributor to the change in behavior exhibited by the control group.

more than 21 million kg of CO_2 abated.

Despite these large Hawthorne effects, we find a significant role for our three experimental treatments. Our information treatment increases effort for Efficient Taxi, but does not increase effort for Fuel Load or Efficient Flight. We find, however, that personal targets increase effort for Efficient Flight and Efficient Taxi. Finally, prosocial incentives increase effort across all three dimensions. Furthermore, we find significant differences between information and the two other treatments while we do not detect differential effects between the target and prosocial treatment groups. That is, adding conditional prosocial incentives in the form of a donation to the captain's chosen charity does not provide further lift beyond the effects of a personal target.[8] Yet, there is an interesting effect of prosocial incentives: they induce a reduction in flying time by an average of 1 minute and 30 seconds per flight relative to the control group, equivalent to more than 80 hours of reduced flight time over the eight-month course of the study.[9]

Our difference-in-difference treatment effect estimates indicate that the various interventions increased implementation of fuel-efficient activities by 1-10 percent above the pre-experimental period (i.e. in addition to the Hawthorne effect).[10] Based on these effects, we estimate that our three treatments saved between 266,000-704,000 kg ($209,000-$553,000) of fuel for the airline over the eight-month experimental period. This fuel savings corresponds to 838,000-2,220,000 kg of CO_2 abated. Since the cost of the treatments is merely the cost of postage materials (here, $855 per treatment group), the marginal abatement cost (MAC) of the treatments is minuscule, falling between $1.02 and $0.39 per ton of carbon saved. However, since the airline benefited from significant cost savings via reduced fuel usage as a result of our interventions, the MAC in this context is -$250 per ton in actuality. Such an astonishingly low MAC outperforms every other reported carbon abatement technology of which we are aware (see Enkvist and Rosander, 2007; McKinsey, 2009).[11]

Our experimental design highlights the usefulness of moving beyond short-run effects in

[8] We believe that we are the first to experimentally estimate the impact of an incentive given to a charity if the worker reaches a certain performance target in his or her job. Our notion of prosocial incentives is therefore different to the social incentives presented in Bandiera et al. (2009, 2010).

[9] These results are based on all flights and are presented in Table A7. The total is obtained by multiplying the average effect of captains in the prosocial treatment group relative to control by the number of flights undertaken in the prosocial treatment group during the study period.

[10] Since there were no upward trends before the experiment began—that is, a Dickey-Fuller test indicates that pre-treatment behaviors were stationary—we can be certain that our experiment improved fuel efficiency from business as usual.

[11] The most cost-effective abatement strategy according to McKinsey (2009) is switching residential lighting from incandescent bulbs to LED bulbs at a MAC of approximately -165 Euro, or about -$177.

favor of understanding long-term embedded behavior change. First, in terms of persistence of the treatment effects throughout the experiment, we find that the largest effects for Fuel Load and Efficient Flight arise in the middle months of the experiment, while the treatment effect for Efficient Taxi is consistently high throughout the experiment. Interestingly, across all three treatments, we find the largest effects for the behavior that is the easiest to change (Efficient Taxi). Once the experiment finishes, however, we find that captains' effort reverts to post-experiment baseline levels (i.e. equivalent attainment to the control group once the experiment terminates) for Fuel Load and Efficient Flight, though the treatment effects remain for Efficient Taxi. With regards to the persistence of the Hawthorne effect, the post-experiment baseline remains considerably improved from the pre-experiment baseline, perhaps indicating that monitoring induces captains to make low-effort efficiency improvements that are quickly and easily habituated. A different interpretation to the Hawthorne effect could be that the Captains now learn that the firm values fuel efficiency (which the Captains probably also believe is a good thing). This relates to the work by Bloom and Van Reenen (2007) and Bloom et al. (2014) on the impact of 'soft' management styles and structures on worker productivity.

Finally, our design allows us to demonstrate welfare benefits pertaining to the employees. We find that captains' job satisfaction is positively influenced by prosocial incentives and job performance. Captains in the prosocial treatment group report a job satisfaction rating 6.5% higher than captains in the control group. Moreover, for every additional personal target met by captains receiving targets or prosocial incentives (out of 24 opportunities in total), job satisfaction increases by 1%, on average. Based on this result, we therefore not only encourage airlines to provide captains with performance-based targets to improve fuel efficiency, but also urge them to discover means by which to support captains in reaching said targets in order to improve their well-being.[12]

Our findings are important for academics, businesses, and policymakers alike. For academics, the theory and experimental results hold implications for environmental, behavioral, labor, and public economics. For example, there exist movements within both applied economics ("X-efficiency"; see Leibenstein, 1966) and environmental economics (the "Porter Hypothesis"; see Porter and van der Linde, 1995) arguing that substantial "free gains" exist within firms. The premise is a behavioral one: rather than modeling firms as fully aware and understanding of all extant means to maximize resource efficiency—thereby exhausting all

[12] While we are dubious of using subjective assessments of well-being as precise measurements of welfare, we measured job satisfaction in our survey since it is a metric commonly used in the airline and other industries to assess the well-being of employees.

cost-efficient measures at each moment in time—this approach considers the firm as a composition of networks of boundedly rational individuals burdened by problematic principal-agent incentive conflicts (Leibenstein, 1966; Perelman, 2011). To support this view, a survey of evidence argues that a typical firm operates at 65% to 97% efficiency (Button and Weyman-Jones, 1992), though much of this evidence is based on observational data and does not assess impacts based on a true counterfactual. Our work complements this environmental and behavioral research by moving in a hitherto unconsidered direction: rather than focus on capital improvements or research and development, we explore efficiency effects of incenting labor directly during their normal course of work. For labor economists considering principal-agent settings, our study suggests that allowing the agent flexibility to achieve goals might be a key trigger in enhancing effort profiles.[13]

For businesses and policymakers, we present a novel and promising approach to combating firm-level externalities: design appropriate incentives for workers. More narrowly, the study provides practical and cost-effective fuel solutions for the air transport industry. Our empirical approach lends itself naturally to related tests across other sectors of the economy. By making use of our theoretical framework to guide experimental treatments in the field, businesses and policymakers can learn not only *what* works, but also *why* it works. This understanding will provide decision-makers with a more effective toolkit to advance efficient policies and procedures.

The remainder of our paper is structured as follows. Section 2 provides background, a sketch of the theory, and the experimental design. Section 3 presents the experimental results. Section 4 provides a discussion related to policy implications and related avenues for future research.

2 Background, Theory, and Experimental Design

A few years ago we began discussions with VAA to partner on a field experiment with the aim of understanding behavioral components of fuel usage without adversely affecting

[13] This leads to another unique feature of the study which is that we are not in a typical principal-agent problem in which the principal does not observe effort. Here, the principal has very good measures of effort. Instead, the principal has contractual restrictions (from the union) against contracting on effort (or on output), which is the typical contracting variable in a basic principal-agent model. Instead, the firm is in a "second-best" world of needing to use behavioral incentives instead of financial incentives.

safety practices or job satisfaction.[14] We developed a theoretical framework and a field experiment (detailed further below) that allow us to remain within institutional constraints while maintaining the integrity of lending theoretical insights to the experimental data. We were permitted to provide monthly tailored feedback to 335 airline captains—the entire eligible captain population of VAA—from February 2014-September 2014. Importantly, *all* eligible VAA captains were included in the experiment—in either control or treatment. VAA captains have absolute authority to make all fuel decisions. They range in experience and fly long-haul flights on various aircraft types (Airbus 330-300, Airbus 340-300, Airbus 340-600, Boeing 744-400, Boeing 787-9). We include a map of destinations in Figure 1.[15]

While many of the captains' choices are important in terms of fuel efficiency outcomes, VAA identified three primary measurable levers to change behavior for the purpose of this study. The first lever is a pre-flight consideration, which VAA denotes as Zero Fuel Weight (ZFW) adjustment. Approximately 90 minutes before each flight, captains utilize flight-specific flight plan information (e.g., expected fuel usage, weather, and aircraft weight) in conjunction with their own professional judgment to determine initial fuel uptake, which usually corresponds to approximately 90% of the anticipated fuel necessary for the flight. This amount is fueled into the aircraft simultaneous to the loading of passengers and cargo. Near to completion of passenger boarding and cargo/baggage loading, the pilots—now on the flight deck—receive updated information regarding the final weight of the aircraft and may adjust the fuel on the aircraft accordingly. The information they receive from Flight Operations includes a ZFW measure, which indicates the weight of the aircraft with the revenue load (i.e. passengers and cargo), as well as the Takeoff Weight (TOW), which includes both revenue load and fuel.

Captains then perform a ZFW calculation in which they first calculate the amount by which they should increase or decrease fuel load based on the final ZFW—a formula that is standard across the airline industry. If they have chosen to increase the fuel load, they subsequently compute a second iteration to account for the additional fuel necessary to carry the fuel that they have chosen to add to the aircraft. If the amount of fuel already on the aircraft is sufficient according to these calculations, the captain may choose not to add any additional fuel.

[14] The study is a component of Change is in the Air, VAA's wider sustainability initiative focused primarily on fuel and carbon reduction (see http://www.virgin-atlantic.com/content/dam/VAA/Documents/sustainabilitypdf/SustainabilityPolicy201407.05.14.pd).

[15] All operations to Aberdeen and Edinburgh are VAA Little Red operations (i.e. branded VAA flights operated by a third party) and were excluded from the analysis. In April 2015, VAA removed its service to Cape Town; this route change took place subsequent to the period covered in our dataset.

For mnemonic purposes, rather than use ZFW we denote this binary outcome variable as Fuel Load. Fuel Load indicates whether this double iteration has been performed and the fuel level adjusted accordingly. We deem the captains' behavior as successful if their final fuel load is within 200 kg of the "correct" amount of fuel as dictated by the calculation. This allowance prevents penalizing captains for rounding and slight over- or under-fuelling on the part of the fueller while providing measurable targets for captains in two of our treatment groups.[16] According to our partner airline, accurate Fuel Load adjustment should ideally be performed on every flight regardless of circumstances, which would correspond to 100% attainment for the performance metric provided.

The second lever is an in-flight consideration: Efficient Flight. The Efficient Flight metric captures whether captains (and their co-pilots) use less fuel during flight than is allotted in the updated flight plan.[17] We use this metric to understand whether captains have made fuel-efficient choices between takeoff and landing. This measure incorporates several in-flight behaviors that augment fuel efficiency, such as requesting and executing optimal altitudes and shortcuts from air traffic control, maintaining ideal speeds, optimally adjusting to en route weather updates, and ensuring efficient aerodynamic arrangements with respect to flap settings as well as takeoff and landing gear. We decided on Efficient Flight to measure in-flight efficiency since it is the only measure considered that affords captains the flexibility to achieve the target while using professional judgment to ensure that safety remains the first priority. Under some uncommon circumstances, operational requirements dictate that captains sacrifice fuel efficiency (and VAA accepts the captains' decisions as final), so we would not expect even a "model" captain to perform this metric on 100% of flights, though the metric should be attainable on a vast majority of flights. In our analysis, Efficient Flight equals 1 if the captain does not exceed the projected fuel use for that flight (adjusted for actual TOW), and 0 otherwise.[18]

VAA's final lever—reduced-engine taxi-in (Efficient Taxi or Efficient Taxiing, hereafter)—

[16] Sustainable Aviation (2012, hereafter "SA") estimates that more accurate fuel-loading can save approximately 0.5% of total fuel burn; with average fuel consumption per flight of 69,500 kg, the corresponding fuel savings is approximately 350 kg fuel per flight. SA is an alliance of UK airlines, airports, aerospace manufacturers, and air navigation service providers with the long-term objective of reducing air and noise pollution. Using data from its 2014 sectors, our partner airline estimated an average fuel savings of 250 kg per sector for correct Fuel Load calculations. Ryerson et al. (2015) attempt to estimate the excess fuel burned for an anonymous airline by too much fuel being loaded onto the plane.

[17] The flight plan is updated subsequent to decisions made on Fuel Load so that decisions regarding the first metric do not affect one's ability to meet this in-flight metric.

[18] We created binary variables for Fuel Load and Efficient Flight so we could assign targets to captains in the targets and prosocial incentives group.

occurs post-flight. Once the aircraft has landed and the engines have cooled, captains may choose to shut down one (or two, in a four-engine aircraft) of their engines while they taxi to the gate, thereby decreasing fuel burn per minute spent taxiing. Captains meet the criteria for this metric if they shut down (at least) one engine during taxi in.[19] As with Efficient Flight, there are circumstances under which the airline would not expect or prescribe the implementation of Efficient Taxi. Obstacles include geographical constraints (e.g., the placement or layout of the runway) and the complexity of the taxi route (e.g., number of stops, turns, or cul-de-sacs). Still, the metric should also be attainable on a vast majority of flights, and obstacles to implementation are uncorrelated with treatment.

Fuel Load, Efficient Flight, and Efficient Taxi are the three primary outcome variables in our experiment. It is important to recognize that fuel is a major cost to airlines—accounting for roughly 33 percent[20] of total operating costs—and has been rising over the last fifteen years (Borenstein, 2011; International Air Transport Association, 2014). For this reason airlines are interested in cost-effective means to reduce fuel burn per flight. Given their renowned expertise and experience in the industry, however, airline captains are granted significant autonomy in their decision-making across several fuel-relevant behaviors, including those described above. Moreover, airline captains are unionized so it is contractually difficult to use performance-related pay to motivate fuel efficiency.[21] As such, we focus on airline captains' behavioral adjustments to reduce fuel usage.

Theoretical Sketch of Captains' Behavior

We model an airline captain's choices using a static game of a principal-agent model that determines a captain's chosen effort in a given period (for parsimony, we briefly sketch the model here and provide details in Appendix II). The tasks consist of the aforementioned pre-flight to post-flight fuel usage metrics. Captains observe their own effort and a signal of fuel usage; the signal is noisy unless the captain receives information. Captain's perspectives on fuel usage and their fuel-relevant decisions are rooted in their own experiences and preferences and are conditional on contextual (i.e. flight- and day-specific) factors.

[19] SA estimates that this practice—in conjunction with reduction in auxiliary power use substitution—prevents the emissions of 100,000 metric tons of CO_2 annually. Fuel savings from Efficient Taxi depend on scheduling and delays as savings are accrued on a per-minute basis. Fuel savings also depend on aircraft type and only begin to accrue after engines have cooled, which takes 2-5 minutes from touch down. Savings per minute for aircraft operated within our study are as follows: 12.5 kg (B744, A330), 8.75 kg (A346), and 6.25 kg (A343).

[20] For the airline represented in this study, fuel accounts for 35% of operating costs.

[21] For a discussion of how unionization can affect the long-run outcomes of firms, see Lee and Mas (2012).

Captains choose how much effort to exert to maximize a utility function that includes utility from wealth, job performance, and charitable giving, as well as disutility from effort exertion and social pressure. The model has the standard prediction from the first order conditions that the captain will expand effort until its marginal cost equals the marginal utility gained from the associated decrease in fuel usage. This prediction occurs on several dimensions, such as utility from job performance, utility from giving to a charity, as well as disutility from social pressure (a la DellaVigna et al. (2012)).

Although our base model follows DellaVigna et al. (2012), we extend the model to incorporate a reference-dependent component to capture the effects of exogenous targets. In line with existing theories of reference dependence, we posit that a change in one's personal expectations from the status quo to an improved outcome can boost performance and, consequently, utility. We therefore introduce feedback to employees providing non-binding targets—i.e. focal points for attainment of the three fuel-relevant behaviors—that encapsulate reference-dependent preferences.[22] We expect utility from job satisfaction to increase for those who meet their targets. As in the Köszegi and Rabin (2006) model of reference-dependent preferences, we assume individuals are loss averse and, as such, performing below the target level will cause more disutility than exceeding the target level will benefit the individual.

The notion that prosocial incentives can motivate behavior change is rooted in theories of pure and impure altruism (Becker, 1974; Andreoni, 1989, 1990). Pure altruism requires that individuals derive utility from the benefits they directly receive from the provision of a public good. Impure altruism posits that individuals gain utility from the act of giving itself, so that an individual whose altruism is completely impure will provide the same dollar value toward the public good regardless of the provision of others. Both pure and impure altruism provide positive utility to (altruistic) economic agents, and we assume that individuals are characterized by some combination of the two (we do not attempt to distinguish

[22]There is a rich psychology literature on goal setting. Heath et al. (1999) present evidence that goals act as reference points inducing loss aversion and diminishing sensitivity in a manner consistent with Prospect Theory. Additionally, Locke and Latham (2006, p. 265) argue that psychology studies show that "specific, high (hard) goals lead to a higher level of task performance than do easy goals or vague, abstract goals such as the exhortation to 'do one's best."' According to this line of research, there are four factors that determine the effectiveness of the target, namely feedback (which people need in order to track their progress); commitment to the goal (which is enhanced by self-efficacy and viewing the goal as important); task complexity (to the extent that task knowledge is harder to acquire on complex tasks); and situational constraints. Clearly, within our experiment, we provide feedback on a monthly basis, though the experiment is characterized by individual-level differences in task complexity, absence of prior commitments, and a very high-stakes context. Psychology studies do not exist that address the complex and high-stake field environment in which our experiment takes place.

between them in our experiment). This characterization provides a prediction that altruistic motivations combined with charitable incentives will augment fuel efficiency.

In equilibrium, captains choose the corresponding effort level that satisfies the first order conditions. These choices lead to several propositions.[23] First, if social pressure is important, then captains in the control group will improve their fuel efficiency due to the enhanced scrutiny of their fuel usage. Second, providing information to captains will cause them to increase (weakly decrease) their effort if estimated fuel usage is lower (higher) than their actual fuel usage. The intuition is that the relationship between captains' estimated fuel usage and their actual fuel usage importantly determines their utility from job satisfaction. For example, informing captains that they are fuel inefficient will induce captains to exert greater effort if they derive disutility from consuming more fuel than their estimated usage. Alternatively, if their fuel usage is deemed lower than their estimated usage, they might exert less effort since effort is costly.

Third, targets set above pre-study fuel use will cause captains to weakly increase their effort.[24] Captains will increase their effort if the marginal gain from the associated decrease in fuel usage due to the target is greater than the marginal cost of effort. Alternatively, captains will not increase their effort if the marginal cost of effort is larger than the marginal gain from the associated decrease in fuel usage in the job satisfaction parameter. Fourth, conditional donations to charity will increase effort if captains' altruism is strictly positive and will not affect their effort otherwise. Fifth, of the three dimensions to lower fuel usage—pre-flight, in-flight, and post-flight—captains will choose to increase their effort the most in tasks for which the targets are least costly to meet (i.e. Efficient Taxi).

In light of these predictions, we design a field experiment to measure how behaviors related to fuel usage are affected by: i) information about recent fuel efficiency, ii) information about target fuel efficiency, and iii) a donation to a chosen charity conditional on achieving the target efficiency. To our knowledge, we are the first to perform a large-scale field experiment on firm employees in a real-world extremely high-stakes labor setting (where

[23]These propositions would be the same if we set up the model in the vein of a multi-tasking model.

[24]All targets were set by the firm to improve on the pre-study outcomes, so this is the only case we consider.

the average salary of a captain is roughly \$175,000-\$225,000[25]).[26] In doing so, we overcome prominent labor market frictions in the airline industry by implementing interventions that do not change contracts of the captains.[27] We outline the field experimental design below.

