Investment in Energy Efficiency by Small and Medium-Sized Firms: An Empirical Analysis of the Adoption of Process Improvement Recommendations

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Abstract

We investigate the adoption of energy efficiency initiatives using information on over 100,000 recommendations provided to more than 13,000 small and medium sized firms under the Industrial Assessment Centers (IAC) program of the US Department of Energy (DOE). We build on an earlier study by Anderson and Newell (2004) that explored the impact of economic factors on the adoption of energy efficiency initiatives, by investigating the role of behavioral factors on the adoption of energy efficiency initiatives. Using a probit instrumental variable model, we investigate three behavioral factors that could affect investment in energy efficiency. First, we find that adoption of a recommendation depends not only on its characteristics but also on the order in which the recommendations are presented. Adoption rates are higher for initiatives appearing early in a list of recommendations. We find evidence that this may in part be due to anchoring effects. Second, we find that adoption is not influenced by the number of options provided to decision makers. Third, we find that adoption is higher for recommendations that need lower managerial effort. Additionally, we identify conditions under which these behavioral factors are mitigated. We draw implications for enhancing adoption of energy efficiency initiatives and for other decision contexts where a collection of process improvement recommendations are made to firms.

Keywords: Process Improvement, Energy Efficiency, Decision Bias, Adoption, Environment, Behavioral Operations

1. Introduction

We investigate the adoption of energy-saving opportunities resulting from recommendations made to small and medium sized manufacturing firms. We use data on over 100,000 recommendations made to over 13,000 small and medium sized firms by Industrial Assessment Centers (IAC) program of the US Department of Energy (DOE). Anderson and Newell (2004) (A&N from here on) found that adoption of energy saving initiatives is influenced by the economic characteristics of the recommendations, such as initial costs, payback and savings. We build on their study and investigate the role of behavioral factors, such as the sequence in which the recommendations are presented, the total number of recommendations, and managerial effort required.

The energy-saving recommendations identified by the IAC program often pertain to process improvements in operations, such as improved management of existing systems, modification or replacement of equipment, minimization of waste or resource usage, enhanced quality management, adoption of preventive maintenance and improvement of productivity and management practices.

Adoption of process improvements contributing to energy efficiency can have a significant impact. For instance, the Intergovernmental Panel on Climate Change (IPCC) estimates that over 2.5 gigatonnes of CO_2 equivalents per year can be saved in 2030 using energy efficiency measures. This is nearly 4% of overall anthropogenic CO_2 emissions forecast for 2030 (Bernstein et al. 2007) and equivalent to the emissions of nearly 54% of the passenger vehicles in the world in 2004 (Bush et al. 2006, Emission Facts 2005). The United States has recognized the immense potential and has been striving to improve energy efficiency since the early seventies. Industry accounts for a third of US energy usage, which is why the DOE has been working to improve energy intensity in industry through the Industrial Technologies Program (ITP).

The IAC program is part of the ITP and provides free energy efficiency assessments to small and medium sized firms. The IAC program has been in existence since 1976 and is estimated to have provided cumulative energy savings of 1,714 trillion BTU by 2007 (Impacts 2007). The energy efficiency assessments are done by faculty and students from accredited engineering schools (Muller et al. 2004). Specific improvement recommendations covering the entire gamut of operational improvements including equipment modification, operating procedures and management practices are provided in a report to the firm. Subsequently, the implementation status of the recommendations is tracked by the respective IAC.

The recommendations usually have very attractive rates of return and their average payback period is just over a year. A former IAC director (one of the authors) illustrates how easy it can be to achieve substantial savings: “A quarter-inch diameter hole in a compressed air system implies $5,000 per year in wasted energy costs.” However, even with attractive rates of return, many energy efficient process improvement recommendations are not implemented. For instance from 1982 to 2006, less than half of the identified energy savings have been implemented.

These observations are in line with what has been observed in the energy efficiency literature. Many studies indicate the presence of profitable improvement opportunities. For instance, Shama (1983), Lovins and Lovins (1993) and many others provide examples of such opportunities which may be realized at negligible costs or provide rates of returns often over 30%. However, DeCanio (1993) points out "Many investments in energy efficiency fail to be made despite their apparent profitability." Further, several studies indicate that a significant proportion of energy efficiency opportunities are not exploited (Expert Group on Energy Efficiency 2007). Jaffe and Stavins (1994a) identify the gap between actual energy use on the one hand and the optimal energy use on the other hand as the "energy-efficiency gap."

The energy efficiency literature has drawn on many fields in a bid to explain the paradox of low adoption rates of profitable energy efficiency improvements. The reasons used in the literature include market-failure and non-market-failure explanations (Jaffe and Stavins 1994b), organizational and institutional factors (DeCanio 1998), technology adoption and learning by using (Mulder et al. 2003), real options framework (Dierderen et al. 2003), and complexity of regulation (Mueller 2006). A&N, the only scholarly study to our knowledge that has used the IAC data, link economic incentives to energy efficiency initiatives and find that adoption depends more on initial cost than on annual savings. However, the literature struggles to explain the high rates of non-adoption of these initiatives.

Behavioral explanations using concepts ranging from bounded rationality to inertia have also been proposed in the literature (Rohdin and Thollander 2006). However, Kempton et al. (1992) point out that much of the psychological research has focused on residential energy users at home. In this paper, we examine how behavioral factors may influence firms' decision-making in this context, focusing primarily on how managers choose between alternatives rather than on the adoption/ non-adoption decision. We find that the adoption of a recommendation is influenced by the sequence in which it is presented. Moreover, we find that anchoring may be a mechanism which drives the order effect. We find that decision makers are not influenced by the total number of recommendations made to them. We also find that adoption rates are higher for recommendations that require lower effort. Further, we identify conditions under which these behavioral effects are mitigated.

This paper aims to make three key contributions. First, it studies behavioral factors which influence adoption decisions related to energy efficiency initiatives by small and medium sized firms. This will facilitate a better understanding of the behavioral issues that influence the overall adoption of energy efficiency opportunities. Second, this understanding would enable adoption of policies and actions to improve adoption rates, in line with the suggestions of Allcott and Mullainathan (2010), who argue that behavioral interventions can be valuable in improving energy efficiency. Further, since the recommendations cover a wide range of operations, this may facilitate adoption of process improvement initiatives more generally. Finally, it highlights behavioral issues using actual field data as opposed to the majority of the behavioral operations literature which uses experiments.

The rest of the paper is organized as follows. In Section 2, we present the hypotheses. In Section 3, we describe the data and the measures used in our analysis. In Section 4, we present our methodology and results. In Section 5, we discuss the results, implications of our findings and limitations of our analysis. In Section 6, we provide a summary, discuss policy implications and indicate areas for further research.

2. Hypotheses

Our hypotheses are grounded in the literature on adoption of innovations and energy-efficiency initiatives while drawing upon the behavioral literature related to heuristics, biases and order effects. We develop four hypotheses related to the adoption of energy-efficiency initiatives.

Our first hypothesis examines the impact of the order in which recommendations are presented to managers. We are not aware of any studies of this effect in the context of energy efficiency, so the literature we draw on here is all behavioral. Anderson (1971) used information integration theory to link judgments to the order in which information is received. He defines the primacy effect as occurring when information presented early in a sequence has a higher effect on judgment and the recency effect when the converse happens. Many studies in the literature highlight the presence of these effects. Symonds (1936), in an experiment with school children, varied the order of presentation of a list of items and studied the effect on ranking of these items. He found that items had a lower rank when they were placed earlier in the list. Ashton and Ashton (1988) investigated the role of information order in an audit context and find support for the recency effect while Anderson and Maletta (1999) find evidence that auditors are susceptible to primacy effects. Kardes and Kalyanaram (1992) performed experiments where consumers were sequentially exposed to information on various brands and find evidence of a primacy effect. Terry (2005) investigated the impact of the serial position of a commercial in a batch of commercials and finds evidence for both primacy and recency effects. Bruine de Bruin (2006) observes serial position effects when options are judged in a sequence, as in the case of figure skating competition, and finds evidence that later performers obtain higher scores. Li and Epley (2009) demonstrate using a series of experiments in different settings that decision makers demonstrate primacy effects when they choose amongst undesirable options and recency effects when they choose amongst desirable options. Mantonakis et. al. (2009) evaluate tasting preferences for wine using experiments and find that choices exhibit primacy effects in the context of the average participant, however when the participants are knowledgeable about wine they find that choices are in line with recency effects. Meredith and Salant (2007) find evidence that the order in which candidates are presented in a ballot influences election outcomes with candidates being listed first gaining a significant advantage.

Overall, the literature finds evidence of both primacy and recency effects but has not been able to clearly delineate the contexts in which primacy or recency effects will dominate. In our context, decision makers are provided a written report with the recommendations in a particular sequence. To predict how the serial position of a recommendation in the report will influence the decision maker's response to a recommendation we appeal to the anchoring and adjustment arguments of Tversky and Kahneman (1974). For instance, consider a decision maker who gets an assessment with n recommendations with payback values pb_1 to pb_n. Assume the decision maker evaluates these recommendations only on payback and the initial threshold for adoption is whether a recommendation has payback lower than or equal to pb_T. If pb_1 is lower than pb_T then the decision maker adopts the first recommendation, and adjusts her adoption threshold to a value $pb_{T^\wedge}$ less than pb_T. The decision maker will evaluate subsequent recommendations against the more stringent payback threshold of $pb_{T^\wedge}$. Consequently, we can expect recommendations which come later in an assessment to face more stringent threshold levels and hence exhibit lower adoption rates. Anchoring effects could hence lead to order effects with lower adoption for recommendations which occur later in the report. This leads to the following hypotheses:

Hypothesis 1a: *Recommendations which occur earlier in a report will have higher adoption rates than recommendations which occur later in a report.*

Hypothesis 1b: *Anchoring effects will influence adoption of recommendations in an assessment, in the sense that recommendations which have shorter payback (or lower cost or higher saving) than the first recommendation in that assessment are more likely to be implemented.*

Our second hypothesis relates to whether the number of recommendations provided to managers affects the number of recommendations they adopt. In the context of energy efficiency, there is again no literature focusing on this effect, but the literature on the asset allocation problem where decision makers allocate assets over a set of choices is relevant. Benartzi and Thaler (2007) highlight many instances of this problem and discuss issues specifically related to retirement savings. They find that many decision makers adopt a naïve strategy of allocating their assets equally over n choices, which they call the "1/n rule". Huberman and Jiang (2006) analyze similar problems when the number of choices is large. They find that decision makers first restrict their choices to a smaller subset of n choices and then allocate the assets equally over the subset of n choices. They call this the "conditional 1/n rule". Iyengar and Lepper (2000) study the cases when consumers are provided a wide array of choice (24 flavors of jam) and limited choice (6 flavors of jam). They find that consumers were more likely to make a purchase when they have limited choice. Sethi-Iyengar et al. (2004) find that 401(k) plan participation levels drop with an increased number of investment options. More recently, scholars have investigated what moderates the “too much choice” effect. For instance, Chernev (2003a and 2003b) demonstrates that when confronted with a situation of some novelty and complexity, decision makers with clearly articulated attribute preferences are more likely to choose from sets with more choices as compared to decision makers without readily available ideal attribute preferences. He argues that this is because decision makers without an ideal attribute preference are confronted with a more challenging task of evaluating the alternatives while simultaneously developing the criteria for evaluation. Gourville and Soman (2005) find that “overchoice” is also moderated by the type of alternatives provided in a choice set. They show that decision makers prefer larger choice sets where alternatives vary along a single compensatory attribute (engine size of a car). However, for choice sets where alternatives vary along multiple non-compensatory attributes (sun roof vis-à-vis leather interiors) decision makers exhibit the “too much choice” effect, on account of increased cognitive effort of processing all of the available information. Berger et al. (2007) show that decision makers may prefer larger choice sets with compatible alternatives (varieties of gourmet chocolates), but also that in choice sets with non-compatible alternatives (varieties of gourmet chocolates and cheeses) having more alternatives can lead to “too much choice” effects. In our context, decision makers are provided a set of recommendations which differ along many attributes. Though decision makers may have a clear idea of the financial criteria on which to evaluate the recommendations, the differences in other attributes of the recommendations (e.g. whether it pertains to manufacturing process, supplier practices, direct labor, etc.) increases the cognitive effort involved in the evaluation of the recommendations. We posit that the cognitive effort will increase with the number of recommendations provided to the decision maker. Consequently, we predict that if a decision maker is provided with a large number of recommendations (choices) her adoption rate will be lower than if she is provided with a limited number of recommendations (choices).

