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

Julian Emami Namini and Sacha Kapoor*

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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, via thousands of real-time labor demand decisions from a retail chain and a discrete choice stopping model, we find a loss aversion coefficient of $\lambda = 4.2$, rising to $\lambda = 9.5$ 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, profit maximization, loss aäqversion, 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 weigh losses about twice as heavily as equivalent gains [Brown et al., 2024], though some weigh losses many times more. A key question is whether frequent exposure to losses amplifies or dampens this bias. Understanding this dynamic is essential, as repeated losses could either reinforce loss aversion, leading to excessive risk avoidance, or weaken it through adaptation. 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.

[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.

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 management 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

[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.

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 $\lambda = 4.2$. 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. $\lambda = 9.5$ 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.

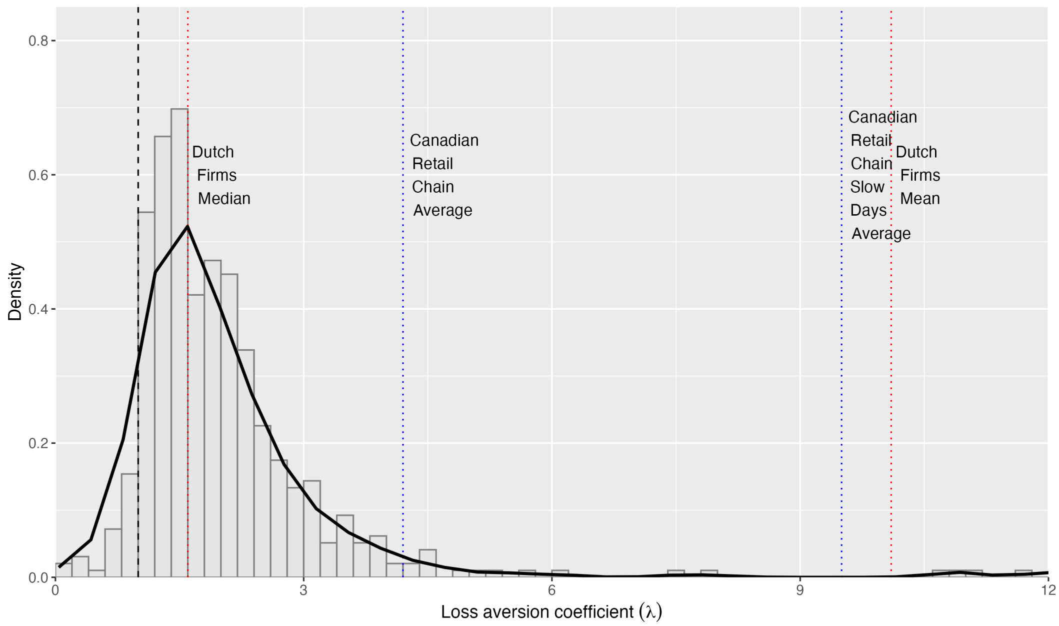
Our second piece of evidence is based on personal interviews with 107 owners or managers in the industry. Personal interviews were costly, but ensured questions were answered by owners and general managers themselves rather than by their assistants. We used the Abdellaoui et al. [2016] method to elicit 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 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, 4.2, 9.5, and 10.1. We have truncated the graph at 12 for visualization purposes. Brown et al. [2024] truncate the graph at 6.

An important consideration when comparing our estimates to the Brown et al. [2024]

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



meta-analysis is stake size. Our elicitation uses €200,000 stakes, substantially larger than most studies in the meta-analysis. However, recent evidence suggests loss aversion is robust to stake size. Bleichrodt and L'Haridon [2023], using the same Abdellaoui et al. [2016] method we employ, find loss aversion coefficients remain significant across both small and high stakes (with high stakes 200 times larger), and if anything, slightly decrease with stake size. Our direct methodological benchmark, [Abdellaoui et al., 2016, p. 17], used large stakes (hundreds and thousands of euros) and report a median loss aversion of 2.2 with interquartile range [1, 4.5-7.3]. Our median of 1.6 with interquartile range [1, 3.3] is comparable and, if anything, more conservative despite our even larger stakes.

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, Hortaçsu and Puller, 2008, Levitt, 2006, Massey and Thaler, 2013, Sweeting, 2012], particularly in small firms [Byrne, 2015, Hortaçsu 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.

