Transitory Shocks, Limited Attention, and a Firm's Decision to Exit*

Avi Goldfarb
Rotman School of Management
University of Toronto
105 St. George Street
Toronto, ON M5S 3E6
416-946-9604
agoldfarb@rotman.utoronto.ca

Mo Xiao
Eller College of Management
University of Arizona
1130 E. Helen Street
Tucson, AZ 85721-0108
520-621-2192
mxiao@eller.arizona.edu

August 2019

ABSTRACT

This paper investigates the incidence of limited attention in a high-stakes business setting: a bar owner may be unable to purge transitory shocks from noisy profit signals when deciding whether to exit. Combining a 24-year monthly panel on the alcohol revenues from every bar in Texas with weather data, we find that inexperienced, distantly located owners overreact to the transitory component of revenue relative to the persistent component. This asymmetric response is muted under higher revenue fluctuations. We formulate and estimate a structural model to endogenize inattention by owners with different thinking cost. We find that 3.9% bars make incorrect exit decisions due to limited attention. Our counterfactual exercises illustrate the welfare trade-offs of inattention and the heterogeneous value of owner experience. Because exit decisions are permanent, owner experience is especially useful when a series of negative shocks propel premature exit.

Keywords: inattention, bounded rationality, exit, behavioral industrial organization

JEL Classification: D9, L2, L8

* We gratefully acknowledge financial support from the Social Sciences and Humanities Council of Canada (grant # 486971). We thank seminar participants at Cornell University, Harvard University, Penn State University, SUNY-Stony Brook, Stanford University, UC Berkeley, the University of Texas, the 2017 NBER IO winter meetings, the 2019 BRIQ conference on structural behavioral economics, and numerous other conferences for helpful comments. Isabella O'Hara, Zakia Chan, Leah Morris, and Eran Poyastro provided excellent research assistance.

1 Introduction

Deliberation about an economic decision is a costly activity. As human cognition is a scarce resource, decision makers cannot consider all possible influences. How do people choose which factors to consider? While this question first appeared in the economics literature over sixty years ago (Simon 1955) and a more recent literature has generated models as well as lab and field experiments (Gabaix et al, 2006; Hanna, Mullainnathan, and Schwartzstein 2014), field evidence remains thin. The best evidence comes from consumer decisions: "buy-it-now" options on eBay (Malmendier and Lee 2011), packaged grocery (Clerides and Courty 2017), add-ons to a larger purchase such as shipping charges (Hossain and Morgan 2006; Brown, Hossain, and Morgan 2010), minutes remaining of cellphone usage plan (Grubb and Osborne 2015), right-digits in used car mileage (Lacetera, Pope, and Sydnor 2012), state taxes (Chetty, Looney, and Croft 2009, Taubinsky and Rees-Jones 2018), financial services (Stango and Zinman 2014), insurance (Handel 2013, Ho, Hogan, and Scott Morton (2015), and electricity bills (Hortacsu, Madanizadeh, and Puller Forthcoming).

We examine inattention and its implications in high-stakes decisions by firms. Firms often need to make forecasts based on repeated, noisy observations and then make an irreversible decision. For example, employers try to predict worker productivity before making firing decisions and venture capitalists try to predict new start-ups' prospects before making investments. In this study we focus on bar owners who try to infer the underlying profitability of their bars before making exit decisions. Owners should form rational expectations of the future profitability of their bars based on the profit record of the bar through time. The profit record, however, is affected by a large of numbers of factors that warrant attention: local demand, the bar's quality and specialty, fixed and variable costs, and, often, transitory shocks such as weather variation, local sports team victories, or a flu outbreak.

We focus the bar owners' limited ability to purge transitory shocks, particularly weather shocks, from their observed profit signals. Transitory shocks temporarily shift profits but a rational decision maker should know to net out of these transitory shocks from future profitability. If an owner already knows her true profitability, a temporary shock should not change her decision to exit. Therefore, the degree to which the owner accounts for past weather shocks in their exit decisions reveals the existence and magnitude of her inattention to these transitory shocks. While there are many factors that bar managers should consider (and perhaps do not), we choose weather shocks because they are exogenous, measurable, and unpredictable, thus capturing the nature of transitory shocks (e.g. Conlin, O'Donoghue, and Vogelsang 2007, Simonsohn 2010). Furthermore, while the economic impact of weather is relatively small for individual bar owners,[1] its aggregate impact on the macroeconomy can be large.[2] Generally, weather shocks enter a (potentially inattentive) decision maker's belief formation process, giving rise to the possibility of misinterpretation and incorrect perception.

To assess the empirical relevance of inattention, we use monthly alcohol revenue for every bar that operated in Texas between January 1995 and November 2018. We supplement this data with Texas weather station data and local market attributes. We find evidence consistent with limited attention, particularly for inexperienced, distantly located bar owners. We first demonstrate that daily weather shocks in heat index, precipitation, and unfavourable characteristics (such as fog, rain drizzle, snow ice pellets, hail, and thunder) do affect alcohol revenue. Such effects are economically small but statistically significant. Decomposing revenue into a persistent component and a transitory component, we then show that owners of different attributes react to these two components differently when making exit decisions. Inexperienced owners and owners with a mailing address distant from the bar overreact to the transitory component relative to the persistent component. In contrast, experienced and closely located bar owners weigh the two components of revenue more correctly, as if they recognize transitory shocks to some degree and therefore choose to respond less to them.

Such asymmetric responses are unlikely due to alternative explanations such as ability to smooth revenue shocks, credit constraints, and projection bias. First, we show the magnitude of weather effects on revenue is similar across inexperienced and experienced owners. Therefore, experienced owners are unlikely to manage their business better to smooth out the impact of the transitory shocks they face. Second, we show owners that are likely to be credit-constrained (because of factors other than experience) respond more to both the persistent and the transitory components of revenue, instead of overreacting to the transitory component relative to the persistent component. Our results on owner experience and distance to owner are therefore unlikely to be driven by credit constraints. Third, we show that owners shift weight from the transitory component to the persistent component when revenue variation is higher, suggesting that owners rationally allocate attention when it is more warranted. This is against the prediction of projection bias because such bias is about the undue influence of the shock at the moment of decision-making. A more volatile environment should not affect an owner's reliance on current states to infer future states.

Motivated by our descriptive results, we formulate a structural model that builds on theory and lab evidence about limited attention. As emphasized in DellaVigna (2017), the structural model allows us to calibrate magnitudes and examine the welfare impact of

[1] For example, it does not seem to be part of standard advice to starting restauranteurs: In the 908-page *Restaurant Manager's Handbook* (Brown 2007), the weather is not mentioned as a profit driver.
[2] Boldin and Wright (2015) find that deviations in weather from seasonal norms can shift the monthly payroll numbers by more than 100,000 in either direction, and the Central Bankers using current major macroeconomic indicators completely ignore such effects.

inattention. We estimate a single-agent model of belief formation and dynamic exit decisions, in which a bar's underlying profitability is initially unknown to the owner. The owner observes (alcohol) revenues, which are noisy signals for the underlying profitability. The owner forms a belief about the underlying profitability through Bayesian learning, and if the present discounted value of future profits falls short of the outside option, the owner exits. In the learning process, we build a "pre-step", in which the owner solves an attention allocation problem to recover the true profit signals. The decision maker needs to weigh the benefit of observing the true state of the world and the cost of casting attention to recognize transitory shocks. The pre-step attention allocation problem incorporates Gabaix's (2014) "sparsity" model of rational inattention. In Gabaix's model, the decision maker allocates attention to build an optimally simplified representation of the world that is "sparse", that is, uses few parameters that are non-zero, and then choose her best action given this sparse representation.[3] We add to Gabaix's model by modeling thinking cost as a stochastic process and linking it to the personal attributes of decision makers, which enables separate identification of establishment characteristics about underlying profitability and owner characteristics about cost of thinking. Estimating this "limited attention" parameter and its relationship with decision makers' attributes allows us to examine variation in mistakes and evaluate heterogeneous welfare trade-offs across firms due to this bounded rationality problem.

Our structural results demonstrate the prevalence of inattention among bar owners. Of the 8,995 owners in our data, an average owner's probability of paying no attention to transitory shocks ranges from 76% to 87%, depending on the specification. Even if an owner is paying attention, her attention only amounts to roughly one third of the full attention spectrum. The amount of attention, however, displays significant heterogeneity across owners in data. This heterogeneity is driven by (i) the within variation of a bar's revenue; (ii) a large, significantly negative effect of owner experience in the thinking cost function and (iii) the distance from owner s mailing address to the establishment location.

The prevalence of inattention has economic consequences. Consistent with Taubinsky and Rees-Jones (2018) who emphasize the importance of incorporating heterogeneity into behavioral welfare analysis, our counterfactual exercises show that 351 bars (3.9% of the total) would have made different exit decisions had they paid full attention. We find this magnitude comforting: Not so high that inattention to transitory shocks is a major mistake but not so low that improvement in decision making is negligible. For these 351 bars, the payoff to better decisions (about $2,000 per month for a median bar) is overwhelmed by a much higher cost of

[3] Compared to other models of rational inattention (Sims, 2003; Reis, 2006; Saint-Paul 2011; Abel, Eberly, and Panageas 2013), an advantage of Gabaix's model is that it yields a single parameter that defines the degree of limited attention.

casting attention (about \$16,000 per month for a median bar). Still, the welfare loss due to mistakes in decisions can be very large because the benefit of correct exit timing is highly skewed to the right.

Our estimated model suggests that owners with experience have substantially lower thinking costs and, in turn, pay more attention to transitory shocks. The value of owner experience is the benefit earned due to more attentive decision-making. In particular, for the median bar that could have made a better exit decision, owners with one additional year of experience generate about \$900 per month, three additional years about \$1,100, and ten additional years about \$1,400. The averages mask large heterogeneity across bar owners, driven by the differences in their personal traits and the businesses they run.

Such inattention may be inconsequential if it merely changes the timing of a decision by a few months; but it can matter greatly if a few negative transitory shocks propel the owner to think the bar is unprofitable and thus the owner decides to exit prematurely. Negative shocks affect welfare more than positive shocks because negative shocks can cause a potentially successful bar to close, eliminating many potential years of profits. In contrast, positive shocks allow a bad bar to stay open, usually delaying the inevitable by a short period of time, so the misinterpretation of the revenue signal affects outcomes to a limited extent. This is particularly relevant in the case of a new entrepreneur with a short operating history to rely on and some unfortunate early negative shocks. Our counterfactual simulations show that experience is especially useful in reducing welfare loss due to incorrect inference when the bar is hit with negative shocks. As we can interpret transitory shocks as luck, we argue that an owner's experience helps her to recognize the role of lucky or unlucky events. When the firm is unlucky, the owner needs experience to correctly assess the situation and avoid a potentially costly error. The difference between the welfare impact of positive and negative shocks means that luck and experience work as substitutes. This contrasts with the existing literature on skill and luck in entrepreneurship, which emphasizes the complementarity between the skill of running a business and the luck of identifying a good business to run (e.g. Plehn-Dujowich 2010).

Going beyond simply documenting the incidence of limited attention, we follow a small but growing literature that assesses the welfare trade-offs of a decision makers' inattention. These papers recover primitive parameters in consumer preferences so they are able to perform counterfactual analysis to evaluate welfare trade-offs (e.g. Lacetera, Pope, and Sydnor 2012, Grubb and Osborne 2015). Public policies, which aim to improve consumer attention, can have large welfare-enhancing effects.

Our work is distinct from the prior literature because of the focus on firms and managers. The traditional economic framework assume firms make fully rational decisions, in which managers seek to maximize the present value of current and future earnings, solve a dynamic optimization problem, and play a Bayesian Nash Equilibrium. These assumptions are well-grounded: the stakes are often higher for firms, and their decisions can involve long and careful deliberations in a collective setting. Perhaps more importantly, the market mechanism should attenuate biases in firms' decision-making processes. Nevertheless, there is an increasing sense that managers may not make optimal decisions. After all, firms are run by humans who may be subject to behavioral biases, mistakes, and limited ability to compute and retain information. Standard dynamic models require extraordinary information retention and processing capabilities (Pakes 2016). Field evidence on behavioral decision-making by firms is, at best, sparse in industrial organization (DellaVigna 2017), though some work has started to explore the situations in which firms do not appear to behave according the standard economic models (e.g. Goldfarb and Yang 2009; Goldfarb and Xiao 2011; Doraszelski, Lewis, and Pakes 2014; Hortacsu, Luco, Puller, and Zhu 2016; DellaVigna and Gentzkow 2017).

One main challenge, perhaps limiting the flow of new work in this area, is to find settings that also offer rich enough data for empirical applications. Our work leverages a distinctive setting with rich data on heterogeneous managers and infrequent firm decisions. Bounded rationality is likely to be more important in such as setting (Camerer and Malmendier 2007). By illustrating the important role that imperfect decision-making processes play in firms, our results can inform broader, macro-level analysis that incorporates such distortions in firm-level decision-making.

We also depart from previous empirical literature on inattention because of the approach we take to model inattention. We model inattention in a cost-benefit analysis rational inattention framework. Rational inattention occurs when people only pay attention to those factors that are sufficiently important that it is worth the cost of thinking (Veldkamp 2011). A rational attention framework allows us to consider the welfare impact of marginal reductions in the cost of paying attention. This contrasts with models that focus on inertia (e.g. Miravete and Palacios-Huert 2013; Handel 2013) or heuristics (e.g. Gabaix et al 2006; Lacetera, Pope, and Sydnor 2012) in which the welfare analysis does not include explicit attention costs. We use observed variation — in monthly revenue record and owner attributes — to measure the benefit and cost of paying attention. Gabaix (2014) emphasizes that this approach is based on robust psychological facts and can be applied to give many classical economic theories a behavioral update.

Taken together, our results highlight the role for heterogeneous decision-making ability in understanding outcomes in high-stakes business settings. Our model has a unique mechanism of heterogeneous decision-making: some decision makers, particularly inexperienced ones, have difficulty separating "observable" noise from true signals.

2 Data

Our raw data were collected in December 2018 and contain the universe of Texas restaurants and bars with licenses to sell alcoholic beverages from January 1995 to November 2018, roughly a 24-year span. We have a monthly panel of establishment identification code, name, street address, and revenue from alcoholic beverages.[4] Moreover, we have the taxpayer identification code for each establishment as well as taxpayer name, address, and telephone number. This feature of the data allows us to separate the owner (the taxpayer) from the establishments she owns. The data are collected for the purpose of tax collection, and are available from the Texas Comptroller of Public Accounts.

Using this information, we generate a bar-month level dataset between January 1998 and October 2018 for all bars that opened in January 1998 or later (251 months in total). As we detail below, we use the first three years of data (1995 to 1997) to create measures of owner experience in the restaurant and bar industry. We use November 2018 data to identify exit for establishments that operate until October 2018.

The January 1995 to October 2018 raw data contain 40,299 establishments and 2,576,506 establishment-month observations. In order to have a consistent measure of establishment experience, we drop all establishments that experienced an ownership change in their operating history. These establishments account for 6.75% of the total number of establishments. We do this because our model relies on the owner being aware of the history of the establishment, in terms of revenue and (if attentive) weather. New owners of a pre-existing establishment may not satisfy this criterion. Furthermore, ownership change could be seen as an exit due to failure, or as a signal of success. Dropping such establishments enables a cleaner interpretation of our empirical results. We then drop all establishments that opened prior to January 1, 1998 because we do not have measures of owner experience (which we measure over the three years prior to the month the establishment opens) for these establishments. These account for 19% of the total number of establishments. Finally, we drop observations from establishment owners with at least 25 different establishments at some point in the data period. This is another 4.99% of the total number of establishments. This leaves 27,885 establishments.

Distinguishing bars from restaurants: To ensure that alcohol revenue accounts for the majority of revenue, we manually cleaned our data to distinguish bars from restaurants. To do so, we searched for each of these 27,885 establishments online between January and March 2019. From online sources, we identified 8,995 from their online profiles that were primarily bars and 13,999 that were primarily restaurants, leaving 4,891 were not clearly one or the other. Where available, we emphasized the Yelp classification. We classified sports bars and dance clubs as bars, and hotel, golf clubs, adult entertainment, cinemas, and legion halls as unsure.

[4] When we refer to bars and restaurants together, we call them "establishments".

Importantly, online sources such as Yelp, Facebook, the Wayback Machine, and local news outlets provide information on many bars and restaurants that have long-closed. Nevertheless, there were 434 establishments that we could not find online and we classified them as unsure. This likely biases our data toward lower exit rates than would be the case if we had been able to classify these establishments. The descriptive statistics on exit rates suggest this bias is present but not large. Overall, 65% of bars go out of business by the end of the sample, compared to 57% of restaurants and 70% of those we could not classify.

The 8,995 bars provide the main data in the analysis, totaling 422,651 bar-months. Constructing the variables for analysis involves creating measures of owner experience, owner attributes, bar exit, bar revenue, bar attributes, and controls for the local business environment. We discuss each of these below. Table 1a presents bar-level information on key variables that we study, including whether a bar ever exited from business during our data span, owner experience, and owner attributes. Table 1b presents information on time-varying bar attributes and local market attributes at the bar-month level.

Bar exit: As noted by Parsa et al (2005), there are several different ways to define exit in this industry: closing, ownership change, or bankruptcy. We focus on closings, defined as situations where an establishment ceases to operate at an address with the same name.[5] That is, an establishment exits even if a new establishment at the same address appears with the same owner. Overall, 65% of the bars in our data exit by the end of the period (the rest are right-censored). On a bar-month basis, 1.3% of bar-months in the data involve an exit. This base rate of exit is roughly in line with estimates by Parsa et al (2005, 2015).

Owner experience: Before we identify whether a bar owner has experience in the industry, we need to identify whether two establishments are owned by the same person. To do so, we first use the taxpayer identification code. If this matches, then there is a common owner. This definition misses matches in which one owner holds multiple establishments in partnerships or holding companies. To fix this problem, we use the other taxpayer information provided in the data. If the taxpayer information for two establishments has the same phone number, the same address, and a similar name, we also assume the establishments have the same owner. While identifying similar names is inherently a judgment call, we looked at inclusion or exclusion of initials (Mary Smith, Mary A. Smith, Mary Andrea Smith), partnerships (Mary Smith, John Smith and Mary Smith), iterations of the same holding company (MAS Inc., MAS II Inc.), and what appear to be misspellings. Because we restrict on matching phone numbers and matching addresses, common names are unlikely to be a problem. At the same time, we likely underestimate owner matches in the sense that it is likely that some holding companies with

[5] As noted above, we believe that ownership changes are not a useful measure of exit because such a change could be a good or bad outcome to the owner, depending on the circumstances. Bankruptcy is relatively rare, and it is difficult to track down comprehensive data and match it to the individual taxpayers. Therefore we do not use it as a measure in our setting.

distinct names are owned by the same person.[6] Our manual cleaning increased the percentage of owners with prior experience in the Texas bar/restaurant industry from 15% to 19%.

Our experience measure focuses on whether the owner owned a bar or restaurant in Texas prior to opening the focal business. We include both bars and restaurants under the experience measure because experience at restaurants is highly relevant to managing bars and vice versa. We emphasize the level of experience at opening for two reasons. First, prior research in entrepreneurship emphasizes differences between first time and "serial" entrepreneurs (e.g. Lafontaine and Shaw 2016). Serial entrepreneurs are more likely to succeed, perhaps because they have a broader set of experience, enabling them to be more of a jack-of-all-trades (Lazear 2005; Lafontaine and Shaw 2016) or perhaps because of better inherent ability. The second reason is for identification: the experience accumulated since the opening of the focal establishment is collinear with a variety of other factors that may affect revenue including learning about quality, building reputation, and selection bias related to accumulated time since opening. Together these reasons suggest that focusing on owners' pre-existing experience at time of opening the focal business provides a cleaner measure of the variation in experience across owners.

We develop two experience measures, one binary and the other continuous. The binary measure is an indicator for whether the owner owned at least one establishment in the previous three years prior to opening the focal establishment. This dummy variable provides a stark distinction between experienced and inexperienced. As shown at Table 1a, 19% of bar owners had owned a bar or restaurant in the three years prior to opening the focal bar. The continuous measure counts the number of establishment-months over all establishments the owner owned in the previous three years prior to opening the focal establishment. For example, if at the time when an owner opens her third establishment, her first one had been open for 24 months and her second one had been open for 6 months, then we measure the owner's pre-existing experience for her third establishment as 30 establishment-months. In our data the average of this experience measure is about 8 establishment-months and the maximum is 562. This variable is highly skewed to the right and therefore we add 1 to this number and take natural log of it in our empirical analysis.

Restaurant revenue: Our data contain rich information about a key source of establishment profitability: Alcohol revenue (Brown 2007). Unfortunately, our data do not contain information on total revenues or profits. Therefore, in the analysis that follows, we assume that alcohol revenues are strong signals of bar profitability, at least up to the power of bar-level random

[6] Investigating whether the chain may provide value in reducing boundedly rational decisions of managers would require data on whether each individual establishment has the same decision maker. Some large chains do appear to use the same taxpayer identification and address while others do not. While this might be indicative of the existence of franchise arrangements, we do not have data to confirm this. For this reason, we only keep owners that never own 25 or more establishments in their operating history.

effects. This is the main reason we distinguish bars from restaurants, rather than using the entire dataset of bars and restaurants. Specifically, we assume that a bar's variation in profitability is proportional to the variation in (log) alcohol revenue. Online Appendix D.1 provides further evidence of the usefulness of alcohol revenue as a proxy for bar or restaurant success, though we cannot directly test the assumption on proportionality of log alcohol revenue to profitability. We deflate all revenues using the Consumer Price Index for all U.S. urban consumers and report in 2018 dollars. The average bar in the data earns slightly more than $52,500 per month in alcohol revenue. This number is highly skewed to the right, with a within-establishment standard deviation of about $30,000 and a between-establishment standard deviation of $56,000.

Weather and weather shocks: Using an establishment's address, we identify the closest weather station and use daily weather reports from that station on temperature (measured in degrees Fahrenheit), relative humidity (measured in percentage), precipitation (measured in inches), and the number of days with unfavorable weather (unfavorable weather includes fog, rain drizzle, snow ice pellets, hail, and thunder). The weather reports we use are Global Summary of the Day, which is computed and reported from global hourly station data by the National Oceanic and Atmospheric Administration.[7]

The top panel of Table 2 report summary statistics of monthly average of daily weather faced by Texas bars. Texas has warm weather with an average of 70 degrees Fahrenheit. In parts of Texas, the warm weather is often accompanied by high levels of humidity during summer months. As humidity affects human comfort and henceforth decisions to dine out, we construct a heat index based on daily mean temperature and relative humidity.[8]

Hurricanes are common near the coast. Using data from the Federal Emergency Management Association (https://www.fema.gov/disasters), we coded whether a hurricane-related disaster was declared for each Texas county in each month. If the incident period of a hurricane included any part of a month in a county, it was coded as having a hurricane that month. Because hurricanes are a salient event that are likely to completely shut down the bars, in the analysis below we do not consider these as transitory shocks that the owners might not notice. Instead, we include them as controls recognizing that the label of "persistent" is not an accurate description for this particular variable.