Experimental Design

In accordance with our theoretical model, our field experiment focuses on three main behavioral motivations for optimizing fuel use: impacts of personalized information, performance targets, and prosocial incentives. The three treatments targeted three main behaviors relevant to fuel use: Fuel Load, Efficient Flight, and Efficient Taxi. Respectively, these three behaviors allow us to capture captains' behavior before takeoff, during the flight, and after landing. Airline captains did not receive detailed information relating their decision-making to their fuel efficiency prior to this experiment (consistent with both airline and industry standards). Recent advances in aircraft data collection allow us to obtain precise data to inform captains of the link between their effort and their efficiency.

[25]This salary range is based on information updated in June 2015: http://www.pilotjobsnetwork.com/jobs/Virgin_Atlantic.

[26]There is a growing literature surrounding field labor economics, but most experiments have focused on simple tasks (List and Rasul, 2011; Bandiera et al., 2011; Levitt and Neckermann, 2014). Bandiera et al. (2007, 2009, 2010), using a before and after design within the same company, demonstrate the effects of managerial compensation and social connections in the workplace on worker productivity and selection in the fruit picking industry. Shearer (2004) finds that piece-rate wages improve worker productivity in tree planting relative to fixed-rate wages; Lazear (1999) finds similar incentive effects of piece-rate wages in an observational study of automobile glass installers. Field experiments on the impact of retail store-level tournaments on sales show mixed results (Delfgaauw et al., 2013, 2014, 2015), while a quasi-experiment showed that simply informing warehouse employees of relative wage standing permanently improved productivity (Blanes i Vidal and Nossol, 2011). One exception to such task simplicity is Gibbs et al. (2014), who analyze the effects of a rewards program on innovation at a large Asian technology firm in a field experimental setting. They find that providing rewards for idea acceptance substantially increases the quality of ideas submitted. In an envelope-stuffing experiment, Al-Ubaydli et al. (2015) find that quality is actually *higher* under piece-rate wages (contrary to predictions from economic theory), speculating a role for beliefs about employers' ability to monitor. In an artefactual field experiment with bicycle messengers, Burks et al. (2009) find that performance pay reduces cooperation in a prisoner's dilemma game relative to a flat wage. There has been some research by Rockoff et al. (2012) that demonstrates that simple information on teacher performance to employers can improve productivity in schools, increase turnover for teachers with low performance estimates, and produce small test score improvements. Our study is different to all of these studies since we are the first to randomize targets and prosocial incentives to increase effort on measurable inputs and outputs within the same company in a very high-stakes field setting.

[27]While a standard principal-agent model would prescribe the use of contracted performance-related pay to align captains' fuel use incentives with those of the airline, the airline workforce is a different labor market to most due to the high skill requirements (and often government safety certifications) necessary to enter this particular labor force. See Borenstein and Rose (2007) for a further discussion of the labor market frictions of the aviation industry.

We partnered with VAA's Sustainability and Fuel Efficiency teams to provide accurate monthly feedback to three treatment groups over the course of eight months across 335 captains; a control group did not receive any feedback but was aware that their fuel usage was being monitored.[28] Printed feedback reports with information from the previous month's flights were sent to the home addresses of treated, so that captains received their first feedback report in mid-March 2014 and their final feedback report in mid-October 2014. Our three treatments can be summarized as follows:

Treatment Group 1: Information. Each feedback report details the captain's performance of the three fuel-relevant behaviors for the prior month. Specifically, the feedback presents the percentage of flights flown during the preceding month for which the captain successfully implemented each of the three behaviors. For instance, if a captain flew four flights in the prior month, successfully performing Fuel Load and Efficient Taxi on two of the flights and Efficient Flight on three of the flights, his feedback report would indicate a 50% attainment level for the former behaviors and a 75% attainment level for the latter.

Treatment Group 2: Targets. Captains in this treatment group received the same information outlined above but were additionally encouraged to achieve personalized targets of 25% above their pre-experimental baseline attainment levels for each metric (capped at 90%). The targets were communicated to these captains prior to the start of the experiment. An additional box is included in the feedback report to provide a summary of performance (i.e. total number of targets met). If at least two of the three targets were met, captains were recognized with an injunctive statement ("*Well Done!*") and encouraged to continue to fly efficiently the following month. If fewer than two targets were met, captains were encouraged to fly more efficiently to reach their targets. Captains were not rewarded or recognized in any public or material fashion for their achievements.

Treatment Group 3: Prosocial Incentives. In addition to the information and targets provided to captains in treatment group 2, those in the prosocial treatment group

[28]In keeping with VAA's culture of transparency, carefully crafted study information sheets were posted to captains' home addresses on January 20, 2014. These information sheets guaranteed captains of the anonymity of their data and assured them that the study was not a step in the direction of competitive league tables. Additionally, captains in treatment groups received a notification of their assigned treatment group with a sample feedback form, including the appropriate targets for captains in Treatment Groups 2 and 3, which were posted on January 27, 2014, five days prior to the first day of monitoring. Since participants were aware that they were part of an experiment, our field experiment should be considered a framed field experiment in the parlance of Harrison and List (2004). Yet, unlike any other framed field experiment of which we are aware, we are estimating a parameter devoid of selection since all captains are experimental subjects. In this way, our behavioral parameter of interest shares much with that estimated in a natural field experiment (see Al-Ubaydli and List, 2015).

were informed that achieving their targets resulted in donations to charity. Specifically, for each target achieved in a given month, £10 was donated to a charity of the captains' choice on their behalf.[29] Therefore, captains in this treatment group each had the opportunity to donate £30 ($51) per month for a total of £240 ($400) to their chosen charity over the course of the eight-month trial. Captains were reminded each month of the remaining potential donations that could result from realizing their targets in the future. To our knowledge, ours is the first randomized field study to use performance-based charitable incentives to increase employee effort.[30] Table 1 outlines the treatments (see Appendix III for examples of each of the three feedback reports).

With this type of "build-on" design, our field experiment allows us to assess whether there are additional benefits of prosocial incentives beyond sole provision of information and personal targets, the latter of which have an extremely low marginal cost to the principal.[31] Within our experiment, we did not change any organizational structures or contracts with the airline captains, although we recognize that these could be important to productivity and efficiency.[32] Importantly, our design uses incentive schemes that permit full flexibility for workers to achieve their goals. In this way, rather than mandate or incent a particular course of action, we follow a more adaptable approach that permits gains to be had in accord with the captains' personal and professional discretion.

Further Experimental Details

Randomization. To randomize subjects across the four groups, the pre-experimental

[29]When captains in the prosocial treatment group were informed of their assignment to treatment, they were offered the opportunity to choose one of five diverse charities to support with their charitable incentives: Free the Children, MyClimate, Help for Heroes, Make A Wish UK, and Cancer Research UK. Eighteen captains selected a charity by emailing the designated project email address, and 67 captains who did not actively select a charity were defaulted to donate to Free the Children. Captains could choose to remain anonymous, otherwise exact donations were attributed to each individual (identified by their first initial and last name).

[30]See Imas (2014) and Charness et al. (2014) for lab experiments on the effect of charitable incentives on effort, and Anik et al. (2013) for a field study of unconditional charitable bonuses. Relatedly, field experimental research into unconditional gifts is a burgeoning area of research—see Gneezy and List (2006); Bellemare and Shearer (2009); Hennig-Schmidt et al. (2010); Englmaier and Leider (2012); Kube et al. (2012) and Cohn et al. (2015).

[31]The closest research to this "free lunch" approach is depicted in the field experiments of Grant and Gino (2010); Kosfeld and Neckermann (2011); Bradler et al. (2013); Chandler and Kapelner (2013); Gubler et al. (2013); Ashraf et al. (2014); Ashraf et al. (2014); Kosfeld et al. (2014).

[32]See Nagin et al. (2002); Hamilton et al. (2003); Karlan and Valdivia (2011); Bandiera et al. (2013); Bloom et al. (2013); Karlan et al. (2015); Bloom et al. (2015). Our design is the single firm experimental setting in the insider econometrics approach (Shaw, 2009).

data (September-November, 2013) were first blocked on five dummy variables that captured whether subjects were above or below average for: i) number of engines on aircraft flown, ii) number of flights executed per month, and iii) attainment for the three selected fuel-relevant behaviors. The former two variables were those that proved significant in determining our outcome behaviors in preliminary regressions, while the three target behaviors are our main dependent variables. Once blocked, subjects in each block were randomly allocated to one of the four study groups through a matched quadruplet design. To ensure that individual-specific observable characteristics are balanced across groups, we performed balance tests for gender, seniority, age, trainer status, and whether the captain participated in the selective pre-study focus group. In addition to checking for balance across the variables on which the data were blocked, we checked for balance on flight plan fuel (i.e. as a proxy for average flight distance) and whether captains flew disproportionately on weekends. In short, an exploration of all available aspects of captain and flight data reveals that our randomization was successful in that the observables are balanced across the four experimental conditions (baseline and three treatments; see Table A1 in Appendix I).

Communication with captains. Two weeks prior to the beginning of the study, all captains were informed that VAA would be undertaking a study on fuel efficiency as part of its Change is in the Air sustainability initiative. The initial letter outlined the behaviors to be measured and the possible study groups to which the captains may be assigned. Captains in treatment groups were to receive letters the following week to inform them of what to expect in the coming months. In the final week of January 2014, letters were sent to all treated captains informing them of the intervention to which they had been assigned. The letter included a sample feedback report and contained the individual's targets if he had been assigned to the targets and prosocial groups.

From February 1, 2014 to October 1, 2014, we gathered all flight-level data on a monthly basis for each captain and mailed a feedback report to the home address of each treated captain. Captains were encouraged to engage with the material and send any questions to an email address created specifically for study inquiries. Once the experiment was complete, we sent treated captains a debrief letter informing them of their overall monthly results with respect to their targets (if in the targets or prosocial treatment groups) and their total charitable donations (if in the prosocial incentives treatment group). All (treatment and control) captains were informed that a follow-up survey would be sent to their company email addresses in early 2015.[33]

Sample. Our data consists of the entire eligible universe of VAA captains (n = 335), of which 329 are male and 6 are female. Of the debrief survey respondents, 97 classified their training as military and 102 as civilian (the remaining declined to state). Eleven captains are "trusted pilots" who were selected for consultation regarding study feasibility and communications, and 62 captains are "trainers" who are responsible for updating and training captains and first officers with the latest flight techniques. Captains ranged from 37 to 64 years of age, where the average captain was 52 years old and had been an employee of the airline for over 17 years when the study initiated. Captains in the sample flew five flights per month on average, where the captain flying most averaged almost eight flights per month and the captain flying least averaged just over two flights per month.[34]

The resulting dataset consists of 42,012 flights, and 110,489 observations of behavior from January 2013 through March 2015 for the captains sampled.[35] We exclude domestic and repositioning flights from our analysis. Among other variables, we observe fuel (kg) onboard the aircraft at four discrete points in time: departure from the outbound gate, takeoff, landing, and arrival at the inbound gate. In addition, we observe fuel (kg) passing through each of the aircraft's engines during taxi, which provides a precise measure of fuel burned while on the ground. We also observe flight duration, flight plan variables (i.e. expected fuel use, flight duration, departure destination, and arrival destination), and aircraft type. We control for several flight-level variables—e.g., ports of departure and arrival, weather on departure and arrival, whether the aircraft had just received maintenance (e.g., belly wash, engine change), and aircraft type—as well as captain-level time-varying observables such as current contracted work hours and whether the captain had attended the annual Ops Day

[33]The follow-up survey was designed and administered by the academic researchers alone. Again, captains were assured that data from their responses would be used for research purposes only, that their responses would remain anonymous, and that VAA would not be privy to individual-level information provided by survey respondents.

[34]During the study, Rolls Royce (Controls and Data Services) provided monthly data to VAA. We (the academic researchers) almost always received access to the data within two weeks of the start of the month, and feedback reports were compiled and returned to VAA within 24 hours to be postmarked the following day. VAA subsequently provided post-study data (October 2014 through March 2015) for persistence analysis.

[35]Efficient Taxiing data is physically stored on QAR cards inside the aircraft, which are removed every 2-4 days to pull data. These cards can corrupt or overwrite themselves, and also can reach full memory capacity before being removed. Therefore, data capture for Efficient Taxi is not complete—exactly 37% of flights are missing data for this metric. The reason for the missing data is purely technical and cannot be influenced by captains. We regress an indicator variable of missing Efficient Taxi data on treatment indicators and find no statistically significant relationship at any meaningful level of confidence (individual and joint $p > 0.4$). Consequently, this phenomenon should not affect results beyond reducing the power of estimates.

training.[36]

3 Experimental Results

Table 2 and Figures 2a-2c provide a summary description of captains' behaviors before and during the experimental period. A preliminary insight is that the pre-experimental behavioral outcomes are balanced across various study groups (see balance table in Appendix I, Table A1). For instance, roughly 42% of captain observations had efficient Fuel Load before our experiment started (Table 2, Row 1), and attainment within the experimental groups is approximately 41-43%. Likewise, figures are similar for Efficient Flight (roughly 31%) and Efficient Taxi (roughly 33%). None of the differences across groups are statistically significant at conventional levels.

A second noteworthy insight is the large difference in behaviors before and during the experiment for the control captains, leading to our first formal result:

Result 1. *Captains in the control group change their behavior considerably after they are informed that they are being monitored.*

Preliminary evidence for this result is contained in Column 1 of Table 2. For example, whereas control captains met our Efficient Flight threshold on 31.1% of flights before the experiment, they met the threshold on 47.6% of flights during the experiment ($p < 0.01$). Likewise, for our Efficient Taxi metric, control captains met the threshold for 50.7% of flights during the experiment compared to 35.2% before the experiment ($p < 0.01$). While the results are not economically large for the Fuel Load variable, they again point in the same direction as the other two measures: after the control captains become aware that their actions are being measured, they increase the precision of their fuel load (44.3% versus 42.1% of flight observations; $p < 0.05$). Figures 2a-2c provide a visual summary of this result, and reinforce the substantial difference in captains' behavior once the experiment began.[37]

While these results are certainly consistent with Result 1, we have not yet accounted for the data dependencies that arise from each captain's provision of more than one data point. To control for the panel nature of the data set, we estimate a regression model of the form:

[36] We additionally control for whether each flight was delayed taking off. We find that 19.78% of flights are delayed by 1-15 minutes and 14.95% are delayed more than 15 minutes in our dataset. We run a regression to understand whether a delayed flight predicts the three fuel-related behaviors. We find that being more than 15 minutes delayed increases Efficient Fuel Load by 3%, decreases Efficient Flight by 4.2%, and decreases Efficient Taxi by 2.2%.

[37] Data on pre-experiment trends were largely flat with noise, ruling out that this result is simply revealing a general trend of behaviors over time (see Table A6 of Appendix I).

$$\text{EfficientBehavior}_{it} = \alpha + \text{Exp}_{it} \cdot T_{it}\beta + X_{it}\gamma + \omega_i + e_{it}$$

where $\text{EfficientBehavior}_{it}$ equals one if captain i performed the fuel-efficient activity on flight t, and equals zero otherwise; Exp_{it} describes the experimental period; T_{it} represents a vector with indicator variables for the three treatments; X_{it} is a vector of control variables; and ω_i is a captain fixed effect. We include all available and relevant flight variables as controls, which include weather (temperature and condition) on departure and arrival, number of engines on the aircraft, airports of departure and arrival, engine washes and changes, and airframe washes. Additionally, we control for captains' contracted flying hours and whether the captain has completed training.[38]

We estimate the above model for each of the fuel-efficient activities using panel data from January 2013 through September 2014, and we treat the first day of the experiment as February 1, 2014, when monitoring of captains begins.[39] Three different empirical approaches yield qualitatively similar results: linear probability model (LPM), probit, and logit. For ease of interpretation, we only present the results of the LPM in Table 3.[40] Robust standard errors are clustered at the pilot level. As an alternative, we present Newey-West standard errors for the same model. Furthermore, we estimate an analogous specification in a difference-in-difference framework which is shown in Table 4.

Estimation results of the LPM model are contained in Table 3. Of import here is the coefficient estimate of the interaction between the experimental period ("Expt") and the control group indicator, which provides a measure of how the control group changed behavior over time. We find a staggering effect: the control group increased their implementation of Efficient Flight by 14.4 percentage points (46.3% effect, 0.31 standard deviations (σ), $p < 0.05$) and of Efficient Taxi by 12.5 percentage points (36% effect, 0.26σ, $p < 0.05$).

Figures 3a-3c demonstrate the pre-experimental trends and provide a visual representation of the differences in implementation of the prescribed metrics before and during the experiment. We use the whole 2013 period and January 2014 as before the experiment, and

[38]There are various types of training courses, foremost of which is time spent in the simulator (majority of training) in which captains must pass assessments; we do not have accurate data on these trainings. We instead control for attendance at the two-day "Ops Day" seminar, a gathering of small groups of pilots (approximately 20 per training) for briefing that includes discussion of the goals and directions of the airline and presentations from various teams, with some informal training for pilots.

[39]All results are robust to use of receipt of the first feedback report (March 15, 2014) as our start date.

[40]Results of probit and logit specifications are available upon request.

estimate a trend for the 13 month period. Across both Fuel Load and Efficient Flight, it is clear that there is no upward trend for any group before the experiment started. For Efficient Taxi, we see some slight upward trend, although there is a large increase in the level during the experimental period across all groups. For robustness, we also estimate the specifications in Table 3 with a linear trend—see Table A2. It is clear that including this trend changes the estimates slightly, especially for the Hawthorne effect in Efficient Taxi—the metric drops by 8.7 percentage points. The Hawthorne effect for Fuel Load increases slightly, by 1.5 percentage points. We also analyze different time trends (cubic, polynomial, etc.) and they provide very similar estimates to the linear trend analysis.[41] These insights lend evidence in favor of the Hawthorne effects and are consistent with the importance of social pressure in our theoretical structure.[42] They do not, however, shed light on the effectiveness of the treatments in stimulating fuel-efficient behaviors. Results 2-4 address this central question:

Result 2. *Providing captains with information on previous performance moderately improves their fuel efficiency, particularly with respect to Efficient Taxi.*

Result 3. *The inclusion of personalized targets increases captains' implementation of all three measured behaviors: Fuel Load, Efficient Flight, and Efficient Taxi.*

Result 4. *While captains in the prosocial treatment significantly outperform the control group, adding a charitable component to the intervention does not induce greater effort than personalized targets.*

Preliminary evidence of Result 2 can be found in Table 2 and Figures 2-4, which demonstrate that—despite increased performance in Fuel Load and Efficient Flight—the differences between the information and control groups are rather slight. Yet, there is a considerable change in Efficient Taxi implementation between the information and control groups (58.8% versus 50.7%). Table 4 complements the raw data in Table 2 by presenting the standard difference-in-difference estimates with captain fixed effects, which indicate that the information treatment induces captains to engage in more fuel-efficient taxiing behavior. The

[41] We believe that these analyses are not evidence for the violation of SUTVA, because we assume that the Hawthorne effect we observe would be applied equally across all groups and not just one or two groups separately.

