Are firms loss averse? Are markets? Theory and evidence from a competitive industry

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Abstract

Behavioral theories of the firm have long recognized the importance of losses for firms. But how reasonable is then the assumption of equal weights on gains and losses in the preferences of management, the objective of the firm, and ultimately the market? We put forth three distinct pieces of evidence supporting the argument that the objective of the small firm reflects loss aversion of prospect theory rather than VNM preferences of expected utility theory, and that these preferences are reflected in market level outcomes. We first examine thousands of high frequency labor demand decisions from two large-scale restaurants, and a stopping model from the literature on loss aversion and labor supply. We find a mean loss aversion coefficient of $\lambda = 4.3$. Next we present evidence of loss aversion (mean $\lambda = 10.1$, median $\lambda = 1.6$) using a small-scale survey of restaurant owners. Loss averse firms are 18-21 percentage points *less* likely to exit after five years. Finally, we use market level data from all US counties over several years to show that entry and participation decisions weigh losses 8.9 times more heavily than gains. We develop a model with monopolistic competition and loss averse firms that squares with our evidence and lets us study the implications for latent productivity, profits, and sharing of profits. Our results suggest employment subsidies targeting small businesses enable the survival of loss averse firms in general equilibrium.

JEL: D21, D22, D43, D58, E71, L21, L83

Keywords: Behavioral firms, loss aversion, prospect theory, small firms, employment subsidies, aggregation

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1 Introduction

Losses have always played a central role in the behavioral theory of the firm. In evolutionary economics firms can survive without maximizing profits, by charging the lowest prices while covering costs, but cannot survive with losses [Alchian, 1950]. The evolutionary paradigm has been used to explain the survival of large businesses that separate claims on residual cash flows from control over decisions that affect cash flow risk [Fama and Jensen, 1983], and helped spawn an enormous literature relating to the separation of ownership from control. Under the neoclassical paradigm, competitive firms operate on the margin between gains and losses, where potential entrants stay out because of the prospect of loss, and where adverse demand or supply shocks generate losses that can cause incumbents to exit [Marshall, 1920]. The neoclassical paradigm has been foundational for several academic literatures, including a macroeconomic literature on aggregate implications of firm behavior, and an industrial organization literature that relies on structural models for measurement.

The importance of losses for firm success in these theories begs questions about the credibility of an objective - profit - that weighs gains and losses symmetrically, especially for small firms that tightly integrate ownership with control, often within a single individual. If owners are active in business decisions and guided by their preferences, then the objective of the firm should reflect the preferences of the owner. But if losses are so important, these preferences may weigh losses more heavily than equivalent gains and, by implication, so too may the objective of the firm. In these regards the importance of losses begs several more pressing questions: *which* preferences are reflected in this objective, von Neumann-Morgenstern (vnm) preferences of expected utility theory, or loss averse preferences of prospect theory (pt) [Kahneman and Tversky, 1979]? What are the implications, if any, for aggregates such as market structure, productivity, profits, and sharing of profits?

In this study we propose that the objective of the small firm is grounded in the loss averse preferences of prospect theory, that these preferences survive aggregation, and investigate the implications for latent market outcomes. Our venue is the restaurant industry. The industry is useful for several reasons. First, preferences are considered a significant determinant of the ownership decision. Ownership reflects non-pecuniary advantages such as menu development and autonomy that can persuade owners to accept a lower wage relative to their outside option.[1] Second, active participation by owners or management more generally

[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

is commonplace. Active participation implies a direct effect of individual preferences on firm level decisions. Third, local market structures are incubators for utility maximization. These markets are rich in producers of horizontally and vertically differentiated products. Product differentiation can generate market power, which enables departures from profit maximization. Fourth, the industry can give rise to loss aversion or influence firm selection. Characteristically high exit probabilities raise fear relating to failure, a fear that has been conceptualized as a form of loss aversion [Morgan and Sisak, 2016]. The prospect of loss can deter entry and promote exit.

Our study has two main parts. In the first, we put forth several empirical facts supporting the presence of loss aversion in the firm's objective and market outcomes. We use administrative data from a Canadian retail chain to look for loss aversion in day-to-day decisions. We also survey firms in the Netherlands to measure loss aversion directly. Finally, we use county level aggregates from the United States to look for the manifestation of loss aversion in market equilibrium. We show that the three datasets imply considerable loss aversion despite yielding measurements at different levels of aggregation and despite being generated in different countries.[2]

In the second part of our study we develop a general equilibrium model with loss averse firms. We use this model to study the implications for latent market aggregates such as productivity, profits, and sharing of profits.

Our first piece of evidence is based on data from a couple of 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

motives relating to flexibility or control. Only 34 percent cite income generation as the primary motive.

[2] We use datasets at three levels of aggregation because we want to learn whether loss aversion is endemic to the industry. We use datasets from three countries because they were the best datasets we could obtain for the industry at these three levels of aggregation. From this last perspective, any variation in loss aversion estimates across contexts may reflect technological or institutional differences across countries.

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 estimate the effect of loss aversion on the probability of firm exit after five years, and subsequent to sizeable COVID-19 employment and fixed cost subsidies for small businesses in the Netherlands. Our basic hypothesis is that if the desire to survive generates loss aversion in profits, and if these subsidies facilitated survival, then the firm of a loss averse owner or manager should be *less* likely to exit. This is what we observe. Firms of loss averse owners and managers are 18-21 percentage points less likely to exit after five years, with a mean exit rate of 0.28. Our evidence from the US is consistent with this argument, but is made using data that covers a much larger scale.

Our third piece of evidence is based on county level data from the US over several years. We treat each county as a market. We use our general equilibrium model to obtain an estimating equation relating the number of firms to market size, entry costs, and payroll gains and losses. Gains and losses are coded as year-over-year decreases or increases in average payroll per establishment. Gain-loss variation is generated by variation in employment, wages, and developments in the payroll sector (e.g., outsourcing). Our econometric specification allows for permanent county-level shocks and time-varying state-level shocks. Identification then assumes no time-varying county-level shocks (except for market size and entry costs) correlating with payroll gains, losses, and number of firms. Ultimately, we find an implied loss aversion coefficient of 8.9 which is generated primarily by small firms.

We summarize our various datasets, estimates, and implications in Table 1. Most of our estimates are large relative to the distribution of loss aversion estimates in the literature [Brown, Imai, Vieider, and Camerer, 2024]. In their meta-analysis, Brown et al. [2024] show loss aversion estimates range from approximately 0 to 6. However, none of the 185 studies in their meta-analysis considers business owners. Large loss aversion coefficients are consistent with the basic motivation for our study, that for business owners losses are top of mind.

Table 1: Summary of datasets, estimates, and implications

Dataset	**Loss Aversion Estimates**	**Key Correlates**	**Implications/Insights**
Canadian Retail Chain	$\lambda = 4.3$ (average), $\lambda = 7.4$ (slow days), no loss aversion on busy days	Stopping times, end-of-shift profits relative to weekly reference points	Loss aversion affects real-time labor demand decisions. Loss aversion diminishes with production scale.
Dutch Firms (Survey)	$\lambda = 10.1$ (mean), $\lambda = 1.6$ (median); 74% have $\lambda > 1$, 30% have $\lambda > 3$	Exit rates post-COVID-19 subsidies; survival probability linked to loss aversion; experience.	Loss averse owners less likely to exit; highlights the survival motivation in competitive markets.
US County Data	$\lambda = 8.9$ (driven by small firms)	Payroll gains/losses (year-over-year), employment and wages, entry costs, market size	Loss aversion is pervasive in small firms and influences market entry/exit dynamics.

Our general equilibrium model builds on the closed economy monopolistic competition model of Melitz [2003]. The main new feature of our model is the introduction of Kőszegi and Rabin [2006] loss averse firms. The entrepreneur is "biased" by loss aversion but is sophisticated in anticipating it before making the entry decision. Entrepreneurs enter the market, draw productivity parameter φ and fixed cost parameter F, and decide whether or not to become active. This decision depends on economic profit for the average incumbent firm, the weights assigned to profit and gain-loss utility, as well as the weights assigned to fixed cost gains (F smaller than reference level F^r) or losses ($F > F^r$). We assume firms are potentially loss averse in fixed cost to match our market level data. The decision to become active then pins down productivity thresholds ϕ^*_G and ϕ^*_L depending on whether the entrepreneur drew a F in the *g*ain or *l*oss domain. Folding the model back to the first stage, the entrepreneur enters if it is profitable relative to sunk market entry cost F^e.

Focusing on the stationary equilibrium of our model, we obtain equations characterizing general equilibrium in every US market in each of our 20 years. In a simplified variant of our model, its equations can be used to generate three latent economic constructs for each market m and year t with data on F^e_{mt}, F_{mt}, and F^r_{mt}:

$$ln(\widetilde{\phi}_G(F_{mt})) = -c(\lambda) - lnF^e_{mt} + ln\Big(F_{mt} + (F_{mt} - F^r_{mt})\mathbb{1}\,(F_{mt} < F^r_{mt})\Big) \tag{1}$$

$$ln(\widetilde{\phi}_L(F_{mt})) = -c(\lambda) - lnF^e_{mt} + ln\Big(F_{mt} + \lambda(F_{mt} - F^r_{mt})\mathbb{1}\,(F_{mt} > F^r_{mt})\Big) \tag{2}$$

$$\chi_{mt} = F^e_{mt} + \mathbb{E}\Big[(F_{mt} - F^r_{mt})\mathbb{P}_G(F_{mt} < F^r_{mt})\Big] + \lambda\mathbb{E}\Big[(F_{mt} - F^r_{mt})\mathbb{P}_L(F_{mt} > F^r_{mt})\Big] \tag{3}$$

where $\widetilde{\phi}_G(F_{mt})$ and $\widetilde{\phi}_L(F_{mt})$ are average productivity levels in the gain and loss domains, and χ_{mt} is implied profit for the average entrepreneur. $c(\lambda)$ is a constant, $\mathbb{1}\,(F_{mt} < F^r_{mt})$ is an indicator function, $\mathbb{P}_G(F_{mt} < F^r_{mt})$ and $\mathbb{P}_G(F_{mt} > F^r_{mt})$ are conditional probabilities of becoming active after having observed a fixed cost gain or loss, and the expectation $\mathbb{E}$ is computed using the marginal distribution for F. We construct the equations above using business applications, payroll data, and lagged payroll data to proxy for F^e_{mt}, F_{mt}, F^r_{mt}.

We use the first two equations to measure unconditional average productivity for vNM and PT firms. We then quantify the productivity bias relative to the vNM benchmark. We find the bias exceeds the vNM benchmark by more than 30 percent. The productivity bias is countercyclical.

We use the third equation to study the differences in profit and profit sharing between vNM and PT firms. The top panel of Figure 1 plots average total county-level firm profit by year. The bottom panel does the same but for the total payroll to total profit ratio. Both figures include county GDP per capita detrended as a point of comparison.

The top panel shows PT firms earn more profits in general. The gap with vNM firms increases over time and sharply during the COVID-19 period. The bottom panel shows vNM firm employees earn a larger and increasing share of profits over time. PT firm employees earn a flat share for most of our sample, and a smaller share during COVID-19. The figures align with two facts about the COVID-19 period: (*i*) the payroll protection program paid employers 2.5 times their payroll costs; (*ii*) the number of employees per firm decreased sharply from 18 to 15.5 (see Appendix Figure A.2.1). Our evidence and these facts support the narrative that employment subsidies for small businesses increase their profitability and profit share, and that these subsidies facilitate the survival of loss averse firms.

