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

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ABSTRACT

This paper investigates the incidence of limited attention in a high-stakes business setting: a restaurant owner may be unable to purge transitory shocks from noisy profit signals when deciding whether to exit. Combining a 20-year quarterly panel on the alcohol revenues from every restaurant in Texas with weather data, we find that owners with pre-existing experience act as if they are able to account for past transitory shocks in the right direction: Given the same revenue record, restaurants with experienced owners are more likely to exit after unusually good weather (and stay in business after unusually bad weather). Driven by this evidence, we formulate and estimate a structural model in which owners have heterogeneous costs of paying attention to transitory shocks, thus misinterpreting revenue signals. Our results show that the owners' pre-existing experience substantially reduces the costs of paying attention to transitory shocks. For the 25,283 restaurants in our data, a median restaurant with three years' owner experience has the cost of paying attention lowered by roughly $900 per quarter. Because exit decisions are permanent, experience is especially useful in reducing welfare loss due to premature exit decisions when the restaurant is hit with negative shocks.

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

JEL Classification: D9, L2, L8

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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 fifty 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 purchases: "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), electricity bills (Hortacsu, Madanizadeh and Puller, forthcoming), and health insurance plans (Handel 2013; Ho, Hogan, and Morton, forthcoming).[1]

In this paper, 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. When making forecasts, the decision maker needs to cast continuous attention on a large number of factors.

We study restaurant owners, who try to infer the underlying profitability of their restaurants before making exit decisions. Owners should form rational expectations of the future profitability of their restaurants based on the profit record of the restaurant through time. The profit record, in turn, is affected by local demand, the restaurant's quality and specialty, fixed and variable costs, and, often, transitory shocks such as weather variation, local sports team victories, or a flu outbreak.

Our empirical analysis focuses on the weather. The weather matters because positive weather shocks temporarily increase profits but a rational decision maker should know to discount revenue produced under these positive transitory shocks. Given the same revenue history, the owner should be more inclined to exit in good weather. Negative weather shocks have the opposite effects and a rational decision maker should act accordingly. When deciding whether to exit, the degree to which the owner accounts for past weather shocks reveals the existence and magnitude of her inattention on these transitory shocks. Weather shocks play a special role in this setting because they should not affect a restaurant's future profitability due to their transitory nature; however, they can enter a decision maker's belief formation process and, in turn, affect the decision.

While there are many factors that restaurant managers should consider (and perhaps do not), we single out weather shocks because such shocks are exogenous and unpredictable, and therefore provide useful instruments for understanding biases in human behavior (e.g. Conlin, O'Donoghue, and Vogelsang 2007, Simonsohn 2010). Furthermore, while the economic impact of weather is relatively small for

[1] See Conlisk (1996) and DellaVigna (2009) for comprehensive reviews of the literature on bounded rationality. Newer research steps into the areas in which individuals fail to pay attention to important financial or health care decisions: Stango and Zinman (2014) and Ho, Hogan, and Morten (2015), for examples.

individual restauranteurs,[2] its aggregate impact on the macro-economy can be large. 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 current major macroeconomic indicators completely ignore such effects. If Central Bankers do not purge the macro data they are provided of these weather effects (Boldin and Wright point out that they do not), they will respond to transitory shocks when making macro policies, which may generate substantial distortions. We argue that the evidence we show in this paper for the same type of distortions in individual firms' decision-making process is a step toward understanding limited attention more broadly.

Such inattention may be inconsequential if it merely changes the timing of a decision by a few months; but it can matter greatly in the restaurant context if a few negative transitory shocks propel the owner to think the restaurant is unprofitable and thus the owner decides to exit prematurely. 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. To assess the empirical relevance of inattention, we use monthly alcohol revenue for every restaurant that opened (and obtained licenses to sell alcoholic drinks) in Texas between January 1995 and August 2015. We supplement this data with Texas weather station data and local market attributes.

Our results are consistent with limited attention, particularly for experienced restaurant owners. In particular, we first demonstrate that weather does affect alcohol revenue: higher revenues are associated with positive weather shocks (i.e. warmer than expected in winter or colder than expected in summer); at the same time, lower revenues are associated with negative weather shocks. The magnitude of this effect is similar across inexperienced and experienced owners. We then show that inexperienced and experienced owners react to the impact of weather shocks differently when deciding whether to exit. Experienced restaurant owners seem to respond to weather shocks correctly: Restaurants with such owners are more likely to exit under positive weather shocks — and less likely to exit under negative weather shocks — given the same revenue record, "as if" the decision makers understand to discount revenue records produced under positive shocks and supplement revenue records produced under negative shocks. In contrast, inexperienced owners do not seem to respond to the weather shocks in the right direction.

The difference between experienced and inexperienced owners suggests a new explanation for the value of experience for entrepreneurs and managers. Al-Ubaydli and List (2016) argue that experience reduces behavioral anomalies. Lafontaine and Shaw (2016), using similar data on Texas businesses, show that "serial entrepreneurs" do better in terms of both revenue and exit rates. They argue that experience provides skills and emphasize learning-by-doing. Our results suggest that experienced entrepreneurs may be better at extrapolating information from noisy signals about the long-run profitability of the business.

Aside from inattention, one possible alternative explanation is credit constraints: Inexperienced owners may be more constrained and therefore may be forced to exit when the weather is bad, even if they recognize that the shock is temporary. We allow this possibility by adding the interaction term between revenue fluctuations and experience into the main specification. While we find evidence of credit

[2] 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 revenue or profit driver.

constraints for inexperienced owners, they do not appear to drive our main result on the correlation between weather shocks, experience, and exit. We also explore other explanations and argue that limited attention provides the most likely explanation for our results.

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 inattention. We estimate a single-agent model of belief formation and exit decisions, in which a restaurant'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 expected profitability falls short of the outside option, the owner exits. In the learning process, we build a "pre-step", in which a decision maker solves an attention allocation problem to "observe" 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.[3] The decision maker builds 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 spare representation. Compared to other models of rational inattention (Sims, 2003; Reis, 2006; Abel, Eberly, and Panageas 2013; Saint-Paul 2011), an advantage of Gabaix's model is that it yields a single parameter that defines the degree of limited attention. We add to Gabaix's model by modeling thinking cost as a stochastic process and linking it to the personal attributes of decision makers,[4] 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 allow us to examine the drivers of this bounded rationality problem and how various mechanisms could alleviate this problem.

Our structural results are consistent with our motivating analysis and measure the economic impact of inattention in this context. Of the 25,283 owners in our data, an average owner's probability of paying no attention at all ranges from 83% to 87%. Even if an owner is paying attention, her attention only amounts to roughly a quarter of the full attention spectrum. In other words, most owners do not pay attention to the idiosyncratic shocks most of the time.

The amount of attention, however, displays significant heterogeneity across owners in data. This heterogeneity is driven by (i) the variability of local weather and (ii) a large, significantly negative effect of owner experience in the thinking cost function. Our simulations show that roughly 3.4% of the restaurants (849 out of 25,283) in the data would have made different exit decisions in a full attention model. We find this magnitude comforting: Not so high that everybody should consider transitory shocks in decisions to exit but not so low that the exercise has no impact. For these 849 restaurants, the cost of paying full attention is high: a median restaurant would have to pay about $17,000 in total up to the

[3] Gabaix's model considers a decision maker who wishes to make a decision that should be a function of a large number of factors. Some of these factors are more relevant than others in the decision-making process. Because it is too difficult to consider all these factors, the decision maker focuses on those factors for which the benefit of considering them outweighs the cost.
[4] Gabaix (2014) models the cost of thinking as a parameter value instead of a function.

quarter when a correct exit decision is made. While beneficial, the payoff to better decisions (about \$14,000 in total for a median restaurant) is overwhelmed by the more substantial cost of casting attention.

Our simulations suggest that one effective channel for the reduction of these costs is through owners' pre-existing experience in the industry before opening new restaurants. In particular, one year of such experience reduces the cost of paying attention for a median restaurant by about \$113 per quarter, three years by about \$931, and ten years by about \$1,727. That is, ten years of experience eliminates most of the estimated \$2000 quarterly cost of paying attention to idiosyncratic shocks.

Our counterfactual simulations also show that experience is especially useful in reducing welfare loss due to incorrect inference when the restaurant is hit with negative shocks. Negative shocks affect welfare more than positive shocks because negative shocks can cause a potentially successful restaurant to close, eliminating many potential years of profits. In contrast, positive shocks allow a bad restaurant to stay open, usually delaying the inevitable by a short period of time, so the misinterpretation of the revenue signal may affect decisions to a limited extent. This asymmetry between the welfare impact of positive and negative shocks means that luck and experience work as substitutes. When the firm is unlucky, the owner needs experience to correctly assess the situation and avoid a potentially costly error. When the firm is lucky, the additional value of experience is smaller.

Overall, these results highlight the role for heterogeneous decision-making ability in understanding outcomes in high-stakes business settings. In doing so, we demonstrate the viability of developing and estimate 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. Our model has a unique mechanism of inattention: some decision makers, particularly inexperienced ones, have difficulty separating "observable" noises from true signals. Furthermore, the model also allows us to measure one dimension of the value of experience. 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), our results suggest experience reduces behavioral biases, even among managers in competitive industries. This builds on prior laboratory and field work that documents how experience generally leads to rational behavior (summarized by Al-Ubaydli and List 2016). Overall, our paper is one of the first empirical studies looking into the black box of firm's imperfect decision making.

Next, we briefly review related literature on inattention, managerial decision-making, and behavioral industrial organization. The data, motivating regressions, model, results and counterfactual simulations follow. We conclude with a discussion of limitations, and the general implications of our findings.

2 Related Literature

In this section, we briefly discuss our position in the literature that spans topics on inattention, exit, and managerial decision-making. More broadly, we relate to the recent effort of introducing behavioral biases into structural models. The objective is not to provide a comprehensive review, but instead to highlight some key models and results that inform the development of our paper and to explain how our research pushes the literature forward.

2.1 Inattention

A growing literature demonstrates that people are not fully attentive to all potential inputs to a decision. It is not only costly to gather and process information but also decide how to respond to collected information. This limited attention problem has economic consequences. Most empirical studies, however, stop at documenting the incidence of limited attention and do not assess the welfare trade-offs of a decision maker's inattention. A few studies have gone one step further: they recover primitive parameters in consumer preferences and/or firm profits so they are able to perform counterfactual analysis to evaluate welfare trade-offs. For example, Lacetera, Pope and Sydnor (2012) show that inattention to right digits of used car mileage leads to $2.4 billion worth of mispricing; Kiss (2017) estimates that media campaigns increase switching to alternative, lower-priced insurance plans by 16% from a baseline of 20% and the salience-increasing effect of the campaign is valued at $15 per consumer; and Grubb and Osborne (2015) show that bill-shock alerts can save an average (inattentive) cellphone user $33 per year. Thus, public policies, which aim to improve consumer attention, can have large welfare-enhancing effects. Our work closely follows this line of research and measures the benefit and cost of paying attention. The main difference of our work is the subject of our study and the approach we adopt to model inattention.

First, rather than consumer inattention we study manager inattention. The common theme of previous studies is that inattentive consumers fail to optimize their choices due to economic or cognitive constraints (the cost of thinking), firms exploit consumers' bounded rationality, and policy intervention improves market outcomes. We ask whether firms are also inattentive. We have solid reasons to be ambivalent on this question: yes because the decision makers in firms are human, subject to typical human biases and mistakes,[5] or no because firms face much higher stakes, decisions are made in a collective setting, and firms need to survive market competition. In this paper, we document the incidence of inattention in firm decisions and propose a likely mechanism through which attention could be deficient. We allow limited attention to occur when the owner makes a forecast using repeated noisy signals, and when paying attention requires continuous effort. Mistakes arise when owners underestimate or ignore the impact of transitory shocks, particularly weather shocks, thus misinterpreting revenue signals. Some owners view these shocks as part of the noise of the revenue signals whereas others recognize that these shocks can be decomposed from the noise. We are able to assess the extent to which the owner accounts for past weather shocks to gauge the magnitude of this firm-level limited attention problem.

Second, we model inattention in a cost-benefit analysis rational inattention framework.[6] In our model, decision makers pay attention to factors that are sufficiently important that it is worth the cost of

[5] For example, DellaVigna and Pollet (2009) find that investors significantly underreact to earnings announcements on Fridays due to limited attention.
[6] Rational inattention is when people pay attention to those factors that are sufficiently important that it is worth the cost of thinking, while irrational inattention is when decision makers cannot overcome the hurdle despite a small or even negligible thinking cost. The reason we would like to make a distinction is because policy remedies for these

thinking (Veldkamp 2011). In particular, as Gabaix (2014) prescribes, we add a stage before a standard empirical framework and in this pre-step the decision maker allocates her attention. We use observed variation — in transitory shocks and owner experience — to measure the benefit and cost of paying attention. Gabaix emphasizes that this approach is based on robust psychological facts and can be applied to give many classical economic theories a behavioral update. There are two other approaches in the literature regarding how to model inattention. One approach is to use heuristics, i.e. an individual pays full attention to the visible component of a relevant variable and only partial attention to the less prominent component of that variable (Gabaix et al 2006; Lacetera, Pope and Sydnor 2012; Kiss 2016). A second approach is to model inattention as inertia (Miravete and Palacios-Huert 2013; Handel 2013). Consumers can be sophisticatedly inattentive, that is, they are aware of own inattention and choose threshold/target/category instead of exact quantity (Ching, Erdem and Keane 2009, 2014; Grubb and Osborne 2015). We use Gabaix's framework because it is empirically parsimonious and conducive to structural estimation and counterfactual analysis.

2.2 Experience, Skill, and Luck in Managerial Decision-Making

Our emphasis on the role of experience builds on prior work examining how individual manager characteristics affect firm behavior and performance (e.g. Bertrand and Schoar 2003). Experience in particular has been shown to matter in a variety of laboratory and field settings. For example, List (2003) shows that the endowment effect diminishes with market experience. List and Millimet (2008) find that violations of consistent preferences are lower among experienced traders. Harrison and List (2008) show that experienced traders in familiar roles were not subject to the winner's curse. Goldfarb and Xiao (2011) show that experienced managers are less likely to enter fiercely competitive markets, suggesting a better understanding of the decisions of others. Generally, Al-Ubaydli and List (2016) emphasize that many behavioral anomalies disappear with market experience.

Perhaps most directly related to our setting, using data on Texas retail goods and services Lafontaine and Shaw (2016) show that "serial entrepreneurs" — entrepreneurs who open repeat businesses — do better. They argue that this is not a pure selection effect in which good owners open new businesses. Instead, experience starting a business provides skills that are useful in running other businesses. Baron and Ensley (2006) and Ucbasaran, Westhead, and Wright (2009) argue that a skill provided by experience is the ability to recognize novel business opportunities. Our results on attention are consistent with this idea in which a skill learned is the ability to recognize the importance of temporary factors in the observed success of the business. In this way, our results on experience relate to the long literature on learning by doing (Arrow 1962, Benkard 2000, Levitt, List, and Syversson 2013).

Both skill and luck have been shown to matter for entrepreneurial success. Gompers et al (2006) also look at serial entrepreneurs and emphasize the importance of skill, while being careful to acknowledge that luck matters to entrepreneurial success. Earlier models of entrepreneurship emphasize luck. For example, Kihlstrom and Laffont (1979) develop a model in which entrepreneurship is entirely defined by

two types of inattention problems are different. It is keen for us to diagnose different forms of bounded rationality and come up with relevant policy remedies for better decision-making and, in turn, welfare improvement.

risk preferences and success is driven by luck rather than skills in running a business. Plehn-Dujowich (2010) shows that skill and luck can be complements, in a model where skill at running a business requires luck of finding a good business to run. In our work, transitory shocks can be interpreted as luck or the lack of luck, so an owner's experience helps her to recognize the role of lucky or unlucky events. This framing, as will be shown in Section 7.3.2, gives us a direct relationship between skill and luck, that is, skills and luck act as substitutes.