[42] Table A6 presents three separate Dickey-Fuller tests of a unit root in the pre-experimental data for the three behaviors. The tests provide insight as to whether an upward trend in the pre-experimental data might explain our sizable Hawthorne effects. We collapse the four study groups and analyze each of the three behaviors for 51 weeks preceding the captains' notification of the experiment. For each of the measured behaviors, we reject the null hypothesis that the data exhibit a unit root and therefore argue that the metrics were stationary prior to January 2014.

coefficient estimate suggests that the percentage of flights for which captains receiving the information treatment turned off at least one engine while taxiing to the gate increased by 8.1 percentage points ($p < 0.05$) relative to the improvement identified in the control group.

Alternatively, when considering the behavior of captains who receive personalized targets in addition to information on previous performance, we observe consistent treatment effects across all three performance metrics. In Tables 2 and 4 and Figures 2-4, we see rather clearly that the targets treatment moved the metrics for each of the three behaviors in the fuel-saving direction and, as with the information group, the effects also appear to be in the fuel-saving direction for the prosocial treatment. Overall, Table 4 shows that the effects for all three behaviors are statistically significantly different from the control group at conventional levels for nearly every behavior-treatment combination both with clustered and Newey-West standard errors (with a lag of one period). For instance, captains in the targets treatment increased implementation by 3.7 percentage points for Efficient Flight (i.e. a 7.7% treatment effect, 0.074σ, $p < 0.05$). Most striking is the effect of the interventions on the occurrence of Efficient Taxi, which occurred on almost 10 percentage points more flights for those in the targets treatment (19.1% effect, 0.194σ, $p < 0.01$).[43]

Since each treatment builds upon the last—e.g., feedback in the targets group builds upon that in the information group by adding personalized exogenous targets, holding everything else constant—we "control" for the contents of previous treatments and are therefore able to make comparisons across treatments as well. As shown in Table 4, the information treatment appears to have a positive effect on the incidence of fuel-efficient behaviors compared to the control group, though motivating captains with personalized targets is more effective than using information alone. For instance, the information treatment only significantly increases the Efficient Taxi behavior while targets also significantly increase Efficient Flight. Furthermore, magnitude and significance of the point estimates are increased for target captains.

That said, prosocial incentives do not appear to provide substantial additional motivation for behavior change beyond targets, although they improve upon the information treatment. The empirical results across the targets and prosocial treatments in Table 4 and Figures 2-4 are nearly identical. To statistically validate these claims, we pool all captains that receive personalized targets, i.e. target and prosocial treatment groups, and compare the pooled group to the information treatment in an additional regression. We find that receiving tar-

[43] We also include specifications where we control for the quadruplet nature of the randomization. Please see Table A3 for these results. Clearly, these specifications do not significantly change the results.

gets significantly increases fuel-efficient behavior for Efficient Flight ($p < 0.05$) and Efficient Taxi ($p < 0.10$). A similar exercise also confirms that prosocial incentives do not significantly improve behavior compared to targets only. Thus, while information is an important mechanism in encouraging fuel-efficient behavior change, targets add an additional effect that prosocial incentives do not further augment. Therefore, of the interventions provided in the study, the combination of information and targets is the most successful (and cost-effective) treatment.

In sum, the experimental treatments provide behavioral structure to our theoretical model. Recall that the effect of information on effort in the model depends on the realized difference between estimated and actual fuel efficiency. Given that the estimates suggest a move toward fuel efficiency among captains in the information group (especially with respect to Efficient Taxi), we argue that captains' *ex ante* beliefs regarding their fuel efficiency are optimistic; therefore, information moderately encourages increased fuel efficiency. Our model suggests that targets set above the baseline performance should (weakly) increase effort. Consistent with this conjecture, we find that targets improve captains' attainment of all three behaviors.

Furthermore, the model predicts that our prosocial treatment should increase effort if a captain's altruism is strictly positive and should not affect his effort otherwise. Given that the performance of captains in this treatment group does not significantly exceed that of the captains in the targets treatment, we cannot conclude that captains' altruism is strictly positive as measured by our experimental manipulation. Finally, according to the model, captains should allocate effort disproportionately toward the behaviors that require the least effort. We know from interviews with captains and airline personnel that Efficient Taxiing is the least effortful behavior of the three we monitored. Our findings support this notion, as we can clearly conclude that the treatment effect sizes from Efficient Taxiing are significantly larger than the treatment effect sizes for both Fuel Load and Efficient Flight for all three treatment groups.[44]

[44]Note that we are making positive, not normative, statements. For example, in computing welfare effects, one might be concerned with treatment impacts on flight duration and safety. Since there is no variation in safety outcomes (zero incidents or flight diversions due to issues pertaining to fuel), we cannot address this concern, though we do have information on flight duration. For instance, one means to improve the chances of an Efficient Flight is that captains fly at efficient speeds and actively seek shortcuts from Air Traffic Control, which may require that captains accelerate or decelerate relative to their habitual speed levels or fly shorter routes than they would otherwise.

Temporal Effects

Importantly, our data provide the ability to go beyond short-run substitution effects and explore treatment effects in the longer run. In this sub-section, we conduct a more nuanced investigation of the treatment effects by exploring their persistence as the experiment progresses.[45] Upon doing so, we find a fifth result:

Result 5. *We do not observe decay effects of treatment for captains within the experimental time frame.*

To examine the treatment effects over the course of the experiment, we plot the month-by-month treatment effects in Figures 4a-4c. The largest effects relative to the baseline appear to be in May for Fuel Load and Efficient Flight and in April for Efficient Taxi. That is, the treatment effects appear to be strongest around the middle of the study (and not immediately after monitoring begins), with no consistent pattern of decay for any of the three behaviors.

Although our theory does not have a dynamic decay prediction, given the experimental results in Gneezy and List (2006), Lee and Rupp (2007), Hennig-Schmidt et al. (2010), and Allcott and Rogers (2014), we expected that our treatment effect might decay through time. Indeed, our results are more consonant with Hossain and List (2012), who report that their incentives maintained their influence over several weeks for Chinese manufacturing workers. What our environment shares with Hossain and List's is the context of a repeated intervention whereas the other studies that find a decay effect are typically set within one-shot work environments or weaker reputational environments. We conjecture that repeated interaction with subjects serves to habituate the incented behaviors, thereby diminishing susceptibility to decay effects. Accordingly, this insight serves to enhance our understanding of the generalizability of the decay insights provided in this literature to date.

Another interesting temporal feature in our data is the persistence of our treatment effects after the experiment concludes. Upon inspection of the post-experiment data, we find a sixth result:

Result 6. *Treatment effects remain intact for post-flight behavioral adjustments only, though Hawthorne effects remain high and even increase with the passage of time.*

[45] Relatedly, we also explored a measure of salience in our experiment, namely that behavior changed in the week following receipt of the message and reverted to the mean thereafter. We do not find such an effect.

Once again we find preliminary evidence for this result in Table 2. For instance, while control captains met the Efficient Flight metric on 31.1% of flights before the experiment and 47.6% of flights during the experiment, they actually increased their attainment to 54.8% of flights in the six-month period following the experiment's end date. Similarly, control captains turned off at least one engine while taxiing for 54.7% of flights after the experiment, compared to 50.7% of flights during the experiment and 35.2% before the experiment. This post-experiment increase is not present for Fuel Load, but the original boost in implementation remains after the experiment ends.

Further evidence on persistence is summarized in Tables 5 and A4. In Table 5, we again see that the control group captains outperform their own pre-experimental attainment with significance across all three fuel-efficient behaviors, and even more astoundingly so for Efficient Flight and Efficient Taxi. However, this time we notice that there are only subtle differences between the treatment groups and the control group—perhaps apart from the Efficient Taxi metric—indicating that the benefits of receiving consistent feedback on high-effort tasks do not persist once the treatment is removed. We explore this phenomenon further in Table A4 where we compare the treatment groups to the control group in terms of their post-experimental versus pre-experimental attainment levels using a difference-in-difference specification. Findings indicate that there are no significant differences across treatments for Fuel Load and Efficient Flight. However, we still detect significant increases in terms of Efficient Taxi for information ($p < 0.10$), target ($p < 0.01$), and prosocial ($p < 0.01$) treatment groups.

Fuel Savings

Given the substantial treatment effects during the experimental period of the study, we report an economically significant fuel and cost savings:

Result 7. *Our experimental treatments directly led to 704,000 kg in fuel savings and $553,000 in cost savings for our partner airline. These estimates dramatically increase after incorporating the estimated Hawthorne effect.*

To provide support for this result, we present two estimations of fuel saved as a result of the experimental treatments. We are in a unique position to use engineering and data-supported fuel estimates to understand the denoted impact of our interventions on efficiency, and we provide both here given that there are pros and cons to each approach. First, we apply engineering estimates to assess fuel savings without requiring data on actual fuel usage or statistical power to detect differences in fuel use pre- and post-intervention. However, the engineering estimates do not account for *actual* changes to fuel usage as a result of behavior change. While the data-supported estimates do incorporate actual changes to fuel use as a result of the study, the approach is generally one that requires statistical power to detect significant differences in fuel use. Our experimental design was powered to detect differences in fuel-efficient behaviors, not changes in fuel use. As such, we use coefficients that capture average effects of treatments on fuel use without the statistical power to demonstrate significance. As a result, we use both engineering estimates and real-time estimates to provide an approximation of fuel saved and CO_2 emissions abated as a result of the treatment groups. We will also provide the marginal abatement cost of a metric ton ("ton" hereafter) of CO_2 as a result of our treatments.

Engineering estimates: VAA projects an average fuel savings of 250 kg per flight as a result of proper execution of Fuel Load. The 0.7%, 2.1% and 2.5% treatment effects for the information, targets, and prosocial incentives groups (respectively) correspond to an increase in the implementation of Fuel Load by 169 flights (saving 250 kg each flight), equivalent to a savings of 42,250 kg of fuel over an eight-month period. Moreover, VAA estimates that an Efficient Flight uses (at least) 500 kg less fuel than the alternative, on average. Our effect sizes for the three groups were 1.7%, 3.7%, and 4.7% (respectively), which translates to 323 additional "efficient" flights over the eight-month period, or 161,500 kg in fuel savings. Finally, VAA estimates an average fuel wastage of 9 kg per minute if no engines are shut down while taxiing, and the average treatment effects for the three groups were 8.1%, 9.7%, and 8.9%, respectively. Given an average taxi-in time of 8 minutes in our dataset, we approximate fuel savings per flight to be 72 kg. An additional 853 extra flights having met Efficient Taxi corresponds to a fuel savings of 61,400 kg over the eight-month study period.

Summing these savings, our interventions led to just under 266,000 kg of fuel saved over the course of the study. Combining the industry's standard conversion of 3.1497 kg of CO_2 per kg of fuel burned with the February 2014 global jet fuel price of $786 per 1000 kg, we estimate a cost savings of $209,000 and a CO_2 savings of 838,000 kg (i.e. $31,000 environmental savings using $37/ton of CO_2 at 3% discount rate in 2015; Interagency Working Group on Social Cost of Carbon, 2013). Our engineering estimates indicate that targets provide the largest benefits to social and private efficiency in this context. These calculations constitute fuel and cost savings stemming directly from the treatments and do not incorporate the sizable Hawthorne effects, which increase the overall cost savings to

\$1,079,000 and CO_2 savings to 4,324,000 kg. The savings associated with the Hawthorne effects come from 233 more flights having efficient Fuel Load, 1,861 more flights having Efficient Flight, and 1,616 extra more flights having Efficient Taxi.

Data-supported estimates: Our data allow us to estimate actual fuel savings from changes in captains' behavior. We estimate differences in fuel usage from before the experiment to the experimental period and across all groups. In essence, we employ an Intent-to-Treat approach and use average treatment effects from this difference-in-difference regression to calculate average and aggregate fuel savings. For Fuel Load, we measure the deviation of actual fuel load from the "ideal" fuel load—i.e. according to the double iteration calculation. We then compare deviations within each group across the pre-experimental and the experimental periods, taking into account the Hawthorne effect (See Table A5). In other words, we report average fuel savings per group that are the sum of the corresponding average treatment effect and the average change from the pre-experimental to the experimental period for the control group (the Hawthorne effect). In doing so, we assume that the Hawthorne effect is constant across groups. On average, captains in the information group decreased fuel use relative to the ideal by 98.5 kg per flight, those in the targets group by 141.3 kg per flight, and captains in the prosocial group by 159.8 kg per flight.

Similarly, for Efficient Flight, we examine changes in captains' fuel use relative to the "ideal" fuel use, or the anticipated fuel use according to the flight plan (adjusted for updates to ZFW). We find that captains in the information, targets, and prosocial groups reduced in-flight fuel use by 371.9, 451.6, and 419.9 kg per flight, respectively. Finally, for Efficient Taxi, we examine changes to fuel use during taxi-in. Fuel savings per flight amounted to 3.7 to 5.1 kg for the information and targets interventions, while the prosocial group increased fuel use during taxi-in by 5 kg.

As a next step, we take these group-level effects and scale them up by the number of flights per treatment group. Put differently, total savings for a given treatment cell are the sum of the average treatment effect and the average Hawthorne effect multiplied by the number of unique flights during the experimental period. Results from this exercise are presented in Table 6. Standard error calculations are based on Newey-West standard errors (lag=1) in the underlying DiD specifications. In aggregate, our interventions led to roughly 6.83 million kg in fuel savings. Of these savings, about 1.57 million kg were saved in both the control and information group, whereas the targets and prosocial group saved more than 1.8 million kg each. Using the same conversions as above (see Table 7), total savings correspond to cost savings of \$5.37 million (equivalent to a reduction of 0.56% of overall fuel costs) and CO_2 savings of 21.5 million kg. We calculate an approximate MAC for such behavioral interventions, which is negative (since abatement is highly profitable in this context). Specifically, the MAC (assuming costless interventions) is simply the price per ton of jet fuel divided by 3.15 tons CO_2 per ton of fuel. Using the February 2014 jet fuel price of $786 per ton, we calculate an average MAC of -$250.

Interestingly, there are significant differences between the engineering and data-driven estimates from our study, especially for those numbers accounting for Hawthorne effects. The disparity may be attributable to underestimates of average savings from the three behaviors—especially for the Efficient Flight metric—as well as differences in the nature of the estimations. That is, unlike the engineering estimates, the data-driven estimates do not account for differences in percentages of flights for which a behavior was met. Rather, they estimate overall average fuel use changes in the study itself and apply these changes to all flights. Even if we apply the most conservative fuel savings estimates to the changes in behavior, we find that these interventions, especially the target groups, led to remarkable cost-savings and return on investment for the airline. Businesses and policymakers should take note of the potential cost-effectiveness of such behavioral interventions in mitigating prominent global externalities.

Heterogeneity and Captain Welfare

We explore various forms of heterogeneity to determine the drivers of our main results (see Figures 5 and 6 as well as Appendix I). For example, are the results driven by a broad behavioral shift amongst all captains or a handful of captains adjusting completely? Are there certain captain types that are more likely to adjust their behavior? To address the first question, we explore within-captain differences in attainment from the pre-experimental period to the intervention period. To answer the second question, we explore heterogeneity based on social preferences.[46] We then identify the effects of both treatment assignment and performance on captains' self-reported job satisfaction. To assess heterogeneity, we use information on captains provided by VAA and data gathered directly from captains via an

[46] To assess captains' social preferences, we asked two questions regarding individuals' private charitable donations in 2013 and in 2014 outside of the context of the study. Captains indicated their donation behavior by selecting one of ten multiple-choice intervals ranging from Â£0 to Â£200+. In addition, we asked captains to rank their job satisfaction on a seven-point scale. This question allows us to examine whether job performance influences job satisfaction—as we propose in our theory—as well as whether our treatments contribute positively or negatively to captains' well-being.

online debrief survey.[47]

A first result is that the Hawthorne effect is prevalent across captains, as is apparent in Figures 5a-5c. These figures show the change in average attainment of the three behaviors for each control captain. Almost all captains increase their implementation of fuel-efficient behaviors in the experimental period, albeit to varying degrees. Indeed, we find that a majority of captains improve their performance relative to the baseline for Fuel Load (60% of captains), Efficient Flight (89% of captains), and Efficient Taxi (82% of captains). Looking at the raw data (i.e. without controls), the standard deviations around the mean changes in these behaviors are quite large (Fuel Load: $\mu = 0.036$, $\sigma = 0.105$; Efficient Flight: $\mu = 0.170$, $\sigma = 0.123$; Efficient Taxi: $\mu = 0.147$, $\sigma = 0.149$).

Turning to the question of whether the treatment effects are uniform across captains, we construct similar charts that net out the mean change in behavior of the control group (see Figures 6a-6c). In other words, we deduct the means reported above from each captains' average difference in implementation between the pre-experimental and experimental periods. For example, a captain who implemented Efficient Taxi on 50% of flights before the experiment and 75% during the experiment experienced a 25% increase in attainment, but the Hawthorne effect confounds this increase; therefore, we subtract 14.7%—the average difference among captains in the control group—from 25%, so that the net 'effect' on the captain is a 10.3% increase in implementation of Efficient Taxi. Figure 6 displays such within-subject differences in attainment for each of the three measured behaviors across experimental conditions.

There does not appear to be a consistent pattern for Fuel Load and Efficient Flight indicating predictable heterogeneity of treatment effects according to initial attainment levels (although targets appear to elicit some strong behavioral responses in both directions for Fuel Load). However, for Efficient Taxi, relatively low-achieving captains in all three treatment groups appear to outperform similar captains in the control group. Interestingly, for Fuel Load, there is a tendency for the highest-achieving captains to respond negatively to the experiment, perhaps implying a phenomenon akin to "crowding out" of intrinsic motivation. These results are not significant at conventional levels.

[47] Each captain received an email on January 29, 2015 with a link to the study debrief survey, and the survey closed three weeks later. A total of 202 captains at least partially completed the survey and 187 completed it, which represents an impressive 60% (56%) response rate. This response rate was achieved after sending each captain up to three emails within four weeks offering incentives up to Â£105. We find that there are no statistically significant differences in terms of survey behavior across treatment groups (joint F-tests feature $p = 0.69$ and $p = 0.68$ for participation and completion indicators, respectively).

We also examine the impact of social preferences on our treatment effects.[48] Table A8 provides estimates from a regression based on the aforementioned DiD econometric specification with additional triple interactions between the post-treatment indicator variable, each treatment group, and the social preference parameter. As expected, our proxy for social preferences helps to predict whether captains will be influenced by our prosocial treatment. We use self-reported donations to charity in 2013 (i.e. before the study began) as a proxy for "altruism" to determine whether subjects' (perceived) social preferences influence their treatment response, particularly to the prosocial incentive treatment. For the prosocial group, an increase of £10 in past donations increases correct implementation of Fuel Load by approximately 0.5 percentage points, while social preferences have no effect at all on those captains in the Information and Targets treatments. Given that Fuel Load is the most sticky behavior, the increase in implementation by more altruistic captains—who presumably put more weight on donating to charity through the study than less altruistic captains—is consistent with both Propositions 4 and 5 (contained in Appendix II).

Beyond these various heterogeneities—and in an era where captains' well-being is especially central to airlines' and travelers' considerations—one might inquire whether the captains themselves are better off. We only take a first step down this important path by considering captains' job satisfaction. Table A9 presents the intent-to-treat estimates for the effects of being in each treatment group on job satisfaction. The coefficient estimates are positive for all treatments. The largest coefficient estimate indicates a positive and significant effect of prosocial incentives, where captains reported a 0.37 point higher job satisfaction rating than captains in the control group ($p = 0.105$). For context, this difference in self-reported job satisfaction is equivalent to that between an employee with poor health compared to an employee with excellent health (see Clark and Oswald, 1996).