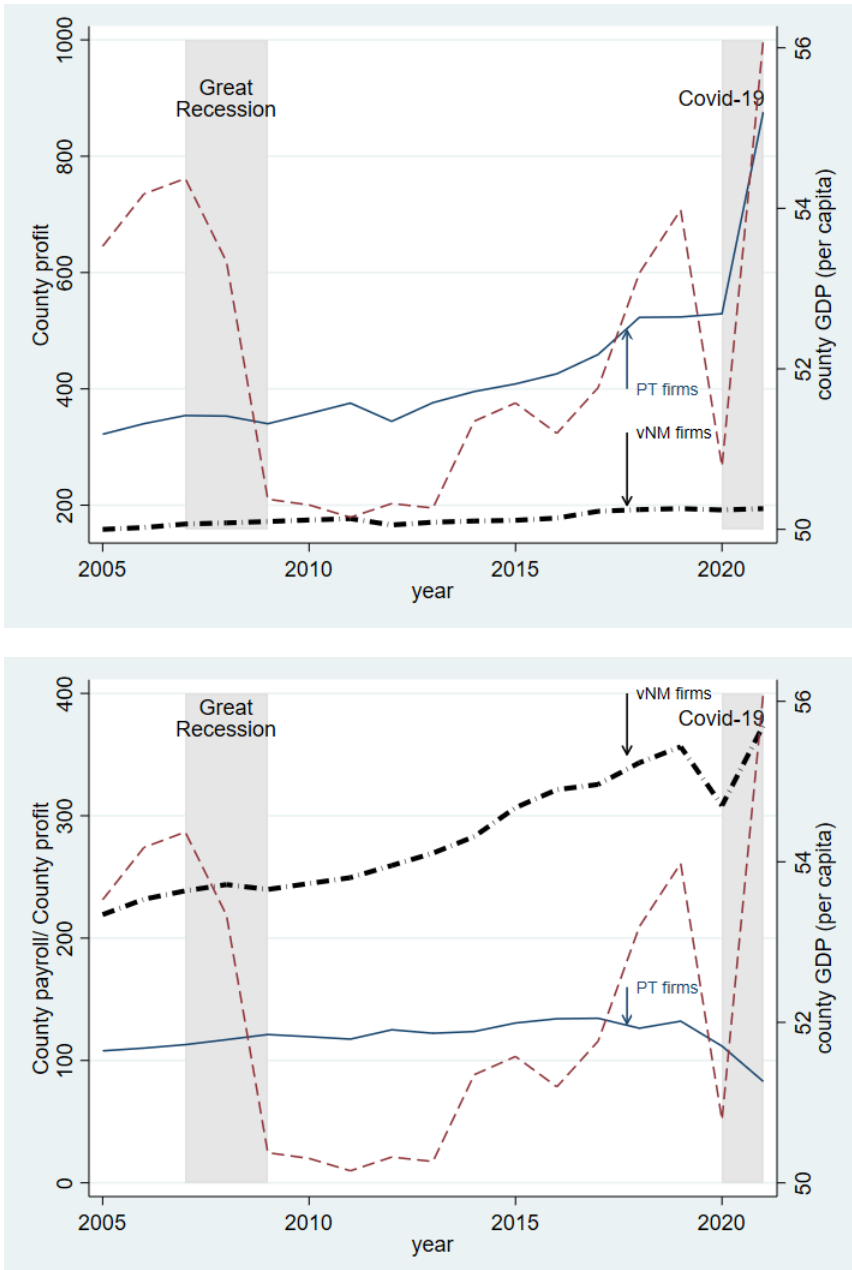
Our study connects the literature on loss aversion in the field with a literature that scrutinizes the profit maximization assumption.[3] The former has documented loss aversion among taxi drivers [Camerer et al., 1997, Crawford and Meng, 2011, Farber, 2005, 2008, 2015, Thakral and Tô, 2021], marathon runners [Allen et al., 2017, Markle et al., 2018], financial professionals [Abdellaoui, Bleichrodt, and Kammoun, 2013, Barberis, Huang, and Santos, 2001, Barberis, Mukherjee, and Wang, 2016, Barberis, Jin, and Wang, 2021], job search [DellaVigna et al., 2017], tax filers [Rees-Jones, 2018], among others [see Camerer, 2001, and O'Donoghue and Sprenger, 2018, for a more comprehensive list]. The present study documents loss aversion among key decision makers in small businesses. The findings support the idea that experts are loss averse [Genesove and Mayer, 2001, Pope and Schweitzer, 2011]. It advances the literature by exploring implications for the behavior and objective function of the firm.

Empirical studies that scrutinize profit maximization typically document departures from profit maximization [Almunia et al., 2022, Byrne, 2015, Hortaçsu and Puller, 2008, Levitt, 2006, Massey and Thaler, 2013, Sweeting, 2012] by comparing marginal benefits and costs,[4] with some detecting more significant departures in small firms [Byrne, 2015, Hortaçsu and Puller, 2008]. Recent work has identified specific anomalies in firm behavior, relating to the adoption of management techniques [Bloom et al., 2013], technology [Atkin et al., 2017], or uniform pricing [Cho and Rust, 2010, Dellavigna and Gentzkow, 2019, Kapoor, 2020]. The present study moves beyond documenting departures from profit maximization or behavioral anomalies towards a descriptive representation of the objective function of the firm. From this perspective, our study fits well with a small literature that explores the implications

[3] 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.

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

Figure 1: County profit and payroll under vNM and PT decision makers.



Notes:

1 County profit is average profit (as in Equation 3) multiplied by the number of firms.

2 Average profit is computed under two scenarios. First, firms are vNM decisions makers who maximize expected utility. Second, firms are PT decision makers who maximize expected utility and gain-loss utility.

3 Dashed red line is county GDP per capita. GDP is the sum of mean GDP and detrended GDP.

of well defined behavioral biases for firm behavior, in particular Goldfarb and Yang [2009] and Goldfarb and Xiao [2011], which structurally estimate strategic thinking by managers and document positive correlations with subsequent survival and performance. It further complements recent work investigating whether memory, impatience, and trust are barriers to the adoption of profitable opportunities among small firms [Gertler et al., 2023].

Our study complements the study by Oprea [2014], who uses a near-continuous time lab experiment to detect survival bias especially when profit maximization and survival conflict. His motivating example for a context where survival and profit maximization conflict is a firm that forgoes allocating profit towards current and future consumption. The firm hoards cash preemptively to bypass the prospect of bankruptcy. He argues the bias reflects a deeply ingrained heuristic in humans towards survival and thus leads subjects to conflate survival with optimization. The basic justification for our study is the idea that this deeply ingrained heuristic generates a bias against losses. Furthermore, we study a context where profit maximization and survival are not conflicting. Against this background, our results suggest a survival bias exists even when profit maximization and survival are not conflicting.

Our study advances a longstanding debate on the relevance of behavioral biases for aggregate outcomes. The status quo argument has long been that these biases are irrelevant because market forces drive biased agents from markets. While the rise of behavioral economics has made the issue first order, and while the debate is not new [e.g., Russell and Thaler, 1985], empirical evidence on this issue is almost nonexistent. A recent exception is Enke, Graeber, and Oprea [2023], who use a series of lab experiments to investigate the role of confidence, and more specifically the correlation between confidence and performance, in aggregate outcomes at the level of the organization or market. Our study uses a series of datasets from the field. It investigates the role of a different type of bias - loss aversion - in aggregate outcomes at the level of the firm or market.

2 Conceptual Background

2.1. Profit maximization. Our null hypothesis is a neoclassical objective function for the firm:

$$\pi(y) = p(y)y - c(y) - F,$$

where $\pi(y)$ is profit, $p(y)$ is the maximum price consumers are willing to pay for y units of output. $p(y)$ is decreasing in y by the law of demand. $c(y)$ is total variable cost, and it is increasing in y. F is a fixed cost. The formulation nests economic profit under perfect competition ($p(y) = p$), monopolistic competition, and monopoly. It also nests economic profit in the very short run (e.g., at the daily level) where prices are fixed $p(y) = p$, even if the market is monopolistic or monopolistically competitive. Uncertainty can be introduced into this objective via $p(y)$, $c(y)$, or additively via F.

For restaurants the primary costs are food, direct and opportunity costs of equipment and commercial space, and labor. Food is a variable cost. Costs of equipment and commercial space are fixed in the short and variable in the long run. In the very short run, at the daily level, labor costs are fixed.[5] In the long run labor costs are variable. In the very short run uncertainty in $p(y)$ and $c(y)$ can be due to the number of consumer arrivals or bottlenecks in production. In the long run it is generated by variation in tastes or fixed production costs.

Profit maximization has been justified by the fact that business owners are themselves consumers [Mas-Colell, Whinston, and Green, 1995]. Since profit increases income, and utility is increasing in consumption, the owners will try to maximize profit themselves or instruct managers to do so. Early debates of the profit maximization assumption centered on its plausibility under uncertainty, and specifically on the notion that humans possess the foresight and computational capacity to maximize profit in every state of the world [Alchian, 1950, Cyert and March, 1963, Friedman, 1953, Hall and Hitch, 1939, Machlup, 1946, March and Simon, 1958, Simon, 1952, 1955, 1979, Simon and Barnard, 1947]. The debates led to the now workhorse assumption of a risk neutral firm that maximizes expected profit. From this perspective, we can interpret π as the expected profit function, and departures from expected profit maximization to reflect violations of the axioms of choice under uncertainty among owners and employees at the firm.

2.2. Loss aversion. Our alternative hypothesis to profit maximization is the objective of loss aversion:

$$V = (1 - \eta)\pi + \eta v(\pi|\pi^r) \tag{4}$$

where $1 - \eta$ is the utility weight assigned to profit, η is the gain-loss utility weight [Kőszegi and Rabin, 2006], $v(\pi|\pi^r)$ is a reference dependent utility function, and π^r the reference profit. We assume $0 \leq \eta < 1$.

[5] Online Appendix Figure A.2.2, bottom panel, confirms this with historical data from the restaurants we study.

The reference profit is the benchmark by which outcomes are coded as gains or losses, and it can be based on the status quo or on expectations [Kahneman and Tversky, 1979]. In the latter case the reference profit can refer to a point or distribution [Kőszegi and Rabin, 2006]. A natural reference profit over the longer run is $\pi^r = 0$, which aligns with the zero profit condition in perfectly or monopolistically competitive markets with free entry. A firm which fails to break even cannot pay all factors of production (labor, lenders, suppliers). Unpaid factors will pressure the firm to pay, moreso when the outstanding debts are substantial. The added pressure steepens the utility slope on the side of losses directly and indirectly via any incidental mental or physical strain on owners and employees. Thus, the steeper slope can reflect a heuristic towards survival. The existence of a compensatory analog on the side of gains is not obvious.

Assume v is differentiable at π^r, with derivatives $v'_\uparrow(\pi^r|\pi^r)$ as π approaches π^r from below, and $v'_\downarrow(\pi^r|\pi^r)$ as π approaches π^r from above. Following Kobberling and Wakker [2005], the loss aversion coefficient is defined as:

$$\frac{v'_\uparrow(\pi^r|\pi^r)}{v'_\downarrow(\pi^r|\pi^r)}. \tag{5}$$

Firm behavior is classified as loss averse if $\frac{v'_\uparrow(\pi^r|\pi^r)}{v'_\downarrow(\pi^r|\pi^r)} > 1$, loss neutral if it equals 1, and gain seeking if it is less than 1. η and $\frac{v'_\uparrow(\pi^r|\pi^r)}{v'_\downarrow(\pi^r|\pi^r)}$ capture the extent to which firm decisions reflect the loss aversion of primary decision makers. Equation 5 nest a familiar representation:

$$v(\pi|\pi^r) = \begin{cases} \pi - \pi^r, & \text{if } \pi \geq \pi^r \\ \lambda(\pi - \pi^r), & \text{if } \pi < \pi^r, \end{cases} \tag{6}$$

where $\lambda > 1$ denotes loss aversion, $\lambda = 1$ loss neutrality, and $\lambda < 1$ gain seeking.

2.3. Economic versus accounting profit. The theoretical part of our analysis assumes decisions are guided by economic profit π. In practice, decisions may be guided by accounting profit. To understand the implications of our assumption, consider the identity $\pi = \pi_{ac} + oc$, where π_{ac} is accounting profit, and oc opportunity cost. If decision makers are guided by accounting profit exclusively, then their utility function is

$$V_{ac} = (1 - \eta)\pi_{ac} + \eta v(\pi_{ac}|\pi^r_{ac}).$$

If they are guided by economic profit, their utility function becomes

$$V_\pi = V_{ac} + (1-\eta)oc + \eta v(oc|oc^r) = V_{ac} + V_{oc},$$

where a separate gain-loss utility for opportunity cost, $v(oc|oc^r)$, exists if the decision maker has a separate reference point for their opportunity cost, i.e. $\pi^r = \pi^r_{ac} + oc^r$.

The term for V_π shows accounting profit and opportunity cost are additively separable, which follows from the definition of profit (revenue minus cost) and the functional form for loss aversion in equation 6. The additive separability implies that the "economic" decision maker can maximize V_π by maximizing V_{ac} and minimizing V_{oc} separately. Thus, in our theoretical model in section 6 we normalize $oc = 0$ without affecting our comparative statics with respect to η and λ.

3 Data

Our evidence draws on three sources: (*i*) high frequency administrative data on labor demand decisions from two large-scale restaurants; (*ii*) small-scale survey data from personal interviews with owners or (residual claimant) managers; (*iii*) market level data from US counties over many years. We describe each dataset in turn.

3.1. High frequency administrative data. We use internal transactions data from two large full service restaurants to look for evidence of loss aversion in a frequent labor demand decision, namely when to send waiters home.

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.[6]

Each shift is partitioned into 15-minutes intervals. The 15-minutes marker is important

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

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.

3.2. Small-scale survey data. We first scraped the website `iens.nl`, which allows customers to evaluate restaurants on the basis of price, food quality, service, and decor. The website provided us with a large list of restaurants and addresses, mostly in the Dutch cities of Rotterdam and Utrecht including addresses of restaurants with no ratings information. Together with our research assistants, we then phoned restaurants to schedule in-person interviews or visited the restaurants for interviews on site.

Overall, we interviewed the owners of 107 restaurants during the summer of 2016. The restaurants make up 15 percent of the population covered by `iens.nl`, and basically all restaurants in the targeted cities. These restaurants employ 1,870 people.

We explore the representativeness of the sample in Online Appendix Table A.2.1. We compare the subset of restaurants with ratings in our sample with non-sampled restaurants on `iens.nl`. We show that sampled and non-sampled ones are similar in terms of average price food, service, and decor ratings. It is worth keeping in mind that the sample is selected on the basis of the willingness and ability of owners to participate in the survey.

The measurement procedure follows the method of Abdellaoui et al. [2016], which allows us to measure loss aversion and the curvature of utility together. It facilitates measures of concavity in the gain domain and convexity in the loss domain, as prospect theory predicts. Loss aversion and curvature were not measured together because in pilot interviews it increased interview times substantially. We instead asked owners about their propensity to take on risk in a separate question. We describe the method in detail in the next section.