[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.

2 Empirical model

2.1. Loss aversion and labor demand. Three important features of our econometric model are drawn from Crawford and Meng [2011]. First, we apply the Kőszegi and Rabin [2006] utility function to restaurant owners' labor-demand decisions, 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.

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. In the following, and if possible, we suppress the d to simplify the notation.

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

$$V_{ift} = (1-\eta)\pi^e_{ft} + \eta v\big(\pi^e_{ft}|\pi^r_f\big), \tag{1}$$

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

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

We further let

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

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

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

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

We proxy for the reference point using profit from the same day of the previous week

$$\pi_f^r = \pi_{fy(w-1)d}$$

where y is year, w the week, and d day of the week. 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.

This year-over-year comparison is not our choice as researchers but reflects the firm's institutional practice. The firm publicly posts revenue and wage bills from the same day last year at the start of each shift and explicitly communicates that the goal is to exceed last year's performance. While this may not be the theoretically optimal benchmark—holidays and calendar misalignment create some noise—it is the actual reference point guiding managerial decisions. Year-over-year comparisons naturally adjust for seasonality and day-of-week effects, and Kapoor [2020] demonstrates that these patterns are remarkably stable in this industry, even to the specific date.

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_{ft}. We proxy for it using predicted values $\widehat{\mathbb{E}[\pi_f|\mathcal{I}_t]}$ 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, 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:

$$\sum_{ift} lnF\Big(\boldsymbol{\pi g}_{f(t+1)} + (1-\eta+\eta\lambda)\boldsymbol{\pi l}_{f(t+1)} + \xi_{ft}\Big),$$

where F is the distribution function for ε_{ift}. 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

$$F^{-1}\Big(\mathbb{P}(\text{STOP}_{ift} = 1|\boldsymbol{\pi g_{f(t+1)}, \pi l}_{f(t+1)}, \xi_{ft})\Big) = \beta_g \boldsymbol{\pi g}_{f(t+1)} + \beta_l \boldsymbol{\pi l}_{f(t+1)} + \xi_{ft}.$$

The target parameter $(1-\eta+\eta\lambda)$ can be recovered using β_l/β_g.

[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.

[6] In the Crawford and Meng [2011] framework, the Kőszegi and Rabin [2006] utility function has the same reduced form as a more classical utility function that exhibits loss aversion (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.

2.2. Identification. There are two sources of variation in $\boldsymbol{\pi g}_{f(t+1)}$ and $\boldsymbol{\pi l}_{f(t+1)}$: *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

Identifying variation.

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

if there are no variables in ε_{t_i} that track $\pi^e_{f(t+1)} - \pi^e_{ft}$, $\pi^e_{f(t+1)} - \pi^r_f$, $\pi^e_{ft} - \pi^r_f$, and stopping decisions for a given realization of ξ_{ft}.

The Crawford and Meng [2011] differenced specification accounts for several threats to 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_{ft}. We operationalize ξ_{ft} 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]

[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.

2.3. Estimation and inference. We estimate the model using ordinary least squares (OLS), which provides a linear probability model approximation to the specification underlying Equation 2. This linear approximation substantially reduces computational burden while producing coefficient estimates and marginal effects nearly identical to maximum likelihood probit estimation. The key advantage of OLS in our setting is computational feasibility: with over 70,000 observations and high-dimensional fixed effects (restaurant-date-service period combinations), probit estimation becomes prohibitively time-intensive.

For the reduced form coefficients (β_g and β_l), we report robust standard errors that account for arbitrary heteroskedasticity. For the loss aversion coefficient $\lambda = \beta_l/\beta_g$, we compute standard errors via bootstrap (999 replications) to account for two sources of uncertainty: sampling variation in the estimated coefficients and the additional uncertainty introduced by our first-stage LASSO predictions of expected profits $\widehat{\mathbb{E}[\pi_f|\mathcal{I}_t]}$. Each bootstrap iteration re-samples observations with replacement and re-estimates both the first-stage profit forecasts and the second-stage stopping model, preserving the estimation sequence.

2.4. 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.

2.5. Results. Figure 2 (top) plots our key sources of identifying variation over the course of a shift: $\boldsymbol{\pi g}_{f(t+1)d}$ (red squares) and $\boldsymbol{\pi l}_{f(t+1)d}$ (blue dots).[9] The figure suggests the firm expects the period-to-period losses to increase initially, decrease during the peak period, before increasing again later in the shift. An opposing pattern emerges for gains.