Finally, among the subjects who received personalized targets (i.e. those in the targets and prosocial groups), captains who met more targets over the course of the experiment experience greater job satisfaction (see Table A10). Further investigation of this phenomenon reveals that performance on Efficient Taxi is correlated with this result, increasing job satisfaction by 0.12 points (on an eleven-point scale) per monthly target met. In other words, a captain who met all of his Efficient Taxi targets (out of a possible 24) would rate his overall job satisfaction 3.12 points higher than a captain who did not meet any of his Efficient Taxi

[48] In similar spirit, we also investigate the impact of seniority and airplane type on outcomes of interest. These regressions do not lead to additional insights and are available upon request.

targets.[49] Thus, airlines may wish to seek means in which to assist captains in reaching fuel-efficiency targets for reasons pertaining not only to cost minimization and environmental outcomes, but also to employee well-being.

4 Discussion

The next time you are sitting on an airplane next to a policymaker, ask her what is the best way to combat pollution externalities. We have posed this question repeatedly working alongside Congresswomen, Senators, and policymakers across governmental agencies. The stock answer is "raise taxes", "set up a cap and trade scheme", or "make firms install particular pollution control devices". Not once have we heard: target workers and design incentives for them to produce more sustainably. In this study, we introduce this approach to combating firm-level pollution externalities.

We showcase this approach by implementing a field experiment in a partnership with *Virgin Atlantic Airways*. The overarching goal was to improve the fuel efficiency of their captains without compromising safety or service quality. While our workplace setting is complex with myriad competing incentives at play, clear measurement of captains' behavior enables innovative strategies to provide the right set of interventions to improve employee productivity and firm performance. Based on our principal-agent model, we randomize three interventions to understand the impact on employee performance of basic informational feedback, exogenous targets associated with said information, and prosocial incentives associated with the above targets and information. We find that all three interventions are successful at inducing fuel-efficient behaviors, and that provision of exogenous targets is the most cost-effective intervention. We conclude that our inexpensive strategies are both a feasible and a profitable means to induce airline captains to fly aircraft more efficiently.

Our research speaks to many fields within economics. For example, in labor economics, how best to incent workers to motivate effort in the workplace has been a principal topic of inquiry for decades. The imperfect relationship between employees' effort and productivity renders firms incapable of rewarding effort with precision (Miller, 1992; Lazear, 1999; Malcomson, 1999; Prendergast, 1999). A burgeoning experimental literature on incentives and workplace initiatives attempts to understand the employee-employer relationship and effective means by which employers may increase effort and productivity (see List and Rasul,

[49] One should take care not to provide a structural interpretation of this result since it is garnered from non-experimental variation.

2011; Levitt and Neckermann, 2014). We attempt to advance this literature by understanding the separate impacts of basic information, personalized targets, and prosocial incentives on workplace performance in a high-stakes setting among well-salaried, experienced, and unionized employees. Our setting does not comprise information asymmetry or team production externalities (i.e. there is no undetected shirking), and therefore there is potential to align individual self-interest with firm efficiency.

This research also has clear policy implications with respect to cost-effective greenhouse gas abatement. We find that the marginal abatement cost (MAC) estimated from no- to low-cost behavioral interventions is around -$250 (using 2014 prices). To our knowledge, this MAC is the lowest currently estimated in academic or policy circles. Thus, such "low-hanging fruits" provide complements—and in some cases perhaps even alternatives—to more traditional approaches to pollution control. Future research should aim to identify additional behavioral motivators to improve the efficiency of workers as a means to minimize abatement costs while simultaneously reducing the operation costs of firms in an effort to promote win-win strategies for the economy and the environment.

