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

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ABSTRACT

This paper investigates bounded rationality in a high-stakes business setting: a restaurant owner's decision to exit. Combining a 20 year quarterly panel on the alcohol revenues from every restaurant in Texas with weather data, we document that, given the same revenue record, restaurants with experienced owners are more likely to exit from business after unusually good weather (and stay in business after unusually bad weather) than those with inexperienced owners. This descriptive evidence motivates a structural model of belief formation and exit decisions. Our model allows an owner to pay limited attention to transitory shocks, thus misinterpreting revenue signals. We find that the vast majority of restaurant owners pay little attention to transitory shocks. The prevalence of inattention is due to the high cost of casting full attention continuously: for the 738 restaurants that could have made better decisions, the cost of paying full attention would have been about $1,500 per quarter for a median restaurant. Owners' pre-existing experiences in the industry before opening new restaurants reduce these costs substantially. For the 25,575 restaurants in our data, a median restaurant with three years' owner experiences has the cost of paying attention lowered by $1,200 per quarter.

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

JEL Classification: D03, 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), consumer packaged goods at a grocery store (Clerides and Courty forthcoming), add-ons to a larger purchase such as shipping charges (Hossain and Morgan 2006; Brown, Hossain, and Morgan 2010), state taxes (Chetty, Looney, and Croft 2009), right-digits in used car mileage (Lacetera, Pope, and Sydnor 2012) and minutes remaining of cellphone usage plan (Grubb and Osborne 2015).[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 revenue record of the restaurant through time. The revenue record, in turn, is affected by local demand, the restaurant's quality and specialty, fixed and variable costs, and, often, transitory shocks such 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. Simonsohn 2010; Conlin, O'Donoghue, and Vogelsang 2007). Furthermore, while the economic impact of weather is relatively small for individual restauranteurs,[2] its aggregate impact on macro-economy can be enormous. Boldin and

[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.
[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.

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 monetary policymakers (U.S. Federal Reserves, for example) 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, 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 restaurant 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 a role for inattention, particularly for inexperienced 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 at all in the exit decision.

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 believe that this is unlikely to drive our results because our results are at least as strong for positive shocks as negative ones. In other words, with positive shocks, it is the experienced owners who are more likely to exit. Thus, credit constraints cannot explain a key aspect of our result. 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. This is 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, a decision maker needs to cast attention to recognize transitory shocks, which we capture by incorporating Gabaix's (2014) "sparsity" model of rational inattention. 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. 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. 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 provide economic magnitude. Of the 25,725 owners in our data, an average owner's probability of paying no attention at all ranges from 83% to 91%. Even if an owner is paying attention, her attention only amounts to roughly a quarter of the full attention spectrum. The amount of attention, however, displays significant heterogeneity across owners in data, which is driven by the variability of local weather and a large, significantly negative effect of owner experiences in the thinking cost function. More importantly, our simulations show that 2.9% of the restaurants (738 out of 25,575) 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 738 restaurants, the cost of paying full attention is high: a median restaurant would have to pay about $1,500 per quarter or about $14,000 in total up to the quarter when a correct exit decision is made. The benefit of better decisions, though having substantial monetary payoffs, is overwhelmed by the more substantial costs of casting attention. Our results 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 $240, three years by about $1,200, and ten years by about $1,500. That is, ten years of experience reduces owners' cost of paying attention to transitory shocks by roughly $500 per month.

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. We build on the thin literature which is at the intersection of behavioral economics and industrial organization.

Next, we briefly review related literature on inattention, exit, and managerial decision making. The data, motivating regressions, model, and results 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 which 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 to evaluate welfare trade off. 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 (2016) estimate that media campaigns increase switching to alternative, lower-priced insurance plans by 12% from a baseline of 20%; and Grubb and Osborne (2015) show that bill-shock alert 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, we expand from consumer decisions to firm decisions. 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, 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, including (and empirically focused on) 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.[3] In our model, decision makers pay attention to factors that are sufficiently important that it is worth the cost of 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 --- variances in transitory shocks and owner experiences --- to measure the benefit and cost of paying attention. This approach is based on robust psychological facts and can be applied to give many classical economic theories a behavioral update.[4] 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 (Lacetera, Pope and Sydnor 2012; Kiss 2016; Gabaix et al, 2006). A second approach is to model inattention as inertia (Miravete and Palacios-Huerta, 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 (Grubb and Osborne, 2015; Ching, Erdem and Keane, 2009, 2014). We use Gabaixs framework because it is empirically parsimonious and conducive to structural estimation and counterfactual analysis.

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

[3] 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 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.
[4] Gabaix(2014) develops multiple applications.

### 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.[5] 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 human beings 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; Hortacsu, Luco, Puller, and Zhu 2016; Goldfarb and Yang 2009; Goldfarb and Xiao 2011; and Doraszelski, Lewis, and Pakes 2014). 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.

## 3 Data

Our raw data contain the universe of Texas restaurants with licenses to sell alcoholic beverages from January 1995 to August 2015, a roughly 20-year span. We have a monthly panel of restaurants' name, exact location, revenue from alcoholic beverages, and an owner-specific taxpayer identification code. The data are collected for the purpose of tax collection, and are available from the Texas Comptroller of Public Accounts.

Using this information, we generate a 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 to create measures of restaurant owner

[5] 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).

experience and the July and August 2015 data to identify exit during the second (March to June) quarter of 2015. We merge this data with information on weather deviations from normal.

The raw data contained 793,280 restaurant-quarters and 44,212 restaurants. 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 6.9% 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. This leaves 738,843 restaurant quarters. Another 322,174 observations were from restaurants that opened prior to January 1, 1998. A further 227 observations were missing data on taxpayer identity and so we could not measure experience. Finally, for the bulk of the analysis we drop 27,957 observations from restaurant owners with at least 25 different restaurants at some point in the data period. This leaves 388,485 restaurant-quarters and 25,275 restaurants for the core analysis. The data are right-censored in third quarter of 2015 in the sense that restaurants that survive into the third quarter of 2015 never exit in the data.

Constructing the variables for analysis involved 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 1 provides descriptive statistics. Most of these are presented at the quarterly level. We also present information on some time-invariant restaurant characteristics at the restaurant level. In the motivating analysis, we model the exit decision as looking back over the previous year. Therefore Table 1 presents values for revenue and weather shocks that look back over the previous year in addition to values that are based on the current quarter.

***Owner Experience:*** Before we identify whether a restaurant owner has experience in the industry, we first 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 several matches in which one owner holds multiple restaurants in partnerships or holding companies. To capture many of these, 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 appeared 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.[6] Our manual cleaning increased the percentage of owners with prior experience in the Texas restaurant industry from 15% to 19%.

[6] 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

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 distinct measures such measures. First, we measure experience as equal to one if the owner owned at least one other restaurant at any point the previous three years. Because we need to be able to look back three years, we drop the first three years of the data 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).

As shown at the top of Table 1, roughly 19% of restaurant owners had owned a restaurant prior to opening the focal restaurant. In terms of restaurant-quarters owned, the variable is highly skewed and therefore we analysis the log values. The (non-logged) average is 1.4 quarters (including the opening quarter of the focal restaurant) and a maximum of 796 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 log restaurant-quarters owned. In the structure, estimation requires a continuous measure of experience for smooth convergence. Therefore, for the structure, we use the definition based on the (log) number of restaurant-quarters of experience prior to opening the focal restaurant.

***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.[7] Overall, 63.5% of the restaurants in our data exit by the end of the period (the rest are right-censored). On a restaurant-quarter basis, 4.1% 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 also contain information on overall profits or total revenues at the restaurant. Therefore, in the analysis that follows, we assume that alcohol

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.