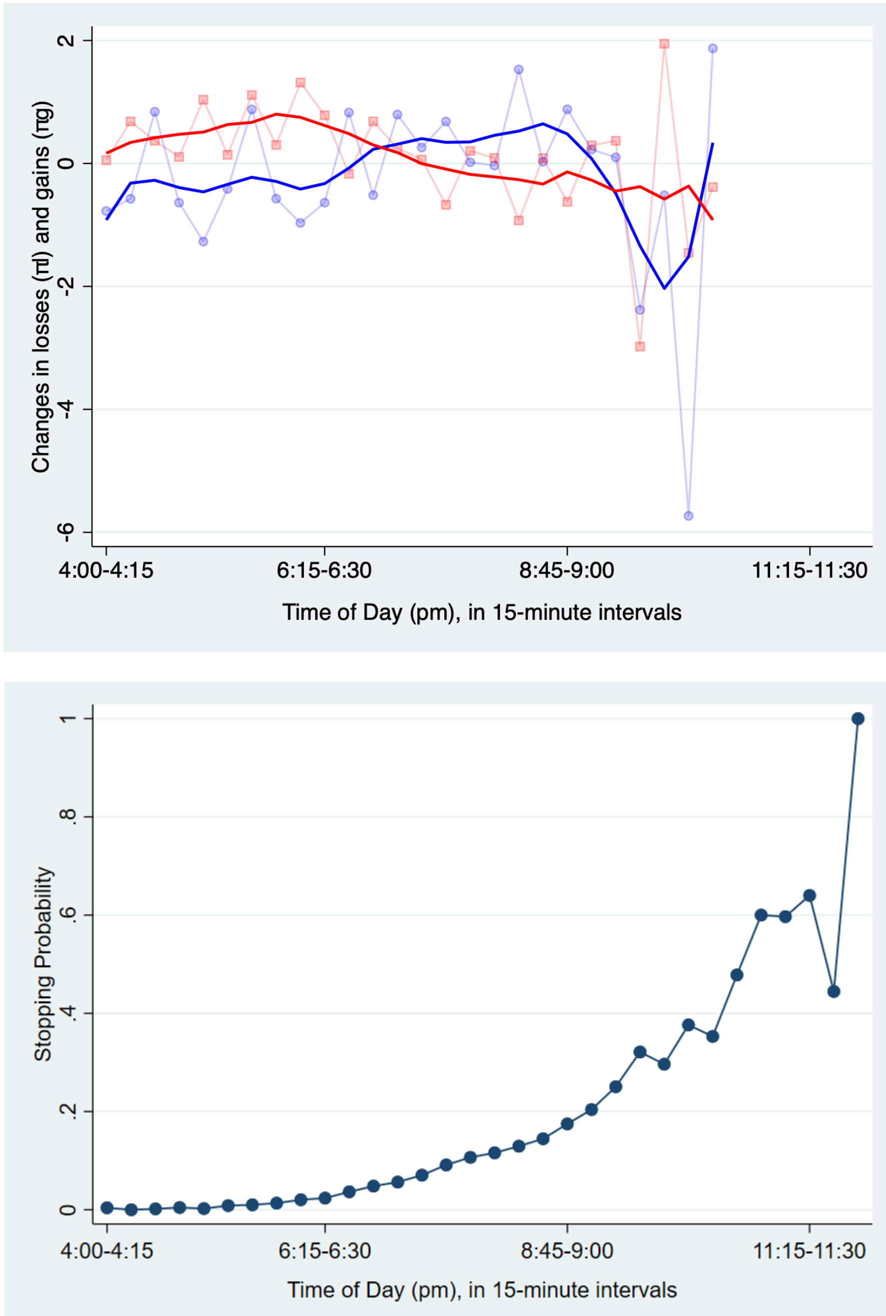
To interpret these patterns, recall that $\boldsymbol{\pi g}_{f(t+1)} = \boldsymbol{g}_{f(t+1)}\Delta\pi_{f(t+1)} - \boldsymbol{g}_{ft}\Delta\pi_{ft}$ captures *changes in gains*—that is, period-to-period changes in how far expected profit exceeds the reference point when the firm anticipates gains. Similarly, $\boldsymbol{\pi l}_{f(t+1)} = \boldsymbol{l}_{f(t+1)}\Delta\pi_{f(t+1)} - \boldsymbol{l}_{ft}\Delta\pi_{ft}$ captures *changes in losses*—period-to-period changes in how far expected profit falls short of the reference point when the firm anticipates losses.