2.3 Behavioral Industrial Organization

There is growing effort to introduce behavioral deviations into the field of empirical industrial organization. Thus far, this effort has emphasized consumers' behavioral biases.[7] Firms are assumed to 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: firms usually have much a higher stake in any decision, and their decisions are often made with long and careful deliberations; 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. Pakes (2016a, 2016b) notes that standard dynamic models require extraordinary information retention and processing capabilities. Borenstein's (2016) keynote address to the International Industrial Organization Conference emphasized "the important roles that imperfect decision-making processes play in firms" (p. 245).

Field evidence on behavioral decision-making by firms is, at best, sparse (Goldfarb et al 2012). Some work has started to explore the situations in which firms do not appear to behave according the standard economic models (e.g. Hortacsu and Puller 2008; Goldfarb and Yang 2009; Goldfarb and Xiao 2011; Doraszelski, Lewis, and Pakes 2014; Hortacsu, Luco, Puller, and Zhu 2016; DellaVigna and Gentzkow 2017). Behavioral economics research suggests that bounded rationality is likely to be more important in manager decisions when decisions are infrequent and do not deliver clear feedback, when the manager does not specialize in that type of decision, or when managers are protected from market pressure and competition (Camerer and Malmendier, 2007). Our work leverages a distinctive setting with data on inexperienced managers and infrequent decisions. We believe there are a number of other situations in which the same type of distortions in the decision-making of firms may apply. Therefore, we argue that our results can inform broader, macro-level analysis that incorporates such distortions in firm-level decision-making.

Perhaps because exit occurs infrequently, Elfenbein and Knott (2015) suggest that exit decisions in particular are likely to exhibit behavioral biases. 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

[7] Examples include Brown, Camerer and Lovallo (2012, 2013), DellaVigna and Malmendier (2006), Grubb and Osborne (2015), and Simonsohn (2010), and the discussions in Ellison (2006) and Spiegler (2011).

exploration of the exit decisions of tens of thousands of restaurant owners provides sufficiently rich data on an infrequent but important decision.

3 Data

Our raw data contain the universe of Texas restaurants with licenses to sell alcoholic beverages from January 1995 to August 2015, roughly a 20-year span.[8] We have a monthly panel of restaurant identification code, name, exact location, and revenue from alcoholic beverages. Moreover, we have the taxpayer identification code for each restaurant as well as taxpayer name, address, and telephone number. The data are collected for the purpose of tax collection, and are available from the Texas Comptroller of Public Accounts. Abbring and Campbell (2003, 2005) use an earlier version of the same data set to study exit decisions, emphasizing the roles of scale and the annual lease cycle.

Using this information, we generate a restaurant-quarter level dataset between the first quarter of 1998 and the second quarter of 2015 for all restaurants that opened in January 1998 or later (70 quarters total). As we detail below, we use the first three years of data (1995 to 1997) to create measures of restaurant owner experience. We use July and August 2015 data to identify exit during the second quarter (March to June) of 2015. We merge this data with information on local weather.

The 1995 quarter 1 to 2015 quarter 2 raw data contain 44,212 restaurants and 793,280 restaurant-quarters In order to have a consistent measure of restaurant experience, we drop all restaurants that experienced an ownership change over the time period of our data. These restaurants make up 6.83% of the data. We do this because our model relies on the owner being aware of the history of the restaurant, in terms of revenue and (if attentive) weather. New owners of a pre-existing restaurant 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 restaurants enables a cleaner interpretation of our empirical results. This leaves 739,075 restaurant quarters. We drop all restaurants that opened prior to January 1, 1998 (322,287 observations) because we do not have measures of restaurant owner experience (which we measure over the three years prior to the quarter the restaurant opens) for these restaurants. Finally, for the bulk of the analysis we drop 27,971 observations from restaurant owners with at least 25 different restaurants at some point in the data period. This leaves 388,817 restaurant-quarters and 25,283 restaurants for the core analysis.

Constructing the variables for analysis involves using or creating measures of owner experience, restaurant exit, restaurant revenue, weather deviations, and controls for the local business environment. We discuss each of these below. Table 1a and Table 1b provide descriptive statistics of our constructed variables. Table 1a presents information on key variables that we study, restaurant exit and owner experience at the restaurant level. Table 1b presents information on restaurant characteristics and local market attributes at the restaurant-quarter level.

[8] We collected data in September 2015 that this is why August 2015 is the last period of data.

Owner Experience: Our experience measure focuses on whether the owner owned a restaurant in Texas prior to opening the current restaurant. 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 experiences enabling them to be more of a jack-of-all-trades (Lazear 2005; Lafontaine and Shaw 2016). The second reason is mechanical: The experience accumulated since the opening of the focal restaurant is collinear with a variety of other factors that may affect revenue including learning about restaurant quality, building the restaurant's reputation, and selection bias related to accumulated time since opening. Together these reasons suggest that focusing on owner experience at time of opening provides a cleaner measure of the variation in experience across owners.

Before we identify whether a restaurant owner has experience in the industry, we need to identify whether two restaurants are owned by the same person. To do so, we first use the taxpayer identification code. If this matches, then the restaurant has the same owner. This definition misses matches in which one owner holds multiple restaurants in partnerships or holding companies. To fix this problem, we use the other taxpayer information. If the taxpayer information for two restaurants has the same phone number, the same address, and a similar name, then we also assume the restaurants have the same owner. While identifying similar names is inherently a judgment call, we focused on similar in terms of 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 only look at 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 distinct names are owned by the same person.[9] Our manual cleaning increased the percentage of owners with prior experience in the Texas restaurant industry from 15% to 19%.

We measure experience in terms of whether the owner had owned a restaurant prior to the opening of the focal restaurant. We focus on two such measures. First, we measure experience as equal to one if the owner owned at least one other restaurant at any point in the previous three years. This is why we drop the first three years of the data (1995 to 1997) and look at restaurants that opened in January 1998 or later. Second, we count the number of restaurant-quarters over which the owner owned a restaurant prior to opening the focal restaurant. For example, if the focal restaurant was the owner's third restaurant. One had been open for 13 quarters prior to the opening of the focal restaurant and the other had been open for 6 quarters prior to the opening of this one, then we count this as having been open for 19 quarters plus the opening quarter of the focal restaurant makes 20 (we include the opening quarter of the current restaurant to make it possible to log this value for all restaurants). We do this count as a total number prior to opening, and as a total over the three years prior to opening.

[9] We also group together restaurant names to combine large chain restaurants such as Applebee's under the same owner. We do this to create consistency for large chains because 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, in most of the analysis we focus on restaurant owners that never own 25 or more restaurants at the same time. This means that the large chain restaurants drop from the data, though the motivating results are robust to alternative thresholds. While it is an interesting question whether the chain may provide value in reducing boundedly rational decisions of managers, that would require data on whether each individual restaurant belongs to a franchise or not. In the absence of such data, we drop the large chains and focus on the decisions of smaller businesses.

As shown at Table 1a, 18.5% of restaurant owners had owned a restaurant in the three years prior to opening the focal restaurant. In terms of restaurant-quarters owned, the variable is highly skewed to the right and therefore we analysis the log values. If we count the number of restaurant-quarters within three years prior to opening the focal restaurants, the average is about 5 restaurant-quarters (including the opening quarter of the focal restaurant) and the maximum is 275; if we relax the three year restriction, the average is about 10 quarters and a maximum of 1,165 quarters. In the motivating analysis, we focus on the dummy for owned a restaurant over the past three years because we think it is a cleaner definition that provides a stark distinction between experienced and inexperienced. We show robustness to the number of restaurant-quarters owned and the log number of restaurant-quarters owned.

Restaurant exit: As noted by Parsa et al (2005), there are several different ways to define exit in the restaurant industry: Restaurant closing, ownership change, or bankruptcy. We focus on restaurant closings, defined as situations where a restaurant ceases to operate at a location with the same name. If a new restaurant at the same address appears (even with the same owner), we call that exit in our main specification.[10] Overall, 64.4% of the restaurants in our data exit by the end of the period (the rest are right-censored). On a restaurant-quarter basis, 4.2% of restaurant-quarters in the data involve an exit. This base rate of exit is roughly in line with estimates by Parsa et al (2005, 2015).

Restaurant revenue: Our data contain rich information about a key source of restaurant profitability: Alcohol revenue (Brown 2007). Unfortunately, our data do not contain information on overall profits or total revenues at the restaurant. Therefore, in the analysis that follows, we assume that alcohol revenues are strong signals of restaurant profitability, at least up to the power of restaurant-level random effects. Specifically, we assume that a restaurant's variation in profitability is proportional to the variation in (log) alcohol revenue. In the raw data, a restaurant reports revenue at the monthly level, so in Table 1b we report revenue averaged over months in a quarter and we later use this measure as our proxy for profit. Using monthly revenue is cleaner than using quarterly revenue, as some restaurants enter or exit in the middle of a quarter so aggregate quarterly revenue may underestimate profitability. We deflate all revenues using the Consumer Price Index for all U.S. urban consumers and report in 2015 dollars. The average restaurant in the data earns slightly more than $32,000 per month in alcohol revenue. Again, this number is highly skewed to the right. A median restaurant earns $15,646 per month in alcohol revenue.

Weather Shocks: Using a restaurant's address, we identify the closest weather station and use weather reports from that station for measures of monthly mean temperature and total monthly precipitation from the National Oceanic and Atmospheric Administration's Climate Data Online tool (http://www.ncdc.noaa.gov/cdo-web/). We aggregate monthly weather data to quarterly level. We define

[10] As noted above, we dropped all restaurants with ownership changes for cleaner measures of what a owner observes about a restaurant' s operating history. We also 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.

quarterly "normal" weather as the average value for a specific quarter over the period of our data (January 1995 to August 2015).[11]

Deviations from "normal" temperature could be good or bad for the restaurant business, depending on the season. Generally, if the shock is such that it is too cold or too hot to go out, relative to normal, then the shock is negative. That is, shocks are positive if they move the average daily temperature toward the ideal degree and negative if they move the average daily temperature away from the ideal. To capture this idea, we define:

$$Temperature\ shock = |ideal\ temp. - normal\ temp.| - |ideal\ temp. - actual\ temp.|$$

In the above definition, the first term on the right hand side of the equation is the distance between the ideal temperature and normal temperature and the second term is the distance between the ideal temperature and actual temperature. If the first term is larger than the second, then the actual temperature is closer to the ideal temperature than the normal temperature is and hence the temperature shock is positive; otherwise the temperature shock is negative. For example, in a cold quarter with normal temperature to be 50 degrees, if the actual temperature is 52 degrees (2 degrees warmer than normal) then the value of the shock variable is 2. If the actual temperature is 47 degrees (3 degrees colder than normal) then the value of the shock variable is -3. In contrast, in a hot quarter with normal temperature to be 80 degrees, 2 degrees warmer than normal yields a shock variable of -2 and 3 degrees colder than normal yields a shock variable of 3.

In the above definition, we measure "ideal temperature" as the temperature that maximizes the correlation between the shock to temperature and revenue. In particular, for each potential ideal temperature from 65 to 75 degrees Fahrenheit, we created a measure of deviation from normal. Figure 1 shows the results of regressing revenue of the temperature shock measure and a variety of controls following equation (1) (introduced in Section 4). We find that the correlation between temperature shock and alcohol revenue is highest when ideal is assumed to be 69 degrees. Thus, for the remaining analysis, we use:

$$Temperature\ shock = |69'F - normal\ temp.| - |69'F - actual\ temp.|$$

Most temperature shocks are small. Reported in Table 1b, the average is near zero (as expected) and the standard deviation is approximately 2 degrees Fahrenheit. A very small fraction of our data (0.3%) contains variations larger than five degrees Fahrenheit.[12]

We define precipitation shocks using almost the same method, the only difference being that we assume an ideal precipitation as zero. Any precipitation would decrease restaurant-going behavior and therefore revenue. We define:

[11] Alternatively, we could have defined normal as the historical average. While results are not substantially different in terms of deviations from normal, we focus on the average in our data because historical average temperatures are systematically lower than the normal defined as the average of the 1995 to 2015 period and so the "shocks" would skew positive.
[12] We show robustness of our motivating results to excluding these observations.

$$\begin{aligned}Precipitation\ shock &= |0 - normal\ \ precipitation| - |0 - actual\ \ precipitation| \\ &= normal\ \ precipitation - actual\ \ precipitation\end{aligned}$$

Therefore, when there is less precipitation than normal, we define that as positive and when there is more precipitation than normal, we define that as negative. Again, the average precipitation shock is near zero, with a standard deviation of less than 2 inches of rainfall. As we discuss below, we have found no significant relationship between precipitation and revenue. Therefore, our results on exit emphasize temperature shocks rather than precipitation shocks.

Controls: We include controls for restaurant and location characteristics. Our choice of controls is informed by prior work on restaurant 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 quarters since the restaurant opened, a dummy for likely lease renewal periods every four quarters (as in Abbring and Campbell 2003, 2005), and (for the random effect specifications) whether the owner has at least five other restaurants, whether the listed taxpayer is an individual's name rather than a business name,[13] and whether the restaurant is not a traditional restaurant but rather a bar or private club.[14]

4 Motivating Analysis

Next we provide descriptive evidence that experienced and inexperienced restaurant owners have different responses to weather shocks in their exit decisions. We do this in three steps. First, we document that weather shocks are positively correlated with revenue. Second, we show that experienced and inexperienced owners do seem to use weather information differently in their exit decisions. Third, we provide evidence supporting our emphasis on the role of inattention, rejecting a number of alternative explanations.

[13] 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.", "restaurant", "ranch", "of", "dallas", "deli", etc.). By inspection, we identified 458 such strings. The remaining restaurant owners were listed as individuals or pairs of individuals.

[14] We use the restaurant's name to define bars and private clubs. In our definition, the words that qualify a restaurant as a bar or private club are "bar", "cantina", "club", "cocktail", "drink", "lounge", "pub", "saloon", "tap", "taberna", and "tavern". The words that disqualify a restaurant as a bar are "bar-b-q", "barbecue", "bistro", "brasserie", "cafe", "caffe", "casa", "cena", "comida", "conference", "country club", "deli", "diner", "dining", "eatery", "eats", "faculty club", "food", "golf club", "grill", "grille", "hotel", "inn", "kitchen", "osteria", "parrilla", "pasta", "pizza", "private club", "oyster", "restaurant", "restaurante", "ristorante", "sandwich", "shrimp", "sports club", "steak", "steakhouse", "sushi", "trattoria", and "yacht club".

Weather and revenue: We first estimate a linear regression of alcohol revenue on weather and a number of controls:[15]

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

As described above, a positive weather shock means unusually cold weather in hot quarters or unusually warm weather in cold quarters and a negative weather shock means unusually hot weather in hot quarters and unusually cold weather in cold quarters. The controls X_{jt} are restaurant attributes and local market attributes that change over time,[16] Q_t contains 16 year dummies and 3 quarter dummies, μ_j is a restaurant-specific random effect, and ε^r_{jt} is an idiosyncratic error term. We use random effects to match the later specifications on exit but show robustness to a fixed effects specification that better controls for restaurant-specific factors.

Table 2 presents the results. Column 1 presents the main specification. It shows that shocks to temperature are correlated with changes in revenue. When the temperature is 1 degree Fahrenheit closer to 69 degrees than average for that quarter, revenue is 0.27% higher. A two standard deviation change in weather suggests roughly one percent change in revenue. While the statistical significance of this result is high, it is important to recognize that the economic magnitude is small. Weather deviations from normal appear to matter, but they are not the primary drivers of revenue over the course of the quarter. This helps motivate our emphasis on inattention to weather: it is a significant driver of revenue but it is not sufficiently important that it is implausible that restaurant owners would ignore it.

Columns 2 through 6 show robustness of this main result. Column 2 includes restaurants that opened before 1998. Column 3 adds a control for precipitation shocks, and column 4 includes precipitation but not temperature. Adding the precipitation shocks does not change the estimated relationship between alcohol revenue and temperature shocks.[17] Column 5 uses fixed effects rather random fixed effects. The value of the core coefficient of interest does not change to four decimal places.[18] Column 6 shows robustness to restaurant owners who own just one establishment at a time.

