Does exposure to losses intensify loss aversion? Evidence from a competitive industry

Julian Emami Namini and Sacha Kapoor*

February 17, 2025

Abstract

Loss aversion is one of the most robust findings in behavioral economics, with individuals typically weighing losses about twice as heavily as equivalent gains, and some even weighing losses many times more than equivalent gains. What drives these differences across individuals? Could it be that frequent exposure to the prospect of loss intensifies this bias? We examine this question in a competitive industry where decision-makers routinely face the prospect of losses that could threaten business survival. Using two distinct approaches, we find evidence of strong to extreme loss aversion. First, analyzing thousands of real-time labor demand decisions from a retail chain, we find a loss aversion coefficient of $\lambda = 4.3$, rising to $\lambda = 7.4$ on slow days with smaller management teams, while disappearing on busy days. Second, through structured interviews with business owners and managers, we document a mean loss aversion coefficient of $\lambda = 10.1$ and median of $\lambda = 1.6$, with 74% having coefficients above 1 and 30% above 3. Importantly, loss aversion increases with market experience.

JEL: D21, D22, L21, L83

Keywords: Behavioral firms, loss aversion, prospect theory, small firms

*Emami Namini (emaminamini@ese.eur.nl), Kapoor (kapoor@ese.eur.nl): Erasmus University Rotterdam, Erasmus School of Economics, Burgemeester Oudlaan 50, 3062PA Rotterdam, The Netherlands. We thank Georgios Angelis, Suzanne Bijkerk, Han Bleichrodt, David Byrne, Robert Dur, Aksel Erbahar, Jonathan Hall, Arvind Magesan, Robert Oxoby, Ivan Png, Vincent Rebeyrol, Laura Rondi, Dirk Schindler, Dana Sisak, Otto Swank, and Dinand Webbink for valuable comments. All omissions and errors are our own.

1 Introduction

Loss aversion - the tendency to weigh losses more heavily than equivalent gains - has emerged as one of the most robust findings in behavioral economics. A recent meta-analysis of 607 estimates from 150 studies quantifies this regularity: individuals typically weight losses about twice as heavily as equivalent gains [Brown et al., 2024], though some weigh losses many times more than equivalent gains. A fundamental question is whether frequent exposure to losses intensifies or moderates this bias. We examine this question in a competitive industry where decision-makers routinely face the prospect of losses that could threaten business survival.

We study this question in the restaurant industry, which offers several features that make it particularly suitable for examining the relationship between loss exposure and loss aversion. The ownership decision in this industry is heavily influenced by preferences - owners frequently accept lower wages compared to their outside options in exchange for non-pecuniary benefits like menu development and autonomy.[1] The active participation of owners in daily operations creates a direct link between individual preferences and firm decisions. Local market structures feature rich arrays of horizontally and vertically differentiated products, generating market power that enables departures from strict profit maximization. Moreover, the industry's characteristically high exit rates heighten the salience of potential losses. This fear of failure, which has been conceptualized as a form of loss aversion [Morgan and Sisak, 2016], can both deter entry and accelerate exit, making the restaurant industry particularly suitable for examining how loss aversion shapes firm behavior and market outcomes.

We put forth two pieces of evidence to examine how exposure to losses shapes loss aversion. First, we analyze administrative data from a Canadian retail chain to measure loss aversion in day-to-day operational decisions. Second, we conduct structured interviews with restaurant owners and managers in the Netherlands to directly elicit their attitudes toward losses.[2]

Our first piece of evidence is based on data from two large-scale chain restaurants. We analyze thousands of labor demand decisions relating to the stopping times of each worker. In this setting stopping times are not known ahead of time. They are determined by man-

[1] Hamilton [2000] shows entrepreneurs tend to earn less than they would in paid employment. Benz and Frey [2004] show entrepreneurs are happier than subordinate employees because of autonomy, despite earning less money. Hurst and Pugsley [2011] show approximately half of new business owners cite nonpecuniary motives relating to flexibility or control. Only 34 percent cite income generation as the primary motive.

[2] Our use of data from different countries follows from our constraints to obtain evidence from the same country. While institutional differences across countries might affect the magnitude of our estimates, the consistent pattern we find suggests a robust relationship between loss exposure and loss aversion.

agement in real time. We model these real-time decisions econometrically using a stopping model inspired by Crawford and Meng [2011]. The model by Crawford and Meng [2011] was developed to measure loss aversion in labor supply. We tailor the model to measure loss aversion in labor demand.

In our setting the decision to stop an individual worker is guided by end-of-shift profits aggregated across all workers. Profit gains and losses are coded relative to a well defined and publicized reference point, which is firm performance on the same day a week ago. The firm anticipates a loss if their forecast of end-of-shift profits at any point in the shift is below the reference point, and a gain otherwise. We construct these forecasts econometrically at high frequencies in a first step via the K-fold cross validation algorithm for LASSO. Since our approach relies on forecasted profits, it falls between Crawford and Meng [2011] and the adaptive reference point framework of Thakral and Tô [2021].

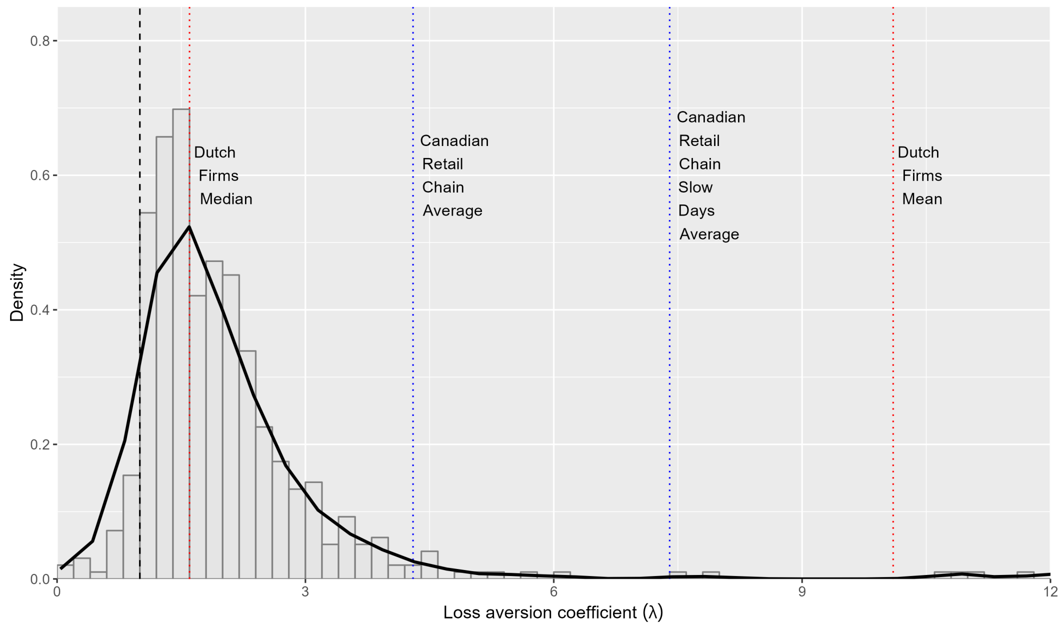
Identification is based on comparisons of next with current period gains and losses. The econometric model uses next versus current period gains and transitions from gains to losses and vice versa to identify the weight placed on gains, and similarly for the weight on losses. Our econometric specification conditions on information shocks specific to the shift and time of day. Identification is then conditional on there being no within-shift time-of-day variation systematically tracking gains, losses, and stopping decisions.