The economic intuition for identification is as follows. Workers are stopped when the one-period-ahead change in value turns negative (equation 2). When gains are growing ($\boldsymbol{\pi g}_{f(t+1)} > 0$), the change in value becomes more positive, making managers *less* likely to stop workers—they want to continue riding the favorable performance. Similarly, when losses are shrinking ($\boldsymbol{\pi l}_{f(t+1)} > 0$, moving closer to the reference point from below), the change in value is less negative, so managers are *less* likely to stop workers as performance recovers toward target. However, when losses accelerate ($\boldsymbol{\pi l}_{f(t+1)} < 0$, falling further behind target),

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

[9]$\boldsymbol{\pi g}_{f(t+1)d}$ and $\boldsymbol{\pi l}_{f(t+1)d}$ are not shown at the end of the shift because we lack sufficient observations to forecast profits for that period.

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) 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). Faded markers show raw data averaged over workers in each 15-minute interval. Solid lines show locally weighted smoothed trends. These patterns provide 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 Horizontal axes reference the time of day in 15-minute intervals.

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

the change in value becomes more negative—and this effect is amplified when $\lambda > 1$—making managers *more* likely to stop workers to limit mounting losses.

Figure 2 (top) reveals three distinct phases that provide identification. Early in the shift (before roughly 7pm), *changes in gains dominate*—the red curve is positive as managers anticipate exceeding last week's performance by growing margins, while the blue curve fluctuates around zero because losses are not yet relevant. During the peak dinner period (roughly 7-9pm), the pattern reverses: *changes in losses dominate but are positive.* Managers now expect to fall short of the reference point, but losses are shrinking—the blue curve is positive, indicating the firm is catching up toward target (e.g., moving from €50 below target to €30 below target). The red curve drops to near zero as gains become irrelevant in the loss domain. Late in the shift (after 9pm), *changes in losses remain dominant but turn sharply negative.* Losses accelerate as dinner service winds down—the blue curve falls sharply, indicating the firm is falling further behind target (e.g., moving from €30 below to €80 below target).

The asymmetric response of stopping decisions across these three phases—gain-dominated periods, loss-dominated periods with improvement, and loss-dominated periods with deterioration—combined with the transitions between them, separately identifies how managers weight gains (β_g) versus losses (β_l). If managers are loss neutral ($\lambda = 1$), stopping decisions should respond symmetrically to equal-magnitude changes in gains and losses. Loss aversion ($\lambda > 1$) predicts amplified responses during the late-shift deterioration phase relative to the early-shift improvement phase.

Figure 2 (bottom) shows how stopping decisions evolve in response to these changing gain-loss patterns. Workers are almost never stopped before 6pm, when the firm anticipates gains and performance is improving (red curve positive in top panel). The stopping probability increases smoothly from 6pm until 10pm, accelerating during the late-shift period (after 9pm) when losses are increasing rapidly (blue curve sharply negative in top panel). The stopping probability continues to increase thereafter, with some volatility reflecting the closure of the dining room at 11pm, and equals 1 after service ends. The correspondence between the gain-loss patterns in the top panel and stopping behavior in the bottom panel provides the identifying variation: stopping intensifies precisely when losses accelerate in the late shift, consistent with loss-averse decision-making.

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. Robustness to nonlinearity in gains and losses are verified in Online Appendix Table A.1.3.

The estimate in Column 1 shows a loss coefficient of 4.17. This coefficient is statistically greater than 1 (1 = loss neutrality) at the 7 percent significance level. The reduced form results indicate that this loss coefficient arises from a large regression coefficient on losses relative to a small coefficient on gains. A potential concern is that the empirical gain distribution is centered at a gain where the utility function is relatively flat, while the empirical loss distribution is centered near zero where the utility function is steep. If so, the estimated loss coefficient might reflect differences in curvature rather than genuine loss aversion. To assess this possibility, we examined centrality measures of the empirical gain and loss distributions. The median gain is 60.32, while the median loss is –60.48, and the mean values show a similar pattern (71.48 vs. –74.10). These similarities indicate that the estimated loss coefficients are not driven by systematically different regions of the empirical gain and loss distributions.