Hypothesis 2: *Adoption rates of individual recommendations will fall as more recommendations are made in the same assessment.*

Our third hypothesis relates to the role of managerial attention, one of the barriers to the adoption of energy-efficiency initiatives identified by DeCanio (1993). Simon (1976) argues that humans display bounded rationality. Ocasio (1997) extends this to the context of organizations and points out that decision makers focus on a limited set of issues and answers. Sullivan (2010) shows how the “urgency effect” generated by problems influences the way organizations allocate their attention when they face new problems while trying to solve old problems. Given the limits on what can be done by managers and the competing demands on managerial attention it is plausible that some opportunities which need significant attention may not get adopted. Hirshleifer and Suh (1992) point out that managerial effort is often essential for maintaining the efficiency of ongoing projects. This is especially true for recommendations that involve substantial changes in operating procedures or adoption of new technologies or practices that could disrupt regular operations. For instance, a recommendation such as "Replace Electrically-Operated Equipment with Fossil Fuel Equipment" involves adopting new technology besides replacing current equipment and would involve substantial managerial effort. However, as Barron and Waddell (2003) mention, increased managerial effort can improve firm performance but the increased effort comes at a cost to the executive. These costs may prompt managers to avoid effort (Harris et al. 1982, Porteus and Whang 1991). Consequently, recommendations such as "Eliminate Leaks In Inert Gas And Compressed Air Lines/Valves" which are part of regular maintenance and involve low managerial effort would have higher rates of adoption.

Hypothesis 3: *Adoption rates are lower for recommendations that need high managerial attention.*

Hypotheses 1-3 explore the impact of various behavioral factors on the adoption of energy saving opportunities. In our fourth hypothesis we seek to examine the conditions which mitigate the impact of these behavioral factors. In our context, decision makers are confronted with a situation where they need to evaluate multiple alternatives on many attributes. If decision makers have well-articulated preferences and beliefs, they can evaluate alternatives and identify the recommendations with the most utility and adopt them. However, decision makers often find it difficult to trade off one attribute against the other. In such instances, decision makers may choose to resolve conflict by selecting alternatives that are superior on the most important attribute (Tversky et al. 1988). This lexicographic procedure avoids the need for a trade-off between attributes and hence reduces cognitive effort. Further, it can be used as a means to justify the chosen alternatives. In the context of the IAC program, the economic characteristics of a recommendation can be considered as the most important attribute based on which decision makers evaluate the recommendations (A&N). Often firms and decision makers have well defined criteria on economic characteristics, for instance a firm may only implement projects with payback period shorter than 3 years. Such well defined preferences are similar to the ideal point as defined by Chernev (2003a, 2003b). However, if the variation in the economic characteristics of recommendations in an assessment is low, then the decision maker will still face the cognitive challenge of choosing between similar options. This will lead to weaker preferences in line with Chernev (2003b), who finds that decision makers with articulated ideal points have weaker preferences when they choose from smaller choice sets. By contrast, if variation in economic characteristics of recommendations in an assessment is high, then the decision maker will face the cognitively simpler task of choosing amongst dissimilar options. The reduced cognitive requirements in such situations will lower the impact of behavioral factors on adoption.

Hypothesis 4: *The impact of behavioral factors related to order effects and choice overload will be mitigated for assessments with higher variation in the economic characteristics of a recommendation.*

3. Data and Measures

3.1 Data and Context

The US Department of Energy's IAC program funds a network of universities to conduct free energy assessments for small and medium-sized manufacturing firms. Assessments are done by engineering faculty and students from universities across the US. Over 50 universities have participated in the program at various times since it started in 1976. In fiscal year 2010, the budget for the IAC program was $3.87 million and 386 assessments were performed (DOE 2011).

Firms eligible for the assessments are chosen based on multiple criteria. These include whether the plant's products are within standard industrial classification codes 20 through 39, whether the plant is within 150 miles of the host campus, has gross annual sales below $100 million, has employee count less than 500, has annual energy bills between $100,000 and $2 million and has no professional in-house staff to perform the assessment (Muller et al. 2004). A small number of larger firms exceeding these criteria were assessed by IAC, on special request of the DOE, and are included in the database.

Firms may either contact the IAC expressing an interest in an assessment or the IAC may directly contact potential firms. The IAC team collects information to understand current energy usage in the firm. The next step is a site visit by the IAC team led by a faculty member. Typically the visit entails interviews with the plant management, plant tours and collection of operational data. Some energy saving opportunities are identified by observing the plant operations. The fourth author, a former IAC director, indicated that in some instances it was surprisingly easy to identify opportunities: "In some plants we hear a constant hiss which indicates compressed air is leaking out." Other recommendations are identified by analyzing the operational data and linking it with observations in the plant visit. As the former IAC director says; "In one plant we saw excess flash (extra material) on parts made using an injection molding process and later using the specific heat values for the molding material we identified they were using around forty times the energy required." Subsequent to the visit, the team provides a written report with specific recommendations to improve efficiency across energy, waste streams and productivity. After six to nine months, the plants are contacted by the IAC to ascertain which of the recommendations have been implemented or will be implemented in the next year. The IAC tracks which recommendations have been adopted over a period of two years. The information on the recommendations and their implementation status is provided to the IAC database managers using standard templates.

Information on the recommendations and the assessments is maintained in a database at a public website hosted by the Center for Advanced Energy Systems at Rutgers University. The database has details of each assessment performed since 1981. As of 2010 there are over 14,800 assessments with over 111,000 recommendations. The information maintained for each assessment includes plant demographics such as annual sales, employees, plant area, production hours, energy consumed, manufacturing sector, date of assessment, etc. For each recommendation the information maintained includes expected savings, quantity of energy conserved, implementation costs, payback calculations, whether the recommendation was implemented or not, etc. Details on the information maintained in the IAC database and on the IAC assessment process are available in "The DOE Industrial Assessment Database Manual" (Muller et al. 2004). The DOE classifies recommendations by Assessment Recommendation Code (ARC) into 25 major categories and over 600 sub-categories. The ARC number for each recommendation and the order in which the recommendations appeared in the report are also stored in the database.

We use the data from the IAC database for the years 1981-2006. In our analysis, we adjust all monetary figures for inflation, scaling to year 2006 US dollars using the producer price index WPUSOP3000 series for finished goods from the Bureau of Labor Statistics (BLS 2008). We exclude 2,824 recommendations which do not pertain to the period 1981-2006, 4,723 recommendations which do not have information on the implementation status, 778 recommendations which have payback longer than nine years, 44 recommendations that involve additional costs and do not provide any positive savings, and 8 recommendations which have negative costs for implementation. These are all outliers and possibly errors; including them does not change our conclusions. We also exclude from our analysis firms whose nominal sales are over $100 million and firms which fall outside the two digit SIC classification from 20 to 39, as these typically represent firms who were audited on special request from the DOE. This represents 3,424 recommendations made to 434 firms. Our conclusions and results do not change if we include these observations in our analysis. The data on 89,299 recommendations are used in the analysis. However, not all observations are included in specific analyses, as indicated later. As the identity of the firm in the IAC database is confidential, we are unable to obtain firm-specific data on profitability, budgets, etc. Consequently, we supplement our data with information from Standard and Poor's (S&P) Annual Compustat database. For each firm in the IAC database we use the 4 digit SIC code, the year of the assessment, and the firm's sales to identify information on average profitability and operating cash flows for comparable firms from the Compustat database.

Table 1 provides descriptive statistics for our data. The average estimated implementation cost across all recommendations is $19,118 while the average estimated annual savings is $17,791. The average estimated simple payback period across all recommendations is just over a year. Firms adopted 50.16% of all recommendations.

One possible concern may pertain to the quality of the recommendations made by the IAC. If only some recommendations are compelling in each assessment, then one could argue that managers implement the few good recommendations and ignore the rest, and this may drive our results. To address this concern, we contacted five firms in California audited under the IAC program who confirmed that they received valid recommendations. The DOE also assessed the efficacy of the IAC program at various times using third parties. For instance, Martin et. al. (1999) evaluate the impact of the IAC program for audits done in 1997 and find that the direct savings realized are in line with the projected savings. Moreover, we control for the individual IAC in all our analyses, and consequently believe any concern related to the quality of the recommendations made by the IAC does not affect our results.

3.2. Variables Used

This section defines the various measures we use. The dependent variables in our analyses are indicators which represent whether a recommendation is adopted or not.

3.2.1 Variables to Represent Hypotheses Discussed in § 2

Serial Position of a Recommendation – We use the actual serial position of the recommendation in the report to evaluate Hypothesis 1 related to order effect.

Anchoring Effects – We define the anchor as the first recommendation in an assessment. Then we define three indicator variables. Anchor_Payback takes on a value of 1 for a specific recommendation if it's payback is less than or equal to that of the first recommendation, Anchor_Cost is defined similarly but using implementation costs, and Anchor_Saving takes on a value of 1 if the annual savings for the recommendation is more than or equal to the annual savings of the first recommendation.

Total Number of Recommendations in an Assessment – This is measured as the number of recommendations made in an assessment and is used to evaluate Hypothesis 2 related to choice overload.

Managerial Attention – The process of classifying the recommendations as requiring low or high managerial attention was done jointly by two authors of this paper, one a former director of an IAC and the other a former operations consultant who has worked for over a decade on projects similar in nature to the IAC assessments. 155 types of recommendations were identified as requiring low managerial attention and 79 as requiring high attention. 450 types of recommendations could not be unambiguously classified and were excluded from this specific analysis. A sample list of recommendations that are classified as requiring low and high managerial attention is provided in Table 2. The kappa statistic measure of inter-rater agreement is 0.85 which is quite high; Landis and Koch (1977) suggest that a kappa statistic of above 0.81 represents almost perfect agreement.

Mitigation of Impact of Behavioral Factors – To evaluate our fourth hypothesis we use the Coefficient of Variation of Payback, Cost, and Savings. The Coefficient of Variation of Payback is defined as the ratio of the standard deviation of payback values of recommendations within an assessment to the mean payback for recommendations in that assessment. Coefficient of Variation of Cost and of Savings are defined analogously.

3.2.2 Variables Used as Controls

Economic Characteristics of a Recommendation – We follow A&N and use six variables to control for the economic characteristics of a recommendation: ln(Payback), $[\ln(\text{Payback})]^2$, ln(Cost), $[\ln(\text{Cost})]^2$, ln(Savings) and $[\ln(\text{Savings})]^2$. Payback represents the simple payback for a recommendation. Cost represents the implementation costs for a recommendation and includes cost of equipment and installation costs. Savings represent the expected annual savings in dollars from adopting a recommendation. Payback, cost and savings have been normalized to equal one at their respective means to ease interpretation of the coefficients. In line with A&N, we use the logarithmic form as it improves the model's fit with the data; using the linear form provides similar results.

Type of a Recommendation – We include indicator variables to identify each recommendation as belonging to one of the twenty-five different mutually exclusive major categories based on the first two digits of the ARC number. This measure controls for the underlying heterogeneity among the recommendations.

Variance of Payback of a Recommendation Type – To capture the uncertainty related to the returns for a recommendation, we compute the variance of payback of a specific type of recommendation i as $\sum_{j \in J(i)} [(\text{Payback})_{ij}-(\text{Average Payback})_i]^2$, where J(i) represents all firms that were given recommendation i. This variable is not a perfect measure of the uncertainty related to the returns as it also captures the underlying heterogeneity of the firms in the dataset, but as long as there is some recommendation-specific component to this overall variance, this measure will be correlated with the uncertainty associated with a recommendation type.

Assessment Year– We use indicator variables for the year the assessment was done.

Assessment Quarter – Stern and Aronson (1984) point out that expenditures that fit into the present budget cycle require fewer approvals. For most firms in the US, budgeting and financial reporting conform to fiscal calendars (Oyer 1998). The 1998 Survey of Small Business Finances by the Federal Reserve Board finds that for nearly 85% of small firms in the US, the fiscal year coincides with the calendar year. Consequently, to capture the impact of budgetary cycles we use indicator variables to identify the specific calendar quarter in which the assessment was done.