[7] As noted above, we dropped all restaurants with ownership changes in order to simplify interpretation of the structural model. 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.

revenues are proportional to total revenue and are major signals of restaurant profitability, at least up to the power of restaurant-level random effects. Generally, we assume that a restaurant's variation in profitability must be proportional to the variation in (log) alcohol revenue. Table 1 shows (log) monthly alcohol revenue and a breakdown by spirits, beer, and wine. The average restaurant in the data earns slight more than $13,000 per month in alcohol revenue.[8]

***Weather Shocks:*** Using an establishment'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 define "normal" weather as the average value over the period of our data (January 1995 to August 2015).[9]

Deviations from "normal" temperature could be good or bad for the restaurant business, depending on seasons. Generally, if the shock is such that it is too cold or too hot to go out, relative to the normal, then the shock is negative. That is, if the shock is such that it moves the temperature to a less comfortable value, then the shock is negative.

In identifying if a weather deviation away from normal is positive or negative for restaurants, we looked to identify the temperature that maximized the correlation between the measured 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. Shocks are positive if they move the average daily temperature toward the ideal degrees and negative if they move the average daily temperature away from the ideal. To capture this idea, we define:

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

Figure 1 shows the results of regressing revenue of the temperature shock measure and a variety of controls. We find that the correlation between temperature shock and revenue is highest when ideal is assumed to be 69 degrees. Thus, for our analysis, we use:

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

The results are not driven by those location-quarters with average temperature near 69 degrees and so is robust to minor deviations away from this ideal. For example, in a cold quarter with normal temperature to be 50 degrees, if the temperature is 54 degrees (4 degrees warmer than normal) then the value of the shock variable is 4. If the temperature is 47 degrees (3 degree 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, 4 degrees warmer than normal yields a shock variable of -4 and 3 degrees colder than normal yields a shock variable of 3.

[8] The averages for spirits, beer, and wine do not add up to the total exactly because there are some missing observations for the breakdown by alcohol type.

[9] 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 period of our data because historical average temperatures are systematically lower than the normal defined as the average of the 1995 to 2015 period.

Most temperature shocks are small, as might be expected. 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 larger variations than five degrees Fahrenheit.[10]

For precipitation, we assume an ideal as zero: Any precipitation would decrease restaurant-going behavior and therefore revenue. We define:

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

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. As we discuss below, we found no significant relationship between precipitation and revenue. We expect this is driven by the nature of rain quantity in Texas: It often involves very large but relatively short rainstorms. Even when the quantity of precipitation is high, it does not have a substantial impact on restaurant-going behavior over the course of three months. Therefore, our results on exit emphasize temperature shocks rather than precipitation shocks.

***Controls:*** We include a variable of 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, 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,[11] and whether the restaurant is not a traditional restaurant but rather a bar or private club.[12]

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[10] We believe these are likely mistakes in data collection at local weather stations. We keep these in the data because we do not know of a systematic way to identify the mistakes and because they are a sufficiently small fraction of the data that they do not affect overall results. We show robustness of our motivating results to excluding these observations.

[11] 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.

[12] 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".

# 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.

***Weather and revenue:*** We first estimate a linear regression of alcohol revenue on weather and a number of controls:[13]

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

As described above, a positive weather shock means unusually cold weather in hot months or unusually warm weather in cold months and a negative weather shock means unusually hotter weather in hot months and unusually colder weather in cold months. The controls $X_{jt}$ are firm attributes and local market attributes that change over time, $Q_t$ contains 16 year dummies and 3 quarter dummies, $\mu_j$ is a restaurant-specific fixed effect, and $\varepsilon_{jt}$ is an idiosyncratic error term. We use fixed effects to better control for restaurant-specific factors, but show robustness to a random effect specification.

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 0.26% higher. 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. Column 5 uses random effects rather than fixed effects (to replicate the structure of the exit regressions in Table 3). 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, and a number of controls:

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[13] Note that the notation in this section does not carry on to the structural model. We plan to fix this problem in the next version of the paper.

$$Exit_{jt} = \beta^0 + \beta^1 \log\left(Revenue_{jt}\right) + \beta^2 Weathershocks_{jt} + \beta^3 Experience_{jt} + \beta^4 Weathershocks_{jt} * Experience_{jt} + X_{jt}\beta^5 + Q_t\beta^6 + \mu_j + \varepsilon_{jt} \quad (2)$$

As before, the controls $X_{jt}$ are firm attributes and local market attributes, $Q_t$ contains 16 year dummies and 3 quarter dummies, $\mu_j$ is a restaurant-specific random effect, and $\varepsilon_{jt}$ is an idiosyncratic error term. Fixed effects are not identified here because each restaurant exits at most once. Therefore, restaurant-specific controls are included. 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 the weather shock is positive. In other words, experienced owners are *more likely* to go out of business 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. 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 shows robustness to the alternative measure of experience that we emphasize in the structural estimation: log number of restaurant-quarters prior to opening.

***Alternative explanations:*** A key alternative explanation for our results is that credit constraints bind more for inexperienced owners than for experienced owners. In this case, negative shocks 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 4 of Table 3 we create separate dummies for positive and negative shocks, and then each is interacted with experience. The results show that, when there are positive weather shocks, experienced owners are relatively more likely to exit. In contrast, when there are negative weather shocks, experienced owners are relative less likely to exit. This suggests that credit constraints alone are unlikely to be driving the results. Instead, it must be a factor that would affect behavior for both positive and negative weather shocks, such as inattention.

Table 4 examines another alternative explanation: the possibility that experienced owners are better at dealing with weather shocks than inexperienced owners. In particular, like table 2, it uses revenue as the dependent variable but adds an interaction between weather shocks and our experience measures (owned a restaurant over the preceding three years and log number of restaurant-quarters). We find no significant difference between the owners with experience and those without in terms of the relationship between weather shocks and revenue. This suggests that 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 for differently-experienced owners.

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 5. Columns 1 through 11 explore general robustness. Columns 1 to 3 define the temperature shock (and relevant revenue) over a different time period. Column 1 looks over the current quarter, column 2 looks over the previous two quarters, and column 3 looks over the previous three years. Columns 4 to 7 include alternative samples. Column 4 includes all restaurants and bars, including those for which the owner had over 25 restaurants. Column 5 drops owners with more than 10 restaurants and column 6 drops owners with more than 50 restaurants. Column 7 includes restaurants but not bars. Column 8 drops the time fixed effects (year and quarter) and column 9 drops the observations with unreasonably large weather shocks. Column 10 defines exit more stringently: The complete exit of all restaurants from that location. In all cases, the interaction between the temperature shock and experience is positive and significant. Column 11 defines experience as the number of restaurant quarters that the owner owned a restaurant prior to opening (rather than its logged value). This is the only robustness check we conducted that did not yield significance on the interaction between experience and the shock to temperature. Because the sign is positive as expected and the logged result is significant, this appears to be driven by a small number of owners with a great deal of experience.

Table 5 Columns 12 and 13 address 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 12 addresses this most directly, showing robustness to including only those restaurant owners who own just one establishment at a time. Column 13 adds a control for the interaction between owners who have at least five restaurants and experience. As in table 3, the main effect of owners with at least five restaurants is included in the regression though it is not shown in table 5.

Overall, we interpret these descriptive results as consistent with a theory of rational inattention. While we cannot rule out all possible other explanations, the results presented above are not consistent with some of most obvious. 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.