We tracked down the firms of surveyed owners in October 2021, more than 5 years after the original survey. We looked for evidence of closures using various sources including Google, Facebook, local newspapers, and the firms' websites. Some firms announced their closures on Facebook. For others Google indicates if the firm has been closed permanently. Local newspapers reported closures of several long-standing firms, often blaming the government for their demise during COVID-19. For survivors, we looked for recent posts on Facebook, opening hours information on Google, as well as whether reservations were still possible.

3.3. Market level data. Our primary source is County Business Pattern (CBP) data for 1998-2019. The data includes the total number of establishments, employees, and total annual payroll (in thousands of US dollars) per county across the US. An establishment is defined by a physical location. The number of employees is measured annually in March. Annual payroll covers all forms of compensation, including wages, salaries, bonuses, commissions, dismissal pay, vacation pay, sick pay, paid employee contributions to pensions. Most compensation costs are fixed from the employer's perspective, particularly the costs of front line restaurant employees (kitchen workers, servers), whose compensation depends on hourly wages and in many cases tips. The CBP data is merged with a housing price index constructed by the Federal Housing Finance Agency (FHSA) and county population estimates by the US Census Bureau.

Our sample is restricted to 1998-2019 because the Census Bureau changed the industry classification in 1998 from the Standard Industry Classification (SIC) system to the North American Industry Classification System (NAICS), and because there is no accepted conversion from SIC to NAICS codes. Our primary estimation sample is restricted to NAICS codes 7221, 7222, and 7223 for 1998-2011 and NAICS code 7225 for 2012-2019. These codes cover "Full-Service Restaurants", "Limited-Service Restaurants", "Cafeterias, Grill Buffets, and Buffets", "Snack and Nonalcoholic Beverage Bars", and "Special Food Services".

Our market analysis also draws on Business Dynamics Statistics (BDS) from the US Census Bureau, as that dataset distinguishes between entry and exit rates directly. We estimate effects for the broader 2-digit NAICS code, which includes accommodation as well as food service (code=72), because entry and exit rates per county are only reported at the 2-digit level.

4 Measurement of loss aversion coefficients

4.1. Loss aversion in labor demand (high frequency admin data). 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 consumption 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.

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:

$$V_{iftd} = (1-\eta)\pi^e_{ftd} + \eta v\big(\pi^e_{ftd}|\pi^r_{fd}\big), \tag{7}$$

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 (***g***ain) or smaller (***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

$$(1-\eta)\Big(\pi^e_{f(t+1)d} - \pi^e_{ftd}\Big) + \eta\Big(\boldsymbol{\pi g}_{f(t+1)d} + \lambda\boldsymbol{\pi l}_{f(t+1)d}\Big) + \xi_{ftd} + \varepsilon_{iftd} < 0 \tag{8}$$

is equivalent to the event $\{\textsc{stop}_{iftd} = 1\}$.

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.

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, 5:45-6:00 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.[7] 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.

[7]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.

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 $(1-\eta+\eta\lambda)$.[8] 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 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

[8] 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.

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.[9]

4.2. Direct measure of loss aversion (small-scale survey data). The measurement procedure follows Abdellaoui et al. [2016]. Let $v(\pi|\pi^r) = u(\pi - \pi^r)$, $\pi^r = 0$, and $u(0) = 0$. The procedure has several steps:

1. Pick a gain g.

2. Solicit the loss l that would make the subject indifferent between $u(0) = 0$ and a mixed prospect paying g with probability p or l with probability $1-p$ ($(g, p; l, 1-p)$ for short), *i.e* which satisfies:

$$w^+(p)u(g) + w^-(1-p)u(l) = 0, \tag{9}$$

   where $w^+(p)$ and $w^-(1-p)$ are strictly increasing probability weighting functions equal to 0 at a probability of 0 and to 1 at a probability of 1.

3. Solicit the certainty equivalent ce_g for the gain prospect $(g, p; 0, 1-p)$:

$$w^+(p)u(g) = u(ce_g). \tag{10}$$

4. Solicit the certainty equivalent ce_l for the loss prospect $(0, p; l, 1-p)$:

$$w^-(1-p)u(l) = u(ce_l). \tag{11}$$

In each case the subject works through several examples to help identify their indifference point. Equations 9-11 imply

$$u(ce_g) = -u(ce_l). \tag{12}$$

[9] 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.

This is relevant because the Kobberling and Wakker [2005] definition of loss aversion in Equation 5 can be operationalized via

$$\frac{u(ce_l)/ce_l}{u(ce_g)/ce_g} = \frac{ce_g}{ce_l}, \tag{13}$$

where the equality follows from Equation 12. Owners are classified as loss averse if $\frac{ce_g}{ce_l} > 1$.

To make the problem less abstract, we frame the decision as a choice between businesses. For example, to solicit the loss l from step 2, we asked respondents: "Which business would you prefer to own? One where:..."

...you are **GUARANTEED**	...a **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.

We also asked: "What loss would just make you willing to own the second business?"

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

We made the stakes sufficiently high to make the amounts meaningful for business persons. The remaining questions used in the procedure can be found in Online Appendix A.1.

We did not distinguish between accounting and economic profit in the survey. We did not expect owners and managers to be familiar with this distinction. Further to this point, our measure of loss aversion is not necessarily invalidated by different interpretations of profit (see subsection 2.3). Moreover, our survey data lets us investigate the role of this distinction empirically. Our sample consists of a relatively even split between owners and managers. Economic profit is more relevant for owners. If the difference in interpretation tracks the owner-manager distinction, then loss aversion should differ across these two groups. We observe no such difference.

To facilitate understanding and expediency, the decision problem was explained as either a coin flip or 50-50 chance ($p = 0.5$). We are therefore measuring loss aversion in decision under risk, where objective probabilities exist and are known. We do not measure loss aversion in decision under ambiguity, where objective probabilities do not exist or are unknown, as is done in Abdellaoui et al. [2016]. Fortunately, the evidence in Abdellaoui et al. [2016] implies measurements under risk and ambiguity yield similar loss aversion coefficient on in equilibrium (market data).

4.3. Loss aversion in equilibrium (market-level data). We estimate

$$ln(M_{it}) = \beta_1 ln(R_{it}) + \beta_2 ln(f^e_{it}) + \beta_g \boldsymbol{g}_{it}(F_{it} - F^r_{it}) + \beta_l \boldsymbol{l}_{it}(F_{it} - F^r_{it}) + \alpha_i + \gamma_{s(i)t} + \varepsilon_{it} \quad (14)$$

where M_{it} is the number of establishments in county i during year t, R_{it} is market size, f^e_{it} are entry costs, F_{it} is average annual payroll (per establishment), $\boldsymbol{g}_{it}$ indicates whether $F_{it} - F^r_{it} < 0$, $\boldsymbol{l}_{it}$ indicates the opposite $F_{it} - F^r_{it} > 0$, α_i is a county fixed effect, $\gamma_{s(i)t}$ is a state-year fixed effect, and ε_{it} is an idiosyncratic error term. We take absolute values of gains and losses to simplify the interpretation of the regression coefficients.

The estimating equation is ultimately a log-linearization of the equilibrium number of firms in the general equilibrium model we develop later. We proxy for market size using annual county GDP. We proxy for entry costs using the number of business applications. We use α_i and $\gamma_{s(i)t}$ to proxy for the level of F_{it} as well as variation in the outside options or opportunity costs of owners and managers. $\gamma_{s(i)t}$ is especially useful because it tracks state specific changes to minimum wages.

Our proxy for the reference point is lagged average payroll, $F^r_{it} = F_{it-1}$. Given this reference point, $\beta_g \boldsymbol{g}_{it}(F_{it} - F^r_{it})$ and $\beta_l \boldsymbol{l}_{it}(F_{it} - F^r_{it})$ measure year-over-year decreases and increases in average payroll respectively. Variation in $\beta_g \boldsymbol{g}_{it}(F_{it} - F^r_{it})$ and $\beta_l \boldsymbol{l}_{it}(F_{it} - F^r_{it})$ is generated therefore by a host of factors including employment, wages, or developments in the payroll sector. In the model this variation is generated by decreases and increases in fixed costs. In reality they can be generated by decreases and increases in variable costs, which in turn can reflect contractions and expansions in county output. Some of this will be reflected in GDP as well as the state-year fixed effects.[10]

Note that the factors generating payroll decreases can differ from factors generating payroll increases. Paying the minimum wage is common practice in this sector. Minimum wages are almost always increasing over time. By this token, changes to minimum wage legislation always generate losses, never gains. Alternatively, technological developments in the payroll sector have been exploited to decrease payroll costs over time.

[10] We use our administrative data to provide evidence that payroll has a strong fixed cost component. See Online Appendix Figure A.2.2 for details.

β_g and β_l are identified if there is no residual variation tracking year-over-year gains (losses) and the number of firms. The assumption can fail if there are county level time varying factors which correlate with gains (losses) and number of firms, such as the diffusion of outsourced or automated payrolls.

5 Empirical Facts

5.1. Facts from high frequency admin data.

FACT 1 A loss aversion coefficient of $\lambda = 4.27$ on average.

FACT 2 A loss aversion coefficient of $\lambda = 7.39$ when the scale of production is low.

FACT 3 No loss aversion as the scale of production increases.

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 2. 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.2.2, which reports the number of consumer arrivals by day of the week. Robustness to worker fixed effects is verified in Online Appendix Table 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 ownership team. There are more owners, co-owners or support staff managing the firm on busy days. The additional support facilitates joint decision making and loss neutrality.

5.2. Facts from small-scale survey data.

FACT 4 A mean loss aversion coefficient of $\lambda = 10.1$. A median of $\lambda = 1.6$. 74 percent have loss aversion coefficients greater than 1. 30 percent have coefficients above 3.

FACT 5 More experienced owners are more loss averse.

FACT 6 The firm of a loss averse owner is 18-21 percentage points less likely to exit after approximately five years (mean=0.28) relative to the firm of a gain-seeking or loss neutral owner.

The first row of Table 3 summarizes the loss aversion estimates.[11] We tested the hypothesis that owners are gain seeking or loss neutral ($\lambda \leq 1$), against the alternative of loss aversion ($\lambda > 1$). The test was applied to the interquartile range, as well as to the full sample. Both applications led to rejection of gain seeking and loss neutrality ($p < 0.01$).

The remaining rows of Table 3 summarize additional information collected during the interviews. On average, owners are 36 years of age, have approximately 12 years of experience, have 17.5 employees, and report a willingness to take risks of 6.67 on a scale from 0 (risk averse) to 10 (fully prepared to take risks).

Owners were asked the following questions: how many customers do you serve per week? how many would you lose if (current) prices went up by 5 percent? 10 percent? 20 percent? The questions yield perceived elasticities at current prices, at 105 percent of current prices, and 110 percent of current prices. The lower panel of Table 3 shows owners perceive an elasticity of -0.98 at current prices, an elasticity of -1.81 at 105 percent of current prices, and of -1.94 at 110 percent of current prices. Owners appear to be setting prices on an inelastic segment of their residual demand curves, which is what we would expect from a firm with at least some market power, and in particular from a differentiated firm operating in a monopolistically competitive market. The alignment with the theory of monopolistic competition is consistent with an expert understanding of market conditions among owners.

Table 4 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

[11] The median and interquartile range are in line with estimates in Abdellaoui et al. [2016].

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 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.

To further evaluate the selection narrative, we constructed an indicator for whether a firm exited by October 2021. 30 firms exited. The implied exit share was 0.28. The share is 0.42 for firms with a gain seeking or loss neutral owner ($\lambda \leq 1$) and 0.22 for firms with a loss averse owner. The 20 percentage point contrast suggests owner loss aversion induces the firm to stay in.

We further estimate

$$Exit_i = \beta_0 + \beta_1 \mathbf{1}(\lambda_i > 1) + \mathbf{X}_i \Gamma + \varepsilon_i$$

where $\mathbf{1}(\lambda_i > 1)$ indicates whether i is loss averse, $\mathbf{X}_i$ are controls, and ε_i is a random variable. The identifying assumption is $\mathbb{E}[\varepsilon_i|\lambda_i, \mathbf{X}_i] = \mathbb{E}[\varepsilon_i|\mathbf{X}_i] = 0$. The timing of events facilitates identification, as λ_i is measured 5 years prior to the exit decision. While the timing facilitates identification, it is insufficient for a causal interpretation because λ_i likely correlates with other relevant but unobserved traits.[13]

Regression estimates are found in Table 5. Column 1 reports the unconditional estimate. Column 2 reports the *ceteris paribus* estimate. The latter implies an 18 percentage point

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

[13] For example, loss aversion, risk seeking in the loss domain, and framing together explain the sunk cost fallacy at the individual and group levels [Whyte, 1986, 1993]. Risk seeking propensity in the loss domain and susceptibility to framing are then in ε_i, their influence is loaded into the estimand for β_1, likely reinforcing the negative correlation between loss aversion and exit decisions.

contrast between firms with and without loss averse owners after the full control set is included. The point estimate is substantive. It is 64 percent of the exit mean in the sample.

5.3. Facts from market-level data.

FACT 7 The observed number of establishments weighs losses more heavily than gains. The ratio of the loss to the gain coefficient is 8.9.

FACT 8 The observed number of small establishments weighs losses more than gains. The observed number of large establishments does not.

FACT 9 A loss-gain ratio for entry rates of 0.1. A loss-gain ratio for exit rates of 4.7.