IAC Control – We use indicator variables to identify which specific IAC undertook the assessment. Additionally, since each IAC operates within a restricted geography this variable also serves as a surrogate control for the state in which the assessed firm is located.

SIC Control – We use indicator variables for each firm's two digit SIC code. Table 3 provides the number of firms in each two digit SIC code.

Other Firm Level Control – We use sales, number of employees and the plant area (in square feet) as additional controls for firm-level effects.

Table 4 provides the correlation of select variables used in our analysis.

4. Methodology and Results

To test our hypotheses, we employ econometric models that relate adoption to the economic drivers and specific characteristics of recommendations, building on and extending A&N. They estimate a conditional logit model and find, as one would expect, that initial costs, savings, and the payback of a recommendation have a significant effect on the adoption of the recommendations. We enhance their model by including several additional variables: the serial position of each recommendation, the total number of recommendations in a report, and the time of year of the audit. These variables enable us to evaluate whether the way in which recommendations are presented impacts the adoption rate. However, one cannot simply incorporate these variables in the conditional logit models by A&N, for two reasons. First, the serial position of the recommendations in a report may be endogenous. Therefore, we use probit instrumental variables models. Second, we cannot use not use firm-level fixed effects with these new variables, so we need to use additional controls such as sales, number of employees, and two digit SIC codes for each firm, and recommendation-level controls to account for the uncertainty in returns. All the analyses were done using STATA version 10.1.

4.1 Instrumental Variables Probit Model

We use an indicator variable Y_{ij} that equals 1 if recommendation i in report j is adopted and equals 0 otherwise. The resultant choice problem is defined by the latent variable model:

$$Y_{ij}^{*} = \alpha + \mathbf{M}_{ij}*\boldsymbol{\beta} + V_{ij}*\gamma + \mathbf{T}_{ij}*\boldsymbol{\rho} + S_{ij}*\zeta + N_{j}*\eta + \mathbf{C}_{j}*\boldsymbol{\chi} + \varepsilon_{ij} \quad (1)$$

$$\varepsilon_{ij} = \delta_{i} + \mu_{j} + \acute{\varepsilon}_{ij} \quad (2)$$

where Y_{ij}^{*} is the net benefit of adopting recommendation i in report j; $\mathbf{M}_{ij}$ is the vector of financial variables for recommendation i in report j; V_{ij} is the variance of payback associated with recommendation i in report j; $\mathbf{T}_{ij}$ is a vector which indicates the type of recommendation i in report j; S_{ij} represents the serial position of the recommendation i in report j; N_j represents the number of recommendations in report j; the matrix $\mathbf{C}_j$ includes controls for the specific IAC, two digit SIC codes, sales, number of employees, the year of assessment and the calendar quarter in which the assessment was done. The error terms ε_{ij} are decomposed into three parts. The first part is δ_i which represents recommendation type-related unobserved characteristics and is partially controlled for by including indicators for recommendation type and the variance in payback. The second part is μ_j which represents assessment-related unobserved characteristics and is partially controlled for by including indicators for specific IAC, two digit SIC codes, firm size and firm-level variables such as sales and number of employees. The third part $\acute{\varepsilon}_{ij}$ are related to the recommendation and firm-specific unobserved characteristics.

Decision makers will adopt a recommendation only if the benefits from adopting it are positive, and thus the probability that a recommendation is adopted is

$$\begin{aligned} \text{Prob}\,[Y_{ij} = 1] &= \text{Prob}[\alpha + \mathbf{M}_{ij}*\boldsymbol{\beta} + V_{ij}*\gamma + \mathbf{T}_{ij}*\boldsymbol{\rho} + S_{ij}*\zeta + N_j*\eta + \mathbf{C}_j*\boldsymbol{\chi} + \varepsilon_{ij} > 0] \\ &= F\,(\alpha + \mathbf{M}_{ij}*\boldsymbol{\beta} + V_{ij}*\gamma + \mathbf{T}_{ij}*\boldsymbol{\rho} + S_{ij}*\zeta + N_j*\eta + \mathbf{C}_j*\boldsymbol{\chi}\,) \end{aligned} \tag{3}$$

where F is the cumulative probability distribution function for ε_{ij}. If we assume the cumulative distribution of ε_{ij} follows a standard normal distribution we have the probit model (Maddala 2003).

Model (1) treats the serial position of the recommendation as exogenous, but this need not be the case. For instance, a plant manager may find some recommendations attractive due to his knowledge or comfort related to those recommendations. As an illustration, the plant manager may not want to implement changes pertaining to labor practices but may be willing to implement changes pertaining to material sourcing practices. The IAC representatives may gauge the attractiveness (or preference) for specific recommendations in their interactions with the firm, and this could influence the way they sequence the recommendations in their report. The IAC team may place attractive recommendations either at the top of the report to increase their chance of implementation, or alternatively they may place the attractive recommendations later so that other recommendations come earlier in the report and get a higher probability of implementation. Some such manipulation is quite probable as the IAC centers are evaluated partly on the number of recommendations implemented and hence they have an incentive to present the recommendations in a manner to increase adoption. If the IAC assessment of the attractiveness of each recommendation were captured by the observable variables then we could use model (1) to obtain consistent results. However, when the IAC assessment of attractiveness is not observable (as in our illustration) the effect of attractiveness will be captured in the error terms. This will imply that the serial position is correlated with the error term and is therefore endogenous in the model. (A Wald test for exogeneity confirms that the serial position is endogenous.) We can address this problem by identifying an instrument that is related to the serial position of the recommendation, but is otherwise unrelated to the error terms (Wooldridge 2002).

We explore two instruments for the serial position of the recommendation. We follow the approach suggested in Wooldridge (2002), as also used in Olivares and Cachon (2009) who analyze the impact of competition on inventory levels. They observe that competition may be correlated with unobserved consumer characteristics, which could lead to biased estimates. To address this endogeneity, they use measures of market population as instruments. They point out that population will be correlated with competition but that it is in no way related to unobserved consumer characteristics, and hence measures of population can serve as valid instruments. Analogously, our first instrument is based on the order in which the recommendations appear in the ARC manual. The ARC manual groups recommendations based on the engineering categories of recommendations such as combustion systems, thermal systems, electrical power, and so forth. We use the ARC code to sequence the recommendations made to a firm so that the recommendation with the lowest ARC code is given the first rank, and so forth. The assessors use the ARC codes to report their recommendations to the IAC Database managers, so their reporting of recommendations in the report may partly follow the sequence in the ARC manual. Hence our instrument based on the order of the recommendation in the ARC manual will be correlated with the serial position of a recommendation in a report. Further, the engineering classification used in the ARC manual will not be correlated with the unobserved attractiveness of a recommendation. Consequently the ranking based on the order in the ARC manual can serve as a valid instrument for the serial position, just as measures of population serve as a valid instrument for competition in Olivares and Cachon (2009).

The second instrument is related to the propensity with which each IAC makes a recommendation. We follow the arguments of Cachon and Olivares (2010) who analyze the impact of production flexibility on finished goods inventory levels. In their estimation approach they point out that there may be a mechanical relationship between production flexibility and the dependent variable. To address this endogeneity, they use production flexibility of other models produced in the same plant as instruments. Analogously, we compile the frequency with which each IAC makes a particular recommendation across all assessments. We use this to sequence the recommendations made to a specific firm so that the recommendation with the highest frequency gets the first serial position and so forth. The resulting sequence is a reflection of the IAC's familiarity with specific recommendations and this may be related to the way in which they present the recommendations to a specific firm. This sequence is based on the IAC's interaction with all firms it has assessed and as such it will not be related to the preferences of a specific firm; hence the instrument should not be correlated with the error term. One concern with the instrument may be that IAC's are likely to recommend initiatives that are attractive and have higher probability of adoption among all firms. To address this concern, we estimate the variance of δ_i relative to

$\acute{\varepsilon}_{ij}$, using a linear mixed model with random effects incorporated at the recommendation and assessment levels to evaluate the variance components. We find that the estimated variance for δ_i is 0.01, much smaller than that for $\acute{\varepsilon}_{ij}$ which is 0.12. Consequently, the possible concern that this instrument may be correlated with recommendation-level unobserved characteristics is minimal, as the overall recommendation type-related unobserved characteristics (captured by δ_i) are much smaller than recommendation- and firm-specific unobserved characteristics (captured by $\acute{\varepsilon}_{ij}$).

We use an instrumental variables probit model to address the inherent endogeneity:

$$Y_{ij}^* = \alpha + \mathbf{M}_{ij}*\boldsymbol{\beta} + V_{ij}*\gamma + \mathbf{T}_{ij}*\boldsymbol{\rho} + S_{ij}*\zeta + N_j*\eta + \mathbf{C}_j*\boldsymbol{\chi} + \varepsilon_{ij} \tag{4a}$$

$$S_{ij} = \mathbf{M}_{ij}*\Pi_{\boldsymbol{\beta}} + V_{ij}*\Pi_{\gamma} + \mathbf{T}_{ij}*\Pi_{\boldsymbol{\rho}} + N_j*\Pi_{\eta} + \mathbf{C}_j*\Pi_{\boldsymbol{\chi}} + \nu_{ij} \tag{4b}$$

In this model the variable serial position S_{ij} is endogenous as opposed to model (1) where S_{ij} is exogenous. The linear projection in equation (4b) represents the reduced form equation for the endogenous explanatory variable S_{ij}. We assume the error terms in (4a) and (4b) are normally distributed and are orthogonal to all regressors. Following A&N, we estimate a "Payback" model and a "Cost-Benefit" model. In the "Payback" model, we use the variables $\ln(\text{Payback})_{ij}$ and $[\ln(\text{Payback})_{ij}]^2$ for the vector $\mathbf{M}_{ij}$. Similarly for the "Cost-Benefit" model, we use the variables $\ln(\text{Cost})_{ij}$, $[\ln(\text{Cost})_{ij}]^2$, $\ln(\text{Savings})_{ij}$ and $[\ln(\text{Savings})_{ij}]^2$ for the vector $\mathbf{M}_{ij}$.

To validate the instruments for model (4a), we ran an OLS regression of the variables for serial position of the recommendation on the instruments related to the ARC code and the IAC propensity to make a type of recommendation. The R^2 we obtain for this regression is 0.23, which is comparable to similar values reported in the literature. For instance, Evans and Schwab (1995), in a paper which uses a similar instrumental variable probit methodology as we do, report R^2 of 0.16 when they regress their endogenous variable -- catholic school -- on their instrument -- catholic religion. We also ran an ordered probit model, and the z-statistics for the instrument related to ARC code and the IAC propensity to make a type of recommendation are 91.90 and 70.64 respectively and both are statistically significant at $p<0.001$. Therefore, the chosen instruments are valid determinants of the serial position of the recommendations for the model (4a).

We evaluated two probit models each for the Payback model and the Cost-Benefit model: one where the variable S_{ij} is treated as exogenous and the other where it is treated as endogenous. Table 5 presents the results for these four models.

Model (4a) captures two distinct effects, one due to the serial position of the recommendations and the other due to the total number of recommendations in an assessment. These variables are inevitably not orthogonal, the correlation is 0.51. Consequently, to disentangle these effects, we formed groups of all recommendations with the same serial position and then we estimated probit models of the adoption rates within each group separately. Table 6 provides the results for these models.

To evaluate the impact of anchoring effects, we defined an indicator variable A_{ij} to identify recommendations that meet the anchoring criteria and used the following specification:

$$Y_{ij}^{*} = \alpha + \mathbf{M}_{ij}*\boldsymbol{\beta} + V_{ij}*\gamma + \mathbf{T}_{ij}*\boldsymbol{\rho} + N_{j}*\eta + A_{ij}*\lambda + \mathbf{C}_{j}*\boldsymbol{\chi} + \varepsilon_{ij} \tag{5}$$

We evaluate three variations of the probit model (5) each for the "Payback" model and the "Cost-Benefit" model, using the indicator variables Anchor_Payback, Anchor_Cost , and Anchor_Savings for A_{ij} respectively. Table 7 provides the results of this analysis.

