Success From Satisficing and Imitation: Entrepreneurs' Location Choice and Implications of Heuristics for Local Economic Development

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Abstract: *This paper presents new data on entrepreneurs' self-described decision processes when choosing where to locate, based on scripted interviews with 49 well-placed business owners and senior managers in charge of location choice. Consideration sets are surprisingly small, especially among those who are successful. According to entrepreneurs' own accounts, locations are frequently discovered by chance. Few entrepreneurs describe decision processes that compare marginal benefits and cost of continuing search, and several speak explicitly against the usefulness of applying probabilistic beliefs to one-off events in a changing environment. Nearly all interviewees describe location choice decisions based on fixed threshold conditions, providing direct evidence of satisficing. Imitation is beneficial for small investment projects. The data regarding entrepreneurs' decision process suggests a need to rethink standard policy tools used to stimulate local economic development.*

Keywords: Process Model, Bounded Rationality, Interviews, Ethnographic, Discrimination, Low-income, Neighborhood, Lexicographic, Non-compensatory, Business Owners

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Section 1: Introduction

This paper takes an empirical approach to describing the process by which business owners make high stakes decisions about where to locate their businesses or new branches of existing businesses. Rather than assuming that location choice necessarily results from a process of optimization, this paper uses a scripted in-depth interview of 49 entrepreneurs (i.e., business owners or senior managers with personal capital at risk when making location choice decisions) in the Dallas-Forth-Worth greater metropolitan area.[2] The interview script elicits information about the size of business owners' consideration sets, the criteria they use to stop searching, and the criteria used to select an element from their consideration or choice sets.

The interview data reveal three main findings. First, entrepreneurs' consideration sets for high stakes decisions of where to locate are extremely small—much smaller than is predicted by many search models.[3] Second, rather than beginning with large-sale search to populate their

[2] Compared with surveys, interviews are a decidedly non-standard data source within economics (Yonay, 2000; Yonay and Breslau, 2006). Nevertheless, interview studies have appeared in the economics and business economics literatures, confirming some of the standard assumptions while casting doubt on others (Schwartz, 1987; Bewley, 1999; Schwartz, 2004; Wennberg and Nykvist, 2007). These papers argue, in addition, that interview data serves as useful source material for developing new economic theories as well as for testing established theory.

[3] A possible objection to this claim is that entrepreneurs are in fact optimizing in response to very large time or information costs. This is a potentially important explanation about which the interview script I used specifically elicits rich descriptive information. None of the entrepreneurs (who were generally sophisticated about quantitative

consideration sets with long lists of alternatives, a surprising number of real-world business locations are apparently discovered by random chance—while entrepreneurs are involved with unrelated business activities or during leisure time. Third, the criteria used by business owners to finalize decisions and choose a single element from their consideration sets are almost always stated as fixed cut-off rules, which I interpret as evidence of satisficing heuristics. In addition, the data reveal that, for purposes of designing policies and other incentive schemes that facilitate local economic development, process models (in contrast to as-if models) lead to new normative implications for business tax policy.

In search models that produce optimal stopping rules based on constrained maximization using the probability of success or some scalar-valued expected payoff as the objective function, it is rarely optimal to search through all items in the choice set (Stigler, 1961; Gittins, 1979; Lippman and McCall, 1979). The process of optimization in search models requires, however, exhaustive consideration of all durations of search and all paths of search (in cases where the path is not exogenously given, as it is, for example, in the canonical "Secretary Problem" [Bruss, 1984]). Optimal search models with variable payoffs typically require, in addition, that decision makers have probabilistic beliefs about the payoff-generating stochastic process, which lead to stopping rules that adjust systematically to each new piece of information acquired.[4] Without

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financial measures such as rates of annual return and net present value) mentioned quantifying the expected benefit of further search or produced any measures of costs of time, information or deliberation. And none discussed adapting the threshold rules they apply as their information accumulates (e.g., increasing search if information about a new and unknown neighborhood were freely provided) or in response to institutional shifts in the environment (e.g., new tax incentives for investing in a neighborhood about which they currently possess little or no information).

[4] Gittins' (1979) index approach handles sequential choice among unknown distributions (i.e., independently evolving distributions in the case of the multi-armed bandit problem, and jointly evolving distributions in the case of

considering all durations and paths of search, and without forming probabilistic beliefs needed to associate an expected payoff to each combination of search duration and search path, there is, in general, no way to be sure a global optimum is achieved.[5] The combinatorics of exhaustive search through the universe of all possible search durations and search paths results in an even more formidable optimization problem than those derived from textbook models of consumer choice that assume costless and instantaneous search of all items in the choice set. This has led some critics of optimal search theory to consider simpler models of search that achieve both superior descriptive validity (e.g., Bearden, Rapoport and Murphy, 2006) and superior performance when simple heuristics are well matched to the environments in which they are used (Bookstaber and Langsam, 1985; Gigerenzer, Todd & The ABC Research Group, 1999; Gigerenzer and Selten, 2001; Goldstein and Gigerenzer, 2009).

Economists often argue that the very essence of economics is the axiomatic assumption of optimization. Looking at the world under the presumption that all observed behavior derives from a process of constrained optimization, however, introduces strong restrictions about what can be inferred from empirical observation and substantively influences prescriptive advice for private agents designing incentive contracts and public policy makers. In the context of local economic development, if one observes a section of a city that, for years, does not attract

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the so-called restless bandit problem). The decision maker's objective function, however, depends on a termination-probability parameter, assumed to be known, which is needed for integrating information from previous observations and updating beliefs about the unknown stochastic processes that generate rewards.