Summary statistics can be found in Table 6. Estimates are found in Table 7. Moving left to right in Table 7 shows estimates for three dependent variables: the number of establishments (in logs), the entry rate, and the exit rate. Note that below average payroll is interpreted as a gain. Above average payroll as a loss. Estimates of the loss-gain ratio β_l/β_g are in the bottom panel.

Column 1 shows a one standard deviation loss increase is associated with 1% fewer establishments ($p < 0.01$). We see no statistical or substantive effect for gains. The corresponding loss-gain ratio is 8.9. It is not statistically different from 1 because the gain coefficient is small and imprecisely estimated.

Column 2 shows gains attract entry. A one standard deviation gain increase increases the percentage change in births by 0.4 points ($p < 0.01$). An equivalent loss has no statistical effect on entry rates. The loss-gain ratio is 0.1.

Column 3 shows losses bring about exit. A one standard deviation loss increase increases the percentage change in deaths by 0.47 points ($p < 0.01$). There is no statistical effect of gains on exit rates. Here the loss-gain ratio is 4.7.

We replicate Table 7 in Appendix Table A.2.4 but with a broader set of controls than is specified by our equilibrium model. More specifically, we show that the results are robust to the number of employees in the sector (in logs), a standardized housing price index, population density (in logs), average year-over-year payroll losses (gains) in neighbouring counties within 25 miles. Our estimate of the loss-gain ratio for the number of establishments is smaller (2.3) but estimated more precisely ($p < 0.01$).

The loss-gain ratios in Columns 1 and 3 of Tables 7 and A.2.4 fit with global evidence on the relationship between entrepreneurship and personal characteristics. Using data generated by the Global Entrepreneurship Monitor, Ardagna and Lusardi [2010] document a robust negative correlation between the propensity to start or own a new business and the answer to the statement "fear of failure would prevent you from starting a business." Ardagna and Lusardi [2010] interpret the answer as a measure of risk aversion. However, one can alternatively interpret it as measuring loss aversion, if fear of failure is coded as a loss relative to some internal yardstick [Morgan and Sisak, 2016].

We study variation in the loss-gain ratios over time. We estimate Equation 14 for every year from 2005-2021 exploiting cross sectional variation across counties (and implicitly by states). The procedure yields loss and gain coefficient estimates $\widehat{\beta}_{lt}$ and $\widehat{\beta}_{gt}$. The estimates are partitioned by firm size and plotted in Figure 4.

The figure suggests our baseline patterns are driven by small firms. The gain and loss coefficients, especially the loss coefficients, are both more extreme than in Figure 4. With large firms we see starkly different patterns. The loss coefficient for large firms always hovers around 0. The gain coefficient is negative initially, but eventually tracks the loss coefficient around 0 towards the end of the sample.

There is a stark contrast between the survey results and Table 7. The surveys shows loss aversion decreases the probability of exit. Table 7 shows losses increase the probability of exit. One simple explanation for the contrast relates to the fact that while loss averse management may want to stay in they are constrained in their capacity to do so by the losses themselves. From this perspective it would be intuitive for losses to increase the probability of exit, regardless of management preferences, as is the case in Table 7. Indeed, this is why we made the assumption $\eta < 1$. However, the owners and general managers we surveyed in 2016 were supported financially by the Dutch government during COVID-19 and the associated lockdowns. The financial support enabled them to survive. This explains why market aggregates can reflect loss aversion in general equilibrium.

6 Model

We build a model with monopolistically competitive firms and loss averse firm owners. While we use some facts to defend model assumptions, the model can reconcile all key facts.

6.1. Technologies and preferences The production side is characterized by a mass of firms, each one producing a unique variety. A firm produces its variety with productivity ϕ and fixed costs $F = wf$, where w is the wage and f a fixed labor input. We choose labor as numéraire, set w equal to 1 and, thus, $F = f$. To produce q units of output, a firm uses $l = \frac{q}{\phi} + f$ units of labor. Each unique variety will be indexed by its productivity parameter

ϕ, and the set of available varieties is Φ.

The utility function of a representative consumer is $Q = \left[\int_{\phi\in\Phi} q(\phi)^{\rho} d\phi\right]^{1/\rho}$, $0 < \rho < 1$, and demand for a single variety ϕ results as: $q(\phi) = RP^{\sigma-1}\left[\frac{1}{p(\phi)}\right]^{\sigma}$, where R denotes aggregate spending on the sector's output and P the price per unit of the aggregate consumption good Q. Revenues of a single firm producing with ϕ are given by: $r(\phi) = R\left[\frac{P}{p(\phi)}\right]^{\sigma-1}$.

Firms choose their price $p(\phi)$ to maximize the owner's utility, which is given by:

$$V(\phi) \;=\; (1-\eta)\pi(\phi) - \eta v\left(F|F^r\right), \tag{15}$$

where $\pi(\phi) = r(\phi) - l(\phi)$ and $v\left(F|F^r\right) = \left(F-F^r\right)^{-} + \lambda\left(F-F^r\right)^{+}$, $\lambda > 1$. $\left(F-F^r\right)^{-} = \min\left\{F-F^r;0\right\}$ measures a perceived fixed costs gain, while $\left(F-F^r\right)^{+} = \max\left\{F-F^r;0\right\}$ measures a perceived fixed costs loss relative to a reference point F^r. We assume $(1-\eta)F + \eta v\left(F|F^r\right) > 0$, i.e. a perceived fixed costs gain can never compensate for the actual fixed costs. The profit maximizing price results as $p(\phi) = \frac{\sigma}{\sigma-1}\frac{1}{\phi}$.

6.2. Market entry and exit Prior to market entry, firms do not know their productivity level ϕ, nor their fixed costs F. Only after paying sunk market entry costs F^e, firms simultaneously draw ϕ and F from exogenously given and independent distributions, characterized by densities $g(\phi)$ and $h(F)$ and cumulative densities $G(\phi)$ and $H(F)$, respectively. Each period a firm may be hit by a negative shock with probability θ, which forces the firm to exit the market.

6.3. General equilibrium First, a zero cutoff profit condition has to be defined for each potential F an entrant might draw after market entry. Given F, the zero cutoff profit condition determines the threshold productivity parameter ϕ^*, at which an entrant realizes zero profits, net of sunk market entry costs—notice that $\pi(\phi) = \frac{r(\phi)}{\sigma} - F$ as $p(\phi) = \frac{\sigma}{\sigma-1}\frac{1}{\phi}$:

$$(1-\eta)\left[\frac{r(\phi^*)}{\sigma} - F\right] - \eta\nu\left(F|F^r\right) \;=\; 0. \tag{16}$$

Assuming a Pareto–distribution for ϕ with shape parameter k and defining an average productivity parameter $\widetilde{\phi}$ as $\widetilde{\phi} = \left(\int_{\phi^*}^{\infty} \phi^{\sigma-1}\frac{g(\phi)}{1-G(\phi^*)}d\phi\right)^{\frac{1}{\sigma-1}}$ implies $\frac{\phi^*}{\widetilde{\phi}} = \left(\frac{k-\sigma+1}{k}\right)^{\frac{1}{\sigma-1}}$. Considering $r(\phi^*) = r(\widetilde{\phi})\left(\frac{\phi^*}{\widetilde{\phi}}\right)^{\sigma-1}$ leads to:

$$r\left(\widetilde{\phi}\right)\frac{k-\sigma+1}{\sigma k}(1-\eta) \;=\; \eta\nu\left(F|F^r\right) + (1-\eta)F. \tag{17}$$

Second, a free entry condition has to hold in general equilibrium:

$$\int_{\underline{F}}^{F^r} [1 - G(\phi_G^*(F))] \, V\left(\widetilde{\phi}_G(F)\right) h(F) dF + \int_{F^r}^{\overline{F}} [1 - G(\phi_L^*(F))] \, V\left(\widetilde{\phi}_L(F)\right) h(F) dF \;\; = \;\; F^e, \tag{18}$$

where the subscripts G and L in equation 18 indicate the relationship between the productivity parameters and F in the case of a perceived fixed costs gain or loss, respectively. ϕ^* and $\widetilde{\phi}$ are functions of F, following from equation 17. The term $1 - G(\phi_x^*(F))$, $x = G, L$ denotes the probability of being active after market entry for a drawn F.

The price index for the aggregate consumption good results as:

$$\begin{aligned} P \;\; = \;\; & \Bigg\{ M_e \Bigg[\int_{\underline{F}}^{F^r} [1 - G(\phi_G^*(F))] \, p(\widetilde{\phi}_G(F))^{1-\sigma} h(F) dF \\ & \qquad + \int_{F^r}^{\overline{F}} [1 - G(\phi_L^*(F))] \, p(\widetilde{\phi}_L(F))^{1-\sigma} h(F) dF \Bigg] \Bigg\}^{\frac{1}{1-\sigma}}, \end{aligned} \tag{19}$$

with M_e denoting the mass of entrants into the market. Considering the definition of V (equation 15) and the zero cutoff profit condition (equation 17), the free entry condition (equation 18) results as:

$$\int_{\underline{F}}^{F^r} [1 - G(\phi_G^*(F))] \, r(\widetilde{\phi}_G(F)) h(F) dF + \int_{F^r}^{\overline{F}} [1 - G(\phi_L^*(F))] \, r(\widetilde{\phi}_L(F)) h(F) dF \;\; = \;\; \frac{\sigma k}{\sigma - 1} \frac{F^e}{1 - \eta}.$$

Using $r(\widetilde{\phi}_x(F)) = RP^{\sigma-1} p(\widetilde{\phi}_x(F))^{1-\sigma}$, $x = G, L$, and P from equation 19 then allows us to solve for the mass of entrants: $M_e = \frac{(\sigma-1)R}{\sigma k} \frac{1-\eta}{F^e}$.

To fully characterize general equilibrium, the function $\phi_x^* = \phi_x^*(F)$, $x = G, L$, still needs to be derived. For that purpose we rewrite equation 17 by using (i) the terms for $r(\widetilde{\phi}_x(F))$, P and M_e, and (ii) the assumption of a Pareto–distribution for ϕ, which implies $1 - G(\phi_x^*(F)) = \left(\frac{\underline{\phi}}{\phi_x^*(F)}\right)^k$ and $\phi_x^* = \widetilde{\phi}_x \left(\frac{k}{k-\sigma+1}\right)^{-\frac{1}{\sigma-1}}$, $x = G, L$:

$$\widetilde{\phi}_x(F) \;\; = \;\; \Theta \left\{ \left[\int_{\underline{F}}^{F^r} h(F) \left(\widetilde{\phi}_G(F)\right)^{\sigma-k-1} dF + \int_{F^r}^{\overline{F}} h(F) \left(\widetilde{\phi}_L(F)\right)^{\sigma-k-1} dF \right] \right\}^{\frac{1}{\sigma-1}} \Phi(F)^{\frac{1}{\sigma-1}},$$

with $\Theta \equiv \left(\frac{(\sigma-1)(1-\eta)}{(k-\sigma+1)f_e} \underline{\phi}^k \left(\frac{k}{k-\sigma+1}\right)^{\frac{k}{\sigma-1}}\right)^{\frac{1}{\sigma-1}}$ and $\Phi(F) \equiv F + \frac{\eta}{1-\eta} \nu\left(F | F^r\right)$. Considering $\widetilde{\phi}_x(F) =$

$\widetilde{\phi}_G(\underline{F}) \left[\frac{\Phi(F)}{\Phi(\underline{F})}\right]^{\frac{1}{\sigma-1}}$ leads to:

$$\widetilde{\phi}_G(\underline{F}) = \Theta \left[\widetilde{\phi}_G(\underline{F})\right]^b \left\{ \int_{\underline{F}}^{F^r} \left[\frac{\Phi(F)}{\Phi(\underline{F})}\right]^b h(F)dF + \int_{F^r}^{\overline{F}} \left[\frac{\Phi(F)}{\Phi(\underline{F})}\right]^b h(F)dF \right\}^{\frac{1}{\sigma-1}} \Phi(\underline{F})^{\frac{1}{\sigma-1}}, \tag{20}$$

with $b \equiv \frac{\sigma-1-k}{\sigma-1} < 0$. Solving equation 20 for $\widetilde{\phi}_G(\underline{F})$ results in:

$$\widetilde{\phi}_G(\underline{F}) = \Theta^{\frac{\sigma-1}{k}} \Phi(\underline{F})^{\frac{1}{\sigma-1}} \left\{\mathbb{E}(\Phi)\right\}^{\frac{1}{k}}, \tag{21}$$

with $\mathbb{E}(\Phi) = \int_{\underline{F}}^{F^r} h(F)\Phi(F)^b dF + \int_{F^r}^{\overline{F}} h(F)\Phi(F)^b dF$. In order to derive the relationship between $\widetilde{\phi}_x$, $x = G, L$, and *any* F, we substitute $\widetilde{\phi}_G(\underline{F}) = \Theta^{\frac{\sigma-1}{k}} \Phi(\underline{F})^{\frac{1}{\sigma-1}} E(\Phi)^{\frac{1}{k}}$ into equation 20 and consider the definition of $\mathbb{E}(\Phi)$ to get:

$$\widetilde{\phi}_x(F) = \Theta^{\frac{\sigma-1}{k}} \mathbb{E}(\Phi)^{\frac{1}{k}} \Phi(F)^{\frac{1}{\sigma-1}}. \tag{22}$$

6.4. Labor market clearing condition Due to loss preferences firm owners might realize monetary profits beyond their wage, or losses which they pay out of their wage income. As firm owners are part of L, they also receive wage w. These monetary profits or losses impact demand for goods and, thus, for labor, which impacts the labor market clearing condition.