# 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 --- revenue --- 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 owner's learning process about the underlying profitability of the restaurant is subject to 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 observe alcohol revenue and use it as a proxy for total revenue.
- $W_{jt}$: 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).[14]
- $Z_j$: owner attributes. We focus on the level of owner experience, as measured in our descriptive analysis.[15]
- $Q_t$: 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 allows for the owner to observe more than the econometricians, especially in their process of learning and paying attention, which we will gradually introduce in later sections. For now, the

[14] As described below, we use restaurants fixed effects in the revenue generating part of the model so we drop the bar indicator and chain indicator as they lack variation over time. In the exit decision part of the model, these two indicators affect the outside option.

[15] 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.

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

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

in which $\varepsilon^o_{jt}$ follows a 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 $\varepsilon^o_{jt}$ is the multiplicative normalization.

The establishment has underlying profitability $\pi_j$, 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 $\pi_j$ given all past observables up to month *t-1*. This belief is about the distribution of $\pi_j$, 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.

## 5.2 Belief Formation

Before receiving any revenue signals, the owner has priors about the establishment's persistent profitability: $\pi_j \sim N\left(\pi^0_j, \sigma^2_0\right)$. The persistent profitability, $\pi_j$, represents the present discounted value of the future stream of profits that will accrue to the owner going forward. The owner compares his expected of present discounted value of operating the establishment to the value that will accrue if she takes the outside option.[16]

From the start of operating an establishment, she receives a quarterly profit signal in the form of $r_{jt}$, where $r_{jt} \sim N\left(\pi_j, \sigma^2_r\right)$. 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

[16] In this way, we simplify the dynamic implications of an exit decision. We do this to focus on how limited attention to past transitory shocks affects owners' 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 need to write down a dynamic model to capture it.

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:

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

where $\upsilon_{jt}$ is the unobservable (by econometrians) component of an establishment' s revenue records. A key non-standard aspect of the model is that part of this unobservable has the same role of weather shocks: they are knowable but not known, i.e., transitory shocks that require attention cast by the owner (for examples, local sports team victories, temporary input price variation, etc.). The rest of the unobservable contains shocks that are effectively unknowable --- shocks which the owner will never figure out, such as a public conversation by a satisfied customer. Following this distinction, we can write $\upsilon_{jt}$ as the summation of two parts:

$$\upsilon_{jt} = \gamma\upsilon^o_{jt} + (1-\gamma)\upsilon^o_{jt} \tag{5}$$

where γ is the proportion of the unobserved shock that is knowable, but unknown to an inattentive owner. Combining equations (4) and (5), we have $\omega_{jt}$ as the true state of the world, upon which the owner allocates her attention:

$$\omega_{jt} = W_{jt}\alpha^w + \gamma\upsilon^o_{jt} \tag{6}$$

That, $\omega_{jt}$ represented the full amount of transitory shocks that are knowable by the owner, if she pays full attention. Attention happens in the current period and the history of $\omega_{jt}$ cannot be traced. Instead, past $\omega_{jt}$ enters the posterior belief of the owner and only affects the owner's perception through the posterior belief. The owner, no matter how much attention she pays to $\omega_{jt}$, knows the variance of $\omega_{jt}$, which is denoted as $\mathrm{var}\left(\omega_{jt}\right)$.

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 $\omega_{jt}$ on revenue: in equation (8) the effect is compounded by a bounded rationality parameter $\tau_j$. The true effect is $\omega_{jt}$, 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 $\tau_j$ according to the sparsity-based model of bounded rationality developed by Gabaix (2014).

The owner's posterior mean about the underlying profitability in the current period is:

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

and her posterior variance about the underlying profitability is

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

## 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 $\tau_j$, 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, $\tau_j$ 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 $\tau_j$. This generates a sparse representation of the world, according to the following optimization problem:

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

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 $\omega_{jt}$, 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 $\omega_{jt}$.

In terms of cost, $\tilde{\kappa}$ is the thinking cost of the owner, which the owner observes but we econometricians do not. We assume that $\tilde{\kappa}$ follows a log normal distribution with mean $\kappa_0 + Z_{jt}\kappa_1$ and variance normalized to 1. That is,

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

Equation (12) specifies the cost of thinking as a random process. Given the same $Z_j$, different decision makers may choose different $\tau_j$ to represent 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 our 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:

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

Note that $\tau_j \in \left[0,1\right]$. 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 $\upsilon_{jt}$, 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 without observing current period's revenues.

The owner compares operating the establishment (an uncertain payoff) with the outside option (for example, closing the restaurant and taking a steady job), and decides on exit. Her expected persistent profitability is $E\left(\pi_j \,\middle|\, R, W, X, Q\right)$ with variance $\sigma^2_{posterior} = \dfrac{\sigma_0^2\sigma_r^2}{\left(t-1\right)\sigma_0^2 + \sigma_r^2}$. Shortly after the restaurant opens, $t$ is small. Therefore, this variance is large. The owner with a new establishment experiencing low expected profit may choose to stay even if expected profit is low. This is because higher variance of the expected values increases the probability of what seems like a wrong decision given the expected values alone. To incorporate this feature, we write down the owner's exit decision as:

$$D_{jt} = \begin{cases} 0 \quad if \quad E\left(\pi_{jt} \middle| R,W,X,Q\right) + \sigma_{posterior}\varepsilon_{jt} \geq \beta^0 + X_{jt}\beta^X + Q_t\beta^Q + \varepsilon_{jt}^0 \\ 1 \quad if \quad E\left(\pi_{jt} \middle| R,W,X,Q\right) + \sigma_{posterior}\varepsilon_{jt} < \beta^0 + X_{jt}\beta^X + Q_t\beta^Q + \varepsilon_{jt}^0 \end{cases} \tag{14}$$

We can then derive an individual establishment's probability of exit, to be used in forming the likelihood function:

$$prob\left(D_{jt} = 1 \middle| R,W,X,Q\right) = 1 - \Phi\left(\frac{E\left(\pi_j \middle| R,W,X,Q\right) - \beta^0 - X_{jt}\beta^X - Q_t\beta^Q}{\sqrt{\sigma_{posterior}^2 + 1}}\right) \tag{15}$$

To summarize, we have a structural model based on standard Bayesian learning from repeated signals of revenues. We inject a modicum of bounded rationality into this model by allowing imperfect recognition of the impact of transitory shocks on these signals. This 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 by maximum likelihood. 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:

$$\begin{aligned} L_j &= L\left(R_{j1},...,R_{j,T_j},D_{j1},...,D_{jT_j} \middle| W,Z,X,Q\right) \\ &= \prod_{s=1}^{T_j} L^R\left(R_{js} \middle| W_{js},X_{js},Q_s\right) \prod_{s=1}^{T_j} L^D\left(D_{js} \middle| R,W,Z,X,Q\right) \end{aligned} \tag{16}$$

where $R,W,Z,X,Q$ denote the entire sequence of observables up to the time period being considered. In equation (16), $L^R\left(R_{js} \middle| W_{js},X_{js},Q_s\right)$ is the contribution to the likelihood from revenue realizations; and $L^D\left(D_{js} \middle| R,W,Z,X,Q\right)$ is the contribution to the likelihood from exit decisions.

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

$$L_j = \prod_{s=1}^{T_j} L^R\left(R_{js} \mid W_{js}, X_{js}, Q_s\right)\left(\frac{1}{NS}\sum_{ns=1}^{NS}\left[\prod_{s=1}^{T_j} L^D\left(D_{js} \mid R, W, Z, X, Q, \pi^0_{j,ns}\right)\right]\right) \tag{17}$$

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

$$\ln L_{simulated} = \sum_{j=1}^{J}\sum_{s=1}^{T_j} \log L^R\left(R_{js} \mid W_{js}, X_{js}, Q_s\right) + \sum_{j=1}^{J} \ln\left\{\frac{1}{NS}\sum_{ns=1}^{NS}\left[\prod_{s=1}^{T_j} L^D\left(D_{js} \mid R, W, Z, X, Q, \pi^0_{j,ns}\right)\right]\right\} \tag{18}$$

where *NS* is the number of simulation draws. Specifically, we take *NS* (*NS* = 20 for now) draws for each establishment from the Normal distribution with mean equal to the population mean of $R_{jt}$ and variance equal to 1. We will write an appendix to explain in detail the individual likelihood components in equation (18).