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5 Figures and Tables

Figure 1
Global Destinations of VAA

Figure 2a
Efficient Fuel, by time period

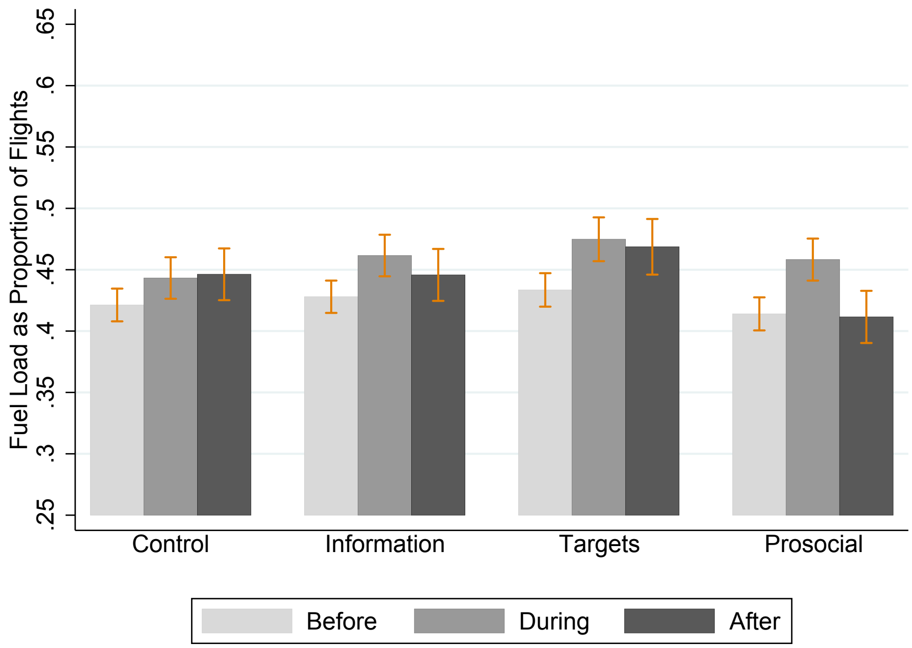


Figure 2b
Efficient Flight, by time period

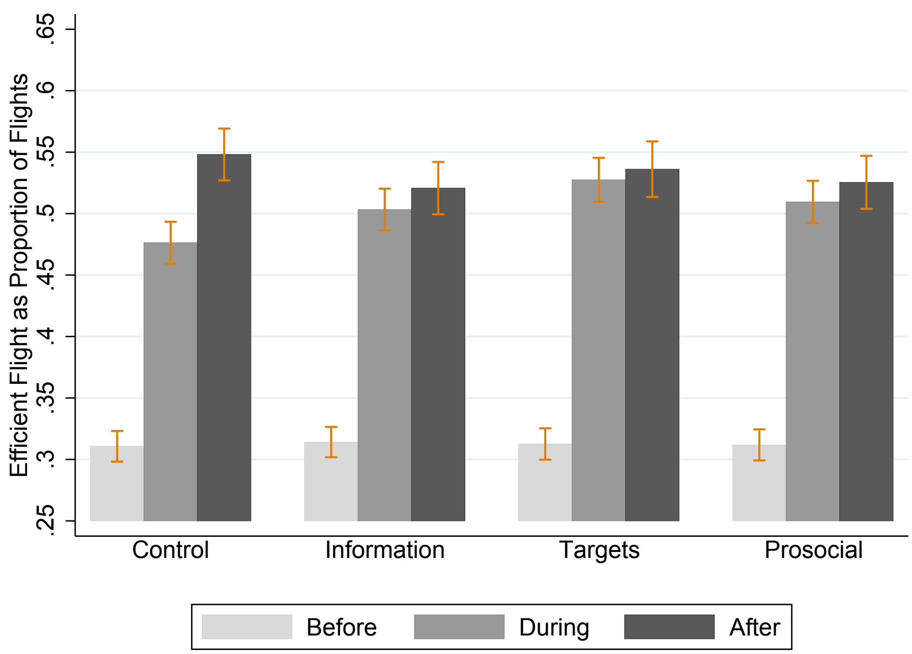


Figure 2c
Efficient Taxi, by time period

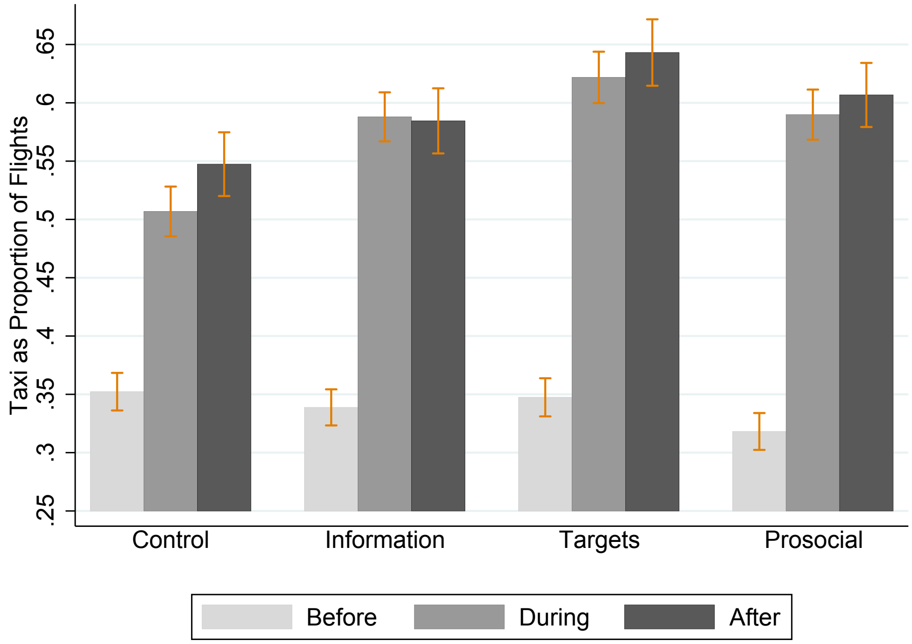


Figure 3a
Fuel Load before and during the experiment

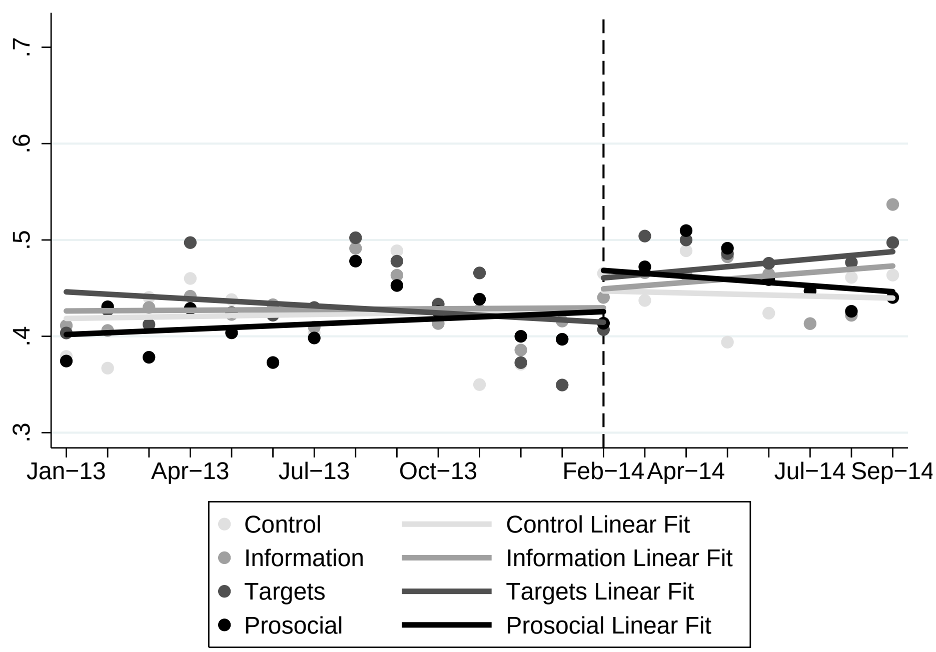


Figure 3b
Efficient Flight before and during the experiment

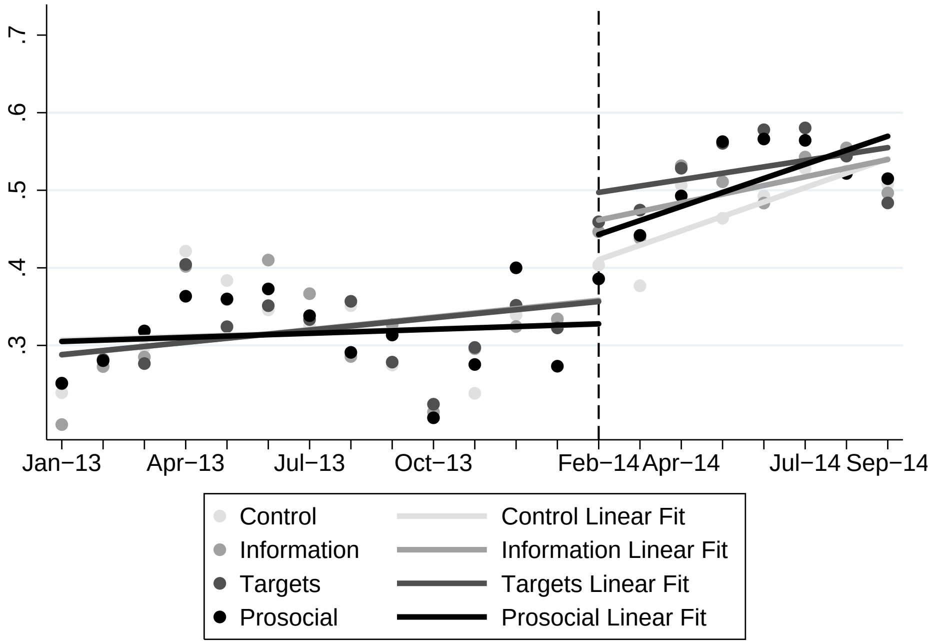


Figure 3c
Efficient Taxi before and during the experiment

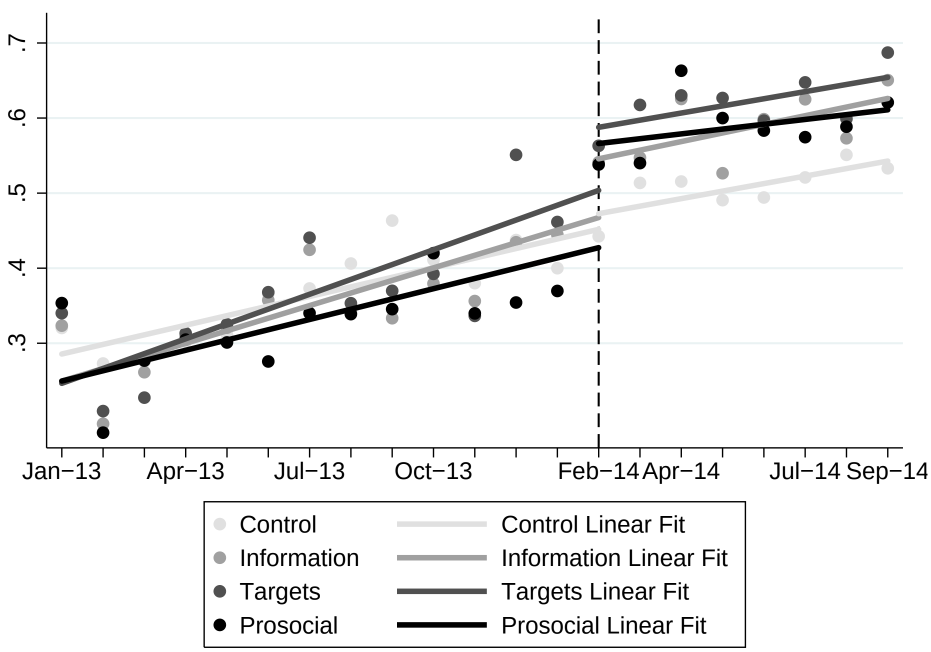


Figure 4a
Treatment effects for Fuel Load during the experiment

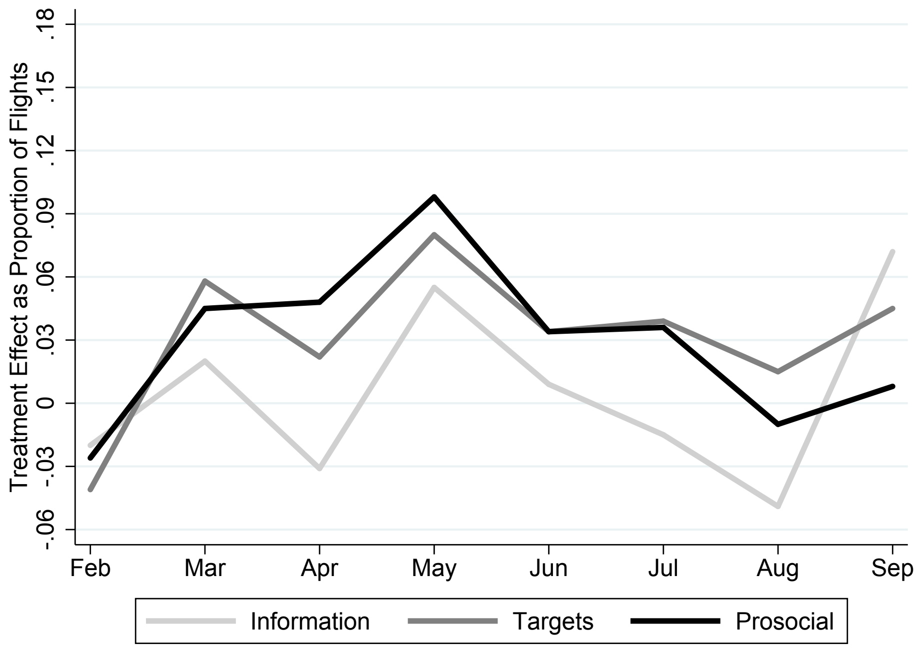


Figure 4b
Treatment effects for Efficient Flight during the experiment

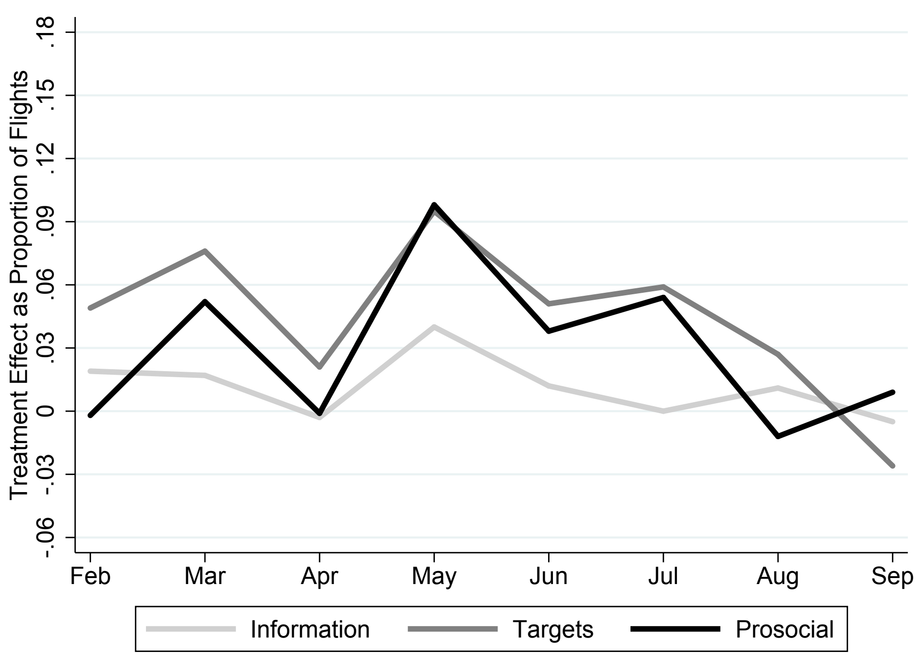


Figure 4c
Treatment effects for Efficient Taxi during the experiment

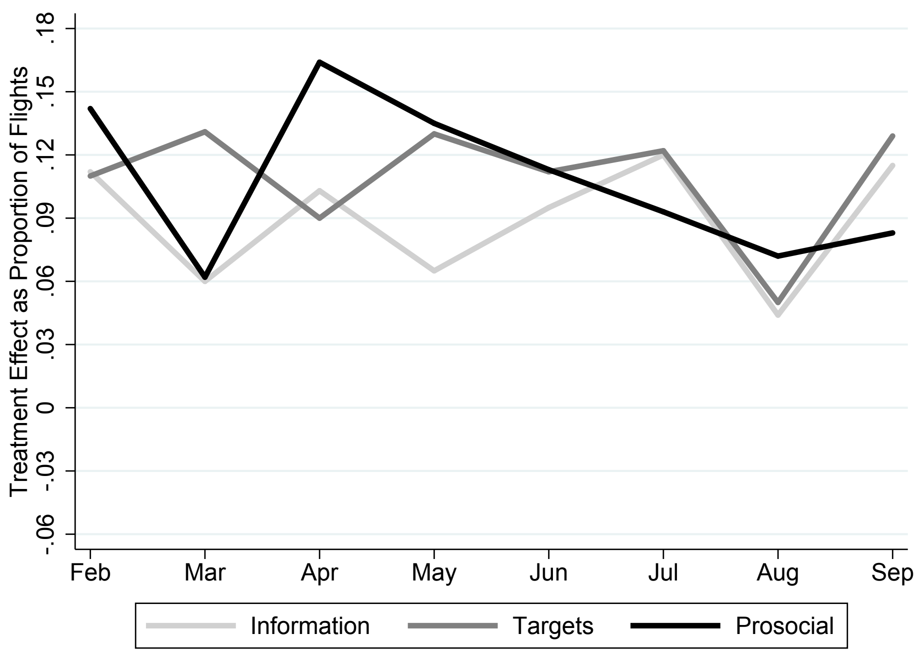
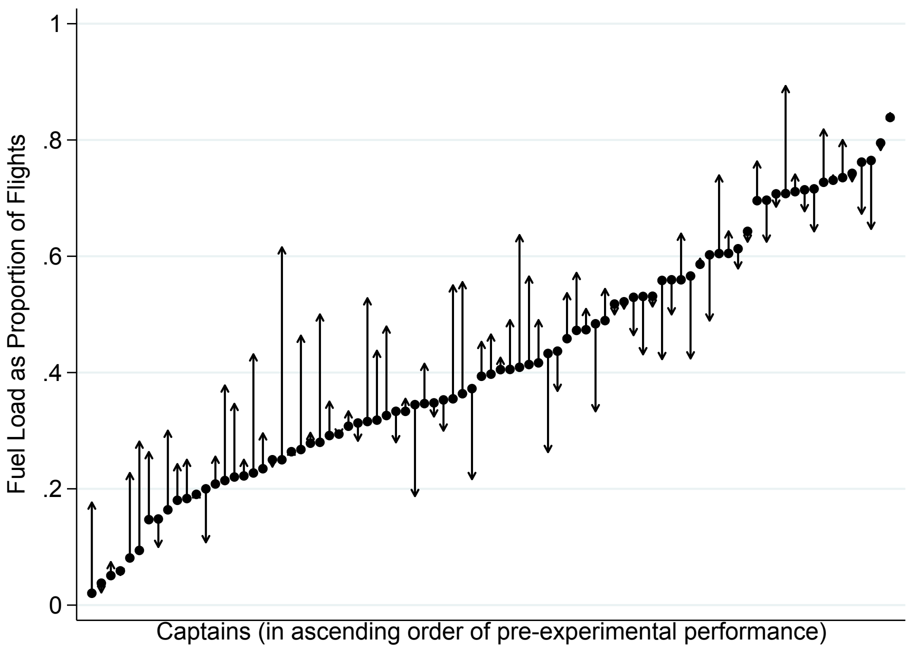
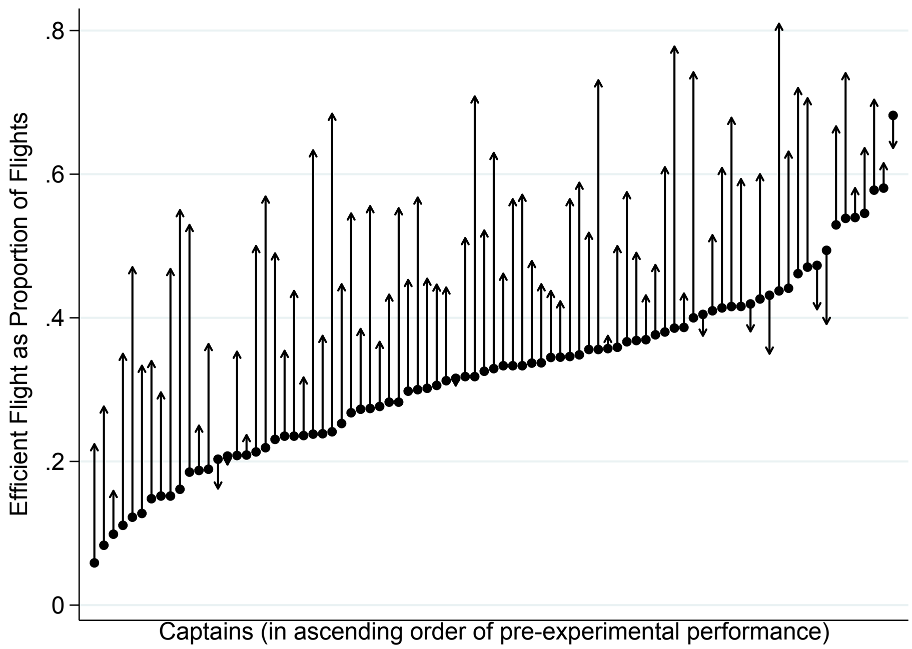


Figure 5a
Within-subject Changes in Control Group - Average Fuel Load Implementation from Before to During the Experiment



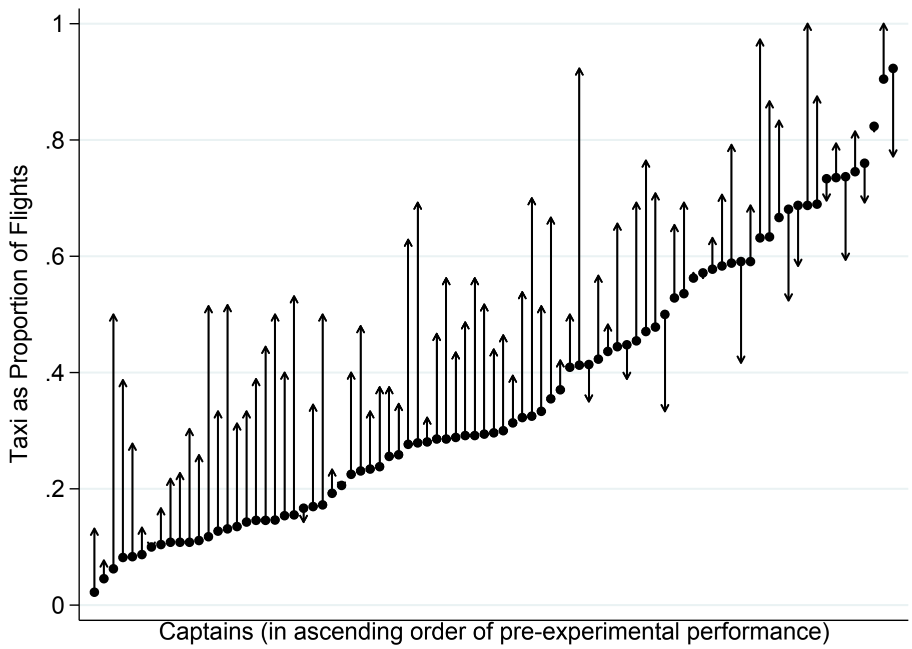
Notes: The data points in the graph represent the proportion of flights for which each captain in the Control Group implemented the Fuel Load behavior before the experiment (January 2013 - January 2014), in ascending order of pre-experimental performance. The vertical arrows indicate represent the same proportion during the experimental period (February 2014 - September 2014). An upward arrow indicates an improvement in implementation (as a proportion of total flights) of the behavior, while a downward arrow indicates a decline in implementation.

Figure 5b
Within-subject Changes in Control Group - Average Efficient Flight Implementation from Before to During the Experiment



Notes: The data points in the graph represent the proportion of flights for which each captain in the Control Group implemented the Efficient Flight behavior before the experiment (January 2013 - January 2014), in ascending order of pre-experimental performance. The vertical arrows represent the same proportion during the experimental period (February 2014 - September 2014). An upward arrow indicates an improvement in implementation (as a proportion of total flights) of the behavior, while a downward arrow indicates a decline in implementation.

Figure 5c
Within-subject Changes in Control Group - Average Efficient Taxi Implementation from Before to During the Experiment



Notes: The data points in the graph represent the proportion of flights for which each captain in the Control Group implemented the Efficient Taxi behavior before the experiment (January 2013 - January 2014), in ascending order of pre-experimental performance. The vertical arrows represent the same proportion during the experimental period (February 2014 - September 2014). An upward arrow indicates an improvement in implementation (as a proportion of total flights) of the behavior, while a downward arrow indicates a decline in implementation.

Figure 6a
Within-subject Changes in All Groups - Average Fuel Load Implementation from Before to During the Experiment (Net of Raw Hawthorne Effects)

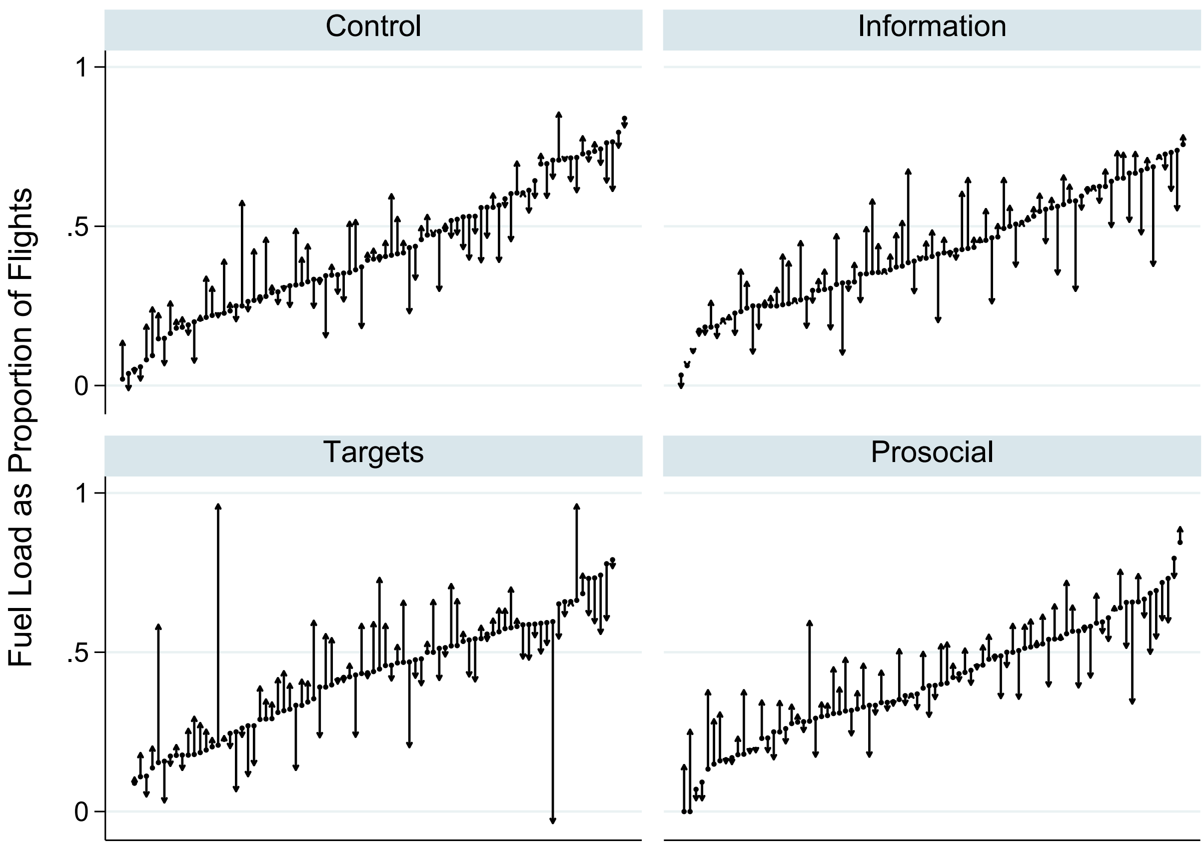


Figure 6b
Within-subject Changes in All Groups - Average Efficient Flight Implementation from Before to During the Experiment (Net of Raw Hawthorne Effects)

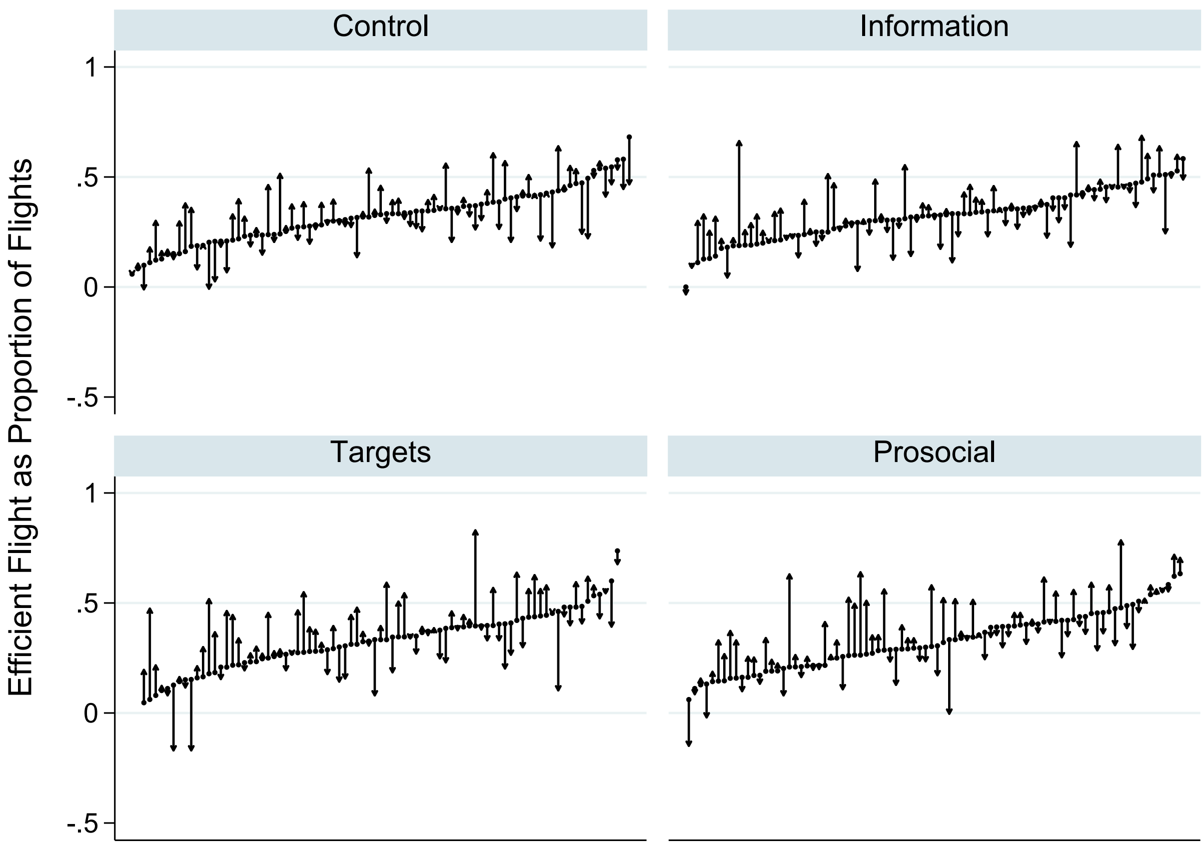


Figure 6c
Within-subject Changes in Control Group - Average Efficient Taxi Implementation from Before to During the Experiment

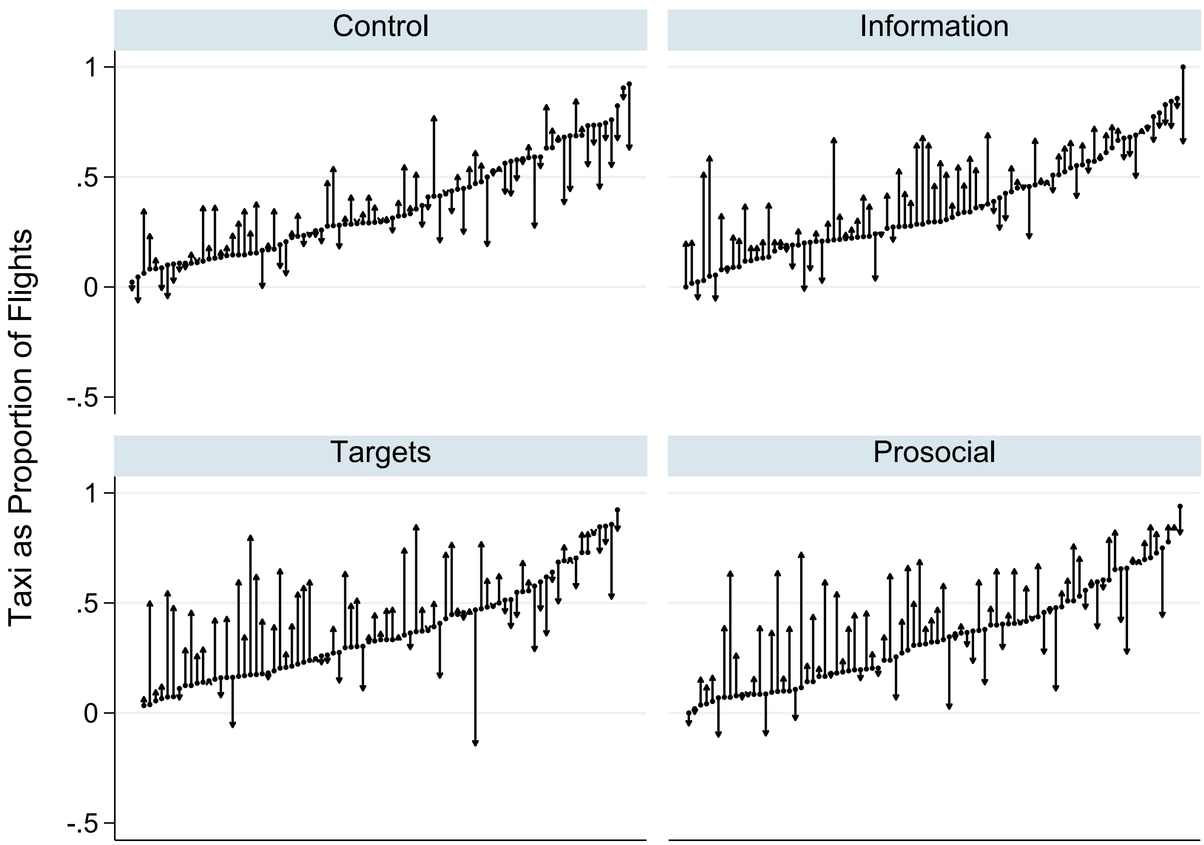


Table 1
Treatment Group Design

	Information	Targets	Prosocial
Control			
Treatment Group 1	✓		
Treatment Group 2	✓	✓	
Treatment Group 3	✓	✓	✓