We estimate a loss aversion coefficient of $\lambda = 4.3$. The estimate implies stopping decisions are guided by a loss averse objective, because $\lambda > 1$ implies loss aversion. Our estimate varies with the scale of production. $\lambda = 7.4$ on slow days with fewer customers and smaller management teams. Loss aversion disappears on busy days. We explain that these results cannot be generated by standard risk aversion.

Our second piece of evidence is based on personal interviews with 107 owners or managers in the industry. Personal interviews were costly, but ensured questions were answered by owners and general managers themselves rather than by their assistants. We used the Abdellaoui et al. [2016] method to elicit loss aversion around zero, a natural and exogenous reference point for firms in highly competitive markets. We show the mean owner has a loss aversion coefficient of $\lambda = 10.1$. The median is $\lambda = 1.6$, which is slightly smaller than lab medians for university students [Abdellaoui et al., 2016]. The mean-median discrepancy in our setting implies the existence of some very loss averse owners. 74% percent have loss aversion coefficients greater than 1, 30% have coefficients greater than 3.

We correlate our loss aversion measures with a range of covariates, including owner experience, their perceptions of demand, firm size, propensity to engage in risk, and age. We

Figure 1: Comparison with metadata from Brown, Imai, Vieider, and Camerer [2024].



find a positive correlation with experience and no other covariate. The positive correlation is robust to the inclusion of covariates. We discuss potential justifications for a positive correlation between experience and loss aversion.

We compare our estimates with the estimates in the meta-analysis of Brown et al. [2024]. We plot a histogram and density of their data in Figure 1. We placed vertical bars at loss neutrality, 1.6, 4.3, 7.4, and 10.1. We have truncated the graph at 12 for visualization purposes. Brown et al. [2024] truncate the graph at 6.

Our study connects several distinct literatures. First, a substantial body of field evidence documents loss aversion across diverse contexts, from taxi drivers [Camerer et al., 1997, Crawford and Meng, 2011, Farber, 2005, 2008, 2015, Thakral and Tô, 2021] and marathon runners [Allen et al., 2017, Markle et al., 2018] to financial professionals [Abdellaoui, Bleichrodt, and Kammoun, 2013, Barberis, Huang, and Santos, 2001, Barberis, Mukherjee, and Wang, 2016, Barberis, Jin, and Wang, 2021], job seekers [DellaVigna et al., 2017], and tax filers [Rees-Jones, 2018] [see Camerer, 2001, and O'Donoghue and Sprenger, 2018, for a more comprehensive list]. While this evidence establishes that experts exhibit loss aversion [Genesove and Mayer, 2001, Pope and Schweitzer, 2011], it leaves open the question of whether repeated exposure to losses moderates or intensifies this bias.

This question becomes particularly relevant when considering a parallel literature that challenges the profit maximization assumption. This literature has documented systematic departures from supposedly optimal behavior [Almunia et al., 2022, Byrne, 2015, Hortaşçu and Puller, 2008, Levitt, 2006, Massey and Thaler, 2013, Sweeting, 2012], particularly in small firms [Byrne, 2015, Hortaşçu and Puller, 2008].[3] Recent work identifies specific behavioral anomalies, from suboptimal adoption of management techniques [Bloom et al., 2013] and technology [Atkin et al., 2017] to uniform pricing [Cho and Rust, 2010, DellaVigna and Gentzkow, 2019, Kapoor, 2020].[4] Our study moves beyond documenting behavioral anomalies to propose a descriptive model of the firm's objective function. This approach complements other work examining how behavioral factors shape firm decisions [Gertler et al., 2023, Goldfarb and Xiao, 2011, Goldfarb and Yang, 2009].

Our findings relate to Oprea [2014], who shows that survival concerns can lead firms to deviate from profit maximization. While such behavior might reflect an evolutionarily ingrained survival heuristic, our evidence suggests this bias may actually intensify with exposure to losses. The positive relationship between experience and loss aversion challenges the conventional wisdom that market forces eliminate behavioral biases, suggesting instead that repeated exposure to losses may reinforce rather than moderate these biases.

2 Empirical model of labor demand

Three important features of our econometric model are drawn from Crawford and Meng [2011]. First, the Kőszegi and Rabin [2006] utility function guides the labor demand decisions of restaurant owners, and in particular their (unilateral) decision of when to stop the worker during a shift. Second, the decision maker "narrow brackets" utility across shifts, i.e. evaluates profit and gain-loss utility on a shift by shift basis. This assumption is grounded in realities of the setting and implies that the stopping decision depends exclusively on shift-specific state variables, such as the number of consumer arrivals or the number of coworkers available. Third, utility is linear away from the kink, which facilitates interpretation and which considers that a constant marginal utility of income seems reasonable in our setting. The contribution of income from a single shift to aggregate (e.g., annual) income should be infinitesimal for a firm that operates 364 shifts per year.

[3] One can test profit maximization without marginal analysis, e.g., using the weak axiom of profit maximization (WAPM) [Varian, 1984].

[4] The explanatory power of loss aversion for anomalies in firm behavior has been considered before, e.g., to rationalize laboratory evidence of behavioral deviations from risk neutral profit maximization in inventory problems [Herweg, 2013, Schweitzer and Cachon, 2000]. Angelis [2024] used it to microfound price stickiness among price-setters, a key ingredient in theoretical macroeconomics models.

We also adapt the econometric model of Crawford and Meng [2011] to our decision problem. We assume stopping decisions are guided by profit rather than by revenue and costs separately, by aggregate profit rather than profit generated by individual workers, and by forecasted aggregate profit rather than by aggregate realized profit. We define:

$$\text{STOP}_{iftd} = \begin{cases} 1, & \text{no more new customers allocated to worker} \\ 0, & \text{worker can take on new customers,} \end{cases}$$

where i indexes the worker, f the firm, $t \in \{1, \cdots, T_{ifd}\}$ indexes the time interval, and d the date. Note that the i are nested within f because no worker works at multiple firms. t is nested within d because shifts have different opening and closing times.

We assume stopping decisions are generated as follows. At each t, the firm forms an expectation $\pi^e_{ftd} = \mathbb{E}[\pi_{fd}|\mathcal{I}_t]$, where $\mathcal{I}_t$ is their information set, and where the expectation $\mathbb{E}$ is formed over all possible draws of π_{fd} for a given $\mathcal{I}_t$. The value of the worker at time t is then:

$$V_{iftd} = (1-\eta)\pi^e_{ftd} + \eta v\left(\pi^e_{ftd}|\pi^r_{fd}\right), \tag{1}$$

where $v(\pi^e_{ftd}|\pi^r_{fd}) = \boldsymbol{g}_{ftd}\Delta\pi_{ftd} + \lambda\boldsymbol{l}_{ftd}\Delta\pi_{ftd}$ and

- $\boldsymbol{g}_{td}$ and $\boldsymbol{l}_{td}$ denote indicator functions that indicate whether π^e_{fd} is larger ($\boldsymbol{g}$ain) or smaller ($\boldsymbol{l}$oss) than the reference point,
- $\Delta\pi_{ftd} \equiv \pi^e_{ftd} - \pi^r_{fd}$,
- λ is the loss aversion coefficient for profit.