In our main empirical analysis, we use three dimensions of weather shocks. We construct these shocks at the daily level and then aggregate them to the monthly level. For heat index and precipitation, we perform the following steps to define monthly weather shocks.

---

[7] The data is available at https://www.ncdc.noaa.gov/cdo-web/datasets.

[8] The heat index is a function of daily mean temperature and relative humidity, as defined by the National Weather Service (see https://www.wpc.ncep.noaa.gov/html/heatindex˙equation.shtml). All our empirical results are robust to using daily mean temperature instead of heat index.

1. For every weather station, we calculate the (long-run) "normal" value of a certain month as the average of the corresponding weather element across all days reported for the month from 1995 to 2018.

2. We calculate the deviation of the actual daily weather element from its normal value in the month.

3. We take the monthly average of the daily weather deviation across all reported days during a year-month combination to construct the "shock" variable.

The definition of the shock for the number of days with unfavorable weather is slightly different. We first sum up all the days with unfavorable weather within a month and then deduct the (long-run) normal of this measure from it.

In total we have three dimensions of weather shocks: heat shocks, precipitation shocks and the number of days with unfavorable weather shocks (often labelled as "Days with unfavorable shocks" in tables to save space). We present the summary statistics of these weather shocks in the bottom panel of Table 2. All three dimensions have a mean of roughly zero, but the standard deviations are large with occasional extreme weather events.

Controls: We include controls for bar and location characteristics to capture persistent demand and cost shifters. Our choice of controls is informed by prior work on restaurant and bar failures (Parsa et al 2005, 2015) that emphasizes local characteristics including demographics, local competition, and chain affiliation. For demographics and local characteristics, we merge in U.S. Census and Zip Code Business Patterns in the corresponding years and use zip code level information on the number of restaurants, population, fraction black, fraction Hispanic, fraction under 18, fraction over 65, average household income, fraction with a bachelor degree, fraction rural, and fraction foreign born. We also add a control for the number of months since the bar opened, the squared term of it, and a dummy for likely lease renewal periods (a multiple of 12 months since opening, as in Abbring and Campbell 2005). For the random effect specifications, we add time-invariant owner attributes, including the distance (in miles) from the location of the bar owner's address for tax purposes to the bar location, whether the owner has only a single establishment, and whether the listed taxpayer is an individual's name rather than a business name.[9]

[9] We define a business name as separate from an individual owner as the listed taxpayer containing information that suggested a company or business ("LLC", "Inc.", "bar", "ranch", "of", "dallas", etc.). By inspection, we identified 458 such strings. The remaining bar owners were listed as individuals or pairs of individuals.

3 Empirical Evidence for Limited Attention

Next, we provide stylized facts that support a model of inattention. Our empirical analysis begins with a decomposition of revenue into two components: one that displays persistence and the other that is transitory in nature. Taking the results of the decomposition as data, we show owners of different attributes have asymmetric responses to the two components of revenue in their exit decisions. In particular, inexperienced, distantly located owners overreact to the transitory component relative to the persistent component. In contrast, experienced owners seem to recognize the nature of transitory shocks and, in turn, have a relatively muted response to them. We then provide evidence supporting our emphasis on the role of inattention against alternative explanations, including revenue smoothing, credit constraints, and projection bias.

3.1 Decomposition of Revenue into Persistent and Transitory Components

We write the logarithm of each establishment's revenue as a linear function of weather shocks, the full set of controls X_{jt}, month-of-the-year fixed effects $Month_t$, year fixed effects $Year_t$, and establishment fixed effects μ_j. For bar j in month t:

$$\log\left(Revenue_{jt}\right) = \alpha^0 + Weathershocks_{jt}\alpha^1 + X_{jt}\alpha^2 + Month_t\alpha^3 + Year_t\alpha^4 + \mu_j + \varepsilon^r_{jt} \quad (1)$$

In equation (1), weather shocks include shocks on three dimensions: heat index, precipitation, and the number of days with unfavorable weather. We assume ε^r_{jt} is independently distributed over time, but correlated across all establishments in a county. We therefore cluster the standard errors at the county level.[10]

Our focus is not on the interpretation of the results. The core assumption is that the estimated weather effects and the estimated time-varying random error represent transitory shocks that should average to zero in the long run. Nevertheless, it is useful to confirm that weather affects revenue as expected. Table 3a column 1 shows the results of this regression pooling all quarters together. Overall, it seems that warmer temperatures are associated with higher alcohol revenue. Precipitation and days with unfavorable weather have a negative and insignificant relationship to alcohol revenue. Columns 2 and 3 show that experienced owners are not significantly different from inexperienced owners in terms of the relationship between the weather and their revenue. We will return to this result below in discussing alternative explanations.

This overall result masks substantial variation across seasons. In our decomposition, it is important that we capture potential seasonal differences in the correlation between weather and

[10] Note that notation in Section 3 does not carry on to the structural model.

revenue to better-capture temporary variation in revenue due to weather shocks. For example, a warm winter may lure consumers to dine out but a hot summer may have the opposite effect. Therefore, columns 4 through 7 run the analysis separately by quarter: January-March, April-June, July-September, and October-December. The most relevant weather shock variables change by quarter. In quarter 1 warmer weather increases revenue but unfavorable weather decreases it; in quarter 2 both warmer weather and more precipitation increases revenue, in quarter 3 more precipitation is bad news, and in quarter 4 the only thing matters (negatively) is the number of days with unfavorable weather.

Given the marked differences of weather effects across seasons, our main results use the quarter-by-quarter estimates in columns 4 through 7 of Table 3a for the decomposition. For every establishment in the data for a given month, we decompose log alcohol revenue into two components: the transitory component and the persistent component:

$$R\_transitory_{jt} = Weathershocks_{jt}\hat{\alpha}^{1} + \hat{\varepsilon}^{r}_{jt} \tag{2}$$

$$R\_persistent_{jt} = \log\left(Revenue_{jt}\right) - R\_transitory_{jt} \tag{3}$$

We repeat the above decomposition exercise separately for each subgroup of establishments that we call during our empirical analysis: inexperienced versus experienced owners, nearby versus distant owners, individual versus business owners, and single versus multiple establishment owners. The purpose of doing this is to allow weather shocks have a flexible effect on every subgroup of establishments and hence the decomposition is accurate for each subgroup.[11]

Table 3b reports the summary statistics of the decomposed revenue components for all bar-months and then for subgroups for owners. The transitory shocks average to zero, which is as expected, with a large standard deviation. More importantly, there is almost no difference across owners with different experience levels and different distances to establishment location. Again, we will return to this result below in discussing alternative explanations.

3.2 Owner Response to Different Components of Revenue

Table 4 examines the responsiveness of an owner's exit decisions to the different components of revenue. It is a linear regression of exit on the transitory component, the persistent component,

[11] We report results by quarter and experience in Online Appendix Table 6, and by quarter and distance in Online Appendix Table 7. In addition, Online Appendix Table 8 shows that our main results are robust to alternative functional forms in creating the decomposition, for example, a spline for the heat index, allowing serial correlation of error term over time, using establishment random effects, etc. We interpret this robustness to suggest the linear functional form we use in our main specification captures the key relationships in the data. We also examine robustness to alternative samples: using owners with only a single establishment, dropping extreme weather, and finally, using restaurants instead of bars.

time-invariant owner attributes (X_j),[12] time-varying establishment and market attributes X_{jt}, month-of-the-year fixed effects $Month_t$, year fixed effects $Year_t$, and lastly, establishment-level random effects ξ_j. Establishment-level fixed effects are not identified here because each bar exits only once. Specifically, the regression equation is:

$$Exit_{jt} = \beta^0 + \beta^1 R\_transitory_{jt} + \beta^2 R\_persistent_{jt} + X_j\beta^3 + X_{jt}\beta^4 + Month_t\beta^5 + Year_t\beta^6 + \xi_j + \varepsilon^x_{jt} \quad (4)$$

In equation (4), we assume ε^x_{jt} is independently distributed over time, but correlated across all establishments in a county. We therefore cluster the standard errors at the county level. Column 1 of Table 4 reports estimation results for equation (4) for all 8,995 bars. Strikingly, variation in the persistent and transitory components of revenue affect exit likelihood equally. That is, a typical owner recognizes little difference between the persistent and transitory components. This is in contrast to the predictions of full attention: without credit constraints, transitory shocks should have no impact on the exit decisions of fully attentive owners. This is our first evidence of inattention.

Column 1, again, masks large differences in the responses of different owners. Columns 2 (inexperienced owners only) and 3 (experienced owners only) of Table 4 provide the key motivating result for our structural model, showing that inexperienced and experienced owners respond to different revenue components asymmetrically. There are two types of asymmetry. First, between the two types of owners, inexperienced owners respond more to the transitory component of revenue than experienced owners do. Second, between the two components of revenue, experienced owners respond less to the transitory component than to the persistent component.

This asymmetry suggests the existence of behavioral bias across different types of owners. Experienced owners behave more in line with attentive decision-making, although not fully so. Inexperienced owners, however are disproportionally over-reacting to the transitory component of revenue, suggesting that they fail to recognize the transitory nature of this component.

Columns 4 (including owners whose mailing address is more than the median distance 5 miles away from establishment location) and 5 (including owners whose mailing address is less than 5 miles from establishment location) of this table report owners' response to the two revenue components with respect to distance. Presumably, local owners are more likely to observe weather variation as well as other on-site demand shocks. These two columns show exactly the same two types of asymmetry in columns 2 and 3 (except that both types of owners

[12] Time-invariant owner attributes include owner experience, distance from owner to establishment location, whether the owner has just a single establishment, and whether the owner's name is not an official business name.

react about the same to the permanent component of revenue). That is, local owners behave more in line with attentive decision-making, but distant owners fail to respond to transitory shocks correctly.[13]

3.3. Alternative Explanations

While these asymmetric responses are consistent with limited attention to transitory shocks, it is possible other explanations could rationalize these results. We consider three alternative explanations:

Shock smoothing: It is possible that experienced owners do a better job smoothing out the effect of negative weather shocks on revenue. For example, an experienced owner may adjust the menu to boost revenue in unusual weather (e.g. iced cocktails in unusually hot weather), and therefore the owner responds less to negative weather shocks. As noted earlier, columns 2 and 3 of Table 3 show that there is no significant difference between experienced and inexperienced owners in terms of relationship between weather and revenue. In particular, these columns use revenue as the dependent variable but add an interaction between weather and two different experience measures. The interactions between weather and experience are all insignificant, suggesting that experienced owners are not better at managing weather shocks. Moreover, Table 3b shows that the transitory component of revenue averages zero with almost identical standard deviations across the different levels of experience and distance. Thus, any significant differences we find in the exit decisions of experienced and inexperienced owners are unlikely to be driven by differences in how the weather shocks affect alcohol revenue.

Credit constraints: It is possible that experienced owners are less subject to credit constraints facing difficult times. Holtz-Eakin, Joulfaian, and Rosen (1994) and Andersen and Nielsen (2012) show that new firm survival is related to the liquidity constraints, using owners' inheritances for identification. While there is some debate over this point (e.g. Hurst and Lusardi 2004), this literature suggests that a key alternative explanation for our results is that credit constraints bind more for inexperienced owners than for experienced owners. In this case, negative transitory shocks lead to negative profits, causing inexperienced owners to go out of business even though they might recognize the role of the temporary (weather) shocks in driving their profits.

[13] Online Appendix Tables 9 to 11 show the robustness of this asymmetric response result. In general, the results hold up strongly with the exception of using restaurants instead of bars. For restaurants, the first asymmetry result holds up: inexperienced restaurant owners do respond more to the transitory component than experienced ones do. The second asymmetry result breaks down: experienced restaurant owners respond more to the transitory component than to the persistent component. As alcohol revenue is a much smaller part of restaurant revenue, we believe the results on bars are more informative.

If credit constraints explain the result, we should expect to see credit-constrained owners respond more to both components of revenue, because cash inflows bear no mark whether it is generated by the persistent or transitory component. In Table 4, however, we show inexperienced owners respond less to the persistent component of revenue than experienced owners do. Thus, it does not appear that inexperienced owners are more credit-constrained. Furthermore, our results on distance from the owner's mailing address to the establishment location are more likely related to onsite observation and monitoring than credit constraints.

Table 5 explores the possible role of credit constraints by examining other dimensions of owner attributes that are also likely correlates of credit constraints. In columns 2 and 3, we compare owners without and with an official business name on their tax filings. Compared to owners with a business name on their tax forms (rather than a personal name), these are likely to be less established businesses. Owners without a formal business name are indeed more responsive to both the persistent component and the transitory component of revenue than owners with a formal business name. Similarly, columns 4 and 5 compare owners of a single establishment to owners of multiple establishment. Owners of multiple establishments may be able to alleviate credit constraints by cross-subsidizing establishments suffering negative shocks. We find that owners of a single establishment are indeed more responsive to both components of revenue than owners with multiple establishments. The contrast between Table 4 and Table 5 suggests that our results on transitory shocks for inexperienced and distant owners are unlikely to be primarily driven by credit constraints.

Projection bias: It is possible that inexperienced owners suffer more projection bias, and therefore overreact to the transitory component of revenue. Projection bias refers to the situation when a decision maker's prediction of future utility is systematically off in the direction of current utility. For example, Conlin, O Donoghue, and Vogelsang (2007) show that people are overly influenced by current weather when placing catalog orders for cold-weather items. A bar owner may think this month's bad weather will persist and then exit the business. If more experienced owners have less projection bias, they will respond less to transitory shocks. This is about false expectations about future states given current states, not about inattention to current states.

Busse *et al* (2015) propose a method to distinguish projection bias from salience (paying too much attention). They argue that projection bias predicts overreaction to shocks in an absolute sense, but salience takes effect when the decision maker observes shocks relative to some benchmark. In our setting, a highly volatile revenue record may propel an owner to pay more attention to the transitory component of revenue. If revenue has does not fluctuate over time, then the owner has no need to pay any attention to transitory shocks. Revenue volatility, however, should not affect the owner's reliance on current states to infer future states. Table 6 provides suggestive evidence in support of limited attention over projection bias by including interaction terms between revenue volatility and the persistent and transitory components of revenue. We measure revenue volatility by the within-establishment standard deviation of a bar's log revenue. Results show that owners shift weight from the transitory component to the persistent component under higher revenue volatility. The significantly positive coefficient before the interaction between the transitory component and revenue volatility means that the owner mute reaction to the transitory component under higher revenue fluctuations. The significantly negative coefficient before the interaction between the persistent component and revenue volatility means that the owner relies more on the persistent component under higher revenue fluctuations. Such effects hold up for different subgroups, as shown from column 2 to column 5. These results are highly consistent with a rational inattention explanation in Gabaix's (2014) framework: owners are able to recognize transitory shocks when attention is warranted because of a more chaotic environment.

Discussion: Overall, we interpret our descriptive results as consistent with a theory of rational inattention. While we cannot rule out all possible other explanations, the results presented above are not consistent with some of most obvious: skill at smoothing out transitory shocks, credit constraints, and projection bias. Therefore, we build a model to incorporate rational inattention into a Bayesian learning model about bar profitability.

Before detailing our inattention model, it is important to note that we do not model the process of learning to pay attention. We identify a difference between experienced and inexperienced owners, but we cannot say whether that difference is driven by the experienced owners learning the importance of weather or by experienced owners being more (inherently) skilled at recognizing the importance overall. In a traditional learning model, all the information is presented to the decision maker, including weather shocks. Then the decision maker learns the relationship between all this information and profitability. Our inattention model puts some structure on the initial state: Given the large amount of information on numerous dimensions, we provide information on what is obviously relevant on day one and which factors predict which people will pay attention to which information. In this way, our model is a useful step forward toward a model in which owners learn to separate signal from noise.

4 Model

Based on the above stylized facts, we formulate a structural model of attention allocation, belief formation, and exit decisions, in which the owner of a bar-establishment (henceforth, an establishment) learns about its persistent profitability over time. In this model, an establishment's underlying profitability is initially unknown to the owner. The owner observes a noisy signal of profitability every time period, which is subject to the influence of transitory shocks such as local demand, cost fluctuations, incidental factors, and most importantly, weather variation. The owner's limited ability to fully attend to the noise in the profit signals prevents her from learning about the true profitability of the establishment. The owner then compares her (potentially biased) expected present discounted value of her establishment with her time-specific outside option when deciding whether the establishment should exit from business. Exiting is the only choice the owner makes. Once exiting, the establishment cannot return.

This outline is similar to standard models in the literature on exit such as Jovanovic (1982) in the sense that a decision maker updates beliefs using signals of different accuracy.. It is also similar to the setup of Abbring and Campbell (2003, 2005) in their analysis of an earlier version of the same data.[14] What is distinct in our model is that we provide a behavioral foundation of attention allocation based on the sparsity-based model of bounded rationality as in Gabaix (2014). In our model of attention allocation, the owner's pre-existing experience, her distance from establishment location, and the variances of the establishment revenue affect her exit decisions only through her attention allocation process. The degree to which the owner accounts for past transitory shocks in her exit decision reveals the existence and magnitude of her limited attention. After setting up the notation and sequence of events, in the following subsections we characterize the four building blocks of our model.

4.1 Model Setup and Notation

At the end of every time period t, the owner of an establishment j observes the following variables:

- R_{jt}: log revenue from the sale of alcoholic drinks of establishment j at period t. The owner also observes the volatility of its log revenue, which we denote as $VarR_j$ and we measure $VarR_j$ as the within-establishment variance of an establishment's log revenue.
- W_{jt}: weather shocks experienced by establishment j at period t, as defined by Section 2. Note that weather shocks are transitory with expected value zero.
- X_{jt}: local market attributes and establishment attributes. Some of these attributes are time-varying such as the number of competing establishments in the zip code, and some are time-invariant. We include two dimensions of time-invariant attributes: whether the owner is an individual and whether the establishment remains a single operation in our observed data.

[14] Abbring and Campbell (2003) model and estimate an entrepreneur's learning process about the persistent component of profit from error-ridden observations of revenues. Their 2005 paper emphasizes the roles of pre-entry scale decisions and the annual lease cycle.

- Z_j: owner attributes. Informed by our stylized facts, we focus on the level of owner experience, as measured by whether the owner has operated on any establishment for any month in 3 years prior to opening the focal establishment or the natural log of such establishment-months. In addition, we include a dummy variable indicating whether the distance from owner to establishment location is greater than 5 miles.
- Q_t: quarterly dummies (quarter 2 to quarter 4) for the current time period to capture seasonality.[15]

We as the econometricians observe the same covariates as the owner. This is a restrictive assumption as the owner may observe other signals of profitability and other factors affecting profitability that are not captured by the data. To address this concern, we allow the owner to observe an establishment-specific random term (described in Section 5.1).

We as the econometricians do not observe, however, the owner's time-varying incidental factors affecting her decision to continue operating the establishment. In each time period, the owner receive two random shocks: ε_{jt}^{o}, the outside option (for example, the expected payoff from another profession) and ε_{jt}, incidental factors that affect her utility of staying in the business (for example, a health issue of the owner). Both ε_{jt}^{o} and ε_{jt} follow an *i.i.d.* type I extreme value distribution. The fixed variance of the distribution is the standard multiplicative normalization in a discrete choice model.

The owner operates an establishment and tries to learn about the establishment's underlying profitability π_j, which is persistent over time and initially unobserved to the owner. The owner understands that she will receive noisy signals period after period but there is a thinking cost separating noise from true signals. At entry, she allocates her attention to this noise recognition problem based on the expected benefit from the information and the cost of thinking. Once attention allocated, her attention to this problem is fixed through the operating life of the establishment.[16]

After entry, this is the sequence of events within a time period t:

- The owner observes $\left[R_{jt}, W_{jt}, X_{jt}, Q_t\right]$.
- The owner forms her belief about π_j given all past observables up to (and including) period t.

[15] We could use 11 monthly dummies instead of 3 quarterly dummies, but this adds substantial computation burden with little gain in model fit. We ran a version of 11 monthly dummies with a static exit model, in which the owner compares her current profit signal (rather than the expected present value of her future profits) with her outside option when deciding on exit, and the results are similar to the version with only 3 quarterly dummies and a static exit model.

[16] This is similar to a "one-time" information processing fee that a decision maker needs to pay in order to gather information. There is a subtle difference though: the thinking cost is a cognitive barrier, not an explicit fee that the decision maker needs to conscientiously pay out of pocket.

- Based on her belief about π_j, the owner forms an expectation about her presented discount value of continuing operating on the establishment.
- The outside option ε^o_{jt} and the utility shock ε_{jt} are presented to the owner.
- The owner makes a decision on whether to exit based on the comparison between her expected present discounted value of continuation and the outside option.
- If exiting, the owner obtains the outside option ε^o_{jt}. If staying, the owner proceeds to the next time period $t+1$ and the same sequence of events happen in the next period.

4.2 Transitory Shocks in the Revenue Generating Process

The owner receives a revenue record in each time period. Variation in the revenue record may be due to many factors, some persistent (for example, a competing bar opening next door) and other transitory (for example, weather shocks). Specifically, revenue R_{jt} can be written as:

$$R_{jt} = \eta_j + X_{jt}\alpha^X + Q_t\alpha^Q + W_{jt}\alpha^W_{quarter} + \upsilon_{jt} \tag{5}$$

In equation (5), η_j is the establishment fixed effect,[17] X_{jt} is a vector of establishment and market attributes, Q_t is a vector of month dummies, and W_{jt} is vector of weather shocks as described in section 2. All α's are model parameters to be estimated. The effect of weather shocks on revenue, $\alpha^W_{quarter}$, depends on the quarter.[18]

At the end of equation (4), the error term υ_{jt} is *i.i.d.* distributed across establishments and across time. We assume $\upsilon_{jt} \sim N\left(0,\sigma_r^2\right)$. As a time-variant component of an establishment's revenue record, υ_{jt} captures all other transitory shocks, for example, local sports team victories, flu season, etc. That is, υ_{jt} takes the same role as weather shocks, which are transitory shocks that require attention cast by the owner. In order to make a fully rational decision, these transitory shocks need to be teased out from persistent profitability by an attentive decision maker. Therefore, we define ω_{jt} as the summation of weather shocks and υ_{jt}.

$$\omega_{jt} \equiv W_{jt}\alpha^W_{quarter} + \upsilon_{jt} \tag{6}$$

[17] We do not estimate this fixed effect; instead, we perform within transformation to net out η_j.

