

Donati, Dante

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The End of Tourist Traps: A Natural Experiment on the Impact of Tripadvisor on Quality Upgrading

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Dante Donati

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Poschingerstr. 5, 81679 Munich, Germany

Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de

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Abstract

Asymmetric information can distort market outcomes. I study how the online disclosure of information affects consumers' behavior and firms' incentives to upgrade product quality in markets where information is traditionally limited. I first build a model of consumer search with firms' endogenous quality decisions. In this model, lower search costs reallocate demand toward higher-quality producers, raising firms' incentives to upgrade quality, and more so for firms selling ex-ante lower-quality products. I then use the access to online reviews to proxy for reductions in consumers' search costs and estimate its impact on the restaurant industry in Rome, exploiting the abolition of mobile roaming charges in the EU in 2017 for identification. Based on a unique dataset combining monthly information from Tripadvisor with administrative social-security records, I find that, after the policy, revenues and total employment in mid- and high-rating restaurants grow by 3-10%. In turn, the probability for low-rating restaurants to exit the market doubles compared to the pre-policy period, while surviving low- and mid-rating establishments hire workers with higher wages and better curricula, eventually improving their Tripadvisor ratings. Overall, the share of low-rating restaurants in the most tourist areas decreases by 2.5 pp. My findings have implications for the role of review platforms in the performance of offline industries under asymmetric information.

JEL-Codes: D820, D830, L150, L800.

Keywords: review platforms, asymmetric information, search costs, service industry, quality.

Dante Donati
Columbia Business School
University of Columbia / New York City / NY / USA
dante.donati@upf.edu
<https://sites.google.com/site/dantedonatiphd>

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1 Introduction

Asymmetric information can distort market outcomes in different ways. For example, when product quality is imperfectly observed, its equilibrium levels are too low, leading to significant welfare losses for both consumers and producers (Akerlof 1970; Leland 1979). Theoretically, removing information frictions should attenuate market inefficiencies by lowering prices or improving qualities (Chan and Leland 1982; Salop and Stiglitz 1977). In this respect, the arrival of the internet was expected to reduce and homogenize market prices, but, in the end, its effects are thought to be limited (Ellison and Fisher Ellison, 2005).¹ Did the internet then have a more positive influence on firms' decisions over product quality? By helping consumers make more informed choices, online review platforms are expected to create reputation mechanisms and enhance firms' incentives to upgrade product quality (Goldfarb and Tucker 2019; Tadelis 2016). Yet, despite the relevance for regulatory decisions, empirical evidence is scarce² due to two main limitations: (1) access to - and the provision of - information is usually endogenous, exacerbating any causal assessment;³ (2) data on product quality are difficult to obtain and, if available, they often come from inspection records and online ratings, which are not informative about firm-specific investment decisions and industry composition.

In this paper, I exploit a natural experiment and unique data from Tripadvisor matched to confidential administrative employer-employee records to study how lower information costs affect consumers' behavior and firms' incentives to upgrade product quality. I derive theoretical predictions from a consumer-search model and empirically investigate the demand and supply effects of online reviews on the restaurant industry in the province of Rome. I assemble a novel dataset combining monthly information on the entire historical records of reviews collected from Tripadvisor with rich administrative establishment-level data. For identification, I take advantage of the 2017 policy that abruptly abolished mobile roaming charges in the EU, generating an arguably exogenous variation in the costs for travelers to access online reviews. This setting allows me to estimate the aggregate effects of a policy that was not deliberately designed to affect the restaurant industry.⁴ Moreover, detailed firm-level data allow me to study firms' response by directly looking at changes in production costs and

¹Empirical studies have documented relatively lower online prices but also the persistence of substantial online price dispersion in the markets for CDs, books, insurance, cars and airlines (Brown and Goolsbee 2002; Brynjolfsson and Smith 2000; Morton et al. 2001; Orlov 2011). More recently, Cavallo (2017) finds that online-offline prices of large multi-channel retailers are identical about 72 percent of the time.

²Some exceptions include Farronato and Zervas (2019) who examine restaurants' incentives to comply with hygiene regulation and Liu et al. (2021) who compare efficiency of Uber and taxi drivers.

³This is a well-known challenge to identifying the causal impact of any type of reputation and information disclosure on demand and supply (e.g., Eliashberg and Shugan 1997).

⁴By contrast, Jin and Leslie (2003) and Klein et al. (2016) study very market-specific quality disclosure programs and feedback systems in online platforms.

hiring decisions, which are used as proxies for quality upgrading.⁵

To inform the empirical exercise, I first build a model in which consumers with heterogeneous search costs engage in costly sequential search to buy one unit of a vertically differentiated product while firms with heterogeneous abilities endogenously select into production and compete in quality. The model borrows insights from theoretical papers on search costs and firms' strategic responses (Bar-Isaac et al. 2012; Fishman and Levy 2015; Goldmanis et al. 2010) but, in contrast to them, abstracts from price competition⁶ and focuses exclusively on firms' incentives to upgrade quality. I show that, when consumers' search costs decrease: (i) the demand faced by firms that were *ex ante* selling high-quality goods increases; (ii) the overall quality level in the industry improves, and this is driven by both the exit of lower-quality providers and the investment in quality upgrading of all surviving firms - and more so of firms selling *ex-ante* lower-quality products.

To empirically study the demand and supply effects of lower consumer search costs, I assemble a novel dataset, which combines information from Tripadvisor, the most popular travel guidance platform in the EU, with administrative employer-employee records maintained at the Italian National Social Security Institute (INPS). For about 5,500 matched restaurants in the province of Rome, the data contain time-invariant information on name, address, price category, type of cuisine and additional covariates, as well as time-varying information on number of Tripadvisor reviews (by origin of reviewer and device), rating, date of opening and closure, number of employees, type of contracts, wages and the full employment history of the workers, observed at monthly intervals between 2007 and 2019. Moreover, for a subset of this sample, the data provide annual information on income statements and balance sheets.

I then use the access to online reviews on Tripadvisor to proxy for reductions in consumer search costs and estimate its impact on the restaurant industry. The identification strategy exploits the approval by the European Parliament, ⁷ which abolished all charges for temporary roaming within the European Economic Area (EEA) as of June 15, 2017. In practice, before that day all EU residents traveling within the EEA were

⁵Others, such as Ananthakrishnan et al. (2019) and Proserpio and Zervas (2017), rely exclusively on online ratings to proxy for quality.