[5] Locally comparing marginal benefit and marginal cost among pairs of search durations and search paths is sufficient for a global optimum only after introducing strong auxiliary assumptions (e.g., those that guarantee globally diminishing marginal benefits) which imply that the decision maker has an instantaneous and costless view of all search-duration and search-path combinations and their functional relationship to payoffs.

business investment, the universal assumption of optimization implies that this absence of commerce must result from a lack of profitable opportunities. If no one is investing in a particular neighborhood, after all, the logic of optimization requires us to conclude that it must not be profitable to do so. The data in this paper cast doubt on this logic. The data also reveal how descriptively false models of location choice can lead policy interventions to fail at attracting new investment (e.g., tax incentives for investing in stigmatized neighborhoods). Modest incentives that attempt to induce additional investment in particular locations by increasing investors' expected return have little chance of attracting new investors to isolated locations that never make it into their consideration sets in the first place.

A typical story is this. One of Dallas' prominent commercial high-rise and residential real estate developers described bumping into a large, undeveloped tract of land while driving to play golf in a northern suburb: "The idea struck me as I was driving by that area that it could be developed into a property of note. I told [my spouse] to drive by to get a feel for the area. We liked it. It felt right. Then I ran the numbers and it looked like we could get at least 20 percent annual return on capital within two or three years. That was enough to make it worthwhile to go ahead."

It is interesting to reflect on what is ruled out by this description. There is no exhaustive search through thousands of potential locations and alternative allocations of investment capital to ensure the highest possible ratio of return to risk. There is no mention of benefits and costs associated with continuation of the search process. The business owner's subsequent elaborations indicated that the information required to compute the net value of continuing search was simply not available and instead a fixed threshold condition was applied. Based on intuition together with quantitative data showing that the simple threshold was met, that by itself satisfied the stopping rule and terminated the search phase, finalizing the decision to invest.

Landlords investing in mall properties talked about requiring an 80 percent occupancy rate within a year. Gas station and convenience store investors talked about requiring at least 10 percent annual return on capital within one or two years. Nearly all business owners stated the decisive factor in their location choices as an inequality: "If I think I can get at least *x* return within *y* years, then I'll do it," where *x* is a prominent number (e.g., 1, 2, 5, 10, 15, 20, 50, or 100 [see Pope, Selten, Kube and von Hagen (2009) for more on prominent numbers]).

Standard economic models (including many search models) stated in terms of calculus require that marginal benefit (approximately) equal marginal cost as a necessary but not sufficient condition for an optimal choice. No one in our interview data mentioned such a condition or described using a decision rule that equates any two quantities. Rather, entrepreneurs' reasoning was characterized by decision procedures stated in terms of simple thresholds or cut-off rules (i.e., satisficing).

Additional findings to emerge from entrepreneurs' descriptions include two less-is-more effects. The decision processes they describe typically focus on one, two, or three pieces of information. Those who avoided too many types of information appear to have a greater chance of meeting or exceeding the return they expected at the time of investment. Second, a decision-tree classification model that predicts self-reported performance (i.e., falling below, meeting, or exceeding expectations) achieves a surprisingly high rate of out-of-sample predictive accuracy—more than 80 percent—and more than 90 percent accuracy in fitting. In contrast, maximum-likelihood estimates (i.e., from ordered probit models) have rates of accuracy uniformly below 50 percent in fitting (and considerably worse for out-of-sample prediction). By comparison, the rate of accuracy when predicting the three-valued dependent variable by random guessing would have an expected value of 33 percent. By using less information, the non-compensatory classification tree model predicts performance with substantially greater accuracy, similar to previous studies of consumer behavior such as Yee, Dahan, Hauser, and Orlin (2007).

There is a debate within behavioral economics concerning how to interpret such findings.[6] When the predictions of standard theory do not match what is observed in the laboratory or the field, one common interpretation is that the people are making mistakes. Some behavioral economists go as far as suggesting that the standard rational choice model enjoys exclusive normative authority and that educators, business schools and lawmakers should seek to "de-bias" people who fail to conform, modifying their behavior to be more in accordance with theories of optimal choice and axiomatic rationality (e.g., Jolls, Sunstein and Thaler, 1998).

A very different conclusion based on the same observed disparity between standard normative decision theory and actual human behavior, however, holds that discrepancies between theory and observation should motivate collection of additional descriptive data to record in detail the decision procedures actually in use, especially among those who perform

[6] A fuller account of the normative debate taking place within behavioral economics is in Berg (2003, 2010) and Berg and Gigerenzer (2010). In contrast to Jolls, Sunstein and Thaler's (1998) interpretation of violations of the standard theory as pathological, several papers document that markets with biased beliefs (Berg and Lien, 2005) or nonstandard behavioral procedures (Berg and Gigerenzer, 2007) can outperform economies populated by agents who conform to the standard normative theory. At the individual level, Berg, Biele and Gigerenzer (2010) and Berg, Eckel and Johnson (2010) present evidence of improved performance among individuals who violate axioms of internal consistency upon which the optimization models are based. This raises the issue of what it means to make a good decision and whether standard rationality axioms provide a useful basis for prescribing how people ought to make decisions, which are discussed below.

well in their respective environments. By describing the reward structure of environments and the decision processes that match them well, empirically-grounded normative assessments can be made based on the principle of ecological rationality rather than axiomatic rationality (Gigerenzer and Selten, 2001; Smith, 2003; Berg and Gigerenzer, 2010).