[18] The number of $\alpha^W_{quarter}$ we estimate is then the dimension of weather shocks multiplied by the number quarters in a year. In total, we 12 parameters for $\alpha^W_{quarter}$.

In equation (6), ω_{jt} represents the true state of the world, which is the full amount of transitory shocks that the owner can recognize. The amount of attention on ω_{jt} depends on the importance of recognizing the true state of the world and the cost of thinking of the decision maker.

4.3 Perception of Transitory Shocks: a Sparsity-based Model of Bounded Rationality

At entry, the owner allocates her attention on ω_{jt}, which are transitory shocks in the revenue generating process. In this subsection we build a behavioral foundation for potential underestimation or even ignorance of ω_{jt} , adapting the sparsity-based model of bounded rationality as in Gabaix (2014).

In Gabaix's model, the decision maker solves an optimization problem featuring a quadratic proxy for the benefits of thinking and a formulation of the costs of thinking. The solution to this problem is an optimally simplified representation of the world that is "sparse", that is it contains few parameters that are non-zero. The decision maker then chooses the optimal action given this sparse representation of the world. Gabaix describes how this model embeds fully rational decision-making as a special case and that it can be easily applied a variety of economic situations.

We set up the following optimization problem as in Gabaix (2014):

$$\min_{\tau_j} \frac{1}{2}\left(\tau_j - 1\right)^2 VarR_j + \tilde{\kappa}_j \left|\tau_j\right| \tag{7}$$

In equation (7), the first term is the utility loss from an imperfect representation of the world, and the second term is the penalty for lack of sparsity, representing the cost of thinking about the true state of the world. The owner chooses τ_j to minimize the sum of utility loss and thinking cost. When is τ_j closer to 1, the utility loss is small but the thinking cost is large; when τ_j is closer to 0, the thinking cost is small but the utility loss is large.

In the utility loss part, we use $VarR_j$, the within establishment variance of revenue R_{jt}, to measure the importance of knowing the true state of the world. When this variance is 0, monthly revenue is a fixed number so there is no need to think about transitory shocks. The higher this variance is, the larger is the loss from not paying attention to ω_{jt}.

In terms of thinking cost, $\tilde{\kappa}_j$ is the time-invariant thinking cost of the owner. We assume that $\tilde{\kappa}_j$ follows a Lognormal distribution with mean $Z_j\kappa$ and variance normalized to 1.[19] That is,

$$\tilde{\kappa}_j \sim \log N\left(Z_j\kappa, 1\right) \tag{8}$$

Equation (8) specifies the cost of thinking as a random process. Given the same Z_j, different decision makers may have different thinking costs and choose different τ_j to recognize the impact of transitory shocks. We use owner experience and the distance from the owner s mailing address to the establishment location as two covariates that shift the mean of the thinking cost distribution. In particular, we interpret our motivating regressions as consistent with a model in which, with different owner experience and different distances, the owner may have different thinking costs in recognizing the impact of transitory shocks. Modeling thinking cost as a stochastic process and linking it to the personal attributes of decision makers is an adaptation of Gabaix (2014), who models the cost of thinking as a parameter value instead of a function. We think it is useful to model the cost of thinking as potentially heterogeneous across individuals. It enables separate identification of establishment characteristics about underlying profitability and owner characteristics about cost of thinking.

To complete the attention allocation model, we now take a stand on how much the owner knows about her own thinking cost. It is unrealistic that in a model of limited attention a decision maker knows exactly what her thinking cost is. Instead, we assume the owner knows the distribution of her thinking cost and knows that when thinking cost is above or below a threshold --- the payoffs of the problem $VarR_j$. When her thinking cost is above $VarR_j$, the owner mutes her attention to zero; when her thinking cost is below $VarR_j$, she pays a fixed amount of attention every period conditional on her knowing that the thinking cost is below $VarR_j$. That is, the owner's solution is:

[19] We normalize the variance to be 1 because multiplying the same constant with $\tilde{\kappa}_j$ and $VarR_j$ gives us the same answer in equation (9). Similarly, equation (9) shows that adding the same constant to $\tilde{\kappa}_j$ and $VarR_j$ only affect the solution marginally (and through functional form). In the attention allocation problem, what matters is the relative importance of the owner attributes compared to the expected benefit of attention. Therefore, we do not have a constant term in the mean of $\tilde{\kappa}_j$.

$$
\tau_j = \begin{cases} 0 & \text{if } \quad \tilde{\kappa}_j > VarR_j \\ 1 - \dfrac{E\left[\tilde{\kappa}_j \middle| \tilde{\kappa}_j \le VarR_j\right]}{VarR_j} & \text{if } \quad \tilde{\kappa}_j \le VarR_j \end{cases} \tag{9}
$$

We derive $E\left[\tilde{\kappa}_j \middle| \tilde{\kappa}_j \le VarR_j\right]$ in Online Appendix C.1. Note that $\tau_j \in [0,1]$. If $\tau_j = 1$, the owner pays full attention to ω_{jt}; if $\tau_j < 1$, she pays muted attention; if $\tau_j = 0$, she pays zero attention. Zero attention means that the owner has no ability to separate transitory shocks out of the revenue record. Limited attention in our model is the outcome of a rational decision-making process. The owner weighs the trade-offs between the utility loss due to a sparse representation of the world and the thinking cost caused by a full representation of the world and derives an optimal solution. Therefore we have a rational inattention problem. This rational inattention may lead to negative outcomes for the decision maker: If the owner underestimates or even ignore the impact of transitory shocks on revenue, she may misinterpret profit signals and make incorrect exit decisions. When the owner decides on attention allocation, she solves an optimization problem in equation (7) instead of fully incorporating the welfare loss due to incorrect decision making. In this sense, this is still a bounded rationality problem.

4.4 Belief Formation

Before receiving any revenue signals, the owner has priors about the establishment's persistent profitability: $\pi_j \sim N\left(\pi_j^0, \sigma_0^2\right)$. The owner knows π_j^0 and σ_0^2 but we econometricians do not. Therefore, we simulate π_j^0 in estimation and assume σ_0^2 is the between-establishment variance of log revenue that we observe in data. At the end of each time period, the owner receives a noisy signal of monthly profits, π_{jt}, and the owner updates her belief about the establishment's persistent profitability.

After observing current revenue R_{jt}, a fully attentive owner recognizes that profit is revenue, net of transitory shocks, minus cost:

$$
\pi_{jt} = \beta^R \left(R_{jt} - \omega_{jt}\right) - X_{jt}\beta^X - Q_t\beta^Q - \beta^0 \tag{10}
$$

Here full attention means that the owner teases out transitory shocks from monthly revenue R_{jt}, and uses a "clean" signal to update her belief about persistent profitability. In equation (10), we assume that $X_{jt}\beta^X + Q_t\beta^Q + \beta^0$ is a linear function of factors that shifts the establishments' variable costs in operation; β^R is a scale parameter, which provides a simple adjustment to account for potential non-linearity between profits and alcohol revenue.

The owner, however, may not fully register the impact of ω_{jt} on revenue due to the existence of limited inattention. This leads the owner to the following interpretation of the current period signal:

$$\pi_{jt} = \beta^R \left(R_{jt} - \tau_j \omega_{jt} \right) - X_{jt} \beta^X - Q_t \beta^Q - \beta^0 \tag{11}$$

The difference between equation (10) and (11) is the perceived effect of ω_{jt} on revenue: in equation (11) the effect is compounded by a bounded rationality parameter τ_j. The true effect is ω_{jt}, but the owner perceives it as $\tau_j \omega_{jt}$ instead. The τ_j parameter functions like the implicit weight consumers place on sales tax as in Chetty, Looney, and Kroft (2009) and Taubinsky and Rees-Jones (2018). It is a sufficient statistic that captures the distortion of a decision maker's perception.

The owner believes $\pi_{jt} \sim N\left(\pi_j, \sigma_r^2\right)$ and uses π_{jt} for Bayesian updating.[20] The owner's posterior mean about the underlying profitability π_j is:

$$\begin{aligned}
S_{jt} &\equiv E_t \left(\pi_j \,\middle|\, R_{j1}, \ldots, R_{j,t}, W_{j1}, \ldots, W_{j,t}, X_{j1}, \ldots X_{j,t-1}, Q_1, \ldots, Q_t \right) \\
&= \frac{\sigma_r^2}{t\sigma_0^2 + \sigma_r^2} \pi_j^0 + \frac{t\sigma_0^2}{t\sigma_0^2 + \sigma_r^2} \frac{\sum_{s=1}^{t} \pi_{jt}}{t} \\
&= \frac{\sigma_r^2}{t\sigma_0^2 + \sigma_r^2} \pi_j^0 + \frac{t\sigma_0^2}{t\sigma_0^2 + \sigma_r^2} \frac{\sum_{s=1}^{t} \left(\beta^R \left(R_{jt} - \tau_j \omega_{jt} \right) - X_{jt} \beta^X - Q_t \beta^Q - \beta^0 \right)}{t}
\end{aligned} \tag{12}$$

Note that S_{jt} is a weighted average of the establishment's past signals. A sufficient statistic for the entire sequence of all past observable signals (DeGroot, 1970), it is a scalar state variable the owner uses to form expectations about present discounted value of future profits. The owner keeps track of $\left[S_{j0}, \ldots, S_{jt} \right]$ rather than the sequence of all observables. In particular, attention happens in the current period and the history of ω_{jt} cannot be traced. Instead, past

[20] Note the variance is the same for owners with different attention levels. The owner is unsophisticated in this sense: she does not recognize her inattention may relate to different variances of the profit signals. Others have modeled decision makers as sophisticatedly inattentive. For example, in Grubb and Osborne (2015), consumers are aware of own inattention.

ω_{jt} enters the posterior belief of the owner and only affects the owner's perception through the posterior belief.

4.5 The (Dynamic) Exit Decision

To make the exit decision, the owner compares the present discounted value of the future stream of profits that will accrue to the owner going forward, with that coming from the outside option ε_{jt}^{o} (for example, closing the bar and taking a steady job). Let $D_{jt}=1$ denote the decision to exit in time period t and $D_{jt}=0$ denote the decision to stay. The owner commits to the exit decision after observing the establishment revenue record up to period t. In period t, the owner's flow profits from exiting ($D_{jt}=1$) are the outside option ε_{jt}^{o}, and her (perceived) flow profits from staying ($D_{jt}=0$) are $S_{jt}+\varepsilon_{jt}$. In her flow profits, ε_{jt} contains idiosyncratic factors affecting the owner's utility of operating the establishment in period t. Recall S_{jt} is the owner's posterior belief about the establishment's monthly profit. Going forward, she expects to receive such profits month after month until she exits. Adopting the Rust (1994) framework, we can write down the Bellman equation for the owner's optimal dynamic exit decision problem (subject to limited attention):

$$V(S_{jt},\varepsilon_{jt},\varepsilon_{jt}^{0})=\max_{D_{jt}}\left\{\varepsilon_{jt}^{0},S_{jt}+\varepsilon_{jt}+\delta E\left(V(S_{j,t+1},\varepsilon_{j,t+1},\varepsilon_{j,t+1}^{0})\mid S_{jt},\varepsilon_{jt},\varepsilon_{jt}^{0}\right)\right\} \tag{13}$$

In the value function $V(S_{jt},\varepsilon_{jt},\varepsilon_{jt}^{0})$, we have three state variables: $[S_{jt},\varepsilon_{jt},\varepsilon_{jt}^{o}]$. We assume the state variable S_{jt} has finite support $\left\{S^{1},...,S^{K}\right\}$. From its random initial value, S_{jt} follows a first-order Markov chain with $K\times K$ transitional probability matrix, with typical element $\Pi_{ik}=\Pr\left(S_{j,t+1}=S^{k}\mid S_{jt}=S^{i}\right)$. This transitional probability matrix is independent of the owner's choices on exit or other owner actions. Both ε_{jt}^{o} and ε_{jt} are independent of S_{jt} and the owner's exit decisions, with *i.i.d.* (across establishment j and time t) type I extreme value distribution. Thus, $[S_{jt},\varepsilon_{jt},\varepsilon_{jt}^{o}]$ are "exogenous" state variables of which the evolution is externally specified, as in Rust (1994). The firm has rational expectations about future states and choices. The owner chooses the action D_{jt} that maximizes her expected present discounted value of future profits, discounted at a factor $\delta=0.99$.

Denote the expected discounted profits net of ε_{jt} corresponding to the staying decision $\overline{V}_{D_{jt}=0}(S_{jt})$, where S_{jt} is the owner's posterior belief about underlying monthly profit as defined by equation (12). We can solve the owner's exit decision problem:

$$D_{jt} = \begin{cases} 0 & if \quad \overline{V}_{D_{jt}=0}(S_{jt}) + \varepsilon_{jt} \geq \varepsilon_{jt}^{0} \\ 1 & if \quad \overline{V}_{D_{jt}=0}(S_{jt}) + \varepsilon_{jt} < \varepsilon_{jt}^{0} \end{cases} \tag{14}$$

To summarize, we have a structural model based on standard Bayesian learning from repeated signals of revenues. We inject a modicum of bounded rationality into this model by allowing imperfect recognition of the impact of transitory shocks on these signals. This particular dimension of limited attention is the focus of this project. Quantifying the magnitude of limited attention in our data gives us a measure of bounded rationality in a high-stakes business setting.

5 Estimation

5.1 Maximum Likelihood Estimation

We estimate the revenue and exit decisions jointly with the simulated maximum likelihood estimation method. Let $L_j = L\left(R_{j1},...,R_{jT_j}, D_{j1},...,D_{jT_j};\theta\right)$ denote the joint likelihood of establishment *j*'s observed sequence of revenue amounts and exit decisions with parameter θ. T_j is the last period we observe in the data for establishment *j*. Given the sequence of observables, this likelihood can be written as:

$$\begin{aligned} L_j &= L\left(R_{j1},...,R_{j,T_j}, D_{j1},...,D_{jT_j} \middle| W, X, Q, Z, VarR;\theta\right) \\ &= \prod_{s=1}^{T_j} L^R\left(R_{js} \middle| W_{js}, X_{js}, Q_s;\theta\right) \prod_{s=1}^{T_j} L^D\left(D_{js} \middle| R, W, X, Q, Z, VarR;\theta\right) \end{aligned} \tag{15}$$

where $\{R, W, X, Q, Z, VarR\}$ denote the entire sequence of observables up to the time period being considered and θ denotes the set of model parameters. In equation (15), $L^R\left(R_{js} \middle| W_{js}, X_{js}, Q_s;\theta\right)$ is the contribution to the likelihood from revenue realizations; and $L^D\left(D_{js} \middle| R, W, X, Q, Z, VarR;\theta\right)$ is the contribution to the likelihood from exit decisions.

As we the econometricians only know the distribution of the owner's prior π_j^0 in the Bayesian updating process, we treat it as a random effect and simulate over it,

$$L_j^{SIM} = \prod_{s=1}^{T_j} L^R\left(R_{js} \middle| W_{js}, X_{js}, Q_s; \theta\right)\left(\frac{1}{NS}\sum_{ns=1}^{NS}\left[\prod_{s=1}^{T_j} L^D\left(D_{js} \middle| R, W, X, Q, Z, VarR, \pi_{j,ns}^0; \theta\right)\right]\right) \tag{16}$$

In equation (16), *NS* is the number of simulation draws. To form the likelihood for the population, we multiply over J firms and perform a log transformation. We can write:

$$\begin{aligned} \ln L^{SIM} &= \sum_{j=1}^{J}\sum_{s=1}^{T_j} \log L^R\left(R_{js} \middle| W_{js}, X_{js}, Q_s; \theta\right) \\ &\quad + \sum_{j=1}^{J} \ln\left\{\frac{1}{NS}\sum_{ns=1}^{NS}\left[\prod_{s=1}^{T_j} L^D\left(D_{js} \middle| R, W, X, Q, Z, VarR, \pi_{j,ns}^0; \theta\right)\right]\right\} \end{aligned} \tag{17}$$

Note in order to calculate (17), we need to solve an establishment's probability of exiting given θ. We numerically solve for the value function within the estimation loop and construct the exit probability for each establishment in each period. In every round of parameter iteration, we recursively compute the expected discounted profits net of ε_{jt} corresponding to the staying decision $\overline{V}_{D_{jt}^{ns}=0}(S_{jt}^{ns})$, using the method of successive approximation. As both ε_{jt}^o and ε_{jt} are with *i.i.d.* type I extreme value distribution, we can construct:

$$prob\left(D_{jt}^{ns} = 1 \middle| S_{jt}^{ns}\right) = \frac{1}{1 + \exp\left(\overline{V}_{D_{jt}^{ns}=0}(S_{jt}^{ns})\right)} \ . \tag{18}$$

In Online Appendix C, we report the details of the value function iteration process and describe in detail the construction of equation (17)

5.2 Identification of Structural Parameters

The set of structural parameters to be estimated is $\theta \equiv \left\{\alpha_{quarter}^W, \alpha^X, \alpha^Q, \beta^O, \beta^X, \beta^Q, \beta^R, \ \sigma_r^2, \kappa\right\}$, that is, the set of parameters in the alcohol revenue generating equation, in the profit function, and in the attention allocation process. We are able to identify all the structural parameters in the model using corresponding data variation.

- $\alpha_{quarter}^W$ from estimating the revenue equation: how weather shocks affect revenue quarter by quarter. The rest of the α values are identified similarly.
- β^O from the mean exit probability (this is the constant term in the exit equation).
- β^X from the conditional relationship between X_{jt} and exit.
- β^Q from the conditional relationship between Q_t and exit.

- β^R from the conditional relationship between alcohol revenue and exit. Because we do not have data on other sources of revenue, this implies that we assume that overall revenue scales linearly with alcohol revenue.
- σ_r from the within-establishment estimation of the revenue equation. In other words, σ reflects profit differences within individual establishments ("within variance").
- κ from how the extent of limited attention varies with owner-specific attributes Z_j, empirically captured by owner experience and the distance from owner to establishment location. Owner attributes affects the owner's thinking cost and, in turn, her recognition of the impact of transitory shocks on revenues. These attributes, however, do not directly affect establishment profits, thereby allowing separate identification of the thinking cost parameters from the other structural parameters in the model.

6 Structural Results

6.1 Model Estimates

We present our key structural estimates in Table 7 (with the full set of parameters in Online Appendix Table 5). In column (1), we use owner experience, measured by a dummy variable indicating whether the owner has owned a bar/restaurant in the 3 years before opening the given establishment in the cost of thinking function. In column (3), we use owner experience, measured in the log number of establishment-months the owner has operated in 3 years before opening the focal establishment in the cost of thinking function. In columns (2) and (4), we add a dummy variable indicating whether the distance from owner mailing address to establishment location is greater than 5 miles into the column (1) and (3) specifications respectively. All four models fit the data well. In particular, the average and variance of the simulated exit probability are almost the same as those of observed exit probability.

All four specifications produce similar, significantly positive β^R, suggesting that log revenue is a good indicator of firm profitability. The higher β^R is, the less likely an establishment will exit. Given the motivating regressions, this is not surprising.

In the thinking cost function, we see both owner experience and distance to owner play a statistically significant role. Qualitatively, owner experience lowers thinking cost, while distance to owner increases it. Such effects are statistically significant for owner experience in all specifications, but lose some statistical power for distance to owner in column 4.

The magnitude is not straightforward to interpret by looking at these coefficients, as the extent of limited attention is a non-linear function of model parameters and data variation. These estimates suggest a high prevalence of inattention. Of the 8,995 owners in our data, an average owner's probability of paying zero attention ranges from 76% to 87%. Even if an owner is paying attention, her attention is limited, on average. Conditional on paying some attention, the mean amount of attention (denoted by $E\left(\tau_j \mid \tilde{\kappa}_j \leq \text{var}\left(\omega_{jt}\right)\right)$) ranges from 0.32 to 0.39 across specifications. The unconditional mean amount of attention (denoted by $E\left(\tau_j\right)$) is even lower, ranging from 0.07 to 0.17 across specifications.

The structural parameter estimates are consistent with the results of the motivating analysis. For example, a comparison of Online Appendix Tables 1 and 5 shows that the coefficients linking weather to revenue are similar in sign and scale except for the heat coefficients in the second and fourth quarters, where the magnitude is small. Likewise, when the coefficients linking demographics to revenue are significantly different from zero, they have the same sign in Online Appendix Tables 1 and 5. In other words, where there are differences in sign, at least one of the coefficients is not significantly different from zero. Furthermore, the main results reported in Table 7 are consistent with the motivating results in Table 4. In particular, the lower cost of attention for experienced owners and for local owners is consistent with the motivating result that transitory shocks are less related to their exit decisions.

The estimates on the mean and variance of $E\left(\tau_j\right)$ indicate that owners pay limited attention to the impact of transitory shocks on their profitability. Taubinsky and Rees-Jones (2018) find that consumers underreact to non-salient sale taxes as if the taxes were only 25% of their size. Chetty, Looney and Kroft (2009) find this number to be 6% for alcoholic beverages and 35% for grocery store purchases. Our estimate $E\left(\tau_j\right)$ has a similar interpretation and falls into the same range. In the specification with the best fit (column 2, Table 7), $E\left(\tau_j\right)$ is roughly 0.15, suggesting owners react to transitory shocks as if the shocks were 15% of their true size.

Also like this prior research, we find substantial heterogeneity in attention allocation, reflected by the estimated variance of inattention. Heterogeneity in attention is driven by a large, significantly negative estimate of the effect of owner experience on thinking costs. Experienced owners have lower cost of thinking relative to the variance of transitory shocks, allowing them to recognize the existence of transitory shocks in their revenue signals. The largest barrier seems to be whether an owner pays attention at all. Once an owner crosses the barrier, the heterogeneity is smaller.

6.2 Welfare Trade Offs of Paying Attention

Next, we assess the cost and benefit of paying attention. In our model, paying attention is valuable if it leads to better decision-making. It can be very costly because the owner has to pay attention in all periods up to the point when decisions with and without attention differ. To capture this trade off, we first simulate exit events under our estimated model ("estimated attention simulation"), and then simulate exit events under the assumption that every owner has $\tau_j = 1$ ("full attention simulation"). In all simulations presented in Table 8 and 9, we use the estimated structural parameters corresponding to column 4, Table 7.

Taking the full attention simulation as the baseline for comparison, we find that roughly 3.9% of the 8,995 bars — 351 bars — in the estimated attention simulation would have made a better decision in the simulated operating history of the full attention simulation. We regard this magnitude to be consistent with our priors. It is not so large to suggest that paying attention to these transitory shocks is of first order importance, nor so small that it will have a negligible aggregate impact.

