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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 business owners. Consideration sets and quantities of information acquisition are surprisingly small, especially among entrepreneurs who are successful at meeting or exceeding their own expected rates of return. Locations are frequently discovered by chance. Few entrepreneurs describe decision processes comparing the marginal benefits and marginal costs of continuing search. Entrepreneurs express skepticism about the utility of applying probabilistic beliefs to one-off high-stakes choices in their changing environments. Nearly all interviewees describe decision-making processes based on threshold conditions that are not updated along the search path and do not depend on the number of feasible locations, which can be interpreted as direct evidence of satisficing. Imitation is beneficial for small investment projects. Policies seeking to stimulate local economic development with tax incentives within enterprise zones should be rethought in light of entrepreneurs' small consideration sets and satisficing decision process. A lexicographic decision-tree analysis of self-reported success (by the standard of falling below, meeting, or exceeding one's expected annual rate of return) far outperforms maximum-likelihood models in terms of fit and out-of-sample predictive accuracy. The data reveal a less-is-more effect by which entrepreneurs with simpler decision procedures (i.e., requiring less information) and smaller consideration sets enjoy far higher chances of exceeding expectations.

1. Introduction

This study takes an empirical approach to describing the process by which business owners make high-stakes decisions about where to locate businesses or new branches of existing businesses. Rather than assuming that location choice results from a process of optimization, this study uses a scripted in-depth interview of 49 entrepreneurs (i.e., business owners or those with personal capital at risk when making location choice decisions) in the Dallas-Fort-Worth greater metropolitan area. The scripted interview seeks to elicit information about the size of business owners' consideration sets, the criteria they use for stopping search, and the criteria used to finally select an element from the consideration or choice set (following interview methodology proposed by Bewley, 1999; Schwartz, 1987, 2004a, 2004b; Wennberg & Nykvist, 2007; Yonay, 2000; Yonay & Breslau, 2006).

The interview data reveal three main findings. First, entrepreneurs' consideration sets are extremely small—much smaller than is predicted by many search models. Second, rather than beginning with a large-scale search to populate an initial universe of feasible locations or some other long list of alternatives for initial consideration, a surprising number of business locations are apparently discovered by chance, while entrepreneurs are involved with unrelated business activities or during leisure time. Third, the criteria used by business owners to finally make a decision and choose a single location from their consideration sets are almost always stated as static threshold rules that are not updated along the search path and do not depend on the number of feasible alternatives. This paper argues that those observations can be interpreted as evidence of satisficing heuristics. In addition, when asked directly about how tax incentives would (or do) influence location choice, the modal reaction was to ignore government's nudges to invest in regions of the city targeted by policies seeking to stimulate local economic growth in particular locations. The data reveal that, for purposes of designing policies aimed at bringing new private investment to regions that have not previously attracted investors, non-optimizing models of entrepreneurial decision process such as the satisficing heuristic (in contrast to as-if optimization models that assume large choice sets and generally imply high degrees of sensitivity to tax incentives) lead to new normative implications for policy regarding business taxation and local economic development.

Winter (1971) identifies decision process as an object of study that ties together numerous research traditions attempting to provide fuller descriptive (and normative) accounts of innovative or entrepreneurial

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behavior. Sarasvathy, Simon, and Lave (1998) similarly focus on characterizing entrepreneurs' decision processes. Sarasvathy (2001), Sarasvathy and Dew (2005), and Dew, Read, Sarasvathy, and Wiltbank (2009) uncover regularities in entrepreneurial decision making that deviate from the logical strictures of axiomatic rationality as defined in neoclassical economics to achieve high degrees of purposeful action (in the Schumpeterian sense), providing motivation for the present paper.