Evidence for inattention to weather in exit decisions: Table 3 is the key motivating table. It is a linear regression of exit on revenue, weather, the interaction between weather and experience, restaurant attributes and market characteristics:

$$\begin{aligned} Exit_{jt} = {} & \beta^0 + \beta^1 \log\left(Revenue_{jt}\right) + \beta^2 Weathershocks_{jt} + \beta^3 Experience_j \\ & + \beta^4 Weathershocks_{jt} * Experience_j + X_{jt}\beta^5 + Q_t\beta^6 + \xi_j + \varepsilon^x_{jt} \end{aligned} \tag{2}$$

[15] Note that the notation in this section does not carry on to the structural model.
[16] In specifications with random effects, we also include time-invariant restaurant attributes as regressors.
[17] The lack of precipitation effect is likely driven by fact that the analysis is done in Texas. In particular, precipitation may be welcome on a hot summer day. Second, precipitation often comes in large quantities over a short period of time due to thunderstorms or even hurricanes. In many cases, a large percentage of the precipitation over a three month period occurs over one or two days.
[18] The coefficients on the controls do change, so that a Hausman test rejects the null that the random effects and the fixed effects specifications are equivalent. Because the core coefficient of interest does not change, and because later exit analysis uses random effects, we nevertheless emphasize the random effects results here.

As before, the controls X_{jt} are firm attributes and local market attributes, Q_t contains 16 year dummies and 3 quarter dummies, ξ_j is a restaurant-specific random effect, and ε_{jt}^{x} is an idiosyncratic error term. Fixed effects are not identified here because each restaurant exits only once. Therefore, time-invariant restaurant attributes controls are included as part of X_{jt}. In order to better-motivate the structural results, and in recognition that exit decisions look back over several periods rather than just one quarter, we define revenue and temperature shocks as the average monthly values over the previous year, rather than the previous quarter as in Table 2.

Table 3 Column 1 presents the main result. Given that the dependent variable is exit, as expected, the first row shows that revenue is negatively correlated with exit. Thus restaurants are more likely to go out of business after a period of low revenue. The second and third rows present the main effects of weather shocks and experience.

The key results are in the fourth row. The interaction between experience and the value of temperature shock is positive. Combining the estimates in row 2 (-0.0009) and row 4 (0.0023), we can see that experienced owners are *more likely* to exit in good weather. Therefore, experienced owners behave in a way that would be predicted by a fully rational model, in which owners take account of, and discount, revenues from weather shocks.

In contrast, inexperienced owners do not. The coefficient on temperature shocks for inexperienced owners (row 2) is small in magnitude and negative. While this coefficient is not focal to our analysis, one explanation is that positive weather shocks may help reducing operating costs such as heating and air conditioning. The other coefficients are perhaps as expected: Experienced owners are generally less likely to exit, non-business owners are more likely to exit, and restaurants with more competitors are more likely to exit.

Column 2 presents the exit regression without the interaction between temperature shock and experience in order to provide a base of comparison for the interaction in column 1. Column 3 and column 4 show robustness to the alternative measure of experience that we emphasize in the structural estimation: the number of restaurant-quarters prior to opening the focal restaurant and the log version of the experience measure. The patterns identified in column 1 hold: The interaction term in row 4 is positive and so the experienced owners appear to discount revenues from weather shocks.

Alternative explanations:

In table 3, we establish a stylized fact: restaurants with experienced owners are more likely to exit facing positive weather shocks. This result can be also phrased as restaurants with experienced owners are less likely to exit facing negative shocks. We have emphasized inattention to transitory shocks as our core explanation. Before detailing the structural model of inattention, we consider several alternative explanations.

First, it is possible that experienced owners do a better job smoothing out the negative effect of negative weather shocks on revenue. For example, an experienced owner may adjust the menu to boost revenue in unusual weather (e.g. hearty, hot soups in unusually cold weather), and therefore the restaurant is less likely to exit facing negative weather shocks. Table 4 shows, in various specifications, that such a relationship between revenue and weather does not exist. In particular, like Table 2, Table 4 uses revenue as the dependent variable but adds an interaction between weather shocks and our experience measures (three different owner experience measures with either restaurant random effects or restaurant fixed effects). The parameter of interest is row 3, corresponding to the interaction between temperature shocks and owner experience. All six columns report insignificant (both economically and statistically) results, suggesting that experienced owners are not better managing weather shocks. 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.

Second, 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 affecting the owners, using inheritances for identification. Evans and Jovanovic (1989) show that the wealthy are more likely to start businesses, and argue that this result is driven by liquidity constraints. 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 liquidity or credit constraints bind more for inexperienced owners than for experienced owners. In this case, negative shocks (implying negative profits, because revenues cannot perfectly capture profits) could cause inexperienced owners to go out of business even though they might recognize the role of the weather in driving their profits. To explore the likelihood that credit constraints drive the results, in Column 1 and 2 of Table 5 we add the interaction between owner experience and the log of alcohol revenue into equation (2), mimicking columns 2 and 1 of Table 3 respectively.

Column 1 does suggest the existence of credit constraints: owner experience attenuates the effect of recent revenue on the exit decision. Combining row 1 and row 5 estimates, the effect of revenue from the current quarter on exit is negative, but attenuated toward zero for experienced owners. This credit constraint effect, however, does not inundate the weather-experience interaction effect. Column 2 shows the weather-experience interaction effect remains the same with or without revenue-experience interaction effect included (0.22 here and 0.23 in table 3). We interpret this to suggest that credit constraints alone are unlikely to be driving our results because the interaction of experience and revenue is a more direct test of credit constraints than the interaction of experience and weather shocks.

Third, it is possible that experienced owners are less subject to projection bias. Projection bias refers to the situation when a decision maker's prediction of future utility is systematically off in the direction of current utility. Conlin, O'Donoghue, and Vogelsang (2007) show that people are overly influenced by current weather when placing catalog orders of cold-weather items; Simonsohn (2010) shows that students are overly influenced by the cloudiness of the campus visit day when they make college enrollment decisions. A restaurant owner may think last quarter's bad weather will persist and then exit the business. If a more experienced owner is less biased, then we will observe that restaurants with experienced owners are less likely to exit facing negative shocks. This is not about inattention. Rather it about false expectations about future states.

To rule out this explanation, in column 3 of Table 5 we only estimate how weather shocks in the current quarter correlate with exit. In column 4 of Table 5 we add back in weather record averaged over past year. If our results are due to projection bias, then past weather shocks should not matter given that we have controlled for current weather. Looking at column (3), the projection bias argument seems to have some bite: The weather in the current quarter correlates with exit. Column (4), however, shows that the result that experienced owners are more likely to exit in good weather is driven by temperature shocks averaged over past year, not by the current temperature shocks (comparing row 4 and row 7 in this column). We interpret this to suggest that projection bias does not drive our core results.

A variety of other alternative explanations may arise with respect to the particular specification and general robustness. Because column 1 of Table 3 is our core result motivating our modeling framework, we vary aspects of that specification in the many robustness checks in Table 6. Columns 1 to 5 include alternative samples. Column 1 includes all restaurants and bars, including those for which the owner had over 25 restaurants. Column 2 drops owners with more than 10 restaurants and column 3 drops owners with more than 50 restaurants. Column 4 includes restaurants but not bars and column 5 has only single-establishment restaurant owners. Column 5 addresses another alternative explanation: that experienced restaurant owners generally own multiple restaurants. Rather than being better able to recognize the impact of the weather because of past experience, they might be better able to get a read on the restaurant business generally because they can see revenue numbers across many restaurants. Column 5 addresses this directly, showing robustness to including only those restaurant owners who own just one establishment at a time. Columns 6 to 8 define the temperature shock and revenue over a different time period. Column 6 looks over the current quarter, column 7 looks over the previous two quarters, and column 8 looks over the previous three years. Column 9 drops the time fixed effects (year and quarter) and column 10 drops the observations with unreasonably large weather shocks. Results are robust across all columns.

Columns 11 to 14 explore subsamples. Column 11 focuses on January to March, column 12 April to June, column 13 July to September, and column 14 October to December. The key result in row 4 is mostly driven by winters and summers. Columns 15 and 16 cluster at different levels. Column 15 clusters at the zip code level, and column 16 clusters at the county level. The standard error in row 4 increases from 0.0006 to 0.0007. Columns 17 to 19 explore different functional forms. The exit decision can be viewed as a duration model. Column 17 adopts the specification of a Cox proportional hazard model, column 18 that of a survival model with exponential distribution, and column 19 that of a survival model with Weibull distribution. Again, results are robust across columns.

Overall, we interpret our descriptive results as consistent with a theory of limited attention. While we cannot rule out all possible other explanations, the results presented above are not consistent with some of most obvious: skill at getting revenue from weather shocks, credit constraints, projection bias, and econometric specification error. Therefore, motivated by the regularities established by the descriptive evidence, we build a model to incorporate rational inattention into a Bayesian learning model in which owners learn about the quality of their restaurant by interpreting revenue signals over time.

Before turning to our inattention model, it is important to note that the above descriptive analysis does not address the process through which experienced owners learn 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 skilled at recognizing the importance overall. Our focus on inattention could be seen as an input into a model in which owners learn to separate signal from noise. 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 quantity of information, what is obviously relevant on day one? Which factors predict which people will pay attention to which information? We view our model as a useful step forward from just assigning diffuse priors to multiple sources of information.

5 Model

We formulate a structural model of belief formation and exit decisions, in which the owner of a restaurant-establishment (henceforth, an establishment) learns about its persistent profitability over time. In our model, the owner decides every time period whether an establishment she owns should exit from business. Once exiting, the establishment cannot return. Exiting is the only choice the owner makes. There is no decision on prices or quantities. 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 local demand, cost fluctuations, and a variety of incidental factors. The owner needs to form an expectation about the underlying profitability from the noisy signals she receives over time, and then compare her expected profits with her time-specific outside option to make the decision on whether to continue her business. The setup is therefore similar to standard models in the literature of exit such as Jovanovic (1982) and Hopenhayn (1992), and similar to the setup of Abbring and Campbell (2003, 2005) in their analysis of an earlier version of the same data. Our model differs from the standard models because the owner's learning process about the underlying profitability of the restaurant allows for rational inattention to random variation in the revenue signals.

5.1 Model Setup and Notation

The owner of the establishment j observes the following variables at the end of every time period t:

- R_{jt}: log revenue from the sale of alcoholic drinks of establishment j at time t. The owner would observe total revenue and profits, but we only have data on alcohol revenue and use it as a proxy.
- W_{jt}: weather shocks experienced by establishment j at time t. Note that weather shocks are transitory with expected value zero.
- X_{jt}: local market attributes and establishment attributes. The local market attributes are 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. The establishment attributes are the number of months the establishment has operated, whether the restaurant is a bar, and whether it is part of a chain.

- Z_j: owner attributes. We focus on the level of owner experience, as measured in our descriptive analysis.[19]
- Q_t: Quarterly dummies for the current time period, which captures seasonality.

We as the econometricians observe the same covariates (listed above) 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 (introduced below).

Our model will allow for the owner to observe more than the econometricians, especially in their process of learning to decompose revenue signals and paying attention, which we will gradually introduce in later sections. For now, the owner observes only one variable that the econometrician does not: O_{jt}, the outside option an owner faces with the establishment (for example, the expected payoff from another profession). We parameterize the outside option as:

$$O_{jt} = \beta^O + X_{jt}\beta^X + Q_t\beta^Q + \varepsilon^o_{jt}, \tag{3}$$

in which ε^o_{jt} follows an *i.i.d.* standard Normal distribution. This outside option is not distinguishable from the time-varying shocks to profits. The constant term in the outside option is, in fact, the difference between time-varying profits and the outside option; the fixed variance of ε^o_{jt} is the multiplicative normalization.

The establishment has underlying profitability π_j, which is persistent over time. This value is unobserved to the owner and she tries to learn it. Within a time period *t*, this is the sequence of events:

- The owner forms her belief about π_j given all past observables up to month *t-1*. This belief is about the distribution of π_j, not only the mean but also the variance.
- The outside option is presented to the owner.
- The owner makes a decision on whether to exit based on the comparison between her belief about the value of operating the restaurant and the outside option given current observables. The current transitory shocks (e.g. weather shocks) are not observed at this moment.
- If the owner decides to continue, monthly revenue record R_{jt} is realized, where R_{jt} contains the effects of all time-varying observables and transitory shocks to revenue and cost. If the owner decides to exit, she obtains the realization of the outside option.

[19] We explored other owner attributes including whether the registered owner name is an individual person rather than a company or partnership and the distance between the owner's zip code (for tax purposes) and establishment's zip code, but neither has any significant effects on results. Kalnins and Lafontaine (2013) use similar data to measure the separate effects of establishment quality and geographic distance between owner and establishment.

5.2 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 persistent profitability, π_j, represents the present discounted value of the future stream of profits that will accrue to the owner going forward.

This simplifies the dynamic implications of an exit decision. We do this to focus on how limited attention to past transitory shocks affects an owner's belief on her establishment's persistent profitability. In our model, paying attention is a static decision — we think this is a fair characterization of the attention allocation process for our setting given that transitory shocks have a small impact on restaurant profitability. If an owner keeps the option value of waiting by staying open so they can pay more attention to weather in the future, intertemporal allocation of attention will become an issue and we would instead need to incorporate such a forward-looking decision process into the dynamic model.

From the start of operating an establishment, the owner receives a quarterly profit signal in the form of r_{jt}, where $r_{jt} \sim N\left(\pi_j, \sigma_r^2\right)$. This signal r_{jt} is obtained from the establishment's revenue record of alcohol sales R_{jt}. Variations in the revenue record may be due to transitional shocks, including weather shocks but may also include demand shocks or cost shocks. In order to make a fully rational decision, these transitional shocks need to be teased out from persistent profitability by an attentive decision maker.

Specifically, revenue R_{jt} can be written as the following equation:

$$R_{jt} = \alpha^R + X_{jt}\alpha^X + Q_t\alpha^Q + \eta_j + \upsilon_{jt} \tag{4}$$

In equation (4), X_{jt} is a vector of establishment and market attributes, Q_t is a vector of quarter dummies, η_j is the establishment fixed effect, and all $\alpha's$ are model parameters. At the end of the equation, υ_{jt} captures transitory shocks, a time-variant component of an establishment's revenue records that are not readily recognizable by the owner. A part of this unobservable is weather shocks, which are transitory shocks that require attention cast by the owner. Another part has the same role of weather shocks, for examples, local sports team victories, temporary input price variation, etc. The rest of the unobservable contains shocks that are effectively unrecognizable --- shocks which the owner will never figure out, such as a public conversation by a satisfied customer. Following this distinction, we can write υ_{jt} as the summation of three parts:

$$\upsilon_{jt} = W_{jt}\alpha^w + \upsilon_{jt}^o = W_{jt}\alpha^w + \gamma\upsilon_{jt}^o + \left(1-\gamma\right)\upsilon_{jt}^o \tag{5}$$

where $W_{jt}\alpha^w$ captures the effect of weather shocks and γ is the proportion of the unobserved shock that can be recognizable by the owner. Combining equations (4) and (5), we have ω_{jt} as the true state of the world, upon which the owner allocates her attention:

$$\omega_{jt} = W_{jt}\alpha^w + \gamma\upsilon_{jt}^o \tag{6}$$

In equation (6), ω_{jt} represents the full amount of transitory shocks that can be recognized by the owner. The owner, no matter how much attention she pays to ω_{jt}, knows the variance of ω_{jt}, which is denoted as $\operatorname{var}\left(\omega_{jt}\right)$.

A fully attentive owner derives the quarterly profit signal r_{jt} in the following way:

$$r_{jt} = \beta^R \left(R_{jt} - \omega_{jt} \right) \tag{7}$$

That is, she teases out transitory shocks from the revenue data, and uses a "clean" signal to update her belief about persistent profitability.