⁶This assumption simplifies the algebra and allows me to solve the model analytically. One potential caveat is that the predictions of the model are just one special case of a more general setting featuring endogenous prices. For instance, Fishman and Levy (2015) study both price and quality competition, yet their framework does not deliver predictions on firm dynamics, which is an important feature of my model.

⁷Specifically, the Regulation (EU) 2015/2120 of the European Parliament and of the Council of 25 November 2015 "aims to establish common rules to safeguard equal and non-discriminatory treatment of traffic in the provision of internet access services and related end-users' rights." The subsequent Commission Implementing Regulation (EU) 2016/2286 of 15 December 2016 states that "roaming providers should not levy any surcharge additional to the domestic retail price on roaming customers in any Member State [...]" <https://europa.eu/youreurope/citizens/consumers/internet-telecoms/mobile-roaming-costs>.

charged an additional price for data consumption on top of the home network rate. After the policy, the same home network rate is applied.

I show that, after the policy, Tripadvisor users from EU countries became 1.4 times more likely to post reviews on their mobile devices as opposed to PC. Moreover, the number of mobile reviews written by EU users, as well as their total (mobile+PC) number of reviews substantially increased after the policy compared to those from the locals. By contrast, reviews from extra-EU and Italian travelers did not exhibit a significant change. Importantly, these results are not driven by an increase in international tourist flows toward Italy. Thus, the policy provides an abrupt and arguably exogenous source of variation in the use of Tripadvisor services by EU travelers, whose reviews constitute about 30% of the total volume in restaurants located in the most tourist areas of Rome.

To identify the parameters of interest, I combine the temporal variation induced by the policy with the spatial variation in tourist demand. In particular, I take advantage of the granularity of my data and construct two measures of restaurants' exposure to tourist clientele that account for the intensity to which each restaurant is potentially affected by the lower information costs induced by the policy. The first measure reflects the probability of finding a restaurant given its location with respect to the closest tourist attraction and the road network around it. In practice, I use information from Google Maps API to define the partial road network that leads to the closest restaurants around each attraction and compute the probability of finding each of these restaurants while walking away from the attraction. I show that higher probability values are positively correlated with the share of reviews from foreigners, while they are negatively correlated with the restaurants' average rating.⁸ The second measure exploits the variation in the number of attractions across ZIP codes as a proxy for potential exposure of all restaurants in a ZIP-code to tourist clientele and, therefore, to the change in information costs.

The identification strategy relies on a Difference-in-Differences specification, which compares the changes over time in the outcomes (on a 5-year period before/after the policy) across restaurants that are differentially exposed to tourist clientele. Particularly, in the baseline specification, I use the median value of the previously-described probability measure to create a binary treatment indicator for high *vs.* low tourist exposure. I conduct the analysis on the sample of restaurants with at least one review in the pre-policy period, as well as on three equally sized sub-samples defined using the tertiles of the restaurants' rating at the time of the policy – namely, low, medium and high-rating categories –, and run the regressions on each group separately. This allows me to assess the presence of differing effects of online

⁸As theory predicts (e.g., [Chan and Leland 1982](#)) firms that more frequently engage with uninformed consumers tend to under-provide quality.

information across establishments. The identification assumption requires that, within each group, changes in the outcomes across restaurants with high and low exposure to tourists would have been the same in the absence of the policy.

I then test the theoretical predictions of the model. From the first one, I expect consumers to reallocate their demand toward restaurants with *ex-ante* higher Tripadvisor ratings, which therefore should expand their sales and employment (output). I obtain several empirical results supporting this prediction. After the policy, annual revenues increased by almost 7% in high-rating restaurants, by approximately 3% in mid-rating ones, and remained the same in the low-rating category, with this positive gradient being statistically significant. As a result, revenues increased by almost 5% overall, pointing out an average growth in sales by approximately 32.5 Thousands Euros a year.⁹ Total monthly employment also expanded by approximately 4% in more tourist restaurants, compared to less tourist ones. With an increase by 10%, the mid-rating category is mostly responsible for the overall growth in firm size. Moreover, the impact appears to be negative for low-rating restaurants, while positive for high-rating ones, yet, in both cases, coefficients are insignificant. The latter might indicate the presence of decreasing returns to labor in the industry. Finally, consistently with consumer learning from online maps, I also document demand reallocation over space, with restaurants located in "hidden" alleys growing more than those in front of tourist attractions.

The second set of theoretical predictions concerns the supply side. In particular, I expect to observe higher exit rates for lower-rated establishments, as well as investment into higher quality inputs (such as hiring more qualified workers) for all operating restaurants, and particularly for those with *ex-ante* lower ratings. I start with the analysis of firm exit. I find that, for low-rating establishments, the probability to exit the market doubled after the policy, compared to the baseline period. By contrast, the policy did not significantly impact the probability that mid- and high-rating restaurants left the industry.¹⁰ Moreover, by aggregating observations at the ZIP-code level to study the joint effect of exit and entry, I find that the share of low-rating firms operating in the most touristy neighborhoods decreased by 2.5 p.p. after the policy, compared to non-touristy ZIP codes. These results suggest that lower search costs – even when experienced by only a fraction of consumers – can alleviate the adverse selection problem and make the industry more quality-oriented.

Then, I analyze the behavior of operating firms. I consider hiring decisions as a proxy for the restaurants' effort to upgrade the service quality through the recruitment of more experienced staff. I find that the probability of hiring a worker with previous experience

⁹These results are in line with those from papers studying the impact of review platforms on firms' sales (e.g., [Anderson and Magruder 2012](#); [Chevalier and Mayzlin 2006](#); [Luca 2016](#), among others).