When behavioral models are introduced, the methodology of behavioral economists typically adds parameters (e.g., representing biases, decision costs, or random noise) to otherwise standard constrained optimization models, rather than testing or substantively modifying the axiomatic assumption of constrained optimization. This purportedly descriptive work based on the axiomatic assumption of as-if constrained optimization reinforces prescriptive advice about how business decisions ought to be made--where conforming to standard normative assumptions is presented as the gold standard of rationality, with adages such as "Consider all the alternatives," "Look before you leap," or "Be sure to consider all the trade-offs." While standard search models qualitatively succeed in predicting partial search as well as the use of threshold conditions as stopping rules, those models generally predict rather large consideration sets (e.g., the well known rule from the Secretary Problem of searching at least *1/3*, or *1/e*, of the elements in the choice set). In contrast, experimental evidence frequently reveals that human subjects stop searching well before the stopping point prescribed by optimal stopping rules (e.g., Bearden, Rapoport and Murphy, 2006). The data presented below demonstrate that, among successful entrepreneurs, larger choice sets and more information are, if anything, negatively associated with performance.[7]

[7] By interviewing established entrepreneurs who operate going concerns, the sample is clearly subject to survivorship bias and not representative of all entrepreneurs. The goal of statistical modeling in subsequent sections is to provide an empirical account of decision processes in location choice among owners of going concerns,

Documenting decision procedures that successful entrepreneurs use draws motivation from the methodological approach of three Nobel Laureates--Herbert Simon, Vernon Smith and Reinhard Selten--which focuses on empirical (rather than axiomatic) evaluation of normative decision making. Whatever the decision processes used by entrepreneurs turn out to be, this paper is based on the premise that students of business, psychology, and economics have a lot to gain from learning how entrepreneurs (with a robust record of operating a going concern in the real world) collect information, process information, stop their search processes and make decisions. Rather than merely documenting yet another deviation from axiomatic rationality and interpreting it as a human foible or systematic limitation of human decision making, this paper seeks to describe in detail what it is that successful business owners do when choosing where to locate. This attempt at empirical normative analysis applies the principle of ecological rationality by analyzing differences in unanticipated returns among successful entrepreneurs and associating these with the degree of match between the heuristics they use and the features of their decision-making environments.

The paper proceeds as follows. Section 2 describes the interview data collected from 2007-2010 and presents findings about the very small consideration sets that sophisticated business owners use when choosing locations. Section 3 filters these entrepreneurs' data regarding self-reported performance (i.e., whether they are falling below, meeting, or exceeding their expected rate of annual return on capital) using compensatory linear-index models and non-compensatory decision-tree classification models. Section 4 interprets these findings in light of local economic development policies commonly put forward on the basis of the standard

associating the quantities of information they use, their capital investments, the heuristics they use, and the sizes of their choice sets with self-reported investment return.

economic model. The importance of making it into decision makers' consideration sets and the consequent shortcomings of tax incentives are then discussed with a focus on how to achieve business development goals by matching the decision-making processes actually used by entrepreneurs to newly designed institutions. Section 5 concludes with a brief interpretation of these findings.

Section 2: Interview Data

Data were collected using a convenience sample targeting well placed business owners or senior management in charge of location choice and with personal capital at risk in the choice of location. All 49 respondents risked substantial personal capital in the investment projects they recounted in interviews.[8] Those interviewed included developers of prominent office high-rises, malls, grocery store chains, major chain convenience stores, independent convenience stores, gas stations, sporting goods stores, veterinaries, concert halls, bars that feature live music, and retailers selling furniture, paints, laundry services, and restaurant owners. Confidentiality was a concern for a number of those interviewed. Some sensitive numbers about the details of their investments were discussed and then grouped into discrete categories, summarized in Table 1.

[Table 1 about here]

[8] A total of 53 interviews were conducted, which included four other experts on location choice who did not risk personal capital in the location choices they described and were therefore excluded from the quantitative analysis. The excluded interviews did, however, reveal a number of interesting insights from consultants with extensive experience on a large number of location choice decisions. They included two bankers who make business loans for a major US bank in Dallas, one location choice consultant with a number of large clients, and a senior official in the City of Dallas' Office of Economic Development. Excluding these four left a sample of 49.

Table 1 provides descriptive statistics for business owners' location choices. Projects are considered *large* if total investment capital at the new location exceeded 1 million dollars and *small* otherwise. Among the 49 projects, 17 (a little over a third) were designated as large. Participants were asked what kinds of information they considered relevant when making location choice decisions. The number of types of information mentioned in this open-ended description is coded as the variable # Types of Information, which ranges from 1 to 5. To illustrate how this variable was coded, consider an expected return maximizer whose objective function is independent of risk and all other aspects of potential investment projects. The expected return maximizer would be expected to respond to questions asking for a description of all information relevant to the location decision by describing only the expected returns of different locations in the consideration set and, consequently, coded as # Types of Information = 1. Similarly, an expected utility maximizer with mean-variance preferences would be expected to discuss only return and volatility of returns, which would be coded as # Types of Information = 2. If, in addition, an interviewee mentioned a desire to locate near other retailers or in neighborhoods with particular demographic characteristics (for reasons other than their influence on return and risk), then the number of types of information would increase. Follow-up questions were used to avoid double counting by teasing out connections between each new piece of information mentioned and those mentioned previously by the interviewee. In the prediction models presented in the next section, this variable is dichotomized as an indicator variable labeled Quantity of Information, coding entrepreneurs as *hi-info* if they mentioned 4 or more distinct types of information needed to make good location choice decisions, and *low-info* otherwise.

The variable # Locations in the Consideration Set is one of the most interesting pieces of evidence collected in the interviews. Nine owners described a location choice process in which only one location was considered. The modal response was a consideration choice with three potential locations, which describes the choice sets of 20 of the entrepreneurs interviewed. A frequency distribution for this variable is presented below. The next row in Table 1 labeled Consideration Set (Large/Small) dichotomizes the size of the consideration set, such that consideration sets with strictly more than three elements are designated as *large*, and *small* otherwise.