The owner, however, may not be fully attentive. In particular, she may not fully register the impact of transitory shocks on revenue due to the existence of rational inattention. This leads to the following interpretation of the current period signal:

$$r_{jt} = \beta^R \left(R_{jt} - \tau_j \omega_{jt} \right) \tag{8}$$

The difference between equation (7) and (8) is the perceived effect of ω_{jt} on revenue: in equation (8) 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. If $\tau_j = 0$, the owner totally ignores the effect of transitory shocks; otherwise, the owner perceives the effect of transitory shocks with a distortion. In the next subsection, we build a behavioral foundation for τ_j according to the sparsity-based model of bounded rationality developed by Gabaix (2014).

The owner updates her belief about the establishment's underlying profitability at the beginning of each period, after observing last period's revenue. The owner's posterior mean about the underlying profitability in the current period is:

$$\begin{aligned} & E_t \left(\pi_j \,\middle|\, R_{j1}, ..., R_{j,t-1}, W_{j1}, ..., W_{j,t-1}, X_{j1}, ... X_{j,t-1}, Q_1, ..., Q_{t-1} \right) \\ & = \frac{\sigma_r^2}{(t-1)\sigma_0^2 + \sigma_r^2} \pi_j^0 + \frac{(t-1)\sigma_0^2}{(t-1)\sigma_0^2 + \sigma_r^2} \frac{\sum_{s=1}^{t-1} \beta^R \left(R_{js} - \tau_j \omega_{js} \right)}{t-1} \end{aligned} \tag{9}$$

And her posterior variance about the underlying profitability is

$$\sigma_{posterior}^2 = \frac{\sigma_0^2 \sigma_r^2}{(t-1)\sigma_0^2 + \sigma_r^2} \tag{10}$$

Note that attention happens in the current period and the history of ω_{jt} cannot be traced. Instead, past ω_{jt} enters the posterior belief of the owner and only affects the owner's perception through the posterior belief.

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

So far we have introduced a behavioral twist: the owner may underestimate or even ignore the impact of transitory shocks on revenue, thus misinterpreting the revenue signals. In this subsection we build a behavioral foundation for the existence of τ_j, 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.

In our setting, if the owner pays full attention to the transitory shocks, τ_j should be equal to 1; however, the owner faces a cost of paying attention to the various inputs into a decision and so she chooses the optimal τ_j. This generates a sparse representation of the world, according to the following optimization problem:

$$\min_{\tau_j} \frac{1}{2}\left(\tau_j - 1\right)^2 \operatorname{var}\left(\omega_{jt}\right) + \tilde{\kappa}_j \left|\tau_j\right| \tag{11}$$

where 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. We use $\operatorname{var}\left(\omega_{jt}\right)$, the establishment-specific variance of ω_{jt}, to scale the importance of knowing the true state of the world. The higher this variance is, the larger is the loss from not paying attention to the magnitude of ω_{jt}.

In terms of cost, $\tilde{\kappa}_j$ is the time-invariant thinking cost of the owner. The owner observes this cost but we the econometricians do not. We assume that $\tilde{\kappa}_j$ follows a Lognormal distribution with mean $\kappa_0 + Z_j \kappa_1$ and variance normalized to 1. That is,

$$\tilde{\kappa}_j \sim \log N\left(\kappa_0 + Z_j \kappa_1, 1\right) \tag{12}$$

Equation (12) specifies the cost of thinking as a random process. Given the same Z_j, different decision makers may have different thinking cost and choose different τ_j to recognize the impact of transitory shocks. We focus on owner experience as the observable factor to the econometrician that shifts cost of thinking. In particular, we interpret our motivating regressions as consistent with a model in which, with different experience, 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.

The solution to the problem in equation (11) is:

$$\tau_j = \begin{cases} 0 & \text{if} \quad \tilde{\kappa}_j > \operatorname{var}(\omega_{jt}) \\ 1 - \dfrac{\tilde{\kappa}_j}{\operatorname{var}(\omega_{jt})} & \text{if} \quad \tilde{\kappa}_j \le \operatorname{var}(\omega_{jt}) \end{cases} \tag{13}$$

Note that $\tau_j \in [0,1]$. If $\tau_j = 1$, the decision maker is fully rational; if $\tau_j < 1$, she is boundedly rational; if $\tau_j = 0$, the transitory shocks are completely hidden in the error term υ_{jt}, which is unattended by the owner. The ability to recognize the impact of transitory shocks is the ability to isolate it from the error term.

5.4 The Exit Decision

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 the start of period t.

To make the exit decision, the owner compares the profit stream coming from operating the establishment, which is an uncertain payoff, with that coming from the outside option $O_{jt} = \beta^O + X_{jt}\beta^X + Q_t\beta^Q + \varepsilon^o_{jt}$ (for example, closing the restaurant and taking a steady job). The owner's expected persistent profitability is $E_t(\pi_j)$[20] with a time-varying variance term $\sigma^2_{posterior} = \dfrac{\sigma_0^2\sigma_r^2}{(t-1)\sigma_0^2 + \sigma_r^2}$.

At any time period t, the owner takes a random draw from the Normal distribution $N\left(E_t(\pi_j), \sigma^2_{posterior}\right)$, which we denote as $E_t(\pi_j) + \sigma_{posterior}\varepsilon_{jt}$. Note that ε_{jt} contains idiosyncratic factors affecting the owner's actual expectation of restaurant profitability at the moment.[21] We can then write down the owner's exit decision as:

$$D_{jt} = \begin{cases} 0 & \text{if} \quad E_t(\pi_j) + \sigma_{posterior}\varepsilon_{jt} \ge \beta^0 + X_{jt}\beta^X + Q_t\beta^Q + \varepsilon^0_{jt} \\ 1 & \text{if} \quad E_t(\pi_j) + \sigma_{posterior}\varepsilon_{jt} < \beta^0 + X_{jt}\beta^X + Q_t\beta^Q + \varepsilon^0_{jt} \end{cases} \tag{14}$$

To summarize, we have a structural model based on standard Bayesian learning from repeated signals of revenues.[22] We inject a modicum of bounded rationality into this model by allowing imperfect

[20] For notation simplicity, here we omit the conditional variables in the owner's expected persistent profitability.

[21] In this exit model, we allow for new restaurants' expectation about "upside potential." Shortly after the restaurant opens, t is small. Therefore, the posterior variance is large. This large posterior variance allows an owner with a new establishment experiencing low expected profit to stay even if expected profit is low.

[22] This model is similar to a Jovanonic (1982) learning model in the sense that a decision maker updates its belief using signals of different accuracy. Our model is distinct because we build a behavioral foundation on why decision makers with different characteristics receive signals of different accuracy.

recognition of the impact of transitory shocks on these signals. This behavioral "twist" is the focus of this project. Quantifying the magnitude of this imperfect recognition gives us a measure of bounded rationality in a high-stakes business setting.

6 Estimation

6.1 Maximum Likelihood Estimation

We estimate the revenue and exit decisions jointly with the simulated maximum likelihood estimation method. Let $L_j = L\left(R_{j1},...,R_{jT_j},D_{j1},...,D_{jT_j}\right)$ denote the joint likelihood of establishment *j*'s observed sequence of revenue amounts and exit decisions. 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:

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

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

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

To form the likelihood for the population, we multiply over J firms and perform a log transformation. We can write:

$$\ln L_{simulated} = \sum_{j=1}^{J}\sum_{s=1}^{T_j} \log L^R\left(R_{js} \mid W_{js},X_{js},Q_s\right) + \sum_{j=1}^{J} \ln\left\{\frac{1}{NS}\sum_{ns=1}^{NS}\left[\prod_{s=1}^{T_j} L^D\left(D_{js} \mid R,W,Z,X,Q,\pi_{j,ns}^0\right)\right]\right\} \tag{17}$$

where *NS* is the number of simulation draws. In the appendix, we explain in detail the individual likelihood components in equation (17).

6.2 Identification of Structural Parameters

The set of structural parameters to be estimated is $\{\alpha^w, \alpha^R, \alpha^X, \alpha^Q, \beta^O, \beta^X, \beta^Q, \beta^R, \sigma_0^2, \sigma_r^2, \gamma, \kappa_0, \kappa_1\}$, that is, the set of parameters in the revenue generating equation, in the outside option, and in the attention allocation process. We are able to identify all the structural parameters in the model using corresponding data variation.

- α^w from estimating the revenue equation: how weather shocks affect revenue. The rest of the α values are identified similarly.
- β^O from the mean exit probability (the constant term in the exit equation)
- β^R from the conditional relationship between revenue and exit.
- β^X from the conditional relationship between X_{jt} and exit.
- β^Q from the conditional relationship between Q_t and exit.
- σ_0 from the between-establishment estimation of the revenue equation. In other words, σ_0 reflects profit differences across individual establishments ("between variance").
- σ_r from the within-establishment estimation of the revenue equation. In other words, σ reflects profit differences within individual establishments ("within variance").
- γ : from the conditional relationship between exit and the unexplained variation in the revenue generating process. This unexplained variation, estimated by us as econometricians in the revenue generating process, is a part of revenue. If this unexplained variation affects exit decisions differently from how revenue affects exit decisions (pinned down by β^R), it must be that owners used them in the attention allocation process.
- κ_0: normalized (as most of the owners in our data appear to pay no attention, this parameter is not well identified).
- κ_1 from how the degree of bounded rationality varies with owner-specific attributes Z_j , empirically captured by owner experience. Owner experience affects the owner's thinking cost and, in turn, her recognition of the impact of transitory shocks on revenues. Owner experience, however, does not directly affect establishment profits, thereby allowing separate identification of the thinking cost parameters from the other structural parameters in the model.

7 Structural Results

7.1 Model Estimates

We present our key structural estimates in Table 7.[23] In column (1), we use owner experience, measured by a dummy variable indicating whether the owner has owned a restaurant before opening the given establishment, in the cost of thinking function. In columns (2) and (3), we use owner experience,

[23] We present the full set of structural parameters in Appendix Table 2.

measured in the number of establishment-quarters the owner has experienced before opening the given establishment and the log of this variable, in the cost of thinking function.[24] All three 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.

As shown in the first two rows of Table 7, weather shocks have a significantly positive effect on log revenue, and log revenue is a good indicator of firm profitability. As in $r_{jt} = \beta^R \left(R_{jt} - \omega_{jt} \right)$, the higher β^R is, the more log alcohol revenue indicates firm profitability and contributes to a restaurant's decision to stay in business. Given the motivating regressions, this is not surprising. The third row of Table 7 reports γ, the proportion unobservable (by the econometricians) in the data generating process of log revenue that can be attended to ($\omega_{jt} = W_{jt}\alpha^w + \gamma v_{jt}^o$). According to our estimate, roughly one third of this unobservable can be attended to by an owner paying full attention.

Our results suggest a high prevalence of inattention. Of the 25,283 owners in our data, an average owner's probability of paying zero attention ranges from 83% 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 (as captured by $E\left[\tau_j \mid \tilde{\kappa}_j \leq \text{var}\left(\omega_{jt} \right) \right]$) is 0.284 in the column 1 specification, 0.281 in column 2, and 0.278 in column 3. Overall, the attention parameter τ_j is estimated to be low, suggesting that owners pay limited attention to the impact of transitory shocks on their profitability.

The amount of attention, however, displays significant heterogeneity across owners in data. The minimum attention is roughly 0.123 in all three specifications, while the maximum is close to 1. This heterogeneity in attention is driven by a large, significantly negative estimate of the effect of owner experience on thinking costs. Experience brings down a decision-maker's cost of thinking relative to the variance of transitory shocks, allowing experienced owners to recognize the existence of transitory shocks in their revenue signals.

7.2 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, and then simulate exit events under our model with full attention in which every owner has $\tau_j = 1$. Comparing these simulations, we find that roughly 3.4% of

[24] We have estimated specifications with two additional covariates into this function: whether the owner is an individual (versus a corporation) and the distance (in thousands of miles) between the owner's location and the restaurant's location. These two owner attributes may affect their decision-making process: an individual may rush to a decision without much deliberation as opposed to in a group-based setting; an owner may fail to pay attention to transitory shocks in a distant locale. Both variables have economically negligible and statistically insignificant coefficients in the cost of thinking function. Therefore, we report the results that do not include them.

our 25,283 restaurants — 849 restaurants, would have made a better decision with respect to exit timing under full attention.[25] 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 zero aggregate impact.

For these 849 restaurants, 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 restaurant in any quarter is how much revenue the owner would have to pay (or receive) so that the owner forms the correct belief about her restaurant's underlying profitability this quarter as if she pays full attention. The benefit is estimated from the penalty of incorrect decisions. It is how much a restaurant's owner is willing to pay (or receive) in order to avoid incorrect staying or exit decisions in the quarter where decisions differ.[26] To evaluate both cost and benefit on a quarterly basis, we divide total cost and total benefit by the number of quarters leading the quarter where decisions differ between the full attention simulation and the simulation based on our estimated parameters.[27]

Panel A of Table 8 reports the cost and benefit analysis of paying full attention for these 849 restaurants. The first two rows report summary statistics about the total cost or benefit for a restaurant. The next two rows report the same summary statistics per restaurant-quarter. These numbers clearly indicate that the benefit of paying full attention is dominated by the cost of doing it. Although the benefit is equivalent to roughly $14,000 for a median restaurant, the cost is roughly $17,000.[28] Both benefit and cost are highly skewed to the right, reflected by much higher means than medians. There is significant heterogeneity across restaurants. For some restaurants, the incorrect timing of exit has catastrophic consequences, but paying full attention to avoid these incorrect decisions is nevertheless too costly.

7.3 The Value of Experience

7.3.1 The Value of Experience, in General

Given the substantial cost of paying attention, the natural question is what alleviates the burden so the owners make better decisions. In our estimated model, it points to the owner's pre-existing experience before opening a restaurant. The majority of owners (81.3%) have no such experience; among the owners with such experience, it can range from 1 quarter to more than 10 years. Experience can be translated into dollar amounts: an owner is willing to pay for a certain number of years of experience because experience helps her cast better attention. In other words, experience helps owners save the costs of

[25] For restaurants that have not made better decisions under full attention in the span of the observed history, it is possible that they make better decisions in the future.
[26] In our simulations, we assume that exit decisions are permanent: once a restaurant exits, it cannot go back in business. This assumption makes incorrect exit decisions and incorrect staying decisions asymmetric when we calculate welfare trade offs. Avoiding an incorrect staying decision yields a benefit over just one period. Avoiding an incorrect exit decision yields a benefit over multiple (consecutive) periods.
[27] For reasons explained in a previous footnote, when paying attention helps to avoid incorrect exit decisions, the denominator is revised to be the number of quarters leading to the last quarter when decisions differ in simulation 1 and 0.
[28] At the restaurant-quarter level, although at the median the benefit is roughly equal to the cost, the benefit is far smaller than the cost at other percentiles.

paying attention, which may lead them to making better decisions. In short, the value of experience is the amount of money needed to compensate for the lack of experience.

To get a representative measure, we evaluate the value of experience for all 25,283 restaurants' operating history in our data and report the numbers in Panel B of Table 8. The first two rows report the value of experience at the restaurant level, and the next two rows at the restaurant-quarter level. On average, the value of experience is large. In particular, gaining one year of experience is equivalent to $114 quarterly for a median restaurant, gaining three years $931, and gaining ten years $1,728. One way to think about these numbers is that they are salary premiums the restaurant might be willing to pay for managers with pre-existing experience in the profession. Under this interpretation, ten years of experience is worth about $575 per month, which may be reflected by higher earnings for more experienced managers.

Overall, our results point to an understudied area of firm-level heterogeneity: heterogeneity in the ability to attend to information in decision-making. Our results suggest that this heterogeneity is correlated with traits of the individual decision makers and highly relevant in business outcomes.

7.3.2 Experiences and Luck as Substitutes

Positive and negative shocks, or lucky and unlucky events, may have asymmetric effects on restaurant owners' welfare. Imagine continuous terrible weather or a mini-recession in a restaurant'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 restaurant owner has accumulated enough profit signals to form an accurate belief about the restaurant's profitability. Similarly, when a restaurant 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 delay the inevitable by a short period of time, so the misinterpretation of the revenue signal may affect decisions to a limited extent. Therefore, when the owner is subject to inattention, the welfare loss due to incorrect decisions should be more severe when a restaurant 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 (ranging from little attention to almost perfect attention).