Table 1: Loss coefficients for stopping decisions.

	Stop Worker (1=yes)		
	All	Slow days	Busy days
	(1)	(2)	(3)
Loss Coefficient			
$1 - \eta + \eta\lambda$ (β_l/β_g)	4.17*	9.49***	0.27
	[0.07]	[0.01]	[0.17]
Reduced Form Coefficients			
β_l	0.00018***	0.00030***	0.00004
	(0.00006)	(0.00009)	(0.00008)
β_g	0.00004	-0.00003	0.00014
	(0.00006)	(0.00009)	(0.00008)
Observations	88479	43232	45247
R^2	0.0647	0.0482	0.0758

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. Columns 1 and 2 test that the loss coefficient greater than 1. Column 3 tests less than 1. 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.

[6] Robust standard errors in round parentheses. Bootstrap p-values (from 999 bootstrap samples) in square parentheses. $***$, $**$ and $*$ denote statistical significance at the 1, 5 and 10 percent levels.

Column 2 shows a loss coefficient of 9.49 on slow days. It is statistically greater than loss neutrality at the 1 percent level. Column 3 shows a loss coefficient of 0.27 on busy days. It is less 1 but not in a statistical sense. 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.

3 Survey

3.1. 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.[10] 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.1.4). 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 (€200,000) to ensure salience for professional decision-

[10] 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 of loss aversion for economic aggregates such as market productivity.

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.

3.2. 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:

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 €200,000	**OR**	Loss of €200,000
Profit of €0	Profit of €200,000	**OR**	Loss of €100,000
Profit of €0	Profit of €200,000	**OR**	Loss of €50,000

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

CERTAIN OPTION	COIN FLIP OPTION		
Profit of €0	Profit of €200,000	OR	Loss of €...

For simplicity, 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 (€200,000) to ensure the scenarios were meaningful for business decision-makers. Recent evidence suggests loss aversion is robust to or slightly decreasing in stake size [Bleichrodt and L'Haridon, 2023], making our choice of large stakes unlikely to inflate our estimates. 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.

3.3. Results. Table 2 presents our key findings on owner preferences and business characteristics.[11] 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 em-

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

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.

ployees. 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%. These estimates let us calculate price elasticities at current prices, at prices that are 5% higher than the current price, and that are 10% higher. If restaurants operate as textbook monopolistic competitors, where product differentiation enables market power, then we expect firms to price on the inelastic part of their perceived demand curves.

Based on responses to a 5% price increase, we observe an average perceived price elasticity of demand of -0.98 at current prices. With this estimate we cannot rule out pricing on the unit elastic part of the perceived demand curve. The discrepancy with textbook frameworks suggests either that these frameworks inadequately capture pricing dynamics in this industry, or that owners' demand perceptions are systematically imprecise. The heterogeneity in responses clarifies the discrepancy: while 64% of owners perceive elasticities well below unity (with most reporting zero elasticity), the remainder perceive elastic demand at or well above unity. The majority's responses align with monopolistic competition predictions, but a substantial minority's perceptions contradict this framework.

This pattern becomes more pronounced as we examine higher price points. Demand is perceived to be more elastic above current prices (-1.81 and -1.94 at prices 5% and 10% above baseline). The proportion perceiving inelastic demand falls from 39% at 5% price increases to 22% at 10% increases.

These patterns suggest considerable heterogeneity in market sophistication, with some owners demonstrating intuitive understanding consistent with monopolistic competition while others appear to have less accurate demand perceptions.

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 ($p < 0.05$).[12] 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 that 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. Galor and Savitskiy [2018] provide an evolutionary framework suggesting loss aversion arises from selection pressures in environments where losses threaten survival. Survival probabilities may be higher for firms with loss averse owners through two channels: they may have a greater propensity for avoiding losses, or they may be more reluctant to exit failing businesses—akin to the disposition effect where investors refuse to sell losing stocks. Both mechanisms would lead to over-representation of loss-averse owners among experienced business owners in our cross-section, though they have different normative implications. Our cross-sectional design cannot definitively separate these mechanisms.[13]

3.4. Loss aversion or risk aversion? An important methodological question is whether our survey design sufficiently distinguishes between loss aversion and pure risk aversion.