In search models that produce optimal stopping rules based on constrained maximization using the probability of success or a related scalar-valued expected payoff as the objective function, it is rarely optimal to search through all items in the choice set (Gittins, 1979; Lippman & McCall, 1979; Stigler, 1961). 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 typically require that decision makers have probabilistic beliefs about the payoff-generating stochastic process, which leads to stopping rules that adjust systematically to each new piece of information acquired (Gittins, 1979). Without considering all durations and paths of search, and without forming probabilistic beliefs needed to associate an expected payoff with each combination of search duration and path, there is, in general, no way to be sure a global optimum is achieved. 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 would imply that the decision maker has an instantaneous and costless view of all combinations of durations and paths and their functional relationship to payoffs. The infinite regress of increasing complexity is well known to those modeling bounded rationality as if the decision maker solves an optimal choice problem with additional cognitive or search costs in the constraint set: the combinatorics of exhaustive search through the universe of all possible search durations and paths results in an even more unrealistically difficult-to-solve optimization problem than those derived from simpler textbook models of consumer choice with costless and instantaneous search over all items in the choice set. This has led some critics of optimal search theory to consider non-optimizing models that achieve superior descriptive validity (e.g., Bearden, Rapoport, & Murphy, 2006; Laville, 2000a, 2000b) and superior performance when simple heuristics are well matched to environments in which they are used (Bookstaber & Langsam, 1985; Gigerenzer & Selten, 2001; Gigerenzer, Todd, & the ABC Research Group, 1999; Goldstein & Gigerenzer, 2009).

Economists often argue that the very essence of economics is the axiomatic assumption of optimization. Interpreting entrepreneurial behavior through the lens of that assumption 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 region of a city that, for years, does not attract business investment, the assumption of optimization implies that the absence of commerce must result from a lack of profitable opportunities. If no one is investing in a particular neighborhood, the logic of optimization requires us to conclude that it must not be profitable to do so. The data here cast doubt on this logic. The data also reveal how descriptively false models of location choice can lead to economic development strategies that fail at attracting new investment (e.g., tax incentives for investing in stigmatized neighborhoods). Modest incentives that attempt to attract investors to particular locations by marginally increasing their expected return have little chance of succeeding if investors use decision processes that do not include those locations in their consideration sets in the first place.

The following story is typical. One of Dallas' prominent commercial high-rise and residential real estate developers describes noticing 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."

Reflecting on what is ruled out by this description is interesting. No exhaustive search exists through thousands of potential locations and alternative allocations of investment capital to ensure the highest possible ratio of return to risk. The literature includes no mention of benefits and costs associated with continuation of the search process. The interview explicitly asked what was expected if search had continued and included numerous questions about the size of the choice set and the other locations that were considered. The business owner's subsequent elaborations indicated that the information required to compute the net value of continuing search was simply unavailable, and instead a fixed threshold condition was applied (i.e., 20 percent return after three years). Combining intuition and limited quantitative information used to compute expected rates of return, the threshold was met that finalized 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]) and *y* is typically one to three years.

Standard economic models (including many search models) stated in terms of calculus or extensions using the calculus of variations require that marginal benefit (approximately) equal marginal cost as a necessary but not sufficient condition for an optimal choice. Not one entrepreneur 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 that emerge from entrepreneurs' descriptions of their decisions 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 had a greater chance of meeting or exceeding the return they expected at the time of investment, the binary definition of success applied in the subsequent analysis. 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 of more than 80% (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% in fitting (and considerably worse for out-of-sample prediction). 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 debate within behavioral economics concerning how to interpret such findings (Berg, 2003, 2010; Berg, Biele, et al., 2010; Berg & Lien (2005); Berg, Eckel, et al., 2010; Berg & Gigerenzer, 2007, 2010). When predictions of standard theory do not match what is observed in the laboratory or field, a common interpretation in behavioral economics 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, & Thaler, 1998).

A very different conclusion based on the same observed disparity between standard normative decision theory and actual human behavior, however, emerges from the data reported below. Based on this gap between normative theory and observed behavior, one can instead call into question the normative theory rather than the non-optimizing behavior of entrepreneurs. Observed departures from optimal search theory coincide with a high degree of self-reported success. These discrepancies call for the collection of additional descriptive data that record in greater detail the decision procedures entrepreneurs actually use, especially among those who perform 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 (Berg & Gigerenzer, 2010; Gigerenzer & Selten, 2001; Smith, 2003).