To quantify the monetary profits or losses firm owners might realize due to loss preferences, we rewrite the free entry condition (equation 18):

$$\begin{aligned}&\int_{\underline{F}}^{F^r} \left[1 - G(\phi_G^*(F))\right] \pi\left(\widetilde{\phi}_G(F)\right) h(F)dF + \int_{F^r}^{\overline{F}} \left[1 - G(\phi_L^*(F))\right] \pi\left(\widetilde{\phi}_L(F)\right) h(F)dF - F^e = \\ &\frac{\eta}{1-\eta} \left\{ F^e + \int_{\underline{F}}^{F^r} \left[1 - G(\phi_G^*(F))\right] h(F)\left(F - F^r\right) dF + \int_{F^r}^{\overline{F}} \left[1 - G(\phi_L^*(F))\right] h(F)\lambda\left(F - F^r\right) dF \right\}.\end{aligned} \tag{23}$$

If $\eta = 0$, i.e. without loss aversion, the average firm owner only receives wage w as part of L. If $\eta > 0$ the average firm owner realizes profits or losses beyond w.

If realized fixed costs are on average substantially larger than the reference level F^r, or if the parameter of loss aversion λ is large, the positive term $\int_{F^r}^{\overline{F}} \left[1 - G(\phi_L^*(F))\right] h(F)\lambda\left(F - F^r\right)$ dF dominates the right hand side of equation 23. This discourages market entry, compared to the case of $\eta = 0$. Thus, the left hand side of equation 23 is positive, and the average firm owner realizes positive profit which we denote by χ. χ leads to additional demand for the average variety equal to $\frac{\chi}{\tilde{\tilde{\phi}}}$. Notice that the markup $\frac{\sigma}{\sigma-1}$ is left out from this term, as firm owners not only pay the markup, but also collect it. The corresponding additional labor demand is $\tilde{\tilde{\phi}}\frac{\chi}{\tilde{\tilde{\phi}}}$, which reduces to χ. This additional labor demand is balanced by a reduction in the mass of active firms, maintaining the labor market clearing condition.

Conversely, if realized fixed costs are on average substantially smaller than the reference level F^r, or if the parameter of loss aversion λ is small, the negative term $\int_{\underline{F}}^{F^r}\left[1-G(\phi_G^*(F))\right] h(F)\,(F-F^r)\,dF$ dominates the right hand side of equation 23. This encourages market entry, compared to the case of $\eta=0$ and the left hand side of equation 23 is negative. The average firm owner thus realizes losses, and χ is negative. The corresponding reduction in labor demand equals χ, and is balanced by an increase in the mass of active firms, maintaining again the labor market clearing condition.

Thus, the labor market clearing condition results as:

$$\begin{aligned} L \;=\; M_e \Bigg\{ & F^e + \int_{\underline{F}}^{F^r} h(F)\left[1-G\left(\phi_G^*(F)\right)\right]\left[F+\frac{q\left(\widetilde{\phi}_G(F)\right)}{\widetilde{\phi}_G(F)}\right] dF \\ & + \int_{F^r}^{\overline{F}} h(F)\left[1-G\left(\phi_L^*(F)\right)\right]\left[F+\frac{q\left(\widetilde{\phi}_L(F)\right)}{\widetilde{\phi}_L(F)}\right] dF + \chi \Bigg\}, \end{aligned} \tag{24}$$

with χ being equal to the left hand side of equation 23. Considering (i) $\frac{q(\phi)}{\phi}=r(\phi)\frac{\sigma-1}{\sigma}$, (ii) $r\left(\phi\right)=\frac{Rp(\phi)^{1-\sigma}}{P^{1-\sigma}}$ and (iii) the price index (equation 19), equation 24 can be rewritten:

$$L = M_e\left[F^e+\int_{\underline{F}}^{F^r}\left[1-G\left(\phi_G^*(F)\right)\right]Fh(F)dF+\int_{F^r}^{\overline{F}}\left[1-G\left(\phi_L^*(F)\right)\right]Fh(F)dF+\frac{\sigma-1}{\sigma}\frac{R}{M_e}+\chi\right]. \tag{25}$$

Substituting $\frac{r(\widetilde{\phi}_x(F))}{\sigma}$ from the zero cutoff profit condition (equation 17) into the free entry condition (equation 18) and simplification leads to:

$$\int_{\underline{F}}^{F^r} h(F)\left[1-G(\phi_G^*(F))\right]FdF+\int_{F^r}^{\overline{F}} h(F)\left[1-G(\phi_L^*(F))\right]FdF \;=\; F^e\frac{k-(\sigma-1)(1-\eta)}{(1-\eta)(\sigma-1)}-\chi. \tag{26}$$

Combining equations 25 and 26 leads to:

$$L = M_e \left[F^e + f_e \frac{k-(\sigma-1)(1-\eta)}{(\sigma-1)(1-\eta)} - \chi + \frac{\sigma-1}{\sigma} \frac{R}{M_e} + \chi \right]. \tag{27}$$

Finally, considering $M_e = \frac{(\sigma-1)R}{\sigma k} \frac{1-\eta}{f_e}$, equation 27 simplifies to: $1 = \frac{1}{\sigma k} \frac{\sigma k}{1}$.

6.5. Key variables and equations. The key variables are: (i) the average productivity parameter for any drawn F: $\widetilde{\phi}_x(F)$, $x = G, F$; (ii) the mass of entrants into the market: M_e; (iii) the mass of active firms: M; (iv) profits of the average entrepreneur: χ. The corresponding 4 equations are:

$$\widetilde{\phi}_x(F) = \Theta^{\frac{\sigma-1}{k}} \mathbb{E}(\Phi)^{\frac{1}{k}} \Phi(F)^{\frac{1}{\sigma-1}} \tag{28}$$

$$M_e = \frac{(\sigma-1)R}{\sigma k} \frac{1-\eta}{f_e} \tag{29}$$

$$M = M_e \left\{ \int_{\underline{F}}^{F^r} \left[1 - G(\phi_G^*(F))\right] h(F)dF + \int_{F^r}^{\overline{F}} \left[1 - G(\phi_L^*(F))\right] h(F)dF \right\} \tag{30}$$

$$\begin{aligned} \chi = & \int_{\underline{F}}^{F^r} \left[1 - G(\phi_G^*(F))\right] \pi\left(\widetilde{\phi}_G(F)\right) h(F)dF \\ & + \int_{F^r}^{\overline{F}} \left[1 - G(\phi_L^*(F))\right] \pi\left(\widetilde{\phi}_L(F)\right) h(F)dF - F^e, \end{aligned} \tag{31}$$

where Θ, $\Phi(F)$ and $\mathbb{E}(\Phi)$ have been defined in subsection 6.3.

Finally, we can define a sector-wide average productivity parameter $\widetilde{\widetilde{\phi}}$ as a weighted average over all possible $\widetilde{\phi}(F)$:

$$\widetilde{\widetilde{\phi}} = \left\{ \frac{\int_{\underline{F}}^{F^r} \left[1 - G\left(\phi_G^*(F)\right)\right] \left(\widetilde{\phi}_G(F)\right)^{\sigma-1} h(F)dF + \int_{F^r}^{\overline{F}} \left[1 - G\left(\phi_L^*(F)\right)\right] \left(\widetilde{\phi}_L(F)\right)^{\sigma-1} h(F)dF}{\int_{\underline{F}}^{F^r} \left[1 - G\left(\phi_G^*(F)\right)\right] h(F)dF + \int_{F^r}^{\overline{F}} \left[1 - G\left(\phi_L^*(F)\right)\right] h(F)dF} \right\}^{\frac{1}{\sigma-1}}. \tag{32}$$

Notice that the price index in equation 19 is identical to a price index $P = \left[Mp\left(\widetilde{\widetilde{\phi}}\right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$, with M being the mass of active firms (equation 30) and $\widetilde{\widetilde{\phi}}$ as defined by equation 32. To understand the impact of loss aversion on $\widetilde{\widetilde{\phi}}$, two counteracting effects of λ on $\widetilde{\widetilde{\phi}}$ need to be considered. First, with an increase in λ the perceived losses for the case of $F > F^r$ increase, ceteris paribus leading to less firm entries. Less firm entries imply less competition in goods markets, decreasing $\phi_x^*(F)$ and $\widetilde{\phi}_x(F)$, $x = G, L$, and, thus, $\widetilde{\widetilde{\phi}}$. Second, with an increase in λ the perceived losses for the case of $F > F^r$ increase, ceteris paribus increasing $\phi_L^*(F)$ and $\widetilde{\phi}_L(F)$ and, thus, $\widetilde{\widetilde{\phi}}$. Which of these two effects dominates crucially depends on the magnitude of F^r and on the distributional assumption for F.

We first show in online appendix A.3 that, if F follows a uniform distribution on a certain interval, $\widetilde{\widetilde{\phi}}$ may increase or decrease with λ, depending on the magnitudes of σ and k. Second, we show in online appendix A.3 that, if F follows a Pareto distribution with an empirically relevant shape parameter of $\kappa = 0.3$, $\widetilde{\widetilde{\phi}}$ increases with λ.

7 Simulated productivity and profit

We use the model to construct measures of productivity, profit and profit sharing between owners and workers. We compare these measures with and without loss aversion. We investigate the cyclicality of the bias due to loss aversion, with emphasis how the bias evolved during COVID-19.

We assume that each US county m is in general equilibrium in each year t. General equilibrium is defined by:

$$\widetilde{\phi}_G(F_{mt}) = \Theta^{\frac{\sigma-1}{k}} \mathbb{E}(\Phi)^{\frac{1}{k}} \Phi_G(F_{mt})^{\frac{1}{\sigma-1}} \tag{33}$$

$$\widetilde{\phi}_L(F_{mt}) = \Theta^{\frac{\sigma-1}{k}} \mathbb{E}(\Phi)^{\frac{1}{k}} \Phi_L(F_{mt})^{\frac{1}{\sigma-1}} \tag{34}$$

$$M_{mt}^e = \frac{(\sigma-1)R_{mt}}{\sigma k} \frac{1-\eta}{F_{mt}^e} \tag{35}$$

$$M_{mt} = M_{mt}^e Pr(A_{mt} = 1 | F_{mt}, F_{mt}^r, F_{mt}^e) \tag{36}$$

where $A_{mt} = 1$ indicates whether an entrant becomes active, $Pr(.)$ denotes their subjective probability:

$$Pr(A_{mt} = 1 | F_{mt}, F_{mt}^r, F_{mt}^e) = \left\{ \int_{\underline{F}}^{F_{mt}^r} \left[1 - G(\phi_G^*(F))\right] h(F) dF + \int_{F_{mt}^r}^{\overline{F}} \left[1 - G(\phi_L^*(F))\right] h(F) dF \right\}.$$

With these objects in hand, we can compute implied profits for the average entrepreneur:

$$\chi_{mt} = \frac{\eta}{1-\eta} \left\{ F_{mt}^e + \int_0^{F_{mt}^r} \left[1 - G(\phi_G^*(F))\right] h(F) \left(F - F_{mt}^r\right) dF + \int_{F_{mt}^r}^{\infty} \left[1 - G(\phi_L^*(F))\right] h(F) \lambda \left(F - F_{mt}^r\right) dF \right\}. \tag{37}$$

To simulate productivity and profit, we first impute values for σ, k, $\underline{\phi}$, η, and λ. We then use our proxies for F^e_{mt}, F_{mt}, F^r_{mt} to generate $\widetilde{\phi}_G(F_{mt})$, $\widetilde{\phi}_L(F_{mt})$, and χ_{mt} for every m and t in our sample.

We simulate two scenarios. One where $\sigma = 4$, $k = 3.4$, $\underline{\phi} = 1$, $\eta = 0$, and $\lambda = 1$. This is the case where firms are vNM decision makers. Another one where $\sigma = 4$, $k = 3.4$, $\underline{\phi} = 1$,$\eta = 0.3$, and $\lambda = 7$. This is the case where firms are PT decision makers. Our choices for σ and k are based on previous literature [Bernard et al., 2007, Melitz and Redding, 2015]. Our choices for η and λ are based on our analysis. $\underline{\phi} = 1$ is a normalization. The results of our simulations are depicted in Figure 5 and subsequently in Figure 1.

The top panel of Figure 5 plots the ratio of average productivities under vNM and PT firms. Measured productivity at vNM firms is approximately 35 percent higher than productivity at PT firms on average. The productivity of vNM firms is more sensitive to the business cycle, and is in fact countercyclical.

The bottom panel of Figure 5 plots implied profits for the average entrepreneur. Profits are always 0 at vNM firms. Profits at PT firms are almost always fluctuating around 0 except during the COVID-19 period. Here we observe an enormous spike in profit at PT firms.

8 Conclusion

We put forth three distinct pieces of evidence supporting the argument that the objective of the small firm reflects loss averse preferences of prospect theory rather than vNM preferences of expected utility theory, and that these preferences are reflected in market level outcomes. We then develop an equilibrium model with loss averse firms that squares with these facts and lets us study the implications of loss aversion for productivity, profit, and profit-sharing.