For these 351 bars, we can express the cost and benefit of paying full attention in dollars. The cost is estimated from the cost of thinking function. The cost for a bar owner in any month is how much revenue the owner would have to pay (or receive) so that the owner forms the correct belief about her bar's monthly profitability as if she pays full attention. The benefit is estimated from the penalty of incorrect decisions. It is how much a bar's owner is willing to pay (or receive) in order to avoid incorrect staying or exit decisions in the month where decisions differ.[21] To evaluate both cost and benefit on a monthly basis, we divide total cost and total benefit by the number of months leading up to the month where decisions differ between the full attention simulation and the estimated attention simulation.

Panel A of Table 8 reports the cost and benefit analysis of paying full attention for these 351 bars. The first two rows report summary statistics about the total cost or benefit for a bar. The next two rows report the same summary statistics per establishment-month. These numbers clearly indicate that the cost of paying full attention dominates the benefit of doing it. Although the benefit is equivalent to roughly $2,000 for a median bar, the cost is roughly $16,000. Both benefit and cost are highly skewed to the right, reflected by much higher means than medians. There is significant heterogeneity across bars. For some bars, the incorrect timing of exit has catastrophic consequences, but paying full attention to avoid these incorrect decisions is nevertheless too costly ex ante.

[21] In our simulations, we assume that exit decisions are permanent: once a bar exits, it cannot return to business. This assumption makes incorrect exit decisions and incorrect staying decisions asymmetric when we calculate welfare trade offs. Avoiding an incorrect staying decision typically yields a benefit over just one period. Avoiding an incorrect exit decision yields a benefit over multiple (consecutive) periods.

6.3 The Value of Having an Experienced Owner

6.3.1 The Value of Having an Experienced Owner, in General

Given the substantial cost of paying attention, a natural question is what alleviates the burden so that the owners make better decisions. In our estimated model, it points to the owner's pre-existing experience before opening a bar. The majority of owners (81%) have no such experience; among the owners with such experience, it can range from 1 month to more than 10 years. Experienced owners have a lower cost of thinking so the owner pays more attention to transitory shocks and, in turn, makes better decisions. Using our estimated model and simulations, we can translate this value into dollar amounts: It is how much a bar's owner is willing to pay (or receive) in order to make better decisions as if she had a certain number of years in experience.

Looking owners whose decisions would be improved if they made decisions like owners with more years of experience, Panel B of Table 8 reports that, on average, the value of having an experienced owner is large. In particular, gaining one year of experience is equivalent to about $900 monthly for a median bar, gaining three years $1,100, and gaining ten years $1,400. One way to think about these numbers is that they are salary premiums the bar might be willing to pay for managers with additional experience in the profession. Under this interpretation, the salary premium associated with one year of industry experience is about $11,000 a year ($900 × 12 months), while the salary premium associated with ten years of industry experience about $17,000 a year ($1,400 × 12 months). These averages mask significant heterogeneity. This heterogeneity in the value of experience is correlated with traits of the individual decision makers (for example, the value of additional experience is small if the owner is already an industry veteran) and attributes of the business environment (for example, the value of experience is small if business is very stable, with little month-to-month variation). Overall, our results point to an understudied area of firm-level heterogeneity: heterogeneity in the ability to attend to information in decision-making.

6.3.2 Experience and Luck as Substitutes

Positive and negative shocks, or lucky and unlucky events, may have asymmetric effects on bar owners' welfare. Imagine continuous terrible weather in a bar's first year. If the owner does not purge the initial negative transitory shocks from profit signals, the owner may interpret profit numbers unfavorably and, in turn, exit business prematurely. This premature exit decision could happen before the bar owner has accumulated enough profit signals to form an accurate belief about the bar's profitability. Premature exit eliminates the possibility of many profitable years, resulting in a severe welfare loss. Similarly, when a bar is hit with a series of fortunate events, the owner may interpret profit numbers too favorably and, in turn, stay in business too long.

This, however, usually only delays the inevitable exit by a short period of time, so the misinterpretation of the revenue signal only affects decisions in a limited way. Therefore, when the owner is subject to inattention, the welfare loss due to incorrect decisions should be more severe when a bar is hit with negative transitory shocks than with positive transitory shocks.

Table 9 illustrates such asymmetric effects between positive shocks and negative shocks. In Table 9, the columns report four regimes of different levels of experience: everyone with no experience, or one year, three years, or ten years of experience. As we move right across columns, the owners gain experience and cast different levels of attention.

The rows report different "luck" regimes: random profit shocks (as in the model); positive shocks for the first quarter (and then random shocks after that), the first two quarters, and the first year; and negative shocks for the first quarter, the first two quarters, and the first year.

We take the full attention simulation under each luck regime as the baseline for comparison. We simulate the percentage of wrong decisions and total welfare loss for each luck-experience combination in the table. We estimate the welfare loss as the amount of money a bar's owner would be willing to pay (or receive) in order to avoid incorrect staying or exit decisions in the months where decisions differ. Because exit is permanent, in our welfare calculations avoiding an incorrect exit decision yields a benefit over multiple (consecutive) periods. In contrast, avoiding an incorrect staying decision yields a benefit that may last just one period.

Comparing Panel A (positive shocks) and Panel B (negative shocks), we can clearly see that although the percentage of mistakes is roughly the same in each corresponding positive and negative shock regime, negative shocks reduce welfare much more substantially than positive shocks do. Furthermore, the more severe the negative shocks are (as we move down the rows in Panel B), the more severe is the welfare loss. The permanent exit decision drives these results. Negative shocks cause a potentially successful bar to close prematurely, eliminating many potential years of profits. In fact, positive shocks are better than the baseline with low levels of experience because the baseline includes the possibility of negative shocks in the first few periods, and incorrect permanent exit decisions.

Moving across columns of Table 9, we can see experience substantially reduces the incidence of wrong decisions and welfare loss in any "luck" regime. Going from no experience to one, three, and ten years of experience, both the percentages of wrong decisions and magnitude of welfare loss decrease rapidly. When every owner has ten years of experience, the incidence of wrong decisions and the resulting welfare loss is less than a half of when every owner has zero years of experience.

Owner experience is especially useful when a bar is hit with a sequence of bad luck. Moving down the rows of Panel B, the percentages of wrong decisions only increase moderately, but the corresponding welfare loss increases rapidly. When no owner has experience, moving from baseline (all random shocks) to an extended period of bad luck (1st quarter of negative shocks) leads to an additional total welfare loss of about $150 million (=275.9 132.0). This number rises substantially as more negative shocks hit the bar. With experience increasing, we see the same pattern as the industry is hit with more negative shocks, but the gap between different luck regimes dwindles. When everyone has 10 years of experience, moving from baseline (all random shocks) to an extended period of bad luck (1st quarter of negative shocks) leads to an additional total welfare loss of about $40 million (=80.4-42.8).

Comparing Panel A and Panel B, we can see different luck regimes generate big swings in welfare loss when owners are inexperienced, but the gaps disappear as the level of experience rises. As reported in columns 7 and 8 of Table 9, the difference between positive and negative shocks is much smaller when every owner has 10 years of industry experience.

Overall, these simulations point to an interaction between luck and skill that departs from the existing literature in management and entrepreneurship. Table 9 shows that owner experience reduces welfare loss due to inattention, especially when the owner is hit a repeated bad luck. Prior work suggests that both luck and skill lead to success: Luck to be in a fortunate position, and skill to take advantage of it (e.g. Gompers et al 2006; Plehn-Dujowich 2010). That is, luck and skill work as complements. Our results suggest a different mechanism: luck and skill act like substitutes. When the decision maker is lucky, experience matters less; when she is unlucky, experience substitutes for luck to allow the owner to make a better decision.

6 Conclusion

In this paper, we document the incidence of inattention in firm decisions and propose a likely mechanism through which deficient attention may have economic consequences. The transitory component of revenue should be netted out of the expectation of future profitability, but inattentive decision makers may not be able to perform the decomposition and hence overreact to these temporary shocks. By estimating a model of exit decisions with an attention allocation pre-stage, we are able to assess the extent to which the owner accounts for past weather shocks. Our results demonstrate the prevalence of inattention. We are able to gauge the economic magnitude of this firm-level limited attention problem and evaluate the value of experience.

Experienced decision makers are better-able to understand the distortions in profit signals due to lucky or unlucky events, thereby avoiding mistakes in decision-making. We demonstrate the viability of developing and estimating a model that incorporates behavioral assumptions in decision-making and that allows us to estimate welfare trade-offs due to limited attention in high-stakes firm decisions. In doing so, we contribute to the recent effort to introduce behavioral deviations into the field of empirical industrial organization. The evidence is this paper is consistent with prior work on consumer and investor inattention and is therefore a step toward understanding limited attention at a larger scale.

Somewhat more speculatively, our results provide insight into the fundamental determinants of market structure, competitiveness, and performance. In the United States, 13.9 million new firms entered between 1991 and 2009, while 12.3 million firms exited over the same period (Elfenbein and Knott 2015). A better understanding of various factors behind a firm's exit serves to inform regulatory, antitrust, and trade policies on competition. As documented by previous empirical work (Dunne, Roberts, and Samuelson, 1988), there is considerable heterogeneity in firm survival by type of entrant within an industry and significant correlations in entry and exit rates across industries. Our work provides a plausible explanation for these stylized facts. If decision makers are subject to different degrees of bounded rationality, their exit decisions will capture this heterogeneity and affect the extent of market competitiveness. If inexperienced managers of good firms often exit too early because of bad luck, then this will reduce competitiveness and enable weaker firms to persist. Perhaps more importantly, bounded rationality may well mark other business decisions. For example, poorly-made entry decisions will lead to ex-post regret and consequently hasty exits, implying positively correlated entry and exit rates. While we model only the exit decision here, we believe our results help inform our understanding of the potential role for bounded rationality in the rich, diverse, and often puzzling patterns others have observed in firm turnover and industry structure.

Before concluding, we acknowledge some important limitations of this project. First, in our bounded rationality framework, we still allow for a substantial degree of rationality. We expect the bar owners to be capable of sophisticated calculation, which may not hold in reality. Second, we cannot separately identify whether the measured difference in experience is driven by selection effects (better bar owners open a second bar) or the causal effects of experience. If the results are driven by a causal effect of experience, it suggests a new explanation for the value of experience for entrepreneurs and managers. Consistent with a small body of work on the role of experience in firm decision-making (Goldfarb and Xiao 2011; Doraszelski, Lewis, and Pakes 2014, Lafontaine and Shaw 2016), a causal interpretation would mean that experience reduces behavioral biases, even among managers in competitive industries. This relates to prior laboratory and field work that documents how experience generally leads to rational behavior (summarized by Al-Ubaydli and List 2016). Third, we focus on exit decisions only. Prior to the exit decision, firms make a variety of other choices that may also suffer from bounded rationality. Finally, we only examine one dimension of sparsity and one dimension of bounded rationality. We pick these particular dimensions in order to more precisely understand one type of frictions in a firm's decision-making process. We hope our work encourages future research into limited attention, bounded rationality, and more fundamentally, the black box of imperfect decision-making at the firm level.

References

Abel, Andrew B., Janice C. Eberly, and Satvros Panageas. 2013. "Optimal Inattention to the Stock Market with Information Costs and Transactions Costs." *Econometrica*, 81(4), 1455-1481.

Abbring, Jaap H. and Jeffrey. R. Campbell. 2003. "A Structural Empirical Model of Firm Growth, Learning, and Survival." NBER Working paper 9712.

Abbring, Jaap H. and Jeffrey. R. Campbell. 2005. "A Firm's First Year." Discussion paper 2005-046/3. Tinbergen Institute. Amsterdam.

Al-Ubaydli, Omar, and John A. List. 2016. "Field Experiments in Markets." NBER Working paper 22113.

Bertrand, Marianne and Antoinette Schoar. 2003. "Managing with Style: The Effect of Managers on Firm Policies." *The Quarterly Journal of Economics*, 118: 1169-1208.

Boldin Michael and Jonathan H. Wright, 2015, "Weather-Adjusting Economic Data." Brookings Papers on Economic Activity, 227-260.

Brown, Douglas Robert. 2007. *The Restaurant Manager's Handbook: How to Set Up, Operate, and Manage a Financially Successful Food Service Operation*. Revised Fourth edition. Atlanta Publishing Group Inc., Ocala FL.

Brown, Jennifer, Tanjim Hossain, and John Morgan. 2010. "Shrouded Attributes and Information Suppression: Evidence from the Field." *The Quarterly Journal of Economics* 125(2), 859-876.

Busse, Meghan R., Devin G. Pope, Jaren C. Pope and Jorge Silva-Risso. 2015. "The Psychological Effect of Weather on Car Purchases." *The Quarterly Journal of Economics* 130(1), 371-414.

Camerer, Colin and Ulrike Malmendier. 2007. "Behavioral Economics and its Applications." In *Behavioral Economics of Organizations*. Princeton University Press.

Chetty, Raj, Adam Looney, and Kory Kroft. 2009. "Salience and Taxation: Theory and Evidence." *The American Economic Review*, 99(4), 1145-77.

Clerides, Sofronis, and Pascal Courty. 2017. "Sales, Quantity Surcharge, and Consumer Inattention." *The Review of Economics and Statistics*, 99(2): 357-370.

Conlin, O'Donoghue, and Vogelsang. 2007. "Projection Bias in Catalog Orders." *The American Economic Review*, 97(4), 1217-1249.

Conlisk, John. 1996. "Why Bounded Rationality?" *Journal of Economic Literature*, 34(2): 669-700.

DeGroot, M. 1970. *Optimal Statistical Decisions*. New York, NY: Mcgraw-Hill College.

DellaVigna, Stefano. 2009. "Psychology and Economics: Evidence from the Field." *Journal of Economic Literature*, 47: 315-372.

DellaVigna, Stefano. 2017. "Structural Behavioral Economics". Forthcoming in *Handbook of Behavioral Economics*, eds. David Laibson, Douglas Bernheim, and Stefano DellaVigna.

DellaVigna, Stefano, and Matthew Gentzkow. 2017. "Uniform Pricing in US Retail Chains." Working paper, UC Berkeley.

Doraszelski, Ulrich, Gregory Lewis, and Ariel Pakes. 2014. "Just starting out: Learning and price competition in a new market." Harvard University working paper.

Dunne, Timothy, Mark J. Roberts, and Larry Samuelson. 1988. "Patterns of Firm Entry and Exit in U.S. Manufacturing Industries." *The RAND Journal of Economics*, 19(4): 495-515.

Elfenbein, Daniel, and Anne M. Knott. 2015. "Time to Exit: Rational, Behavioral, and Organizational Delays." *Strategic Management Journal* 36(7), 957-975.

Gabaix, Xavier. 2014. "A Sparsity-Based Model of Bounded Rationality." *The Quarterly Journal of Economics* 129(4), 1661-1710.

Gabaix, Xavier, David Laibson, Guillermo Moloche, and Stephen E.Weinberg. 2006. "Costly Information Acquisition: Experimental Analysis of a Bounded Rational Model." *The American Economic Review*, 96(4): 1043-1068.

Goldfarb, Avi, and Botao Yang. 2009. "Are All Managers Created Equal?" *Journal of Marketing Research* 46(5), 612-622.

Goldfarb, Avi and Mo Xiao. 2011. "Who Thinks about the Competition? Managerial Ability and Strategic Entry in US Local Telephone Markets." *The American Economic Review*, 101(7): 3130-3161.

Gompers, Paul, Anna Kovner, Josh Lerner, and David Scharfstein. 2006. Skill vs. Luck in Entrepreneurship and Venture Capital: Evidence from Serial Entrepreneurs. NBER Working Paper 12592.

Grubb, Michael and Matthew Osborne. 2015. "Cellular Service Demand: Biased Beliefs, Learning, and Bill Shock." *The American Economic Review*, 105(1), 234-271.

Handel, Ben. 2013, "Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts." *The American Economic Review*, 103(7), 2643-2682.

Ho, Kate, Joseph Hogan, and Fiona Scott Morton. 2015. "The Impact of Consumer Inattention on Insurer Pricing in the Medicare Part D Program." The RAND Journal of Economics.

Holtz-Eakin, Douglas, David Joulfaian, and Harvey S. Rosen. 1994. "Sticking it Out: Entrepreneurial Survival and Liquidity Constraints." *Journal of Political Economy*, 102(1), 53-75.

Hortacsu, Ali, Fernando Luco, Steven Puller, and Dongni Zhu. 2016. "Does Strategic Ability Affect Efficiency? Evidence from Electricity Markets." Working paper, University of Chicago.

Hortacsu, Ali, Seyed Ali Madanizadeh, and Steven Puller. *Forthcoming*. "Power to Choose? An Analysis of Consumer Inertia in the Residential Electricity Market." *The American Economic Journal: Economic Policy*.

Hossain, Tanjim and John Morgan. 2006. "…Plus Shipping and Handling: Revenue (Non)Equivalence in Field Experiments on eBay." *B.E. Journal of Economic Analysis & Policy* 5(2).

Hurst, Erik, and Aannamaria Lusardi. 2004. "Liquidity Constraints, Household Wealth, and Entrepreneurship." *Journal of Political Economy,* 112(2): 319-347.

Jovanovic, Boyan. 1982. "Selection and the Evolution of Industry." *Econometrica*, 50, 649-670.

Lacetera, Nicola, Devin Pope, and Justin R. Sydnor, 2012. "Heuristic Thinking and Limited Attention in the Car Market." *The American Economic Review*, 102(5): 2206-2236.

Lafontaine, Francine and Kathryn L. Shaw. 2016. "Serial Entrepreneurship: Learning by Doing?" *Journal of Labor Economics* . 34(2), S217-S254.

Lazear, Edward P. 2005, "Entrepreneurship." *Journal of Labor Economics*, 23(4): 349-380.

Malmendier, Ulrike, and Young Han Lee. 2011. "The Bidder's Curse," *The American Economic Review,* 101(2), 749-787.

Miravete, Eugenio J., and Ignacio Palacios-Huerta. 2014. "Consumer Inertia, Choice Dependence, and Learning from Experience in a Repeated Decision Problem." *The Review of Economics and Statistics*, 96(30) 524-537.

Pakes, Ariel. 2016. "Methodological Issues in Analyzing Market Dynamics." NBER Working Paper 21999.

Parsa, H.G., John T. Self, David Njite, and Tiffany King. 2005. "Why Restaurants Fail." *Cornell Hotel and Restaurant Administration Quarterly*, 46(3): 304-322.

Parsa, H.G., Jean-Pierre I. van der Rest, Scott R. Smith, Rahul A. Parsa, and Milos Bujisic. 2014. "Why Restaurants Fail? Part IV: The Relationship between Restaurant Failures and Demographic Factors." *Cornell Hospitality Quarterly*, 51(1): 80-90.

Plehn-Dujowich, Jose (2010). "A Theory of Serial Entrepreneurship." *Small Business Economics*, 35(4), 377-398.

Reis, Ricardo. 2006. "Inattentive Consumers." *Journal of Monetary Economics*, 53(8), 1761-1800.

Rust, John. 1994. "Structural estimation of Markov decision processes." *Handbook of Econometrics*, 4, 3081-3143.

Saint-Paul, Gilles. 2011. "A Quantized Approach to Rational Inattention." IDEI Working Paper.

Simon, Herbert A. 1955. "A Behavioral Model of Rational Choice." *The Quarterly Journal of Economics*, 69(1): 99-118.

Simonsohn, Uri. 2010. "Weather to Go to College." *Economic Journal*, 120(543), 270-280.

Sims, Christopher A. 2003. "Implications of Rational Inattention," *Journal of Monetary Economics*, 50(3): 665-690.

Stango, Victor, and Jonathan Zinman. 2014. "Limited and Varying Consumer Attention: Evidence from Shocks to the Salience of Bank Overdraft Fees." *The Review of Financial Studies*, 27(4), 990-1030.

Taubinsky, Dmitry, and Alex Rees-Jones. 2018. "Attention Variation and Welfare: Theory and Evidence from a Tax Salience Experiment." *The Review of Economic Studies* (85), 2462-2496.

Veldkamp, Laura. 2011. *Information Choice in Macroeconomics and Finance*. Princeton: Princeton University Press.

Table 1a: Bar-Level Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Ever exit	0.649	0.477	0	1
Owned a bar or restaurant, 3 years before open	0.190	0.393	0	1
# establishment-months owned, 3 years before open	8.114	32.759	0	562
Log(1 + # estab.-months owned, 3 years before open)	0.617	1.346	0	6.33
Owner distance to location	49.681	187.994	0	3,178.672
Owner distance to location: over 5 miles	0.495	0.500	0	1
Owner distance to location: over 10 miles	0.329	0.470	0	1
Owner distance to location: over 15 miles	0.231	0.421	0	1
Owner name is not a business name	0.173	0.378	0	1
Owner has just one establishment	0.856	0.351	0	1
# bars		8,995		

Table 1b: Bar-Month Level Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Bar Attributes				
Exit: no longer bar with same name at address	0.014	0.117	0	1
Alcohol revenue in a month ($ thousand, in 2018 dollars)	52.675	68.713	0.001	5,639.440
log(alcohol revenue in a month)	10.264	1.226	0.110	15.545
Time since bar opened, in years	3.883	3.643	0.083	20.750
Likely lease renewal (multiple of 12 months since opening)	0.0735	0.2609	0	1
Market Attributes at the Zip Code Level				
# other bars	11.469	18.798	0	122
Population (in thousands)	29.902	18.953	0	114.124
Fraction black	0.111	0.124	0	0.936
Fraction Hispanic	0.386	0.246	0	1
Fraction age under 18	0.228	0.088	0	0.428
Fraction age 65 and over	0.103	0.053	0	0.505
Median household income ($ thousand, in 2018 dollars)	59.805	25.449	0	208.858
Fraction bachelor degree	0.301	0.188	0	0.849
Fraction rural	0.053	0.156	0	1
Fraction foreign born	0.173	0.103	0	0.603
# bar-months		422,651		

Table 2: Weather and Weather Shocks

Variable	Mean	Std. Dev.	Min	Max
Weather: monthly average of daily weather				
Heat index (in degree Fahrenheit)	69.797	15.072	26.759	113.217
Mean temperature (in degree Fahrenheit)	69.306	12.756	30.514	96.622
Relative humidity (in %)	63.074	11.875	10.689	100
Precipitation (in inches)	0.075	0.098	0	1.262
Days with unfavorable weather	8.876	5.693	0	31
Hurricane	0.010	0.098	0	1
Weather shocks: monthly average of daily deviations				
Heat shocks	0.173	2.974	-14.856	15.480
Precipitation shocks	0.003	0.081	-0.545	1.084
Days with unfavorable shocks	-0.254	3.842	-15.042	17.450
# bar-months		422,651		

Table 3a: Effect of Weather on Monthly Revenue

Dependent Variable	Log(monthly alcohol revenue)						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All year	Owner Experience: binary	Owner Experience: continuous	Jan-Mar	Apr-June	July-Sept	Oct-Dec
Heat shocks	0.0007	0.0006	0.0007	0.0016	0.0012	0.0015	-0.0008
	(0.0003)	(0.0003)	(0.0003)	(0.0005)	(0.0007)	(0.0010)	(0.0005)
Precipitation shocks	-0.0109	-0.0150	-0.0146	0.0315	0.0664	-0.1134	0.0454
	(0.0233)	(0.0213)	(0.0213)	(0.0260)	(0.0206)	(0.0257)	(0.0344)
Days with unfavorable shocks	-0.0001	4.6e-5	4.7e-5	-0.0017	0.0008	0.0022	-0.0008
	(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0007)	(0.0015)	(0.0005)
Heat shocks × Experience		0.0006	0.0001				
		(0.0011)	(0.0003)				
Precipitation shocks × Experience		0.0219	0.0058				
		(0.0232)	(0.0066)				
Days with unfavorable shocks × Experience		-0.0009	-0.0003				
		(0.0007)	(0.0002)				
# bar-months	422,651	422,574	422,574	103,372	106,516	108,350	104,413
# bars	8,995	8,995	8,995	8,230	8,436	8,549	8,580
R-squared	0.853	0.853	0.913	0.871	0.874	0.869	0.870

Notes: Column headers describe differences from column (1). In Column (2), owner experience is a dummy variable indicating whether the owner owned any bar or restaurant in 3 years before opening the focal one; in Column (3), owner experience is log (1 + # establishment-months owned in 3 years before opening the focal one). Regressions include year fixed effects, monthly dummies, and bar fixed effects. Clustered standard errors (at the county level) reported in parentheses. R^2 measure includes all fixed effects. Full set of coefficients shown in Online Appendix Table 1.