To evaluate our hypothesis on managerial attention, the indicator variable H_{ij} identifies recommendations as requiring low or high managerial attention, as follows:

$$Y_{ij}^{*} = \alpha + \mathbf{M}_{ij}*\boldsymbol{\beta} + V_{ij}*\gamma + \mathbf{T}_{ij}*\boldsymbol{\rho} + S_{ij}*\boldsymbol{\zeta} + N_{j}*\eta + H_{ij}*\omega + \mathbf{C}_{j}*\boldsymbol{\chi} + \varepsilon_{ij} \tag{6a}$$

$$S_{ij} = \mathbf{M}_{ij}*\Pi_{\boldsymbol{\beta}} + V_{ij}*\Pi_{\gamma} + \mathbf{T}_{ij}*\Pi_{\boldsymbol{\rho}} + N_{j}*\Pi_{\eta} + H_{ij}*\Pi_{\omega} + \mathbf{C}_{j}*\Pi_{\boldsymbol{\chi}} + \nu_{ij} \tag{6b}$$

We use the same approach as for models (4a) and (4b) to evaluate models (6a) and (6b). Table 8 provides the results of this analysis.

To evaluate our fourth hypothesis on the mitigation of the impact of behavioral factors, we divide the assessments into four quartiles by coefficient of variation of payback. For each group, we estimate the "Cost-Benefit" models (4) where the variable S_{ij} is treated as endogenous. We repeat this using the coefficients of variation of cost and of savings. Table 9 provides the results of this analysis for the groupings by the coefficient of variation of payback and of savings; the analysis on grouping by coefficient of variation of cost is similar and hence omitted.

5. Results, Implications and Limitations

In this section, we present our main results, draw implications and discuss limitations and alternative explanations. We also performed several robustness checks which reinforce our findings, but we do not present them here to keep our arguments brief and focused.

With respect to Hypothesis 1a on order effects, we observe that the average adoption rate falls for recommendations that occur later in the report (as demonstrated in Figure 1), from over 50% for the earliest recommendations to around 40% for the last ones. Further, we observe that the coefficient of the serial position of the recommendation is negative and significant at the $p<0.001$ level across all models in Table 5. This supports Hypothesis 1a that the probability of adoption falls as the recommendation occurs later in the report. In Table 5 for the 'IV Probit' Cost-Benefit Model, if we consider an average assessment and move a recommendation from the fourth to the fifth position in the report then its probability of adoption will fall by 0.0593. Increasing the cost of implementation by \$31,540 from the average level of \$19,118 would have the same effect. In Table 5, the coefficient of the serial position is over five times larger for the 'IV Probit' model than for the 'Probit' models. This indicates that the impact of the serial position in the 'Probit' models tends to be understated due to the endogeneity. Overall, these results provide empirical support for Hypothesis 1a.

For Hypothesis 1b related to anchoring effects we refer to Table 7, where the coefficients of the variables related to anchoring effects (Anchor on Payback, Anchor on Cost, and Anchor on Saving) are positive in all models and significant at the $p<0.05$ level in five of the six models. This supports Hypothesis 1b that adoption is influenced by anchoring effects. Further, from Table 4 we observe that the anchoring variables have negative correlations with the serial position variables ranging between -0.32 to -0.35. The significance of the variables related to anchoring coupled with negative correlations between the variables for anchoring and serial position are consistent with our argument that recommendation which come later in an assessment face more stringent thresholds and hence exhibit lower adoption rates. This supports our assertion that anchoring mechanisms could lead to order effects.

As the recommendation order variable is also related to the total number of recommendations, a possible concern may be that the effect we identified is partly due to the total number of recommendations. We performed two additional robustness checks to address this concern. First, we redid the analysis related to Table 5 with a normalized measure of serial position instead of the absolute serial position. Second, we formed groups of all assessments with the same total number of recommendations and redid the probit instrumental variables analysis within each group. The results of these two additional analyses also support the inference that the sequence of recommendations is significant in explaining the adoption rates. Another possible concern is that there may be also a recency effect. To address this we tested for end-of-sequence effects by including indicator variables for the last few (up to three) recommendations in an assessment. We do not find any evidence that supports recency effects. Our results suggest that the IAC teams must be careful on how they sequence the recommendations in an assessment. The IAC teams could leverage these findings to increase the number of recommendations adopted in an assessment. Our results point to a relatively basic mechanism that may induce higher overall energy savings, which is especially relevant given that less than half the energy savings identified by IAC program from 1982 to 2006 have been implemented. This implication may also carry over to other contexts, such as consultants providing reports to clients, or firms providing retirement saving options to their employees, or internet firms providing choices to prospective customers, etc. (In all these situations, decision makers are exposed to a set of choices and may be influenced by the sequence in which those choices are presented to them.)

A possible alternative explanation is that firms might plan to adopt all the recommendations but decide to do so in the sequence in which they are presented. Hence, when the IAC contacts them within two years to check on the implementation status, they would have implemented those recommendations which appeared earlier in the report. This would still be consistent with our findings as this would imply that firms are using the sequencing of recommendations to guide their decision making as opposed to focusing only on the merits of a recommendation.

For Hypothesis 2, we see that the coefficient of the number of recommendations made is positive in all models and significant at the $p<0.01$ level in three out of four models in Table 5. This does not support Hypothesis 2 that adoption rates fall as more recommendations are made in an assessment. A possible concern may be that the effect of the total number of recommendations is captured by the serial position variable. To address this concern we refer to Table 6, where we see that the coefficient of the number of recommendations is positive in five of the six models and not significant in all models. Additionally, we see in Figure 2 that nearly 50% of the recommendations are implemented irrespective of the number of recommendations made to a firm. This might indicate that decision makers are not adopting a choice heuristic of the type as suggested by Iyengar and Lepper (2000) but are adopting some other simplifying heuristic (Gilovich et al. 2002). Further research could take a firm-based perspective to explain variation in adoption patterns across firms, rather than the recommendation and audit-level analysis we do here. This result may have implications for situations in which a list of recommendations is provided to operations managers. In many instances consultants tend to focus on providing a few critical recommendations in the belief that adoption may increase if the set of choices is limited. However, in our context, managers do not seem to be overwhelmed by choices, at least within the range (up to 29) exhibited in the IAC data, so it may be advisable to present all opportunities.

With respect to Hypothesis 3, the coefficient for high managerial attention has a negative sign and is significant at the $p<0.001$ level across all four models in Table 8. This supports the hypothesis that recommendations that require high managerial attention have lower adoption rates than those which require low attention. In Table 8 for the 'IV Probit' Cost-Benefit Model, for an average assessment if a recommendation is changed from requiring high managerial attention to not requiring attention then its probability of adoption will fall by 0.1794. Increasing the cost of implementation by $353,293 from the average level of $19,118 would have the same effect. (Note that the dollar amount here corresponds to the difference between recommendations that "can clearly be classified as requiring low attention" vs. "recommendations that can clearly be classified as requiring high attention".) This suggests that non-financial attributes play a role in adoption decisions, an element largely overlooked in the energy literature so far. Our results indicate that the IAC should either focus on recommendations which require low managerial attention or they should find ways to reduce the need for managerial attention. Possible strategies could include providing additional details for such recommendations or identifying third parties who could implement such projects on a turnkey basis.

With respect to Hypothesis 4, to identify the conditions under which the sequence effect and the choice overload effects are mitigated we refer to Table 9. Here, we observe that the magnitude and significance of the serial position variables decrease as the economic attributes of the recommendations in an assessment are more widely dispersed. For instance in model (1) of Table 9 the coefficient of serial position is -0.1921 and significant at $p<0.001$ while in model (4) the coefficient of serial position has a lower magnitude of -0.0992 and is significant only at $p<0.1$. Similarly in model (5) the coefficient of serial position is -0.2557 and significant at $p<0.001$ while in model (8) the coefficient of serial position has a lower magnitude of -0.0669 and is significant only at $p<0.1$. These results indicate that the sequence effects are lower for assessments with higher variation in economic attributes and hence support Hypothesis 4.

Unrelated to our hypotheses, we also observe that the coefficients for the cost variables are significant at the $p<0.001$ level and larger than those for the savings variables in the 'IV Probit' model in Table 5. These observations are similar to A&N, who also find that initial costs have a greater impact on adoption than annual savings. However, our result is more in line with prior literature. A&N find that the effect of $1 in upfront costs is 40% greater than that of $1 in annual savings. However, we find that costs have between two ('Probit' models) and eight ('IV Probit' models) times the effect of savings in Table 5. The higher impact is due to the correction for the endogeneity of the serial position. This may have significant implications for the IAC program as well as other initiatives where managers are provided costs and savings for investment opportunities. In particular, given managers' apparent focus on one-time cost at the expense of annual savings, it is imperative to put the savings figure on the same scale as the cost figure, e.g. reporting the NPV of savings rather than the annual number. We also observe that the coefficient for the assessment in 1st quarter is positive and significant at $p<0.05$ level in both 'IV Probit' models in Table 5. This provides evidence that adoption rates are higher for assessments done in the 1st quarter as compared to the 4th quarter. This suggests that the IAC program may enhance adoption rates by trying to concentrate assessments earlier in the firm's budget year. Additionally, we see that the coefficient for the variance of payback is negative and significant at $p<0.001$ levels in all models in Table 5, which is as expected and indicates that the variable is capturing the uncertainty related to the returns for a recommendation.

One potential limitation of our results is that we could not include firm-level profits and cash availability in our analysis, as the identity of the firms in the IAC database is confidential. It could be argued that the emphasis on costs, evidence of order effects, or the absence of choice overload may be due to profitability or operating cash related issues. To address these concerns we performed additional robustness checks. First, we use the four-digit SIC code for each firm in the IAC database, to identify the average industry level profitability and operating cash availability for the year in which the assessment was done. Next, we use the average industry profitability and average industry operating cash availability as controls in our models and redo our analyses. Our results do not change in the presence of these additional controls.

7. Summary and Discussion

In this paper we investigate three factors that affect adoption of energy-efficiency recommendations made to small and medium-sized firms. First, we find that recommendations which appear earlier in a report have higher adoption rates than recommendations which appear later. One possible implication could be to include recommendations that have larger societal impact earlier in the report. We also find that anchoring effects influence adoption and may manifest themselves as order effects. Consequently the IACs must pay particular attention to which recommendation to list first in the report as it can significantly influence adoption of other recommendations. Second, we do not find evidence of choice overload: adoption does not decrease with the number of recommendations provided. This implies that withholding recommendations to avoid choice overload is not necessary. Third, we find that adoption rates are lower for recommendations which require high managerial attention. This means that IACs should focus on recommendations which do not demand high managerial attention, or reduce the need for managerial attention by providing additional information or identifying vendors whose services could significantly reduce managerial involvement. Finally, we find that biases related to order effects are mitigated when there is high variation in the economic characteristics of recommendations in an assessment, as the cognitive task is simpler. One implication may be to provide information on prior adoption rates if there is not much variation in the economic characteristics. This may simplify the cognitive task and facilitate higher adoption.

Our study highlights behavioral patterns which have been previously unobserved in the operations management literature. Our findings may well have broader implications for the adoption of other types of process improvements in operations.