## 6.2 Identification of Structural Parameters

We are able to identify all the structural parameters in the model using corresponding data variation.

- $\alpha^w$ from estimating the revenue equation: how weather shocks affect revenue. The rest of the $\alpha$ values are identified similarly.
- $\beta^O$ from the mean exit probability (the constant term in the exit equation)
- $\beta^R$ from the conditional relationship between revenue and exit.
- $\beta^X$ from the conditional relationship between $X_{jt}$ and exit.
- $\beta^Q$ from the conditional relationship between $Q_t$ and exit.
- $\sigma_0$ from the between-establishment estimation of the revenue equation. In other words, $\sigma_0$ reflects profit differences across individual establishments ("between variance").
- $\sigma_r$ from the within-establishment estimation of the revenue equation. In other words, $\sigma$ reflects profit differences within individual establishments ("within variance").
- $\gamma$ : from the conditional relationship between exit and transitory shocks (unexplained variation in the revenue generating process). These unexplained variations are part of revenue, and we as econometricians can recover them in the revenue generating process. If these explained variations affect exit decisions differently than how revenue affects exit decisions, it must be that owners used (part of them) in the attention allocation process.
- $\kappa_0$: normalized (as most of the owners in our data appear to pay no attention, this parameter is not well identified).
- $\kappa_1$ 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 6.[17] 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 column (2), we use owner experience, measured in the (log) number of establishment-quarters the owner has experienced before opening the given establishment, in the cost of thinking function.[18] Both 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.[19]

As shown in the first two rows of Table 6, weather shocks have a significantly positive effect on log revenue and log revenue is a good indicator of firm profitability. Given the motivating regressions, this is not surprising. As in $r_{jt} = \beta^R \left( R_{jt} - \omega_{jt} \right)$, the higher $\beta^R$ is, the more log alcohol revenue indicates firm profitability and contributes to a restaurant's decision to stay in business. The third row of Table 6 reports $\gamma$, 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 the prevalence of inattention. Of the 25,725 owners in our data, an average owner's probability of paying no attention at all ranges from 83% to 91%. 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 $\tau_j$) is 0.289 in column (1) specification and 0.233 in column (2) specification. Overall, the attention parameter $\tau_j$ 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, 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.

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

[18] 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.

[19] We will write a subsection to discuss goodness of fit.

### 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 2.87% of our 25,725 restaurants, equivalently 738 restaurants, would have made a better decision with respect to exit timing under full attention.[20] 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 738 firms, we could 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.[21] 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.[22]

Panel A of Table 7 reports the cost and benefit analysis of paying full attention for these 738 restaurants. The first two rows report summary statistics about the cost or benefit in total for a restaurant, and the next two rows reports 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 \$11,000 for a median restaurant, the cost is roughly \$14,000.[23] 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 to exit has catastrophic costs, but paying full attention to avoid these incorrect decisions is also costly.

[20] Note for restaurants that have not made better decision under full attention in the span of the observed history, it is potential that they make better decisions in the future.

[21] 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. To avoid an incorrect staying decision, the benefit will occur in just one period when the owner experiences a revenue reduction in this period so the outside option looks more attractive. To avoid incorrect exit decisions, the benefit will occur in multiple (consecutive) periods in which the owner experiences revenue increases in these periods so that the outside options in these periods look less attractive.

[22] 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.

[23] A median restaurant takes in roughly \$15,000 in alcohol revenue on a monthly basis in our data.

### 7.3 The Value of Experience

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 (81.2%) 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 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 experiences for all 25,725 restaurants' operating history in our data and report the numbers in Panel B of Table 7. 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 $238 quarterly for a median restaurant, gaining three years $1,205, and gaining ten years $1,562. 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 $520 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.

## 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 nesting rationality and bounded rationality. The model has a rational benchmark with "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. Almost 3% 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. 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 yields reduces the cost of paying attention to transitory shocks by about $500 per month.

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 establishments entered between 1991 and 2009, while 12.3 million establishments 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, leading to 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 marketplace. Before concluding, we acknowledge several limitations of this project at its current stage. 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. 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 larger scale. Thus, despite these limitations, we believe we have made an important first step that we hope will invite more scholars to build upon this research agenda.

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Table 1: Descriptive Statistics

| Variable | # Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| RESTAURANT LEVEL | | | | | |
| Ever exit | 25,725 | 0.6354 | 0.4813 | 0 | 1 |
| Owned a restaurant in the 3 years before open | 25,725 | 0.1875 | 0.3903 | 0 | 1 |
| Log(# restaurant-quarters prior to open) | 25,725 | 0.2818 | 0.9959 | 0 | 6.6834 |
| RESTAURANT-QUARTER LEVEL | | | | | |
| EXPERIENCE | | | | | |
| Owned a restaurant in the 3 years before open | 388,485 | 0.2034 | 0.4025 | 0 | 1 |
| log(# restaurant-quarters prior to open) | 388,485 | 0.3542 | 1.1059 | 0 | 6.6834 |
| EXIT | | | | | |
| No longer restaurant with same name at address | 388,485 | 0.0413 | 0.1991 | 0 | 1 |
| QUARTER LEVEL REVENUE | | | | | |
| log(average monthly alcohol revenue) | 388,485 | 9.5009 | 1.4617 | 0.0013 | 15.0412 |
| log(average monthly spirits revenue) | 367,208 | 8.7415 | 1.5782 | -1.0669 | 14.2438 |
| log(average monthly beer revenue) | 320,397 | 6.6190 | 2.1715 | -1.0973 | 13.4359 |
| log(average monthly wine revenue) | 384,101 | 8.4721 | 1.4634 | -0.2437 | 14.5643 |
| QUARTERLY WEATHER SHOCKS | | | | | |
| Shock to mean daily temperature (flF) | 388,485 | -0.1443 | 2.0664 | -18.9771 | 10.6371 |
| Shock to precipitation (inches) | 388,485 | 0.1624 | 1.1099 | -41.7255 | 6.7313 |
| YEAR LEVEL | | | | | |
| log(average monthly alcohol rev. over past year) | 388,485 | 9.5328 | 1.4195 | 0.1339 | 14.8790 |
| Shock to mean daily temperature (flF) | 388,485 | -0.1184 | 1.2274 | -11.0763 | 10.4240 |
| CONTROLS | | | | | |
| Time since restaurant opened in quarters | 388,485 | 14.5762 | 12.9466 | 1 | 70 |
| Owner name is not a business name | 388,485 | 0.1088 | 0.3114 | 0 | 1 |
| Bar | 388,485 | 0.1767 | 0.3814 | 0 | 1 |
| Owner has at least five more restaurants | 388,485 | 0.0678 | 0.2514 | 0 | 1 |
| # of other restaurants in zipcode | 388,485 | 31.9127 | 33.4044 | 0 | 225 |
| Zipcode population (millions) | 388,485 | 0.0296 | 0.0182 | 0 | 0.1141 |
| Zipcode % black | 388,485 | 0.1039 | 0.1138 | 0 | 0.9422 |
| Zipcode % Hispanic | 388,485 | 0.3181 | 0.2330 | 0 | 0.9980 |
| Zipcode % age under 18 | 388,485 | 0.2384 | 0.0780 | 0 | 0.4350 |
| Zipcode % age 65 and over | 388,485 | 0.1063 | 0.0556 | 0 | 0.6270 |
| Zipcode logged avg hh income (000s) | 388,485 | 10.8626 | 0.4566 | 0 | 12.4422 |
| Zipcode % bachelor degree | 388,485 | 0.3035 | 0.1839 | 0 | 0.8490 |
| Zipcode % rural | 388,485 | 0.0942 | 0.2125 | 0 | 1 |
| Zipcode % foreign born | 388,485 | 0.1601 | 0.1013 | 0 | 0.6030 |

Uses data on restaurants that opened after January 1, 1998 whose owners never owned 25 or more restaurants at the same time.