Table 2
Average Attainment of Fuel Load, Efficient Flight, and Efficient Taxi in all Time Periods (Raw Data)

	Control	**Treatment 1: Information**	**Treatment 2: Targets**	**Treatment 3: Prosocial**	**All Captains**
Fuel Load					
Before Experiment	0.421 (0.494) 5258 obs	0.428 (0.495) 5429 obs	0.434 (0.496) 5070 obs	0.414 (0.493) 5140 obs	0.424 (0.494) 20,897 obs
During Experiment	0.443 (0.497) 3321 obs	0.462 (0.499) 3330 obs	0.475 (0.499) 3016 obs	0.458 (0.498) 3258 obs	0.459 (0.498) 12,925 obs
After Experiment	0.446 (0.497) 2140 obs	0.446 (0.497) 2120 obs	0.469 (0.499) 1867 obs	0.412 (0.492) 2063 obs	0.442 (0.497) 8190 obs
Efficient Flight					
Before Experiment	0.311 (0.463) 5258 obs	0.314 (0.464) 5429 obs	0.313 (0.464) 5070 obs	0.312 (0.463) 5140 obs	0.312 (0.463) 20,897 obs
During Experiment	0.476 (0.500) 3321 obs	0.503 (0.500) 3330 obs	0.528 (0.499) 3016 obs	0.510 (0.499) 3258 obs	0.504 (0.500) 12,925 obs
After Experiment	0.548 (0.498) 2140 obs	0.521 (0.500) 2120 obs	0.536 (0.499) 1867 obs	0.525 (0.499) 2063 obs	0.533 (0.499) 8190 obs
Efficient Taxi					
Before Experiment	0.352 (0.478) 3380 obs	0.339 (0.473) 3596 obs	0.348 (0.476) 3260 obs	0.318 (0.466) 3341 obs	0.339 (0.473) 13,577 obs
During Experiment	0.507 (0.500) 2117 obs	0.588 (0.492) 2109 obs	0.622 (0.485) 1864 obs	0.590 (0.492) 2014 obs	0.575 (0.494) 8104 obs
After Experiment	0.547 (0.498) 1277 obs	0.585 (0.493) 1201 obs	0.643 (0.479) 1090 obs	0.607 (0.489) 1218 obs	0.594 (0.489) 4786 obs

Notes: The table reports the proportion of flights for which captains in a given group performed each of the three selected behaviors. Due to random memory errors, Efficient Taxi data is unavailable for 35.0% of pre-experimental flights and 37.2% of post-experimental flights. This missing data is in no way systematic and therefore does not bias the results, though it moderately reduces the power of the Efficient Taxi estimates. Standard deviations are reported in parentheses, which is followed by the total number of observations (flights) from which the summary statistics are calculated.

Table 3
Difference in Attainment from Before Experiment to During Experiment for all Experimental Conditions

	(1) Fuel Load	(2) Eff Flight	(3) Eff Taxi	(4) Fuel Load	(5) Eff Flight	(6) Eff Taxi
Expt · Control	0.018	0.144***	0.125***	0.018*	0.144***	0.125***
	(0.012)	(0.012)	(0.017)	(0.011)	(0.011)	(0.013)
Expt · Information	0.025*	0.161***	0.206***	0.025**	0.161***	0.206***
	(0.013)	(0.012)	(0.019)	(0.011)	(0.011)	(0.013)
Expt · Targets	0.039***	0.181***	0.222***	0.039***	0.181***	0.222***
	(0.015)	(0.014)	(0.022)	(0.012)	(0.011)	(0.014)
Expt · Prosocial	0.043***	0.191***	0.214***	0.043***	0.191***	0.214***
	(0.012)	(0.013)	(0.022)	(0.011)	(0.011)	(0.013)
Observations	33,822	33,822	21,681	33,822	33,822	21,681
N	335	335	335	335	335	335
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors:						
Clustered	Yes	Yes	Yes			
Newey-West				Yes	Yes	Yes

Notes: The table shows the results of two panel linear probability regressions with captain fixed effects for conventional robust standard errors and Newey-West standard errors with a lag of one period. The regressions compare pre-experiment behavior (January 2013-January 2014) to behavior during the experiment 'Expt' (February 2014-September 2014) for all experimental conditions, including the control group. We present the results of panel OLS specification—as opposed to those of panel logit or probit specifications—due to constraints on the conditional logit/probit models, which cannot provide marginal effects due to lack of estimation of fixed effects (i.e. intercepts), though results for post-estimation of the various models are nearly identical. The dependent variables in the regressions are dummies capturing whether the fuel-efficient behavior was performed, and since predicted values are not constrained between 0 and 1, we do not report a constant and instead focus on treatment effects. As such, the coefficients indicate the proportion of flights for which the behavior of interest was successfully performed. Robust errors are clustered at the captain level. Controls include weather on departure and arrival, number of engines on the aircraft, aircraft type, ports of departure and arrival, aircraft maintenance, captains' contracted hours, and whether the captain has completed training. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table 4
Treatment Effect Identification using Difference-in-Difference Regression

	(1) Fuel Load	(2) Eff Flight	(3) Eff Taxi	(4) Fuel Load	(5) Eff Flight	(6) Eff Taxi
Expt	0.018	0.144***	0.125***	0.018	0.144***	0.125***
	(0.012)	(0.012)	(0.017)	(0.011)	(0.011)	(0.013)
Expt · Information	0.007	0.017	0.081***	0.007	0.017	0.081***
	(0.017)	(0.016)	(0.025)	(0.015)	(0.014)	(0.017)
Expt · Targets	0.021	0.037**	0.097***	0.021	0.037**	0.097***
	(0.018)	(0.018)	(0.026)	(0.015)	(0.015)	(0.018)
Expt · Prosocial	0.025	0.047***	0.089***	0.025*	0.047***	0.089***
	(0.016)	(0.017)	(0.027)	(0.015)	(0.014)	(0.018)
Observations	33,822	33,822	21,681	33,822	33,822	21,681
N	335	335	335	335	335	335
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors:						
Clustered	Yes	Yes	Yes			
Newey-West				Yes	Yes	Yes

Notes: The table shows the results of two difference-in-difference regression specifications with captain fixed effect comparing pre-experiment behavior (January 2013-January 2014) to behavior during the experiment (February 2014-September 2014). The dependent variables in the regressions are dummies capturing whether the fuel-efficient behavior was performed, and since predicted values are not constrained between 0 and 1, we do not report a constant and instead focus on treatment effects. As such, the coefficients indicate the increase in the proportion of flights beyond the control group for which the behavior of interest was successfully performed. We provide conventional robust standard errors which are clustered at the captain level and Newey-West standard errors (lag=1). Total flight observations are provided. Controls include weather on departure and arrival, number of engines on the aircraft, aircraft type, ports of departure and arrival, aircraft maintenance, captains' contracted hours, and whether the captain has completed training. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table 5
Persistence: Difference in Attainment from Before Experiment to After Experiment for all Experimental Conditions

	(1) Fuel Load	(2) Eff Flight	(3) Eff Taxi	(4) Fuel Load	(5) Eff Flight	(6) Eff Taxi
Post · Control	0.049**	0.215***	0.152***	0.049**	0.215***	0.152***
	(0.024)	(0.021)	(0.035)	(0.021)	(0.020)	(0.029)
Post · Information	0.042*	0.195***	0.192***	0.042**	0.195***	0.192***
	(0.022)	(0.023)	(0.040)	(0.021)	(0.019)	(0.030)
Post · Targets	0.067***	0.218***	0.209***	0.067***	0.218***	0.209***
	(0.023)	(0.023)	(0.037)	(0.021)	(0.019)	(0.030)
Post · Prosocial	0.029	0.217***	0.210***	0.029	0.217***	0.210***
	(0.025)	(0.021)	(0.037)	(0.021)	(0.019)	(0.030)
Observations	29,087	29,087	18,363	29,087	29,087	18,363
N	335	335	335	335	335	335
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors:						
Clustered	Yes	Yes	Yes			
Newey-West				Yes	Yes	Yes

Notes: The table shows the results of two panel linear probability regressions with captain fixed effects for conventional robust standard errors and Newey-West standard errors with a lag of one period. The regressions compare pre-experiment behavior (January 2013-January 2014) to post-experiment behavior ("Post": October 2014-March 2015) for all experimental conditions, including the control group. We present the results of panel OLS specification—as opposed to those of panel logit or probit specifications—due to constraints on the conditional logit/probit models, which cannot provide marginal effects due to lack of estimation of fixed effects (i.e. intercepts), though results for post-estimation of the various models are nearly identical. The dependent variables in the regressions are dummies capturing whether the fuel-efficient behavior was performed, and since predicted values are not constrained between 0 and 1, we do not report a constant and instead focus on treatment effects. As such, the coefficients indicate the proportion of flights for which the behavior of interest was successfully performed. Robust errors are clustered at the captain level. Controls include weather on departure and arrival, number of engines on the aircraft, aircraft type, ports of departure and arrival, aircraft maintenance, captains' contracted hours, and whether the captain has completed training. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table 6
Data-Supported Estimates of Fuel Savings (in tons)

	Fuel Load	Efficient Flight	Efficient Taxi	Total	Per Flight
Control	-425.48***	-1,146.46***	-1,45	-1,573.38	-0.474
	(80.51)	(102.26)	(13.17)		
Information	-327.88***	-1,238.44***	-12.21	-1,578.52	-0.474
	(76.37)	(96.51)	(11.86)		
Targets	-426.03***	-1,361.95***	-15.28	-1,803.26	-0.598
	(66.58)	(83.53)	(12.50)		
Prosocial	-520.53***	-1,368.16***	16.30	-1,872.39	-0.575
	(78.65)	(97.58)	(12.60)		
Total	-1,699.91	-5,115.01	-12.63	-6,827.55	-0.828

Notes: The table presents estimates of total fuel savings by treatment group. Savings are based on regression coefficients from a difference-in-difference specification with captain fixed effects comparing pre-experiment behavior (January 2013-January 2014) to behavior during the experiment (February 2014-September 2014). The dependent variable is the deviation from ideal fuel usage in each of the three flight periods as described in the text. We calculate fuel savings with an Intent-to-Treat approach where the regression coefficient of each group (i.e. the group's average treatment effect) and the average Hawthorne effect (i.e. the coefficient of the Experimental-period indicator) are multiplied by the number of flights in each group (3321, 3330, 3016, and 3258 respectively). In other words, we assume that the Hawthorne effect is proportional to the number of flights. Standard error calculations are based on Newey-West standard errors (lag=1). Controls include weather on departure and arrival, number of engines on the aircraft, aircraft type, ports of departure and arrival, aircraft maintenance, captains' contracted hours, and whether the captain has completed training. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table 7
Costs of Fuel Usage

	Purchase Cost	CO_2 Cost	Total Cost
Fuel (1 ton)	\$786	\$116.55	\$902.55

Notes: The table shows the cost of fuel usage. We use global jet fuel prices in February 2014 (first month of treatment), estimates of the social cost of carbon of \$37/ton, and the September 30, 2014 exchange rate (1\$ = 0.6167£) for all calculations. One ton of fuel emits about 3.15 tons of CO_2. These values are used for calculations of savings in the text.

A Appendix I: Additional Tables

Table A1
VAA Experiment - Balance Table

Groups	Gender	Seniority	Age	Trainer	Trusted Pilot	Weekend	Plan Ramp Fuel	Number of Engines	Flights per Month	Above Average PRF	Above Average NOE	Above Average FPM	Fuel Load	Efficient Flight	Efficient Taxi
C, T1	1.000	0.272	0.735	0.687	0.700	0.309	0.831	0.749	0.889	0.539	0.645	1.000	0.920	0.613	0.391
C, T2	0.560	0.678	0.430	0.838	0.650	0.273	0.860	0.755	0.844	0.443	0.878	0.878	0.899	0.683	0.390
C, T3	0.560	0.962	0.918	0.551	0.650	0.879	0.719	0.898	0.637	0.167	0.759	0.759	0.960	0.512	0.603
T1, T2	0.560	0.519	0.627	0.843	0.406	0.957	0.969	0.991	0.726	0.878	0.759	0.878	0.817	0.925	0.995
T1, T3	0.560	0.299	0.653	0.846	0.406	0.219	0.892	0.851	0.516	0.443	0.878	0.759	0.960	0.880	0.779
T2, T3	1.000	0.715	0.370	0.695	1.000	0.187	0.858	0.858	0.785	0.539	0.878	0.645	0.859	0.811	0.775
Test	χ^2	t-test	t-test	χ^2	χ^2	t-test	t-test	t-test	t-test	χ^2	χ^2	χ^2	t-test	t-test	t-test

Notes: The numbers in the table are p-values for the comparison of means across treatment groups, where C denotes the Control group ($n = 85$), T1 denotes the Information group ($n = 85$), T2 denotes the Targets group ($n = 81$), and T3 denotes the Prosocial group ($n = 84$). Respectively, treatment assignment was balanced on captains' gender; seniority; age; trainer status; Trusted Pilot status; proportion of flights flown on weekends; flight plan ramp fuel (as a proxy for average distance flown); average number of engines on aircraft flown; average number of flights flown per month in the pre-experimental period; indicators for whether the captains is characterized by above average plan ramp fuel (PRF), number of engines (NOE), and flights per month (FPM); and attainment of the three outcome variables of interest (Fuel Load, Efficient Flight, and Efficient Taxi).

Table A2
Difference in Attainment from Before Experiment to During Experiment for all Experimental Conditions with Time Components

	(1) Fuel Load	(2) Eff Flight	(3) Eff Taxi	(4) Fuel Load	(5) Eff Flight	(6) Eff Taxi
Expt · Control	0.033**	0.132***	0.038**	0.030	0.237***	0.118***
	(0.013)	(0.013)	(0.016)	(0.023)	(0.021)	(0.026)
Expt · Information	0.040***	0.149***	0.117***	0.037	0.254***	0.196***
	(0.014)	(0.013)	(0.016)	(0.023)	(0.021)	(0.026)
Expt · Targets	0.055***	0.169***	0.134***	0.053**	0.274***	0.213***
	(0.014)	(0.013)	(0.017)	(0.023)	(0.021)	(0.027)
Expt · Prosocial	0.058***	0.179***	0.126***	0.055**	0.283***	0.206***
	(0.014)	(0.013)	(0.017)	(0.023)	(0.021)	(0.027)
Observations	33,822	33,822	21,681	33,822	33,822	21,681
N	335	335	335	335	335	335
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Component:						
Linear Trend	Yes	Yes	Yes			
Month-of-Sample FEs				Yes	Yes	Yes

Notes: The table shows the results of two panel linear probability regressions with captain fixed effects for Newey-West standard errors with a lag of one period. The regressions compare pre-experiment behavior (January 2013-January 2014) to behavior during the experiment 'Expt' (February 2014-September 2014) for all experimental conditions, including the control group. Columns (1)-(3) include a linear trend component; columns (4)-(6) include month-of-sample fixed effects. We present the results of panel OLS specification—as opposed to those of panel logit or probit specifications—due to constraints on the conditional logit/probit models, which cannot provide marginal effects due to lack of estimation of fixed effects (i.e. intercepts), though results for post-estimation of the various models are nearly identical. The dependent variables in the regressions are dummies capturing whether the fuel-efficient behavior was performed, and since predicted values are not constrained between 0 and 1, we do not report a constant and instead focus on treatment effects. As such, the coefficients indicate the proportion of flights for which the behavior of interest was successfully performed. Robust errors are clustered at the captain level. Controls include weather on departure and arrival, number of engines on the aircraft, aircraft type, ports of departure and arrival, aircraft maintenance, captains' contracted hours, and whether the captain has completed training. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table A3
Treatment Effect Identification using Difference-in-Difference Regression with Quadruplet Controls

	(1) Fuel Load	(2) Eff Flight	(3) Eff Taxi	(4) Fuel Load	(5) Eff Flight	(6) Eff Taxi
Expt	0.022	0.146***	0.140***	0.022**	0.146***	0.140***
	(0.015)	(0.013)	(0.016)	(0.010)	(0.009)	(0.011)
Expt · Information	0.017	0.023	0.065***	0.017	0.023**	0.065***
	(0.020)	(0.016)	(0.022)	(0.012)	(0.011)	(0.014)
Expt · Targets	0.022	0.041**	0.092***	0.022*	0.041***	0.092***
	(0.020)	(0.016)	(0.022)	(0.012)	(0.012)	(0.015)
Expt · Prosocial	0.011	0.042***	0.078***	0.011	0.042***	0.078***
	(0.019)	(0.016)	(0.023)	(0.012)	(0.011)	(0.014)
Observations	33,822	33,822	21,681	33,822	33,822	21,681
N	335	335	335	335	335	335
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors:						
Clustered	Yes	Yes	Yes			
Newey-West				Yes	Yes	Yes

Notes: The table shows the results of two difference-in-difference regression specifications with quadruplet fixed effects comparing pre-experiment behavior (January 2013-January 2014) to behavior during the experiment (February 2014-September 2014). The dependent variables in the regressions are dummies capturing whether the fuel-efficient behavior was performed, and since predicted values are not constrained between 0 and 1, we do not report a constant and instead focus on treatment effects. As such, the coefficients indicate the increase in the proportion of flights beyond the control group for which the behavior of interest was successfully performed. We provide conventional robust standard errors which are clustered at the captain level and Newey-West standard errors (lag=1). Total flight observations are provided. Controls include weather on departure and arrival, number of engines on the aircraft, aircraft type, ports of departure and arrival, aircraft maintenance, captains' contracted hours, and whether the captain has completed training. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table A4
Persistence: Treatment Effect Identification using Difference-in-Difference Regression comparing Before Experiment to After Experiment for all Experimental Conditions

	(1) Fuel Load	(2) Eff Flight	(3) Eff Taxi	(4) Fuel Load	(5) Eff Flight	(6) Eff Taxi
Post	0.049**	0.215***	0.152***	0.049**	0.215***	0.152***
	(0.024)	(0.021)	(0.035)	(0.021)	(0.020)	(0.029)
Post · Information	-0.007	-0.021	0.040	-0.007	-0.021	0.040*
	(0.020)	(0.021)	(0.030)	(0.017)	(0.016)	(0.021)
Post · Targets	0.018	0.003	0.057**	0.018	0.003	0.057***
	(0.020)	(0.022)	(0.026)	(0.018)	(0.017)	(0.022)
Post · Prosocial	-0.020	0.002	0.058**	-0.020	0.002	0.058***
	(0.021)	(0.020)	(0.025)	(0.017)	(0.016)	(0.021)
Observations	29,087	29,087	18,363	29,087	29,087	18,363
N	335	335	335	335	335	335
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors:						
Clustered	Yes	Yes	Yes			
Newey-West				Yes	Yes	Yes