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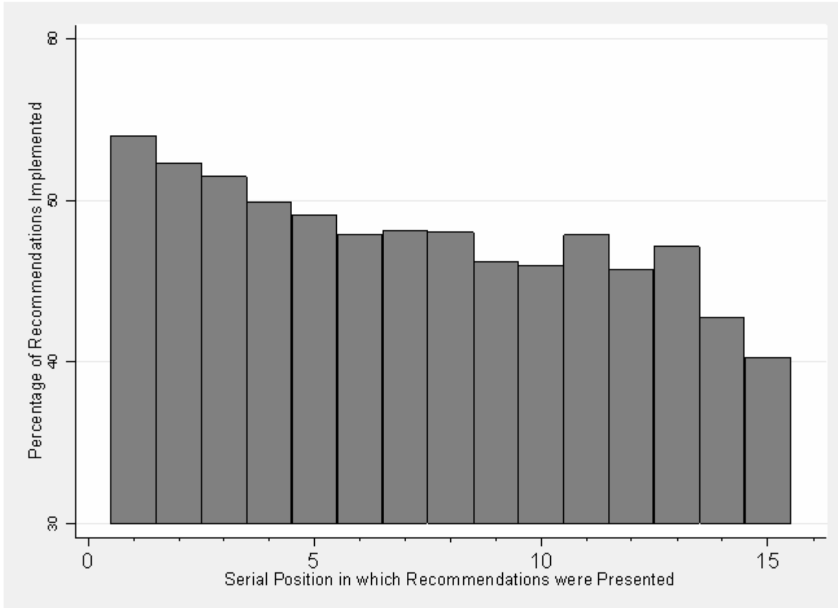
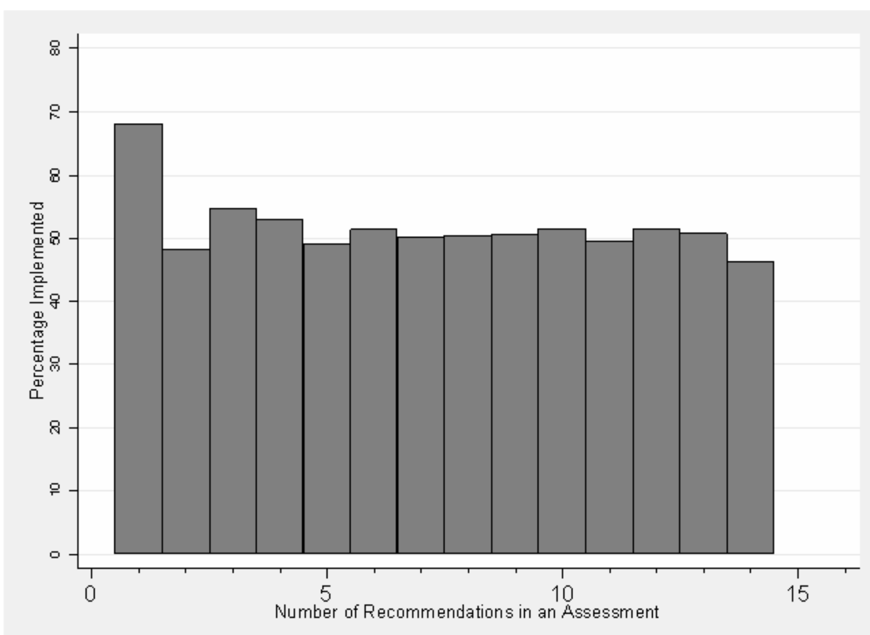
Figure 1: Adoption Rate vs. Serial Position of Recommendation in the Report



A drop in adoption rates of over 13% is observed between recommendations which occur in the 1st vs. 15th position in a report.

Figure 2: Adoption Rate vs. Number of Recommendations in an Assessment



On average, approximately half of the recommendations are implemented irrespective of the number of recommendations made to a firm (except for assessments with a single recommendation).

Table 1: Descriptive Statistics

Variable	Mean	S.D	Minimum	Maximum
Adopted*	0.5016	0.50	0	1
Payback (years)	1.06	1.29	0	9
Implementation Cost (US$)	19,117.74	237,804.30	0	34,643,628
Annual Savings (US$)	17,790.80	113,238.70	1.12	8,519,905
Number of Recommendations	8.37	3.03	1	29
Serial Position	4.69	2.97	1	29
Annual Sales (US $)	30,961,110	26,361,626	0**	155,426,368
Employees	164.27	139.59	0**	3,200
Annual Energy Cost (US$)	628,994	1,054,627	0**	33,914,308

Note: Statistics are based on data for the 89,299 recommendations, representing 12,269 assessments.
Monetary figures are in 2006 US Dollars.
* Adopted =1 if the recommendation is implemented and 0 otherwise
****** Data is missing and coded as 0 for: 1) Annual Sales (745 records), 2) Employees (101 records) and 3) Annual Energy Costs (37 records). All the analysis has also been done by removing the missing data and the results of the study are still valid.

Table 2: Select List of Recommendations that Need Low or High Managerial Attention

ARC Code	Description of Recommendations that Need Low Managerial Attention
2.7142	Utilize Higher Efficiency Lamps And/or Ballasts
2.4236	Eliminate Leaks In Inert Gas And Compressed Air Lines/ Valves
2.4221	Install Compressor Air Intakes In Coolest Locations
2.4111	Utilize Energy-efficient Belts And Other Improved Mechanisms
2.2511	Insulate Bare Equipment
2.4231	Reduce The Pressure Of Compressed Air To The Minimum Required
2.7143	Use More Efficient Light Source
2.7135	Install Occupancy Sensors
2.1233	Analyze Flue Gas For Proper Air/fuel Ratio
2.7261	Install Timers And/or Thermostats

ARC Code	Description of Recommendations that Need High Managerial Attention
2.1311	Replace Electrically-Operated Equipment With Fossil Fuel Equipment
2.4141	Use Multiple Speed Motors or AFD for Variable Pump, Blower and Compressor Loads
2.2434	Recover Heat from Air Compressor
2.1123	Install Automatic Stack Damper
2.2411	Use Waste Heat from Hot Flue Gases to Preheat Combustion Air
2.2531	Re-size Charging Openings Or Add Movable Cover Or Door
2.1222	Install Turbulators
2.4131	Replace Over-size Motors And Pumps With Optimum Size
2.3415	Use A Fossil Fuel Engine To Cogenerate Electricity Or Motive Power; And Utilize Heat
2.5194	Redesign Process

Table 3: Number of Firms in Each 2 Digit SIC classification

Two Digit SIC Code	Number of Firms
20 - - FOOD AND KINDRED PRODUCTS	1426
21 - - TOBACCO PRODUCTS	7
22 - - TEXTILE MILL PRODUCTS	414
23 - - APPAREL AND OTHER TEXTILE PRODUCTS	282
24 - - LUMBER AND WOOD PRODUCTS	623
25 - - FURNITURE AND FIXTURES	326
26 - - PAPER AND ALLIED PRODUCTS	685
27 - - PRINTING AND PUBLISHING	529
28 - - CHEMICALS AND ALLIED PRODUCTS	569
29 - - PETROLEUM AND COAL PRODUCTS	108
30 - - RUBBER AND MISC. PLASTICS PRODUCTS	1331
31 - - LEATHER AND LEATHER PRODUCTS	75
32 - - STONE, CLAY, AND GLASS PRODUCTS	466
33 - - PRIMARY METAL INDUSTRIES	820
34 - - FABRICATED METAL PRODUCTS	1637
35 - - INDUSTRIAL MACHINERY AND EQUIPMENT	1238
36 - - ELECTRONIC & OTHER ELECTRIC EQUIPMENT	697
37 - - TRANSPORTATION EQUIPMENT	558
38 - - INSTRUMENTS AND RELATED PRODUCTS	272
39 - - MISC. MANUFACTURING INDUSTRIES	206

Table 4: Correlations for Variables Used in Analysis

	Correlations																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 Implementation Status	1.00																			
2 Serial Position	-0.05	1.00																		
3 Number of Recommendations	0.00	0.50	1.00																	
4 Payback shorter than Anchor	0.00	-0.35	-0.17	1.00																
5 Cost lower than Anchor	0.03	-0.32	-0.16	0.74	1.00															
6 Saving higher than Anchor	-0.13	-0.32	-0.17	0.48	0.26	1.00														
7 ln(Payback)	-0.13	0.01	-0.06	-0.29	-0.22	-0.06	1.00													
8 $\ln(\text{Payback})^2$	0.06	-0.01	0.04	0.21	0.15	0.07	-0.75	1.00												
9 ln(Cost)	-0.15	-0.11	-0.02	-0.12	-0.23	0.30	0.56	-0.38	1.00											
10 $\ln(\text{Cost})^2$	0.11	0.10	0.02	0.12	0.22	-0.20	-0.57	0.51	-0.82	1.00										
11 ln(Saving)	-0.07	-0.13	0.03	0.10	-0.08	0.41	-0.18	0.19	0.71	-0.49	1.00									
12 $\ln(\text{Saving})^2$	0.02	0.16	-0.03	-0.11	0.06	-0.29	0.18	-0.15	-0.51	0.54	-0.76	1.00								
13 Variance of Payback	-0.10	-0.07	-0.05	-0.09	-0.10	0.09	0.41	-0.21	0.39	-0.31	0.11	-0.06	1.00							
14 Sales	-0.01	0.05	0.10	-0.01	-0.01	-0.01	-0.04	0.04	0.14	-0.10	0.20	-0.15	0.00	1.00						
15 Employees	0.00	0.04	0.08	-0.01	-0.01	-0.01	-0.02	0.02	0.11	-0.09	0.16	-0.13	0.00	0.48	1.00					
16 Annual Energy Cost	-0.02	0.06	0.10	-0.02	-0.01	-0.02	-0.04	0.04	0.17	-0.08	0.23	-0.12	0.01	0.34	0.23	1.00				
17 Quarter 1	0.01	0.00	0.01	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.02	0.00	0.00	1.00			
18 Quarter 2	0.00	0.03	0.05	-0.01	-0.01	-0.01	-0.02	0.01	-0.01	0.01	0.01	0.00	0.00	-0.01	0.00	0.01	-0.38	1.00		
19 Quarter 3	0.00	-0.02	-0.05	0.00	0.00	0.01	0.02	-0.01	0.00	0.00	-0.01	0.01	0.01	0.00	-0.01	-0.01	-0.35	-0.39	1.00	
20 Quarter 4	-0.01	-0.01	-0.01	0.02	0.01	0.01	0.00	0.00	0.01	-0.01	0.01	-0.01	0.00	0.00	0.01	0.00	-0.28	-0.31	-0.28	1.00

Table 5: Instrumental Variables Probit Estimates of Adoption of Recommendations

Dependent Variable : Adopted (equals 1 if recommendation is implemented, 0 otherwise)

	Payback Models		Cost-Benefit Models	
	Probit	IV Probit	Probit	IV Probit
ln(Payback)	-0.1483 ***	-0.1043 ***		
	(0.006)	(0.015)		
ln(Payback)^2	-0.0167 ***	-0.0147 ***		
	(0.002)	(0.002)		
ln(Cost)			-0.1643 ***	-0.1445 ***
			(0.007)	(0.009)
ln(Cost)^2			-0.0097 ***	-0.0082 ***
			(0.001)	(0.001)
ln(Saving)			0.0796 ***	0.0156
			(0.008)	(0.014)
ln(Saving)^2			-0.0009	0.0023
			(0.002)	(0.002)
Serial Position	-0.0207 ***	-0.1720 ***	-0.0268 ***	-0.1488 ***
	(0.002)	(0.036)	(0.002)	(0.022)
Number of Recommendations	0.0478 +	0.6588 ***	0.0685 **	0.5576 ***
	(0.025)	(0.146)	(0.025)	(0.091)
Variance of Payback	-0.0791 ***	-0.1209 ***	-0.0657 ***	-0.0755 ***
	(0.008)	(0.012)	(0.007)	(0.007)
Sales	-0.0023	-0.0001	0.0066	0.0236 +
	(0.014)	(0.013)	(0.014)	(0.014)
Energy Costs	-0.0077	-0.0025	0.0024	0.0155 **
	(0.005)	(0.005)	(0.005)	(0.006)
Employees	0.0000	0.0000	0.0000	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Assessment in 1st Quarter	0.0386 +	0.0415 *	0.0385 +	0.0405 *
	(0.021)	(0.020)	(0.021)	(0.021)
Assessment in 2nd Quarter	0.0213	0.0236	0.0217	0.0244
	(0.020)	(0.019)	(0.020)	(0.020)
Assessment in 3rd Quarter	0.0153	0.0222	0.0166	0.0232
	(0.022)	(0.020)	(0.022)	(0.021)
Other Controls				
Recommendation Type (No. significant at p<0.05 out of 25 recommendation types)	5	2	22	9
IAC Centers (No. significant at p<0.05 out of 45 IAC centers)	38	35	38	34
Years (No. significant at p<0.05 out of 26 Years)	0	0	0	0
SIC Code (No. significant at p<0.05 of 20 groupings of 2 digit SIC Codes)	0	0	0	0
Observations	76070	76070	76070	76070
Firms (Assessments)	12236	12236	12236	12236
Log-PseudoLikelihood	-49737 ***	-224636 ***	-49658.7 ***	-221033 ***
Exogeneity Wald Statistic	-	14.48		26.78

+ p< 0.1, * p<0.05, ** p<0.01, *** p<0.001 ; standard errors are in parantheses

Notes: Data pertains to recommendations made by IAC centers from 1981-2006. Estimation method is Maximum Likelihood. Standard errors reported are using robust clustered variance covariance matrix. 1 IAC center and its 12 related recommendations were dropped from the full sample as all the recommendations were not adopted. 13,187 recommendations were dropped as they have payback equal to zero and the logarithmic form for payback is not defined. Including these recommendations in a model without logarithmic transformation does not change the inferences we derive from this model. The IV Probit models use instrumental variables to instrument the serial position of a recommendation (using sequence generated based on the ARC manual and the propensity with which each IAC makes recommendations).