Table 3b: Persistent Revenue versus Transitory Revenue

VARIABLES: Components of Revenue

	Mean	Std. Dev.	Min	Max
Persistent Revenue	10.264	1.144	0.158	14.344
Transitory Revenue	9.74e-5	0.440	-9.654	4.662
# bar-months	422,651			

	Inexperienced		**Experienced**	
	Mean	Std. Dev.	Mean	Std. Dev.
Persistent Revenue	10.250	1.144	10.323	1.146
Transitory Revenue	7.76e-5	0.441	1.81e-4	0.440
# bar-months	341,964		80,687	

	Distance to Owner over 5 miles		**Distance to Owner under 5 miles**	
	Mean	Std. Dev.	Mean	Std. Dev.
Persistent Revenue	10.345	1.215	10.229	1.078
Transitory Revenue	9.92e-5	0.449	9.59e-5	0.433
# bar-months	197,225		225,396	

Table 4: Asymmetric Responses to Different Revenue Components by Owner Type

Dependent variable	Bar exit				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	All	Inexperienced only	Experienced only	Distance to owner over 5 miles	Distance to owner under 5 miles
Transitory revenue	-0.0376	-0.0383	-0.0349	-0.0433	-0.0321
	(0.0020)	(0.0020)	(0.0034)	(0.0020)	(0.0023)
Persistent revenue	-0.0372	-0.0358	-0.0382	-0.0368	-0.0364
	(0.0023)	(0.0021)	(0.0049)	(0.0024)	(0.0027)
Experience	-0.0014			-0.0012	-0.0019
	(0.0023)			(0.0027)	(0.0029)
Distance to owner (1000 miles)	0.0215	0.0177	0.0297	0.0143	2.6548
	(0.0052)	(0.0036)	(0.0118)	(0.0044)	(0.8270)
Owner with single estab.	0.0035	0.0126	-0.0069	0.0021	0.0105
	(0.0022)	(0.0027)	(0.0039)	(0.0021)	(0.0033)
Owner name not a business name	-0.0046	-0.0054	0.0035	-0.0054	-0.0029
	(0.0039)	(0.0038)	(0.0062)	(0.0047)	(0.0046)
# bar-months	422,651	341,964	80,687	197,255	225,396
# bars	8,995	7,283	1,712	4,449	4,546
R-squared	0.0168	0.0173	0.0164	0.0203	0.0149

Notes: Owner experience is a dummy variable indicating whether the owner owned any bar or restaurant in 3 years before opening the focal one. Regressions include year fixed effects, monthly dummies, and bar random effects. Clustered standard errors (at the county level) reported in parentheses. Full set of coefficients shown in Online Appendix Table 2.

Table 5: Credit-Constrained Owners React to Both Components of Revenue

Dependent variable	Bar exit				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	All	Owner name not a business name	Owner name is a business name	Owner with single establishment	Owner with multiple establishments
Transitory revenue	-0.0376	-0.0403	-0.0371	-0.0399	-0.0281
	(0.0020)	(0.0046)	(0.0018)	(0.0021)	(0.0031)
Persistent revenue	-0.0372	-0.0509	-0.0333	-0.0393	-0.0241
	(0.0023)	(0.0035)	(0.0020)	(0.0021)	(0.0041)
Experience	-0.0014	0.0074	-0.0034	-0.0070	0.0114
	(0.0023)	(0.0056)	(0.0019)	(0.0027)	(0.0031)
Distance to owner (000 miles)	0.0215	0.0242	0.0181	0.0278	0.0075
	(0.0052)	(0.0425)	(0.0056)	(0.0069)	(0.0062)
Owner with single establishment	0.0035	0.0166	0.0013		
	(0.0022)	(0.0071)	(0.0018)		
Owner name not a business name	-0.0046			-0.0050	-0.0076
	(0.0039)			(0.0044)	(0.0066)
# bar-months	422,651	57,519	365,132	348,682	73,969
# bars	8,995	1,557	7,452	7,702	1,293
R-squared	0.0168	0.0156	0.0170	0.0183	0.0117

Notes: Dependent variable is bar exit. Owner experience is a dummy variable indicating whether the owner owned any bar or restaurant in 3 years before opening the focal one. Regressions include year fixed effects, monthly dummies, and bar random effects. Clustered standard errors (at the county level) reported in parentheses. Full set of coefficients shown in Online Appendix Table 3.

Table 6: Higher Revenue Volatility Induces Attention to Transitory-Persistent Difference

Dependent variable	Bar exit				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	All	Inexperienced only	Experienced only	Distance to owner over 5 miles	Distance to owner under 5 miles
Transitory revenue	-0.0563	-0.0573	-0.0522	-0.0720	-0.0435
	(0.0034)	(0.0037)	(0.0043)	(0.0039)	(0.0037)
Transitory revenue × revenue volatility	0.0248	0.0260	0.0209	0.0369	0.0159
	(0.0028)	(0.0029)	(0.0057)	(0.0041)	(0.0034)
Persistent revenue	-0.0190	-0.0189	-0.0200	-0.0179	-0.0201
	(0.0020)	(0.0022)	(0.0023)	(0.0021)	(0.0025)
Persistent revenue × revenue volatility	-0.0054	-0.0054	-0.0025	-0.0044	-0.0059
	(0.0031)	(0.0036)	(0.0042)	(0.0032)	(0.0045)
Revenue volatility	0.0585	0.0588	0.0301	0.0508	0.0602
	(0.0296)	(0.0345)	(0.0414)	(0.0310)	(0.0449)
Experience	-0.0020			-0.0011	-0.0031
	(0.0013)			(0.0016)	(0.0018)
Distance to owner (000 miles)	0.0116	0.0130	0.0069	0.0060	1.8454
	(0.0026)	(0.0027)	(0.0048)	(0.0020)	(0.5040)
Owner with single establishment	0.0045	0.0109	-0.0034	0.0043	0.0085
	(0.0013)	(0.0019)	(0.0016)	(0.0013)	(0.0018)
Owner name not a business name	0.0004	0.0003	0.0008	0.0015	-0.0002
	(0.0026)	(0.0028)	(0.0030)	(0.0029)	(0.0029)
# bar-months	422,530	341,869	80,661	197,190	225,340
# bars	8,874	7,188	1,686	4,384	4,490
R-squared	0.0227	0.0229	0.0234	0.0304	0.0183

Notes: Owner experience is a dummy variable indicating whether the owner owned any bar or restaurant in 3 years before opening the focal one. Revenue volatility is the standard deviation of log(monthly alcohol revenue) within an establishment. Regressions include year fixed effects, monthly dummies, and bar random effects. Clustered standard errors (at the county level) reported in parentheses. Full set of coefficients shown in Online Appendix Table 4.

Table 7: Results on Key Structural Parameters

	(1)	(2)	(3)	(4)
	Experience is whether owner owned a bar/restaurant, 3 years before open		Experience is log(1 + # establishment-months, 3 years before open	
Key parameters in belief updating				
β^R: proportion of log revenue that proxies for profitability	0.4661 (0.0090)	0.4659 (0.0092)	0.4661 (0.0090)	0.4658 (0.0093)
Parameters in thinking cost function				
κ^1: owner experience	-4.4550 (1.5644)	-4.4000 (1.2400)	-0.5000 (0.1533)	-0.7011 (0.1657)
κ^2: distance to owner over 5 miles		0.5750 (0.3022)		0.4556 (0.2879)
Incidence of limited attention				
Mean: probability of paying zero attention	0.7566	0.7819	0.8652	0.8586
Variance: probability of paying zero attention	0.1310	0.1223	0.0465	0.0580
Mean: unconditional amount of attention	0.1733	0.1521	0.0660	0.0748
Variance: unconditional amount of attention	0.0939	0.0818	0.0182	0.0257
Mean: amount of attention conditional on paying attention	0.3865	0.3640	0.3160	0.3155
Variance: amount of attention conditional on paying attention	0.0500	0.0452	0.0127	0.2748
Log Likelihood	-312,512.6	-312,511.7	-312,515.3	-312,514.3
# bar-months		422,651		

Standard errors in parentheses. The number of simulation draws is 20. Full set of structural coefficients in Online Appendix Table 5.

Table 8: Measuring the Value of Paying Attention

	(1) 25th percentile	(2) 50th percentile	(3) 75th percentile	(4) Mean	(5) Std. Dev.
Panel A: The Cost and Benefit of Paying Full Attention (in $)					
Total Cost	26,371	99,339	413,510	520,711	1,310,237
Cost per Month	5,212	14,927	33,092	27,820	41,543
Total Benefit	4,061	16,115	64,075	343,122	1,139,694
Benefit per Month	566	2,192	9,681	19,640	63,386
N = 351 bars					
Panel B: The Value of Owner with Experience (in $)					
Having One Additional Year					
Total Benefit	1,685	7,168	24,434	88,813	429,157
Benefit per Month	256	871	3,152	6,171	28,389
N = 143 bars					
Having Three Additional Years					
Total Benefit	2,129	8,975	32,876	130,996	599,306
Benefit per Month	310	1,129	4,231	8,460	35,321
N = 192 bars					
Having Ten Additional Years					
Total Benefit	2,738	19,951	40,466	197,131	810,179
Benefit per Month	393	1,401	5,421	11,672	44,172
N = 246 bars					

Notes: Counterfactual results based on Column 4 of Table 7. The number of simulation draws is 20. The reported number of bars is the number of bars that could have made better exit decisions due to more attentive decision-making.

Table 9: Substitution between Experience and Luck

	Everyone inexperienced		Everyone has 1 year experience		Everyone has 3 years experience		Everyone has 10 years experience	
	(1) % wrong decisions	(2) Total welfare loss ($ m)	(3) % wrong decisions	(4) Total welfare loss ($ m)	(5) % wrong decisions	(6) Total welfare loss ($ m)	(7) % wrong decisions	(8) Total welfare loss ($ m)
Status quo: all random shocks	4.09	132.0	3.28	94.8	2.62	71.0	1.81	42.8
Panel A: Positive Shocks								
1st quarter pos. shocks	5.09	59.2	4.02	45.5	3.20	35.5	2.21	23.1
1st two quarters pos. shocks	6.66	35.8	5.20	28.5	4.07	22.5	2.76	15.1
1st year pos. shocks	8.95	31.4	6.66	26.0	5.46	20.7	3.73	13.6
Panel B: Negative Shocks								
1st quarter neg. shocks	4.97	275.9	3.70	190.6	2.98	137.1	2.02	80.4
1st two quarters neg. shocks	6.46	562.1	4.91	376.6	3.77	260.1	2.53	144.6
1st year neg. shocks	8.69	1,362.2	6.57	914.9	5.03	617.2	3.36	333.5
N = 8,995 bars								

Notes: Counterfactual results based on Column 4 of Table 7. The number of simulation draws is 20.

Online Appendix: Not for Publication

Appendix A Tables 1-5: Full set of coefficients from main tables

Appendix B Tables 6-12: Robustness of motivating analysis and additional results

Appendix C: Constructing the likelihood function

Appendix D: Additional analysis and information

Appendix A

Tables 1-5

Full sets of coefficients from main tables

Appendix Table 1: Full set of regression coefficients for Table 3

VARIABLES	(1) All year	(2) Owner Exp.: binary	(3) Owner Exp.: continuous	(4) Jan-Mar	(5) Apr-June	(6) July-Sept	(7) Oct-Dec
Heat shocks	0.0007	0.0006	0.0007	0.0016	0.0012	0.0015	-0.0008
	(0.0003)	(0.0003)	(0.0003)	(0.0005)	(0.0007)	(0.0010)	(0.0005)
Precipitation shocks	-0.0109	-0.0150	-0.0146	0.0315	0.0664	-0.1134	0.0454
	(0.0233)	(0.0213)	(0.0213)	(0.0260)	(0.0206)	(0.0257)	(0.0344)
Days with unfavorable shocks	-0.0001	4.6e-5	4.7e-5	-0.0017	0.0008	0.0022	-0.0008
	(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0007)	(0.0015)	(0.0005)
Heat shocks × Experience		0.0006	0.0001				
		(0.0011)	(0.0003)				
Precipitation shocks × Experience		0.0219	0.0058				
		(0.0232)	(0.0066)				
Days with unfavorable shocks x Experience		-0.0009	-0.0003				
		(0.0007)	(0.0002)				
Time since bar opened in years	0.0537	0.0540	0.0540	0.0537	0.0925	0.0592	0.0294
	(0.0500)	(0.0501)	(0.0501)	(0.0558)	(0.0516)	(0.0539)	(0.0543)
Time since bar opened in years squared	-0.0003	-0.0003	-0.0003	-0.0003	-0.0002	-0.0002	-0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Likely lease renewal period	0.0045	0.0044	0.0044	0.0303	0.0260	0.0319	0.0304
	(0.0024)	(0.0024)	(0.0024)	(0.0063)	(0.0050)	(0.0069)	(0.0060)
Hurricane	-0.0497	-0.0495	-0.0495		0.0338	-0.0695	0.0103
	(0.0160)	(0.0160)	(0.0159)		(0.0500)	(0.0257)	(0.0162)
Zipcode: # other bars	0.0012	0.0012	0.0012	0.0036	0.0010	-0.0004	0.0004
	(0.0012)	(0.0011)	(0.0011)	(0.0018)	(0.0011)	(0.0012)	(0.0011)
Zipcode: pop. (millions)	6.3044	6.2897	6.2860	9.7131	5.9160	6.4301	5.6268
	(7.3903)	(7.3908)	(7.3910)	(7.5014)	(8.3782)	(7.1901)	(6.9234)
Zipcode: % black	-0.5118	-0.5186	-0.5180	-0.7178	-0.2914	-0.7359	-0.4081
	(0.9655)	(0.9666)	(0.9667)	(0.8798)	(1.0196)	(1.1046)	(0.9198)
Zipcode: % Hispanic	0.7190	0.7139	0.7146	0.5970	0.8105	0.6827	0.5992
	(0.7255)	(0.7254)	(0.7255)	(0.7407)	(0.7114)	(0.7807)	(0.7775)
Zipcode: % age under 18	-1.8857	-1.8759	-1.8768	-1.5418	-2.3440	-1.8045	-1.6423
	(1.8373)	(1.8370)	(1.8370)	(1.8370)	(1.8569)	(1.9865)	(1.7341)
Zipcode: % age 65 and over	2.8606	2.8624	2.8625	3.3781	3.7351	2.4599	2.1506
	(1.4166)	(1.4115)	(1.4121)	(1.8236)	(1.4347)	(1.3009)	(1.3387)
Zipcode: logged median hh income	-0.0454	-0.0516	-0.0515	0.0034	0.1182	-0.0972	-0.1923
	(0.2799)	(0.2804)	(0.2804)	(0.2624)	(0.3307)	(0.3160)	(0.2597)
Zipcode: % bachelor degree	0.9663	0.9728	0.9730	0.7081	0.8662	1.1660	1.0335
	(0.5439)	(0.5445)	(0.5443)	(0.5532)	(0.6572)	(0.5528)	(0.5360)
Zipcode: % rural	-0.6426	-0.6427	-0.6428	-0.9801	-0.4198	-0.4532	-0.7941
	(0.1547)	(0.1546)	(0.1546)	(0.2092)	(0.1686)	(0.1679)	(0.2431)
Zipcode: % foreign born	-1.7384	-1.7265	-1.7268	-1.3049	-1.8963	-2.1502	-1.5072
	(0.6103)	(0.6121)	(0.6125)	(0.5980)	(0.6124)	(0.6500)	(0.7029)
# bar-months	422,651	422,574	422,574	103,372	106,516	108,350	104,413
# bars	8,995	8,995	8,995	8,230	8,436	8,549	8,580
R-squared	0.853	0.853	0.913	0.871	0.874	0.869	0.870

Notes: Dependent variable is log(monthly alcohol revenue). Column headers describe differences from column (1). In Column (2), owner experience is a dummy variable indicating whether the owner owned any bar or restaurant in 3 years before opening the focal one; in Column (3), owner experience is log (1 + # establishment-months owned in 3 years before opening the focal one). Regressions include year fixed effects, monthly dummies, and bar fixed effects. Clustered standard errors (at the county level) reported in parentheses. R^2 measure includes all fixed effects.

Appendix Table 2: Full set of regression coefficients for Table 4

VARIABLES	(1) All	(2) Inexperienced only	(3) Experienced only	(4) Distance to owner over 5 miles	(5) Distance to owner under 5 miles
Transitory revenue	-0.0376	-0.0383	-0.0349	-0.0433	-0.0321
	(0.0020)	(0.0020)	(0.0034)	(0.0020)	(0.0023)
Persistent revenue	-0.0372	-0.0358	-0.0382	-0.0368	-0.0364
	(0.0023)	(0.0021)	(0.0049)	(0.0024)	(0.0027)
Experience	-0.0014			-0.0012	-0.0019
	(0.0023)			(0.0027)	(0.0029)
Distance to owner	0.0215	0.0177	0.0297	0.0143	2.6548
(000 miles)	(0.0052)	(0.0036)	(0.0118)	(0.0044)	(0.8270)
Owner with single	0.0035	0.0126	-0.0069	0.0021	0.0105
establishment	(0.0022)	(0.0027)	(0.0039)	(0.0021)	(0.0033)
Owner name not a	-0.0046	-0.0054	0.0035	-0.0054	-0.0029
business name	(0.0039)	(0.0038)	(0.0062)	(0.0047)	(0.0046)
Time since bar	0.0075	0.0077	0.0063	0.0077	0.0074
opened in years	(0.0003)	(0.0003)	(0.0006)	(0.0004)	(0.0004)
Time since bar	-0.0004	-0.0004	-0.0003	-0.0004	-0.0004
opened in years squared	(2.0e-05)	(2.0e-05)	(3.1e-05)	(3.1e-05)	(2.0e-05)
Likely lease	0.0041	0.0055	-0.0011	0.0051	0.0032
renewal period	(0.0008)	(0.0010)	(0.0010)	(0.0011)	(0.0009)
Hurricane	-0.0016	-0.0012	-0.0027	-0.0033	0.0000
	(0.0021)	(0.0024)	(0.0032)	(0.0030)	(0.0024)
Zipcode: # other	0.0001	3.6e-05	0.0002	3.2e-05	0.0001
bars	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Zipcode: pop.	0.0683	0.0507	0.1005	0.0011	0.1397
(millions)	(0.0426)	(0.0562)	(0.1228)	(0.0704)	(0.0566)
Zipcode: % black	-0.0137	-0.0080	-0.0396	-0.0127	-0.0131
	(0.0067)	(0.0072)	(0.0134)	(0.0073)	(0.0093)
Zipcode: %	0.0135	0.0173	-0.0015	0.0061	0.0229
Hispanic	(0.0060)	(0.0061)	(0.0125)	(0.0088)	(0.0059)
Zipcode: % age	-0.0508	-0.0398	-0.0913	-0.0389	-0.0698
under 18	(0.0136)	(0.0151)	(0.0240)	(0.0155)	(0.0161)
Zipcode: % age 65	0.0099	0.0162	-0.0307	0.0462	-0.0192
and over	(0.0205)	(0.0210)	(0.0491)	(0.0208)	(0.0274)
Zipcode: logged	0.0059	0.0034	0.0202	0.0086	0.0056
median hh income	(0.0038)	(0.0041)	(0.0082)	(0.0047)	(0.0032)
Zipcode: %	0.0157	0.0261	-0.0431	0.0148	0.0128
bachelor degree	(0.0126)	(0.0122)	(0.0204)	(0.0112)	(0.0138)
Zipcode: % rural	-0.0258	-0.0220	-0.0452	-0.0276	-0.0190
	(0.0056)	(0.0063)	(0.0085)	(0.0099)	(0.0072)
Zipcode: % foreign	0.0007	-0.0026	0.0205	0.0395	-0.0400
born	(0.0119)	(0.0129)	(0.0208)	(0.0116)	(0.0178)
# bar-months	422,651	341,964	80,687	197,255	225,396
# bars	8,995	7,283	1,712	4,449	4,546
R-squared	0.0168	0.0173	0.0164	0.0203	0.0149

Notes: Dependent variable is bar exit. Owner experience is a dummy variable indicating whether the owner owned any bar or restaurant in 3 years before opening the focal one. Regressions include year fixed effects, monthly dummies, and bar random effects. Clustered standard errors (at the county level) reported in parentheses.