The next three binary variables code entrepreneurs' self-described decision process relating to a specific location choice. These binary variables indicate whether interviewees, at least once, described a process of maximization, a process of satisficing, a process of imitation, or any combination of those three. Perhaps surprisingly, the language of superlatives (i.e., finding the "best") was infrequent in owners' descriptions of how they chose their location. One interviewee described both processes of maximization and satisficing. And every respondent described satisficing thresholds. A strong majority (39 out of 49) described wanting to locate in an area where other businesses were already active, coded as imitation.

Five other characteristics of business owners and their investment projects were recorded, which have special relevance to local economic development policy. A potentially statistical control (elicited from each entrepreneur) is the number of competitors in the Dallas area. Table 1 shows that this variable ranges from 0 to 5, with the value of 5 indicating a response of "5 or more" competitors.

Dallas' South Dallas neighborhood is thought of by many Dallasites as a low-income, high-crime area that many business owners would never consider as a potential location. As one respondent put it, “The city could offer subsidies and incentives until my rents are entirely free, and I still would never consider locating my business in South Dallas.” This respondent mentioned high crime, the stress that he believed the South Dallas environment would have on his employees, and a general sense of anxiety concerning public order.[9] The variable labeled Transformation of South Dallas Possible measures each owner’s subjective assessment about whether urban revitalization, gentrification, or sustained improvements in economic growth, are possible for South Dallas.[10] Only 11 of 49 respondents responded affirmatively.

The major policy tool considered in recent decades for simulating growth in neighborhoods that seem to have trouble attracting business investment is tax incentives. The interviews revealed great skepticism—among business owners—about this approach. Only 3 respondents stated that tax incentives “might” induce them to consider investing in South Dallas. As the earlier quotation suggests, most respondents would need something altogether different—a transformative signal about opportunities in South Dallas—to include South Dallas in their consideration sets.

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[9] Whether this is founded in statistical realities is an important issue not addressed in this paper. There is evidence that much of the crime in South Dallas neighborhoods is concentrated within one or two addresses within a census blockgroup, which raises questions about how fair it is to characterize an entire neighborhood with crime statistics generated by only a few residents. Evidence suggests that perceptions and fears are exaggerated relative to actual crime frequencies. (See the discussion and Dallas-specific citations on this point in Berg and Murdoch, 2008).

[10] Some residents and advocacy groups working to attract investment to South Dallas do not aim for gentrification and worry openly that, if and when a wave of investment comes to that neighborhood, rents will make the neighborhood largely unaffordable for long-time residents. The goal of the interview item was to elicit beliefs about how likely it would be, and under what conditions, that substantial levels of commercial investment would flow into to South Dallas.

Another important policy tool for local economic development is public transportation. Dallas has invested substantially in building new light rail lines from the northern suburbs to provide greater access in and out of South Dallas and other neighborhoods that, in recent decades, do not appear to attract large in-flows of non-residents for daily commercial activity. Only two respondents said that the location of public transportation influenced, or would influence, their location choice decisions.

Finally, because of local economic development studies that have emphasized the role of artists in predicting new business starts, patent applications, and other measures of local economic development, all interviews contained discussion items about the arts (Florida, 2002; Frey, 2005). Nine of the respondents owned projects directly connected to Dallas' arts scene. Many others described positive spillovers from the Dallas arts scene to the world of commerce, and sentiments among the entrepreneurs were strongly in favor of arts and their role in local economic development.

The final three rows in Table 1 describe an ordered discrete outcome generated by participants' responses to this question: "In the most recent year of operation, would you say the rate of return on your investment is below, meeting, or above, the rate of return you expected at the time you made the decision to choose your current location?" I could have analyzed the actual rate of return. But because different projects have different risk levels, the most meaningful outcome for this analysis with a heterogeneous sample of different kinds of businesses is to ask whether actual return is below, above, or just meeting the expectation that owners had at the time the location decision was made. The interviewed group is, according to their self reports, generally successful at meeting or exceeding expectations. Only 29 percent had returns below expectations. 33 percent met expectations, and 39 percent exceeded expectations.

The next section uses ordered probit statistical models based on a linear index that weights seven predictors summarized in Table 1 to predict the three-valued dependent variable based on investment returns during the previous year (i.e., annual return is below, meets, or above expectations). The predictive accuracy of this standard linear-index model is then compared with the predictive accuracy (in fitting and out-of-sample prediction) of a non-compensatory classification tree based on a theory of heuristics and their match to the business investment environment in Dallas.

Section 3: Statistical Models of Business Performance

The first step in this section is to estimate an ordered probit prediction model as a benchmark of predictive accuracy. Let y_i represent whether the recent year's returns are below ($y_i = -1$), meet ($y_i = 0$) or exceed ($y_i = 1$) expectations at the time the location decision was made. The following linear index, using seven variables in Table 1, serves as the unobserved latent variable:[11]

$$Y^* = \beta_1\,\mathrm{QuantityOfInformation}_i + \beta_2\,\mathrm{SizeOfInvestment}_i + \beta_3\,\mathrm{Imitation}_i + \beta_4\,\mathrm{ConsiderationSet}_i + \beta_5\,\mathrm{Ncompetitors}_i + \beta_6\,\mathrm{ArtsIndustry}_i + \beta_7\,\mathrm{PublicTransportInfluenced}_i + \varepsilon_i,$$

[11] The count variables from which dichotomized indicator variables were constructed are of course omitted to avoid repeating the same information in multiple right-hand-side variables. Maximization and Satisficing are omitted because these variables have little or no variation. Transformation of South Dallas Possible bears no theoretical link to business performance and is therefore omitted. Tax Incentives Matter is likely to suffer from endogeneity because taking advantage of tax incentives directly affects investment return. That leaves the remaining seven variables from Table 1 that are included in the linear index.