Table 6: Probit Estimates of Adoption of Recommendations – Grouped by Serial Position of Recommendations

Dependent Variable : Adopted (equals 1 if recommendation is implemented, 0 otherwise)												
	Probit for groups with serial position 1, 3, 5, 7, 9, 11 respectively											
	1		**3**		**5**		**7**		**9**		**11**	
ln(Cost)	-0.1725	***	-0.1914	***	-0.2033	***	-0.1880	***	-0.1349	***	-0.1398	***
	(0.015)		(0.021)		(0.024)		(0.026)		(0.036)		(0.052)	
ln(Cost)^2	-0.0116	***	-0.0122	***	-0.0155	***	-0.0137	***	-0.0025		0.0101	
	(0.003)		(0.003)		(0.004)		(0.004)		(0.006)		(0.008)	
ln(Saving)	0.0710	***	0.1144	***	0.1277	***	0.0817	**	0.0348		0.0181	
	(0.017)		(0.025)		(0.025)		(0.027)		(0.034)		(0.049)	
ln(Saving)^2	-0.0021		0.0018		0.0080		0.0007		-0.0073		-0.0197	*
	(0.004)		(0.005)		(0.005)		(0.005)		(0.006)		(0.010)	
Number of Recommendations	0.0196		0.0606		0.1011		0.0316		-0.0329		0.0135	
	(0.047)		(0.046)		(0.053)		(0.070)		(0.108)		(0.187)	
Variance of Payback	-0.0904	***	-0.0738	***	-0.0722	***	-0.0397		-0.1192	**	-0.1462	*
	(0.020)		(0.020)		(0.023)		(0.024)		(0.039)		(0.061)	
Sales	0.0157		0.0065		0.0246		0.0310		0.0544		0.1492	
	(0.026)		(0.025)		(0.027)		(0.032)		(0.048)		(0.082)	
Energy Cost	0.0283	**	0.0032		-0.0114		-0.0020		-0.0155		-0.0641	
	(0.011)		(0.010)		(0.011)		(0.013)		(0.017)		(0.033)	
Employees	0.0001		-0.0001		0.0000		0.0000		-0.0001		-0.0001	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Assessment in 1st Quarter	0.0072		0.0581		0.0013		0.0642		0.0397		0.2517	
	(0.039)		(0.039)		(0.042)		(0.052)		(0.076)		(0.126)	
Assessment in 2nd Quarter	0.0143		0.0236		-0.0069		0.0649		0.0051		0.0816	
	(0.038)		(0.038)		(0.041)		(0.050)		(0.074)		(0.119)	
Assessment in 3rd Quarter	-0.0031		0.0326		-0.0444		0.0468		0.1249		-0.0412	
	(0.039)		(0.039)		(0.042)		(0.053)		(0.078)		(0.131)	
Controls												
Recommendation Type	Yes		Yes		Yes		Yes		Yes		Yes	
IAC Centers	Yes		Yes		Yes		Yes		Yes		Yes	
Year	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	10442		10418		9014		5940		2870		1158	
Log-PseudoLikelihood	-6468.9	***	-6743.5	***	-5880.4	***	-3869.6	***	-1819.5	***	-698.59	***

* p<0.05, ** p<0.01, *** p<0.001; standard errors are in parantheses

Data pertains to recommendations made by IAC centers from 1981-2006. Estimation method is Maximum Likelihood. Standard errors reported are using robust clustered variance covariance matrix.

Table 7: Probit Estimates of Adoption of Recommendations for Anchoring Effects

Dependent Variable : Adopted (equals 1 if implemented, 0 otherwise)

	Anchor on Payback		Anchor on Cost		Anchor on Saving	
	Payback	Cost-Benefit	Payback	Cost-Benefit	Payback	Cost-Benefit
ln(Payback)	-0.1462 ***		-0.1488 ***		-0.1524 ***	
	(0.007)		(0.006)		(0.006)	
ln(Payback)^2	-0.0162 ***		-0.0166 ***		-0.0169 ***	
	(0.002)		(0.002)		(0.002)	
ln(Cost)		-0.1588 ***		-0.1634 ***		-0.1664 ***
		(0.007)		(0.007)		(0.007)
ln(Cost)^2		-0.0099 ***		-0.0099 ***		-0.0099 ***
		(0.001)		(0.001)		(0.001)
ln(Saving)		0.0830 ***		0.0912 ***		0.0831 ***
		(0.008)		(0.008)		(0.008)
ln(Saving)^2		-0.0017		-0.0018		-0.0018
		(0.002)		(0.002)		(0.002)
Payback shorter than Anchor	0.0332 *	0.0547 ***				
	(0.013)	(0.013)				
Cost lower than Anchor			0.0419 **	0.0325 *		
			(0.013)	(0.013)		
Saving higher than Anchor					0.0061	0.0577 ***
					(0.011)	(0.014)
Number of Recommendations	-0.0320	-0.0328	-0.0338	-0.0369	-0.0345	-0.0302
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Variance of Payback	-0.0729 ***	-0.0625 ***	-0.0712 ***	-0.0628 ***	-0.0729 ***	-0.0638 ***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Sales	-0.0024	0.0035	-0.0023	0.0025	-0.0027	0.0048
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Energy Costs	-0.0083 +	-0.0003	-0.0084 +	-0.0010	-0.0083 +	0.0011
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Employees	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Assessment in 1st Quarter	0.0387 +	0.0393 +	0.0388 +	0.0386 +	0.0378 +	0.0382 +
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Assessment in 2nd Quarter	0.0214	0.0218	0.0214	0.0213	0.0209	0.0212
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Assessment in 3rd Quarter	0.0141	0.0149	0.0143	0.0151	0.0141	0.0148
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Other Controls						
Recommendation Type	Yes	Yes	Yes	Yes	Yes	Yes
IAC Centers	Yes	Yes	Yes	Yes	Yes	Yes
Years	Yes	Yes	Yes	Yes	Yes	Yes
SIC Code	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76070	76070	76070	76070	76070	76070
Firms (Assessments)	12236	12236	12236	12236	12236	12236
Log-PseudoLikelihood	-49791 ***	-49735 ***	-49787.7 ***	-49743.5 ***	-49795.75 ***	-49736.05 ***

+ p< 0.1, * p<0.05, ** p<0.01, *** p<0.001 ; standard errors are in parantheses

Notes: Data pertains to recommendations made by IAC centers from 1981-2006. Estimation method is Maximum Likelihood. Standard errors reported are using robust clustered variance covariance matrix. 1 IAC center and its 12 related recommendations were dropped from the full sample as all the recommendations were not adopted. 13,187 recommendations were dropped as they have payback equal to zero and the logarithmic form for payback is not defined. Including these recommendations in a model without logarithmic transformation does not change the inferences we derive from this model.

Table 8: Instrumental Variables Probit Estimates of Adoption of Recommendations – (Only For Recommendations Classified as Requiring Low Or High Managerial Attention for Adoption)

Dependent Variable : Adopted (equals 1 if recommendation is implemented, 0 otherwise)

	Payback Models		Cost-Benefit Models	
	Probit	IV Probit	Probit	IV Probit
ln(Payback)	-0.1261 ***	-0.0653 ***		
	(0.007)	(0.016)		
ln(Payback)^2	-0.0127 ***	-0.0110 ***		
	(0.002)	(0.002)		
ln(Cost)			-0.1586 ***	-0.1282 ***
			(0.010)	(0.014)
ln(Cost)^2			-0.0113 ***	-0.0081 ***
			(0.002)	(0.002)
ln(Saving)			0.1021 ***	0.0098
			(0.011)	(0.027)
ln(Saving)^2			0.0000	0.0004
			(0.002)	(0.002)
Serial Position	-0.0268 ***	-0.2141 ***	-0.0266 ***	-0.1608 ***
	(0.002)	(0.035)	(0.003)	(0.034)
Number of Recommendations	0.0588 *	0.7760 ***	0.0581 *	0.5680 ***
	(0.028)	(0.136)	(0.029)	(0.129)
Variance of Payback	0.0091	-0.0658 ***	0.0141	-0.0145 ***
	(0.009)	(0.017)	(0.009)	(0.012)
Sales	0.0113	0.0170	0.0111	0.0341 *
	(0.016)	(0.014)	(0.016)	(0.016)
Energy Costs	-0.0052	0.0006	-0.0032	0.0130 +
	(0.006)	(0.005)	(0.006)	(0.008)
Employees	0.0000	0.0000	0.0000	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Assessment in 1st Quarter	0.0190	0.0213	0.0194	0.0211
	(0.025)	(0.022)	(0.025)	(0.024)
Assessment in 2nd Quarter	0.0104	0.0167	0.0111	0.0176
	(0.024)	(0.022)	(0.024)	(0.023)
Assessment in 3rd Quarter	-0.0036	0.0015	-0.0027	0.0022
	(0.025)	(0.023)	(0.025)	(0.024)
High Managerial Attention	-0.5644 ***	-0.4744 ***	-0.5446 ***	-0.4551 ***
	(0.027)	(0.041)	(0.028)	(0.041)
Other Controls				
Recommendation Type (No. significant at p<0.05 out of 25 recommendation types)	14	0	15	6
IAC Centers (No. significant at p<0.05 out of 45 IAC centers)	34	34	34	34
Years (No. significant at p<0.05 out of 26 Years)	3	6	4	4
SIC Code (No. significant at p<0.05 of 20 groupings of 2 digit SIC Codes)	0	0	0	0
Observations	50033	50033	50033	50033
Firms (Assessments)	12055	12055	12055	12055
Log-PseudoLikelihood	-32388	-145948	-32365.9	-143182
Exogeneity Wald Statistic	-	20.37		13.79

+ p< 0.1, * p<0.05, ** p<0.01, *** p<0.001 ; standard errors are in parantheses

Notes: Data pertains to recommendations made by IAC centers from 1981-2006. Estimation method is Maximum Likelihood. Standard errors reported are using robust clustered variance covariance matrix. The IV Probit models use instrumental variables to instrument the serial position of a recommendation (using sequence generated based on the ARC manual and the propensity with which each IAC makes recommendations).