## Table 2: Weather Affects Revenue

| | (1) Main | (2) Include restaurants opening before 1998 | (3) Includes precip-itation | (4) Precip-itation | (5) Restaurant random effects | (6) Only single-establishment restaurant owners |
|---|---|---|---|---|---|---|
| Shock to temperature (degrees Fahrenheit) | 0.0026** | 0.0021** | 0.0027** | | 0.0027** | 0.0030** |
| | (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 quarters | -0.0118 | -0.0019 | -0.0118 | -0.0118 | -0.0032** | -0.0062 |
| | (0.0120) | (0.0046) | (0.0120) | (0.0120) | (0.0010) | (0.0156) |
| # of other restaurants in zipcode | -0.0008 | -0.0006 | -0.0008 | -0.0008 | 0.0005 | 0.0002 |
| | (0.0007) | (0.0005) | (0.0007) | (0.0007) | (0.0005) | (0.0008) |
| Zipcode population (millions) | 2.6620 | 2.2580+ | 2.6645 | 2.6816 | 0.0351 | 3.9517 |
| | (2.3289) | (1.3301) | (2.3290) | (2.3289) | (1.2484) | (2.4469) |
| Zipcode % black | -0.3863 | 0.1458 | -0.3881 | -0.3876 | -0.0503 | -0.0291 |
| | (0.3850) | (0.1928) | (0.3850) | (0.3850) | (0.1753) | (0.4296) |
| Zipcode % Hispanic | 0.5364 | 0.4084* | 0.5369 | 0.5339 | 0.7544** | 0.9063* |
| | (0.3782) | (0.2039) | (0.3782) | (0.3783) | (0.1363) | (0.4360) |
| Zipcode % age under 18 | -1.9306** | -1.0902** | -1.9281** | -1.9268** | -2.7949** | -2.4503** |
| | (0.6439) | (0.3246) | (0.6439) | (0.6441) | (0.3383) | (0.7066) |
| Zipcode % age 65 and over | -0.7676 | -0.5983+ | -0.7696 | -0.7655 | -1.0183** | -0.3465 |
| | (0.6382) | (0.3575) | (0.6382) | (0.6382) | (0.3606) | (0.6947) |
| Zipcode logged avg hh income (000s) | -0.0451 | 0.1411+ | -0.0461 | -0.0454 | 0.0020 | -0.0572 |
| | (0.1132) | (0.0784) | (0.1132) | (0.1133) | (0.0648) | (0.1248) |
| Zipcode % bachelor degree | 0.7748** | 0.4634** | 0.7744** | 0.7731** | 1.0898** | 1.0006** |
| | (0.2553) | (0.1363) | (0.2553) | (0.2553) | (0.1700) | (0.2893) |
| Zipcode % rural | -0.1260 | -0.2197** | -0.1263 | -0.1251 | -0.3584** | -0.1149 |
| | (0.1311) | (0.0829) | (0.1312) | (0.1311) | (0.0873) | (0.1397) |
| Zipcode % foreign born | -0.7806+ | -0.6111* | -0.7862+ | -0.7809+ | -1.0360** | -0.9223 |
| | (0.4653) | (0.2616) | (0.4653) | (0.4654) | (0.2398) | (0.5707) |
| Observations | 388,485 | 688,283 | 388,485 | 388,485 | 388,485 | 320,594 |
| # of restaurants | 25,275 | 35,467 | 25,275 | 25,275 | 25,275 | 22,281 |
| R-squared | 0.0266 | 0.0463 | 0.0266 | 0.0265 | 0.0847 | 0.0672 |

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(revenue from beer, wine, and spirits combined), 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 fixed effects. Shock is defined during the quarter. Column headings of other columns specify how differ from column (1).

## Table 3: Experienced owners appear to discount the weather in exit decisions

| | (1)<br>Main | (2)<br>Without interaction | (3)<br>Experience is log(# restaurant-quarters prior to opening) | (4)<br>Negative and positive shocks |
|---|---|---|---|---|
| Log(alcohol revenue) | -0.0297** | -0.0297** | -0.0297** | -0.0296** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Shock to temperature (degrees | -0.0012** | -0.0007+ | -0.0008* | |
| Fahrenheit) | (0.0004) | (0.0004) | (0.0004) | |
| Experience | -0.0083** | -0.0088** | -0.0036** | -0.0095** |
| | (0.0019) | (0.0019) | (0.0007) | (0.0021) |
| Shock to temperature | 0.0027** | | 0.0004* | |
| x Experience | (0.0006) | | (0.0002) | |
| Positive shock dummy | | | | -0.0038** |
| | | | | (0.0010) |
| Negative shock dummy | | | | 0.0047** |
| | | | | (0.0010) |
| Positive shock dummy | | | | 0.0062** |
| x Experience | | | | (0.0018) |
| Negative shock dummy | | | | -0.0029+ |
| x Experience | | | | (0.0017) |
| Time since restaurant opened in | 0.0021** | 0.0021** | 0.0021** | 0.0021** |
| quarters | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Owner name is not a business | 0.0265** | 0.0265** | 0.0263** | 0.0264** |
| name | (0.0027) | (0.0027) | (0.0027) | (0.0027) |
| Bar | 0.0153** | 0.0153** | 0.0151** | 0.0154** |
| | (0.0019) | (0.0019) | (0.0019) | (0.0019) |
| Owner has at least five more | -0.0275** | -0.0275** | -0.0252** | -0.0274** |
| restaurants | (0.0026) | (0.0026) | (0.0029) | (0.0026) |
| # of other restaurants in zipcode | 0.0001** | 0.0001** | 0.0001** | 0.0001** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Zipcode population (millions) | -0.0290 | -0.0289 | -0.0270 | -0.0282 |
| | (0.0503) | (0.0503) | (0.0503) | (0.0502) |
| Zipcode % black | 0.0385** | 0.0385** | 0.0390** | 0.0386** |
| | (0.0083) | (0.0083) | (0.0083) | (0.0083) |
| Zipcode % Hispanic | 0.0416** | 0.0417** | 0.0419** | 0.0411** |
| | (0.0059) | (0.0059) | (0.0059) | (0.0059) |
| Zipcode % age under 18 | -0.0043 | -0.0042 | -0.0046 | -0.0042 |
| | (0.0155) | (0.0155) | (0.0155) | (0.0155) |
| Zipcode % age 65 and over | 0.0323* | 0.0320* | 0.0318* | 0.0320* |
| | (0.0160) | (0.0160) | (0.0160) | (0.0160) |
| Zipcode logged avg hh income | -0.0013 | -0.0013 | -0.0013 | -0.0013 |
| (000s) | (0.0026) | (0.0026) | (0.0026) | (0.0026) |
| Zipcode % bachelor degree | 0.0236** | 0.0237** | 0.0238** | 0.0235** |
| | (0.0080) | (0.0080) | (0.0080) | (0.0080) |
| Zipcode % rural | -0.0092* | -0.0092* | -0.0091* | -0.0092* |
| | (0.0045) | (0.0045) | (0.0045) | (0.0045) |
| Zipcode % foreign born | -0.0038 | -0.0040 | -0.0041 | -0.0033 |
| | (0.0102) | (0.0102) | (0.0102) | (0.0101) |
| Observations | 388,485 | 388,485 | 388,485 | 388,485 |
| # of restaurants | 25,275 | 25,275 | 25,275 | 25,275 |
| R-squared | 0.00643 | 0.00641 | 0.00642 | 0.00650 |