Appendix Table 3: Full set of regression coefficients for Table 5

VARIABLES	(1) All	(2) Owner name not a business name	(3) Owner name is a business name	(4) Owner with single establishment	(5) Owner with multiple establishments
Transitory revenue	-0.0376	-0.0403	-0.0371	-0.0399	-0.0281
	(0.0020)	(0.0046)	(0.0018)	(0.0021)	(0.0031)
Persistent revenue	-0.0372	-0.0509	-0.0333	-0.0393	-0.0241
	(0.0023)	(0.0035)	(0.0020)	(0.0021)	(0.0041)
Experience	-0.0014	0.0074	-0.0034	-0.0070	0.0114
	(0.0023)	(0.0056)	(0.0019)	(0.0027)	(0.0031)
Distance to owner (000 miles)	0.0215	0.0242	0.0181	0.0278	0.0075
	(0.0052)	(0.0425)	(0.0056)	(0.0069)	(0.0062)
Owner with single establishment	0.0035	0.0166	0.0013		
	(0.0022)	(0.0071)	(0.0018)		
Owner name not a business name	-0.0046			-0.0050	-0.0076
	(0.0039)			(0.0044)	(0.0066)
Time since bar opened in years	0.0075	0.0111	0.0070	0.0082	0.0050
	(0.0003)	(0.0010)	(0.0003)	(0.0003)	(0.0005)
Time since bar opened in years squared	-0.0004	-0.0005	-0.0004	-0.0004	-0.0002
	(2.0e-05)	(0.0001)	(2.2e-05)	(2.9e-05)	(2.9e-05)
Likely lease renewal period	0.0041	0.0131	0.0026	0.0043	0.0030
	(0.0008)	(0.0026)	(0.0006)	(0.0009)	(0.0015)
Hurricane	-0.0016	-0.0005	-0.0016	-0.0015	-0.0015
	(0.0021)	(0.0068)	(0.0016)	(0.0024)	(0.0042)
Zipcode: # other bars	0.0001	0.0005	0.0001	8.1e-05	0.0002
	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Zipcode: pop. (millions)	0.0683	-0.0318	0.0577	0.0952	-0.0672
	(0.0426)	(0.1176)	(0.0442)	(0.0449)	(0.1060)
Zipcode: % black	-0.0137	-0.0037	-0.0145	-0.0144	-0.0056
	(0.0067)	(0.0247)	(0.0087)	(0.0082)	(0.0135)
Zipcode: % Hispanic	0.0135	0.0297	0.0117	0.0190	-0.0130
	(0.0060)	(0.0165)	(0.0069)	(0.0063)	(0.0078)
Zipcode: % age under 18	-0.0508	-0.0527	-0.0383	-0.0633	0.0105
	(0.0136)	(0.0648)	(0.0094)	(0.0161)	(0.0252)
Zipcode: % age 65 and over	0.0099	0.1591	-0.0070	0.0053	0.0560
	(0.0205)	(0.0960)	(0.0141)	(0.0220)	(0.0422)
Zipcode: logged median hh income	0.0059	0.0157	0.0045	0.0066	0.0019
	(0.0038)	(0.0198)	(0.0027)	(0.0044)	(0.0072)
Zipcode: % bachelor degree	0.0157	0.0737	0.0103	0.0218	-0.0133
	(0.0126)	(0.0429)	(0.0104)	(0.0128)	(0.0187)
Zipcode: % rural	-0.0258	-0.0093	-0.0272	-0.0262	-0.0175
	(0.0056)	(0.0157)	(0.0057)	(0.0060)	(0.0134)
Zipcode: % foreign born	0.0007	-0.0419	0.0112	-0.0082	0.0459
	(0.0119)	(0.0466)	(0.0133)	(0.0151)	(0.0250)
# bar-months	422,651	57,519	365,132	348,682	73,969
# bars	8,995	1,557	7,452	7,702	1,293
R-squared	0.0168	0.0156	0.0170	0.0183	0.0117

Notes: Dependent variable is bar exit. Owner experience is a dummy variable indicating whether the owner owned any bar or restaurant in 3 years before opening the focal one. Regressions include year fixed effects, monthly dummies, and bar random effects. Clustered standard errors (at the county level) reported in parentheses.

Appendix Table 4: Full set of regression coefficients for Table 6

VARIABLES	(1) All data	(2) Inexperienced only	(3) Experienced only	(4) Dist. to owner over 5 miles	(5) Dist. to owner under 5 miles
Transitory revenue	-0.0563	-0.0573	-0.0522	-0.0720	-0.0435
	(0.0034)	(0.0037)	(0.0043)	(0.0039)	(0.0037)
Transitory revenue × revenue volatility	0.0248	0.0260	0.0209	0.0369	0.0159
	(0.0028)	(0.0029)	(0.0057)	(0.0041)	(0.0034)
Persistent revenue	-0.0190	-0.0189	-0.0200	-0.0179	-0.0201
	(0.0020)	(0.0022)	(0.0023)	(0.0021)	(0.0025)
Persistent revenue × revenue volatility	-0.0054	-0.0054	-0.0025	-0.0044	-0.0059
	(0.0031)	(0.0036)	(0.0042)	(0.0032)	(0.0045)
Revenue volatility	0.0585	0.0588	0.0301	0.0508	0.0602
	(0.0296)	(0.0345)	(0.0414)	(0.0310)	(0.0449)
Experience	-0.0020			-0.0011	-0.0031
	(0.0013)			(0.0016)	(0.0018)
Distance to owner (000 miles)	0.0116	0.0130	0.0069	0.0060	1.8454
	(0.0026)	(0.0027)	(0.0048)	(0.0020)	(0.5040)
Owner with single establishment	0.0045	0.0109	-0.0034	0.0043	0.0085
	(0.0013)	(0.0019)	(0.0016)	(0.0013)	(0.0018)
Owner name not a business name	0.0004	0.0003	0.0008	0.0015	-0.0002
	(0.0026)	(0.0028)	(0.0030)	(0.0029)	(0.0029)
Time since bar opened in years	0.0062	0.0064	0.0052	0.0056	0.0064
	(0.0002)	(0.0002)	(0.0005)	(0.0003)	(0.0003)
Time since bar opened in years squared	-0.0003	-0.0003	-0.0002	-0.0003	-0.0003
	(1.5e-05)	(1.6e-05)	(2.5e-05)	(2.7e-05)	(1.7e-05)
Likely lease renewal period	0.0035	0.0049	-0.0019	0.0043	0.0027
	(0.0008)	(0.0009)	(0.0010)	(0.0011)	(0.0009)
Hurricane	-0.0004	-3.0e-05	-0.0019	-0.0023	0.0011
	(0.0020)	(0.0024)	(0.0031)	(0.0030)	(0.0023)
Zipcode: # other bars	4.5e-05	3.7e-05	0.0001	6.8e-05	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Zipcode: pop. (millions)	0.0359	0.0401	0.0079	0.0211	0.0601
	(0.0302)	(0.0391)	(0.0939)	(0.0423)	(0.0499)
Zipcode: % black	-0.0061	-0.0036	-0.0120	-0.0037	-0.0082
	(0.0047)	(0.0053)	(0.0072)	(0.0053)	(0.0069)
Zipcode: % Hispanic	0.0087	0.0111	0.0009	0.0029	0.0162
	(0.0038)	(0.0038)	(0.0067)	(0.0047)	(0.0043)
Zipcode: % age under 18	-0.0167	-0.0129	-0.0301	-0.0121	-0.0310
	(0.0093)	(0.0106)	(0.0126)	(0.0103)	(0.0116)
Zipcode: % age 65 and over	0.0048	0.0113	-0.0227	0.0283	-0.0141
	(0.0099)	(0.0106)	(0.0202)	(0.0126)	(0.0148)
Zipcode: logged median hh income	0.0029	0.0016	0.0092	0.0039	0.0033
	(0.0018)	(0.0020)	(0.0032)	(0.0026)	(0.0017)
Zipcode: % bachelor degree	0.0128	0.0179	-0.0078	0.0108	0.0126
	(0.0058)	(0.0065)	(0.0056)	(0.0067)	(0.0064)
Zipcode: % rural	-0.0128	-0.0120	-0.0169	-0.0137	-0.0091
	(0.0035)	(0.0043)	(0.0072)	(0.0053)	(0.0047)
Zipcode: % foreign born	0.0063	0.0050	0.0097	0.0291	-0.0199
	(0.0076)	(0.0081)	(0.0110)	(0.0060)	(0.0123)
# bar-months	422,530	341,869	80,661	197,190	225,340
# bars	8,874	7,188	1,686	4,384	4,490
R-squared	0.0227	0.0229	0.0234	0.0304	0.0183

Notes: Dependent variable is bar exit. Owner experience is a dummy variable indicating whether the owner owned any bar or restaurant in 3 years before opening the focal one. Revenue volatility is the standard deviation of log(monthly alcohol revenue) within an establishment. Regressions include year fixed effects, monthly dummies, and bar random effects. Clustered standard errors (at the county level) reported in parentheses.

Appendix Table 5 a): Full Structural Results for Table 7, column 1

Parameters in the revenue equation: weather shocks		**Parameters in the revenue equation: controls**		**Parameters in the belief equation**	
Quarter 1 shocks: Heat	0.0020 (0.0004)	Hurricane	-0.0421 (0.0060)	Hurricane	-0.0468 (0.3992)
Precipitation	0.0904 (0.0306)	Years since bar opened	-0.0091 (0.0002)	Years since bar opened	-0.0003 (0.0324)
Days unfavorable	-0.0024 (0.0004)	Years since bar opened, squared	-0.0003 (0.0001)	Years since bar opened, squared	-0.0087 (0.0033)
Quarter 2 shocks: Heat	-0.0005 (0.0006)	Likely lease renewal period	-0.0001 (0.0028)	Likely lease renewal period	0.0157 (0.6300)
Precipitation	0.0697 (0.0195)	Zipcode: # other bars	0.0022 (0.0001)	Zipcode: # other bars	0.0027 (0.0012)
Days unfavorable	0.0013 (0.0004)	Zipcode: population (millions)	0.0589 (0.0937)	Zipcode: population (millions)	-0.0434 (0.8325)
Quarter 3 shocks: Heat	0.0007 (0.0006)	Zipcode: % black	-0.4911 (0.0191)	Zipcode: % black	-0.0268 (0.1246)
Precipitation	-0.1125 (0.0178)	Zipcode: % Hispanic	-0.4360 (0.0144)	Zipcode: % Hispanic	0.0004 (0.0988)
Days unfavorable	0.0028 (0.0004)	Zipcode: % age under 18	-0.3640 (0.0262)	Zipcode: % age under 18	0.0076 (0.2833)
Quarter 4 shocks: Heat	0.0002 (0.0005)	Zipcode; % age 65 and over	3.2715 (0.0319)	Zipcode; % age 65 and over	0.0002 (0.3113)
Precipitation	0.0453 (0.0220)	Zipcode logged avg. hh income (000s)	0.1148 (0.0045)	Zipcode logged avg. hh income (000s)	-0.0002 (0.0567)
Days unfavorable	-0.0012 (0.0004)	Zipcode; % bachelor degree	0.0206 (0.0097)	Zipcode; % bachelor degree	0.1659 (0.1503)
		Zipcode: % rural	-0.6484 (0.0085)	Zipcode: % rural	-0.0016 (0.0951)
		Zipcode: % foreign born	-0.8656 (0.0212)	Zipcode: % foreign born	0.8263 (0.1540)
		Quarter 2 dummy	-0.0101 (0.0017)	Quarter 2 dummy	0.1704 (0.1705)
		Quarter 3 dummy	-0.0198 (0.0014)	Quarter 3 dummy	-0.0001 (0.1323)
		Quarter 4 dummy	-0.0137 (0.0018)	Quarter 4 dummy	0.3390 (0.1573)
				Single establishment dummy	-0.0010 (0.0348)
				Taxpayer not a business name	0.0018 (0.0330)
Parameters in the thinking cost function				Constant	0.1080 (0.6144)
κ_1 : owner experience	-4.4550 (1.5644)			σ_r : std. dev. of profit signals	0.4720 (0.0001)
κ_2 : distance to owner over 5 miles				β^R: log revenue scale parameter	0.4661 (0.0090)
Log Likelihood	-312,512.6			*N = 422,651*	

Appendix Table 5 b): Full Structural Results for Table 7, column 2

Parameters in the revenue equation: weather shocks		**Parameters in the revenue equation: controls**		**Parameters in the belief equation**	
Quarter 1 shocks: Heat	0.0020 (0.0004)	Hurricane	-0.0414 (0.0060)	Hurricane	-0.0457 (0.3991)
Precipitation	0.0880 (0.0306)	Years since bar opened	-0.0090 (0.0002)	Years since bar opened	-0.0003 (0.0325)
Days unfavorable	-0.0025 (0.0004)	Years since bar opened, squared	-0.0003 (0.0001)	Years since bar opened, squared	-0.0088 (0.0034)
Quarter 2 shocks: Heat	-0.0005 (0.0006)	Likely lease renewal period	-0.0001 (0.0028)	Likely lease renewal period	0.0157 (0.6306)
Precipitation	0.0702 (0.0195)	Zipcode: # other bars	0.0022 (0.0001)	Zipcode: # other bars	0.0027 (0.0012)
Days unfavorable	0.0013 (0.0004)	Zipcode: population (millions)	0.0585 (0.1007)	Zipcode: population (millions)	-0.0437 (0.8323)
Quarter 3 shocks: Heat	0.0007 (0.0006)	Zipcode: % black	-0.4941 (0.0191)	Zipcode: % black	-0.0269 (0.1247)
Precipitation	-0.1128 (0.0178)	Zipcode: % Hispanic	-0.4371 (0.0146)	Zipcode: % Hispanic	0.0004 (0.0987)
Days unfavorable	0.0028 (0.0004)	Zipcode: % age under 18	-0.3653 (0.0265)	Zipcode: % age under 18	0.0076 (0.2839)
Quarter 4 shocks: Heat	0.0002 (0.0005)	Zipcode; % age 65 and over	3.2612 (0.0320)	Zipcode; % age 65 and over	0.0002 (0.3113)
Precipitation	0.0475 (0.0220)	Zipcode logged avg. hh income (000s)	0.1155 (0.0045)	Zipcode logged avg. hh income (000s)	-0.0002 (0.0568)
Days unfavorable	-0.0013 (0.0004)	Zipcode; % bachelor degree	0.0203 (0.0099)	Zipcode; % bachelor degree	0.1672 (0.1503)
		Zipcode: % rural	-0.6484 (0.0085)	Zipcode: % rural	-0.0016 (0.0952)
		Zipcode: % foreign born	-0.8639 (0.0214)	Zipcode: % foreign born	0.8244 (0.1537)
		Quarter 2 dummy	-0.0101 (0.0017)	Quarter 2 dummy	0.1697 (0.1706)
		Quarter 3 dummy	-0.0197 (0.0014)	Quarter 3 dummy	-0.0001 (0.1322)
		Quarter 4 dummy	-0.0137 (0.0018)	Quarter 4 dummy	0.3366 (0.1573)
				Single establishment dummy	-0.0010 (0.0348)
				Taxpayer not a business name	0.0018 (0.0330)
Parameters in the thinking cost function				Constant	0.1078 (0.6144)
κ_1 : owner experience	-4.4000 (0.2400)			σ_r : std. dev. of profit signals	0.4719 (0.0001)
κ_2 : distance to owner over 5 miles	0.5750 (0.3022)			β^R: log revenue scale parameter	0.4659 (0.0092)
Log Likelihood	-312,511.7			*N = 422,651*	

Appendix Table 5 c): Full Structural Results for Table 7, column 3

Parameters in the revenue equation: weather shocks		**Parameters in the revenue equation: controls**		**Parameters in the belief equation**	
Quarter 1 shocks: Heat	0.0020 (0.0004)	Hurricane	-0.0415 (0.0060)	Hurricane	-0.0448 (0.3978)
Precipitation	0.0890 (0.0306)	Years since bar opened	-0.0089 (0.0002)	Years since bar opened	-0.0003 (0.0324)
Days unfavorable	-0.0025 (0.0004)	Years since bar opened, squared	-0.0003 (0.0001)	Years since bar opened, squared	-0.0087 (0.0033)
Quarter 2 shocks: Heat	-0.0005 (0.0006)	Likely lease renewal period	-0.0001 (0.0028)	Likely lease renewal period	0.0158 (0.6304)
Precipitation	0.0708 (0.0195)	Zipcode: # other bars	0.0022 (0.0001)	Zipcode: # other bars	0.0027 (0.0012)
Days unfavorable	0.0013 (0.0004)	Zipcode: population (millions)	0.0573 (0.0938)	Zipcode: population (millions)	-0.0443 (0.8330)
Quarter 3 shocks: Heat	0.0007 (0.0006)	Zipcode: % black	-0.4932 (0.0191)	Zipcode: % black	-0.0266 (0.1244)
Precipitation	-0.1124 (0.0177)	Zipcode: % Hispanic	-0.4352 (0.0144)	Zipcode: % Hispanic	0.0004 (0.0986)
Days unfavorable	0.0028 (0.0004)	Zipcode: % age under 18	-0.3693 (0.0262)	Zipcode: % age under 18	0.0076 (0.2838)
Quarter 4 shocks: Heat	0.0002 (0.0005)	Zipcode; % age 65 and over	3.2690 (0.0319)	Zipcode; % age 65 and over	0.0002 (0.3107)
Precipitation	0.0465 (0.0220)	Zipcode logged avg. hh income (000s)	0.1155 (0.0045)	Zipcode logged avg. hh income (000s)	-0.0002 (0.0567)
Days unfavorable	-0.0012 (0.0004)	Zipcode; % bachelor degree	0.0202 (0.0097)	Zipcode; % bachelor degree	0.1673 (0.1500)
		Zipcode: % rural	-0.6472 (0.0085)	Zipcode: % rural	-0.0016 (0.0950)
		Zipcode: % foreign born	-0.8537 (0.0212)	Zipcode: % foreign born	0.8260 (0.1539)
		Quarter 2 dummy	-0.0101 (0.0017)	Quarter 2 dummy	0.1681 (0.1704)
		Quarter 3 dummy	-0.0197 (0.0014)	Quarter 3 dummy	-0.0001 (0.1323)
		Quarter 4 dummy	-0.0136 (0.0018)	Quarter 4 dummy	0.3342 (0.1573)
				Single establishment dummy	-0.0010 (0.0347)
				Taxpayer not a business name	0.0018 (0.0329)
Parameters in the thinking cost function				Constant	0.1075 (0.6141)
κ_1 : owner experience	-0.5000 (0.1533)			σ_r : std. dev. of profit signals	0.4720 (0.0001)
κ_2 : distance to owner over 5 miles				β^R: log revenue scale parameter	0.4661 (0.0090)
Log Likelihood	-312,515.3			*N = 422,651*	

Appendix Table 5 d): Full Structural Results for Table 7, column 4

Parameters in the revenue equation: weather shocks		**Parameters in the revenue equation: controls**		**Parameters in the belief equation**	
Quarter 1 shocks: Heat	0.0020 (0.0004)	Hurricane	-0.0417 (0.0061)	Hurricane	-0.0449 (0.3982)
Precipitation	0.0876 (0.0306)	Years since bar opened	-0.0089 (0.0002)	Years since bar opened	-0.0003 (0.0325)
Days unfavorable	-0.0025 (0.0004)	Years since bar opened, squared	-0.0003 (0.0001)	Years since bar opened, squared	-0.0088 (0.0034)
Quarter 2 shocks: Heat	-0.0005 (0.0006)	Likely lease renewal period	-0.0001 (0.0028)	Likely lease renewal period	0.0159 (0.6309)
Precipitation	0.0710 (0.0195)	Zipcode: # other bars	0.0022 (0.0001)	Zipcode: # other bars	0.0027 (0.0012)
Days unfavorable	0.0013 (0.0004)	Zipcode: population (millions)	0.0580 (0.1001)	Zipcode: population (millions)	-0.0444 (0.8339)
Quarter 3 shocks: Heat	0.0007 (0.0006)	Zipcode: % black	-0.4959 (0.0191)	Zipcode: % black	-0.0269 (0.1247)
Precipitation	-0.1123 (0.0178)	Zipcode: % Hispanic	-0.4339 (0.0146)	Zipcode: % Hispanic	0.0004 (0.0987)
Days unfavorable	0.0028 (0.0004)	Zipcode: % age under 18	-0.3747 (0.0265)	Zipcode: % age under 18	0.0077 (0.2844)
Quarter 4 shocks: Heat	0.0002 (0.0005)	Zipcode; % age 65 and over	3.2681 (0.0320)	Zipcode; % age 65 and over	0.0002 (0.3113)
Precipitation	0.0467 (0.0220)	Zipcode logged avg. hh income (000s)	0.1161 (0.0045)	Zipcode logged avg. hh income (000s)	-0.0002 (0.0568)
Days unfavorable	-0.0012 (0.0004)	Zipcode; % bachelor degree	0.0203 (0.0099)	Zipcode; % bachelor degree	0.1619 (0.1502)
		Zipcode: % rural	-0.6481 (0.0085)	Zipcode: % rural	-0.0016 (0.0951)
		Zipcode: % foreign born	-0.8534 (0.0214)	Zipcode: % foreign born	0.8195 (0.1540)
		Quarter 2 dummy	-0.0101 (0.0017)	Quarter 2 dummy	0.1681 (0.1705)
		Quarter 3 dummy	-0.0197 (0.0014)	Quarter 3 dummy	-0.0001 (0.1323)
		Quarter 4 dummy	-0.0137 (0.0018)	Quarter 4 dummy	0.3326 (0.1574)
				Single establishment dummy	-0.0010 (0.0348)
				Taxpayer not a business name	0.0018 (0.0331)
Parameters in the thinking cost function				Constant	0.1073 (0.6149)
κ_1 : owner experience	-0.7011 (0.1657)			σ_r : std. dev. of profit signals	0.4720 (0.0001)
κ_2 : distance to owner over 5 miles	0.4556 (0.2879)			β^R: log revenue scale parameter	0.4658 (0.0093)
Log Likelihood	-312,514.3			*N = 422,651*	