Table 9: Instrumental Variables Probit Estimates of Adoption of Recommendations (Grouping by Coefficient of Variation of Payback and of Savings)

Dependent Variable : Adopted (equals 1 if recommendation is implemented, 0 otherwise)

	Cost-Benefit Models							
	Groups by Coefficient of Variation of Payback				Groups by Coefficient of Variation of Savings			
	smallest			highest	smallest			highest
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Cost)	-0.1390 ***	-0.1461 ***	-0.1669 ***	-0.1322 ***	-0.1362 ***	-0.1562 ***	-0.1414 ***	-0.1307 ***
	(0.0185)	(0.0177)	(0.0181)	(0.0145)	(0.0222)	(0.0221)	(0.0194)	(0.0124)
ln(Cost)^2	-0.0038	-0.0080 ***	-0.0122 ***	-0.0072 ***	-0.0118 ***	-0.0108 ***	-0.0076 **	-0.0036 +
	(0.0028)	(0.0023)	(0.0024)	(0.0019)	(0.0029)	(0.0026)	(0.0025)	(0.0019)
ln(Saving)	-0.0029	-0.0013 +	0.0764 *	0.0099	-0.0244	-0.0251	0.0017	0.0362 +
	(0.0247)	(0.0279)	(0.0361)	(0.0306)	(0.0357)	(0.0396)	(0.0433)	(0.0199)
ln(Saving)^2	-0.0017	0.0053	0.0074 *	-0.0025	0.0097 *	0.0025	-0.0001	-0.0040
	(0.0035)	(0.0032)	(0.0033)	(0.0034)	(0.0047)	(0.0036)	(0.0032)	(0.0029)
Serial Position	-0.1921 ***	-0.1916 ***	-0.0928	-0.0992 +	-0.2557 ***	-0.2093 ***	-0.1490 ***	-0.0669 +
	(0.0332)	(0.0384)	(0.0566)	(0.0526)	(0.0332)	(0.0430)	(0.0671)	(0.0372)
Number of Recommendations	0.8314 ***	0.7060 ***	0.3142	0.2906	1.0653 ***	0.7494 ***	0.5982 *	0.2185
	(0.1392)	(0.1632)	(0.2265)	(0.2156)	(0.1377)	(0.1795)	(0.2737)	(0.1575)
Variance of Payback	-0.0479 ***	-0.0756 ***	-0.0898 ***	-0.1109 ***	-0.1010 ***	-0.0718 ***	-0.0748 ***	-0.0706 ***
	(0.0128)	(0.0152)	(0.0177)	(0.0148)	(0.0136)	(0.0156)	(0.0133)	(0.0163)
Sales	0.0436 +	0.0035	0.0052	0.0485 +	0.0390	0.0284	0.0034	0.0326
	(0.0264)	(0.0263)	(0.0282)	(0.0275)	(0.0268)	(0.0269)	(0.0271)	(0.0261)
Energy Costs	0.0196 +	0.0227	0.0193	0.0086	0.0232	0.0342 *	0.0317 *	0.0043
	(0.0101)	(0.0148)	(0.0148)	(0.0090)	(0.0205)	(0.0163)	(0.0143)	(0.0069)
Employees	0.0000	0.0003 *	0.0001	-0.0001	0.0001	0.0003 *	0.0000	-0.0032
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0202)
Assessment in 1st Quarter	0.0865 *	0.0415	-0.0130	0.0360	0.0112	0.0090	0.0678 +	0.0552
	(0.0405)	(0.0405)	(0.0419)	(0.0420)	(0.0376)	(0.0398)	(0.0407)	(0.0427)
Assessment in 2nd Quarter	0.0241	0.0799 *	-0.0119	-0.0131	0.0211	0.0426	0.0008	0.0260
	(0.0391)	(0.0390)	(0.0402)	(0.0402)	(0.0368)	(0.0376)	(0.0391)	(0.0416)
Assessment in 3rd Quarter	0.0351	0.0210	-0.0055	0.0235	0.0085	0.0144	-0.0225	0.0743 +
	(0.0405)	(0.0405)	(0.0426)	(0.0433)	(0.0376)	(0.0398)	(0.0425)	(0.0443)
Other Controls								
Recommendation Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IAC Centers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC Code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21283	19733	18452	16577	19123	18982	19064	18861
Log-PseudoLikelihood	-59768 ***	-57290 ***	-54462 ***	-48503 ***	-53061 ***	-54750 ***	-55517 ***	-56418
Exogeneity Wald Statistic	19.37	14.75	1.12	2.32	34.29	13.70	2.79	1.15

+ p< 0.1, * p<0.05, ** p<0.01, *** p<0.001 ; standard errors are in parantheses

Notes: Data pertains to recommendations made by IAC centers from 1981-2006. Estimation method is Maximum Likelihood. Standard errors reported are using robust clustered variance covariance matrix. The assessments are divided into four groups based on Coefficient of Variation of Payback. Model (1) represents assessments with lowest Coefficient of Variation of Payback and Model (4) represents assessments with highest Coefficient of Variation of Payback. Similarly, Model (5) represents assessments with lowest Coefficient of Variation of Saving and Model (8) represents assessments with highest Coefficient of Variation of Saving. The models use instrumental variables to instrument the serial position of a recommendation (Using sequence generated based on the ARC manual and the propensity with which each IAC makes recommendations).

Appendix – Robustness Checks

This section presents the various robustness checks incorporated in our study. We provide a brief description of the various robustness checks and then present the results of related analyses.

The first robustness check addresses the relation between the serial position variable and the total number of recommendations in a report. We first normalize the serial position of the recommendation within the assessment so that the mean value is 1. For instance, in an assessment with five recommendations the serial positions will be recorded as 1, 2, 3, 4, and 5 in the first version, while it will be recorded as 1/3, 2/3,1,4/3, and 5/3 in the second version. We then redo the probit and instrumental variables probit analyses related to Table 5. The results of these analyses are in Table I. We observe that the normalized serial position variable is significant at $p<0.001$ levels in all the models with a negative sign. This provides further support to the inference that the sequence of recommendations is significant in explaining the adoption rates and indicates the presence of primacy effects.

In the second robustness check we grouped recommendations with the same total number of recommendations and undertook the probit instrumental variables analysis (of models 4a and 4b) within each group. Table II includes the results of these analyses. We observe that the serial position variable is significant at $p<0.001$ and negative. This provides additional support to the inference that the sequence of recommendations is significant in explaining the adoption rates and indicates the presence of primacy effects.

The third robustness check examines the impact of profitability and cash availability on the results. We could not include firm-level profits and cash availability in our analysis, as the identity of the firms in the IAC database is confidential. We use the four-digit SIC code for each firm in the IAC data base, to identify the average industry level profitability and operating cash availability for the year in which the assessment was done. Next, we use these as controls in our models and redo our analyses. These results are provided in Tables III and IV. We examine the coefficients of serial position, number of recommendations and observe that our results do not change in the presence of these additional controls.

Our fourth robustness check investigates the presence of recency effects. To address this we examine for end of sequence effects by developing probit models for adoption that include indicator variable for the last few (up to three) recommendations in an assessment. The results of these analyses are presented in Table V. We examine the variables last, one before last, and two before last which are indicator variables for the last 3 recommendations in a report. These variables are not significant across all models of Table V and hence we do not find any evidence for the presence of recency effects.

In Table VI we provide a summary of the results obtained in different regression models in the paper.

Table I: Instrumental Variables Probit Estimates of Adoption of Recommendations with Normalized Serial Position

Dependent Variable : Adopted (equals 1 if implemented, 0 otherwise)

	Payback Models		Cost-Benefit Models	
	Probit	IV Probit	Probit	IV Probit
ln(Payback)	-0.1476 ***	-0.0321 *		
	(0.006)	(0.014)		
ln(Payback)^2	-0.0167 ***	-0.0090 ***		
	(0.002)	(0.002)		
ln(Cost)			-0.1640 ***	-0.1170 ***
			(0.007)	(0.009)
ln(Cost)^2			-0.0097 ***	-0.0063 ***
			(0.001)	(0.001)
ln(Saving)			0.0787 ***	-0.0394 **
			(0.008)	(0.014)
ln(Saving)^2			-0.0008	0.0055 ***
			(0.002)	(0.002)
Serial Position (Normalized)	-0.1123 ***	-1.5870 ***	-0.1443 ***	-1.2225 ***
	(0.009)	(0.103)	(0.010)	(0.093)
Number of Recommendations	-0.0370	-0.0448 **	-0.0411 +	-0.0557 **
	(0.024)	(0.017)	(0.024)	(0.021)
Variance of Payback	-0.0798 ***	-0.1506 ***	-0.0661 ***	-0.0807 ***
	(0.008)	(0.008)	(0.007)	(0.007)
Sales	-0.0023	0.0014	0.0068	0.0360 **
	(0.014)	(0.010)	(0.014)	(0.012)
Energy Costs	-0.0078	0.0010	0.0024	0.0234 ***
	(0.005)	(0.004)	(0.005)	(0.006)
Employees	0.0000	0.0000	0.0000	0.0001 *
	(0.000)	0.000	(0.000)	(0.000)
Assessment in 1st Quarter	0.0385 +	0.0359 *	0.0385 +	0.0381 *
	(0.021)	(0.015)	(0.021)	(0.019)
Assessment in 2nd Quarter	0.0214	0.0232	0.0218	0.0261
	(0.020)	(0.015)	(0.021)	(0.018)
Assessment in 3rd Quarter	0.0152	0.0228	0.0164	0.0247
	(0.022)	(0.015)	(0.022)	(0.019)
Other Controls				
Recommendation Type (No. significant at p<0.05 out of 25 recommendation types)	5	10	21	17
IAC Centers (No. significant at p<0.05 out of 45 IAC centers)	38	30	38	30
Years (No. significant at p<0.05 out of 26 Years)	0	0	0	0
SIC Code (No. significant at p<0.05 of 20 groupings of 2 digit SIC Codes)	0	0	0	0
Observations	76070	76070	76070	76070
Firms (Assessments)	12236	12236	12236	12236
Log-PseudoLikelihood	-49729 ***	-101315 ***	-49647.4 ***	-97691.8 ***
Exogeneity Wald Statistic	-	69.36	-	87.87

+ p< 0.1, * p<0.05, ** p<0.01, *** p<0.001 ; standard errors are in parantheses

Notes: Data pertains to recommendations made by IAC centers from 1981-2006. Estimation method is Maximum Likelihood. Standard errors reported are using robust clustered variance covariance matrix. 1 IAC center and its 12 related recommendations were dropped from the full sample as all the recommendations were not adopted. 13,187 recommendations were dropped as they have payback equal to zero and the logarithmic form for payback is not defined. Including these recommendations in a model without logarithmic transformation does not change the inferences we derive from this model. The IV Probit models use instrumental variables to instrument the serial position of a recommendation (using sequence generated based on the ARC manual and the propensity with which each IAC makes recommendations).

Table II: Instrumental Variables Probit Estimates of Adoption of Recommendations – Grouped by Total Number of Recommendations

Dependent Variable : Adopted (equals 1 if recommendation is implemented, 0 otherwise)

	IV Probit (for groups by total number of recommendations)			
	5	**7**	**9**	**11**
ln(Cost)	-0.082 ***	-0.089 ***	-0.092 ***	-0.139 ***
	(0.0240)	(0.0220)	(0.0270)	(0.0280)
ln(Cost)^2	-0.003	-0.007 *	-0.005	-0.007 **
	(0.0040)	(0.0030)	(0.0030)	(0.0040)
ln(Saving)	-0.036	-0.066 *	-0.091 ***	-0.054
	(0.0280)	(0.0270)	(0.0330)	(0.0360)
ln(Saving)^2	0.007	0.009 *	0.007	0.014 *
	(0.0050)	(0.0040)	(0.0040)	(0.0070)
Serial Position	-0.459 ***	-0.379 ***	-0.299 ***	-0.247 ***
	(0.0420)	(0.0390)	(0.0330)	(0.0370)
Variance of Payback	-0.118 ***	-0.096 ***	-0.074 ***	-0.05 *
	(0.0210)	(0.0170)	(0.0170)	(0.0250)
Sales	0.006	-0.002 ***	-0.003	0.031
	(0.0110)	0.0000	(0.0190)	(0.0240)
Energy Cost	0.007	0.001	0.031	0.039
	(0.0080)	(0.0020)	(0.0110)	(0.0190)
Employees	0.000	0.001 ***	0.052 *	0.000
	(0.0001)	(0.0001)	(0.0240)	(0.0004)
Assessment in 1st Quarter	0.120 *	0.007	-0.086	0.081
	(0.0540)	(0.0410)	(0.0500)	(0.0700)
Assessment in 2nd Quarter	0.049	-0.026	-0.063	0.101
	(0.0520)	(0.0410)	(0.0480)	(0.0660)
Assessment in 3rd Quarter	0.063	0.013	-0.085	0.132
	(0.0530)	(0.0400)	(0.0520)	(0.0710)
Controls				
Recommendation Type	Yes	Yes	Yes	Yes
IAC Centers	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
2 Digit SIC Code	Yes	Yes	Yes	Yes
Observations	7356	12171	9444	5183
Firms (Assessments)	1733	2040	1231	551
Log-PseudoLikelihood	-17290 ***	-32720 ***	-27371.1	-15821.2
Exogeneity Wald Statistic	56.9	34.2	30.7	17.1

* p<0.05, ** p<0.01, *** p<0.001; standard errors are in parantheses

Data pertains to recommendations made by IAC centers from 1981-2006. Estimation method is Maximum Likelihood. Standard errors reported are using robust clustered variance covariance matrix. The models use instrumental variables to instrument the serial position of a recommendation (using sequence generated based on the ARC manual and the propensity with which each IAC makes recommendations).