where ε_i is a standard normal random variable, and the cutoff parameters μ_1 and μ_2 partition the range of Y* into three discrete categories coded by y_i:

$$Pr(y_i = -1) = Pr(Y^* < \mu_1);\ Pr(y_i = 0) = Pr(\mu_1 < Y^* < \mu_2);\ \text{and } Pr(y_i = 1) = Pr(\mu_2 < Y^*).$$

The nine parameters denoted with Greek symbols (except for ε_i) are estimated by maximum likelihood and the model's fit is measured as follows. Replacing all parameters in the theoretical latent variable equation with their estimated values and replacing ε_i with its expected value (conditional on the predictors) of zero, predicted values of Y* are computed for each observation, denoted Y^{*pred}_i. Next, these predicted values are mapped into estimated probabilities for each of the three dependent variable outcomes, denoted p_{-1i} , p_{0i} and p_{+1i} , respectively:

$$p_{-1i} = \Phi(\mu_1 - Y^{*pred}_i);\ p_{0i} = \Phi(\mu_2 - Y^{*pred}_i) - \Phi(\mu_1 - Y^{*pred}_i);\ \text{ and } p_{1i} = 1 - \Phi(\mu_2 - Y^{*pred}_i).$$

Finally, discrete dependent variable predictions are defined as the outcome with the maximum fitted probability:

$$y^*_i = \text{argmax}_{\,j \in \{-1,\, 0,\, 1\}}\ p_{ji}\ ,$$

which provides a benchmark of predictive accuracy as the percentage of observations i that are correctly predicted ($y^*_i = y_i$): 46.9 percent. Out-of-sample prediction rates were somewhat lower, although still better than the chance rate of accuracy for a three-valued outcome which would be 33.3 percent.

Yee, Dahan, Hauser, and Orlin (2007) use non-compensatory classification trees to predict consumers’ decisions when choosing cell phones. They show that non-compensatory trees perform significantly better than compensatory linear models do. Spanning a wide range of literatures from operations research to psychology, the advantages of using fewer predictors is well established, revealing interesting less-is-more effects relevant to the data presented here (Hogarth and Karelia, 2005, 2006; Baucells, Carrasco and Hogarth, 2008; Goldstein and

Gigerenzer, 2009). Gigerenzer, Todd and The ABC Research Group (1999) show less-is-more effects from specific decision heuristics in both real-world and simulated environments, and this is given additional theoretical justification in Berg and Hoffrage (2008), demonstrating that ignoring information and conditioning on a small number of factors is consistent with payoff maximization.

[Figure 1 about here]

Inspired by this work on non-compensatory decision making, where one predictor can completely over-rule all others, a non-compensatory investment return classification tree was constructed using a strict subset of the available information, depicted in Figure 1. The tree was fitted using MATLAB classification tree algorithms, achieving a within-sample hit rate of 45 out of 49. Next 10,000 samples using 2/3 of the data were randomly drawn; new prediction trees were fit; and out-of-sample hit rates were computed using the remaining 1/3 of the observations. The mean out-of-sample hit rate was just over 80% (0.8055 with a standard deviation of 0.0997) easily beating the corresponding hit rates for the ordered probit model by well more than three standard deviations.

According to Figure 1, a business owner who takes too much time collecting many different kinds of information will perform below average (the right terminal branch at the top of the tree in Figure 1). Half of the 14 projects with below-expectation returns are concentrated at this node of the tree, classified solely on the basis of paying attention to what can be interpreted as too much information rather than focusing on the handful of attributes that matter most. The tree then bifurcates into small versus large investment projects. Large projects at locations chosen without imitation appear to perform better than those chosen with imitation, suggesting that contrarian heuristics for large projects may be beneficial. On the other hand, imitation for small projects by entrepreneurs with small choice sets, who seem to have made something that could be described as a snap decision regarding location, had better-than-expected returns. There were 17 projects at the above-expectations node (low information, small project, imitation, small choice set), 16 of which fit correctly. In contrast, the 6 low-info small projects at locations chosen by imitation using large choice sets (all of which fit correctly by the tree model) reveal another less-is-more effect, in that larger choice sets were associated with below-expectation returns.

On the left-most terminal node (following the branch low-info/small-project/no-imitate), five observations are predicted to have returns that meet expectations, four of which are accurate. The model suggests that small projects which do not imitate will meet expectations when they have small consideration sets, which likely means doing the “obvious thing” (e.g., following local zoning to locate in a central business area). For smaller projects, imitation can exploit information that was collected by others (thereby saving the own costs of collecting that information anew), resulting in agglomeration that makes it easier for customers to find retails (e.g., locating a gas station near other gas stations, or a restaurant near other restaurants). For large investment projects, however, imitation does not pay. Perhaps large projects benefit from boldly going somewhere no others have bet on before. The model suggests that, for sufficiently large projects, ignoring what others are doing generates higher returns than conditioning location choice on the locations of others. Thus, the qualitative effects of imitation on performance are reversed for small versus large projects, a finding revealed clearly in the non-compensatory classification tree but which would have been opaque in a compensatory linear model without interaction terms in the econometric specification.

The classification tree in Figure 2 makes predictions based on the three principles: less is more when collecting information upon which to base a high stakes decision; large projects benefit from originality whereas small projects benefit from a heuristic of imitation, reflecting a principle of ecological rationality; choosing from small choice sets is quicker, leads to less regret, and focuses on the high-stakes question of what belongs inside the consideration set (Gigerenzer, Todd and the ABC Research Group, 1999; Gigerenzer and Selten, 2001; Schwartz, 2004). The information-frugal model in Figure 1 correctly fits 45 out of 49 observations (92 percent accuracy).