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

We simulate the percentage of wrong decisions and total welfare loss for each luck-experience combination in the table. We benchmark the welfare loss of wrong decisions compared to an ideal where the owner pays perfect attention. The welfare loss is estimated as the amount a restaurant's owner would be willing to pay (or receive) in order to avoid incorrect staying or exit decisions in the quarters where decisions differ. Note that in our model exit is a permanent decision: once a restaurant exits, it cannot go back in business. This assumption makes wrong exit decisions and wrong staying decisions asymmetric when we calculate welfare trade-offs. In our welfare calculation, 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 negative shocks reduce welfare much more substantially than positive shocks do. The welfare loss from mistakes with three years of negative shocks, is 50% higher than the welfare loss from mistakes with three years of positive shocks. The permanent exit decision drives these results. Furthermore, the more severe the negative shocks are (as we move down the rows in Panel B), the more severe is the welfare loss. This is because negative shocks cause a potentially successful restaurant to close prematurely, eliminating many potential years of profits.[29] 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 mistaken 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 is almost negligible.

Owner experience is especially useful when a restaurant is hit with a series of unfortunate events. Moving down the rows of Panel B, the percentages of wrong decisions only increase marginally, but the corresponding welfare loss increases substantially. When no owner has experience, moving from baseline (all random shocks) to an extended period of bad luck (1st three years of negative shocks) leads to a welfare loss of more than $50 million. With experience, we see the same, steadily increasing pattern as the industry in hit with more negative shocks, but the gap due to bad luck dwindles. Not only the welfare loss plummets as owners gain experience. The gap between different "luck" regimes also changes. Different luck regimes generate big swings in welfare loss when owners are inexperienced, but the gaps disappear as the level of experience rises. We illustrate this point in Figure 2.

When a restaurant is hit with a series of fortunate events, experienced owners still receive a reduction in welfare loss, but it is a much smaller reduction. As reported in columns 7 and 8 of Table 9, the difference between positive and negative shocks is very small when every owner has almost perfect attention.

Overall, these simulations point to an interaction between luck and skill that departs from the existing literature. Table 9 shows that owner experience reduces welfare loss due to inattention, especially when the owner is hit a series of unfortunate events. 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

[29] Note that the welfare calculations allow for mistakes in all years that the restaurant is open, and the total welfare numbers include the welfare consequences of numerous shocks that happen after the period of simulated only-positive and only-negative shocks.

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.

8 Conclusion

This research investigates the existence and the degree of bounded rationality in high-stakes business situations: the decisions of restaurants to exit from business. We utilize a setting where incidental factors — weather shocks — have a small but significant impact on firms' revenue and in turn should enter the owners' inference process when deciding on exit. If owners ignore or underestimate these incidental factors, this suggests boundedly rational behavior by firms in their exit decisions in the form of inattention to small but relevant factors.

We show that good weather helps restaurants' revenue. We then show that in good weather, the experienced owners are more likely to exit given the same revenue record and in bad weather, the experienced owners do the reverse. In contrast, weather does not predict the exit behavior of the inexperienced owners, conditional on revenue.

This descriptive evidence motivates a structural model of rational inattention, in which the owner of a restaurant establishment tries to learn about its underlying profitability given noisy revenue signals. The manager' s learning process has both a standard Bayesian component and a behavioral twist—the cost of thinking may prevent the manager from giving consideration to the impact of transitory shocks. We build a behavioral foundation for the owner's rational inattention by incorporating Gabaix (2014)'s sparsity-based model as a key element. This is a highly tractable, yet quite general, model with a rational benchmark and a modicum of bounded rationality injected into this benchmark. There is only one parameter to pin down bounded rationality, and this parameter can be heterogeneous across individuals and over time. Using this model, estimation and identification are transparent: weather is random and should be net out of the expectation of future profitability, while other factors may have permanent effects on underlying profitability.

Our structural estimates suggest that limited attention to transitory shocks can be costly to firms. Roughly 3.4% of the restaurants in our data appear to have made mistaken exit decisions because of this limited attention. Correct decisions would have yielded thousands of additional dollars per quarter for a single restaurant. At the same time, our estimates do not suggest irrational behavior, but rather boundedly rational behavior. This bounded rationality arises as the cost of paying attention, though not so high as to be unreasonable, outweighs the benefit of paying attention. Furthermore, our estimates show that experience reduces the cost of paying attention. Ten years of experience reduces the cost of paying attention to transitory shocks by about $500 per month. The results also show that experience is more valuable in the presence of bad luck than in the presence of good luck. Experience and luck act like substitutes. Experience enables decision-makers to understand that what seems like bad luck is merely a distorted signal.

Somewhat more speculatively, our results provide insight into a high stakes and fundamental determinant of market structure, competitiveness, and performance (Dunne, Roberts, and Samuelson, 1988). 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. It is also an important component of understanding job creation and productivity growth (Haltiwanger 2012). 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 emphasize 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.

This paper examines whether and how a particular type of bounded rationality persists in the marketplace. Before concluding, we acknowledge several limitations of this project. First, in our bounded rationality framework, we still allow for a substantial degree of rationality. We expect the restaurant owners to be capable of sophisticated calculation, which may not hold in reality. Second, we emphasize a stark contrast between experienced and inexperienced restaurant owners. With richer data on the types of experience, it would be possible a deeper understanding of when and how experience improves decision-making. We also cannot separately identify whether the measured difference in experience is driven by selection effects (better restaurant owners open a second restaurant) or the causal effects of experience. 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 so we more precisely understand imperfect decision-making by firms. Understanding small distortions in individual firms' decision-making process is a necessary step to understand potential distortions at a larger scale. Thus, despite these limitations, we believe we have made an important early step in understanding limited attention in managerial decision-making.

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.

Arrow, Kenneth. 1962. "The Economic Implications of Learning by Doing." *The Review of Economic Studies,* 29(3), 155-173.

Baron, Robert A., and Michael D. Ensley. 2006. "Opportunity Recognition as the Detection of Meaningful Patterns: Evidence from Comparisons of Novice and Experienced Entrepreneurs." *Management Science*, 52(9): 1331-1344.

Benkard, C. Lanier. 2000. "Learning and Forgetting: The Dynamics of Aircraft Production." *The American Economic Review*, 90(4): 1034-1054.

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

Borenstein, Severin. 2016. "The Power and the Limits of Industrial Organization." *Review of Industrial Organization* 48, 241-246.

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

Brown, Alexander L., Colin F. Camerer, and Dan Lovallo. 2012. "To Review or Not to Review? Limited Strategic Thinking at the Movie Box Office." *The American Economic Journal: Microeconomics,* 4(2): 1-26.

Brown, Alexander L., Colin F. Camerer, and Dan Lovallo. 2013. "Estimating Structural Models of Equilibrium and Cognitive Hierarchy Thinking in the Field: the Case of Withheld Movie Reviews." *Management Science,* 59(3), 733-747.

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.

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.

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.

DellaVigna, Stefano, and Ulrike Malmendier. 2006. "Paying Not to Go to the Gym." *The American Economic Review*, 96(3): 694-719.

DellaVigna, Stefano, and Joshua M. Pollet. 2009. "Investor Inattention and Friday Earnings Announcements." *The Journal of Finance*, 64(2): 709-749.

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

Dow, James. 1991. "Search Decisions with Limited Memory." *The Review of Economic Studies,* 58(1): 1-14.

Dunne, Timothy, Shawn Klimek, Mark J. Roberts, and Daniel Y. Xu. 2013. "Entry, Exit, and the Determinants of Market Structure." *The RAND Journal of Economics* 44(3), 462-487.

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.

Ellison, Glenn. 2006. Bounded Rationality in Industrial Organization. *Econometric Society Monographs*, 42, 142.

Evans, David S. and Boyan Jovanovic. 1989. "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints." *Journal of Political Economy,* 97(4), 808-827.

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, Teck-Hua Ho, Wilfred Amaldoss, Alexander Brown, Yan Chen, Tony Haitao Cui, Alberto Galasso, Tanjim Hossain, Min Hsu, Noah Lim, Mo Xiao, and Botao Yang. 2012. "Behavioral Models of Managerial Decision-Making," *Marketing Letters,* 23(2), 405-421.

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.

Greenwood, Robin and Samuel G. Hanson. 2015. "Waves in Ship Prices and Investment." *The Quarterly Journal of Economics*, 55-109.

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.

Harrison, Glen W. and John List. 2008. "Naturally Occurring Markets and Exogenous Laboratory Experiments: A Case Study of the Winner's Curse," *Economic Journal*, 118(528): 822-843.

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.

Hopenhayn, Hugo. 1992. "Entry, Exit, and firm Dynamics in Long Run Equilibrium." *Econometrica, 60*(5), 1127-1150.

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 and Steven Puller. 2008. "Understanding strategic bidding in multi-unit auctions: a case study of the Texas electricity spot market." *The RAND Journal of Economics* 39(1), 86-114.

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.

Kalnins, Arturs and Francine Lafontaine. 2013. "Too Far Away? The Effect of Distance to Headquarters on Business Establishment Performance." *The American Economic Journal: Microeconomics*, 5(3): 157-79.

Kihlstrom, Richard E., and Jean-Jacques Laffont (1979), "A General Equilibrium Entrepreneurial Theory of Firm Formation based on Risk Aversion." *Journal of Political Economy* 87(4), 719-748.

Kiss, Andras, 2017, "Salience and Switching." Working paper, University of Amsterdam.

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.

Levitt, Steve, John A. List, and Chad Syverson. 2013. "Toward an Understanding of Learning by Doing: Evidence from an Automobile Plant." *Journal of Political Economy*, 121(4), 643-681.

List, John A. 2003. "Does market experience eliminate market anomalies?" *The Quarterly Journal of Economics*, 118(1): 47-71.

List, John A. and Daniel L. Millimet. 2008. "The Market: Catalyst for Rationality and Filter for Irrationality." *The B.E. Journal of Economics Analysis & Policy,* 8(1), 1-55.

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

Meyer, Wulf-Uwe, Michael Niepel, Udo Rudolph, and Achim Schutzwohl. 1991. "An Experimental Analysis of Surprise." *Cognition & Emotion*, 5(4), 295-311.

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. 2016a. "Methodological Issues in Analyzing Market Dynamics." NBER Working Paper 21999.

Pakes, Ariel. 2016b. "Empirical Tools and Competition Analysis: Past Progress and Current Problems." NBER Working paper 22086.

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.

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

Simonsohn, Uri. 2010b. "eBay's Crowded Evenings: Competition Neglect in Market Entry Decisions." *Management Science*, 56(7): 1060-1073.

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

Spiegler, Ran, 2011. Bounded Rationality and Industrial Organization. Oxford University Press, Oxford UK.

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.

Ucbasaran, Deniz, Paul Westhead, Mike Wright. 2009. "The Extent and Nature of Opportunity Identification by Experienced Entrepreneurs." *Journal of Business Venturing*, 24(2): 99-115.

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

Table 1a: Restaurant-Level Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Ever exit	0.644	0.479	0	1
Owned a restaurant, 3 years before open	0.187	0.390	0	1
# restaurant-quarters, 3 years before open	5.024	16.136	1	275
Log(#restaurant-quarters, 3 years before open)	0.483	1.089	0	5.617
# restaurant-quarters prior to open	10.727	47.288	1	1,166
Log(#restaurant-quarters prior to open)	0.591	1.333	0	7.061
Owner name is not a business name	0.135	0.342	0	1
Restaurant is a bar	0.185	0.388	0	1
# restaurants		25,283		

Table 1b: Restaurant-Quarter Level Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Restaurants				
Exit: No longer restaurant with same name at address	0.042	0.200	0	1
Experience: Owned a restaurant, 3 years before open	0.203	0.402	0	1
Experience: # restaurant-quarters, 3 years before open	5.798	17.763	1	275
Log(#restaurant-quarters, 3 years before open)	0.547	1.165	0	5.617
Experience: # restaurant-quarters prior to open	11.811	47.531	1	1,166
Experience: log(# restaurant-quarters prior to open)	0.663	1.408	0	7.061
Average monthly alcohol revenue in a quarter ($ thousand)	32.003	55.904	0.001	3406.408
log(average monthly alcohol revenue in a quarter)	9.501	1.4616	0.0013	15.0412
Time since restaurant opened in years	3.644	3.236	0.25	17.5
Likely lease renewal period (multiple of 4 quarters since opening)	0.226	0.418	0	1
Owner has at least five more restaurants	0.068	0.251	0	1
Weather				
Temperature shocks (degrees Fahrenheit)	-0.145	2.067	-18.977	10.637
Precipitation shocks (inches)	0.079	1.775	-41.726	6.731
Market Attributes at the Zip Code Level				
# other restaurants	33.8857	35.4828	0	240
Population (millions)	0.030	0.018	0	0.114
Fraction black	0.104	0.114	0	0.942
Fraction Hispanic	0.318	0.233	0	0.998
Fraction age under 18	0.238	0.078	0	0.435
Fraction age 65 and over	0.106	0.056	0	0.627
log(average household income)	10.884	0.457	0	12.525
Fraction bachelor degree	0.305	0.184	0	0.849
Fraction rural	0.094	0.212	0	1
Fraction foreign born	0.160	0.101	0	0.603
# restaurant-quarters			388,817	

Table 2: Weather Affects Revenue

	(1) Main	(2) Include restaurants opening before 1998	(3) Includes precip-itation	(4) Precip-itation	(5) Restaurant fixed effects	(6) Only single-establishment restaurant owners
Shock to temperature (degrees Fahrenheit)	0.0027**	0.0022**	0.0028**		0.0027**	0.0031**
	(0.0004)	(0.0003)	(0.0004)		(0.0004)	(0.0004)
Shock to precipitation (inches)			0.0007	0.0002		
			(0.0006)	(0.0006)		
Time since restaurant opened in years	-0.0019	-0.0118	-0.0118	-0.0118	-0.0032**	-0.0062
	(0.0046)	(0.0120)	(0.0120)	(0.0120)	(0.0010)	(0.0156)
Time since opened in years squared	-0.0019	-0.0118	-0.0118	-0.0118	-0.0032**	-0.0062
	(0.0046)	(0.0120)	(0.0120)	(0.0120)	(0.0010)	(0.0156)
Likely lease renewal period	-0.0006	-0.0008	-0.0008	-0.0008	0.0005	0.0002
	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0005)	(0.0008)
Owner name is not a business name	-0.0006	-0.0008	-0.0008	-0.0008	0.0005	0.0002
	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0005)	(0.0008)
Bar	-0.0006	-0.0008	-0.0008	-0.0008	0.0005	0.0002
	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0005)	(0.0008)
Owner has at least five more restaurants	-0.0006	-0.0008	-0.0008	-0.0008	0.0005	0.0002
	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0005)	(0.0008)
# other restaurants in zipcode	-0.0006	-0.0008	-0.0008	-0.0008	0.0005	0.0002
	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0005)	(0.0008)
Zipcode population (millions)	2.2580+	2.6620	2.6645	2.6816	0.0351	3.9517
	(1.3301)	(2.3289)	(2.3290)	(2.3289)	(1.2484)	(2.4469)
Zipcode fraction black	0.1458	-0.3863	-0.3881	-0.3876	-0.0503	-0.0291
	(0.1928)	(0.3850)	(0.3850)	(0.3850)	(0.1753)	(0.4296)
Zipcode fraction Hispanic	0.4084*	0.5364	0.5369	0.5339	0.7544**	0.9063*
	(0.2039)	(0.3782)	(0.3782)	(0.3783)	(0.1363)	(0.4360)
Zipcode fraction age under 18	-1.0902**	-1.9306**	-1.9281**	-1.9268**	-2.7949**	-2.4503**
	(0.3246)	(0.6439)	(0.6439)	(0.6441)	(0.3383)	(0.7066)
Zipcode fraction age 65 and over	-0.5983+	-0.7676	-0.7696	-0.7655	-1.0183**	-0.3465
	(0.3575)	(0.6382)	(0.6382)	(0.6382)	(0.3606)	(0.6947)
Zipcode logged avg hh income (000s)	0.1411+	-0.0451	-0.0461	-0.0454	0.0020	-0.0572
	(0.0784)	(0.1132)	(0.1132)	(0.1133)	(0.0648)	(0.1248)
Zipcode fraction bachelor degree	0.4634**	0.7748**	0.7744**	0.7731**	1.0898**	1.0006**
	(0.1363)	(0.2553)	(0.2553)	(0.2553)	(0.1700)	(0.2893)
Zipcode fraction rural	-0.2197**	-0.1260	-0.1263	-0.1251	-0.3584**	-0.1149
	(0.0829)	(0.1311)	(0.1312)	(0.1311)	(0.0873)	(0.1397)
Zipcode fraction foreign born	-0.6111*	-0.7806+	-0.7862+	-0.7809+	-1.0360**	-0.9223
	(0.2616)	(0.4653)	(0.4653)	(0.4654)	(0.2398)	(0.5707)
Observations	388,817	688,933	388,817	388,817	388,817	320,749
# of restaurants	25,283	35,487	25,283	25,283	25,283	22,289
R-squared	0.117	0.103	0.117	0.117	0.0270	0.130

Unit of observation is the restaurant-quarter. Standard errors in parentheses clustered by restaurant +significant at 10%; * significant at 5%; ** significant at 1%. Column headers describe differences from the main specification in column (1). Unless otherwise specified, dependent variable is log(alcohol revenue), restaurants include all with owners with fewer than 25 restaurants that opened after January 1, 1998, and regressions include year fixed effects, 3 quarterly dummies, and restaurant random effects (expect in column 5). Column headings of other columns specify how differ from column (1).