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. The purportedly descriptive modeling exercise based on 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 "Consider all the tradeoffs." While standard search models succeed in predicting the partial rather than exhaustive search observed in real-world settings as well as the use of threshold conditions such 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 people stop searching well before the stopping point prescribed by optimal stopping rules (e.g., Bearden et al., 2006). The data presented below show that, among successful entrepreneurs, larger choice sets and more information are, if anything, negatively associated with performance, consistent with Laville (2000a, 2000b) and Koppl (2008). By interviewing established entrepreneurs who operate going concerns, the sample is clearly subject to survivorship bias, and no claims can be made to having drawn a random sample 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, 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 relative to expectations.

Documenting decision procedures that successful entrepreneurs use draws motivation from the methodological approach of three Nobel Laureates—Herbert Simon, Vernon Smith and Reinhard Selten—by focusing 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 by 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 cognitive limitation, 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.

A caveat regarding the simple binary definition of entrepreneurial *success* employed in this paper is in order. Lewin (2011, p11) points out that success in real-world entrepreneurial decision making is often far from binary, summarizing this among other paradoxes he observes about entrepreneurship: "Entrepreneurs act on plans that are never completely successful. Entrepreneurial action is both equilibrating and disequilibrating, successful and unsuccessful." The point is well taken, as are criticisms from Austrian economists about conflicting characterizations of entrepreneurial behavior (see Endres & Woods, 2006, 2010, for an erudite exegesis of primary sources) in Schumpeter (1934, 1954), in Kirzner (1995, 1997, 1999), and in the behavioral approaches of Simon (1958, 1978, 1986), Cyert and March (1975), Shackle (1961, 1972, 1979), Winter (1971), and Nelson and Winter (1982). See Lachmann (1976), Casson (1982), Earl (1990, 1996, 2013), Buchanan and Vanberg (1991), Harper and Earl (1996), Harper (1998), Witt (1999, 2007, 2009), Sautet (2000), Lewin (2002, 2011), Cowen (2003), Fagerberg (2003), Endres and Woods (2006, 2010), and Basili and Zappia (2009) regarding both overlap and divergence in Austrian and behavioral economics—especially the problem of discovery in environments characterized by non-probabilistic uncertainty as articulated by Knight (1921) and developed by Shackle (1961, 1972, 1979), Loasby (1967, 1971, 1976, 1982, 1984) and Earl and Potts (2013).

The paper proceeds as follows. The Interview data section describes the interview data and presents findings about the very small consideration sets that sophisticated business owners use when choosing locations. The section, Statistical models of entrepreneurial success, reports the data on 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, or lexicographic, decision-tree classification models. The section, Location choice and implications for local economic development, interprets these findings in light of local economic development policies commonly used by cities and regional governments on the basis of the standard economic model. The importance of whether potential locations make 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. The Conclusion section provides a brief interpretation of these findings.

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. 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.

Table 1 provides descriptive statistics for the main variables that were coded to facilitate quantitative analysis. Projects are considered *large* if total investment capital at the new location was greater or equal to 1 million dollars and *small* otherwise. Among the 49 projects, 17 (a little over a third) are classified as large. Participants were asked what kinds of information they considered relevant when making location choice decisions, with persistent follow-up questions attempting to exhaustively characterize the categories of information that decision makers used. The number of categories or types of information 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

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 > $1 mil (large/small)	0	0.347	1	32	17
#Types of Information	1	2.388	5		
Quantity of information (large/small)[a]	0	0.163	1	41	8
#Locations in the consideration set	1	3.010	10		
Consideration set (large/small)[b]	0	0.184	1	40	9
Describe process of maximization	0	0.020	1	48	1
Describe process of satisficing	1	1.000	1	0	49
Describe process of imitation	0	0.204	1	39	10
#Competitors[c]	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