[12]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 $\frac{1+\bar{\lambda}}{\bar{\lambda}}$, where $\bar{\lambda}$ is the sample men, to get 0.19. Multiply this by 0.083, which is equivalent to one additional year of experience (over the mean).

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

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				-0.04	-0.04
(0: Risk Averse; 10: fully prepared to take risks)				(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. $***$, $**$ and $*$ denote statistical significance at the 1, 5 and 10 percent levels.

Individuals could reject mixed gambles due to either: (i) loss aversion—the asymmetric weighting of losses versus gains, or (ii) risk aversion—concave utility over final wealth that makes risky prospects less attractive than their expected value.

Our survey controls for risk preferences through self-reported willingness to take risks (0-10 scale). Table 3 treats this as a continuous variable, while Online Appendix Table A.1.5 demonstrates robustness using a binary specification (equal to 1 if at or above the median of 7). The positive correlation between experience and our loss aversion measure persists across both specifications.

However, our elicitation design lacks the independent variation needed to cleanly separate risk aversion from loss aversion. As discussed earlier, such separation requires comparing gain-only gambles (isolating pure risk aversion) with mixed gambles, or systematically varying reference points. Our survey design, adapted from Abdellaoui et al. [2016] for practical field implementation, does not include these elements. Consequently, our measured coefficients could reflect pure loss aversion, moderate loss aversion combined with risk aversion, or, in principle, strong risk aversion alone—though the last interpretation seems implausible given coefficients substantially exceeding unity (mean $\lambda = 10.1$, median $\lambda = 1.6$).

Importantly, our central finding remains meaningful under any interpretation: whether the mechanism is pure asymmetric loss weighting or includes conventional risk aversion, the positive correlation with experience suggests that exposure to competitive pressures intensifies rather than moderates behavioral biases in business decision-making.

3.5. Robustness to extreme values and alternative specifications. An important concern is whether our finding that loss aversion increases with experience is driven by extreme values or by the functional form transformation $ln(1+\lambda)$. We examined the response patterns underlying extreme loss aversion estimates. The extreme values are primarily driven by very small certainty equivalents for losses ($X <$ €1,000), i.e. by owners who will only accept tiny guaranteed losses rather than face 50-50 gambles between a larger loss and breaking even.

Most responses appear internally consistent. However, one case ($\lambda = 200$) with a certainty equivalent for gains of €200,000—valuing a 50-50 gamble at twice its expected value—may reflect either extreme risk-seeking preferences or possible misunderstanding. Excluding this observation does not affect our results. The remaining extreme cases show plausible patterns consistent with owners operating in a high-stakes competitive environment.

To ensure our results are not artifacts of the $ln(1+\lambda)$ transformation or extreme values, Online Appendix Table A.1.6 examines alternative functional forms of the dependent variable. The positive correlation between experience and loss aversion remains statistically significant across most functional forms. The correlation is insignificant only for the binary indicator $\lambda > 1$ but becomes significant at thresholds of $\lambda \geq 1.5$, indicating our core finding is robust to alternative specifications.

4 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 4.2 that rises to 9.5 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.

Our analysis has two main limitations. First, as discussed in Section 3.4, our survey design cannot fully separate loss aversion from risk aversion, meaning our coefficients may reflect a combination of both. Second, we lack exogenous variation in loss exposure, so the positive correlation between experience and our measure could reflect learning, differential survival, or both. These limitations notwithstanding, our core finding—that behavioral biases are more pronounced among experienced decision-makers in a highly competitive industry—challenges the conventional wisdom that market forces eliminate such biases.

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.

Conflict of interest statement. On behalf of all authors, the corresponding author states that there is no conflict of interest.

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

Online Appendix

Julian Emami Namini and Sacha Kapoor

December 4, 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			
$1 - \eta + \eta\lambda\ (\beta_l/\beta_g)$	4.39*	7.92***	0.27
	[0.06]	[0.01]	[0.17]
Reduced Form Coefficients			
β_l	0.00018***	0.00030***	0.00004
	(0.00006)	(0.00009)	(0.00008)
β_g	0.00004	-0.00004	0.00014
	(0.00006)	(0.00009)	(0.00008)
Observations	88479	43232	45247
R^2	0.0659	0.0500	0.0771

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. Columns 1 and 2 test that the loss coefficient greater than 1. Column 3 tests less than 1. 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.