Appendix B

Tables 6-11

Robustness of motivating results to alternative specifications

Appendix Table 6: Quarterly by experience for Table 3

VARIABLES	(1) Inexperienced, Jan-Mar	(2) Inexperienced, Apr-June	(3) Inexperienced, July-Sept	(4) Inexperienced, Oct-Dec	(5) Experienced, Jan-Mar	(6) Experienced, Apr-June	(7) Experienced, July-Sept	(8) Experienced, Oct-Dec
Heat shocks	0.0014	0.0006	0.0020	-0.0010	0.0025	0.0034	-0.0009	-0.0001
	(0.0005)	(0.0008)	(0.0012)	(0.0006)	(0.0011)	(0.0012)	(0.0018)	(0.0012)
Precipitation shocks	0.0235	0.0632	-0.1094	0.0398	0.0805	0.0808	-0.1142	0.0756
	(0.0318)	(0.0188)	(0.0270)	(0.0288)	(0.1028)	(0.0527)	(0.0331)	(0.0768)
Days with unfavorable	-0.0016	0.0006	0.0026	-0.0008	-0.0021	0.0013	-0.0002	-0.0009
shocks	(0.0009)	(0.0008)	(0.0015)	(0.0006)	(0.0016)	(0.0011)	(0.0017)	(0.0012)
Time since bar/rest.	0.0799	0.1065	0.0725	0.0297	-0.1086	0.0162	-0.0050	0.0167
opened in years	(0.0666)	(0.0600)	(0.0571)	(0.0593)	(0.1040)	(0.0554)	(0.0850)	(0.0648)
Time since bar/rest.	-0.0006	-0.0005	-0.0004	-0.0007	0.0006	0.0007	0.0006	0.0004
opened in years squared	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Likely lease renewal	0.0313	0.0237	0.0293	0.0377	0.0242	0.0328	0.0475	0.0092
period	(0.0063)	(0.0056)	(0.0085)	(0.0066)	(0.0150)	(0.0120)	(0.0148)	(0.0118)
Hurricane		0.0497	-0.0798	0.0071		-0.0727	-0.0257	0.0188
		(0.0518)	(0.0263)	(0.0179)		(0.0331)	(0.0390)	(0.0601)
Zipcode: # other bars	0.0037	0.0012	0.0002	0.0009	0.0027	-0.0009	-0.0033	-0.0022
	(0.0023)	(0.0015)	(0.0017)	(0.0014)	(0.0018)	(0.0028)	(0.0034)	(0.0033)
Zipcode: pop. (millions)	12.0964	8.9788	10.1982	7.8970	-1.1677	-6.2431	-9.8159	-3.1634
	(8.7898)	(9.2593)	(9.0907)	(8.3303)	(8.5696)	(9.2509)	(8.3486)	(5.2523)
Zipcode: % black	-0.8188	-0.3825	-0.7897	-0.3944	-1.6392	-1.7683	-2.2302	-2.4199
	(1.0020)	(1.2030)	(1.3465)	(1.0369)	(0.9135)	(1.1819)	(1.1076)	(1.0284)
Zipcode: % Hispanic	0.0373	0.1736	0.1165	0.2490	3.1783	3.3809	3.4076	2.0997
	(0.9100)	(0.9213)	(0.9416)	(0.9824)	(1.0096)	(0.9731)	(1.1807)	(1.1206)
Zipcode: % age under	-0.7663	-1.7681	-1.1978	-0.8195	-4.1227	-4.0657	-3.6509	-4.1692
18	(2.3762)	(2.2965)	(2.4502)	(2.1989)	(1.8700)	(2.9720)	(2.7077)	(2.6855)
Zipcode: % age 65 and	4.0076	4.0990	2.7487	2.7760	-1.7433	0.6251	-0.9394	-2.5058
over	(2.1414)	(1.7150)	(1.5657)	(1.5694)	(2.0413)	(2.4217)	(2.3365)	(2.4447)
Zipcode: logged median	-0.1684	-0.1526	-0.3930	-0.4277	0.7617	1.3663	1.2628	0.9266
hh income	(0.2756)	(0.3720)	(0.3354)	(0.2925)	(0.4190)	(0.4033)	(0.3066)	(0.4131)
Zipcode: % bachelor	0.9397	1.1876	1.3908	1.4099	-0.3479	-1.1337	0.0658	-1.3823
degree	(0.5958)	(0.6566)	(0.6155)	(0.5615)	(1.5179)	(1.6096)	(0.6396)	(1.7170)
Zipcode: % rural	-0.7522	-0.1279	-0.1530	-0.3822	-1.6597	-1.4364	-1.4590	-2.2312
	(0.3275)	(0.2105)	(0.2229)	(0.2179)	(0.4094)	(0.3641)	(0.4072)	(0.5464)
Zipcode: % foreign born	-0.9811	-1.5308	-2.0902	-1.4790	-2.2838	-2.8758	-2.1939	-1.0976
	(0.7398)	(0.7097)	(0.8959)	(0.8398)	(0.8708)	(0.7623)	(0.8219)	(1.1722)
# bar-months	83,303	85,977	87,670	85,014	20,069	20,539	20,680	19,399
# bars	6,645	6,825	6,910	6,966	1,585	1,611	1,639	1,614
R-squared	0.872	0.873	0.869	0.869	0.869	0.880	0.870	0.874

Notes: Dependent variable is log(monthly alcohol revenue). Regressions include year fixed effects, monthly dummies, and bar fixed effects. Clustered standard errors (at the county level) reported in parentheses. R^2 measure includes all fixed effects.

Appendix Table 7: Quarterly by distance for Table 3

VARIABLES	(1) Distance to owner over 5 miles, Jan-Mar	(2) Distance to owner over 5 miles, Apr-June	(3) Distance to owner over 5 miles, July-Sept	(4) Distance to owner over 5 miles, Oct-Dec	(5) Distance to owner under 5 miles, Jan-Mar	(6) Distance to owner under 5 miles, Apr-June	(7) Distance to owner under 5 miles, July-Sept	(8) Distance to owner under 5 miles, Oct-Dec
Heat shocks	0.0007	0.0021	0.0026	4.8e-05	0.0025	0.0003	0.0006	-0.0015
	(0.0005)	(0.0011)	(0.0015)	(0.0008)	(0.0007)	(0.0008)	(0.0017)	(0.0006)
Precipitation shocks	0.0715	0.0724	-0.1092	0.0551	-0.0054	0.0599	-0.1173	0.0367
	(0.0455)	(0.0291)	(0.0411)	(0.0447)	(0.0349)	(0.0298)	(0.0192)	(0.0354)
Days with unfavorable shocks	-0.0018	0.0004	0.0019	-0.0018	-0.0015	0.0011	0.0027	0.0001
	(0.0012)	(0.0011)	(0.0014)	(0.0008)	(0.0009)	(0.0007)	(0.0016)	(0.0008)
Time since bar/rest. opened in years	0.1029	0.2367	0.1282	0.1519	0.0265	-0.0065	0.0165	-0.0680
	(0.0568)	(0.0584)	(0.0727)	(0.0739)	(0.0823)	(0.0748)	(0.0647)	(0.0596)
Time since bar/rest. opened in years squared	0.0006	0.0005	0.0008	0.0003	-0.0012	-0.0009	-0.0010	-0.0011
	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Likely lease renewal period	0.0334	0.0382	0.0261	0.0262	0.0280	0.0178	0.0360	0.0348
	(0.0101)	(0.0095)	(0.0102)	(0.0068)	(0.0077)	(0.0072)	(0.0081)	(0.0077)
Hurricane		-0.0432	-0.0725	-0.0197		0.1202	-0.0664	0.0362
		(0.0689)	(0.0275)	(0.0219)		(0.0591)	(0.0282)	(0.0161)
Zipcode: # other bars	0.0027	0.0011	-0.0014	-0.0006	0.0035	-1.1e-05	-0.0005	0.0003
	(0.0030)	(0.0028)	(0.0022)	(0.0027)	(0.0017)	(0.0013)	(0.0015)	(0.0012)
Zipcode: pop. (millions)	15.5960	12.3263	12.4924	8.7524	3.1942	-0.4766	0.5577	2.9182
	(6.3941)	(7.5665)	(6.6438)	(7.0163)	(13.1102)	(14.0468)	(12.0671)	(10.6671)
Zipcode: % black	-2.5130	-1.5591	-2.2120	-1.5197	0.7143	0.6957	0.5890	0.3335
	(1.1323)	(1.0860)	(1.5160)	(1.3399)	(1.4673)	(1.4558)	(1.2839)	(1.3522)
Zipcode: % Hispanic	1.1658	1.8868	1.4494	1.4712	-0.1901	-0.3604	-0.2164	-0.3162
	(0.8718)	(0.7818)	(0.9804)	(0.9747)	(0.8978)	(0.9122)	(0.9615)	(0.9816)
Zipcode: % age under 18	1.4599	0.0874	0.6176	0.4152	-3.8673	-4.0841	-3.6097	-2.9209
	(2.0046)	(1.9553)	(2.3449)	(1.9247)	(2.3764)	(2.4800)	(2.2279)	(2.3425)
Zipcode: % age 65 and over	6.3375	6.8497	4.7581	4.3497	0.4385	0.7248	-0.1017	0.0179
	(2.7208)	(2.4558)	(2.3581)	(2.2898)	(1.6512)	(1.5137)	(1.1252)	(1.3401)
Zipcode: logged median hh income	0.1016	0.2359	-0.1745	-0.1965	-0.1638	-0.0927	-0.1402	-0.3170
	(0.2968)	(0.3010)	(0.2871)	(0.2513)	(0.2935)	(0.3980)	(0.3609)	(0.3198)
Zipcode: % bachelor degree	0.6261	0.8476	1.2432	1.4003	0.7231	0.9107	1.0349	0.7818
	(0.6715)	(0.7063)	(0.7086)	(0.7563)	(0.7859)	(0.9470)	(0.7471)	(0.7370)
Zipcode: % rural	-1.6205	-1.1238	-1.1503	-1.4396	-0.4781	-0.1067	-0.0301	-0.4704
	(0.3762)	(0.4096)	(0.3689)	(0.7187)	(0.2415)	(0.2417)	(0.2441)	(0.2168)
Zipcode: % foreign born	-1.1664	-2.6816	-2.8356	-1.2806	-0.5014	-0.4674	-0.8375	-0.9485
	(1.2005)	(1.1052)	(1.3671)	(0.9092)	(1.4406)	(1.5214)	(1.2852)	(1.4662)
# bar-months	48,338	49,769	50,394	48,754	55,034	56,747	57,956	55,659
# bars	4,038	4,146	4,198	4,228	4,192	4,290	4,351	4,352
R-squared	0.883	0.883	0.878	0.878	0.860	0.866	0.860	0.861

Notes: Dependent variable is log(monthly alcohol revenue). Regressions include year fixed effects, monthly dummies, and bar fixed effects. Clustered standard errors (at the county level) reported in parentheses. R^2 measure includes all fixed effects.

Appendix Table 8: Additional robustness for Table 3, all years together

VARIABLES	(1) Single establishment	(2) Drop extreme weather	(3) Spline for heat	(4) Driscoll-Kraay std errors[22]	(5) Random effects	(6) Restaurants
Heat shocks	0.0007	0.0001		0.0007	0.0007	0.0010
	(0.0004)	(0.0003)		(0.0002)	(0.0003)	(0.0003)
Precipitation shocks	0.0005	0.0311	-0.0111	-0.0109	-0.0140	0.0050
	(0.0258)	(0.0245)	(0.0243)	(0.0115)	(0.0229)	(0.0200)
Days with unfavorable shocks	-0.0003	-0.0012	-0.0002	-0.0001	-0.0001	-0.0008
	(0.0007)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0003)
Heat shocks 45-49'F			-0.0059			
			(0.0073)			
Heat shocks 50-54'F			-0.0056			
			(0.0129)			
Heat shocks 55-59'F			-0.0056			
			(0.0142)			
Heat shocks 60-64'F			-0.0069			
			(0.0148)			
Heat shocks 65-69'F			-0.0074			
			(0.0188)			
Heat shocks 70-74'F			-0.0116			
			(0.0184)			
Heat shocks 75-79'F			-0.0214			
			(0.0214)			
Heat shocks 80-84'F			-0.0082			
			(0.0221)			
Heat shocks 85-90'F			-0.0122			
			(0.0240)			
Heat shocks over 90'F			-0.0058			
			(0.0219)			
Experience (owned rest. or bar, 3 years before open					-0.0726	
					(0.0345)	
Owner with single establishment					-0.3563	
					(0.0349)	
Owner name is not a business name					-0.6274	
					(0.2064)	
Time since bar opened in years	0.0634	0.0780	0.0537	0.0537	0.0095	-0.0036
	(0.0532)	(0.0471)	(0.0506)	(0.0211)	(0.0074)	(0.0472)
Time since bar opened in years squared	-0.0006	-0.0002	-0.0003	-0.0003	-0.0003	-0.0007
	(0.0005)	(0.0004)	(0.0004)	(0.0001)	(0.0004)	(0.0003)
Likely lease renewal period	0.0022	0.0064	0.0045	0.0045	0.0048	0.0010
	(0.0024)	(0.0031)	(0.0024)	(0.0006)	(0.0024)	(0.0021)
Hurricane	-0.0533	-0.0418	-0.0521	-0.0497	-0.0501	-0.0308
	(0.0153)	(0.0352)	(0.0168)	(0.0233)	(0.0158)	(0.0091)
Zipcode: # other bars (restaurants in col. 6)	0.0013	0.0006	0.0012	0.0012	-0.0003	-0.0029
	(0.0010)	(0.0014)	(0.0012)	(0.0007)	(0.0009)	(0.0013)
Zipcode: pop. (millions)	1.6138	6.5691	6.3142	6.3044	4.9032	2.0815
	(7.6721)	(7.1971)	(7.4738)	(1.2323)	(3.4198)	(2.4140)
Zipcode: % black	0.7255	-0.7603	-0.5136	-0.5118	-0.3950	-1.8104
	(1.0460)	(0.9508)	(0.9770)	(0.2254)	(0.2997)	(0.5929)
Zipcode: % Hispanic	1.0747	0.8436	0.7201	0.7190	0.1792	0.4754
	(0.9429)	(0.7318)	(0.7329)	(0.3218)	(0.2809)	(0.5757)
Zipcode: % age under 18	-3.8872	-2.1482	-1.8928	-1.8857	-2.0724	-1.6495
	(2.3135)	(1.8612)	(1.8587)	(0.3506)	(0.7183)	(0.8950)
Zipcode: % age 65 and over	2.6188	3.0264	2.8583	2.8606	1.4799	-1.8547
	(1.8895)	(1.4408)	(1.4323)	(0.4911)	(0.9236)	(1.1280)
Zipcode: logged median hh income	-0.0907	-0.0310	-0.0457	-0.0454	0.0478	0.0335
	(0.4427)	(0.2835)	(0.2830)	(0.0433)	(0.1753)	(0.2074)
Zipcode: % bachelor degree	1.3559	1.0115	0.9647	0.9663	0.9668	-0.2329
	(0.5906)	(0.5798)	(0.5489)	(0.1159)	(0.3835)	(0.3843)
Zipcode: % rural	-0.7812	-0.6683	-0.6422	-0.6426	-0.5912	0.1427
	(0.1999)	(0.1528)	(0.1564)	(0.0479)	(0.1081)	(0.2448)
Zipcode: % foreign born	-1.4564	-1.8597	-1.7389	-1.7384	-1.2364	-1.0046
	(0.8153)	(0.6337)	(0.6161)	(0.2616)	(0.3584)	(0.6616)
# estab.-months	348,682	315,174	422,651	422,651	422,651	725,056
# estab.	7,702	8,908	8,995	8,995	8,995	13,999
R-squared	0.853	0.854	0.853	0.853	0.154	0.913

Notes: Dependent variable is log(monthly alcohol revenue). Regressions include year fixed effects, monthly dummies, and bar fixed effects. Clustered standard errors (at the county level) reported in parentheses. R^2 measure includes all fixed effects.

[22] Driscoll and Kraay (1998) propose a nonparametric covariance matrix estimator which produces heteroscedasticity consistent standard errors that are robust to very general forms of spatial and temporal dependence.

Appendix Table 9: Robustness of Columns 2 and 3 of Table 4

VARIABLES	(1) Single estab., Inexperienced	(2) Single estab., Experienced	(3) No extreme weather, Inexperienced	(4) No extreme weather, Experienced	(5) Spline for heat, Inexperienced	(6) Spline for heat, Experienced	(7) Ideal heat is 72'F, Inexperienced	(8) Ideal heat is 72'F, Experienced	(9) Random effects,, Inexperienced	(10) Random effects,, Experienced
Transitory revenue	-0.0401	-0.0396	-0.0376	-0.0334	-0.0383	-0.0349	-0.0383	-0.0349	-0.0391	-0.0356
	(0.0022)	(0.0022)	(0.0022)	(0.0036)	(0.0020)	(0.0034)	(0.0020)	(0.0034)	(0.0021)	(0.0036)
Persistent revenue	-0.0375	-0.0435	-0.0375	-0.0385	-0.0358	-0.0383	-0.0358	-0.0383	-0.0324	-0.0355
	(0.0020)	(0.0047)	(0.0018)	(0.0042)	(0.0021)	(0.0050)	(0.0021)	(0.0049)	(0.0019)	(0.0044)
Distance to owner	0.0207	0.0950	0.0123	-0.0070	0.0177	0.0299	0.0177	0.0299	0.0168	0.0279
(000 miles)	(0.0048)	(0.0254)	(0.0027)	(0.0041)	(0.0036)	(0.0118)	(0.0036)	(0.0118)	(0.0034)	(0.0112)
Owner with single			-0.0070	0.0033	0.0126	-0.0069	0.0126	-0.0069	0.0130	-0.0060
establishment			(0.0036)	(0.0059)	(0.0027)	(0.0040)	(0.0027)	(0.0040)	(0.0026)	(0.0037)
Owner name is not a	-0.0062	0.0127	0.0181	0.0300	-0.0054	0.0036	-0.0054	0.0036	-0.0031	0.0053
business name	(0.0041)	(0.0082)	(0.0037)	(0.0122)	(0.0038)	(0.0063)	(0.0038)	(0.0062)	(0.0036)	(0.0059)
Time since bar opened	0.0083	0.0062	0.0077	0.0063	0.0077	0.0063	0.0077	0.0063	0.0075	0.0063
in years	(0.0003)	(0.0009)	(0.0003)	(0.0006)	(0.0003)	(0.0006)	(0.0003)	(0.0006)	(0.0003)	(0.0006)
Time since bar opened	-0.0004	-0.0003	-0.0004	-0.0003	-0.0004	-0.0003	-0.0004	-0.0003	-0.0004	-0.0003
in years squared	(3.6e-05)	(0.0001)	(3.0e-05)	(2.0e-05)	(2.0e-5)	(3.1e-5)	(2.0e-05)	(3.1e-05)	(3.1e-05)	(2.0e-05)
Likely lease renewal	0.0057	-0.0046	0.0055	-0.0011	0.0054	-0.0011	0.0055	-0.0011	0.0054	-0.0012
period	(0.0011)	(0.0019)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Hurricane	-0.0016	0.0006	-0.0013	-0.0027	-0.0012	-0.0027	-0.0012	-0.0027	-0.0010	-0.0026
	(0.0027)	(0.0057)	(0.0025)	(0.0032)	(0.0024)	(0.0032)	(0.0024)	(0.0032)	(0.0024)	(0.0032)
Zipcode: # other bars	-4.7e-07	0.0001	2.3e-05	0.0002	3.6e-5	0.0002	3.6e-05	0.0002	4.0e-05	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Zipcode: pop.	0.0460	0.5398	0.0568	0.1005	0.0506	0.1006	0.0507	0.1006	0.0430	0.0994
(millions)	(0.0505)	(0.1739)	(0.0573)	(0.1233)	(0.0562)	(0.1228)	(0.0562)	(0.1228)	(0.0537)	(0.1220)
Zipcode: % black	-0.0088	-0.0592	-0.0092	-0.0401	-0.0080	-0.0399	-0.0080	-0.0399	-0.0052	-0.0356
	(0.0086)	(0.0208)	(0.0074)	(0.0128)	(0.0072)	(0.0135)	(0.0072)	(0.0134)	(0.0068)	(0.0127)
Zipcode: % Hispanic	0.0196	0.0036	0.0176	-0.0015	0.0173	-0.0015	0.0173	-0.0015	0.0169	-0.0010
	(0.0056)	(0.0242)	(0.0061)	(0.0126)	(0.0061)	(0.0126)	(0.0061)	(0.0126)	(0.0058)	(0.0119)
Zipcode: % age under	-0.0467	-0.1848	-0.0428	-0.0923	-0.0397	-0.0918	-0.0398	-0.0917	-0.0334	-0.0829
18	(0.0154)	(0.0526)	(0.0156)	(0.0232)	(0.0151)	(0.0241)	(0.0151)	(0.0240)	(0.0143)	(0.0230)
Zipcode: % age 65 and	0.0135	-0.0742	0.0160	-0.0312	0.0162	-0.0308	0.0162	-0.0308	0.0178	-0.0266
over	(0.0214)	(0.0535)	(0.0214)	(0.0506)	(0.0210)	(0.0492)	(0.0210)	(0.0492)	(0.0196)	(0.0472)
Zipcode: logged	0.0049	0.0205	0.0035	0.0204	0.0034	0.0203	0.0034	0.0203	0.0032	0.0186
median hh income	(0.0040)	(0.0121)	(0.0042)	(0.0080)	(0.0041)	(0.0083)	(0.0041)	(0.0083)	(0.0039)	(0.0075)
Zipcode: % bachelor	0.0260	-0.0294	0.0282	-0.0435	0.0261	-0.0436	0.0261	-0.0435	0.0231	-0.0398
degree	(0.0131)	(0.0246)	(0.0122)	(0.0206)	(0.0122)	(0.0206)	(0.0122)	(0.0206)	(0.0115)	(0.0193)
Zipcode: % rural	-0.0235	-0.0435	-0.0230	-0.0458	-0.0221	-0.0455	-0.0220	-0.0454	-0.0198	-0.0408
	(0.0063)	(0.0129)	(0.0063)	(0.0093)	(0.0063)	(0.0085)	(0.0063)	(0.0085)	(0.0061)	(0.0082)
Zipcode: % foreign	-0.0050	-0.0185	-0.0051	0.0203	-0.0025	0.0205	-0.0026	0.0205	0.0014	0.0221
born	(0.0133)	(0.0412)	(0.0138)	(0.0213)	(0.0129)	(0.0209)	(0.0129)	(0.0209)	(0.0123)	(0.0200)
# bar-months	307,989	40,693	341,964	80,687	341,887	80,687	341,964	80,687	341,964	80,687
# bars	6,798	904	7,283	1,712	7,281	1,712	7,283	1,712	7,283	1,712
R-squared	0.0181	0.0238	0.0168	0.0164	0.0173	0.0164	0.0173	0.0164	0.0185	0.0171

Notes: Dependent variable is bar exit. Owner experience is a dummy variable indicating whether the owner owned any bar or restaurant in 3 years before opening the focal one. Regressions include year fixed effects, monthly dummies, and bar random effects. Clustered standard errors (at the county level) reported in parentheses. In columns (7) and (8), ideal heat is 72'F means that we use $Heat\ shock\ 72'F = |72'F - normal\ heat| - |72'F - actual\ heat|$ to replace heat shock when estimating equation (1) and performing the revenue decomposition.