[a] Quantity of Information is defined as large or *high-info* if the business owner describes strictly more than three types of information used in location choice, and small or *low-info*otherwise.
[b] The consideration set is defined as large if strictly more than three potential locations were considered, and small otherwise.
[c] 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.

maximizer would be expected to respond to questions asking for descriptions 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, a risk-averse expected utility maximizer with textbook 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 mentions 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. In the prediction models presented in the next section, this variable is dichotomized as an indicator variable labeled Quantity of Information, coding entrepreneurs as *high-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 dichotomizes the size of the consideration, such that consideration sets with strictly more than three elements are designated as *large*, and *small* otherwise.

The next three binary variables record entrepreneurs' self-described decision process relating to a specific location choice (c.f., Selby & Petäjistö, 2008; Valliere, 2008). Respondents were asked to focus on one recent high-stakes project in which the choice of location was regarded as an important part of their decision-making process. 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 these responses were both recorded implying that the categories coded by these indicator variables are not always mutually exclusive. Every single respondent described satisficing thresholds—a result that was not anticipated and necessitated a shift away from the original statistical design for which more variation in satisficing behavior was expected. 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 important 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 reported they would never consider as a potential location (Berg & Murdoch, 2008). 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. 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. Only 11 of 49 respondents responded affirmatively.

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

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 have attracted 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 and "the creative class" in predicting new business starts, patent applications, and other measures of local economic development, all interviews contained 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 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 coding self-reported success relative to expectations 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 that you expected at the time you made the decision to choose your current location?" Actual rates of return could have been specified as the dependent variable in the statistical models. But because different projects have different risk levels, the dependent outcome for this analysis with a heterogeneous sample of different kinds of businesses was coded according to whether realized returns were below, just meeting, or above the rate of return expected at the time the location decision was made. The entrepreneurs who were interviewed were, according to their self-reports, generally successful at meeting or exceeding expectations. Only 29% had returns below expectations. 33% met expectations, and 39% exceeded expectations. Interviewees were given assurances that personally identifying information would not be divulged. Insofar as these assurances were credible, the interview protocol applied considerable effort to facilitating honest introspection and avoiding public relations speech or bluster.

Researchers who study entrepreneurs in the tradition of Schumpeter or the Austrian school would, in many cases, ask for a richer, less mechanistic definition of success. While acknowledging the value of pluralistic notions of success and the rather narrow definition employed here, the next section proceeds in attempting to extract meaningful information about real-world entrepreneurial behavior using the coding scheme as defined above (Murphy, Trailer, & Hill, 1996).

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 coding success relative to expectation based on investment returns during the previous year (i.e., whether investment return is below, just meeting, or above expectation). 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 environment in Dallas.

3. Statistical models of entrepreneurial success

The first step in this section is to establish a baseline compensatory model of entrepreneurial success (i.e., where all predictors can compensate for each other and shift predicted probabilities continuously in either direction). The ordered probit model serves as the 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:

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

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:

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

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 latent variable equation with their estimated values and replacing ε_i with its expected value (conditional on the predictors) of zero, the 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} (which sum to 1):

$$\begin{aligned} p_{-1i} = {} & \Phi\left(\mu_1 - Y^{*pred}{}_i\right);\ p_{0i} = \Phi\left(\mu_2 - Y^{*pred}{}_i\right) - \Phi\left(\mu_1 - Y^{*pred}{}_i\right);\ \text{and}\ p_{1i} \\ = {} & 1 - \Phi\left(\mu_2 - Y^{*pred}{}_i\right), \end{aligned}$$

where Φ is the standard normal cdf. Finally, discrete dependent variable predictions are defined as the outcome with the maximum fitted probability:

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

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

Yee et al. (2007) use non-compensatory classification trees to predict consumers' decisions when choosing cell phones. They show that non-compensatory trees (i.e., lexicographic classification trees, where one predictor can over-rule all lower-ranking predictors) 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 are well established, revealing interesting less-is-more effects relevant to the data presented in the previous section (Baucells, Carrasco, & Hogarth, 2008; Goldstein & Gigerenzer, 2009; Hogarth & Karelaia, 2005, 2006). Gigerenzer et al. (1999) show a less-is-more effect using simple decision and inference rules in both real-world and simulated environments. These less-is-more effects are given additional theoretical justification by Berg and Hoffrage (2008), who demonstrate that ignoring information and conditioning on a small number of factors can be consistent with payoff maximization.