Our study may have implications for a literature that tries to understand the positive correlation between firm productivity and size. Previous research has focused on factors such as learning by doing, vertical integration for facilitating intangible input transfers within the firm, market competition, or regulatory influences.[14] By contrast, we underscore the pivotal role of ownership or management team size in prioritizing profit-related objectives, ultimately enhancing measured firm productivity.

Our study sheds light on why loans to small firms under the Paycheck Protection Program, initiated during the COVID-19 period, had a limited impact on employment rates in the United States.[15] Our results suggest employment subsidies that target small businesses

[14] An extensive summary of this previous research is provided by Syverson [2011].

[15] The limited impact, in particular for small firms, has been documented by, e.g., Autor et al. [2022], Granja et al. [2022], and Chetty et al. [2020].

facilitate the survival of nonpecuniary preferences and, ultimately, the existence of loss averse firms in equilibrium.

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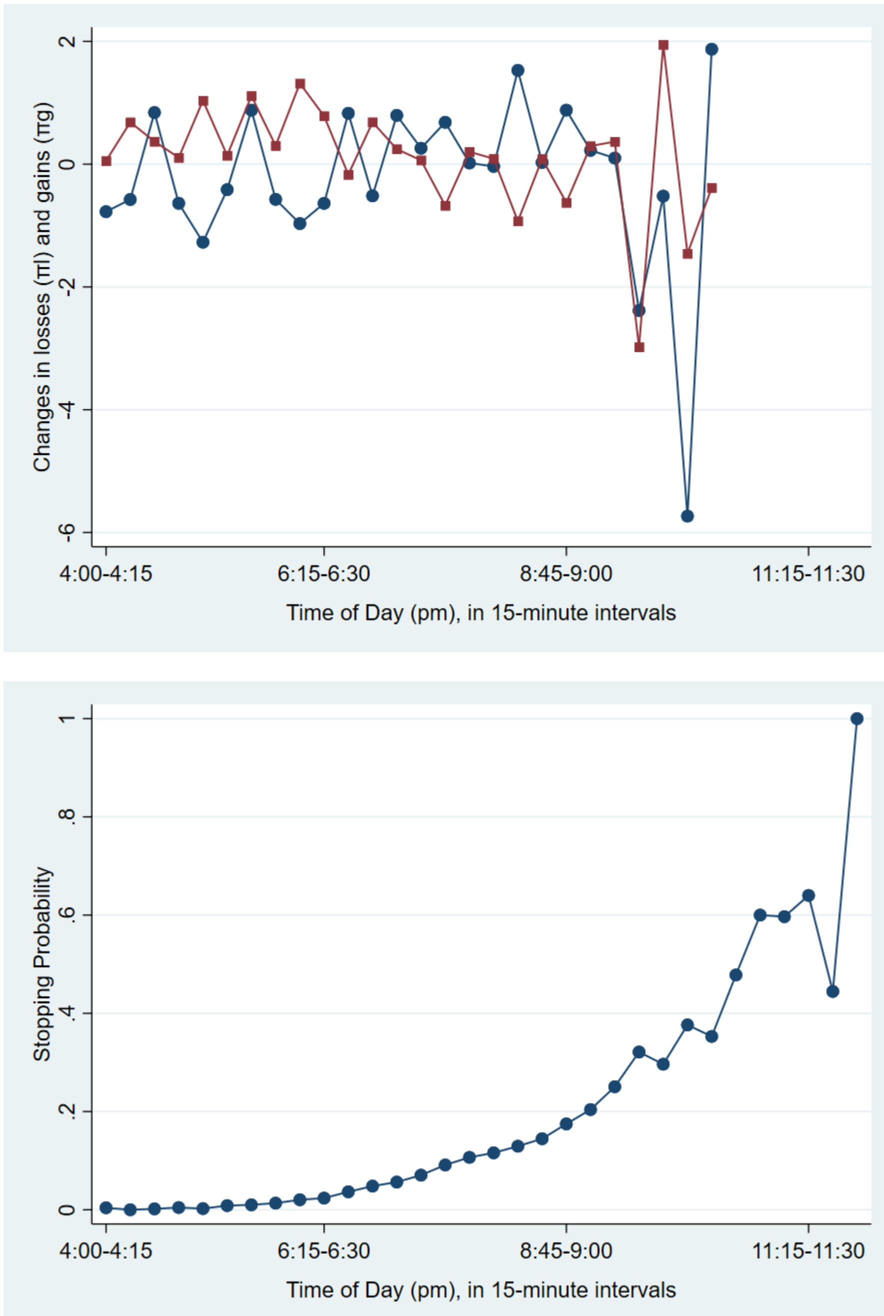
Figures and Tables

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 2: 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 3: 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 4: 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, with *** for $p < 0.01$, ** for $0.01 < p < 0.05$, and * for $p < 0.1$.

Table 5: Exit probability and loss aversion.

	Exit	
	(1)	(2)
Loss averse ($\lambda > 1$; yes=1, no=0)	-0.21**	-0.18*
	(0.10)	(0.10)
Controls	N	Y
Firms	107	102
R^2	0.05	0.08

Notes:

[1] Table reports regression estimates of the effects of owner loss aversion on exit decision of firm.

[2] Dependent variable equals 1 if the firm closed permanently as of October 2021 and 0 otherwise, more than five years after the original survey. The mean of the exit variable is 0.28.

[3] Control variables include the log of owner experience, log of customer volume, log of number of employees, owner perceptions of the price elasticity of demand, their willingness to take risks, and their age.

[4] Robust standard errors in parenthesese, with *** for $p < 0.01$, ** for $0.01 < p < 0.05$, and * for $p < 0.1$.

Table 6: Summary statistics for U.S. restaurant industry (1998-2019)

	Mean	SD	Min	Max	N
Establishments (total number)	163.78	562.34	1.00	20,840	68279
GDP (thousands of 2021 dollars)	4,963,405	21,505,450	4,418	785361615	59131
Business applications	880.25	3,635.64	0.00	128,114	47138
Annual payroll per establishment (US$ 1000s)	154.69	94.02	0.00	754.80	68279
Annual payroll per establishment (change)	6.01	26.88	-681.05	754.80	68169
Above average payroll (frequency)	0.69	0.46	0.00	1.00	70899
Below average payroll (frequency)	0.31	0.46	0.00	1.00	70899
Above average payroll (Amount)	11.37	19.01	0.00	754.80	68169
Below average payroll (Amount)	-5.36	15.47	-681.05	0.00	68169

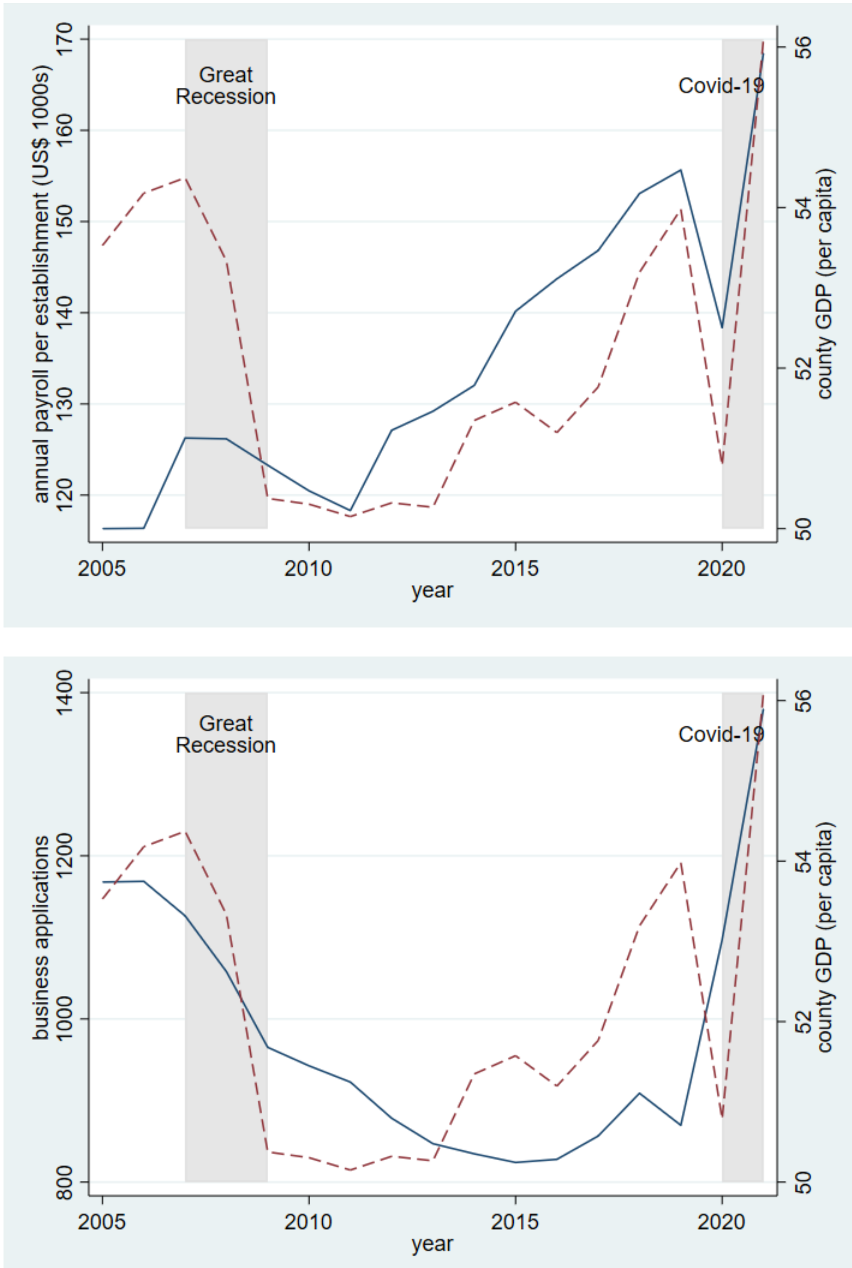
Notes:

[1] Statistics based on County Business Pattern data. Data is produced and distributed by the United State Census Bureau.

[2] Unit of observation is the county and year. There are 3152 counties.

[3] Above average payroll refers to the difference between payroll in the current and last year when the difference is positive. Below average payroll refers to the difference between payroll in the current and last year when the difference is negative.

Figure 3: Annual payroll per establishment (US$ 1000s) and business applications over time.



Notes:

1 Figures depict the two key variables that we input into our model in order to generate measures of profit and productivity.

2 Annual payroll per establishment and business applications are in blue. Both are the sum of their mean and the detrended variable.

3 Dashed red line is county GDP. GDP is the sum of mean GDP and detrended GDP.

Table 7: Loss-gain ratios in equilibrium

	Establishments (in logs) (1)	Entry Rate (2)	Exit Rate (3)
GDP (in logs)	0.114***	-0.210	0.345
	(0.018)	(0.499)	(0.556)
Business applications (in logs)	0.050***	2.495***	0.057
	(0.008)	(0.388)	(0.353)
β_l: Above average payroll (standardized, absolute value)	-0.010***	0.039	0.471***
	(0.002)	(0.067)	(0.092)
β_g: Below average payroll (standardized, absolute value)	0.001	0.407***	0.100
	(0.002)	(0.071)	(0.101)
Constant	1.899***	0.200	5.132
	(0.253)	(6.711)	(7.528)
H_0: $\beta_l/\beta_g = 1$	8.900	0.095***	4.689
	(13.426)	(0.173)	(5.109)
County fixed effects	Y	Y	Y
State-Year fixed effects	Y	Y	Y
Observations	45431	32250	34389
R^2	0.992	0.337	0.311

Notes:

[1] Table reports estimates of the effect of year-over-year payroll increases and decreases on the number of establishments, entry rates, and exit rates. Unit of observation is the county and year. There are 3152 counties.

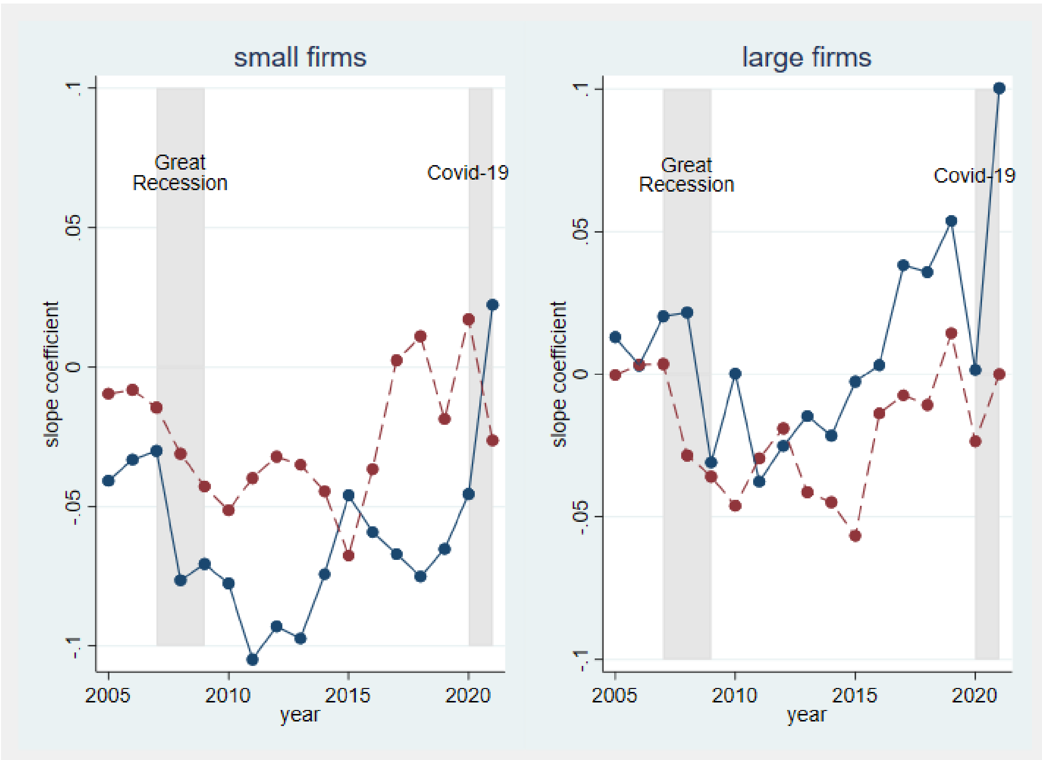
[2] Entry and exit rates come from the Business Dynamics Statistics (BDS), produced and distributed by the U.S. Census Bureau. Entry rates are 100 multiplied the count of establishments born within the last 12 months divided by the average count for the last two years. Exit rates are constructed similarly.