Section 4: Location Choice and Implications for Local Economic Development

There is an unmistakable normative interpretation built into the assumption that all observed behavior derives from constrained optimization.[12] Since all opportunities for individual improvements in payoffs have been exhausted, by assumption, in a model with optimizing agents, there can be no role for entrepreneurs to pursue unexploited opportunities that are yet to be discovered. As a consequence of the optimization assumption, locations with little or no

[12] Berg's (2003) "Normative Behavioral Economics" investigates how policy conclusions are tacitly built into purportedly descriptive models. This methodological complaint was raised before the US Congress recently by Nobel Laureate Robert Solow. He complained that macroeconomic models (in this case, the Dynamic Stochastic General Equilibrium model), which are used to make important macroeconomic predictions, rule out the most important features of the macroeconomy that economists should be working to improve. For example, models with equilibrium in labor markets rule out involuntary unemployment. And so-called representative agent models, where the entire economy's key aggregate outcomes are modeled as if they are guided by a single decision maker, cannot explain fraudulent behavior in the financial sector that played a role in bringing about the economic crisis which began in 2008.

business activity are interpreted as lacking any profitable opportunities. The data in this paper suggest alternative explanations and raise the possibility of profitable opportunities in locations that remain unexploited over sustained periods.

The premise that neighborhoods with little commerce suffer from a lack of profitable opportunities would undoubtedly be true if investors systematically and exhaustively considered all elements in their choice sets (or independently considered all search paths with positive expected net value). Under such assumptions, the observation that few businesses are present at a particular address would indeed imply that many investors had undertaken independent benefit-cost analyses and, each time, came to the conclusion that it was unprofitable. The interview data speak against this scenario, however.

Rather than justifying the conclusion that many independent negative assessments on the part of entrepreneurs gave rise to the commerce-deprived neighborhoods we observe, the entrepreneurs' small consideration sets and high prevalence of imitation imply at least the possibility that urban geographies with "deserts" devoid of commerce might instead result from mismatch between heuristics and the environments in which they are used. The modal size of business owners' consideration sets is 3, and many owners only consider one location. This alone would seem to imply the possibility of long-unexploited opportunities in particular neighborhoods of Dallas.

The second important finding revealed by the interview data is the high degree of dependence among business owners' (especially small business owners') location choice decisions. Some 80 percent of respondents (39 out of 49) describe using an imitation heuristic that positively conditions location choice on the locations of other firms (i.e., locating where other firms have already chosen to locate). For smaller investment projects, imitation is not foolish behavior. Rather, it economizes on the research and decision costs of others, and exploits the publically observable information in other firms' location choices.

There is a large literature on mechanisms that lead to spatial agglomerations. Imitation can be an economical way to choose a location where consumers can easily find one's business, usefully coordinating economic activity in a city's urban geography. Imitation also represents a self-reinforcing mechanism by which areas with few businesses may fail to attract business investment despite having untapped investment opportunities. From the perspective of local economic development policy, these two interpretations contain an important distinction. Firms overlooking an untapped opportunity (perhaps because of imitation, or because no single investor wants to alone bear the cost of acquiring information) is very different than evidence that many entrepreneurs have independently considered the location and decided against it. This suggests that bold steps to undertake new investments in locations long regarded as unlikely to produce profits could generate economically significant surprises, while providing jobs and business opportunities to poor neighborhoods that badly need it.

Weissbourd (1999) describes enormous untapped profit opportunities in micro lending and business development in low income neighborhoods. Firms as sophisticated as Starbucks and Home Depot have seen their own revenue forecast models for location choice, which heavily condition location choice on neighborhood income, refuted by their own profitable experiences in low-income areas (Weissbourd, 1999; Helling and Sawicki, 2003; Sabety and Carlson, 2003). Cydnie Horwat, Vice President of Starbucks Store Development, writes: "Our Urban Coffee Opportunities joint venture has essentially shown that Starbucks can penetrate demographically diverse neighborhoods in underserved communities, such as our store in Harlem, which is not something that we had previously looked at" (Francica, 2000).

Why would Starbucks have overlooked profitable opportunities in low-income neighborhoods for so long? And why did it require a new joint initiative with nonprofit groups working to expand opportunities for low-income residents to discover that the coffee giant could operate profitably in low-income neighborhoods?

One answer concerns a too-often-forgotten lesson from first-year statistics courses on linear regression: predictions that extrapolate outside the range of variation of the data collected produce unreliable forecasts. For firms that have always conditioned location choices on neighborhood income in the past, the entire database of store revenue and neighborhood information was, at least initially, censored to exclude low-income neighborhoods. It may very well be that, among middle and upper class neighborhoods, higher income predicts greater store revenues. Extrapolating in the opposite direction beyond the range of variation in the data, however, leads to inaccurate revenue prediction and the possibility of untapped opportunities in low-income neighborhoods. Before experimenting in low-income neighborhoods, both Starbucks and Home Depot's revenue forecast models predicted very low revenues in poor neighborhoods. Their predictions were based on almost no data collected on own-store revenue in low-income neighborhoods and turned out to be wrong.

Several food and coffee sellers in Dallas have reported that their highest revenue stores are in low-income neighborhoods (see references in Berg and Murdoch, 2008). One reason is likely to be the lack of competition. Compared to affluent northern suburbs where one commonly finds, for example, two or three grocery stores at major street intersections, a retailer who sets up shop in an area that most others have ignored may enjoy unusually high profits. This underscores the question raised earlier: Are neighborhoods that retailers avoid really less profitable, or do interdependencies among firms’ location choices lead to inefficient lock-in at a status quo where few stores decide to locate there simply because few stores have decided to locate there in the past?

Small Consideration Sets and Tax Incentives for Investors

Table 2 presents the frequency distribution for the number of elements in the interviewees' consideration sets. One interviewee could not decide whether he had considered three or four locations before deciding, which is coded as 3.5. These data suggest that, for policy makers wanting to stimulate new investment in poor neighborhoods, one crucial component is to find a mechanism that puts the target location into investors' consideration sets. Given the small sizes of the consideration sets in Table 2, simply making it into the consideration set may be a much more substantial hurdle than expected return.