Table 3: Exit Decisions Relate to Owner Experiences

	(1) Main	(2) Without interaction	(3) Experience is # restaurant-quarters prior to opening / 1000	(4) Experience is log(# restaurant-quarters prior to opening)
Log(alcohol revenue)	-0.0234**	-0.0234**	-0.0235**	-0.0234**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Shock to temperature (degrees Fahrenheit)	-0.0009*	-0.0005	-0.0005	-0.0007*
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Experience	-0.0071**	-0.0075**	-0.0421**	-0.0034**
	(0.0015)	(0.0015)	(0.0101)	(0.0004)
Shock to temperature x Experience	0.0023**		0.0076+	0.0005**
	(0.0006)		(0.0041)	(0.0002)
Time since restaurant opened in years	0.0129**	0.0130**	0.0130**	0.0129**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Time since restaurant opened in years squared	-0.0007**	-0.0007**	-0.0007**	-0.0007**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Likely lease renewal period	0.0081**	0.0081**	0.0081**	0.0081**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Owner name is not a business name	0.0173**	0.0173**	0.0173**	0.0172**
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Bar	0.0137**	0.0137**	0.0137**	0.0135**
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Owner has at least five more restaurants	-0.0225**	-0.0225**	-0.0228**	-0.0180**
	(0.0020)	(0.0020)	(0.0020)	(0.0021)
# other restaurants in zipcode	0.0001**	0.0001**	0.0001**	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Zipcode population (millions)	-0.0408	-0.0407	-0.0395	-0.0415
	(0.0384)	(0.0384)	(0.0384)	(0.0384)
Zipcode fraction black	0.0319**	0.0319**	0.0320**	0.0318**
	(0.0064)	(0.0064)	(0.0064)	(0.0063)
Zipcode fraction Hispanic	0.0329**	0.0329**	0.0328**	0.0328**
	(0.0046)	(0.0046)	(0.0046)	(0.0046)
Zipcode fraction age under 18	0.0090	0.0091	0.0081	0.0088
	(0.0115)	(0.0115)	(0.0115)	(0.0115)
Zipcode fraction age 65 and over	0.0248*	0.0247*	0.0238*	0.0246*
	(0.0120)	(0.0120)	(0.0120)	(0.0120)
Zipcode logged avg hh income (000s)	-0.0010	-0.0010	-0.0010	-0.0010
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Zipcode fraction bachelor degree	0.0226**	0.0226**	0.0224**	0.0223**
	(0.0058)	(0.0058)	(0.0058)	(0.0058)
Zipcode fraction rural	-0.0063+	-0.0063+	-0.0059+	-0.0064+
	(0.0034)	(0.0034)	(0.0034)	(0.0034)
Zipcode fraction foreign born	0.0003	0.0002	0.0007	-0.0004
	(0.0079)	(0.0079)	(0.0079)	(0.0079)
Observations	388,817	388,817	388,817	388,817
# of restaurants	25,283	25,283	25,283	25,283
R-squared	0.00794	0.00791	0.00789	0.00802

Unit of observation is the restaurant-quarter. Standard errors in parentheses clustered by restaurant +significant at 10%; *significant at 5%; **significant at 1%. Dependent variable is taxpayer exit from that location, revenue and shock are defined as average monthly values over the previous year, experience is defined as whether owner had a restaurant in the 3 years prior to opening (except in columns 3 and 4), and restaurants include all owners with fewer than 25 restaurants. Regressions include year fixed effects, 3 quarterly dummies, and restaurant random effects.

Table 4: No significant effect of experience on the relationship between revenue and weather

	(1) Main (Experience is owned a restaurant in 3 years prior to opening), RE	(2) Experience is # restaurant-quarters prior to opening / 1000, RE	(3) Experience is log(# restaurant-quarters prior to opening), RE	(4) Main (Experience is owned a restaurant in 3 years prior to opening), FE	(5) Experience is # restaurant-quarters prior to opening / 1000, FE	(6) Experience is log(# restaurant-quarters prior to opening), FE
Shock to temperature	0.0030**	0.0028**	0.0029**	0.0030**	0.0028**	0.0029**
(degrees Fahrenheit)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)
Experience	0.1653**	1.2045**	0.0626**			
	(0.0230)	(0.2663)	(0.0070)			
Shock to temperature	-0.0014	-0.0051	-0.0002	-0.0015	-0.0056	-0.0002
x Experience	(0.0010)	(0.0085)	(0.0003)	(0.0010)	(0.0085)	(0.0003)
Time since restaurant	0.0034	0.0036	0.0038	-0.0324	-0.0325	-0.0324
opened in years	(0.0043)	(0.0043)	(0.0043)	(0.0480)	(0.0480)	(0.0480)
Time since restaurant	-0.0011**	-0.0011**	-0.0011**	-0.0010**	-0.0010**	-0.0010**
opened in years squared	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Likely lease renewal	0.0018	0.0018	0.0018	0.0014	0.0014	0.0014
period	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Owner name is not a	-0.5895**	-0.5880**	-0.5856**			
business name	(0.0494)	(0.0494)	(0.0493)			
Bar	0.3028**	0.3040**	0.3066**			
	(0.0262)	(0.0262)	(0.0262)			
Owner has at least five	0.0495*	0.0483*	0.0445*			
more restaurants	(0.0196)	(0.0198)	(0.0197)			
# of other restaurants in	0.0002	0.0001	0.0002	-0.0012+	-0.0012+	-0.0012+
zipcode	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0007)
Zipcode population	-0.0485	-0.0537	-0.0446	2.5029	2.5017	2.5025
(millions)	(1.2286)	(1.2289)	(1.2287)	(2.3430)	(2.3429)	(2.3429)
Zipcode fraction black	-0.0727	-0.0737	-0.0738	-0.4227	-0.4222	-0.4224
	(0.1723)	(0.1723)	(0.1722)	(0.3853)	(0.3853)	(0.3853)
Zipcode fraction	0.8282**	0.8323**	0.8323**	0.5192	0.5193	0.5192
Hispanic	(0.1343)	(0.1343)	(0.1343)	(0.3803)	(0.3802)	(0.3803)
Zipcode fraction age	-2.7575**	-2.7519**	-2.7580**	-1.9146**	-1.9148**	-1.9147**
under 18	(0.3385)	(0.3384)	(0.3384)	(0.6480)	(0.6480)	(0.6480)
Zipcode fraction age 65	-1.0375**	-1.0299**	-1.0362**	-0.7993	-0.7985	-0.7988
and over	(0.3566)	(0.3567)	(0.3566)	(0.6413)	(0.6413)	(0.6413)
Zipcode logged avg hh	-0.0002	0.0003	0.0001	-0.0452	-0.0452	-0.0452
income (000s)	(0.0640)	(0.0640)	(0.0640)	(0.1118)	(0.1118)	(0.1118)
Zipcode fraction	1.1007**	1.1044**	1.1011**	0.8218**	0.8219**	0.8218**
bachelor degree	(0.1691)	(0.1690)	(0.1690)	(0.2573)	(0.2573)	(0.2573)
Zipcode fraction rural	-0.3535**	-0.3567**	-0.3521**	-0.1016	-0.1018	-0.1018
	(0.0846)	(0.0846)	(0.0845)	(0.1281)	(0.1280)	(0.1280)
Zipcode fraction foreign	-1.0619**	-1.0680**	-1.0596**	-0.7745+	-0.7739+	-0.7742+
born	(0.2371)	(0.2371)	(0.2371)	(0.4701)	(0.4701)	(0.4701)
Observations	388,817	388,817	388,817	388,817	388,817	388,817
# of restaurants	25,283	25,283	25,283	25,283	25,283	25,283
R-squared	0.117	0.116	0.116	0.0270	0.0270	0.0270

Unit of observation is the restaurant-quarter. Standard errors in parentheses clustered by restaurant +significant at 10%; *significant at 5%; **significant at 1%. Column headers describe differences from the main specification in column (1). Dependent variable is log(revenue from alcohol). Restaurants include all with owners with fewer than 25 restaurants. Columns 1-3 include restaurant random effects. Columns 4-6 include restaurant fixed effects. Unless otherwise specified, experience is a dummy for whether owned a restaurant in the three years prior to opening, and regressions include year fixed effects and 3 quarterly dummies. Shock is defined during the quarter.

Table 5: Support for the inattention model

	(1) Revenue- experience interaction	(2) Main plus revenue-experience interaction	(3) Quarter-level shocks only	(4) Quarter- and year-level shocks
Log(alcohol revenue)	-0.0247**	-0.0247**	-0.0234**	-0.0247**
	(0.0005)	(0.0005)	(0.0004)	(0.0005)
Shock to temperature (degrees Fahrenheit)	-0.0005 (0.0004)	-0.0009* (0.0004)		-0.0004 (0.0004)
Experience	-0.0684**	-0.0677**	-0.0073**	-0.0676**
	(0.0094)	(0.0094)	(0.0015)	(0.0094)
Shock to temperature x Experience		0.0022** (0.0006)		0.0017* (0.0007)
Log(alcohol revenue) x Experience	0.0064** (0.0009)	0.0064** (0.0009)		0.0064** (0.0009)
Shock to temperature in quarter (degrees Fahrenheit)			-0.0006** (0.0002)	-0.0005* (0.0002)
Shock to temperature in quarter x Experience			0.0011** (0.0004)	0.0006 (0.0004)
Time since restaurant opened in years	0.0130** (0.0003)	0.0130** (0.0003)	0.0129** (0.0003)	0.0130** (0.0003)
Time since restaurant opened in years squared	-0.0007** (0.0000)	-0.0007** (0.0000)	-0.0007** (0.0000)	-0.0007** (0.0000)
Likely lease renewal period	0.0081**	0.0081**	0.0081**	0.0081**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Owner name is not a business name	0.0171** (0.0022)	0.0170** (0.0022)	0.0173** (0.0022)	0.0170** (0.0022)
Bar	0.0139**	0.0139**	0.0137**	0.0139**
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Owner has at least five more restaurants	-0.0235** (0.0019)	-0.0236** (0.0019)	-0.0225** (0.0020)	-0.0236** (0.0019)
# of other restaurants in zipcode	0.0001**	0.0001**	0.0001**	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Zipcode population (millions)	-0.0390	-0.0391	-0.0408	-0.0392
	(0.0384)	(0.0384)	(0.0384)	(0.0384)
Zipcode fraction black	0.0312**	0.0312**	0.0319**	0.0312**
	(0.0063)	(0.0063)	(0.0064)	(0.0063)
Zipcode fraction Hispanic	0.0331**	0.0331**	0.0329**	0.0331**
	(0.0046)	(0.0046)	(0.0046)	(0.0046)
Zipcode fraction age under 18	0.0078	0.0077	0.0091	0.0078
	(0.0115)	(0.0115)	(0.0115)	(0.0115)
Zipcode fraction age 65 and over	0.0232+	0.0233+	0.0247*	0.0232+
	(0.0120)	(0.0120)	(0.0120)	(0.0120)
Zipcode logged avg hh income (000s)	-0.0010 (0.0018)	-0.0010 (0.0018)	-0.0010 (0.0018)	-0.0011 (0.0018)
Zipcode fraction bachelor degree	0.0225**	0.0225**	0.0226**	0.0225**
	(0.0058)	(0.0058)	(0.0058)	(0.0058)
Zipcode fraction rural	-0.0066+	-0.0066+	-0.0063+	-0.0066+
	(0.0034)	(0.0034)	(0.0034)	(0.0034)
Zipcode fraction foreign born	-0.0010	-0.0009	0.0002	-0.0010
	(0.0079)	(0.0079)	(0.0079)	(0.0079)
Observations	388,817	388,817	388,817	388,817
# of restaurants	25,283	25,283	25,283	25,283
R-squared	0.00802	0.00804	0.00794	0.00806

Unit of observation is the restaurant-quarter. Standard errors in parentheses clustered by restaurant +significant at 10%; *significant at 5%; **significant at 1%. Dependent variable is taxpayer exit from that location, revenue and shock are defined as average monthly values over the previous year unless otherwise specified, experience is defined as whether owner had a restaurant in the 3 years before opening, and restaurants include all owners with fewer than 25 restaurants. Regressions include year fixed effects, 3 quarterly dummies, and restaurant random effects.