[3] Entry and exit rates are based on 2-digit NAICS code number 72, which encapsulates accommodation as well as food service, and is the lowest level of aggregation available at the county level.

[4] Entry rate regressions use lagged controls. Exit rate regressions use contemporaneous controls. These specifications better reflect the nature and timing of entry and exit rate decisions.

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

Figure 4: Loss and gain coefficients over time for small and large firms.



Notes:

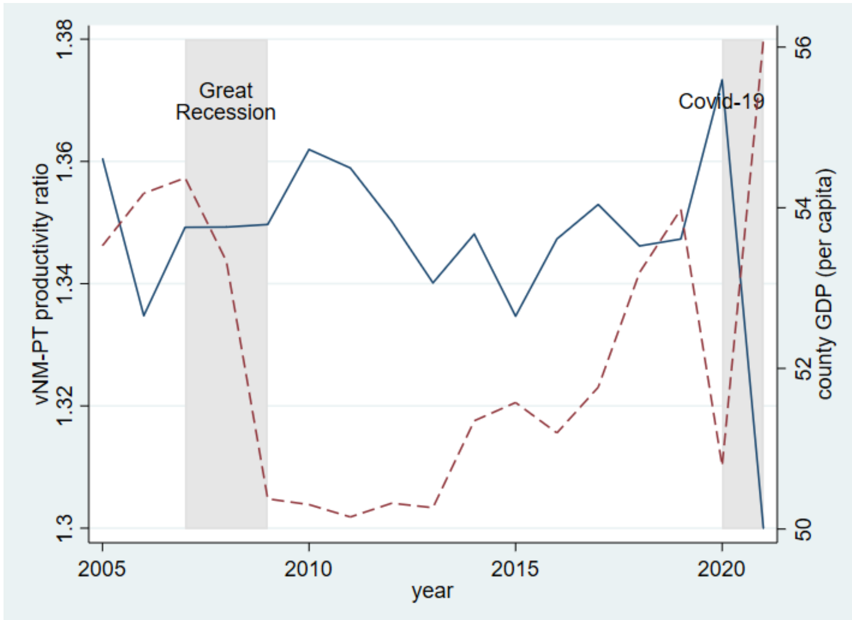
1 Estimates of the effects of year-over-year increases (losses) and decreases (gains) in annual payroll on the number of small and large firms (in logs).

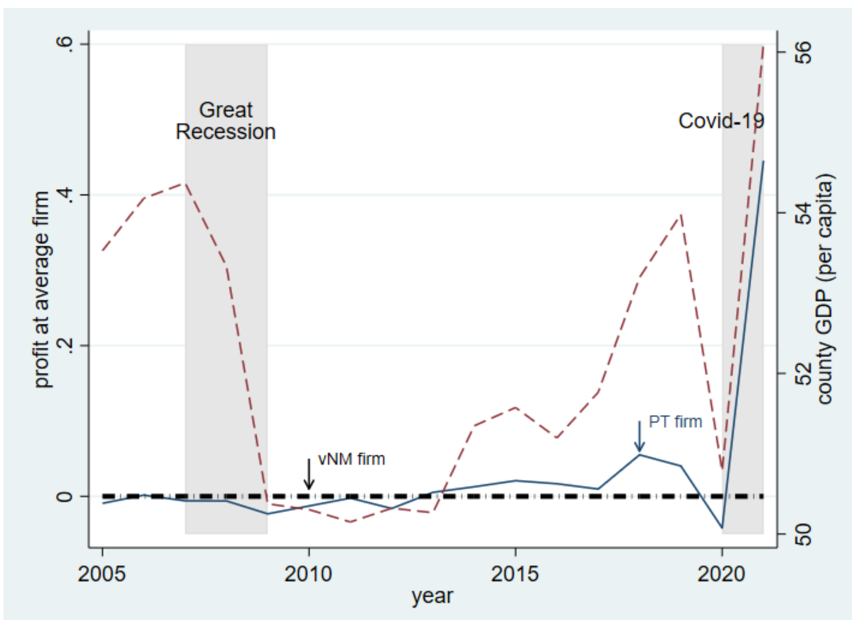
2 Number of small firms (< 20 employees) used in left figure. Right figure uses number of large firms.

3 Each dot represents a coefficient estimates based on the cross section of counties (and states) for the relevant year.

4 Solid blue line uses estimates of loss coefficients. Dashed red line uses estimates of gain coefficients.

Figure 5: Productivity and profits of vNM and PT decision makers.





Notes:

1 vNM decision makers maximize expected utility. PT decision makers maximize a linear combination of expected utility and gain-loss utility.

2 The top figure plots $\frac{\widetilde{\widetilde{\phi}}_{vNM}}{\widetilde{\widetilde{\phi}}_{PT}}$ against the year, where $\widetilde{\widetilde{\phi}}$ is the productivity of the average firm, $\widetilde{\widetilde{\phi}}_{vNM}$ is our estimate if the firm is run by expected utility maximizers, and $\widetilde{\widetilde{\phi}}_{PT}$ is our estimate if the firm is run by reference dependent utility maximizers.

3 Bottom figure plots our estimates of profit at the average firm against the year. Profit of a vNM firm is always 0 and in black. Profit of a PT firm is in solid blue.

4 Dashed red line is county GDP. GDP is the sum of mean GDP and detrended GDP.

Are firms loss averse? Are markets?
Theory and evidence from a competitive industry

Online Appendix

Julian Emami Namini and Sacha Kapoor

December 12, 2024

A.1 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:

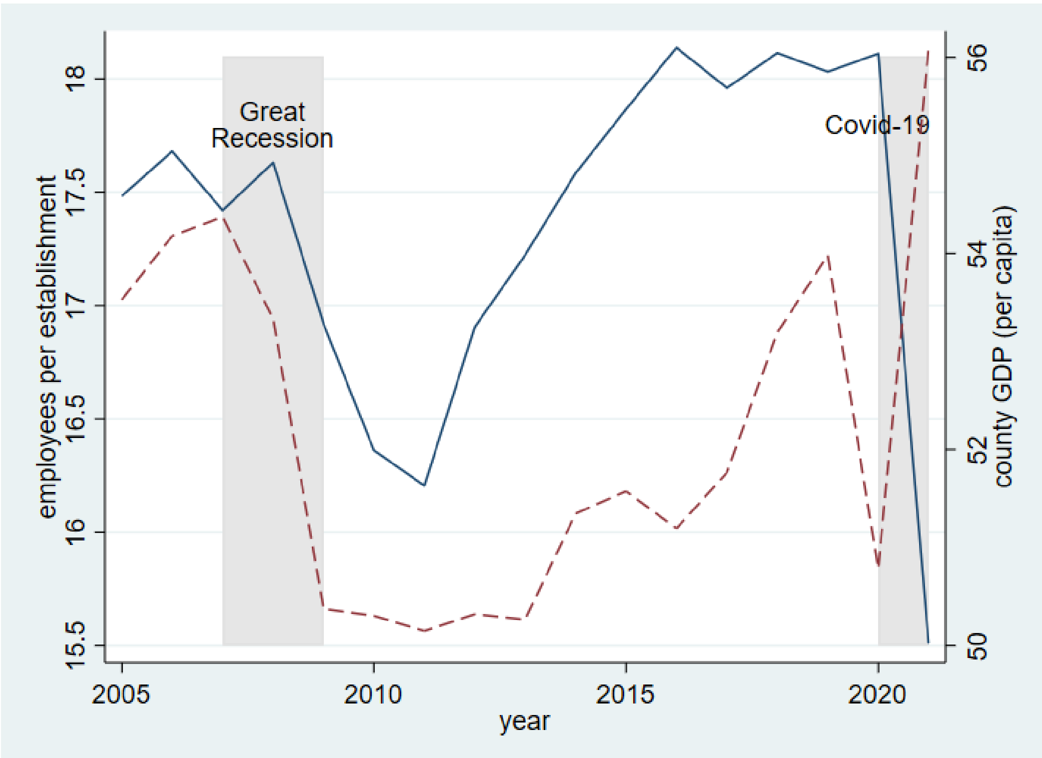
you are **GUARANTEED**	**COIN FLIP** determines whether you earn		
a loss of €	a loss of € L=	**OR**	a profit of € 0
a loss of €	a loss of € L=	**OR**	a profit of € 0
a loss of €	a loss of € L=	**OR**	a profit of € 0

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

A.2 Additional figures and tables

Figure A.2.1: Employees per establishment over time.

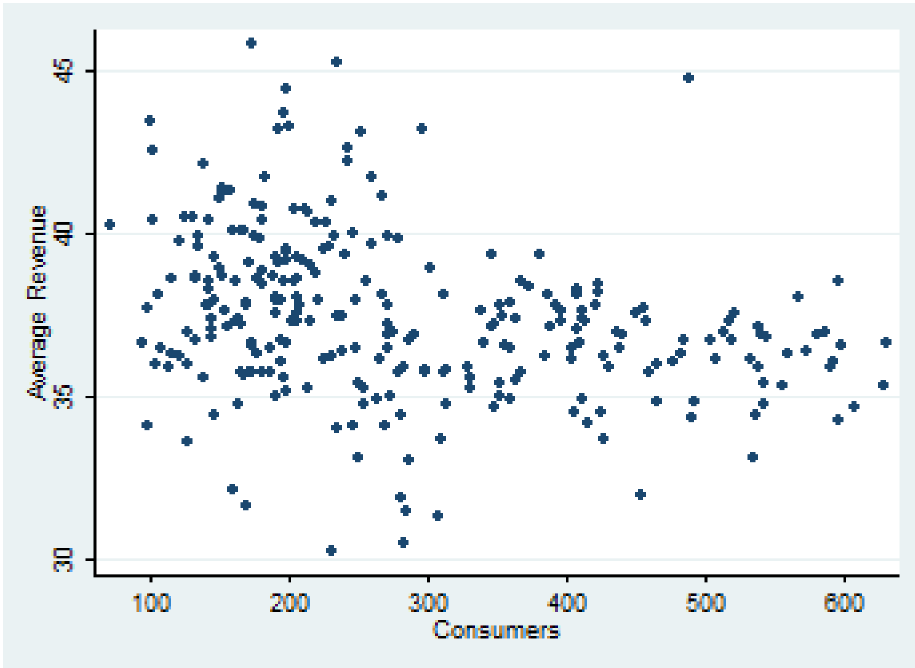


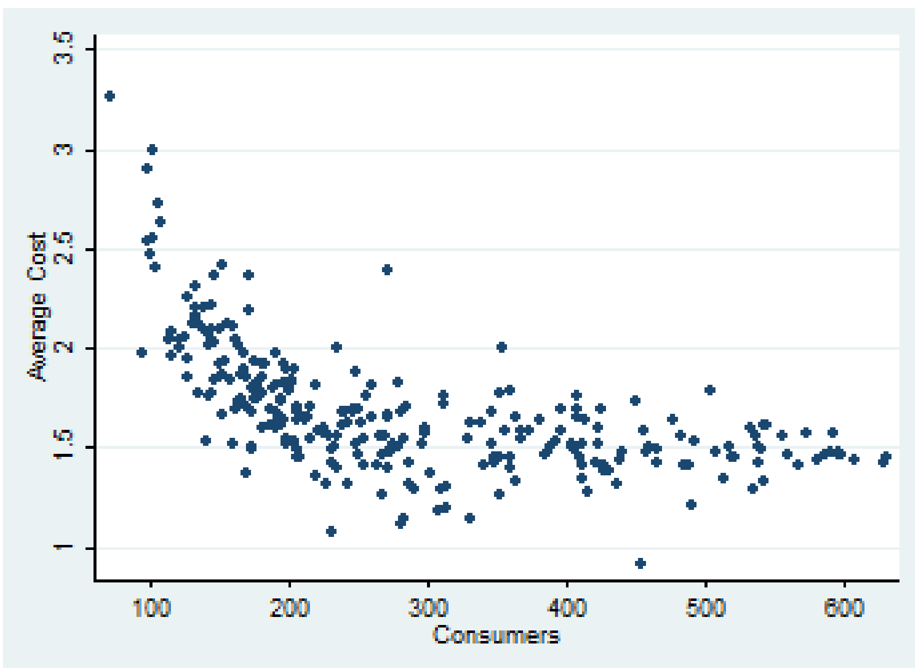
Notes:

1 This graph uses data that is not captured by our model. It shows that employmet per establishment decreases. This could be for deleterious reasons or simply because the advent of online delivery made it easier to have fewer employees on staff.