[Table 2 about here]

When policy makers use tax incentives to induce investment in a particular region of a city, this policy tool may tip an investor already considering that area in favor of going ahead based on what usually amounts to modest increases in expected return over a limited number of years. There is little evidence, however, to suggest that tax incentives induce investors to broaden their consideration sets. Tax incentives rest on the optimization model, which assumes that many investors consider the location in question and simply need a small push to raise net present value above a finely calibrated hurdle (in units of percentage points) to trigger investment in the location being targeted by policy makers.

Only three of the 49 participants in this study said that tax incentives would induce them to consider investing in South Dallas. These three already had undertaken previous projects in low-income areas of Dallas. Among the remaining 46 who had never invested in South Dallas, several indicated that virtually any subsidy, even if it reduced costs to zero, would not induce them to consider locating a store in what they perceived to be undesirable neighborhoods. Others gave specific conditions that they would require to be satisfied before including South Dallas in their consideration sets--visible signals of well-functioning middle-class commercial districts such as the absence of trash, absence of broken-down cars, and absence of loiterers. The importance of pharmacies as a positive signal about investing in re-developing neighborhoods was mentioned with surprising frequency, as were grocery stores and other stores selling basic staples.

A large fraction of respondents gave descriptions of how they discovered the location of their most recent investment which included a large role for random chance. The interview data contain numerous accounts of bumping into new neighborhoods by accident or inadvertently coming into contact with the location that wound up in the entrepreneur's consideration set as a strong possibility for a new project. The role of chance in the discovery of locations for new business investment raises additional challenges and perhaps new opportunities for the plight of urban neighborhoods that are ethnically segregated or economically isolated. If few residents from other parts of the city come into contact with a neighborhood, this by itself appears to present a substantial barrier to the flow of investment capital and the random face-to-face encounters that support it (See Berg, Hoffrage, and Abramczuk, 2010, for more on the surprising power of random face-to-face encounters to re-shape a city’s spatial geography).

Imitation in Location Choice and Consequences for Local Economic Development

Pairwise correlation between imitation and recent business performance is positive among the 32 smaller investment projects and negative among the 17 larger projects. This, together with the event tree model from Figure 1, suggests that imitation in location choice is a useful heuristic that finds good-enough locations (i.e., meeting or exceeding expectations) for a large majority of business owners undertaking small projects.

Large projects, in contrast, appear to suffer from imitation and benefit from originality (i.e., not conditioning location strongly on the location decisions of others). This can be interpreted as evidence in favor of a contrarian spirit leading to location choices in areas not previously considered by many others. These results suggest the need for further theoretical and empirical work on several related issues. One further question concerns the benefits and costs of economizing on information which imitation affords. If A undertakes costly search, and B imitates A, then B benefits from the information that is made public when A chooses his location. This pooling of the common information resource through imitation (i.e., the information that A collected and then revealed by his choice of location) will be analyzed in a future paper.

A related issue is the social-welfare consequences of imitation. On the one hand, sharing of information would tend to achieve spatial coordination without the waste implied by each individual undertaking independent information search. On the other hand, the potential for inefficient lock-in, whereby an untapped profit opportunity lies unexploited over a sustained period of time, is a potentially significant social cost. A theoretical model that quantifies both of these aggregate effects from individuals' use of imitation would be useful.

Arts and Local Economic Development

The role of arts venues seems to play a large role in the thinking of entrepreneurs in a variety of industries (Florida, 2002). Interviews with leaders of arts venues, and with leaders of businesses that have no direct contact with the arts, reveal a rich portrait of attitudes about the arts among high-level decision makers in the Dallas, Texas, business community. Nearly all of the non-arts-industry entrepreneurs, when asked about the arts, creativity and innovation, spoke about the importance of arts for the cultural life of the city and its spillovers to the city's world of commerce. This intersection of commerce and culture revealed itself time and again as interviewees were asked to envision future scenarios for the city's business community and describe the desired characteristics of the local economic growth that they hoped to see. The ideas in Florida (2002) linking arts to economic growth seem to be well corroborated, albeit indirectly, in these ethnographic accounts showing that entrepreneurs were nearly unanimous in agreeing that arts and creative people play a special role in cross-fertilizing innovation in the business environment.

Section 5: Conclusion

This paper used scripted interviews of 49 well placed business owners and senior managers in charge of deciding where to locate new businesses. Location choice provides an opportunity to compare the predictions of optimization models (whether textbook models based on exhaustive search, or search models that produce threshold conditions or optimal stopping rules) with the actual decision processes used by entrepreneurs when making high-stakes decisions about where to locate investment capital. Consideration sets, especially among the most successful businesses, are surprisingly small, with a large-magnitude, negative, and statistically significant pairwise correlation between investment return and the event of having a large choice set. Locations that do make it into consideration are frequently discovered by chance rather than systematic search. No interviewees describe a decision process that comes close to the standard optimal stopping condition of continuing search as long as marginal benefit of searching one more location exceeds its marginal cost. Nearly all interviewees described threshold conditions that can be expressed as satisfying an inequality, which provide direct evidence of satisficing.