Appendix Table 10: Table 4 using restaurants not bars

VARIABLES	(1) All	(2) Inexperienced only	(3) Experienced only	(4) Distance to owner over 5 miles	(5) Distance to owner under 5 miles
Transitory revenue	-0.0336	-0.0348	-0.0300	-0.0412	-0.0266
	(0.0013)	(0.0015)	(0.0023)	(0.0019)	(0.0012)
Persistent revenue	-0.0204	-0.0216	-0.0146	-0.0219	-0.0176
	(0.0010)	(0.0011)	(0.0009)	(0.0011)	(0.0011)
Experience	0.0038			0.0063	0.0002
	(0.0012)			(0.0015)	(0.0015)
Distance to owner (000 miles)	0.0100	0.0114	0.0049	0.0071	2.7844
	(0.0022)	(0.0027)	(0.0026)	(0.0021)	(0.2971)
Owner with single establishment	0.0128	0.0157	0.0088	0.0185	0.0089
	(0.0017)	(0.0018)	(0.0022)	(0.0023)	(0.0015)
Owner name not a business name	0.0031	0.0027	0.0049	0.0051	0.0029
	(0.0023)	(0.0024)	(0.0038)	(0.0040)	(0.0019)
Time since restaurant opened in years	0.0061	0.0066	0.0047	0.0062	0.0059
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Time since restaurant opened in years sq	-0.0003	-0.0003	-0.0002	-0.0003	-0.0003
	(1.1e-5)	(1.4e-5)	(1.2e-5)	(2.0e-5)	(9.8e-6)
Likely lease renewal period	0.0059	0.0070	0.0026	0.0061	0.0056
	(0.0006)	(0.0008)	(0.0007)	(0.0008)	(0.0007)
Hurricane	0.0031	0.0044	-0.0009	0.0027	0.0035
	(0.0020)	(0.0025)	(0.0021)	(0.0023)	(0.0021)
Zipcode: # other restaurants	0.0001	0.0001	0.0001	0.0001	0.0001
	(3.3e-5)	(3.6e-5)	(3.4e-5)	(4.1e-5)	(3.6e-5)
Zipcode: pop. (millions)	-0.0472	-0.0434	-0.0028	-0.1136	0.0472
	(0.0300)	(0.0387)	(0.0503)	(0.0683)	(0.0636)
Zipcode: % black	0.0110	0.0038	0.0372	0.0226	-0.0010
	(0.0048)	(0.0057)	(0.0137)	(0.0108)	(0.0091)
Zipcode: % Hispanic	0.0243	0.0253	0.0216	0.0252	0.0235
	(0.0059)	(0.0065)	(0.0071)	(0.0077)	(0.0067)
Zipcode: % age under 18	-0.0339	-0.0392	-0.0210	-0.0438	-0.0250
	(0.0134)	(0.0154)	(0.0180)	(0.0182)	(0.0162)
Zipcode: % age 65 and over	-0.0002	0.0016	0.0007	0.0026	0.0061
	(0.0130)	(0.0173)	(0.0155)	(0.0177)	(0.0144)
Zipcode: logged median hh income	0.0041	0.0045	0.0021	0.0074	0.0013
	(0.0024)	(0.0023)	(0.0039)	(0.0040)	(0.0025)
Zipcode: % bachelor degree	0.0201	0.0215	0.0189	0.0117	0.0258
	(0.0054)	(0.0064)	(0.0091)	(0.0076)	(0.0071)
Zipcode: % rural	-0.0073	-0.0081	-0.0022	-0.0048	-0.0050
	(0.0042)	(0.0045)	(0.0061)	(0.0066)	(0.0039)
Zipcode: % foreign born	-0.0198	-0.0213	-0.0192	-0.0046	-0.0315
	(0.0113)	(0.0132)	(0.0104)	(0.0126)	(0.0119)
# estab.-months	725,056	536,242	188,814	389,280	335,776
# estab.	13,999	10,694	3,305	7,673	6,326
R-squared	0.0121	0.0125	0.0116	0.0163	0.0093

Notes: Dependent variable is restaurant exit. Owner experience is a dummy variable indicating whether the owner owned any bar or restaurant in 3 years before opening the focal one. Regressions include year fixed effects, monthly dummies, and restaurant random effects. Clustered standard errors (at the county level) reported in parentheses.

Appendix Table 11: Robustness of Table 4 columns 4 and 5 to other distances

VARIABLES	(1) Distance to owner over 10 miles	(2) Distance to owner under 10 miles	(3) Distance to owner over 15 miles	(4) Distance to owner under 15 miles
Transitory revenue	-0.0434	-0.0347	-0.0459	-0.0352
	(0.0023)	(0.0023)	(0.0032)	(0.0021)
Persistent revenue	-0.0356	-0.0375	-0.0339	-0.0379
	(0.0026)	(0.0025)	(0.0025)	(0.0029)
Experience	-0.0012	-0.0016	-0.0012	-0.0016
	(0.0042)	(0.0026)	(0.0034)	(0.0024)
Distance to owner	0.0096	0.7712	0.0065	0.8010
(1000 miles)	(0.0052)	(0.2788)	(0.0053)	(0.2247)
Owner with single	0.0047	0.0075	0.0047	0.0073
establishment	(0.0030)	(0.0030)	(0.0031)	(0.0027)
Owner name not a	-0.0038	-0.0046	0.0016	-0.0059
business name	(0.0054)	(0.0042)	(0.0074)	(0.0046)
Time since bar opened	0.0071	0.0078	0.0067	0.0078
in years	(0.0004)	(0.0004)	(0.0006)	(0.0004)
Time since bar opened	-0.0004	-0.0004	-0.0004	-0.0004
in years squared	(3.3e-05)	(2.0e-05)	(4.1e-05)	(2.3e-05)
Likely lease renewal	0.0047	0.0038	0.0030	0.0044
period	(0.0012)	(0.0009)	(0.0017)	(0.0009)
Hurricane	-0.0061	0.0004	-0.0035	-0.0010
	(0.0032)	(0.0019)	(0.0041)	(0.0019)
# competitors in	0.0001	7.5e-05	0.0002	7.8e-05
zipcode	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Zipcode population	-0.0196	0.1149	-0.0612	0.1026
(millions)	(0.0856)	(0.0579)	(0.0942)	(0.0433)
Zipcode fraction	-0.0116	-0.0167	-0.0239	-0.0116
black	(0.0133)	(0.0093)	(0.0148)	(0.0074)
Zipcode fraction	0.0009	0.0203	-0.0123	0.0223
Hispanic	(0.0087)	(0.0062)	(0.0102)	(0.0069)
Zipcode fraction age	-0.0120	-0.0752	-0.0124	-0.0654
under 18	(0.0229)	(0.0172)	(0.0305)	(0.0149)
Zipcode: % age 65	0.0413	-0.0041	0.0334	0.0017
and over	(0.0291)	(0.0226)	(0.0329)	(0.0232)
Zipcode logged avg	0.0044	0.0063	0.0023	0.0060
hh income (000s)	(0.0036)	(0.0046)	(0.0045)	(0.0043)
Zipcode: % bachelor	0.0155	0.0166	-0.0052	0.0243
degree	(0.0111)	(0.0144)	(0.0205)	(0.0123)
Zipcode fraction	-0.0291	-0.0229	-0.0387	-0.0209
rural	(0.0095)	(0.0069)	(0.0095)	(0.0066)
Zipcode fraction	0.0308	-0.0165	0.0252	-0.0091
foreign born	(0.0101)	(0.0151)	(0.0175)	(0.0141)
# bar-months	131,475	291,176	92,851	329,800
# bars	2,959	6,036	2,077	6,918
R-squared	0.0205	0.0161	0.0225	0.0162

Notes: Dependent variable is bar exit. Owner experience is a dummy variable indicating whether the owner owned any bar or restaurant in 3 years before opening the focal one. Regressions include year fixed effects, monthly dummies, and bar random effects. Clustered standard errors (at the county level) reported in parentheses.

Appendix Table 12: Additional Results for Table 9

	Everyone inexperienced		Everyone has 1 year experience		Everyone has 3 years experience		Everyone has 10 years experience	
	(1) % months with wrong decisions	(2) % bars with wrong decisions in the 1st year	(3) % months with wrong decisions	(4) % bars with wrong decisions in the 1st year	(5) % months with wrong decisions	(6) % bars with wrong decisions in the 1st year	(7) % months with wrong decisions	(8) % bars with wrong decisions in the 1st year
Status quo: all random shocks	0.66	2.63	0.52	2.03	0.40	1.57	0.27	1.07
Panel A: Positive Shocks								
1st quarter pos. shocks	1.31	3.51	1.01	2.71	0.78	2.10	0.52	1.41
1st two quarters pos. shocks	1.51	4.64	1.16	3.54	0.90	2.70	0.60	1.78
1st year pos. shocks	1.68	5.44	1.29	4.16	0.99	3.18	0.67	2.12
Panel B: Negative Shocks								
1st quarter neg. shocks	0.32	3.38	0.24	2.48	0.19	1.88	0.13	1.23
1st two quarters neg. shocks	0.38	4.46	0.28	3.24	0.21	2.42	0.14	1.58
1st year neg. shocks	0.47	5.22	0.33	3.79	0.25	2.82	0.17	1.84
N = 8,995 bars								

Notes: Counterfactual results based on Column 4 of Table 7. The number of simulation draws is 20.

Appendix C: Constructing the likelihood function

In this appendix we describe the steps in constructing the simulated joint likelihood function we use for estimation.

1. Let $\pi^0_{j,ns}$ denote a single draw ns $(ns=1,2,...,NS)$ for bar j. Let NS be 20. Take NS random draws from the Normal distribution $\pi^0_{j,ns} \sim N\left(mean\left(R_{js}\right),1\right)$ for each bar.
2. Construct the log likelihood function for the revenue generation process as described by equation (5):

$$\sum_{j=1}^{J}\sum_{s=1}^{T_j}\log L^R\left(R_{js}\,\middle|\,W_{js},X_{js},Q_s\right)$$

$$=-\frac{1}{2}\left(J\sum_{s=1}^{T_j}\log\left(2Pi\right)+\sum_{j=1}^{J}\sum_{s=1}^{T_j}\log\left(\sigma_r^2\left(1+\frac{1}{T_j^{\,2}}\right)\right)+\sum_{j=1}^{J}\sum_{s=1}^{T_j}\frac{\upsilon_{jt}^{d}\,'\upsilon_{jt}^{d}}{\sqrt{\sigma_r^2\left(1+\frac{1}{T_j^{\,2}}\right)}}\right), \qquad \text{(A1.1)}$$

where $\upsilon^d_{jt}=\tilde{R}_{jt}-\tilde{X}_{jt}\alpha^X-\tilde{Q}_t\alpha^Q-\tilde{W}_{jt}\alpha^W_{quarter}$. Note $\left[\tilde{R}_{jt},\tilde{X}_{jt},\tilde{Q}_t,\tilde{W}_{jt}\right]$ are $\left[R_{jt},X_{jt},Q_t,W_{jt}\right]$ demeaned by bar averages to allow for establishment fixed effect. Define $\upsilon^o_{jt}=R_{jt}-X_{jt}\alpha^X-Q_t\alpha^Q-W_{jt}\alpha^W_{quarter}$ and calculate $\sigma_0^2=\text{var}\left(\upsilon^o_{jt}\right)-\sigma_r^2$.
3. For each draw $\pi^0_{j,ns}$, each establishment j and each time period t, construct the posterior belief on monthly profit conditional on whether the owner pays attention:

If $\tilde{\kappa}_j > VarR_j$, we construct

$$S^{ns}_{jt}\left(R,W,X,Q,Z,VarR,\pi^0_{j,ns},\tilde{\kappa}_j > VarR_j\right)$$

$$=\frac{\sigma_r^2}{\left(t-1\right)\sigma_0^2+\sigma_r^2}\pi^0_{j,ns}+\frac{\left(t-1\right)\sigma_0^2}{\left(t-1\right)\sigma_0^2+\sigma_r^2}\frac{\sum_{s=1}^{t-1}\left(\beta^R R_{js}-\beta^0-X_{jt}\beta^X-Q_t\beta^Q\right)}{t-1} \qquad \text{(A1.2)}$$

If $\tilde{\kappa}_j \le VarR_j$, we construct

$$S^{ns}_{jt}\left(,W,X,Q,Z,VarR,\pi^0_{j,ns},\tilde{\kappa}_j \le VarR_j\right)$$

$$=\frac{\sigma_r^2}{\left(t-1\right)\sigma_0^2+\sigma_r^2}\pi^0_{j,ns}+\frac{\left(t-1\right)\sigma_0^2}{\left(t-1\right)\sigma_0^2+\sigma_r^2}\frac{\sum_{s=1}^{t-1}\left(\beta^R\left(R_{js}-E\left[\tau_j\mid\tilde{\kappa}_j\le VarR_j\right]\omega_{js}\right)-\beta^0-X_{jt}\beta^X-Q_t\beta^Q\right)}{t-1}$$

(A1.3)

In equation (A1.3),

$$E\left[\tau_j \mid \tilde{\kappa}_j \le VarR_j\right] = 1 - \frac{e^{Z_j\kappa_1 + \frac{1}{2}}}{VarR_j} \frac{\Phi\left(\ln\left(VarR_j\right) - Z_j\kappa - 1\right)}{\Phi\left(\ln\left(VarR_j\right) - Z_j\kappa\right)} \tag{A1.4}$$

4. Conditional on whether the owner pays attention, we discretize S_{jt}^{ns} into $K = 9$ values and calculate the transitional probability matrix with typical element $\Pi_{ik} = \Pr\left(S_{j,t+1}^{ns} = S^k \mid S_{jt}^{ns} = S^i\right)$.

5. Compute recursively the expected discounted profits net of ε_{jt} corresponding to the staying decision $\overline{V}_{D_{jt}=0}(S_{jt}^{ns})$, using the method of successive approximation.[23] With $\overline{V}_{D_{jt}=0}(S_{jt}^{ns})$, we construct:

$$prob\left(D_{jt}^{ns} = 1 \middle| S_{jt}^{ns}\right) = \frac{1}{1 + \exp\left(\overline{V}_{D_{jt}=0}(S_{jt}^{ns})\right)} \tag{A1.5}$$

Again, we construct the probability of exit separately for owners paying zero attention and owners who pay some attention.

6. Construct the exit probability of bar j at time period t unconditional on its action of paying attention:

$$\begin{aligned} &prob\left(D_{jt}^{ns} = 1 \middle| R, W, X, Q, Z, VarR, \pi_{j,ns}^0\right) \\ &= \Phi\left(\log\left(VarR_j\right) - Z_j\kappa_1\right) prob\left(D_{jt}^{ns} = 1 \middle| S_{jt}^{ns}, \tilde{\kappa}_j \le VarR_j\right) \\ &\quad + \left(1 - \Phi\left(\log\left(VarR_j\right) - Z_j\kappa_1\right)\right) prob\left(D_{jt}^{ns} = 1 \middle| S_{jt}^{ns}, \tilde{\kappa}_j > VarR_j\right) \end{aligned} \tag{A1.6}$$

7. Construct the likelihood function for bars' exit decisions:

$$\begin{aligned} &L^D\left(D_{jt} \middle| R, W, X, Q, Z, VarR, \pi_{j,ns}^0\right) \\ &= prob\left(D_{jt}^{ns} = 1 \middle| R, W, X, Q, Z, VarR, \pi_{j,ns}^0\right)^{D_{jt}} \left(1 - prob\left(D_{jt}^{ns} = 1 \middle| R, W, X, Q, Z, VarR, \pi_{j,ns}^0\right)\right)^{1-D_{jt}} \end{aligned} \tag{A1.7}$$

where D_{jt} are actual exit decisions we observe in data.

8. Finally, with $L^D\left(D_{js} \middle| R, W, X, Q, Z, VarR_j, \pi_{j,ns}^0\right)$ we construct equation (17):

$$\ln L_{simulated} = \sum_{j=1}^{J}\sum_{s=1}^{T_j} \log L^R\left(R_{js} \middle| W_{js}, X_{js}, Q_s\right) + \sum_{j=1}^{J} \ln\left\{\frac{1}{NS}\sum_{ns=1}^{NS}\left[\prod_{s=1}^{T_j} L^D\left(D_{js} \middle| R, W, X, Q, Z, VarR_j, \pi_{j,ns}^0\right)\right]\right\} \tag{A1.8}$$

[23] Our dynamic problem is a version of Abbring and Klein (2015). Abbring and Klein (2015) show that this computation is a contraction, so that the method of successive approximation converges linearly and globally to a point with a positive maximum absolute distance (= 0.01). We adapt the Matlab code developed by the authors and acknowledge their work.

Appendix C.1.:

Prove $E\left[\tau_j \mid \tilde{\kappa}_j \le VarR_j\right] = 1 - \frac{e^{Z_j\kappa_1 + \frac{1}{2}}}{\operatorname{var}\left(R_{jt}\right)} \frac{\Phi\left(\ln\left(VarR_j\right) - Z_j\kappa - 1\right)}{\Phi\left(\ln\left(VarR_j\right) - Z_j\kappa\right)}$

Proof: Note the conditional expectation of a Lognormal random variable $X \sim \log normal\left(\mu, \sigma^2\right)$ with respect to a threshold a is:

$$E\left[X \mid X \le a\right] = e^{\mu + \frac{\sigma^2}{2}} \frac{\Phi\left(\frac{\ln(a) - \mu - \sigma^2}{\sigma}\right)}{\Phi\left(\frac{\ln(a) - \mu}{\sigma}\right)} \tag{A1.9}$$

In our model the thinking cost $\tilde{\kappa}_j$ is drawn from a Lognormal distribution with mean $Z_{jt}\kappa_1$ and variance normalized to 1. That is, $\tilde{\kappa}_j \sim \log normal\left(Z_j\kappa_1, 1\right)$. Following equation (A1,9), we can then derive:

$$E\left[\tilde{\kappa}_j \middle| \tilde{\kappa}_j \le VarR_j\right] = e^{Z_j\kappa_1 + \frac{1}{2}} \frac{\Phi\left(\ln\left(VarR_j\right) - Z_j\kappa - 1\right)}{\Phi\left(\ln\left(VarR_j\right) - Z_j\kappa\right)}. \tag{A1.10}$$

Plug (A1,10) into equation (9), we have:

$$\begin{aligned}
&E\left[\tau_j \mid \tilde{\kappa}_j \le VarR_j\right] \\
&= E\left[\left(1 - \frac{\tilde{\kappa}_j}{\operatorname{var}\left(R_{jt}\right)}\right) \middle| \tilde{\kappa}_j \le VarR_j\right] = 1 - \frac{1}{\operatorname{var}\left(R_{jt}\right)} E\left[\tilde{\kappa}_j \mid \tilde{\kappa}_j \le VarR_j\right] \\
&= 1 - \frac{e^{Z_j\kappa_1 + \frac{1}{2}}}{VarR_j} \frac{\Phi\left(\ln\left(VarR_j\right) - Z_j\kappa_1 - 1\right)}{\Phi\left(\ln\left(VarR_j\right) - Z_j\kappa_1\right)}
\end{aligned} \tag{A1.11}$$

Q.E.D.

Appendix D: Additional Analysis and Information

D.1: Alcohol revenue as a proxy for profits

We focus on bars because alcohol revenue is the major revenue source for bars, and it is more likely to proxy for profits for bars only than for all bars and restaurants combined. In addition, we have collected a variety of additional evidence that alcohol revenue is a good proxy for overall success for bars and restaurants. In particular:

1. Fang (2019) uses the same data source as ours to answer a different question related to consumer learning through restaurant reviews. She argues that the number of Yelp reviews is a proxy for total number of customers. She shows that log alcohol revenue is proportional to the log of the number of Yelp reviews. She interprets this to suggest that a change in alcohol revenue represents an equivalent percent change in total revenue.
2. Reimers and Xie (2019) also use the same data source as ours to answer a different question related to online coupons. Using consumer survey, they show that a typical consumer spends about 30-40% of their bill on alcohol in restaurants and over 50% in bars.
3. For the state of Minnesota, there is public data on annual county level alcohol and overall sales for restaurants (NAICS 722): https://www.revenue.state.mn.us/sales-and-use-tax-2008-statistics. Using the data from 2008 through 2016, the correlation between alcohol revenue per capita and overall sales revenue per capita is 0.577 (not controlling for population gives a correlation of 0.998).
4. Some jurisdictions have restrictions on the fraction of overall sales that can be from alcoholic beverages. For example, Virginia has a requirement of under 55% of revenue from alcohol. Rome and Alpharetta GA have a requirement of under 50% of revenue from alcohol. Linnekin (2017) notes that this is done to limit the number of bars. This suggests that it is common for bars to receive over 50% of revenue from alcohol.
5. The book *Restaurant Success by the Numbers* (Fields 2007) notes that beverage sales of 25-35% of total sales is typical. In addition, it emphasizes the importance of alcohol sales to profits because of higher profit margins. For example, on page 112, it notes, "Because the profit margins on alcohol sales are much higher than on food, alcoholic beverage sales can be so much more profitable than food sales, the greater the percentage of your total sales is from alcohol, the better it will be for your bottom line."
6. The book *The Restaurant Managers Handbook Revised Fourth Edition* (Brown 2007) notes that "In restaurants with a higher percentage of beverage than food sales, profits are generally higher because there is a greater profit margin on beverages" (p. 397).

Combined, this suggests that variation in alcohol revenue is a good proxy for variation in overall revenue for bars. It also suggests that alcohol revenue is relatively important for profitability at both bars and restaurants. It does not directly test the assumption that variation in alcohol revenue at bars is proportional to variation in profits.

D.2: References for Online Appendix

Abbring, Jaap H. and Tobias J. Klein. 2015. Dynamic Discrete Choice Models: Methods, Matlab Code, and Exercises. Working paper, Tilburg University.

Brown, Douglas Robert. 2007. *The Restaurant Manager s Handbook: How to Set Up, Operate, and Manage a Financially Successful Food Service Operation*. Revised Fourth edition. Atlanta Publishing Group Inc., Ocala FL.

Driscoll, John C., and Aarl. C. Kraay. 1998. Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *Review of Economics and Statistics* 80: 549 560.

Fang, Limin. 2019. The Effects of Online Review Platforms on Restaurant Revenue, Survival Rate, Consumer Learning, and Welfare. Working paper, University of British Columbia.

Fields, Roger. 2007. *Restaurant Success by the Numbers.* Ten Speed Press, Berkeley CA.

Linnekin, Baylen. 2017. Here's Why It s Dumb to Tell a Restaurant How Much Booze it Can Sell. https://reason.com/2017/01/21/heres-why-its-dumb-to-tell-a-restaurant. Accessed online June 27, 2018.

Reimers, Imke, and Claire (Chunying) Xie (2019) Do Coupons Expand or Cannibalize Revenue? Evidence from an e-Market. Management Science 65(1):286-300.