Notes: The table shows the results of two difference-in-difference regression specifications with captain fixed effect comparing pre-experiment behavior (January 2013-January 2014) to post-experiment behavior ("Post": October 2014-March 2015). The dependent variables in the regressions are dummies capturing whether the fuel-efficient behavior was performed, and since predicted values are not constrained between 0 and 1, we do not report a constant and instead focus on treatment effects. As such, the coefficients indicate the increase in the proportion of flights beyond the control group for which the behavior of interest was successfully performed. We provide conventional robust standard errors which are clustered at the captain level and Newey-West standard errors (lag=1). Total flight observations are provided. Controls include weather on departure and arrival, number of engines on the aircraft, aircraft type, ports of departure and arrival, aircraft maintenance, captains' contracted hours, and whether the captain has completed training. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table A5

Data-Supported Estimates of Average Fuel Savings per Flight (in kilograms)

	Fuel Load	Efficient Flight	Efficient Taxi
Control	-128.12***	-345.21***	-0.43
	(24.24)	(30.79)	(3.97)
Information	-98.46***	-371.90***	-3.67
	(22.93)	(28.98)	(3.56)
Targets	-141.26***	-451.57***	-5.07
	(22.07)	(27.69)	(4.14)
Prosocial	-159.77***	-419.94***	5.00
	(24.14)	(29.95)	(3.87)

Notes: The table presents estimates of average fuel savings by treatment group. Savings are based on regression coefficients from a difference-in-difference specification with captain fixed effects comparing pre-experiment behavior (January 2013-January 2014) to behavior during the experiment (February 2014-September 2014). The dependent variable is the deviation from ideal fuel usage in each of the three flight periods as described in the text. We calculate fuel savings with an Intent-to-Treat approach where we sum the regression coefficient of each group (i.e. the group's average treatment effect) and the average Hawthorne effect (i.e. the coefficient of the Experimental-period indicator). In other words, we assume that the Hawthorne effect is constant across grous. Standard error calculations are based on Newey-West standard errors (lag=1). Controls include weather on departure and arrival, number of engines on the aircraft, aircraft type, ports of departure and arrival, aircraft maintenance, captains' contracted hours, and whether the captain has completed training. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table A6

Test of a Unit Root of Pre-Experiment Behaviors

	Fuel Load	Eff Flight	Eff Taxi
$Z(t)$	-3.765***	-2.562*	-6.431***
	(0.003)	(0.010)	(0.000)
Observations (weeks)	51	51	51

Notes: The table shows the Dickey-Fuller (DF) test for a unit root for the 51 weeks before the experiment started, collapsing all the groups into one for each behavior. The null of the DF test is a unit root, and the rejection of the null is that the data follows a random walk. $Z(t)$ is the DF test statistic. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table A7
Difference-in-Difference Regression of Flight Time

	Flight Time
Post	1.788***
	(0.522)
Post · Information	0.011
	(0.687)
Post · Targets	0.114
	(0.733)
Post · Prosocial	-1.586*
	(0.849)
N	335 subjects
Observations	33,822
Controls	Yes

Notes: The dependent variable in this regression is flight time in minutes. Captain fixed effects are included and Newey-West standard errors (lag = 1) are reported below estimates in parentheses. Total flight observations are provided. Controls include weather on departure and arrival, number of engines on the aircraft, aircraft type, ports of departure and arrival, aircraft maintenance, captains' contracted hours, and whether the captain has completed training. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table A8
Heterogeneity Analysis: Interactions between Social Preferences and Treatment Effects

	Social Preferences		
	Fuel Load	Eff Flight	Eff Taxi
Expt	0.0501*	0.1447***	0.0980***
	(0.0284)	(0.0268)	(0.0365)
Information	-0.0145	0.0186	0.0334
	(0.0244)	(0.0219)	(0.0312)
Targets	-0.0100	0.0257	0.0087
	(0.0248)	(0.0229)	(0.0317)
Prosocial	-0.0908***	-0.0090	-0.1060***
	(0.0227)	(0.0204)	(0.0278)
Expt · Information	-0.0005	-0.0277	0.0340
	(0.0386)	(0.0360)	(0.0497)
Expt · Targets	0.0236	0.0864**	0.1215**
	(0.0400)	(0.0380)	(0.0492)
Expt · Prosocial	-0.0519	0.0150	0.1488***
	(0.0359)	(0.0335)	(0.0447)
Don13	0.0001	0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)
Expt · Don13	-0.0002	-0.0000	0.0002
	(0.0002)	(0.0002)	(0.0002)
Info · Don13	0.0000	-0.0000	-0.0004**
	(0.0001)	(0.0001)	(0.0002)
Targets · Don13	-0.0001	-0.0003**	-0.0000
	(0.0002)	(0.0001)	(0.0002)
Prosocial · Don13	0.0003**	0.0000	0.0007***
	(0.0001)	(0.0001)	(0.0002)
Expt · Information · Don13	0.0001	0.0002	0.0004
	(0.0002)	(0.0002)	(0.0003)
Expt · Targets · Don13	0.0001	-0.0000	-0.0000
	(0.0002)	(0.0002)	(0.0003)
Expt · Prosocial · Don13	0.0005**	0.0002	-0.0003
	(0.0002)	(0.0002)	(0.0003)
Observations	18,776	18,776	11,987
N	187	187	187
Controls	Yes	Yes	Yes

Notes: The table shows the results of a difference-in-difference regression specification comparing pre-experiment behavior (January 2013-January 2014) to behavior during the experiment (February 2014-September 2014). The dependent variables in the regressions are dummies capturing whether the fuel-efficient behavior was performed, and since predicted values are not constrained between 0 and 1, we do not report a constant and instead focus on treatment effects. As such, the coefficients indicate the increase in the proportion of flights beyond the control group for which the behavior of interest was successfully performed. Newey-West standard errors (lag = 1) are reported below estimates in parentheses. Total flight observations are provided. The covariate specific to this regression is captains' pro-social behavior proxied by donations in 2013 (Don13 captures the midpoints of ten donation amount intervals). Interactions of this variable with all treatment groups are reported as well. Other controls include weather on departure and arrival, number of engines on the aircraft, aircraft type, ports of departure and arrival, aircraft maintenance, captains' contracted hours, and whether the captain has completed training. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table A9
Job Satisfaction and Treatment Group

	Job Satisfaction
Information	0.212
	(0.224)
Targets	0.0242
	(0.249)
Prosocial	0.365
	(0.224)
Constant	5.58***
	(0.174)
N	202

Notes: The dependent variable in this regression is a 7-point scale of job satisfaction, where self-reported job satisfaction increases in the scale. Robust standard errors are reported below estimates in parentheses. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

Table A10
Job Satisfaction and Job Performance

Groups	Control and Information		Targets and Prosocial	
	Job Satisfaction		Job Satisfaction	
Fuel Load Targets Met	0.042	-	0.065	-
	(0.052)		(0.060)	
Eff Flight Targets Met	-0.071	-	-0.017	-
	(0.056)		(0.054)	
Eff Taxi Targets Met	0.037	-	0.120**	-
	(0.038)		(0.054)	
Overall Targets Met	-	0.000	-	0.058*
		(0.025)		(0.025)
Constant	5.714***	5.687***	5.341***	5.326***
	(0.263)	(0.258)	(0.358)	(0.326)
N	N=103 subjects		N=99 subjects	
Obs	103		99	
Controls	None		None	

Notes: The dependent variable in these regressions is a 7-point scale of job satisfaction, where self-reported job satisfaction increases in the scale. Robust standard errors are reported below estimates in parentheses. The independent variables indicate the number of targets met per behavior and overall over the course of the study. $^{***}p < 0.01$ $^{**}p < 0.05$ $^{*}p < 0.10$

B Appendix II: Theoretical Model

B.1 Model Setup

We consider a static choice-problem that determines a captain's chosen effort on the job in a certain period. In our model, we assume that captains, who have vast flying experience, are at an equilibrium fuel usage with respect to their wealth, experience, effort, and concerns for safety, the environment, and company profitability.[50]

A captain faces the following additively separable utility function:

$$U(w, s, e, f, g) = u(w, e, g) + a \cdot v(d(e) \cdot g, g_0, G_{-i}) + y(s, e, f) - c(e) - s(e) \tag{1}$$

where $u(\cdot)$ is utility from monetary wealth, $v(\cdot)$ is utility from giving to charity (pro-social behavior), $y(\cdot)$ is utility from job performance, $c(\cdot)$ is disutility from exerting effort, and $s(\cdot)$ describes disutility from social pressure. Effort is chosen for all three flight tasks, j, i.e. Fuel Load, Efficient Flight, and Efficient Tax. Captains observe their effort perfectly. They also receive a noisy signal of fuel usage $f_{it} + \epsilon_{it} = \bar{f}_{it}$. f_{it} describes the estimated fuel usage by captain i for flight t which depends on the chosen effort for the fuel-efficient activities. $\bar{f}_{it}$ is actual fuel use, observed *ex post* by the airline, which also includes a random component.[51] Furthermore, each captain has an ideal fuel usage f_I, which is based on her own experience and environmental and firm profit preferences. By revealed preference the equilibrium pre-study fuel usage $f_I = \bar{f}$.

Experimental treatments in this study alter three model parameters. First, receiving information on fuel use, $i = 1(\text{information})$, removes the noisiness of the fuel signal, i.e. $f_{it} + (1 - i)\epsilon_{it} = \bar{f}_{it}$. Second, provision of a target, $r = 1(\text{target})$, changes the captain's ideal fuel usage, f_I, because the employer exogenously imposes a target level. Then, $f_I = f_T$ if $r = 1$ where f_T reflects the signaled optimal usage from the point of view of the airline. Third, in the pro-social behavior treatment a donation, g, is made by the airline in the name of the captain. This donation is conditional on meeting the target which has a probability

[50] In a survey, captains in the study expressed a concern over fuel usage and fuel cost, both for environmental reasons and company profitability. To become an airline captain requires many years of training and experience within an airline; if a captain loses her job with one airline and seeks employment in another, she loses her prior seniority and must work for many years to reinstate it. Thus, for the sake of their own job security, captains care about minimizing fuel costs.

[51] Due to the vast experience of captains, we assume $E(\epsilon_{it}) = 0$, i.e. captains predict fuel usage correctly, on average.

of $d(e)$ in this treatment.[52] In all other treatments, reaching particular fuel use levels does not lead to donations, i.e. $d(e) = 0$. Parameters and elements of the utility function are explained in more detail below.

(Dis)utility from social pressure. In the spirit of DellaVigna et al. (2012, "DLM" hereafter) and Bénabou and Tirole (2006), we assume that captains are either affected by social pressure due to their actions being observed or exhibit some sort of social signaling in which they want to appear to be good employees. In this framework, captains are aware of an optimal, social effort level, e^{social}. Because exerting effort is costly to the captain and because her actions are imperfectly observed with probability $\pi^{\text{observed}} < 1$, generally $e < e^{\text{social}}$.[53] In this study, captains in both the control group and treatment group are made aware that their actions are monitored and data on their effort are used for an internal and academic study. Consequently, we expect the probability of detection of deviations from the social effort level to increase for all participants in the study relative to the pre-study period, i.e. $\pi^{\text{observed}}_{\text{study}} > \pi^{\text{observed}}_{\text{pre}}$. We parameterize social pressure as follows:

$$s(e) = [\pi^{\text{observed}} \cdot (e^{\text{social}} - e) + (1 - \pi^{\text{observed}}) \cdot 0] \cdot 1(e < e^{\text{social}})$$

Social pressure decreases utility if the chosen effort level is below the socially optimal effort level of the captain. This disutility is increasing in the distance from the optimal effort level and in the probability of these actions being observed by the airline. The second term captures the fact that unobserved deviations do not lead to disutility. For agents that exert more effort than e^{social}, $s(e)$ simply drops out of their utility function. Consequently, captains can directly impact the level of disutility by exerting more (costly) effort.

Note that $s(e)$ enters the utility of every captain below the social effort level, regardless of treatment assignment. If social pressure is important, even control captains should respond to this increased cost of low effort.[54] Because $s(e)$ is orthogonal to treatment, we omit it in

[52] Captains can directly influence the probability with their effort. That is, captains can be certain that they do not meet a target if they put in little effort, and they can be certain that they have achieved the target if they put in sufficient effort.

[53] It is plausible to argue that effort is perfectly observed in the aviation industry with modern technology. However, captains might not expect these data to be analyzed on a regular basis.

[54] Alternatively, we could interpret e^{social} as a level of effort induced by the researcher, leading to experimenter-demand effects. Put differently, pilots in the study could think they are expected to increase effort and not doing so imposes utility costs on them.

the following discussion and in the derivation of comparative statics.[55]

Utility from wealth. Similar to DLM, for wealth w, charitable giving from the airline g for meeting the target (if applicable), and other charitable giving g_0, u is defined as follows:

$$u(w, e, g) = u(w - g_0(d(e) \cdot g) + \widetilde{a} \cdot d(e) \cdot g)$$

$$\text{where } \widetilde{a} = \begin{cases} 0 & \text{if } a < 0 \\ a & \text{if } 0 \leq a \leq 1 \\ 1 & \text{if } a > 1 \end{cases}$$

Private consumption is an individual's wealth minus the amount given to charity from that person's wealth (i.e. not from this study). However, to ensure that u is continuously differentiable, we need to account for the effect of charitable donations resulting from our treatments on utility from private consumption. To capture this effect, we multiply the individual's expected donation, $d(e) \cdot g$, by a function of a—a parameter capturing preferences for giving—which we call $\widetilde{a}$. As in DLM, the parameter a is non-negative in the case of pure or impure altruism and negative in the case of spite[56], and $\widetilde{a}$ is simply a truncated at 0 and 1.

The reasons for creating such boundaries on the term capturing preferences for giving are twofold. First, an individual with spiteful preferences ($a < 0$) does not get less utility from private consumption when she donates to charity than when she does not donate to charity; therefore, $\widetilde{a}$ is censored from below at 0. Second, an individual with pure or impure altruistic preferences will get additional utility from her private consumption by giving to charity through our treatment because it corresponds to an outward shift in the budget constraint in the dimension of giving to the chosen charity. However, $\widetilde{a}$ is censored from above at 1 because an individual will experience weakly more utility from increases in w than from giving to the chosen charity (i.e. $\frac{\partial u}{\partial w} \geq \frac{\partial u}{\partial g}$). This relation holds since increases in w shift the budget constraint outward in all dimensions—including the charitable giving dimension—so

[55] Social pressure is additively separable from other utility elements in a linear model. Consequently, it does not affect the sign of comparative statics derived below and, if interactions are present, only attenuates treatment effect estimates.

[56] As defined in Andreoni (1989, 1990), pure and impure altruism capture two possible motivations for giving. The first stems from a preference solely for provision of the public good, so that an individual's donations are entirely crowded out by donations from other sources. Impure altruism, on the other hand, refers to the phenomenon whereby individuals receive direct utility from the act of giving itself, i.e. through "warm glow". Spite, as defined in DLM, exists when an individual gets disutility from donating to the charity.

these must be weakly preferred to shifts in only one dimension. This stipulation is important to assume differentiability in u in a standard expected utility framework, as in DLM.

Please note that the amount an individual gives to other charities will be related to the amount that she gives to charity in the context of this study. Captains will smooth their consumption for giving. If a captain normally gives \$100 to charity each year and this year she gives \$10 through the context of the study, we would expect her total giving to be between \$100 and \$110, or $g_0 + g \in [100, 110]$. The realization of the sum depends on the value of a and whether a stems from pure altruism, impure altruism, or spite. We should expect that an individual who has a negative a value does not donate to charity outside of the context of this study since donating to charity decreases that individual's utility.

Utility from charitable giving. The v term is also adapted from DLM and follows the same properties for each type of individual (pure or impure altruistic and spiteful). The main difference between the v term in this study and that in DLM is that in this study, not everyone has the opportunity to donate to charity (i.e. $d(e) > 0$ for only one treatment group). We also assume that v is separable in its parameters, as follows:

$$v(d(e) \cdot g, g_0, G_{-i}) = v_1(d(e) \cdot g, G_{-i}) + v_2(\theta g_0, G_{-i})$$

where θ is the cost of giving through channels other than the study and G_{-i} is total giving by other individuals. In this specification, v_1 represents utility from giving in the study context and v_2 represents utility from giving from one's personal wealth. Note that $v_1(0, G_{-i}) = 0$ since if $d(e) = 0$, then a captain is not able to donate to the charity through the context of the study, so v_1 should not affect the utility function (similar to the spite case). Based on the arguments made above with respect to consumption smoothing, $v|_{d=0} \leq v|_{d=p}$, $0 = v_1|_{d=0} \leq v_1|_{d=p}$, $v_2|_{d=0} \geq v_2|_{d=p}$. That is, a captain's utility from giving is at least as high for those captains for whom $d(e) = p$ as it is for those captains for whom $d(e) = 0$, which follows from our assumption that giving in the study context can only decrease giving from one's own wealth or not affect it at all. Finally, since $\frac{\partial p}{\partial e} > 0$, we have $\frac{\partial v}{\partial e} \geq 0$.

In the case of pure altruism, an individual should get the same utility from giving to charity from her personal wealth as from giving to charity through the context of the study, since the benefit to the charity is identical. In this sense, v can be thought to represent the charity's production function. In the case of impure altruism, an individual should also get the same utility from donating to charity through her personal wealth as she does from donating through the context of the study because the amount donated on her behalf is the same. Lastly, in the case of spite, $g_0 = 0$ since giving to charity decreases utility and so those individuals will not give to charity independently of the study. Note, $v(0) = 0$ because if a person does not give to charity in person then her utility from giving to charity in person is 0.

Utility from job performance. Since captains care about fuel efficiency, and since imposing exogenous targets on performance affects a captain's perception of how well she is doing her job, we include a parameter y capturing job performance.[57] We assume y is separable in safety (s) and fuel (f) because changes in fuel as a result of the study do not affect safety levels, as argued in our assumption above. A captain whose performance exceeds her target will achieve higher utility under this parameter than a captain who does not achieve her target. Similarly, a captain will experience less (more) utility the further below (above) the target is her performance. We therefore incorporate job performance into the model as follows:

$$y(s, e, f) = y_1(s) + y_2(e, f) = y_1(s) + y_2(-\bar{f}| - f_I)$$

where

$$y_2(-\bar{f}| - f_I) = y_{2m}(-\bar{f}) + y_{2n}(-\bar{f}| - f_I)$$

and

$$y_{2n}(-\bar{f}| - f_I) = r \cdot \mu(y_{2m}(-\bar{f}) - y_{2m}(-f_I))$$

Here, y_2 is defined as in Köszegi and Rabin (2006, "KR" hereafter). We denote the components of y_2 "m" and "n" to mirror the notation in KR. As in KR, m represents the "consumption utility" and n represents the "gain-loss utility." These terms are separable across dimensions. Finally, μ is the "universal gain-loss function" and has the associate properties outlined in KR. To be clear, we use the targets in our second treatment group as an exogenous reference point that airline captains perceive as a reference point.