We further let

- ξ_{ftd} encapsulate shocks observed by the firm between t and $t+1$ but not by us, including shocks to the opportunity costs of managers,
- $\varepsilon_{iftd} \sim Normal(0, \sigma)$ encapsulate idiosyncratic shocks that satisfy conditional independence with respect to observables and ξ_{ftd},
- $\boldsymbol{\pi g}_{f(t+1)d} = \boldsymbol{g}_{f(t+1)d}\Delta\pi_{f(t+1)d} - \boldsymbol{g}_{ftd}\Delta\pi_{ftd}$,
- $\boldsymbol{\pi l}_{f(t+1)d} = \boldsymbol{l}_{f(t+1)d}\Delta\pi_{f(t+1)d} - \boldsymbol{l}_{ftd}\Delta\pi_{ftd}$.

Stopping decisions are then determined by the one period ahead change in worker value, where

$$(1-\eta)\Big(\pi^e_{f(t+1)d} - \pi^e_{ftd}\Big) + \eta\Big(\boldsymbol{\pi g}_{f(t+1)d} + \lambda \boldsymbol{\pi l}_{f(t+1)d}\Big) + \xi_{ftd} + \varepsilon_{iftd} < 0 \tag{2}$$

is equivalent to the event $\{\text{STOP}_{iftd} = 1\}$.

Let $d = ywd'$, where y is year, w the week, and d' day of the week. We proxy for the reference point using profit from the same day of the previous week

$$\pi^r_{fd} = \pi_{fy(w-1)d'}.$$

This is a next best alternative to the more natural reference point of profit from the same day last year, $\pi_{f(y-1)wd'}$. $\pi_{f(y-1)wd'}$ is the more natural reference point because the firm publicly posts revenue and the wage bill from the same day last year, and because the firm makes sure everyone knows the goal is more revenue in less time than last year. We cannot use profit from the same day last year because we have two years of data for one firm and one year for the other.

Our empirical strategy differs from Thakral and Tô [2021], who study responses to surprises. In our setting, managers operate under an explicit week-over-week performance metric that guides their real-time staffing decisions. Rather than responding to unexpected deviations from a flexible reference point, managers in our context make decisions based on whether they anticipate meeting or missing a clearly defined target. This institutional feature - where performance evaluation and management decisions revolve around a fixed benchmark - makes the target comparison more relevant than surprise-based reference points for understanding loss aversion in our setting.

We do not observe π^e_{ftd}. We proxy for it using predicted values $\widehat{\mathbb{E}[\pi_{fd}|\mathcal{I}_t]}$ generated via repeated applications of the K-fold cross validation algorithm for LASSO. Specifically, we construct a dataset that is specific to each restaurant and each 15 minute interval (e.g., firm 1, 5:45-6:00pm is one dataset). We keep data sets where the 15 minute interval is observed in at least 150 shifts. Within each dataset, we apply the K-fold cross validation algorithm for LASSO to predict end-of-shift profits.[5] As controls, we use reference points from the same day last week, same day last year (while adjusting for missing values), evolving state variables such as aggregate revenue and wages per worker and period, worker fixed effects,

[5] We experimented with several different folds. We settled on 5 folds because the more common 10 folds was not stable enough to give the sample sizes of several of our firm-interval datasets.

interactions between worker fixed effects and worker start times, as well as fixed effects for the year, month, and day of week. We repeat this algorithm for each firm-interval dataset to obtain predicted values for every 15 minute interval in the main data.

From here we can build the log-likelihood function:

$$\sum_{iftd} ln\Phi\Big\{\Big[\boldsymbol{\pi g}_{f(t+1)d} + (1-\eta+\eta\lambda)\boldsymbol{\pi l}_{f(t+1)d} + \xi_{ftd}\Big]/\sigma\Big\},$$

where Φ is the distribution function for a standard normal random variable. As in Crawford and Meng [2011], the target parameter is $(1-\eta+\eta\lambda)$.[6] To explore the requirements for identification of $(1-\eta+\eta\lambda)$, we can invert the link function and consider the reduced form

$$\Phi^{-1}\Big(\mathbb{P}(\text{STOP}_{iftd} = 1|\boldsymbol{\pi g_{f(t+1)d}}, \boldsymbol{\pi l}_{f(t+1)d}, \xi_{ftd})\Big) = \beta_g \boldsymbol{\pi g}_{f(t+1)d} + \beta_l \boldsymbol{\pi l}_{f(t+1)d} + \xi^*_{ftd}$$

where $\beta_g = 1/\sigma$, $\beta_l = (1-\eta+\eta\lambda)/\sigma$, $\xi^*_{ftd} = \xi_{ftd}/\sigma$, and the target parameter can be recovered using β_g/β_l.

There are two sources of variation in $\boldsymbol{\pi g}_{f(t+1)d}$ and $\boldsymbol{\pi l}_{f(t+1)d}$: *i*) period to period changes in profit when there is no transition from losses to gains or vice versa; *ii*) period to period changes in losses and gains when there is a transition. Gains in adjacent periods contribute nothing to the identification of β_l. Adjacent losses contribute nothing to β_g. Transitions contribute to both. See below for further illustration. β_l and β_g are identified if there are no

Identifying variation.

	$\boldsymbol{l}_{f(t+1)d} = 1$	$\boldsymbol{g}_{f(t+1)d} = 1$
$\boldsymbol{l}_{ftd} = 1$	$\pi^e_{f(t+1)d} - \pi^e_{ftd}$ recovers β_l no contribution to β_g	$\pi^e_{f(t+1)d} - \pi^r_{fd}$ recovers β_l $\pi^e_{ftd} - \pi^r_{fd}$ recovers β_g
$\boldsymbol{g}_{ftd} = 1$	$\pi^e_{ftd} - \pi^r_{fd}$ recovers β_l $\pi^e_{f(t+1)d} - \pi^r_{fd}$ recovers β_g	no contribution to β_l $\pi^e_{f(t+1)d} - \pi^e_{ftd}$ recovers β_g

variables in $\varepsilon_{t_{id}}$ that track $\pi^e_{f(t+1)d} - \pi^e_{ftd}$, $\pi^e_{f(t+1)d} - \pi^r_{fd}$, $\pi^e_{ftd} - \pi^r_{fd}$, and stopping decisions for a given realization of ξ_{ftd}.