Whether these satisficing heuristics can be rationalized within a search theoretic model is left for the reader to decide. We note, however, that the threshold rules that entrepreneurs described were fixed rather than adjusting as a function of the last unit observed. And the values of thresholds used were almost always coarsely rounded numbers (sometimes referred to as prominent numbers) such as 5, 10 or 15 percent. I do not interpret this as evidence of any lack of numeracy or imprecision in the thinking of entrepreneurs. Rather, the interview data reveal that entrepreneurs betting their own capital had given considerable thought to the profound uncertainty in their environment and the futility of applying probabilistic beliefs to one-off events. It was not that entrepreneurs did not know enough to compute marginal benefit and marginal cost, but rather the rapid rate of change in their real-world environments that, in their view, made irrelevant the exercise of collecting samples of historical data to estimate parameters needed to apply stopping rules derived from optimization models.

Imitation in location choice is beneficial for relatively small investment projects. The smallness of consideration sets and high frequency of imitative reasoning in entrepreneurs' location choices calls into question a key assumption about policies aimed at stimulating local economic development. Neighborhoods that do not attract investment capital are assumed to be unprofitable under the standard model. An alternative explanation based on these data is that when firms condition their own location choices on the location choices of others, an inefficient lock-in prevents the discovery of untapped profit opportunities in stigmatized sectors of a city.

Rather than tax incentives at the margin, a bold push by one non-imitative investor in a long-ignored area could “seed the cloud” and induce a beneficial cascade of new investment and commercial activity based on the same imitative mechanism. Local policies that facilitate more chance interaction among residents, giving them positive reasons to personally spend time in different sections of the city, would seem to have a better chance at moving isolated neighborhoods into entrepreneurs' consideration sets and spurring new investment in those areas.

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Table 1: Descriptive Statistics for Business Owners' Location Choice (N=49)

variables	min	mean	max	# No (0)	# Yes (1)
description of decision maker's location choice and investment at new location					
Size of Investment >$1mil (Large/Small)	0	0.347	1	32	17
# Types of Information	1	2.388	5	.	.
Quantity of Information (Large/Small)*	0	0.163	1	41	8
# Locations in the Consideration Set	1	3.010	10	.	.
Consideration Set (Large/Small)**	0	0.184	1	40	9
Describe Process of Maximization	0	0.020	1	48	1
Describe Process of Satisficing	0	1.000	1	0	49
Describe Process of Imitation	0	0.204	1	39	10
# Competitors***	0	3.531	5	.	.
Transformation of South Dallas Possible	0	0.224	1	38	11
Tax Incentives Matter	0	0.061	1	46	3
Public Transportation Influenced	0	0.041	1	47	2
Arts Industry	0	0.184	1	40	9
firm's performance in most recent year (ordered dependent variable)					
Return Below Expectation	0	0.286	1	35	14
Return Meets Expectation	0	0.327	1	33	16
Return Above Expectation	0	0.388	1	30	19

*Quantity of Information is defined as *large* if the business owner describes strictly more than three types of information used in location choice, and *small* otherwise.

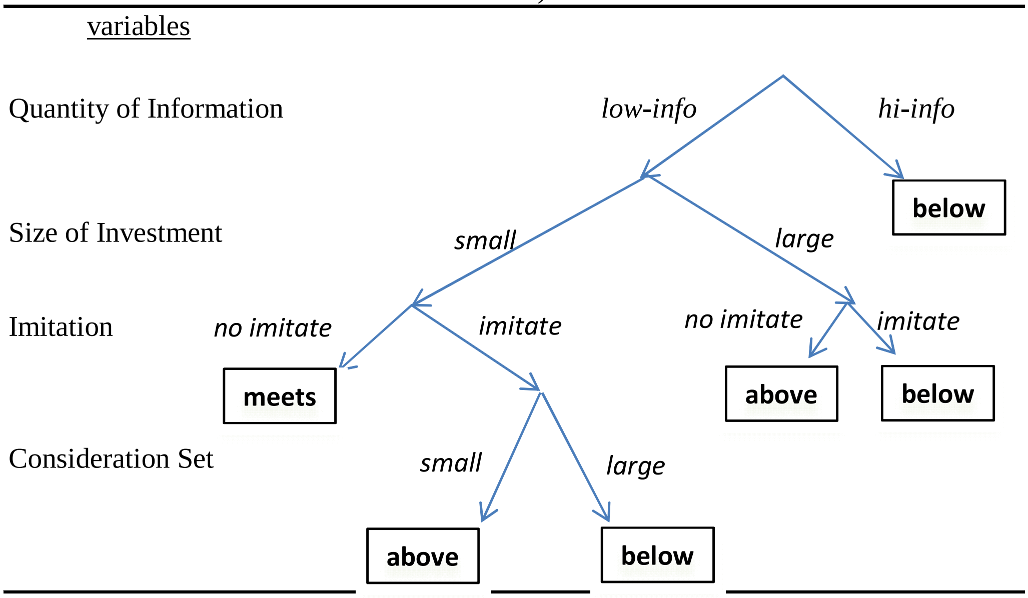
**The consideration set is defined as *large* if strictly more than three potential locations were considered, and *small* otherwise.

***The variable # Competitors counts the number of firms or organizations that the interviewee regarded as a competitor. If five or more competitors were mentioned, then the response was coded as 5.

Table 2: Frequency Distribution for the Number of Locations in Entrepreneurs' Consideration Sets

# locations in consideration set	Frequency	Percent
1	9	18.4
2	11	22.5
3	20	40.8
3.5	1	2.0
4	1	2.0
5	1	2.0
6	3	6.1
8	2	4.1
10	1	2.0

Figure 1: Information-Frugal Classification Tree of Entrepreneurs' Investment Returns (Whether Returns are Below, Meet, or are Above Expected Return in the Most Recent Year)



This investment return classification tree predicts whether entrepreneurs' returns in the most recent year fall below, meet, or are above the expected return at the time the location choice was made. This classification tree fits 45 out of 49 observations (92 percent) correctly. In contrast, a fitted ordered probit model using the four variables in this model plus three additional variables coded from the interviews fits outcomes correctly less than 50 percent of the time.

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