Table 6: Robustness for Table 3

	(1) All restaurants and bars, including over 25 restaurants	(2) Drops over 10 restaurants	(3) Drops over 50 restaurants	(4) No bars	(5) Only single-establishment restaurant owners	(6) Shock defined over previous quarter	(7) Shock defined over previous half year	(8) Shock defined over previous 3 years	(9) No quarter or year fixed effects	(10) Drops obs. With shocks over 5 degrees
Log(alcohol revenue)	-0.0219**	-0.0240**	-0.0231**	-0.0222**	-0.0315**	-0.0367**	-0.0280**	-0.0198**	-0.0304**	-0.0243**
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0004)	(0.0006)	(0.0004)
Shock to temperature	-0.0008*	-0.0009*	-0.0008*	-0.0008*	-0.0011**	-0.0005**	0.0002	-0.0013**	-0.0043**	-0.0013**
(degrees Fahrenheit)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0004)	(0.0003)	(0.0004)
Experience	-0.0086**	-0.0072**	-0.0069**	-0.0085**	-0.0072**	-0.0065**	-0.0069**	-0.0070**	-0.0161**	-0.0075**
	(0.0014)	(0.0015)	(0.0014)	(0.0016)	(0.0026)	(0.0015)	(0.0015)	(0.0015)	(0.0018)	(0.0015)
Shock to temperature	0.0017**	0.0020**	0.0017**	0.0020**	0.0021*	0.0010**	0.0013**	0.0035**	0.0033**	0.0023**
x Experience	(0.0005)	(0.0007)	(0.0006)	(0.0007)	(0.0011)	(0.0004)	(0.0005)	(0.0008)	(0.0007)	(0.0006)
Observations	416,788	371,036	402,090	320,133	320,749	388,817	388,817	388,817	388,817	387,774
# of restaurants	26,420	24,476	25,883	20,615	22,289	25,283	25,283	25,283	25,283	25,261
R-squared	0.00783	0.00772	0.00801	0.00724	0.00651	0.0176	0.0108	0.00589	0.00858	0.00773

	(11) January-March only	(12) April-June only	(13) July-September only	(14) October-December only	(15) Cluster by zip	(16) Cluster by county	(17) Cox proportional hazard	(18) Survival model exponential distribution	(19) Survival model Weibull distributio n
Log(alcohol revenue)	-0.0233**	-0.0281**	-0.0265**	-0.0275**	-0.0234**	-0.0234**	-0.2916**	-0.2789**	-0.3024**
	(0.0009)	(0.0010)	(0.0010)	(0.0010)	(0.0006)	(0.0014)	(0.0058)	(0.0056)	(0.0060)
Shock to temperature	-0.0041**	-0.0033**	-0.0000	-0.0038**	-0.0009*	-0.0009	-0.0166+	-0.0175*	-0.0207
(degrees Fahrenheit)	(0.0007)	(0.0010)	(0.0009)	(0.0009)	(0.0004)	(0.0005)	(0.0100)	(0.0078)	(0.0126)
Experience	-0.0077**	-0.0073*	-0.0043	-0.0099**	-0.0071**	-0.0071**	-0.0903**	-0.0879**	-0.1102**
	(0.0029)	(0.0030)	(0.0033)	(0.0035)	(0.0015)	(0.0014)	(0.0230)	(0.0228)	(0.0234)
Shock to temperature	0.0025*	0.0015	0.0031**	0.0015	0.0023**	0.0023**	0.0705**	0.0603**	0.0647**
x Experience	(0.0010)	(0.0011)	(0.0011)	(0.0015)	(0.0007)	(0.0007)	(0.0181)	(0.0161)	(0.0202)
Observations	97,925	101,025	93,710	96,157	388,817	388,817	388,817	388,817	388,817
# of restaurants	23,488	24,103	22,974	23,264	25,283	25,283	25,283	25,283	25,283
R-squared	0.00497	0.00771	0.00588	0.0122	0.0120	0.0129	N/A	N/A	N/A
Log pseudolikelihood	N/A	N/A	N/A	N/A	N/A	N/A	-150,776	-30,875	-28,768

Unit of observation is the restaurant-quarter. Standard errors in parentheses clustered by restaurant + significant at 10%; * significant at 5%; ** significant at 1%. Column headings specify how differ from column (1) of table 3. Includes same controls as table 3. In column 17, proportional hazards assumption fails.

Table 7: Structural Results on Key Structural Parameters

	(1) Experience is whether owner owned a restaurant in 3 years prior to opening	(2) Experience is # restaurant-quarters prior to opening	(3) Experience is log(# restaurant-quarters prior to opening)
α^W: effects of temperature shocks on log revenue	0.0035** (0.0003)	0.0035** (0.0003)	0.0035** (0.0003)
β^R: proportion of log revenue that proxies for profitability	0.138** (0.006)	0.134** (0.003)	0.134** (0.003)
Parameter in ω_{jt}			
γ: proportion of transitory shocks that can be attended to	0.328** (0.089)	0.312** (0.070)	0.328** (0.088)
Parameters in the cost of thinking function			
κ_{1}: Owner experiences	-6.162** (1.297)	-0.318** (0.095)	-1.887** (0.453)
Average probability of paying zero attention	0.833	0.865	0.856
The amount of attention conditional on paying some attention $E\left[\tau_j \mid \tilde{\kappa}_j \leq \mathrm{var}\left(\omega_{jt}\right)\right]$			
Min	0.123	0.123	0.123
Mean	0.284	0.281	0.278
Max	0.998	1.000	1.000
Std. Dev.	0.225	0.259	0.230
Log Likelihood	-304680.073	-304677.782	-304676.060
N	388,817	388,817	388,817

Standard errors in parentheses. +significant at 10%; *significant at 5%; **significant at 1%; Results include controls for the covariates from Table 2 column 1 as controls (in X). The number of simulation draws is 50. Full structural results available in Appendix Table 2.

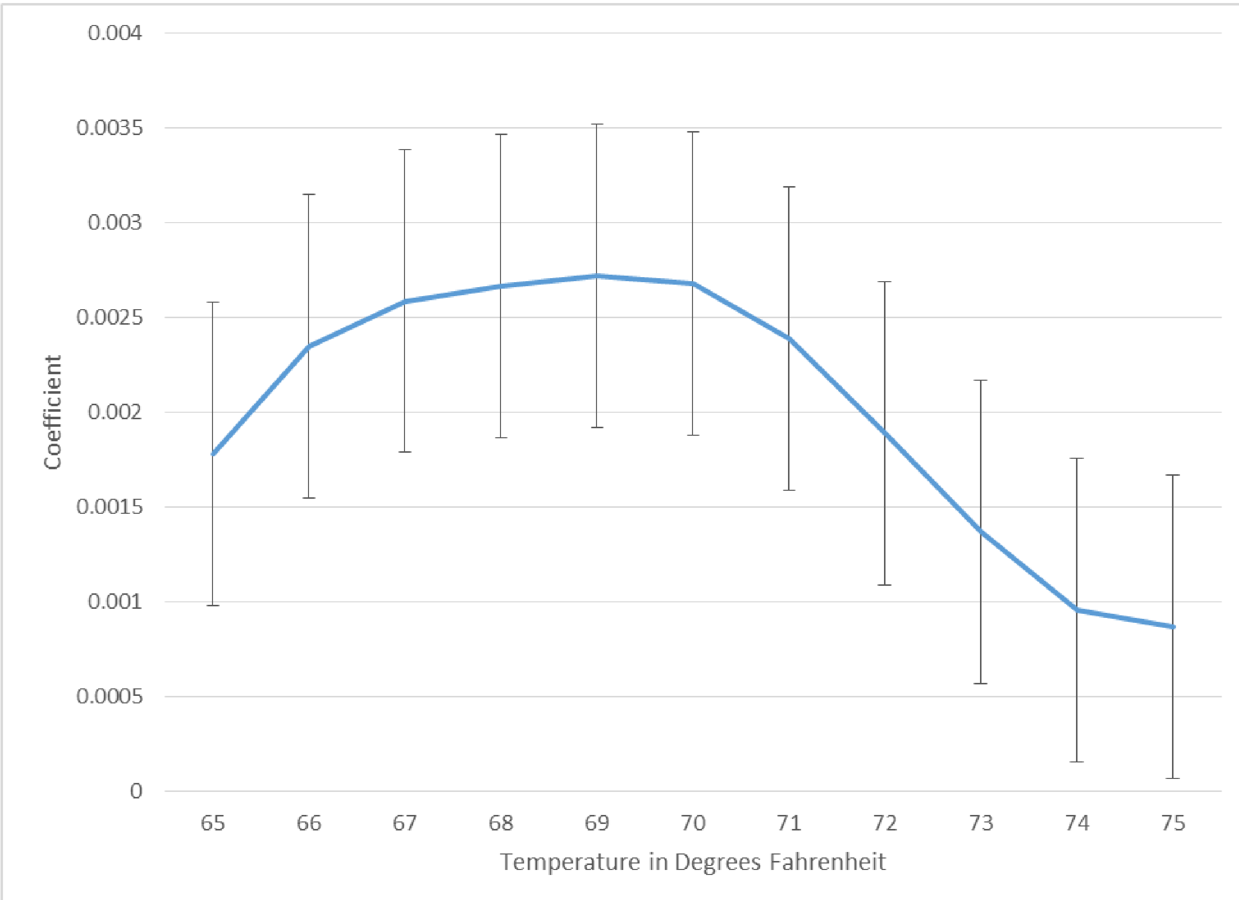
Table 8 Measuring the Value of Paying Attention

	(1) 25th percentile	(2) 50th percentile	(3) 75th percentile	(4) Mean	(5) Std. Dev.
Panel A: Cost/benefit of paying full attention					
At the restaurant level:					
Cost of paying full attention	\$5693.4	\$17396.6	\$106093.7	\$294757.6	\$1268780.9
Benefit of paying full attention	\$2179.4	\$13773.6	\$64644.0	\$205321.9	\$711570.3
At the restaurant-quarter level:					
Cost of paying full attention	\$1424.1	\$1962.0	\$17252.8	\$26549.9	\$84126.0
Benefit of paying full attention	\$621.6	\$2058.9	\$8206.2	\$15755.8	\$44743.0
N = 849 restaurants					
Panel B: Value of experience					
At the restaurant level:					
Gaining one year	\$11.7	\$1509.1	\$7200.0	\$29135.0	\$211049.9
Gaining three years	\$3048.6	\$12658.1	\$48778.7	\$147489.3	\$892973.6
Gaining ten years	\$7218.4	\$24636.2	\$89630.1	\$240921.7	\$1361683.1
At the restaurant-quarter level:					
Gaining one year	\$1.1	\$113.5	\$476.1	\$1857.6	\$12754.4
Gaining three years	\$440.2	\$931.3	\$3769.8	\$8892.9	\$43417.8
Gaining ten years	\$1099.5	\$1727.7	\$7683.0	\$15189.3	\$66443.4
N = 25,283 restaurants					

Table 9: Substitution between Experience and Luck

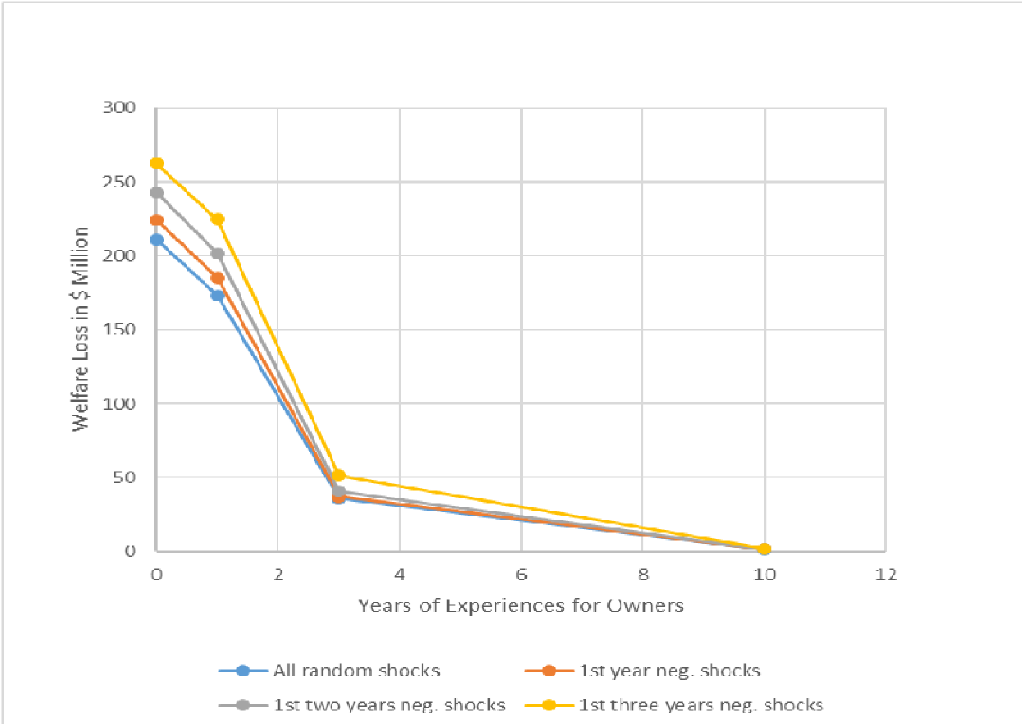
	Everyone inexperienced		Everyone has 1 year experience		Everyone has 3 years experience		Everyone has 10 years experience	
	(1) % wrong decisions	(2) Total welfare loss ($ m)	(3) % wrong decisions	(4) Total welfare loss ($ m)	(5) % wrong decisions	(6) Total welfare loss ($ m)	(7) % wrong decisions	(8) Total welfare loss ($ m)
Status quo: all random shocks	0.0383	211.0	0.0354	173.3	0.0193	35.8	0.0036	1.3
Panel A: Positive Shocks								
1st year pos. shocks	0.0363	198.7	0.0338	164.6	0.0195	37.8	0.0040	1.8
1st two years pos. shocks	0.0360	184.3	0.0341	156.4	0.0212	40.8	0.0048	2.7
1st three years pos. shocks	0.0359	173.9	0.0344	152.1	0.0228	46.9	0.0056	3.8
Panel B: Negative Shocks								
1st year neg. shocks	0.0407	224.5	0.0380	185.3	0.0221	37.2	0.0046	1.4
1st two years neg. shocks	0.0413	242.8	0.0391	201.7	0.0245	40.7	0.0057	1.5
1st three years neg. shocks	0.0416	262.4	0.0398	224.7	0.0265	51.5	0.0065	1.7
N = 25,283 restaurants								

Figure 1: Coefficient of Revenue on Temperature Shock Using Different Ideal Temperatures



Shows the coefficient of for Table 2 column 1 with different choices for optimal temperature. Error bars represent 95% confidence intervals. Regressions results shown in Appendix Table 1.

Figure 2: Welfare Loss Due to Bad Luck Decreases as Experience Increases



Online Appendix

Appendix Table 1: Regression Coefficients for Table 2 Column 1 by Focal Temperature

Appendix Table 2: Full Structural Results

Appendix: Constructing the Likelihood Function

Appendix Table 1: Regression Coefficients for Table 2 Column 1 by Focal Temperature

	65fl	66fl	67fl	68fl	69fl	70fl	71fl	72fl	73fl	74fl	75fl
Shock to temperature (degrees Fahrenheit)	0.00178**	0.00235**	0.00259**	0.00267**	0.00272**	0.00268**	0.00239**	0.00189**	0.00137**	0.00096*	0.00087*
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Time since restaurant opened in years	0.0028	0.0029	0.0029	0.0029	0.0029	0.0029	0.0029	0.0029	0.0028	0.0028	0.0028
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
Time since restaurant opened in years squared	-0.0011**	-0.0011**	-0.0011**	-0.0011**	-0.0011**	-0.0011**	-0.0011**	-0.0011**	-0.0011**	-0.0011**	-0.0011**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Likely lease renewal period	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Owner name is not a business name	-0.5935**	-0.5935**	-0.5935**	-0.5935**	-0.5936**	-0.5936**	-0.5936**	-0.5936**	-0.5936**	-0.5936**	-0.5936**
	(0.0495)	(0.0495)	(0.0495)	(0.0495)	(0.0495)	(0.0495)	(0.0495)	(0.0495)	(0.0495)	(0.0495)	(0.0495)
Bar	0.2987**	0.2986**	0.2986**	0.2986**	0.2986**	0.2986**	0.2986**	0.2986**	0.2987**	0.2987**	0.2987**
	(0.0262)	(0.0262)	(0.0262)	(0.0262)	(0.0262)	(0.0262)	(0.0262)	(0.0262)	(0.0262)	(0.0262)	(0.0262)
Owner has at least five more restaurants	0.0571**	0.0571**	0.0571**	0.0571**	0.0571**	0.0571**	0.0571**	0.0571**	0.0571**	0.0571**	0.0571**
	(0.0195)	(0.0195)	(0.0195)	(0.0195)	(0.0195)	(0.0195)	(0.0195)	(0.0195)	(0.0195)	(0.0195)	(0.0195)
# of other restaurants in zipcode	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Zipcode population (millions)	-0.0692	-0.0712	-0.0726	-0.0729	-0.0726	-0.0732	-0.0725	-0.0704	-0.0677	-0.0656	-0.0651
	(1.2285)	(1.2286)	(1.2286)	(1.2287)	(1.2287)	(1.2287)	(1.2287)	(1.2287)	(1.2287)	(1.2287)	(1.2286)
Zipcode fraction black	-0.0726	-0.0726	-0.0726	-0.0726	-0.0726	-0.0725	-0.0725	-0.0725	-0.0725	-0.0725	-0.0726
	(0.1723)	(0.1723)	(0.1723)	(0.1723)	(0.1723)	(0.1723)	(0.1723)	(0.1723)	(0.1723)	(0.1723)	(0.1723)
Zipcode fraction Hispanic	0.8285**	0.8286**	0.8287**	0.8287**	0.8288**	0.8288**	0.8286**	0.8284**	0.8283**	0.8283**	0.8284**
	(0.1343)	(0.1343)	(0.1343)	(0.1343)	(0.1343)	(0.1343)	(0.1343)	(0.1343)	(0.1343)	(0.1343)	(0.1343)
Zipcode fraction age under 18	-2.7495**	-2.7496**	-2.7499**	-2.7499**	-2.7499**	-2.7498**	-2.7499**	-2.7497**	-2.7495**	-2.7494**	-2.7500**
	(0.3385)	(0.3385)	(0.3384)	(0.3384)	(0.3384)	(0.3384)	(0.3384)	(0.3385)	(0.3385)	(0.3385)	(0.3385)
Zipcode fraction age 65 and over	-1.0307**	-1.0307**	-1.0306**	-1.0305**	-1.0305**	-1.0304**	-1.0302**	-1.0299**	-1.0297**	-1.0296**	-1.0299**
	(0.3567)	(0.3567)	(0.3567)	(0.3567)	(0.3567)	(0.3567)	(0.3567)	(0.3567)	(0.3567)	(0.3567)	(0.3567)
Zipcode logged avg hh income (000s)	0.0005	0.0005	0.0006	0.0006	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005
	(0.0640)	(0.0640)	(0.0640)	(0.0640)	(0.0640)	(0.0640)	(0.0640)	(0.0640)	(0.0640)	(0.0640)	(0.0640)
Zipcode fraction bachelor degree	1.1047**	1.1048**	1.1048**	1.1047**	1.1048**	1.1048**	1.1047**	1.1047**	1.1049**	1.1050**	1.1050**
	(0.1691)	(0.1691)	(0.1691)	(0.1691)	(0.1691)	(0.1691)	(0.1691)	(0.1691)	(0.1691)	(0.1691)	(0.1691)
Zipcode fraction rural	-0.3608**	-0.3609**	-0.3609**	-0.3609**	-0.3608**	-0.3608**	-0.3608**	-0.3607**	-0.3606**	-0.3605**	-0.3605**
	(0.0847)	(0.0847)	(0.0847)	(0.0847)	(0.0847)	(0.0847)	(0.0847)	(0.0847)	(0.0847)	(0.0847)	(0.0847)
Zipcode fraction foreign born	-1.0685**	-1.0684**	-1.0683**	-1.0685**	-1.0688**	-1.0688**	-1.0687**	-1.0685**	-1.0682**	-1.0680**	-1.0681**
	(0.2370)	(0.2370)	(0.2370)	(0.2371)	(0.2370)	(0.2370)	(0.2370)	(0.2371)	(0.2371)	(0.2371)	(0.2370)
Observations	388,817	388,817	388,817	388,817	388,817	388,817	388,817	388,817	388,817	388,817	388,817
# of restaurants	25,283	25,283	25,283	25,283	25,283	25,283	25,283	25,283	25,283	25,283	25,283
R-squared	0.117	0.117	0.117	0.117	0.117	0.117	0.117	0.117	0.117	0.117	0.117