Table III: Instrumental Variables Probit Estimates of Adoption of Recommendations with Average SIC Income Incorporated

Dependent Variable : Adopted (equals 1 if recommendation is implemented, 0 otherwise)

	Payback Models		Cost-Benefit Models	
	Probit	IV Probit	Probit	IV Probit
ln(Payback)	-0.1448 ***	-0.0975 ***		
	(0.006)	(0.016)		
ln(Payback)^2	-0.0167 ***	-0.0142 ***		
	(0.002)	(0.002)		
ln(Cost)			-0.1581 ***	-0.1374 ***
			(0.007)	(0.009)
ln(Cost)^2			-0.0090 ***	-0.0075 ***
			(0.001)	(0.001)
ln(Saving)			0.0721 ***	0.0061
			(0.008)	(0.015)
ln(Saving)^2			-0.0015	0.0018
			(0.002)	(0.002)
Serial Position	-0.0214 ***	-0.1796 ***	-0.0278 ***	-0.1546 ***
	(0.002)	(0.038)	(0.002)	(0.024)
Number	0.0771 **	0.7152 ***	0.0991 ***	0.6076 ***
	(0.026)	(0.153)	(0.026)	(0.096)
Variance of Payback	-0.0776 ***	-0.1224 ***	-0.0637 ***	-0.0748 ***
	(0.008)	(0.012)	(0.008)	(0.008)
Sales	-0.0077	-0.0044	0.0024	0.0217
	(0.014)	(0.013)	(0.014)	(0.014)
Energy Cost	-0.0063	-0.0012	0.0038	0.0167 **
	(0.005)	(0.005)	(0.005)	(0.006)
Employees	0.0000	0.0000	0.0000	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Assessment in 1st Quarter	0.0390 +	0.0426 *	0.0386 +	0.0404 *
	(0.022)	(0.021)	(0.022)	(0.021)
Assessment in 2nd Quarter	0.0112	0.0137	0.0113	0.0135
	(0.022)	(0.020)	(0.022)	(0.021)
Assessment in 3rd Quarter	0.0144	0.0220	0.0156	0.0222
	(0.023)	(0.021)	(0.023)	(0.022)
Average SIC Income	-0.00003	-0.00003	-0.00003	-0.00003
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Controls				
Recommendation Type (No. significant at p<0.05 out of 25 recommendation types)	6	3	24	24
IAC Centers (No. significant at p<0.05 out of 45 IAC centers)	36	31	36	31
Years (No. significant at p<0.05 out of 26 Years)	0	0	0	0
SIC Code (No. significant at p<0.05 of 20 groupings of 2 digit SIC Codes)	0	0	0	0
Observations	67742	67742	67742	67742
Firms (Assessments)	10861	10861	10861	10861
Log-PseudoLikelihood	-44300 ***	-199986 ***	-44228.1 ***	-196837.3 ***
Exogeneity Wald Statistic	-	13.74	-	25.07

+ p< 0.1, * p<0.05, ** p<0.01, *** p<0.001 ; standard errors are in parantheses

Notes: Data pertains to recommendations made by IAC centers from 1981-2006. Estimation method is Maximum Likelihood. Standard errors reported are using robust clustered variance covariance matrix. 1 IAC center and its 12 related recommendations were dropped from the full sample as all the recommendations were not adopted. 13,187 recommendations were dropped as they have payback equal to zero and the logarithmic form for payback is not defined. Including these recommendations in a model without logarithmic transformation does not change the inferences we derive from this model. Additionally 8,328 recommendations were not included in the analysis as the average income for firms with these SIC codes was not available in the Compustat database for the relevant years. The IV Probit models use instrumental variables to instrument the serial position of a recommendation (using sequence generated based on the ARC manual and the propensity with which each IAC makes recommendations).

Table IV: Instrumental Variables Probit Estimates of Adoption of Recommendations with Average SIC Operating Cash Flows Incorporated

Dependent Variable : Adopted (equals 1 if recommendation is implemented, 0 otherwise)

	Payback Models		Cost-Benefit Models	
	Probit	IV Probit	Probit	IV Probit
ln(Payback)	-0.1434 ***	-0.1053 ***		
	(0.007)	(0.015)		
ln(Payback)^2	-0.0166 ***	-0.0145 ***		
	(0.002)	(0.002)		
ln(Cost)			-0.1522 ***	-0.1360 ***
			(0.008)	(0.009)
ln(Cost)^2			-0.0082 ***	-0.0071 ***
			(0.001)	(0.001)
ln(Saving)			0.0681 ***	0.0105
			(0.008)	(0.015)
ln(Saving)^2			-0.0019	0.0015
			(0.002)	(0.002)
Serial Position	-0.0225 ***	-0.1544 ***	-0.0293 ***	-0.1416 ***
	(0.002)	(0.039)	(0.002)	(0.024)
Number	0.1150 ***	0.6448 ***	0.1380 ***	0.5865 ***
	(0.028)	(0.155)	(0.029)	(0.098)
Variance of Payback	-0.0729 ***	-0.1115 ***	-0.0598 ***	-0.0690 ***
	(0.008)	(0.013)	(0.008)	(0.008)
Sales	-0.0071	-0.0044	0.0030	0.0203
	(0.015)	(0.014)	(0.015)	(0.015)
Energy Cost	-0.0064	-0.0020	0.0034	0.0150 *
	(0.005)	(0.005)	(0.005)	(0.006)
Employees	-0.0001	0.0000	0.0000	0.0080
	(0.000)	(0.000)	(0.000)	(0.012)
Assessment in 1st Quarter	0.0365	0.0412 +	0.0363	0.0391 +
	(0.023)	(0.022)	(0.023)	(0.023)
Assessment in 2nd Quarter	0.0115	0.0145	0.0121	0.0145
	(0.023)	(0.022)	(0.023)	(0.022)
Assessment in 3rd Quarter	0.0208	0.0268	0.0224	0.0275
	(0.024)	(0.023)	(0.024)	(0.023)
Average SIC Operating Cash Availability	-0.00004	-0.00004	-0.00004 +	-0.00004 +
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Controls				
Recommendation Type (No. significant at p<0.05 out of 25 recommendation types)	6	2	24	12
IAC Centers (No. significant at p<0.05 out of 45 IAC centers)	35	31	35	29
Years (No. significant at p<0.05 out of 26 Years)	20	6	20	6
SIC Code (No. significant at p<0.05 of 20 groupings of 2 digit SIC Codes)	1	1	1	0
Observations	60422	60422	60422	9489
Firms (Assessments)	9489	9489	9489	60422
Log-PseudoLikelihood	-39634 ***	-178204 ***	-39573 ***	-175216.4
Exogeneity Wald Statistic	-	10.07	-	19.68

+ p< 0.1, * p<0.05, ** p<0.01, *** p<0.001 ; standard errors are in parantheses

Notes: Data pertains to recommendations made by IAC centers from 1981-2006. Estimation method is Maximum Likelihood. Standard errors reported are using robust clustered variance covariance matrix. 1 IAC center and its 12 related recommendations were dropped from the full sample as all the recommendations were not adopted. 13,187 recommendations were dropped as they have payback equal to zero and the logarithmic form for payback is not defined. Including these recommendations in a model without logarithmic transformation does not change the inferences we derive from this model. Additionally 15,648 recommendations were not included in the analysis as the average income for firms with these SIC codes was not available in the Compustat database for the relevant years. The IV Probit models use instrumental variables to instrument the serial position of a recommendation (using sequence generated based on the ARC manual and the propensity with which each IAC makes recommendations).

Table V: Probit Estimates of Adoption of Recommendations to Examine Impact of Last Three Recommendations in a Report

Dependent Variable : Adopted (equals 1 if recommendation is implemented, 0 otherwise)

	Payback Models			Cost-Benefit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Payback)	-0.1483 ***	-0.1482 ***	-0.1482 ***			
	(0.006)	(0.006)	(0.006)			
ln(Payback)^2	-0.0167 ***	-0.0167 ***	-0.0167 ***			
	(0.002)	(0.002)	(0.002)			
ln(Cost)				-0.1644 ***	-0.1644 ***	-0.1644 ***
				(0.007)	(0.007)	(0.007)
ln(Cost)^2				-0.0097 ***	-0.0097 ***	-0.0097 ***
				(0.001)	(0.001)	(0.001)
ln(Saving)				0.0795 ***	0.0796 ***	0.0797 ***
				(0.008)	(0.008)	(0.008)
ln(Saving)^2				-0.0009	-0.0009	-0.0009
				(0.002)	(0.002)	(0.002)
Serial Position	-0.0211 ***	-0.0193 ***	-0.0176 ***	-0.0275 ***	-0.0260 ***	-0.0242 ***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Number	0.0497 +	0.0384	0.0264	0.0730 **	0.0628 *	0.0506 +
	(0.026)	(0.027)	(0.029)	(0.026)	(0.027)	(0.029)
Variance of Payback	-0.0791 ***	-0.0790 ***	-0.0790 ***	-0.0657 ***	-0.0656 ***	-0.0656 ***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Sales	-0.0023	-0.0024	-0.0025	0.0066	0.0065	0.0065
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Energy Cost	-0.0077	-0.0076	-0.0076	0.0025	0.0025	0.0025
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Employees	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Assessment in 1st Quarter	0.0386 +	0.0385 +	0.0385 +	0.0385 +	0.0385 +	0.0384 +
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Assessment in 2nd Quarter	0.0213	0.0213	0.0214	0.0217	0.0217	0.0218
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Assessment in 3rd Quarter	0.0153	0.0153	0.0154	0.0166	0.0166	0.0167
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
1st From Bottom	0.0054	-0.0058	-0.0177	0.0124	0.0023	-0.0100
	(0.015)	(0.017)	(0.020)	(0.015)	(0.017)	(0.020)
2nd From Bottom		-0.0242	-0.0344 *		-0.0219	-0.0323 +
		(0.015)	(0.017)		(0.015)	(0.018)
3rd From Bottom			-0.0205			-0.0210
			(0.015)			(0.016)
Controls						
Recommendation Type	Yes	Yes	Yes	Yes	Yes	Yes
IAC Centers	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
SIC Code	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76070	76070	76070	76070	76070	76070
Firms (Assessments)	12236	12236	12236	12236	12236	12236
Log-PseudoLikelihood	-49737.2 ***	-49736.1 ***	-49735.4 ***	-49658.4 ***	-49657.5 ***	-49656.7 ***

+ p< 0.1, * p<0.05, ** p<0.01, *** p<0.001 ; standard errors are in parantheses

Notes: Data pertains to recommendations made by IAC centers from 1981-2006. Estimation method is Maximum Likelihood. Standard errors reported are using robust clustered variance covariance matrix. The variables 1st From Bottom, 2nd From Bottom, and 3rd From Bottom are indicator variables which represent the position of a recommendation from the bottom of a report.

Table VI: Summary of Coefficient Estimates Across Various Models Used in Paper

Regression Models	Summary of Estimates Across Different Models Used in the Paper	Payback Models		Cost-Benefit Models	
		Probit	IV Probit	Probit	IV Probit
Abolute Serial Position	Serial Position	-0.0207 ***	-0.1720 ***	-0.0268 ***	-0.1488 ***
		(0.002)	(0.036)	(0.002)	(0.022)
	Number of Recommendations	0.0478 +	0.6588 ***	0.0685 **	0.5576 ***
		(0.025)	(0.146)	(0.025)	(0.091)
Normalized Serial Position	Serial Position (Normalized)	-0.1123 ***	-1.5870 ***	-0.1443 ***	-1.2225 ***
		(0.009)	(0.103)	(0.010)	(0.093)
	Number of Recommendations	-0.0370	-0.0448 **	-0.0411 +	-0.0557 **
		(0.024)	(0.017)	(0.024)	(0.021)
Anchoring Effect Models	Payback better than Anchor	0.0332 *		0.0547 ***	
		(0.013)		(0.013)	
	Cost better than Anchor	0.0419 **		0.0325 *	
		(0.013)		(0.013)	
	Saving better than Anchor	0.0061		0.0577 ***	
		(0.011)		(0.014)	
Model for Managerial Attention	High Managerial Attention	-0.5644 ***	-0.4744 ***	-0.5446 ***	-0.4551 ***
		(0.027)	(0.041)	(0.028)	(0.041)