Note that pilots get utility from using less fuel $\frac{\partial y_2}{\partial f} \leq 0$ and, conditional on receiving a reference point, get utility (disutility) from performing above (below) the target, which

[57] Evidence indicates that influencing job performance positively influences job satisfaction (or utility), whether through increased self-esteem or perceived managerial support for autonomous decision-making (Christen et al., 2006; Pugno and Depedri, 2009).

increases with distance from the target according to μ. We assume μ is linear and $\mu(x) = \eta x$ if $x > 0$ and $\mu = \eta\lambda x$ if $x \leq 0$ for $\eta > 0$, $\lambda > 1$, in accordance with theories of loss aversion. Moreover, following naturally from our definition of μ, we assume $y(x) = x$. If a captain does not receive a reference point, her utility does not comprise gain-loss utility, so for these individuals $y_2 = y_{2m}$. That is, if $r = 0$, captains do not receive information regarding ideal performance with respect to fuel efficiency, so their job performance parameter depends solely on fuel consumption.[58]

Additionally, based on industry standards and emphasis on safety—as well as the design of the treatments—we assume that captains' job performance utility from flying safely is constant across treatments, therefore:

$$\frac{\partial y}{\partial s} = S \geq 0$$

(Dis)utility from effort. Finally, c represents the cost of effort. Importantly, the individual

cost functions for each fuel-efficient task are allowed to differ to convey that various tasks have different costs associated with them. The cost structure is a function of the difficulty of the task itself (e.g., it may be easier to turn off one engine after landing than to have an efficient flight for several hours) and resistance due to previous habit formation (e.g., captains who for many years have not properly performed the Zero Weight Fuel calculation may find it difficult or bothersome to begin doing so). Additionally, the costs for each task are separable since the tasks are done independently. Therefore,

$$c(e) = \sum_j c_j(e_j)$$

For a captain to decrease her fuel use, she must also increase her effort, i.e. $\frac{\partial f}{\partial e} < 0$. Note that $c(e)$ is subtracted in the utility equation, so $\frac{\partial U}{\partial c} < 0$, $\frac{\partial c}{\partial e} > 0$. Based on interviews with captains, the cost of effort increases at an increasing rate. Defining the cost of effort as a quadratic function of effort implies that the cost of effort increases with the amount of effort exerted (i.e. $\frac{\partial^2 c}{\partial e^2} > 0$).

[58] To be clear, given that our reference point is exogenously imposed, one cannot clearly assess whether the individual captain is better off in the targets group than in another group.

B.2 Model Predictions

Captains will choose how much effort to exert based on the treatments (information, targets, prosocial incentives) as in the moral hazard model (see Hölmstrom, 1979). The model is simplified because agents are current employees whose base salaries are not affected by the study. The treatments do affect job satisfaction and charitable giving, however. Different treatments represent different contracts.

We now define $V(-f)$ to be the utility of the firm (the principal) from the perspective of the employee (the agent) as a function of firm costs, i.e. fuel costs. V is highly related to y since an employee's job satisfaction is linked to the well-being of the firm itself. We assume V is independent of treatment status, τ, because the marginal benefit and marginal cost to the firm do not depend directly on treatment, but rather on the amount of fuel used (i.e. for the same level of fuel but two different treatments, V is the same). Additionally, salaries are fixed and donations to charity are paid by an outside donor.

We further define $U(e, \tau)$ to be the utility function under treatment τ with effort e and $\bar{U}$ as a captain's outside option.[59] Let $\dot{e}$ be the pre-study amount of effort and $\ddot{e}$ be the chosen effort under τ. Note that the profit-maximizing principal (VAA) wants to design contracts (treatments) that induce the optimal level of effort from the point of view of the principal. In this case, the principal observes both the outcome (fuel usage) and the effort by the agent but is restricted regarding contractual changes in terms of monetary compensation based on effort levels of the fuel-efficient behaviors.

Therefore, the problem becomes:

$$\begin{aligned}
&\max_{e,g_0} && E[V(-f)] \\
&\text{s.t.} && E[U(w,s,\ddot{e},f_I,g,\tau)] \geq \bar{U} \\
&\text{and} && \ddot{e} \in \underset{\ddot{e}'}{\operatorname{argmax}}\, E[U(w,s,\ddot{e}',f_I,g,\tau)]
\end{aligned}$$

The first-order condition is $\frac{V'(-f)}{U'(w,s,\ddot{e},f_I,g,\tau)} = \lambda$ and so $U'(w,s,\ddot{e},f_I,g,\tau) = \lambda \cdot V'(-f)$. Captains choose the effort level that satisfies the marginal conditions.

Proposition 1. *Captains in the control group will change their behavior if they are influenced by social pressure. That is, they will generally increase effort if their effort level is below the social effort level.*

[59] Our notation differs slightly from the Hölmstrom (1979) since the cost of the action is embedded in the utility function of the agent.

Proof: We argued above that scrutiny due to the intervention is likely to (weakly) increase either the probability of detection of a sub-optimal effort level ($\pi^{observed}$) or the perceived level of socially optimal level of effort (e^{social}) or both. Both effects increase the social cost component of the utility function for captains in all treatment cells, including the control group. Put differently, for a given level of effort $\bar{e} < e^{social}$, the intervention increases the marginal social cost of exerting low effort $\frac{\partial U}{\partial s}|\bar{e}$. Consequently, captains respond to these new marginal conditions and increase their effort if they are below the (perceived) socially optimal level.[60]

Proposition 2. *Information will cause captains to increase or decrease their effort and thereby increase or decrease fuel usage respectively or choose the outside option, depending on the realization of the difference between estimated (f_{it}) and actual ($\bar{f}_{it}$) fuel usage (i.e. the value of the parameter ϵ_{it}).*

Proof: Let the pre-study period be $t = 0$ and the study period be $t = 1$.

Assume in period $t = 0$, $\epsilon_{i0} < 0$, then $f_{i0} > \bar{f}_{i0}$, so that when captains receive information in $t = 1$, they learn that $y_{2m}(-\bar{f}) > E[y_{2m}(-\bar{f})]$. In other words, they were more fuel-efficient in $t = 0$ than they expected to be. Therefore, if they provide the same level of effort in period $t = 1$, they will experience a level of utility greater than their pre-study equilibrium. They pay the same cost of effort but receive more utility from job satisfaction. They will then weakly decrease their chosen level of effort. How much depends on the functional form of the y and c functions and their pre-study effort level. Captains in the information or targets treatments—where wealth and the charities' production functions are independent of effort—will not decrease their effort if y is steeper than c around their chosen values. This scenario is possible since there is a random shock of ϵ_{i0} to their location of $-\bar{f}$ and we are agnostic about the functional form of y. Without the shock, they would not be in equilibrium if y were steeper with respect to effort than c at the chosen level of effort because they could increase effort and pay a slightly higher cost but get much more utility from job satisfaction. They will not choose their outside option since if

$$E[U(w, s, \dot{e}, f_I, g, \tau = \text{“pre-study, no treatment”})] \geq \bar{U},$$

[60]Because of orthogonality to treatment, this simply increases baseline effort. Furthermore, because utility is additively separable, qualitative findings from the subsequent comparative statics analysis are unchanged. If there are interactions between social pressure and the treatments, these interactions just attenuate point estimates because all treatments are designed to increase effort against a now greater baseline.

then

$$E[U(w, s, \ddot{e}, f_I, g, \tau = \text{“information”})] \geq \bar{U}.$$

In other words, they can hold y constant and decrease effort and thereby increase U, while $\bar{U}$ is held fixed.

Now assume $\epsilon_{i0} > 0$, then $f_{i0} < \bar{f}_{i0}$ and so when captains receive information, they learn that $y_{2m}(-\bar{f}) < E[y_{2m}(-\bar{f})]$, i.e. they were less fuel-efficient than expected. Therefore, if they provide the same level of effort in period $t = 1$, they will receive below their pre-study equilibrium amount of utility. They pay the same cost of effort but receive less utility from job satisfaction. They will weakly increase their effort if the change in y is more than the change in c, which depends on the functional form of these functions and their pre-study effort level. They will not increase their effort if c is steeper than y for similar reasons described in the previous case. They will choose their outside option if the change in y leads to $E[U(w, s, \ddot{e}, f_I, g, \tau = \text{“information”})] < \bar{U}$, which could occur if increases in effort lead to larger increases in c than in y. Whether or not it occurs also depends on captains' outside option.

Finally, assume $\epsilon_{i0} = 0$. Then captains are at their equilibrium with $y_{2m}(-\bar{f}) = y_{2m}(-f_I)$ and do not change their effort.

Proposition 3. *Targets set above pre-study use will cause captains to weakly increase their effort or choose their outside option.*[61]

Proof: Since the target is set above pre-study use (i.e. captains are meeting the targets fewer times than is optimal from the perspective of the firm), upon receiving a target, the captains learn $f > f_T$ and get reference-dependent loss utility equal to $y_{2n} < 0$. Therefore, captains are strictly below their equilibrium in effort and strictly above in fuel usage since in the pre-study period $y_{2n} = 0$ from the assumption that $f_I = \bar{f}$.

Captains will not increase their effort if the increased cost of effort is larger than the gain from the associated decrease in fuel usage in the job satisfaction function. Captains will increase their effort if the gain from the associated decrease in fuel usage is more than the cost of effort. This depends on the functional form of these functions, the value of μ, and the captains' initial values during the pre-study period. Their chosen level of effort comes from the first order condition with $\tau = \text{“receive targets”}$.

[61] All targets were set above the pre-study attainment level, so this is the only case we consider.

Since captains experience a negative utility shock from receiving a target, they will choose the outside option if $E[U(w, s, \ddot{e}, f_I, g, \tau = \text{"receive targets"})] \leq \bar{U}$.

Proposition 4. *Donations made to charity for meeting targets will weakly increase effort if captains' altruism is strictly positive and the donations do not affect their effort otherwise.*

Proof: Let $V_c(d(e), g)$ be the production function of the charity. Note that in the case of pure altruism $V_c = v_1$, as defined in the previous section. $\forall d(e) \cdot g \geq 0$, we have $V_c > 0$ and $V_c = 0$ if and only if $d(e) \cdot g = 0$. Then, captains solve the following optimization problem:

$$\begin{aligned} &\max_{e,g_0} \quad E[V(-f) + \tilde{a} \cdot V_c] \\ &\text{s.t.} \quad E[U(w, s, \ddot{e}, f_I, g, \tau)] \geq \bar{U} \\ &\text{and} \quad \ddot{e} \in \operatorname*{argmax}_{\ddot{e}'} E[w, s, \ddot{e}', f_I, g, \tau)] \end{aligned}$$

with first-order condition $\frac{V'(-f)+\tilde{a}\cdot V_c'}{U'(w,s,\ddot{e},f,g,\tau)} = \lambda$. If a captain has zero altruism, i.e. $\tilde{a} = 0$, then this equation reduces to the original and effort does not increase above the effect described in Proposition 1. If $\tilde{a} > 0$, then the numerator of the first-order condition is weakly larger than the control case. It is strictly larger if $d > 0$. Captains with strictly positive altruism may choose an effort level corresponding to $d = 0$ if the additional cost of increased effort required for meeting the target is more than the gain in utility from donating to charity. The probability of this occurring is decreasing in the level of altruism.

Since λ is a constant, increases in the sum of the production functions of the firm and charity cause increases in effort, $\dot{e} < \ddot{e}$.

Proposition 5. *Captains in the targets and prosocial conditions will choose to increase their effort the most in tasks for which the targets are easiest to meet.*

Proof: Since the firm sets the targets and donations exogenously[62], the utility for meeting a target is constant across tasks. The donation to charity is the same across tasks as exogenously determined, and since the targets are also exogenously determined, the captains believe that the firm values them all equally by revealed preference. If the firm did not value them equally, then it would not offer the same reward. However, the cost function is not constant across tasks for reasons described earlier, which implies that the captains will

[62]Note that the "firm" here refers to both VAA and the academic researchers, who jointly made most decisions with respect to experimental design.

choose to increase their effort on tasks for which targets are easiest to meet.[63] Within our airline context, the least effortful behavior to attain is Efficient Taxi, followed by Fuel Load, then Efficient Flight. The determination of this ordering is based on discussions with many airline captains and trusted pilots groups.

[63]Our theory and interventions are rooted in Hölmstrom's 1979 "Informativeness Principle", which states that any accessible information about an agent's effort should be used in the design and enforcement of optimal contracts. Our interventions are not aimed at the efficient allocation of effort across these tasks—as proposed in Hölmstrom and Milgrom (1991) and Baker (1992)—since we assume our three behaviors are not substitutable (since they occur during different phases of flight). We acknowledge the possibility that additional fuel-efficient behaviors exist that we do not measure that may be fully or partially neglected due to our treatments.

C Appendix III: Examples of Treatment Groups

Figure A1
Treatment Group 1: Information

virgin atlantic

Fuel and carbon efficiency report for Capt. John Smith

Below is your monthly fuel and carbon efficiency report for **Month 2014**

1. Zero Fuel Weight	2. Efficient Flight	3. Reduced Engine Taxy In
Proportion of flights for which the ZFW calculation was completed and fuel load adjusted as necessary	*Proportion of flights for which actual fuel use is less than planned fuel use (e.g. optimised speed, altitude etc)*	*Proportion of flights for which at least one engine was shut off during taxy in*
RESULT: **XX% of flights**	RESULT: **XX% of flights**	RESULT: **XX% of flights**

We will continue to keep you updated on your monthly performance for the next **X months**, John.

Please see reverse side for further details of the three behaviours.

Questions? We are here to help! Please email us at project.uoc@fly.virgin.com.

All data gathered during this study will remain anonymous and confidential. Safety remains the absolute and overriding priority. This study will be carried out within Virgin's existing and highly robust safety standards, using our existing fuel procedures and policies. Captains retain full authority, as they always have done in VAA, to make decisions based on their professional judgment and experience.

Figure A2
Treatment Group 2: Targets

Fuel and carbon efficiency report for Capt. John Smith

Below is your monthly fuel and carbon efficiency report for **Month 2014**

1. Zero Fuel Weight	**2. Efficient Flight**	**3. Reduced Engine Taxy In**
Proportion of flights for which the ZFW calculation was completed and fuel load adjusted as necessary	*Proportion of flights for which actual fuel use is less than planned fuel use (e.g. optimised speed, altitude etc)*	*Proportion of flights for which at least one engine was shut off during taxy in*
TARGET: **XX% of flights**	TARGET: **XX% of flights**	TARGET: **XX% of flights**
RESULT: **XX% of flights**	RESULT: **XX% of flights**	RESULT: **XX% of flights**
You ACHIEVED/MISSED your target.	**You ACHIEVED/MISSED your target.**	**You ACHIEVED/MISSED your target.**

What Was Your Overall Outcome?

You achieved X of your 3 targets last month.

WELL DONE! We will continue to keep you updated on your monthly performance for the next **X months**, John.

Please continue to fly efficiently next month to achieve your targets.

Please see reverse side for further details of the three behaviours.

Questions? We are here to help! Please email us at project.uoc@fly.virgin.com.

All data gathered during this study will remain anonymous and confidential. Safety remains the absolute and overriding priority. This study will be carried out within Virgin's existing and highly robust safety standards, using our existing fuel procedures and policies. Captains retain full authority, as they always have done in VAA, to make decisions based on their professional judgment and experience.

Figure A3
Treatment Group 3: Prosocial

Fuel and carbon efficiency report for Capt. John Smith

Below is your monthly fuel and carbon efficiency report for **Month 2014**

1. ZERO FUEL WEIGHT	2. EFFICIENT FLIGHT	3. REDUCED ENGINE TAXY IN
Proportion of flights for which the ZFW calculation was completed and fuel load adjusted as necessary	*Proportion of flights for which actual fuel use is less than planned fuel use (e.g. optimised speed, altitude etc)*	*Proportion of flights for which at least one engine was shut off during taxy in*
TARGET: **XX% of flights**	TARGET: **XX% of flights**	TARGET: **XX% of flights**
RESULT: **XX% of flights**	RESULT: **XX% of flights**	RESULT: **XX% of flights**
You ACHIEVED/MISSED your target and earned/missed out on £10 in donations to Charity Name.	**You ACHIEVED/MISSED your target and earned/missed out on £10 in donations to Charity Name.**	**You ACHIEVED/MISSED your target and earned/missed out on £10 in donations to Charity Name.**

WHAT WAS YOUR OVERALL OUTCOME?

Due to your fuel and carbon efficient decision making last month, you achieved X of your 3 targets and secured £XX of a possible £30 for your chosen charity, Charity Name.

WELL DONE! For the next **X months**, you still have the ability to donate **£X to Charity Name.** Please continue to fly efficiently next month to achieve your targets so your charity does not lose out.

Please see reverse side for further details of the three behaviours.

Questions? We are here to help! Please email us at project.uoc@fly.virgin.com.

All data gathered during this study will remain anonymous and confidential. Safety remains the absolute and overriding priority. This study will be carried out within Virgin's existing and highly robust safety standards, using our existing fuel procedures and policies. Captains retain full authority, as they always have done in VAA, to make decisions based on their professional judgment and experience.

Figure A4
All Treatment Groups: Reverse Side of Report

THE THREE BEHAVIOURS WE ARE MEASURING

Behaviour 1: Zero Fuel Weight Adjustment (ZFW) - Pre Flight

This measure compares Actual Ramp against Plan Ramp adjusted for changes in ZFW. It captures whether a double iteration adjustment has been implemented for ZFW in line with Plan Burn Adjustment and any further amendments to flight plan fuel that have been entered into ACARS. This behaviour has a tolerance of 200kg, which ensures that rounding in the fuel request / loading procedure will not adversely affect the result.

Behaviour 2: Efficient Flight (EF) - During Flight

This measure examines the actual fuel burn per minute compared against the expected fuel burn per minute from OFF to ON (expected fuel burn is Plan Trip adjusted for ZFW). It highlights pilot technique (e.g. optimum settings are realised, optimum levels are sought, speed is optimised, etc.).

Behaviour 3: Reduced Engine Taxy In (RETI) - Post Flight

This measure observes if an engine has been shut down during taxy in. RETI is considered to have taken place if one engine burns less than 70% of the average of other engines during taxy in. If taxy in is shorter than the cool down period required, the flight is omitted, as RETI was not possible.

We hope the above information is beneficial to you. If you require more information about any of the behaviours, please email us at project.uoc@fly.virgin.com.

D Appendix IV: Survey Materials

D.1 Prosocial Incentives

To the best of your knowledge, how much (if any) did you donate to charity **in 2013**?

- £0 (I did not donate to charity in 2013.)
- £1 - £10
- £11 - £20
- £21 - £30
- £31 - £40
- £41 - £50
- £50 - £75
- £75 - £100
- £100 - £200
- more than £200

How much (if any) did you donate to charity **in 2014 outside of the context of the study**?

- £0 (I did not donate to charity in 2014 outside of the context of the study.)
- £1 - £10
- £11 - £20
- £21 - £30
- £31 - £40
- £41 - £50
- £50 - £75
- £75 - £100
- £100 - £200
- more than £200

D.2 Job Satisfaction

All things considered, how **satisfied** are you with...

	Not at all satisfied 1	2	3	4	5	6	Extremely Satisfied 7
...your present job overall?	○	○	○	○	○	○	○