¹⁰This result is in line with findings by [Hui et al. \(2018\)](#).

in the restaurant industry increased overall by 10% with respect to the pre-policy mean. This effect is driven by low- and mid-rating establishments, where such probability went up by 9 and 16%, respectively. By contrast, the coefficient for high-rating restaurants is close to 0 and not statically significant. Moreover, additional evidence suggests that low-rating establishments accumulated human capital at the expenses of high-rating ones. As a result, daily salaries paid by low-rating restaurants increased by more than €1 (2% of their pre-policy mean), while they decreased by a similar amount in high-rating restaurants. Eventually, these opposite recruiting strategies had differing effects on the online reputation of the restaurants, as measured by the average 5-month Tripadvisor rating. I find that restaurants in the low- and mid-rating groups received better reviews after the policy, as their 5-month Tripadvisor rating improved by 0.09 points (2.5%) and 0.08 points (1.9%), respectively.¹¹ By contrast, reputation remained unchanged in restaurants that were already at the top of the rating distribution. Estimates tend to be even larger when restaurants that exited the market are excluded from the sample. Overall, these results point out the role of review platforms in alleviating the moral hazard problem in the experience goods market.

I carry out a number of placebo exercises to validate the identifying assumption. For example, I report event-study estimates, which confirm the absence of diverging trends in the outcomes before the roaming regulation became effective. Moreover, a series of policy-permutation tests conducted in the pre-policy period provides further evidence on the exogeneity of the policy date with respect to other potential factors (such as seasonality) that might explain the observed results. Finally, I show that the main estimates are robust to the use of alternative measurements, samples and clustering units.

My results suggest that review platforms have important economy-wide consequences on the whole Italian restaurant industry. Back-of-the-envelope calculations suggest that abating the costs for all consumers to access Tripadvisor leads to an overall increase in restaurant revenues, employment and exit rate by 1.6%, 1.5% and 0.5 pp, respectively. The first two figures correspond to about 12% and 5% of the overall growth in revenue and employment experienced by restaurants between 2016 and 2019, respectively. While the last figure corresponds to almost 3% of the exit rate faced by the industry during the first year of the Covid-19 pandemic. All together, these results indicate that facilitating access to review platforms can have real effects on the performance and composition of firms operating in industries generally affected by asymmetric information.

This paper contributes to several strands of literature. First, existing studies estimate the effects of reviews and ratings on sales, and find that online reputation is a significant driver of them ([Anderson and Magruder 2012](#); [Cabral and Hortacsu 2010](#); [Chevalier and Mayzlin](#)

¹¹These results are similar to those by [Ananthkrishnan et al. \(2019\)](#) and [Proserpio and Zervas \(2017\)](#).

2006; Fang 2022; Lewis and Zervas 2019; Luca 2016; Reimers and Waldfogel 2021; Resnick et al. 2006). Others examine the interaction between consumer reviews and firms' advertising decisions (Chen and Xie 2005, 2008; Hollenbeck et al. 2019), as well as the relationship between firms' use of management responses and their online reputation (Chevalier et al. 2018; Proserpio and Zervas 2017; Wang and Chaudhry 2018). A common conclusion of these studies is that review platforms have not only changed how consumers make decisions, but also how firms behave in the marketplace. However, empirical evidence on whether sellers react to reviews by boosting quality is scarce, with the exceptions of Ananthakrishnan et al. (2019), who exclusively rely on online ratings as a proxy for hotel quality, and Farronato and Zervas (2019), who examine restaurants' compliance with hygiene standards looking at inspections records. In contrast, I am able to assess the impact of reviews on firms' subsequent behavior, quality upgrading and industry composition thanks to the richness of my data and the exogenous variation in information.

Second, I contribute to the literature on information and product quality. While there are strong theoretical reasons why information should matter (see Section 2), empirical evidence is scarce. Some studies measure the effect of market-specific quality disclosure programs and the introduction of feedback systems in online markets on consumers choices, firms financial performance and incentives to deliver better quality (Bai 2018; Dai and Luca 2020; Elfenbein et al. 2015; Ershov 2020; Hui et al. 2018; Jin and Leslie 2009; Klein et al. 2016). Particularly, Jin and Leslie (2003) find that consumers are sensitive to the information disclosed by restaurants' health inspections, which are shown to be an effective way to incentivize restaurants to be clean. However, their setting does not allow to study general equilibrium effects. In contrast, I can estimate the aggregate effects of increased information. Moreover, compared to all above-mentioned papers, I show that user-generated content on the consumer side provides sufficient incentives for firms to invest in quality upgrading.

Finally, and more broadly, this paper also relates to the literature looking at information frictions as one source of demand constraints impeding firm growth (Aker et al. 2020; Allen 2014; Anderson et al. 2018; Atkin et al. 2017; Bai 2021; Hjort et al. 2020; Jensen 2007; Jensen and Miller 2018; Startz 2018). The general lesson from this work is that improving information in the market enhances growth through a reallocation of market share toward the most productive firms. While this literature has primarily focused on product markets, my paper shows that similar results hold in the service industry.

The remainder of the paper is organized as follows. Section 2 presents the theory and Section 3 discusses the study setting and data; Section 4 describes the empirical strategy and Section 5 reports the main results; Sections 6 and 7 show placebo exercises and robustness checks; finally, Section 8 discusses the magnitudes and Section 9 draws the conclusions.

2 Theoretical framework

2.1 Experience vs search goods in the digital era

Restaurant meals are a typical example of *experience goods* (Nelson, 1970): their quality can be truly assessed only by consuming them, not before. As a result, because of this type of asymmetric information, equilibrium quality levels tend to be lower than the optimal scenario with perfect information (Riordan, 1986). Repeat purchases, brand reputation, and the use of standards/certifications may offer consumers a way to learn about and exert control over quality. However, in many occasions - such as tourists visiting a city - consumption is transient and regulation only applies to minimum quality standards (e.g. hygiene inspections). Thus, consumers are left with two options to get at least partial information on quality prior to the purchase: the physical inspection of the restaurants (e.g., through publicly displayed hygiene cards and certificates of excellence) and the use of guidebooks or word-of-mouth.

The digital era has changed the way consumers get and share information. The decreasing costs of the internet and the diffusion of review platforms like Yelp and Tripadvisor in the last two decades have made information about quality and other characteristics (e.g., price, location and type of cuisine) of restaurants more readily available, helping consumers to make more informed choices (Ghose et al., 2013). In this respect, the possibility to gather some relevant product's information via online search makes restaurant meals closer to the essence of *search goods*.¹² Because this paper focuses on the effects of a reduction in costs to access information online, throughout the rest of it I consider restaurant meals a search good.