Inspired by this work on non-compensatory decision making, where one predictor completely over-rules all others, a non-compensatory classification tree for entrepreneurial success was constructed using a strict subset of the available information, as depicted in Fig. 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). This hit rate using fast-and-frugal prediction trees easily beat the corresponding out-of-sample hit rate for the ordered probit model (which was less than 50%) by more than three standard deviations.

According to Fig. 1, a business owner who takes too much time collecting many different kinds of information performs below average (the right terminal branch at the top of the tree in Fig. 1). Half of the 14 projects with returns below expectation 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 bold contrarian heuristics for large projects are beneficial and a mark of larger-scale entrepreneurial success. 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 simple 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 or locating in a central business district). For smaller projects, imitation can exploit information that was collected by others (thereby saving the own costs of collecting new information), 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 others have not previously ventured. 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

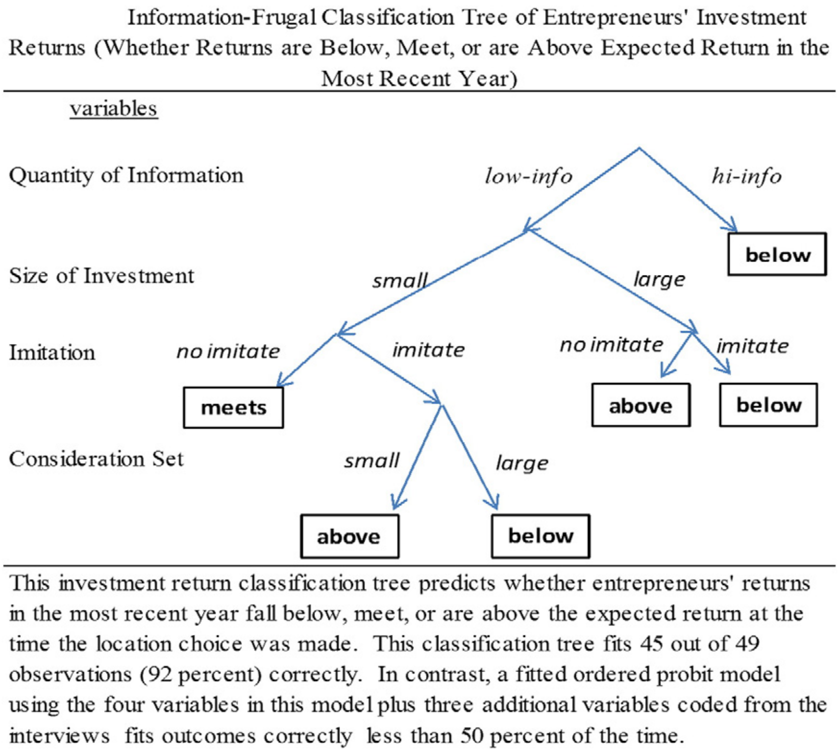

Fig. 1. Information-frugal classification tree of entrepreneurs' investment returns (whether returns are below, meet, or are above expected return in the most recent year).

which would have been opaque in a compensatory linear model without interaction terms in the econometric specification.

The classification tree in Fig. 1 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 while small projects benefit from a heuristic of imitation, reflecting the principle of ecological rationality; and 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 & Selten, 2001; Gigerenzer et al., 1999; Schwartz, 2004a, 2004b). The information-frugal model in Fig. 1 correctly fits 45 out of 49 observations (92 percent accuracy).