The Crawford and Meng [2011] differenced specification accounts for several threats to

[6] In the Crawford and Meng [2011] framework, the Kőszegi and Rabin [2006] utility function has the same reduced form as a more classical loss averse utility function (with $\eta = 1$). This is because the reference point is the same from period to period and because, consequently, one period changes in profit cannot be decoupled from one period ahead changes in losses and gains. From this reduced form perspective, the target parameter can be interpreted either as a weighted average of 1 and λ or simply as λ itself.

identification. This includes worker specific determinants such as their intrinsic motivation or table assignment, calendar date specific determinants such as average temperature, as well as evolving state variables such as the consumer arrival rate, production bottlenecks, or number of workers remaining. Remaining threats to identification depend on our operationalization of ξ_{ftd}. We operationalize ξ_{ftd} via fixed effects that index the firm, calendar date, and service period, where the service period indexes 15 minute intervals that are realized in the pre-peak, peak, or post-peak period. This means that the main remaining threats to identification are within service period shocks that track the gain-loss differences and stopping decisions.[7]

3 Data

We estimate our empirical model of labor demand using internal transactions data from two large full service restaurants. The restaurants are franchises in the same large Canadian "big-box" retail chain. The restaurants are only open for dinner. They are designed for scale and accordingly provide customers with uniform product and service quality. They have approximately 2800 customer arrivals each per week. Each customer spends approximately $45 dollars. Total potential revenue is around $126,000 per restaurant per week.

There are 71 waiters in the two restaurants combined. Waiters handle 2-4 tables each, or 10-16 seats, depending on the day, and do not share tables. The number of waiters in a shift ranges from 10 to 20. There are 690 shifts and 10 to 15 (co-)owners are making stopping decisions. The data are taken from 2 years: 2008-2009 and 2009-2010. Hereafter we will refer to waiters as workers and owners as the firm.[8]

Each shift is partitioned into 15-minutes intervals. The 15-minutes marker is important for payments to workers. Workers who stop working at 6:14pm get paid until 6pm. Workers who stop at 6:15pm get paid until 6:15 pm. Notice that both start and end times are worker specific. Start times are set well in advance of each work week and are generally staggered, except for Saturdays where all workers start at the same time. The order in which workers stop is the same as the order in which they start. The control problem for the firm is not whom to stop, only when.

[7]The exogeneity of gains and losses seems more plausible here than for labor supply. With labor supply, workers generate income, hours, and control stopping decisions. With labor demand, workers generate revenue and costs but have no control over stopping decisions.

[8]Extra information about the context can be found in Kapoor [2020] and Kapoor and Magesan [2019].

4 Results

Figure 2 (top) plots our key sources of identifying variation over the course of shift: $\boldsymbol{\pi g}_{f(t+1)d}$ (red squares) and $\boldsymbol{\pi l}_{f(t+1)d}$ (blue dots). The figure suggests the firm expects the period-over-period loss to increase initially, decrease during the peak period, before increasing again later in the shift. An opposing pattern emerges for gains.

Figure 2 (bottom) shows how the stopping probability differs with the time of day. Workers are almost never stopped before 5:45pm. The stopping probability increases smoothly from 6 until 10pm. It continues to increase thereafter, but with some volatility, reflecting the closure of the dining room at 11pm. The stopping probability equals 1 thereafter, consistent with the revenue-wage comparison in the top panel of Figure 2.

Loss coefficient estimates can be found in the top panel of Table 1. Reduced form estimates are in the bottom panel. Column 1 estimates are based on the full sample. Column 2 estimates are based on the subsample of slower days when excess demand for seating is rare (Sundays through Thursdays). Column 3 reports estimates based on the subsample of busier days when there is almost always excess demand for seating (Fridays and Saturdays). The partition is justified in Online Appendix Table A.1.1, which reports the number of consumer arrivals by day of the week. Robustness to worker fixed effects is verified in Online Appendix Table A.1.2.

The estimate in Column 1 shows a loss coefficient of 4.27. The estimate is statistically different from 1 (loss neutrality).

Column 2 shows a loss coefficient of 7.39 on slow days. It is statistically different from loss neutrality at the 1 percent level. Column 3 shows a loss coefficient of 0.29 on busy days. It is statistically different from loss neutrality. While there are a number of potential explanations for the difference between slow and busy days, a natural one relates to the size of the management team. On slow days, when management teams are smaller and individual decisions carry more weight, loss aversion intensifies. Conversely, on busy days, when larger management teams share responsibility and individual decisions carry less weight, loss aversion disappears.

5 Survey

5.1. Sampling. To measure loss aversion more directly, we conducted face-to-face interviews with restaurant owners and managers in Rotterdam and Utrecht during summer 2016.[9] Our sampling frame came from `iens.nl`, a popular Dutch restaurant review platform. Through a combination of scheduled appointments and direct visits, we interviewed 107 establishments, representing approximately 15% of the platform's listings in these cities. These businesses collectively employed 1,870 workers.

To assess potential selection bias, we examined whether interviewed establishments differed systematically from non-participants along observable dimensions (see Online Appendix Table A.1.3). Our comparative analysis of platform ratings showed no significant differences in price points, food quality, service levels, or ambiance scores, though we acknowledge potential selection on willingness to participate.

Our measurement approach adapts the experimental methodology developed by Abdellaoui et al. [2016]. We presented participants with a series of business scenarios framed around substantial monetary stakes (€200000) to ensure salience for professional decision-makers. Each scenario offered a choice between a guaranteed outcome and a risky prospect with equal probabilities of gains and losses. Through systematic variation of the loss amounts and elicitation of certainty equivalents, we could identify individual-specific loss aversion parameters.

To enhance accessibility and maintain reasonable interview durations, we focused specifically on loss aversion under risk (known 50-50 probabilities) rather than ambiguity. While this represents a simplification relative to the full Abdellaoui et al. [2016] protocol, prior evidence suggests loss aversion measures remain stable across risk and ambiguity contexts.

Five years after our initial interviews (October 2021), we followed up to determine establishment survival. This involved triangulating multiple data sources including social media presence, online business listings, local news coverage, and direct verification of operational status through reservation systems.

5.2. Measurement. Our measurement strategy builds on experimental economics techniques designed to elicit risk and loss preferences. Consider a reference-dependent utility function $v(\pi|\pi^r) = u(\pi - \pi^r)$ where $\pi^r = 0$ and $u(0) = 0$. The elicitation involves four key steps:

[9] A detailed description of this survey data can also be found in Emami Namini and Kapoor [2025], which uses the same data to calibrate a general equilibrium model with loss averse firms and, ultimately, to quantify the implications for economic aggregates such as market productivity.

1. Select an initial gain value g

2. Determine a loss value l such that the decision maker is indifferent between a certain zero payoff and a probabilistic prospect $(g, p; l, 1-p)$ that yields:

$$w^+(p)u(g) + w^-(1-p)u(l) = 0 \tag{3}$$

   Here $w^+(p)$ and $w^-(1-p)$ represent probability weighting functions that map the unit interval to itself

3. Find the certainty equivalent ce_g that satisfies:

$$w^+(p)u(g) = u(ce_g) \tag{4}$$

4. Find the certainty equivalent ce_l that satisfies:

$$w^-(1-p)u(l) = u(ce_l) \tag{5}$$

From equations 3-5, we can derive:

$$u(ce_g) = -u(ce_l) \tag{6}$$

Following Kobberling and Wakker [2005], we measure loss aversion as:

$$\frac{u(ce_l)/ce_l}{u(ce_g)/ce_g} = \frac{ce_g}{ce_l} \tag{7}$$

where the equality follows from equation 6. Values above unity indicate loss aversion.