2.2 A model of consumer search and quality upgrading

This model extends the work of Goldmanis, Hortaçsu, Syverson and Emre (2010) to account for limited information about quality rather than prices. Such a framework allows to study how reductions in search costs affect the equilibrium quality in the market through both (1) their effect on the behavior of producers (what I refer to as moral hazard) and (2) their effect on the type of producers involved in the market (what I refer to as adverse selection). To do so, I borrow elements from two distinct theoretical literatures.

The first strand of the literature is the set of models on sequential consumer search and endogenous producer choices, such as price, product design and online categorization (Anderson and Renault 1999; Bar-Isaac et al. 2012; Fershtman et al. 2018). In particular,

¹²According to Klein (1998), it is the relatively higher cost of search with respect to direct purchase that makes a good an experience good. Thus, when consumers can obtain important product information via new interactive media at decreasing costs prior to the purchase, the product can be considered a search good.

Fishman and Levy (2015) show that lower search costs can have both positive and negative impacts on firms’ incentives to invest in quality, because of their differential effects on prices.¹³ However, their framework – like most of existing models on consumer search and quality provision (e.g., Moraga-González and Sun 2020; Wolinsky 2005) – does not feature endogenous firm entry and, in turn, is not suitable to assess the effects on industry composition.

To overcome this limitation, I draw from a second strand of the literature, namely, the set of industry equilibrium models with heterogeneous producers and endogenous selection into production (e.g., Hopenhayn 1992; Melitz 2003; Syverson 2004). Endogenizing the set of equilibrium producers allows to study the relationship between producer type and product quality, to eventually assess how a reduction in search costs affects the industry composition (i.e., entry/exit choices by type of producer). This represents an important contribution to the current literature on consumer search and product quality, and allows to investigate the effects of search costs on quality provision through moral hazard and adverse selection, separately.

2.2.1 Model setup

There is a continuum of firms, each of which sells one quality $q \in \mathbb{R}_+$ of a vertically differentiated good at a common and exogenous price p to a continuum of consumers whose total mass is fixed and normalized to one.¹⁴ All consumers have perfectly inelastic unit demand but are heterogeneous in their search costs $s \in \mathbb{R}_+$, with $s \sim Z$ (and density z). A consumer that buys one unit of quality q at price p gets utility (net of any search costs) $u = q - p$. Without loss of generality, I normalize the price p to one, so that utility becomes $u = q - 1$. There is no outside good in the market. Firms are also heterogeneous, differing in their underlying abilities (types), which affect their cost of producing a good of a certain quality. The total mass of firms L is endogenously determined through a zero-profit condition.

The timing is the following. At the beginning of the period, potential firms consider entering the market. If a firm decides to enter, it pays the sunk cost of entry $\kappa \in \mathbb{R}_+$ and learns its own ability parameter $\lambda \in \mathbb{R}_+$, which is drawn i.i.d. from a publicly known probability distribution with cdf Γ and pdf γ . Next, firms decide whether to stay in the market or not. Those firms that choose to stay then decide the quality level of their good and produce.

¹³While they increase the market shares of high-quality firms, lower search costs also reduce their prices and profits more than those of low-quality firms, hence the effect on incentives to invest in quality is ambiguous.

¹⁴Assuming exogenous prices has two advantages: (1) it keeps the algebra tractable and allows me to solve the model analytically; (2) it excludes the possibility that prices are used by firms to signal quality (as in Wolinsky 1983) and therefore to reduce the asymmetric information problem. At the same time, however, the assumption may sound implausible. To make the model more realistic, one could think of a segmented market (e.g., fast-food vs. starred restaurants) where firms compete in quality and charge the same price within each segment (but not across segments), and consumers search exclusively within a segment. This scenario would not qualitatively change the results of the model.

Production requires a fixed cost of operation $C(q, \lambda)$, which depends positively on the chosen quality level and negatively on the exogenous ability parameter of the firm (i.e., $C'_q > 0$ and $C'_\lambda < 0$). This cost can be avoided if the firm chooses to stay out of the market.

2.2.2 Consumers' problem

Consumers have full information on the price of the goods being sold. However, they only know the quality distribution, F (with density f) and must engage in costly search to learn the quality provided by any particular firm. This is in line with the idea that information on the price of a meal might be gathered before the purchase, for instance, by reading the restaurants' menu on the window. Consumers' search is undirected and sequential: they visit stores one-by-one to learn their quality and after every visit compare the expected benefit and cost of continued search. If the expected quality gain from visiting another store is lower than the marginal cost of search s , the consumer continues to search; otherwise, they buy the product with the highest quality in hand. Following [McCall \(1970\)](#), in this context, the optimal stopping rule is characterized by a reservation quality level $\rho(s)$ (i.e., the minimum acceptable quality of a good) such that a consumer stops searching and buys only if they find a product with quality $q \geq \rho(s)$. Particularly, $\rho(s)$ is implicitly defined by

$$h(\rho, q) \equiv \int_{\rho(s)}^{\infty} [q - \rho(s)] f(q) dq - s = 0, \quad (1)$$

where the integral is the expected quality gain from another search, accounting for the option value of discarding lower quality draws. Using integration by parts, one can rewrite (1) as

$$h(\rho, q) \equiv \int_{\rho(s)}^{\infty} [1 - F(q)] dq - s = 0. \quad (2)$$

Applying the implicit function theorem to (2) yields $\rho'(s) = -1/[1 - F[\rho(s)]]$, that is, the reservation quality is strictly decreasing in the search cost (i.e., consumers with lower s are pickier). This also implies that $\rho(s)$ is invertible and its inverse is given by $\rho^{-1}(r) = \int_r^{\infty} 1 - F(q) dq$.

2.2.3 Producers' problem

Firms do not know the ability parameters and the qualities produced by their rivals in the market, but they do know their distributions (Γ and F). Moreover, firms only know the distribution of search costs Z , and not the search cost of any individual consumer. Each firm takes as given these distributions, and determines its optimal quality based on the demand it

faces, characterized by the reservation quality rule $\rho(s)$ implied by (1).