4. Location choice and implications for local economic development

An unmistakable normative interpretation occurs in the assumption that all observed behavior derives from constrained optimization. Since all profit opportunities have, by assumption, been exhausted in a models based on profit maximization, there can be no role for entrepreneurs to pursue unexploited opportunities that are yet to be discovered (c.f., Baumol, 1968; Demsetz, 1983, on the missing entrepreneur in neoclassical optimization models). As a consequence of the optimization assumption, locations with little or no 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 long 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. Importantly, this does not imply that entrepreneurs are making systematic mistakes. In contrast to "small worlds" with stable probability distributions described in standard optimal search models, entrepreneurs appear to employ satisficing or threshold-based decision rules that function well most of the time in a profoundly non-static environment — environments in which reliable stochastic characterizations of the joint distribution of locations and investment returns are unavailable.

Rather than justifying the conclusion that many independent negative assessments on the part of entrepreneurs gave rise to optimally low-commerce neighborhoods, 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 inherent instability, non-probabilistic uncertainty, or perhaps a mismatch between location-choice heuristics and the environments in which they are used. The modal size of business owners' consideration sets is 3, and a number of owners only consider one location. This alone would seem to imply the possibility of long-unexploited opportunities in particular neighborhoods of Dallas, whose investment value might be realized if greater geographical flows of face-to-face contacts emerged in ways that increased the chance that those locations might enter entrepreneurs' consideration sets. In the meantime, those interviewed were busy successfully applying their heuristics to uncover opportunities elsewhere.

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% 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. It appears to economize 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 provide an economical way to choose a location that consumers can easily find and usefully coordinate economic activity within in a city's complex urban geography. Imitation also represents a self-reinforcing mechanism by which areas with few businesses may fail to attract business investment despite the presence of long-untapped investment opportunities. From the perspective of local economic development policy, these interpretations contain an important distinction. Observing firms to have routinely overlooked an untapped opportunity at a particular location (perhaps because of imitation, or because no single investor wants to alone bear the cost of acquiring information) is different than having observed many entrepreneurs independently considering and deciding against that location. To the contrary, few entrepreneurs interviewed considered South Dallas at all. This suggests that bold steps to undertake new investments in locations long regarded as unlikely to produce profits might very well be capable of generating economically significant surprises, while providing jobs and business opportunities to neighborhoods that badly need them.

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 on neighborhood income, refuted by their own profitable experiences after moving into low-income areas against the negative revenue predictions of their own forecasting models (Helling & Sawicki, 2003; Sabety & Carlson, 2003; Weissbourd, 1999). 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).

This is not merely motivated by public relations concerns and has been confirmed by unexpectedly large same-store sales numbers after establishing new stores in poor neighborhoods. 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 on linear regression: predictions that extrapolate outside the data's range of variation are unreliable. For firms such as Starbucks and Home Depot that accumulated databases of own-store sales located primarily in middle and upper-income neighborhoods, positive correlations between store revenue and neighborhood income were thought to imply that revenues at stores in low-income neighborhoods (if there *were* stores there) would generate below-average sales. Using sales databases that happened to be censored (at least initially) to exclude low-income neighborhoods based on previous location decisions, these firms extrapolated in the opposite direction beyond the range of income variation in their data to conclude (as it turns out, erroneously) that low-income neighborhoods were a bad bet. Those unfavorable revenue predictions for poor neighborhoods have proven inaccurate, suggesting wider possibility of untapped opportunities in low-income neighborhoods, even in markets dominated by sophisticated retailers.

Several food and coffee sellers in Dallas have reported that their highest revenue stores are in low-income neighborhoods (see references in Berg & Murdoch, 2008). One reason is likely to be 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 simply because few stores have decided to locate there in the past?

4.1. 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. The data suggest that, for policy makers wanting to stimulate new investment in poor neighborhoods, it will be crucial 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 would appear to be a more substantial hurdle than expected returns affected by tax breaks or other subsidies within enterprise zones.