To make these abstract concepts concrete for business owners, we framed choices in terms of business scenarios. A typical elicitation question read:

CERTAIN OPTION	**COIN FLIP OPTION**		
Profit of €0	Profit of €200000	**OR**	Loss of €200000
Profit of €0	Profit of €200000	**OR**	Loss of €100000
Profit of €0	Profit of €200000	**OR**	Loss of €50000

We then asked for the loss amount that would make them indifferent:

CERTAIN OPTION	COIN FLIP OPTION		
Profit of €0	Profit of €200000	**OR**	Loss of €...

For simplicity and clarity, we restricted attention to symmetric probabilities ($p = 0.5$), focusing on decisions under risk rather than ambiguity. While this represents a simplification relative to the general case, prior evidence suggests loss aversion measures remain stable across these contexts. We deliberately chose substantial monetary stakes (€200000) to ensure the scenarios were meaningful for business decision-makers. The complete set of elicitation questions appears in Online Appendix A.2.

Notably, we did not explicitly differentiate between accounting and economic profit in our scenarios. While this might raise concerns about interpretation, our sample's even split between owners and managers provides a natural test - since economic profit is more relevant for owners, systematic differences in interpretation should manifest as differences in measured loss aversion across these groups. We find no such differences.

5.3. Results. Table 2 presents our key findings on owner preferences and business characteristics.[10] Statistical tests strongly favor loss aversion ($\lambda > 1$) over gain-seeking or loss-neutral preferences ($\lambda \leq 1$), with significance at the 1% level both for the interquartile range and the full sample.

Our survey captured detailed demographic and operational data. The sample consists primarily of mid-career professionals—the typical owner is 36 years old with 12 years of industry experience. These establishments are substantial enterprises, averaging 17.5 employees. When rating their risk tolerance on a scale from 0 (completely risk-averse) to 10 (fully prepared to take risks), owners reported a mean score of 6.67.

To gauge market sophistication, we elicited perceived demand responses to hypothetical price increases. Specifically, owners estimated customer volume changes following price increases of 5%, 10%, and 20%. The responses reveal increasing price elasticity: -0.98 at current prices, rising to -1.81 and -1.94 at prices 5% and 10% above baseline. Operating where demand is inelastic suggests these firms possess market power, consistent with differentiated products in monopolistic competition. This sophisticated understanding of demand

[10] The distribution of loss aversion parameters aligns closely with experimental evidence from Abdellaoui et al. [2016].

conditions suggests owners understand their competitive environment.

Table 3 reports estimates of the correlation between $ln(1+\lambda)$ and the other covariates. The natural logarithmic transformation of loss aversion limits the influence of owners with large and extreme λ. The transformation $1+\lambda$ prevents the introduction of new outliers due to taking logs of values between 0 and 1. The $ln(1+\lambda)$ transformation facilitates use of the full sample.

The only statistically significant correlate of loss aversion is experience. The first column shows one more year of experience is associated with the owner being 2 percent more loss averse ($p < 0.05$).[11] The remaining columns show a robust correlation to controls for their perceptions of demand, firm size, propensity to engage in risk, and age.

What explains the positive and robust correlation with experience? One explanation is experience causes owners to become more loss averse. For instance, experienced owners may have learned losses are especially unpleasant, perhaps creditors are especially unpleasant. This explanation is difficult to validate empirically. Another explanation relates to selection. Survival probabilities may be higher for firms with loss averse owners because they have a greater propensity for avoiding losses.[12]

6 Conclusion

The evidence we present suggests that exposure to losses intensifies loss aversion. Studying decision-makers in a competitive industry where losses pose significant threats to business survival, we find loss aversion coefficients substantially higher than the typical range of 1.8 to 2.1 documented in the behavioral economics literature. Analysis of real-time labor demand decisions reveals a coefficient of 4.3 that rises to 7.4 on slow days, while direct elicitation from owners and managers yields a mean coefficient of 10.1, with 30% of respondents showing coefficients above 3.

However, an important limitation of our analysis is that we do not have exogenous variation in exposure to losses. While we document that loss aversion varies systematically with conditions that proxy for loss exposure - such as operational scale and industry experience

[11] We describe how the point estimate for a percentage change in $1+\lambda$ is transformed into a percentage change in λ. Take the differential $dln(1+\lambda) = \beta dln(x)$, which implies $\frac{d\lambda}{(1+\lambda)} = \beta \frac{dx}{x}$, and $\frac{d\lambda}{(1+\lambda)} \frac{x}{dx} = 0.17$. Multiply both sides by $\frac{1+\bar{\lambda}}{\bar{\lambda}}$ to get 0.19. Multiply this by 0.083, which is equivalent to one additional year of experience (over the mean).

[12] For additional analysis of the relationship between loss aversion and survival, see Emami Namini and Kapoor [2025].

- we cannot definitively establish a causal relationship. Our evidence, while consistent with loss exposure intensifying loss aversion, remains circumstantial.

Our findings have implications for understanding how firms develop and maintain behavioral biases. Rather than market experience tempering psychological biases, exposure to losses appears to reinforce them. This suggests that competitive pressures alone may not drive firms toward more symmetric treatment of gains and losses, even in settings where such symmetry might enhance survival prospects. These results speak to broader questions about market selection, firm dynamics, and the potential role of policy in industries dominated by small businesses.

References

Mohammed Abdellaoui, Han Bleichrodt, and Hilda Kammoun. Do financial professionals behave according to prospect theory? an experimental study. *Theory and Decision*, 74(3): 411–429, 2013.

Mohammed Abdellaoui, Han Bleichrodt, Olivier L'Haridon, and Dennie van Dolder. Measuring loss aversion under ambiguity: A method to make prospect theory completely observable. *Journal of Risk and Uncertainty*, 52:1–20, 2016.

Eric J. Allen, Patricia M. Dechow, Devin G. Pope, and George Wu. Reference-dependent preferences: Evidence from marathon runners. *Management Science*, 63(6):1657–1672, 2017.

Miguel Almunia, Jonas Hjort, Justine Knebelmann, and Lin Tian. Strategic or Confused Firms? Evidence from "Missing" Transactions in Uganda. *The Review of Economics and Statistics*, pages 1–35, 03 2022.

Georgios Angelis. Price setting and price stickiness: A behavioral foundation of inaction bands. *Journal of the European Economic Association*, October 2024.

David Atkin, Azam Chaudhry, Shamyla Chaudry, Amit K. Khandelwal, and Eric Verhoogen. Organizational barriers to technology adoption: Evidence from soccer-ball producers in pakistan. *The Quarterly Journal of Economics*, 132(3):1101–1164, 2017.