[6] Robust standard errors in round parentheses. Bootstrap p-values (from 999 bootstrap samples) in square parentheses. $***$, $**$ and $*$ denote statistical significance at the 1, 5 and 10 percent levels.

Table A.1.3: Loss coefficients for stopping decisions (with nonlinear gain/loss changes).

	Stop Worker (1=yes)		
	All	Slow days	Busy days
	(1)	(2)	(3)
Loss Coefficient			
$1-\eta+\eta\lambda$ (β_l/β_g)	4.03*	7.35***	0.31
	[0.07]	[0.01]	[0.19]
Observations	88479	43232	45247

Notes:

[1] This table reports loss coefficient estimates for profit per worker conditional on quadratics in gain/loss changes: $(\boldsymbol{\pi g}_{f(t+1)})^2$ and $(\boldsymbol{\pi l}_{f(t+1)})^2$.

[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 are with reference to loss neutrality. Columns 1 and 2 test that the loss coefficient greater than 1. Column 3 tests less than 1.

[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.

[6] Robust standard errors in round parentheses. Bootstrap p-values (from 999 bootstrap samples) in square parentheses. $***$, $**$ and $*$ denote statistical significance at the 1, 5 and 10 percent levels.

Table A.1.4: Representativeness of owner sample.

Variable	Not Sampled	Sampled	Difference
	(1)	(2)	(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. $***$, $**$ and $*$ denote statistical significance at the 1, 5 and 10 percent levels.

Table A.1.5: Loss aversion and experience - robustness to binary risk measure.

	Loss Aversion, $ln(1+\lambda)$				
	(1)	(2)	(3)	(4)	(5)
Experience (months, in logs)	0.17***	0.17***	0.17**	0.19***	0.17***
	(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	0.21	0.22
		(0.29)	(0.29)	(0.29)	(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	-0.02
		(0.11)	(0.12)	(0.12)	(0.12)
Number of Employees (in logs)			0.09	0.08	0.12
			(0.14)	(0.14)	(0.16)
Willingness to Take Risks (=1 if reported 7 or above on 0-10 scale)				-0.14 (0.20)	-0.14 (0.20)
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 owner loss aversion using a binary rather than a 0-10 risk measure. Our binary equals 1 if the 0-10 measure is 7 or above.

[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. $***$, $**$ and $*$ denote statistical significance at the 1, 5 and 10 percent levels.

Table A.1.6: Robustness of Experience-Loss Aversion Correlation to Alternative Functional Forms.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	λ	$\mathbb{1}(\lambda > 1)$	$\mathbb{1}(\lambda > 2)$	$\mathbb{1}(\lambda > 3)$	$\mathbb{1}(\lambda > 5)$	$ln(1+\lambda)$	$ln(1+\lambda)$
Experience, in logs	3.930**	-0.001	0.105***	0.096***	0.064***	0.145***	0.100**
	(1.768)	(0.030)	(0.027)	(0.026)	(0.023)	(0.051)	(0.040)
Winsorization	None	None	None	None	None	Winsorized 95th	Winsorized 90th
firms	107	107	107	107	107	107	107
R^2	0.025	0.000	0.100	0.094	0.059	0.051	0.045

Notes:

[1] This table examines robustness of the experience-loss aversion correlation to alternative functional forms of the dependent variable.

[2] Column (1) uses untransformed λ; columns (2)-(5) use binary indicators $\mathbb{1}()$ for various loss aversion thresholds; columns (6)-(7) use $ln(1+\lambda)$ after winsorizing at the 95th and 90th percentiles.

[3] All regressions include log experience alone as the independent variable.

[4] Robust standard errors in parentheses. $***$, $**$ and $*$ denote statistical significance at the 1, 5 and 10 percent levels.

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 €200,000	**OR**	a loss of €200,000
a profit of €0	a profit of €200,000	**OR**	a loss of €100,000
a profit of €0	a profit of €200,000	**OR**	a loss of €50,000

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 €200,000	**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 €175,000	a profit of €200,000	**OR**	a profit of €0
a profit of €150,000	a profit of €200,000	**OR**	a profit of €0
a profit of €125,000	a profit of €200,000	**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 €200,000	**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