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 before opening (except in column 3), 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) | (2) Experience is log(# restaurant-quarters prior to opening) | (3) Restaurant random effects |
|---|---|---|---|
| Shock to temperature (degrees Fahrenheit) | 0.0029** (0.0005) | 0.0026** (0.0004) | 0.0029** (0.0005) |
| Experience | N/A | N/A | 0.1643** (0.0230) |
| Shock to temperature x Experience | -0.0014 (0.0010) | 0.0000 (0.0004) | -0.0013 (0.0010) |
| Time since restaurant opened in quarters | -0.0117 (0.0120) | -0.0118 (0.0120) | -0.0022* (0.0010) |
| # of other restaurants in zipcode | -0.0008 (0.0007) | -0.0008 (0.0007) | 0.0005 (0.0005) |
| Zipcode population (millions) | 2.6634 (2.3290) | 2.6619 (2.3290) | 0.0940 (1.2306) |
| Zipcode % black | -0.3868 (0.3850) | -0.3862 (0.3850) | -0.0628 (0.1730) |
| Zipcode % Hispanic | 0.5362 (0.3782) | 0.5364 (0.3782) | 0.8325** (0.1346) |
| Zipcode % age under 18 | -1.9300** (0.6439) | -1.9307** (0.6439) | -2.7053** (0.3348) |
| Zipcode % age 65 and over | -0.7681 (0.6383) | -0.7676 (0.6382) | -0.9804** (0.3560) |
| Zipcode logged avg hh income (000s) | -0.0452 (0.1132) | -0.0451 (0.1132) | 0.0003 (0.0640) |
| Zipcode % bachelor degree | 0.7747** (0.2553) | 0.7748** (0.2553) | 1.0591** (0.1689) |
| Zipcode % rural | -0.1259 (0.1312) | -0.1261 (0.1311) | -0.3623** (0.0864) |
| Zipcode % foreign born | -0.7812+ (0.4653) | -0.7805+ (0.4653) | -1.0788** (0.2361) |
| Observations | 388,485 | 388,485 | 388,485 |
| # of restaurants | 25,275 | 25,275 | 25,275 |
| R-squared | 0.0266 | 0.0266 | 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 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. 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, 3 quarterly dummies, and restaurant fixed effects. Shock is defined during the quarter.

## Table 5: Robustness for table 3

| | (1) Shock defined over previous quarter | (2) Shock defined over previous half year | (3) Shock defined over previous 3 years | (4) All restaurants and bars, including over 25 restaurants | (5) Drops over 10 restaurants | (6) Drops over 50 restaurants | (7) Includes all restaurants but no bars |
|---|---|---|---|---|---|---|---|
| Log(alcohol revenue) | -0.0498** | -0.0370** | -0.0236** | -0.0282** | -0.0303** | -0.0294** | -0.0280** |
| | (0.0007) | (0.0006) | (0.0005) | (0.0005) | (0.0006) | (0.0005) | (0.0006) |
| Shock to temperature | -0.0005** | 0.0001 | -0.0017** | -0.0012** | -0.0012** | -0.0011** | -0.0010* |
| (degrees Fahrenheit) | (0.0002) | (0.0003) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| Experience | -0.0066** | -0.0077** | -0.0085** | -0.0105** | -0.0081** | -0.0077** | -0.0101** |
| | (0.0020) | (0.0019) | (0.0019) | (0.0018) | (0.0019) | (0.0018) | (0.0020) |
| Shock to temperature | 0.0012** | 0.0016** | 0.0044** | 0.0023** | 0.0024** | 0.0022** | 0.0026** |
| x Experience | (0.0004) | (0.0004) | (0.0008) | (0.0006) | (0.0007) | (0.0006) | (0.0007) |
| Observations | 388,485 | 388,485 | 388,485 | 416,373 | 370,708 | 401,691 | 319,858 |
| R-squared | 25,275 | 25,275 | 25,275 | 26,410 | 24,468 | 25,875 | 20,610 |
| # of restaurants | 0.0166 | 0.00953 | 0.00426 | 0.00679 | 0.00611 | 0.00681 | 0.00594 |

| | (8) No quarter or year fixed effects | (9) Drops obs. With shocks over 5 degrees | (11) Exit defined as no restaurant at address | (10) Experience is # restaurant-quarters prior to opening in 000s | (12) Only single-establishment restaurant owners | (13) Interaction for shock by Owner has 5 more restaurants |
|---|---|---|---|---|---|---|
| Log(alcohol revenue) | -0.0309** | -0.0302** | -0.0242** | -0.0297** | -0.0324** | -0.0297** |
| | (0.0006) | (0.0006) | (0.0005) | (0.0006) | (0.0006) | (0.0006) |
| Shock to temperature | -0.0016** | -0.0018** | -0.0009** | -0.0007+ | -0.0014** | -0.0012** |
| (degrees Fahrenheit) | (0.0003) | (0.0004) | (0.0003) | (0.0004) | (0.0004) | (0.0004) |
| Experience | -0.0101** | -0.0087** | -0.0039* | -0.0612** | -0.0029 | -0.0083** |
| | (0.0020) | (0.0019) | (0.0017) | (0.0160) | (0.0029) | (0.0019) |
| Shock to temperature | 0.0027** | 0.0028** | 0.0008 | 0.0069 | 0.0030** | 0.0025** |
| x Experience | (0.0006) | (0.0007) | (0.0005) | (0.0054) | (0.0010) | (0.0007) |
| Shock to temperature | | | | | | 0.0007 |
| x Owner has 5 more rest. | | | | | | (0.0010) |
| Observations | 388,485 | 387,442 | 388,485 | 388,485 | 320,594 | 388,485 |
| R-squared | 25,275 | 25,251 | 25,275 | 25,275 | 22,281 | 25,275 |
| # of restaurants | 0.00577 | 0.00647 | 0.00750 | 0.00636 | 0.00614 | 0.00643 |

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.

Table 6: Structural Results on Key Structural Parameters

| | (1) Experience is whether owner owned a restaurant in 3 years prior to opening | (2) Experience is log(# restaurant-quarters prior to opening) |
|---|---|---|
| $\alpha^W$ : effects of temperature shocks on log revenue | 0.0036*** (0.0003) | 0.0036*** (0.0003) |
| $\beta^R$ : proportion of log revenue that proxies for profitability | 0.138*** (0.003) | 0.135*** (0.003) |
| **Parameter in $\omega_{jt}$** | | |
| $\gamma$ : proportion of transitory shocks that can be attended to | 0.353*** (0.001) | 0.269*** (0.001) |
| **Parameters in the cost of thinking function** | | |
| $\kappa_{1:}$ Owner experiences | -6.084*** (0.604) | -2.474*** (0.624) |
| **Average probability of paying zero attention** | 0.831 | 0.912 |
| **The amount of attention $\tau$ conditional on paying some attention** | | |
| *Min* | 0.123 | 0.123 |
| *Mean* | 0.289 | 0.233 |
| *Max* | 0.998 | 1.000 |
| *Std. Dev.* | 0.227 | 0.212 |
| Log Likelihood | - 304125.35 | -304131.16 |
| N | 388,485 | 388,485 |