Nicholas Barberis, Ming Huang, and Tano Santos. Prospect theory and asset prices. *The Quarterly Journal of Economics*, 116(1):1–53, 2001.

Nicholas Barberis, Abhiroop Mukherjee, and Baolian Wang. Prospect theory and stock returns: An empirical test. *The Review of Financial Studies*, 29(11):3068–3107, 07 2016.

Nicholas Barberis, Lawrence J. Jin, and Baolian Wang. Prospect theory and stock market anomalies. *The Journal of Finance*, 76(5):2639–2687, 2021.

Matthias Benz and Bruno S Frey. Being independent raises happiness at work. *Swedish economic policy review*, 11(2):95–134, 2004.

Nicholas Bloom, Benn Eifert, Aprajit Mahajan, David McKenzie, and John Roberts. Does management matter? evidence from india. *The Quarterly Journal of Economics*, 128(1): 1–51, 2013.

Alexander L. Brown, Taisuke Imai, Ferdinand M. Vieider, and Colin F. Camerer. Meta-analysis of empirical estimates of loss aversion. *Journal of Economic Literature*, 62(2): 485–516, June 2024.

David P. Byrne. Testing models of differentiated products markets: Consolidation in the cable tv industry. *International Economic Review*, 56(3):805–850, August 2015.

Colin Camerer. Prospect theory in the wild: Evidence from the field. In Daniel Kahneman and Amos Tversky, editors, *Choices, Values, and Frames*, chapter 10, pages 266–290. Cambridge University Press, Cambridge, 2001.

Colin Camerer, Linda Babcock, George Loewenstein, and Richard Thaler. Labor supply of new york city cabdrivers: One day at a time. *The Quarterly Journal of Economics*, 112 (2):407–441, 1997.

Sungjin Cho and John Rust. The flat rental puzzle. *The Review of Economic Studies*, 77 (2):560–594, April 2010.

Vincent P. Crawford and Juanjuan Meng. New york city cab drivers' labor supply revisited: Reference-dependent preferences with rational-expectations targets for hours and income. *American Economic Review*, 101(5):1912–32, 2011.

Stefano DellaVigna and Matthew Gentzkow. Uniform pricing in u.s. retail chains. *The Quarterly Journal of Economics*, 134(4):2011–2084, June 2019.

Stefano DellaVigna, Attila Lindner, Balázs Reizer, and Johannes F. Schmieder. Reference-dependent job search: Evidence from hungary. *The Quarterly Journal of Economics*, 132 (4):1969–2018, 05 2017.

Julian Emami Namini and Sacha Kapoor. Are markets loss averse? theory and evidence from a competitive industry. *Working Paper*, 2025.

Henry S. Farber. Is tomorrow another day? the labor supply of new york city cabdrivers. *Journal of political Economy*, 113(1):46–82, 2005.

Henry S. Farber. Reference-dependent preferences and labor supply: The case of new york city taxi drivers. *American Economic Review*, 98(3):1069–82, 2008.

Henry S. Farber. Why you can't find a taxi in the rain and other labor supply lessons from cab drivers. *The Quarterly Journal of Economics*, 130(4):1975–2026, 2015.

David Genesove and Christopher Mayer. Loss aversion and seller behavior: Evidence from the housing market. *The Quarterly Journal of Economics*, 116(4):1233–1260, 2001.

Paul Gertler, Sean Higgins, Ulrike Malmendier, and Waldo Ojeda. Why small firms fail to adopt profitable opportunities. *Working Paper*, August 2023.

Avi Goldfarb and Mo Xiao. Who thinks about the competition? managerial ability and strategic entry in us local telephone markets. *American Economic Review*, 101(7):3130–61, December 2011.

Avi Goldfarb and Botao Yang. Are all managers created equal? *Journal of Marketing Research*, 46(5):612–622, 2009.

Barton H. Hamilton. Does entrepreneurship pay? an empirical analysis of the returns to self-employment. *Journal of Political Economy*, 108(3):604–631, 2000.

Fabian Herweg. The expectation-based loss-averse newsvendor. *Economics Letters*, 120(3): 429–432, 2013.

Ali Hortaçsu and Steven L. Puller. Understanding strategic bidding in multi-unit auctions: a case study of the texas electricity spot market. *Rand Journal of Economics*, 39(1):86–114, Spring 2008.

Erik G. Hurst and Benjamin W. Pugsley. What do small businesses do? *Brookings Papers on Economic Activity*, pages 73–143, 2011.

Sacha Kapoor. Inefficient incentives and nonprice allocations: Experimental evidence from big-box restaurants. *Journal of Economics & Management Strategy*, 29(2):401–419, 2020.

Sacha Kapoor and Arvind Magesan. Having it easy: Discrimination and specialization in the workplace. *Journal of Economic Behavior & Organization*, 166:153–173, 2019.

Botond Kőszegi and Matthew Rabin. A model of reference-dependent preferences. *The Quarterly Journal of Economics*, 121(4):1133–1165, 2006.

Vanessa Kobberling and Peter Wakker. An index of loss aversion. *Journal of Economic Theory*, 122:119–131, 2005.

Steven D. Levitt. An economist sells bagels: A case study in profit maximization. *NBER Working Papers*, (12152), April 2006.

Alex Markle, George Wu, Rebecca White, and Aaron Sackett. Goals as reference points in marathon running: A novel test of reference dependence. *Journal of Risk and Uncertainty*, 56(1):19–50, 2018.

Cade Massey and Richard H. Thaler. The loser's curse: Decision making and market efficiency in the national football league draft. *Management Science*, 59(7):1479–1495, 2013.

John Morgan and Dana Sisak. Aspiring to succeed: A model of entrepreneurship and fear of failure. *Journal of Business Venturing*, 31(1):1–21, 2016.

Ted O'Donoghue and Charles Sprenger. Reference-dependent preferences. In *Handbook of Behavioral Economics: Applications and Foundations 1*, volume 1, pages 1–77. 2018.

Ryan Oprea. Survival versus profit maximization in a dynamic stochastic experiment. *Econometrica*, 82(6):2225–2255, 2014.

Devin G. Pope and Maurice E. Schweitzer. Is tiger woods loss averse? persistent bias in the face of experience, competition, and high stakes. *The American Economic Review*, 101 (1):129–157, February 2011.

Alex Rees-Jones. Quantifying Loss-Averse Tax Manipulation. *The Review of Economic Studies*, 85(2):1251–1278, 04 2018.

Maurice E Schweitzer and Gérard P Cachon. Decision bias in the newsvendor problem with a known demand distribution: Experimental evidence. *Management Science*, 46(3):404–420, 2000.