Unit of observation is the restaurant-quarter. Standard errors in parentheses clustered by restaurant +significant at 10%; *significant at 5%; **significant at 1%. Column headers are potential ideal temperature. Dependent variable is log(revenue from alcohol), restaurants include all with owners with fewer than 25 restaurants that opened after January 1, 1998, and regressions include year fixed effects, 3 quarterly dummies, and restaurant random effects. Shock is defined during the quarter.

Appendix Table 2: Full Structural Results

	(1) Experience is if owner owned a restaurant in 3 years prior to opening		(2) Experience is # restaurant-quarters prior to opening		(3) Experience is log(# restaurant-quarters prior to opening)	
	Parameters in the Revenue Equation	**Parameters in the outside option**	**Parameters in the Revenue Equation**	**Parameters in the outside option**	**Parameters in the Revenue Equation**	**Parameters in the outside option**
α^W : effects of temperature shocks on log revenue	0.0035**		0.0035**		0.0035**	
	(0.0003)		(0.0003)		(0.0003)	
Time since restaurant opened in years	0.0116**	0.0201**	0.0115**	0.0202**	0.0115**	0.0198**
	(0.0003)	(0.0037)	(0.0003)	(0.0037)	(0.0003)	(0.0037)
Time since restaurant opened in years squared	-0.0010**	-0.0030**	-0.0010**	-0.0030**	-0.0010**	-0.0029**
	(0.00002)	(0.0003)	(0.00002)	(0.0003)	(0.00002)	(0.0003)
Likely lease renewal period	0.0019	0.0894**	0.0019	0.0894**	0.0018	0.0895**
	(0.0016)	(0.0088)	(0.0016)	(0.0088)	(0.0016)	(0.0088)
# other restaurants in zipcode/100	-0.0073	0.0982**	-0.0064	0.0983**	-0.0066	0.0979**
	(0.0062)	(0.0161)	(0.0062)	(0.0161)	(0.0062)	(0.0161)
Zipcode population (millions)*10	0.2526**	-0.0168	0.2533**	-0.0143	0.2537**	-0.0196
	(0.0118)	(0.0253)	(0.0118)	(0.0253)	(0.0118)	(0.0253)
Zipcode fraction black	-0.5756**	0.1860**	-0.5758**	0.1870**	-0.5747**	0.1860**
	(0.0250)	(0.0400))	(0.0250)	(0.0400)	(0.0250)	(0.0400)
Zipcode fraction Hispanic	-0.6710**	0.1288**	-0.6673**	0.1301**	-0.6672**	0.1287**
	(0.0188)	(0.0288))	(0.0188)	(0.0288)	(0.0188)	(0.0288)
Zipcode fraction age under 18	-0.5487**	0.1565+	-0.5429**	0.1569+	-0.5523**	0.1570+
	(0.0356)	(0.0883)	(0.0356)	(0.0882)	(0.0356)	(0.0882)
Zipcode fraction age 65 and over	-0.6443**	0.1850*	-0.6484**	0.1868*	-0.6434**	0.1901*
	(0.0414)	(0.0848)	(0.0414)	(0.0846)	(0.0414)	(0.0846)
Zipcode logged avg hh income (000s)	0.1382**	0.0061	0.1379**	0.0052	0.1378**	0.0058
	(0.0062)	(0.0157)	(0.0062)	(0.0157)	(0.0062)	(0.0157)
Zipcode fraction bachelor degree	-0.3984**	0.0084	-0.3972**	0.0115	-0.3981**	0.0103
	(0.0124)	(0.0395)	(0.0124)	(0.0395)	(0.0124)	(0.0394)
Zipcode fraction rural	-0.0897**	-0.0481*	-0.0894**	-0.0467*	-0.0909**	-0.0480*
	(0.0119)	(0.0255)	(0.0119)	(0.0225)	(0.0119)	(0.0225)
Zipcode fraction foreign born	-0.3921**	0.0655	-0.3988**	0.0633	-0.3980**	0.0709
	(0.0267)	(0.0494)	(0.0267)	(0.0494)	(0.0267)	(0.0494)
Quarter 2 dummy	0.0386**	0.0907**	0.0387**	0.0908**	0.0387**	0.0909**
	(0.0019)	(0.0109)	(0.0019)	(0.0109)	(0.0019)	(0.0109)
Quarter 3 dummy	-0.0088**	0.0883**	-0.0088**	0.0885**	-0.0088**	0.0882**
	(0.0017)	(0.0111)	(0.0017)	(0.0111)	(0.0017)	(0.0111)
Quarter 4 dummy	-0.0071**	0.1990**	-0.0071**	0.1994**	-0.0071**	0.1995**
	(0.0020)	(0.0107)	(0.0020)	(0.0107)	(0.0020)	(0.0107)
β^R : proportion log revenue that proxies for profitability	0.1343**		0.1339**		0.1343**	
	(0.0029)		(0.0029)		(0.0029)	
Bar indicator		0.1040**	0.1041**		0.1043**	
		(0.0093)	(0.0094)		(0.0093)	
Chain indicator		-0.2226**	-0.2239**		-0.2236**	
		(0.0189)	(0.0189)		(0.0189)	
Constant		-0.8653**	-0.8672**		-0.8638**	
		(0.1697)	(0.1690)		(0.1690)	
Parameter in ω_{jt}						
γ : proportion of transitory shock that can be attended to	0.3251**		0.3121**		0.3282**	
	(0.0890)		(0.0698)		(0.0884)	
Parameter in the cost of thinking function						
κ_1: Owner experience	-6.1615**		-0.3177**		-1.8871**	
	(1.2974)		(0.0953)		(0.4529)	
Log Likelihood	- 304680.073		-304677.781		-304676.060	
N	388,817		388,817		388,817	

Bar indicator and Chain indicator drop from the revenue equation because they lack variation within a restaurant.
+significant at 10%; *significant at 5%; **significant at 1%.

Appendix: Constructing the Likelihood Function

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

1. Let $\pi^0_{j,ns}$ denote a single draw ns $\left(ns=1,2,...,NS\right)$ for restaurant j. Let NS be 50. Take NS random draws from the Normal distribution $\pi^0_{j,ns} \sim N\left(mean\left(R_{js}\right),1\right)$ for each restaurant.

2. Construct the log likelihood function for the revenue generation process as described by equations (4) and (5):

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

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

where $\upsilon^d_{jt} = \tilde{R}_{jt} - \alpha^R - \tilde{X}_{jt}\alpha^X - \tilde{Q}_t\alpha^Q - \tilde{W}_{jt}\alpha^w$. 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 restaurant averages to allow for restaurant fixed effect.

3. For each draw $\pi^0_{j,ns}$, each restaurant j and each time period t, construct the exit probability conditional on different degrees of paying attention:

If $\tilde{\kappa}_j \le \text{var}\left(\omega_{jt}\right)$,

$$prob\left(D^{ns}_{jt}=1 \,\middle|\, R, W, X, Q, Z, \pi^0_{j,ns}, \tilde{\kappa}_j \le \text{var}\left(\omega_{jt}\right)\right)$$

$$= 1-\Phi\left(\frac{E_t\left(\pi_j \,\middle|\, R, W, X, Q, Z, \pi^0_{j,ns}, \tilde{\kappa}_j \le \text{var}\left(\omega_{jt}\right)\right) - \beta^0 - X_{jt}\beta^X - Q_t\beta^Q}{\sqrt{\sigma^2_{posterior}+1}}\right)$$

$$= 1-\Phi\left(\frac{\frac{\sigma_r^2}{\left(t-1\right)\sigma_0^2+\sigma_r^2}\pi^0_{j,ns} + \frac{\left(t-1\right)\sigma_0^2}{\left(t-1\right)\sigma_0^2+\sigma_r^2}\frac{\sum_{s=1}^{t-1}\beta^R\left(R_{js} - E\left[\tau_j \mid \tilde{\kappa}_j \le \text{var}\left(\omega_{js}\right)\right]\omega_{js}\right)}{t-1} - \beta^0 - X_{jt}\beta^X - Q_t\beta^Q}{\sqrt{\frac{\sigma_0^2\sigma_r^2}{\left(t-1\right)\sigma_0^2+\sigma_r^2}+1}}\right) \quad \text{(A1.1)},$$

where

$$E\left[\tau_j \mid \tilde{\kappa}_j \le \operatorname{var}(\omega_{js})\right]$$

$$= E\left[\left(1-\frac{\tilde{\kappa}_j}{\operatorname{var}(\omega_{js})}\right)\middle| \tilde{\kappa}_j \le \operatorname{var}(\omega_{js})\right] = 1-\frac{1}{\operatorname{var}(\omega_{js})} E\left[\tilde{\kappa}_j \mid \tilde{\kappa}_j \le \operatorname{var}(\omega_{js})\right] \tag{A1.2}$$

$$= 1-\frac{e^{(\kappa_0+Z_j\kappa_1)+\frac{1}{2}}}{\operatorname{var}(\omega_{js})}\frac{\Phi\left(\ln\left(\operatorname{var}(\omega_{js})\right)-\left(\kappa_0+Z_j\kappa_1\right)-1\right)}{\Phi\left(\ln\left(\operatorname{var}(\omega_{js})\right)-\left(\kappa_0+Z_j\kappa_1\right)\right)}$$

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 :

$$E\left[X \mid X \le a\right] = e^{\mu+\frac{\sigma^2}{2}} \frac{\Phi\left(\frac{\ln(a)-\mu-\sigma^2}{\sigma}\right)}{\Phi\left(\frac{\ln(a)-\mu}{\sigma}\right)}. \tag{A1.3}$$

In our model the thinking cost $\tilde{\kappa}_j$ is drawn from a Lognormal distribution with mean $\kappa_0 + Z_{jt}\kappa_1$ and variance normalized to 1. That is, $\tilde{\kappa}_j \sim \log normal\left(\kappa_0+Z_j\kappa_1,1\right)$. Following equation (A1,3), we can then derive: $E\left[\tilde{\kappa}_j \middle| \tilde{\kappa}_j \le \operatorname{var}(\omega_{js})\right] = e^{(\kappa_0+Z_j\kappa_1)+\frac{1}{2}} \frac{\Phi\left(\ln\left(\operatorname{var}(\omega_{js})\right)-\left(\kappa_0+Z_j\kappa_1\right)-1\right)}{\Phi\left(\ln\left(\operatorname{var}(\omega_{js})\right)-\left(\kappa_0+Z_j\kappa_1\right)\right)}$.

If $\tilde{\kappa}_j > \operatorname{var}(\omega_{jt})$,

$$prob\left(D_{jt}^{ns}=1 \mid R,W,X,Q,Z,\pi_{j,ns}^0,\tilde{\kappa}_j > \operatorname{var}(\omega_{jt})\right)$$

$$= 1-\Phi\left(\frac{E_t\left(\pi_j \mid R,W,X,Q,Z,\pi_{j,ns}^0,\tilde{\kappa}_j > \operatorname{var}(\omega_{jt})\right)-\beta^0-X_{jt}\beta^X-Q_t\beta^Q}{\sqrt{\sigma_{posterior}^2+1}}\right) \tag{A1.4}$$

$$= 1-\Phi\left(\frac{\frac{\sigma_r^2}{(t-1)\sigma_0^2+\sigma_r^2}\pi_{j,ns}^0+\frac{(t-1)\sigma_0^2}{(t-1)\sigma_0^2+\sigma_r^2}\frac{\sum_{s=1}^{t-1}\beta^R R_{js}}{t-1}-\beta^0-X_{jt}\beta^X-Q_t\beta^Q}{\sqrt{\frac{\sigma_0^2\sigma_r^2}{(t-1)\sigma_0^2+\sigma_r^2}+1}}\right)$$

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

$$prob\left(D_{jt}^{ns}=1 \,\middle|\, R,W,X,Q,Z,\pi_{j,ns}^{0}\right)$$
$$=\Phi\left(\log\left(\operatorname{var}\left(\omega_{jt}\right)\right)-\kappa_0-Z_j\kappa_1\right) prob\left(D_{jt}^{ns}=1 \,\middle|\, R,W,X,Q,Z,\pi_{j,ns}^{0},\tilde{\kappa}_j\le \operatorname{var}\left(\omega_{jt}\right)\right)$$
$$+\left(1-\Phi\left(\log\left(\operatorname{var}\left(\omega_{jt}\right)\right)-\kappa_0-Z_j\kappa_1\right)\right) prob\left(D_{jt}^{ns}=1 \,\middle|\, R,W,X,Q,Z,\pi_{j,ns}^{0},\tilde{\kappa}_j> \operatorname{var}\left(\omega_{jt}\right)\right) \tag{A1.5}$$

5. Construct the likelihood function for restaurants' exit decisions:

$$L^D\left(D_{jt} \,\middle|\, R,W,X,Q,Z,\pi_{j,ns}^{0}\right)$$
$$= prob\left(D_{jt}^{ns}=1 \,\middle|\, R,W,X,Q,Z,\pi_{j,ns}^{0}\right)^{D_{jt}}\left(1-prob\left(D_{jt}^{ns}=1 \,\middle|\, R,W,X,Q,Z,\pi_{j,ns}^{0}\right)\right)^{1-D_{jt}} \tag{A1.6}$$

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

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

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