2 Solid blue line is employment per establishment. Dashed red line is county GDP per capita.

Figure A.2.2: Average revenue and cost in 2006-2007





Notes:

1 Administrative data for the 2006-2007 season. Each dot corresponds to a particular date and firm.

2 Average Revenue is the ratio of total revenue to total number of customers for that date and firm. Average cost is the ratio of hourly wages paid to waiters to total number of customers.

3 Top panel implies convergence of revenue per customer around $37 when the production scale is large. Bottom panel implies labor is a fixed cost for the firm at the shift level.

4 Source: Kapoor [2020].

Table A.2.1: 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 $p < 0.1$.

Table A.2.2: 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.2.3: 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.2.4: Loss-gain ratios in equilibrium with additional controls.

	Establishments (in logs) (1)	Entry Rate (2)	Exit Rate (3)
GDP (in logs)	-0.003	0.083	1.081
	(0.020)	(0.823)	(1.128)
Business applications (in logs)	0.033***	0.430	0.079
	(0.009)	(0.613)	(0.370)
β_l: Above average payroll (standardized, absolute value)	-0.017***	-0.046	0.534***
	(0.002)	(0.079)	(0.108)
β_g: Below average payroll (standardized, absolute value)	0.007***	0.524***	0.030
	(0.002)	(0.083)	(0.155)
Constant	-0.148	20.621**	25.932
	(0.307)	(9.862)	(16.675)
H_0: $\beta_l/\beta_g = 1$	2.336***	0.099***	17.075
	(0.496)	(0.143)	(97.006)
County fixed effects	Y	Y	Y
State-Year fixed effects	Y	Y	Y
Additional control variables	Y	Y	Y
Observations	29303	23221	23052
R^2	0.995	0.352	0.339

Notes:

[1] Table replicates Table 7 but with a broader set of county-time control variables relative to the estimating equation from general equilibrium model.

[2] Control variables include the number of employees in the sector (in logs), a standardized housing price index, population density (in logs), average year-over-year payroll losses and gains in neighbouring counties within 25 miles.

[3] Housing price index constructed by the Federal Housing Finance Agency (FHSA). County population estimates constructed by the US Census Bureau.

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

A.3 Comparative statics of $\widetilde{\widetilde{\phi}}$ with respect to λ.

We study how the parameter of loss aversion λ affects sector-wide average productivity, which is given by:

$$\widetilde{\widetilde{\phi}} = \left\{ \frac{\int_{\underline{F}}^{F^r} [1 - G(\phi_G^*(F))] \left(\widetilde{\phi}_G(F)\right)^{\sigma-1} h(F)dF + \int_{F^r}^{\overline{F}} [1 - G(\phi_L^*(F))] \left(\widetilde{\phi}_L(F)\right)^{\sigma-1} h(F)dF}{\int_{\underline{F}}^{F^r} [1 - G(\phi_G^*(F))] h(F)dF + \int_{F^r}^{\overline{F}} [1 - G(\phi_L^*(F))] h(F)dF} \right\}^{\frac{1}{\sigma-1}}. \tag{38}$$

We use a Pareto–distribution for each $\phi(F)$ on $[\underline{\phi}, \infty)$. Using equation 22 for $\widetilde{\phi}_x(F)$, $x = G, L$, and the definition of $\mathbb{E}(\Phi)$, equation 38 simplifies to:

$$\widetilde{\widetilde{\phi}}^{\sigma-1} = \Theta^{\frac{(\sigma-1)^2}{k}} \frac{\left[\int_{\underline{F}}^{F^r} \Phi(F)^b h(F)dF + \int_{F^r}^{\overline{F}} \Phi(F)^b h(F)dF\right]^{\frac{b-2}{b-1}}}{\int_{\underline{F}}^{F^r} \Phi(F)^{b-1} h(F)dF + \int_{F^r}^{\overline{F}} \Phi(F)^{b-1} h(F)dF}. \tag{39}$$

Notice that the comparative statics of $\widetilde{\widetilde{\phi}}^{\sigma-1}$ with respect to λ are qualitatively identical to those of $\widetilde{\widetilde{\phi}}$ with respect to λ, as $\sigma - 1 > 0$. Linearizing the terms $\Phi(F)^b$ and $\Phi(F)^{b-1}$ around a point F^0 according to a first order Taylor approximation leads to:

$$\begin{aligned}
\Phi(F)^b\Big|_{F<F^r} &\approx \left(F^0\alpha_1 - (\alpha_1 - 1)F^r\right)^b + b\left(F^0\alpha_1 - (\alpha_1 - 1)F^r\right)^{b-1} \alpha_1(F - F^0) \\
\Phi(F)^b\Big|_{F\geq F^r} &\approx \left(F^0\alpha_\lambda - (\alpha_\lambda - 1)F^r\right)^b + b\left(F^0\alpha_\lambda - (\alpha_\lambda - 1)F^r\right)^{b-1} \alpha_\lambda(F - F^0) \\
\Phi(F)^{b-1}\Big|_{F<F^r} &\approx \left(F^0\alpha_1 - (\alpha_1 - 1)F^r\right)^{b-1} + (b-1)\left(F^0\alpha_1 - (\alpha_1 - 1)F^r\right)^{b-2} \alpha_1(F - F^0) \\
\Phi(F)^{b-1}\Big|_{F\geq F^r} &\approx \left(F^0\alpha_\lambda - (\alpha_\lambda - 1)F^r\right)^{b-1} + (b-1)\left(F^0\alpha_\lambda - (\alpha_\lambda - 1)F^r\right)^{b-2} \alpha_\lambda(F - F^0),
\end{aligned}$$

with $\alpha_1 \equiv \frac{1}{1-\eta}$, and $\alpha_\lambda \equiv \frac{1-\eta+\eta\lambda}{1-\eta}$. $\widetilde{\widetilde{\phi}}^{\sigma-1}$ increases (decreases) with λ if the elasticity of the numerator with respect to λ is larger (smaller) than the elasticity of the denominator with respect to λ in equation 39, i.e. if the following holds:

$$\frac{\frac{b-2}{b-1}\frac{\partial\left(\int_{F^r}^{\overline{F}}\Phi(F)^b h(F)dF\right)}{\partial\lambda}}{\int_{\underline{F}}^{F^r}\Phi(F)^b h(F)dF+\int_{F^r}^{\overline{F}}\Phi(F)^b h(F)dF} > (<) \frac{\frac{\partial\left(\int_{F^r}^{\overline{F}}\Phi(F)^{b-1}h(F)dF\right)}{\partial\lambda}}{\int_{\underline{F}}^{F^r}\Phi(F)^{b-1}h(F)dF+\int_{F^r}^{\overline{F}}\Phi(F)^{b-1}h(F)dF}. \tag{40}$$

First, we will show with an example that ">" and "<" are possible. In this example we assume (i) a uniform distribution for F on $[0;1]$, i.e. the densities $h(F)$ in inequality 40 cancel out, and (ii) $F^0 = F^r$. Solving the integrals in inequality 40 with $F^0 = F^r$ and afterwards taking the corresponding partial derivatives with respect to λ allows us to express inequality 40 as:

$$\frac{\frac{b-2}{b-1}b\left[(F^r)^2\frac{1}{2}-F^r+\frac{1}{2}\right]}{(F^r)^2 b\frac{\alpha_\lambda-\alpha_1}{2}+F^r(1-b\alpha_\lambda)+\frac{b\alpha_\lambda}{2}} \lesseqgtr \frac{(b-1)\left[(F^r)^2\frac{1}{2}-F^r+\frac{1}{2}\right]}{(F^r)^2(b-1)\frac{\alpha_\lambda-\alpha_1}{2}+F^r(1-(b-1)\alpha_\lambda)+\frac{(b-1)\alpha_\lambda}{2}}.$$

Further simplification leads to: $(F^r)^2\frac{\alpha_\lambda-\alpha_1}{2}-F^r\left[\alpha_\lambda+\frac{1}{b(1-b)}\right]+\frac{\alpha_\lambda}{2}\lesseqgtr 0$. If $F^r=0$, we get: $\frac{\alpha_\lambda}{2}>0$. However, if $F^r=1$, and after plugging in the terms for α_1 and b we get:

$$-\frac{1}{2(1-\eta)}-\frac{(\sigma-1)^2}{(\sigma-1-k)k} \lesseqgtr 0.$$

If $\eta\to 1$, or if $\eta\to 0$ and, e.g., $\sigma=2$ and $k>2$, the left hand side is *negative*. Thus, both ">" and "<" are possible in inequality 40.

Second, we will show that the left hand side is *always* larger than the right hand side in inequality 40, implying that $\widetilde{\widetilde{\phi}}$ increases with λ, if F follows a Pareto distribution on the interval $[\underline{F},\infty)$ with density $h(F)=\frac{\kappa\underline{F}^\kappa}{F^{\kappa+1}}$ and $\kappa=0.3$. Notice that inequality 40 leads to an ∞/∞ indeterminate form on both sides as the terms with $F^{1-\kappa}$ approach infinity at $\overline{F}\to\infty$. This becomes evident when solving the two integrals with upper bound $\overline{F}\to\infty$:

$$\int_{F^r}^{\infty}\Phi(F)^b h(F)dF = \kappa\underline{F}^\kappa\frac{\left[\frac{F^0\alpha_\lambda(1-b)-(\alpha_\lambda-1)F^r}{-\kappa}F^{-\kappa}+\frac{b\alpha_\lambda}{1-\kappa}F^{1-\kappa}\right]_{F^r}^{\infty}}{\left[F^0\alpha_\lambda-(\alpha_\lambda-1)F^r\right]^{1-b}} \tag{41}$$

$$\int_{F^r}^{\infty}\Phi(F)^{b-1}h(F)dF = \kappa\underline{F}^\kappa\frac{\left[\frac{\left[F^0\alpha_\lambda(2-b)-(\alpha_\lambda-1)F^r\right]}{-\kappa}F^{-\kappa}+\frac{(b-1)\alpha_\lambda}{1-\kappa}F^{1-\kappa}\right]_{F^r}^{\infty}}{\left[F^0\alpha_\lambda-(\alpha_\lambda-1)F^r\right]^{2-b}}. \tag{42}$$

Thus, we apply L'Hopital's rule with respect to $\overline{F}^{1-\kappa}$ to both sides of inequality 40. Simplification then allows us to express inequality 40 as follows:

$$\frac{b-2}{b-1}\frac{\partial\alpha_\lambda}{\partial\lambda}b\frac{\left(F^0-F^r\right)b\alpha_\lambda+F^r}{b\alpha_\lambda\left(F^0\alpha_\lambda-(\alpha_\lambda-1)F^r\right)} \;>\; \frac{\partial\alpha_\lambda}{\partial\lambda}(b-1)\frac{\left(F^0-F^r\right)(b-1)\alpha_\lambda+F^r}{(b-1)\alpha_\lambda\left(F^0\alpha_\lambda-(\alpha_\lambda-1)F^r\right)}. \quad (43)$$

Notice that the ">" sign implies that $\tilde{\tilde{\phi}}$ increases with λ. We can divide both sides by $\frac{\partial\alpha_\lambda}{\partial\lambda}$ and multiply both sides by α_λ without changing the inequality sign:

$$\frac{b-2}{b-1}\frac{b\alpha_\lambda\left(F^0-F^r\right)+F^r}{F^0\alpha_\lambda-(\alpha_\lambda-1)F^r} \;>\; \frac{(b-1)\alpha_\lambda\left(F^0-F^r\right)+F^r}{F^0\alpha_\lambda-(\alpha_\lambda-1)F^r}. \quad (44)$$

Multiplying both sides with $b-1$ changes the unequal sign:

$$(b-2)\frac{b\alpha_\lambda\left(F^0-F^r\right)+F^r}{F^0\alpha_\lambda-(\alpha_\lambda-1)F^r} \;<\; (b-1)\frac{(b-1)\alpha_\lambda\left(F^0-F^r\right)+F^r}{F^0\alpha_\lambda-(\alpha_\lambda-1)F^r}. \quad (45)$$

If the denominator in inequality 45 is positive, i.e. if $F^0 > \frac{\eta\lambda}{1-\eta+\eta\lambda}F^r$, we can simplify inequality 45 to:

$$F^0 \;>\; \frac{\eta\lambda}{1-\eta+\eta\lambda}F^r. \quad (46)$$

If the denominator in inequality 45 is negative, i.e. if $F^0 < \frac{\eta\lambda}{1-\eta+\eta\lambda}F^r$, we can simplify inequality 45 to:

$$F^0 \;<\; \frac{\eta\lambda}{1-\eta+\eta\lambda}F^r. \quad (47)$$

Thus, regardless of the magnitude of the linearization point F^0, the left hand side of inequality 40 is *always* larger than the right hand side. This implies that $\tilde{\tilde{\phi}}$ increases with λ in the case of a Pareto distribution for F on the interval $[\underline{F},\infty)$ and with shape parameter $\kappa = 0.3$.