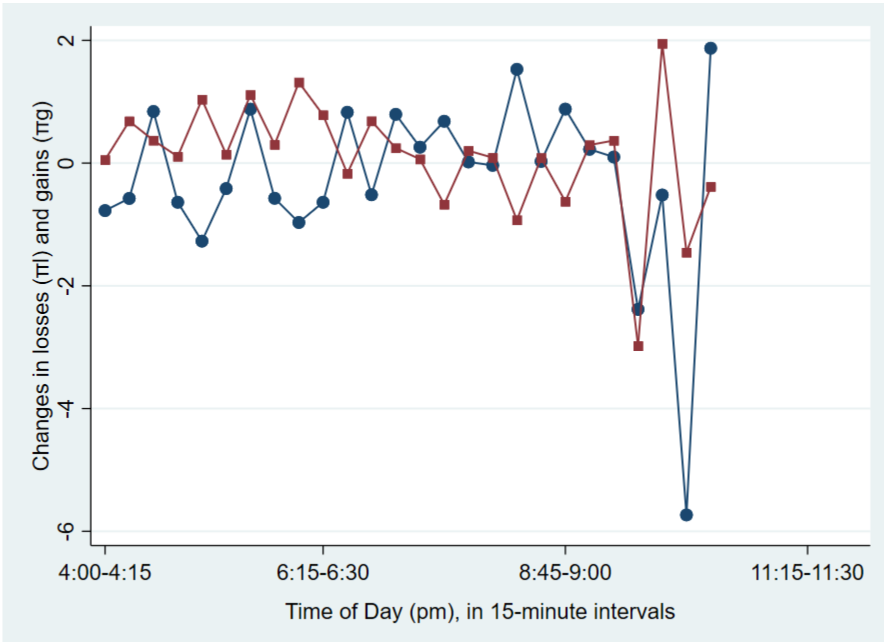
Andrew Sweeting. Price dynamics in perishable goods markets: The case of secondary markets for major league baseball tickets. *Journal of Political Economy*, 120(6):1133–1172, December 2012.

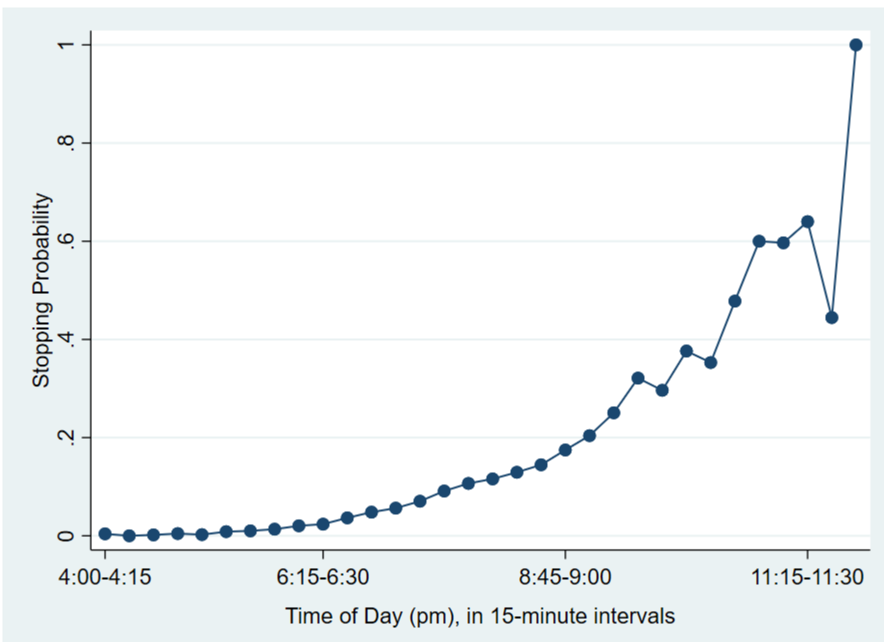
Neil Thakral and Linh T. Tô. Daily labor supply and adaptive reference points. *American Economic Review*, 111(8):2417–43, August 2021.

Hal R Varian. The nonparametric approach to production analysis. *Econometrica: Journal of the Econometric Society*, pages 579–597, 1984.

Figures and Tables

Figure 2: Gains, losses, and stopping decisions.





Notes:

1 Top figure plots changes in losses $\boldsymbol{\pi l}_{f(t+1)d} = \boldsymbol{l}_{f(t+1)d}\Delta\pi_{f(t+1)d} - \boldsymbol{l}_{ftd}\Delta\pi_{ftd}$ (blue dots) and changes in gains $\boldsymbol{\pi g}_{f(t+1)d} = \boldsymbol{g}_{f(t+1)d}\Delta\pi_{f(t+1)d} - \boldsymbol{g}_{ftd}\Delta\pi_{ftd}$ (red squares). These are the sources of identifying variation in the stopping model. Figure is truncated because these 15 minute intervals did not meet the 150 observation requirement for predicting end-of-shift profit via the K-fold cross validation algorithm for LASSO.

2 Vertical axis in the bottom figure references the proportion of workers who stop taking customers.

3 Each dot or square is the average over workers in a 15-minute interval.

4 Horizontal axes reference the time of day in 15-minute intervals.

5 Workers are paid in accordance with these 15-minute intervals.

Table 1: Loss coefficients for stopping decisions.

	Stop Worker (1=yes)		
	All	Slow days	Busy days
	(1)	(2)	(3)
Loss Coefficient			
$1-\eta+\eta\lambda$	4.27***	7.39***	0.29
	(0.05)	(0.06)	(0.08)
Reduced Form Coefficients			
$\beta_l = 1-\eta+\eta\lambda/\sigma$	0.0013***	0.0018***	0.0005
	(0.0005)	(0.0006)	(0.0008)
$\beta_g = 1/\sigma$	0.0003	-0.0002	0.0017
	(0.0005)	(0.0005)	(0.0008)
Observations	71105	34857	36248
Log-likelihood	-20717	-12376	-8339

Notes:

[1] Top panel reports loss coefficient estimates for profit per worker. Bottom panel reports reduced form coefficient estimates.

[2] Reference point proxy is profit per worker from the same day last week: $\pi^r_{fd} = \pi_{fy(w-1)d'}$, where $d = ywd'$ is the calendar date, y is year, w the week, and d' day of the week.

[3] Null hypotheses in top panel are with reference to loss neutrality. Null hypotheses for reduced form coefficients is 0.

[4] Busy days are Fridays and Saturdays. 46 percent of consumer demand is generated on these days.

[5] Regressions condition on fixed effects for the restaurant-date-service period. There are three service periods for every date: pre-peak, peak (6-10), and post-peak.

[5] Standard errors in parentheses. $***$ and $**$ denote statistical significance at the 1 and 5 percent levels.

Table 2: Owner survey descriptives (Firms=107).

Variable	Mean	Standard deviation	Minimum	Maximum
Loss aversion	10.14	35.06	0.0001	260.00
	Median = 1.57, Interquartile Range = [1,3.33]			
Age	35.93	10.35	20	63
Experience (months)	144.88	124.25	1.5	456
Number of employees	17.48	17.02	0	130
Willingness to take risks 0: risk averse 10: fully prepared to take risks	6.67	1.76	0	10
Customer volume (per week)	1124.21	1348.19	75	10000
Percentage change in customer volume after a				
5 percent increase in the current price	0.98	2.00	0	12
5 percent increase at 105 percent of current price	1.81	2.90	0	20
10 percent increase at 110 percent of current price	1.94	2.10	0	10

Notes:
[1] Owners are loss neutral if the estimate of their loss aversion coefficient is 1, gain seeking if it is less than 1, and loss averse if it is greater than 1.
[2] We tested the hypothesis that owners are either gain seeking or loss neutral, against the alternative where they are loss averse. The t-statistic for the test had a p-value of 0.004 over the full sample. It had a p-value of 0.000 over the interquartile range. The statistics leads us to reject the hypothesis that owners are either gain seeking or loss neutral.