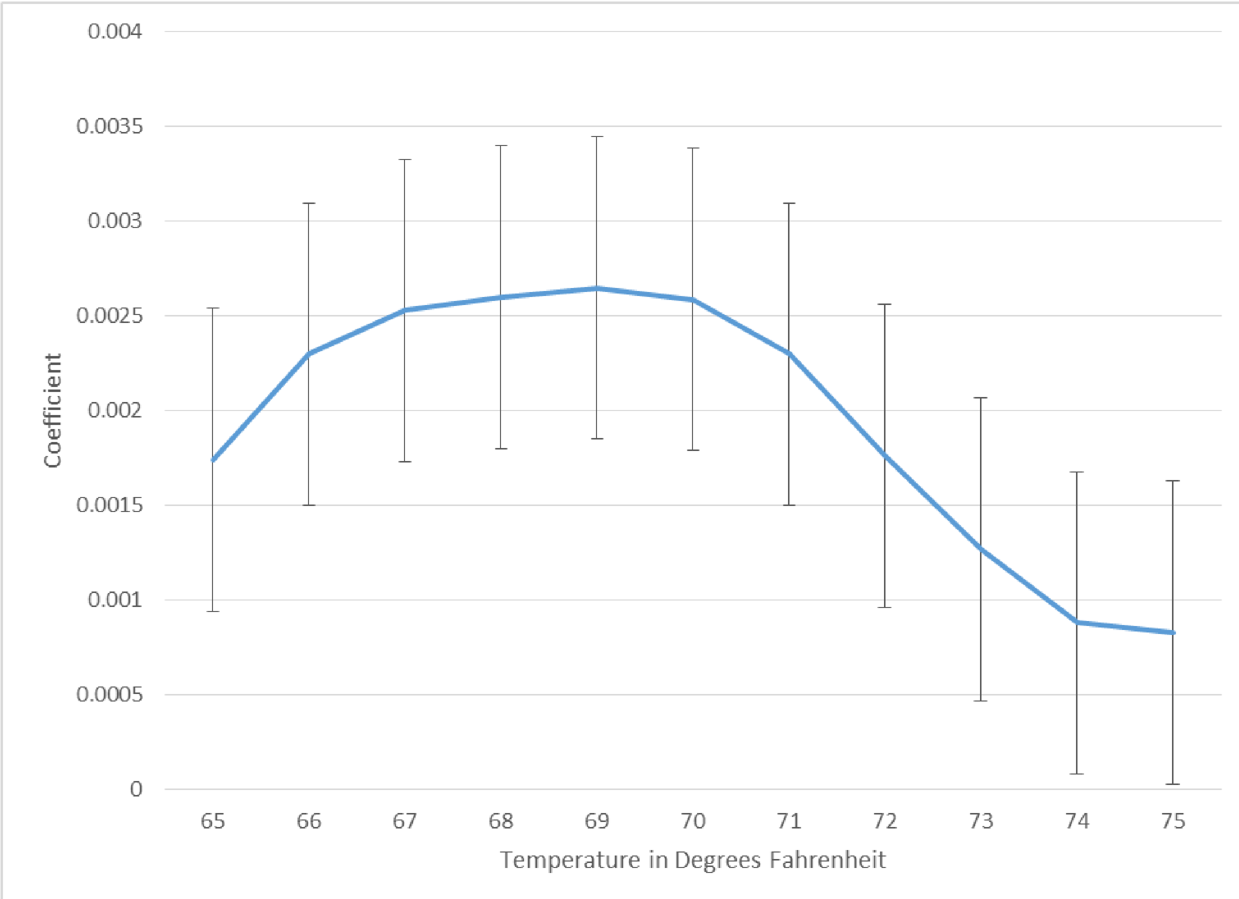
Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%; In estimating the structural results, experience is the number of establishments-quarters the owner has had before opening an establishment. Results include controls the covariates from Table 2 column 1 as controls (in X).

## Table 7 Welfare Trade Offs of Paying Attention

| | (1)<br>25th percentile | (2)<br>50th percentile | (3)<br>75th percentile | (4)<br>Mean | (5)<br>Std. Dev. |
|---|---|---|---|---|---|
| **Panel A: Cost/benefit of paying full attention** | | | | | |
| At the restaurant level: | | | | | |
| Cost of paying full attention | $4609.3 | $14154.0 | $97203.4 | $269161.6 | $1201272.2 |
| Benefit of paying full attention | $1762.8 | $11131.9 | $54313.0 | $159823.3 | $625083.3 |
| At the restaurant-quarter level: | | | | | |
| Cost of paying full attention | $1150.8 | $1563.8 | $15376.7 | $23828.3 | $84898.4 |
| Benefit of paying full attention | $517.0 | $1623.4 | $6342.3 | $11876.8 | $39364.6 |
| N = 738 restaurants | | | | | |
| **Panel B: Value of experiences** | | | | | |
| At the restaurant level: | | | | | |
| Gaining one year | $439.2 | $3182.2 | $13491.1 | $47921.9 | $337813.8 |
| Gaining three years | $5316.4 | $18153.8 | $68187.1 | $192377.1 | $1158962.8 |
| Gaining ten years | $7777.8 | $24075.2 | $87928.2 | $231234.0 | $1332813.5 |
| At the restaurant-quarter level: | | | | | |
| Gaining one year | $52.4 | $238.6 | $940.8 | $2984.3 | $17398.6 |
| Gaining three years | $767.5 | $1204.8 | $5821.1 | $11899.9 | $52878.3 |
| Gaining ten years | $1094.9 | $1562.4 | $8142.5 | $15183.7 | $63257.0 |
| N = 25,275 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.