I analyze the optimization problem of a firm with ability parameter λ that chooses to stay in the market. To determine the quantity as a function of the quality chosen by the firm, $x(q)$, one should start from the optimal search rule. Only consumers with reservation qualities $\rho(s)$ below q will buy from the firm. Consider a consumer with reservation quality $r < q$. Since the quality distribution in the market is F and the total mass of operating firms is L , the mass of firms producing quality q above r is $L[1 - F(r)]$. The consumer is equally likely to buy from any one of these firms. That is, the probability that they will buy from a particular firm producing quality q is $1/L[1 - F(r)]$. Integrating over all consumers with a reservation quality lower than q yields the following formula for quantity:

$$x(q) = \int_0^q \frac{g(r)}{L[1 - F(r)]} dr, \quad (3)$$

where $g(r)$ is the pdf of the reservation quality. This formula can be expressed in terms of the search cost and quality distributions, so to obtain the following standard residual demand curve (algebra in Appendix A):

$$x(q) = \frac{1}{L} \int_0^q z[\rho^{-1}(r)] dr. \quad (4)$$

Equation (4) states that the demand faced by a firm is determined by its own quality as well as its competitors' qualities. Note that demand is increasing in quality, since $x'(q) = \frac{1}{L} z[\rho^{-1}(q)] > 0$. However, quality is costly. Higher-quality output requires higher-quality inputs, which come at a cost (e.g., searching for better suppliers and hiring workers with better curricula/experience). I assume that these costs do not depend on the quantity produced, yet they depend on the innate ability of the firm, which is governed by the parameter λ .¹⁵ Hence, the cost function of a firm with ability λ is $C(q, \lambda)$, with $C'_q > 0$, $C''_{qq} > 0$, $C'_\lambda < 0$ and $C''_{q\lambda} < 0$. The last conditions imply that more capable firms (higher λ) are more efficient, so that their fixed cost to produce a given quality is lower or, alternatively, they produce a higher quality product spending the same cost.¹⁶ Hence, the optimization problem of a firm

¹⁵Assuming quantity-dependent costs does not qualitatively alter the results, yet it makes the algebra more cumbersome.

¹⁶The positive relationship between managerial skills (human capital) and firm productivity has been well established in the literature (e.g., [Gennaioli et al. 2013](#)). In my context, high-skill owners/managers/chefs make a more efficient use of their inputs, and therefore save in costs. For instance, managerial skills help owners self-train their room staff, or cooking abilities allow firms to avoid expensive products and nevertheless make fabulous dishes.

with ability λ choosing to stay in the market is

$$\max_q \pi[q(\lambda), \lambda] = x[q(\lambda)] - C[q(\lambda), \lambda]. \quad (5)$$

The equilibrium quality function $q(\cdot)$ follows from the first-order condition for an optimum

$$x'_q[q(\lambda)] - C'_q[q(\lambda), \lambda] = 0, \quad (6)$$

with the second-order condition for a maximum requiring that

$$x''_{qq}[q(\lambda)] - C''_{qq}[q(\lambda), \lambda] < 0. \quad (7)$$

2.2.4 Equilibrium

Let $q(\cdot)$ and $x(\cdot)$ be the quality and residual demand function in equilibrium, respectively. Then, the following properties follow (proofs are in Appendix A):

Property 1: The equilibrium quality function is increasing in the ability parameter: $q'_\lambda(\lambda) > 0$, $\forall \lambda$.

Property 2: The demand function is increasing in the ability parameter: $x'_\lambda[q(\lambda)] > 0$, $\forall \lambda$.

Property 3: The profit function is increasing in the ability parameter: $\pi'_\lambda[q(\lambda), \lambda] > 0$, $\forall \lambda$.

From Property 3 it follows that the decision rule for staying in the market or leaving is characterized by a cut-off value $\underline{\lambda}$ such that firms stay in the market if and only if $\lambda \geq \underline{\lambda}$, with $\underline{\lambda}$ satisfying

$$\pi(\underline{\lambda}) = x[q(\underline{\lambda})] - C[q(\underline{\lambda}), \underline{\lambda}] = 0. \quad (8)$$

In the initial stage, potential entrants have to decide whether or not to start producing. Assuming unlimited entry into the market, firms keep entering until the expected value of post-entry profits equals the sunk entry cost. That is, the entry condition requires that

$$\kappa = \int_{\underline{\lambda}}^{\infty} \pi(\lambda) \gamma(\lambda) d\lambda = \int_{\underline{\lambda}}^{\infty} [x[q(\lambda)] - C[q(\lambda), \lambda]] \gamma(\lambda) d\lambda. \quad (9)$$

Finally, it is possible to express the distribution of qualities F in terms of the distribution of abilities Γ . Property 1 implies that qualities will be distributed with support $[q, \bar{q}]$, where $q = q(\underline{\lambda})$ and $\bar{q} = q(\infty)$. Thus, for $v \in [q, \bar{q}]$, the cdf will be given by

$$F(v) = Pr\{q(\lambda) \leq v \mid \pi(\lambda) \geq 0\} = \frac{Pr\{\lambda \leq q^{-1}(v) \ \& \ \lambda \geq \underline{\lambda}\}}{Pr\{\lambda \geq \underline{\lambda}\}} = \frac{\Gamma[q^{-1}(v)] - \Gamma(\underline{\lambda})}{[1 - \Gamma(\underline{\lambda})]}. \quad (10)$$

Note that $F(v) = 0$ for $v \leq q$ and $F(v) = 1$ for $v \geq \bar{q}$. I can now define the equilibrium in

this market.

Definition 1: A search equilibrium is a set $\{\rho : \mathbb{R}_+ \rightarrow \mathbb{R}_+, q : \mathbb{R}_+ \rightarrow \mathbb{R}_+, x : \mathbb{R}_+ \rightarrow \mathbb{R}_+, F : \mathbb{R}_+ \rightarrow [0, 1], \lambda > 0\}$ satisfying (2), (4), (6), (7), (8), (9) and (10).

2.2.5 Comparative statics

The equilibrium functions and values defined above depend on the search costs that consumers face. My goal is to determine how a decrease in these costs will affect the equilibrium quality schedule $q(\cdot)$ and cost function $C(\cdot)$ of operating firms, their demand as well as the operating cut-off level of ability λ . For this purpose, I impose further assumptions that make the model more aligned with the empirical exercise explained in Section 3.

Assumption 1: *The search cost distribution is uniform on $[0, a]$ for $a > 0$.*

This assumption allows to study changes in search costs that are heterogeneous across consumers. In particular, I will focus on a cost reduction that only affect consumers with ex ante the highest costs (a).¹⁷

Assumption 2: *The firms' cost function takes the form*

$$C(q, \lambda) = \frac{q}{1-q} \frac{1}{\lambda}, \quad (11)$$

which satisfies the requirements described in section 2.2.3 for $q \in (0, 1)$ and $\lambda > 0$.