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

When policy makers use tax incentives to induce investment in a particular region of a city, this policy tool may nudge an investor already considering that area to go ahead based on what usually amounts to modest increases in expected return over a limited number of years. The data on sizes of consideration sets provide little grounds for concluding that tax incentives will induce investors to broaden their consideration sets. Tax incentives rest on the optimization model that assumes many investors are considering the location in question and simply need a marginal push to raise net present value above a finely calibrated hurdle (in units of percentage points) to trigger investment in the target location.

Only three of the 49 participants in this study said that tax incentives would induce them to consider investing in South Dallas. These three had already undertaken previous projects in low-income areas of Dallas. Among the remaining 46 who had never invested in South Dallas and reported having hardly ever spent time in those neighborhoods, several indicated that virtually any subsidy, even if it reduced rents to zero, would not induce them to consider locating a store in what they perceived to be undesirable neighborhoods. Others gave specific conditions that would be required for them to include 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 number of respondents gave descriptions of how they discovered the location of their most recent investment that included a large role for chance face-to-face contact. 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 serious consideration 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 random face-to-face encounters that support it. (See Berg, Hoffrage, et al., 2010, on the surprising power of random face-to-face encounters to re-shape a city's spatial geography, and Viswanathan, Sridharan, & Ritchie, 2010, on the important role of face-to-face contact as a conduit for information flow in so-called “1-to-1” or subsistence marketplaces).

4.2. 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 Fig. 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 choosing locations in areas not previously considered by many others. These results suggest the need for further theoretical and empirical work on several related issues. One 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 costly-to-obtain information through imitation (i.e., the information that A collected and then revealed by his choice of location) will be analyzed in a future paper.

The social-welfare consequences of imitation are a related issue. 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 where an untapped profit opportunity lies unexploited over a long period of time is a potentially significant social cost as well as being a missed private opportunity for some businesses. A theoretical model that quantifies both of these aggregate effects from individuals using imitation heuristics in location choice would be useful (Nikolaeva, 2014).

4.3. 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 both with leaders of arts venues and owners 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, by entrepreneurs who were nearly unanimous in agreeing that arts and people working in creative fields play a special role in cross-fertilizing innovation and growth throughout the broader business environment.

5. Conclusion

This study uses scripted interviews of business owners and senior managers with personal capital at risk who were 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) against the actual decision processes used by entrepreneurs when making high-stakes decisions about where to locate. Consideration sets, especially among the most successful businesses, are surprisingly small, with a large-magnitude, negative, and statistically significant pairwise correlation between investment return relative to expectation 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. Because these thresholds were not updated during the search process and were not sensitive to the number of elements in the universe of feasible locations, the data can be interpreted as providing 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 static rather than adjusting as a function of the last unit observed (as required in many models of optimal search) or the number of feasible locations (as required using the fixed-fraction-of-feasible-alternatives in the optimal search rule from the classic Secretary Problem mentioned in the Introduction section of this paper). Furthermore, the values of thresholds entrepreneurs used were almost always coarsely rounded numbers (sometimes referred to as prominent numbers) such as 5, 10 or 15%. This should not be interpreted as reflecting a lack of numeracy or some kind of pathological cognitive deficit commonly attributed by behavioral economists to people who deviate from the prescriptions of optimal choice models. Rather, the interview data reveal entrepreneurs risking their own capital after giving 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. They were instead taking into account the rapid rate of change in their real-world environments that, in their view, made the exercise of collecting samples of historical data to estimate parameters needed to apply optimal stopping rules irrelevant.

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 of profit maximization. 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 blocks the discovery of untapped profit opportunities in stigmatized sectors of a city. Rather than enterprise zones providing tax incentives at the margin, the decision process data suggest different possibilities. For example, a bold push by one non-imitative investor in a long-ignored area might just prime the pump, inducing a beneficial cascade of new investment and commercial activity generated by other entrepreneurs using an imitation heuristic (c.f., Manimala, 1996; Ucbasaran, Westhead, & Wright, 2001; Zahra, Gedajlovic, Neubaum, & Shulman, 2009). 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.

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