Table 3: Loss aversion and experience.

	Loss Aversion, $ln(1+\lambda)$				
	(1)	(2)	(3)	(4)	(5)
Experience (months, in logs)	0.17***	0.17***	0.17***	0.18***	0.16***
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
Percentage Change in Customer Volume after a					
5 percent increase in the current price		-0.14	-0.13	-0.13	-0.11
		(0.13)	(0.13)	(0.13)	(0.13)
5 percent increase at 105 percent of current price		0.19	0.21	0.19	0.20
		(0.29)	(0.29)	(0.30)	(0.32)
10 percent increase at 110 percent of current price		-0.02	-0.03	-0.03	-0.07
		(0.17)	(0.18)	(0.18)	(0.18)
Customer Volume (per Week, in logs)		0.02	-0.02	-0.02	-0.03
		(0.11)	(0.11)	(0.12)	(0.12)
Number of Employees (in logs)			0.08	0.08	0.12
			(0.14)	(0.14)	(0.16)
Willingness to Take Risks (0: Risk Averse; 10: fully prepared to take risks)				-0.04	-0.04
				(0.05)	(0.08)
Age					0.01
					(0.01)
Firms	107	105	105	105	102
R^2	0.05	0.06	0.07	0.07	0.08

Notes:
[1] Table reports regression estimates of the effects of various covariates on the loss aversion of the owner.
[2] The transformation $ln(1+\lambda)$ reduces the influence of large outliers, without introducing new ones (a few λ are less than 1). Taking logs of Experience, Customer Volume, and the Number of Employees further reduces the influence of outliers.
[3] The elasticities are in absolute values, and standardized by their mean and standard deviation.
[4] Robust standard errors in parentheses, with *** for $p < 0.01$, ** for $0.01 < p < 0.05$, and * for $p < 0.1$.

Does exposure to losses intensify loss aversion?
Evidence from a competitive industry

Online Appendix

Julian Emami Namini and Sacha Kapoor

February 17, 2025

A.1 Additional figures and tables

Table A.1.1: Scale and Demand Volatility. Customer arrivals includes customers who were served by the firm and ones who left upon learning the wait time for a seat. Standard deviations in parentheses.

	Customer Arrivals						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Minimum	82	108	169	126	211	271	207
Mean	218.59	246.47	282.87	335.30	538.83	747.75	412.06
	(75.41)	(52.99)	(61.10)	(80.23)	(93.04)	(131.85)	(147.33)
Maximum	619	417	560	602	716	1243	1220
Observations	95	100	94	94	110	110	94

Table A.1.2: Loss coefficients for stopping decisions (with worker fixed effects).

	Stop Worker (1=yes)		
	All	Slow days	Busy days
	(1)	(2)	(3)
Loss Coefficient			
$1 - \eta + \eta\lambda$	4.87***	6.46***	0.30
	(0.05)	(0.06)	(0.08)
Reduced Form Coefficients			
$\beta_l = 1 - \eta + \eta\lambda/\sigma$	0.0013***	0.0018***	0.0005
	(0.0005)	(0.0006)	(0.0008)
$\beta_g = 1/\sigma$	0.0003	-0.0002	0.0016
	(0.0005)	(0.0005)	(0.0009)
Observations	71105	34857	36248
Log-likelihood	-20660	-12335	-8305

Notes:

[1] Top panel reports loss coefficient estimates for profit per worker. Bottom panel reports reduced form coefficient estimates.

[2] Reference point proxy is profit per worker from the same day last week: $\pi^r_{fd} = \pi_{fy(w-1)d'}$, where $d = ywd'$ is the calendar date, y is year, w the week, and d' day of the week.

[3] Null hypotheses in top panel are with reference to loss neutrality. Null hypotheses for reduced form coefficients is 0.

[4] Busy days are Fridays and Saturdays. 46 percent of consumer demand is generated on these days.

[5] Regressions condition on fixed effects for the restaurant-date-service period and for the worker.

[5] Standard errors in parentheses. $***$ and $**$ denote statistical significance at the 1 and 5 percent levels.

Table A.1.3: Representativeness of owner sample.

Variable	Not Sampled (1)	Sampled (2)	Difference (2)-(1)
Price	20.59	20.87	-0.27
	(11.44)	(8.83)	[2.24]
Food Rating (/10)	7.77	7.60	0.17
	(0.60)	(0.67)	[0.11]
Service Rating (/10)	7.69	7.51	0.18
	(0.0.67)	(0.76)	[0.12]
Decor Rating (/10)	7.51	7.64	-0.13
	(0.61)	(0.55)	[0.11]
Observations	595	31	626

Notes:

1 The table presents data from iens.nl, a website where consumers can evaluate restaurants based on their price, food, service, and decor.

2 Column 1 presents information for restaurants not sampled in our survey, but were from the neighbourhoods of the sampled restaurants (Column 2). Note we could not locate ratings for all the restaurants we sampled in our survey.

3 Estimates of the standard deviation are in round parentheses. Standard errors for the difference is in square parentheses, with *** for $p < 0.01$, ** for $0.01 < p < 0.05$, and * for $p < 0.1$.

A.2 Loss aversion measurement

1. Which business would you prefer to own? One where:

you are **GUARANTEED**	**COIN FLIP** determines whether you earn		
a profit of €0	a profit of €200000	**OR**	a loss of €200000
a profit of €0	a profit of €200000	**OR**	a loss of €100000
a profit of €0	a profit of €200000	**OR**	a loss of €50000

2. What loss would just make you willing to own the second business?

you are **GUARANTEED**	**COIN FLIP** determines whether you earn		
a profit of €0	a profit of €200000	**OR**	a loss (or profit) of €L=

3. Which business would you prefer to own? One where:

you are **GUARANTEED**	**COIN FLIP** determines whether you earn		
a profit of €175000	a profit of €200000	**OR**	a profit of €0
a profit of €150000	a profit of €200000	**OR**	a profit of €0
a profit of €125000	a profit of €200000	**OR**	a profit of €0

4. How small would the guarantee have to be for you to be willing to own the second business?

you are **GUARANTEED**	**COIN FLIP** determines whether you earn		
a profit of €G=	a profit of €200000	**OR**	a profit of €0

5. Which business would you prefer to own? One where:

you are **GUARANTEED**	**COIN FLIP** determines whether you earn		
a loss of €	a loss of € L=	**OR**	a profit of € 0
a loss of €	a loss of € L=	**OR**	a profit of € 0
a loss of €	a loss of € L=	**OR**	a profit of € 0

6. What would the guarantee have to be for you to be willing to own the second business?

you are **GUARANTEED**	**COIN FLIP** determines whether you earn	
a loss of € X=	a loss of € L=	**OR** a profit of € 0