This assumption has two direct implications. First, the quality level chosen by any firm is bounded between $(0, 1)$, and so is the reservation quality $\rho(s)$. This is consistent with the way individuals value and rate the quality of a meal on review platforms, which exhibit a finite scale (e.g., 1 to 5). In this respect, the upper bound equal to 1 becomes the natural limit of quality via the reputation mechanism, so that firms have no incentive to deliver a level of quality beyond that value. The second implication of equation (11) is that costs are increasingly steeper in quality, and tend to infinity as $q \rightarrow 1$, for a given λ . This assumption reflects the idea that superb quality requires the owner to completely rethink and change the business model of the restaurant, which is unfeasible in the short-term.¹⁸

From Assumption 1, it follows that for $q \in (q, 1)$ the demand function (4) becomes

$$x(q) = \frac{1}{L} \int_0^q \frac{1}{a} \mathbb{1}_{\{\rho^{-1}(r) \in [0, a]\}} dr = \frac{1}{aL} \int_0^q \mathbb{1}_{\{r \in [\rho(a), \rho(0)]\}} dr = \frac{1}{aL} [q - \rho(a)]. \quad (12)$$

Note that $x'(q) = 1/aL > 0$ and $x''(q) = 0$ so that, together with Assumption 2, the

¹⁷In the empirical framework these consumers are identified with foreign tourists, which bear the highest costs to browse the Internet in the presence of roaming tariffs.

¹⁸Results are qualitatively unchanged when alternative convex cost functions are used (e.g., $C = 1/q \lambda$ or $C = q^2/\lambda$), provided that quality q is bounded between 0 and 1.

second-order condition (7) holds. Substituting (11) and (12) into (6), the first-order condition simplifies to

$$q(\lambda; a) = 1 - \sqrt{\frac{aL}{\lambda}}, \quad (13)$$

and the additional condition in order for the ability parameter to yield admissible quality levels follows:

$$q(\lambda) \in (0, 1) \iff \lambda > aL. \quad (14)$$

In other words, firms need to have at least some ability in order to produce positive qualities.

Consistently with Property 1, the equilibrium quality schedule (13) is increasing in λ , that is $q'(\lambda) = \sqrt{\frac{aL}{\lambda}} \frac{1}{2\lambda} > 0$. Moreover, the function is concave, that is $q''(\lambda) = -\frac{3}{4\lambda^2} \sqrt{\frac{aL}{\lambda}} < 0$. This is a direct consequence of the functional form of the firm's production cost (11). As $q \rightarrow 1$, more capable firms will use their ability-advantage mostly to save in costs rather than to deliver a higher quality product. Hence, the quality decision becomes less sensitive to the ability parameter as λ gets larger.

From the equilibrium quality schedule, it follows that the demand, cost and profit functions reduce to

$$x(\lambda; a) = \frac{1}{aL} \left[1 - \sqrt{\frac{aL}{\lambda}} - \rho(a) \right], \quad (15)$$

$$C(\lambda; a) = \frac{1}{\lambda} \left[\sqrt{\frac{\lambda}{aL}} - 1 \right] \text{ and} \quad (16)$$

$$\pi(\lambda; a) = \frac{1}{aL} \left[1 - \sqrt{\frac{aL}{\lambda}} - \rho(a) \right] - \frac{1}{\lambda} \left[\sqrt{\frac{\lambda}{aL}} - 1 \right], \quad (17)$$

and the operating threshold value for ability, λ , follows from (8). That is,

$$\lambda := \pi(\lambda) = 0 \iff \lambda(a) = \frac{aL}{\left(1 - \sqrt{\rho(a)}\right)^2}, \quad (18)$$

such that only for firms with $\lambda \geq \lambda$ it is convenient to stay in the market and produce. Note that λ satisfies condition (14). Finally, the lower and upper limits of the support of the equilibrium quality distribution are $\underline{q} = q(\lambda) = \sqrt{\rho(a)}$ and $\bar{q} = q(\infty) = 1$.

To conclude the comparative statics exercise, it remains to demonstrate how a decrease in search costs for consumers with *ex-ante* the highest costs – i.e., a reduction in a – affects the above quantities, and how these changes depend on the ability parameter of the firm. For this purpose, it is convenient to formalize two preliminary observations that will be used to derive the subsequent results (all proofs are in Appendix A). First, I define the quantity

$\delta(a) \equiv a L(a)$, where I emphasize the dependence of L on a .

Lemma 1: $\delta(a)$ is increasing in search costs, that is $\delta'_a(a) > 0$.

Note that $\delta(a)$ can be interpreted as the inverse of the per-firm density of consumers with a given level of search costs. Hence, Lemma 1 states that such a density is decreasing in the search costs. The second observation is about the profit function of a firm with ability λ , described in equation (17). It is possible to show that, if an increase in search costs reduces the profits of any currently operating firm, it must also reduce those of all firms with higher abilities. Formally,

Lemma 2: If there exists $\lambda_0 \geq \underline{\lambda}(a)$ such that $\pi'_a(\lambda_0; a) \leq 0$, then $\pi'_a(\lambda; a) \leq 0 \forall \lambda > \lambda_0$.

I can now state the following key results:

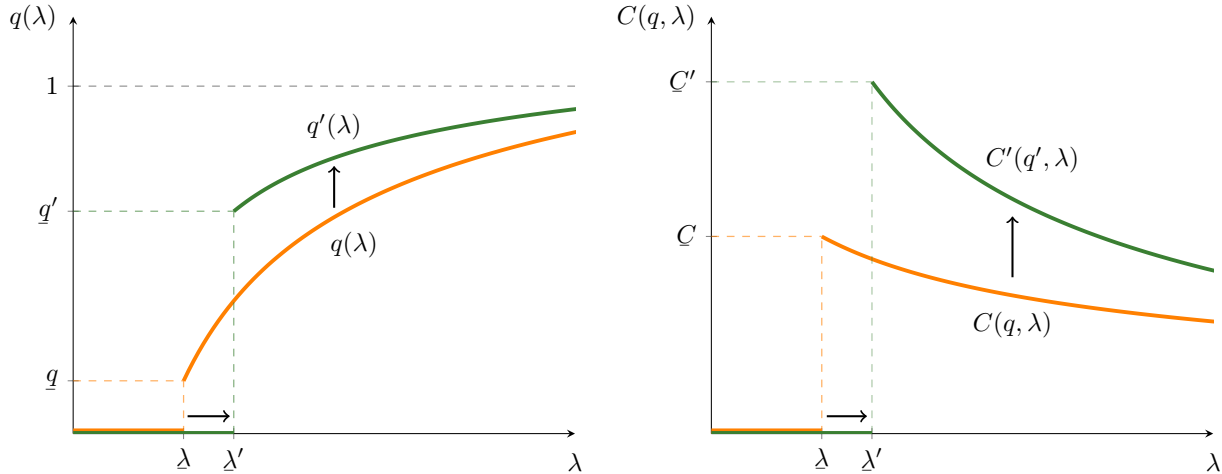
Proposition 1: When search costs decrease, the quality $q(\cdot)$ produced by a firm with ability λ increases $\forall \lambda \geq \underline{\lambda}$, and more so for firms with lower ability. That is, $q'_a(\cdot) < 0$ and $q''_{a\lambda}(\cdot) > 0$.

Proposition 2: When search costs decrease, the production costs $C(\cdot)$ of a firm with ability λ increase $\forall \lambda \geq \underline{\lambda}$, and more so for firms with lower ability. That is, $C'_a(\cdot) < 0$ and $C''_{a\lambda}(\cdot) > 0$.

Proposition 3: When search costs decrease, the cut-off ability value $\underline{\lambda}(\cdot)$ increases. That is, $\underline{\lambda}'_a(\cdot) < 0$.

Corollary 1: A decrease in search costs causes the demand $x(\lambda; a)$ faced by all firms with sufficiently high ability to increase: for each a , there exists $\hat{\lambda}(a) \geq \underline{\lambda}(a)$ such that $x'_a(\lambda; a) < 0 \forall \lambda > \hat{\lambda}(a)$.

Figure 1: The effect of lower search costs on quality, ability threshold and production costs



Notes: The orange (green) lines report the equilibrium schedules when search costs are higher (lower), that is $a : a \rightarrow a' < a$.

Figure 1 graphically describes the consequences of a decrease in the parameter $a : a \rightarrow a' < a$ on the ability threshold and equilibrium qualities (left panel) as well as on the cost schedule (right panel). The first consequence of a decrease in consumer search costs is that

some firms with the lowest abilities exit the industry, as λ shifts to the right. All other firms that remain in the market (i.e. $\lambda > \lambda'$) upgrade their quality when a decreases, and more so those firms that were initially producing lower-quality products (i.e., firms with lower abilities). As a result, production costs change. In fact, all operating firms bear higher costs, indicating that the process of quality upgrading is overall costly. Particularly, firms that were initially producing lower qualities exhibit the largest cost increase.

These results show that two simultaneous mechanisms make the industry more quality oriented when search costs fall. First, the upward shift in the equilibrium quality schedule for all operating firms is a consequence of a reduction in moral hazard: lower search costs make consumers more demanding and their choices more sensitive to the characteristics of the products, hence firms' incentives to upgrade quality increase. Second, the rightward shift in the cut-off ability level is a consequence of a reduction in adverse selection: when search costs fall, demand to lower capable firms decrease, so do their profits, pushing some of them out of the market.

The results of Propositions 1, 2 and 3 together with Corollary 1 constitute the main theoretical predictions of the paper. Declines in search costs in the restaurant industry driven by the advent and diffusion of online review platforms have differing effects across businesses. Low-type sellers are hurt, sometimes to the point of being forced to exit. Higher types, however, gain from the shift as their demand grows. Incentives to upgrade quality arise, resulting in higher quality levels, especially for surviving low-type firms.

2.3 Hypotheses

In order to test the model predictions, it is necessary to identify the empirical counterparts of the quantities described in the theoretical framework. Objective measures of quality are difficult to obtain, especially for experience goods and, particularly, for the restaurant industry, where the quality of a meal reflects multiple dimensions (e.g., service and food) whose evaluation is to a large extent subjective. Following [Ananthakrishnan et al. \(2019\)](#), I use Tripadvisor ratings as a proxy for that dimension of quality that is mainly subjective and can be referred to as reputation. Importantly, this is the dimension that is revealed to consumers once they pay the search cost and visit the Tripadvisor profile of the restaurant. Hence, owners and managers care about such a measure and seek to maximize it.

Moreover, since quality decisions are likely to affect firms' production costs through the labor market (e.g., [Shin et al. 2021](#)), I rely on hiring choices to capture objective quality upgrading. Particularly, I consider the curriculum of newly-hired employees and their wages to explicitly measure investment into service quality of restaurants. Finally, proxies for output

are obtained considering annual revenues as well as the total number of employees, while information on the firm’s presence (or not) in the market is retrieved from the official date of opening/closure of the business.

One potential caveat is that the empirical counterpart of the ability parameter λ remains unobserved. Nevertheless, equations (10) and (13) state that, for operating firms, there exists a one to one mapping between ability and quality. Hence, I can rely on the Tripadvisor rating of the restaurant at baseline (i.e., before the reduction in internet tariffs) to proxy for the underlying ability parameter. Therefore, the above theoretical predictions can be translated in the following testable empirical hypotheses. When search costs for consumers fall (as a consequence of the access to review platforms):

1. The demand faced by firms with *ex-ante* sufficiently high Tripadvisor rating increases: their revenues and number of employees grow.
2. The overall quality level in the industry improves:
 - (a) Some of the firms with *ex-ante* the lowest ratings will exit the market: a reduction in adverse selection;
 - (b) Surviving firms will invest in quality upgrading (e.g., hiring workers with better curricula) eventually improving their online ratings. These effects will be larger for firms with *ex-ante* lower ratings: a reduction in moral hazard.

3 Study setting and data

3.1 The EU roaming regulation

Following recent empirical literature on consumer search (e.g., Ershov 2020), I take advantage of online platforms to characterize reductions in search costs. In particular, I rely on an exogenous reduction in the costs of mobile internet caused by the abolition of roaming tariffs in the European Union, which promoted the use of review platforms like Tripadvisor.