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

| | (1)<br>65fl | (2)<br>66fl | (3)<br>67fl | (4)<br>68fl | (5)<br>69fl | (6)<br>70fl | (7)<br>71fl | (8)<br>72fl | (9)<br>73fl | (10)<br>74fl | (11)<br>75fl |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Shock to temperature | 0.00174** | 0.00230** | 0.00253** | 0.00260** | 0.00265** | 0.00259** | 0.00230** | 0.00176** | 0.00127** | 0.00088* | 0.00083* |
| (degrees Fahrenheit) | (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 | -0.0118 | -0.0118 | -0.0118 | -0.0118 | -0.0118 | -0.0118 | -0.0118 | -0.0118 | -0.0118 | -0.0118 | -0.0118 |
| opened in quarters | (0.0120) | (0.0120) | (0.0120) | (0.0120) | (0.0120) | (0.0120) | (0.0120) | (0.0120) | (0.0120) | (0.0120) | (0.0120) |
| # of other restaurants | -0.0008 | -0.0008 | -0.0008 | -0.0008 | -0.0008 | -0.0008 | -0.0008 | -0.0008 | -0.0008 | -0.0008 | -0.0008 |
| in zipcode | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Zipcode population | 2.6670 | 2.6631 | 2.6608 | 2.6610 | 2.6620 | 2.6613 | 2.6623 | 2.6658 | 2.6703 | 2.6738 | 2.6749 |
| (millions) | (2.3287) | (2.3288) | (2.3289) | (2.3289) | (2.3289) | (2.3289) | (2.3290) | (2.3290) | (2.3290) | (2.3290) | (2.3291) |
| Zipcode % black | -0.3863 | -0.3858 | -0.3859 | -0.3862 | -0.3863 | -0.3862 | -0.3861 | -0.3861 | -0.3863 | -0.3864 | -0.3868 |
| | (0.3850) | (0.3850) | (0.3850) | (0.3850) | (0.3850) | (0.3850) | (0.3850) | (0.3850) | (0.3850) | (0.3850) | (0.3851) |
| Zipcode % Hispanic | 0.5351 | 0.5354 | 0.5357 | 0.5360 | 0.5364 | 0.5364 | 0.5361 | 0.5357 | 0.5352 | 0.5348 | 0.5348 |
| | (0.3782) | (0.3782) | (0.3782) | (0.3782) | (0.3782) | (0.3782) | (0.3782) | (0.3783) | (0.3783) | (0.3783) | (0.3783) |
| Zipcode % age under | -1.9289** | -1.9298** | -1.9305** | -1.9305** | -1.9306** | -1.9306** | -1.9304** | -1.9299** | -1.9292** | -1.9286** | -1.9289** |
| 18 | (0.6440) | (0.6440) | (0.6439) | (0.6439) | (0.6439) | (0.6439) | (0.6439) | (0.6439) | (0.6440) | (0.6440) | (0.6440) |
| Zipcode % age 65 and | -0.7677 | -0.7682 | -0.7681 | -0.7678 | -0.7676 | -0.7673 | -0.7668 | -0.7663 | -0.7657 | -0.7654 | -0.7656 |
| over | (0.6383) | (0.6383) | (0.6383) | (0.6382) | (0.6382) | (0.6382) | (0.6382) | (0.6382) | (0.6383) | (0.6383) | (0.6383) |
| Zipcode logged avg hh | -0.0452 | -0.0451 | -0.0450 | -0.0450 | -0.0451 | -0.0451 | -0.0450 | -0.0450 | -0.0451 | -0.0451 | -0.0450 |
| income (000s) | (0.1133) | (0.1133) | (0.1132) | (0.1132) | (0.1132) | (0.1132) | (0.1132) | (0.1133) | (0.1133) | (0.1133) | (0.1133) |
| Zipcode % bachelor | 0.7737** | 0.7742** | 0.7745** | 0.7746** | 0.7748** | 0.7748** | 0.7746** | 0.7744** | 0.7743** | 0.7742** | 0.7742** |
| degree | (0.2553) | (0.2553) | (0.2553) | (0.2553) | (0.2553) | (0.2553) | (0.2553) | (0.2553) | (0.2553) | (0.2553) | (0.2553) |
| Zipcode % rural | -0.1260 | -0.1262 | -0.1262 | -0.1262 | -0.1260 | -0.1260 | -0.1260 | -0.1258 | -0.1257 | -0.1254 | -0.1253 |
| | (0.1311) | (0.1311) | (0.1311) | (0.1311) | (0.1311) | (0.1311) | (0.1311) | (0.1311) | (0.1311) | (0.1311) | (0.1311) |
| Zipcode % foreign born | -0.7803+ | -0.7797+ | -0.7794+ | -0.7799+ | -0.7806+ | -0.7807+ | -0.7806+ | -0.7803+ | -0.7798+ | -0.7795+ | -0.7796+ |
| | (0.4653) | (0.4653) | (0.4653) | (0.4653) | (0.4653) | (0.4653) | (0.4653) | (0.4653) | (0.4653) | (0.4653) | (0.4654) |
| Observations | 388,485 | 388,485 | 388,485 | 388,485 | 388,485 | 388,485 | 388,485 | 388,485 | 388,485 | 388,485 | 388,485 |
| # of restaurants | 25,275 | 25,275 | 25,275 | 25,275 | 25,275 | 25,275 | 25,275 | 25,275 | 25,275 | 25,275 | 25,275 |
| R-squared | 0.0265 | 0.0266 | 0.0266 | 0.0266 | 0.0266 | 0.0266 | 0.0266 | 0.0266 | 0.0265 | 0.0265 | 0.0265 |

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 fixed effects. Shock is defined during the quarter.

# Appendix Table 2: Full Structural Results

| | (1) Experience is whether owner owned a restaurant in 3 years prior to opening | | (2) 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 |
| $\alpha^W$ : effects of temperature shocks on log revenue | 0.0036***<br>(0.0003) | | 0.0036***<br>(0.0003) | |
| Time since restaurant opened in quarters | -0.0003***<br>(0.00005) | | -0.0003***<br>(0.0005) | |
| # of other restaurants in zipcode/100 | 0.0326***<br>(0.0067) | 0.0982***<br>(0.0165) | 0.0325***<br>(0.0067) | 0.0980***<br>(0.0165) |
| Zipcode population (millions)*10 | 0.3010***<br>(0.0118) | -0.0088<br>(0.0246) | 0.3011***<br>(0.0118) | -0.0076<br>(0.0246) |
| Zipcode % black | -0.6367***<br>(0.0250) | 0.1153***<br>(0.0388) | -0.6347***<br>(0.0250) | 0.1574***<br>(0.0388) |
| Zipcode % Hispanic | -0.7288***<br>(0.0188) | 0.1055***<br>(0.0275) | -0.7340***<br>(0.0187) | 0.1070***<br>(0.0275) |
| Zipcode % age under 18 | -0.5231***<br>(0.0355) | 0.1846**<br>(0.0847) | -0.5255***<br>(0.0355) | 0.1784**<br>(0.0848) |
| Zipcode % age 65 and over | -0.7601***<br>(0.0416) | 0.0986<br>(0.0819) | -0.7615***<br>(0.0416) | 0.1052<br>(0.0819) |
| Zipcode logged avg hh income (000s) | 0.0292***<br>(0.0065) | -0.0146<br>(0.0150) | 0.0294***<br>(0.0065) | -.0.0126<br>(0.0151) |
| Zipcode % bachelor degree | -0.3921***<br>(0.0126) | 0.0087<br>(0.0392) | -0.3907***<br>(0.0126) | 0.0048<br>(0.0392) |
| Zipcode % rural | -0.0974***<br>(0.0117) | -0.0544**<br>(0.0219) | -0.0989***<br>(0.0117) | -0.0534**<br>(0.0219) |
| Zipcode % foreign born | -0.4197***<br>(0.0269) | 0.0531<br>(0.0481) | -0.4177***<br>(0.0269) | 0.0601<br>(0.0481) |
| Quarter 2 dummy | 0.0390***<br>(0.0019) | 0.0924***<br>(0.0109) | 0.0390***<br>(0.0019) | 0.0923***<br>(0.0109) |
| Quarter 3 dummy | -0.0082***<br>(0.0017) | 0.0930***<br>(0.0111) | -0.0082***<br>(0.0017) | 0.0929***<br>(0.0111) |
| Quarter 4 dummy | -0.0064***<br>(0.0020) | 0.2070***<br>(0.0107) | -0.0064***<br>(0.0020) | 0.2069***<br>(0.0107) |
| $\beta^R$ : proportion of log revenue that proxies for profitability | 0.1381***<br>(0.0029) | | 0.1348***<br>(0.0027) | |
| Bar indicator | | 0.1055***<br>(0.0090) | 0.1054***<br>(0.0090) | |
| Chain indicator | | -0.2353***<br>(0.0185) | -0.2379***<br>(0.0185) | |
| Constant | | -0.5725***<br>(0.1605) | -0.6269***<br>(0.1607) | |
| ***Parameter in $\omega_{jt}$*** | | | | |
| $\gamma$ : proportion of transitory shocks that can be attended to | 0.3525***<br>(0.0010) | | 0.2694***<br>(0.001) | |
| ***Parameter in the cost of thinking function*** | | | | |
| $\kappa_{1}$: Owner experience | -6.0842***<br>(0.6037) | | -2.4744***<br>(0.6235) | |
| Log Likelihood | - 304125.35 | | -304131.16 | |
| N | 388,485 | | 388,485 | |