International mobile roaming regulations apply when customers use their mobile phones while occasionally travelling outside the country where they live (specifically, outside the geographical coverage area of the home operator’s network). This paper exploits the approval by the European Parliament of a new policy on the EU roaming regulation – known as “Roam like at home”¹⁹ –, which led to the abolition of all charges for temporary roaming within the European Economic Area (EEA) as of June 15, 2017. In practice, if before that day all EU

¹⁹<https://europa.eu/youreurope/citizens/consumers/internet-telecoms/mobile-roaming-costs>

residents traveling within the EEA were charged at least € 0.05 per MB of data (on top of the home network rate), after the policy the same home network rate is applied with no additional charges.²⁰

The EU roaming regulation consists of a series of policy packages that started in 2007 and regulate wholesale and retail international roaming tariffs. The policy was initially motivated by the 2006 European Commission impact assessment, which pointed out a large gap between the roaming prices charged to consumers and the actual cost of providing the wholesale service. Therefore, the underlying objectives of the reform were the intensification of the competition among providers and the promotion of market integration (digital single market). The last decisive step took place on June 15, 2017, when wholesale and retail price caps for data were set to 0. [Grzybowski and Muñoz \(2020\)](#) show that the European Commission has succeeded to avoid unintended increases in domestic tariffs and induced operators to absorb the negative effects of the reform. At the same time, [Quinn et al. \(2021\)](#) show that, after the policy, daily mobile data consumption (sum of uploads and downloads) for EU travelers while abroad grew by at least 54MB.

For the purpose of this paper, the reform induced an exogenous shock to the costs of accessing online information for EU travelers while abroad. In particular, information contained in review platforms such as Tripadvisor became available to all EU travelers at virtually zero cost. Hence, the search costs for certain tourists looking for restaurants while visiting a city drastically decreased compared to the pre-policy period.

3.2 Data sources

To study the consequences of lower information costs on the restaurant industry, I focus on the whole Province of Rome. Looking at a large geographical area allows me to exploit spatial variation in the intensity of exposure to tourist clientele, an attractive feature for empirical identification. Specifically, I assemble a novel dataset on restaurants in the Province combining three data sources.

The first source is Tripadvisor, the most popular travel guidance platform in Italy and Europe.²¹ Listing an establishment on the platform is free and can be done either by the clients or by the owners/managers of the firm. I collect information on listed restaurants (e.g., name, address, price category and type of cuisine) as well as, for each restaurant, the entire historical record of reviews (date, rating, device, text, country and language of reviewer, etc.)

²⁰Note that the policy also affected the prices of SMSs/phone calls, but only toward the country of origin. Calling/texting local restaurants while abroad remained equally expensive, hence this type of communication is unlikely to play any role in the observed results.

²¹SimilarWeb, unique users de-duplicated monthly, March 2022.

from 2007 to 2019, for a total of approximately 3 million reviews. Since the format of the data is unstructured, I combine them together to create a panel at the restaurant-month level. Importantly, I used the historical record of reviews to retrieve the average rating of the restaurants in any month between 2007-2019. The Tripadvisor sample contains information on 14,146 establishments with at least one review as of December 2019. Of them, 11,595 had at least one review in May 2017, i.e. the month before the roaming policy was effective.²² Moreover, from Tripadvisor I also gather information on location and attributes of the top-100 tourist attractions in the Province, according to their total volume of reviews.²³ These will be used in the empirical strategy described in Section 4.

The second data source is provided by administrative social security records collected and maintained under restricted-use access at the Italian National Social Security Institute (INPS). For each establishment in the Province of Rome, the records contain information for the last 15 years on location (ZIP code), date of opening and closure, legal status of the firm, monthly number of employees, type of contracts and qualification of the workers, their wage bill and demographics, as well as their full employment history. According to this dataset, 10,391 restaurants operated in the Province and had an active profile at the Social Security Institute in at least one month between 2015 and 2019.²⁴

The third data source contains proprietary annual information on income statements and balance sheets originally collected and maintained at the Italian Business Registry (Chamber of Commerce) and accessed through the Cerved database.²⁵ This dataset provides information on revenues, costs, profits and other financial indicators, and it covers most of those firms with an LLC proprietorship status.²⁶ In particular, almost 5,000 restaurants in the Province were obliged to report their financial information to the Registry at any point in time between 2015 and 2018, which is the last available year.

²²It is worth mentioning that having a Tripadvisor profile with a positive number of reviews at a particular point in time does not necessarily imply that a restaurant is an active business at that time. For instance, it might be the case that the restaurant has closed, but the Tripadvisor profile still exists.

²³I consider as tourist attractions those activities that on Tripadvisor belong to the categories "Sites of interests" and "Monuments". With almost 128,000 as of 2019, the Colosseum is the most-reviewed attraction, while the National Roman Museum ranks 100th on the list, with almost 600 reviews.

²⁴I use information on the primary activity of the firm (ATECO code) to identify restaurants. Particularly, I restrict the attention to the following ATECO codes: 56.10.11 (dine-in restaurants), 56.10.12 (agriturismi), 56.10.20 (take-away restaurants), 56.10.30 (bakeries).

²⁵Particularly, I access the version of Cerved data that is available at the Social Security Institute in Rome, where the last available year is 2018.

²⁶In the restaurant industry in the Province of Rome, LLC companies represent about 57% of the total. These businesses are owned by shareholders, who have limited personal liability for business related debts and are required by the law to report financial statement information at the Chamber of Commerce on an annual basis. By contrast, firms with no financial data are usually unlimited liability partnerships and sole proprietorship businesses, which are generally smaller and more likely to be family-owned restaurants.

3.3 Dataset construction

To conduct the empirical analysis, I matched the Tripadvisor sample with social security and financial records. Combining crowd-sourced data with administrative archives is challenging because of the very different nature and confidentiality protocols of the two sources. Specifically, in performing such a matching I faced two main obstacles, namely (1) the anonymity of the administrative records and (2) the lack of official business identifiers in the Tripadvisor data. Regarding the former, access to both INPS and Cerved databases was granted under a specific program (VisitINPS).²⁷ The program requires researchers to conduct the empirical analysis at the data center in Rome, where they obtain *de-identified* information on employers and employees. Particularly, names, addresses and unique business identifiers of the firms – i.e., the VAT codes – remain unknown to the researchers for confidentiality purposes. On the other hand, Tripadvisor records do contain names and addresses of the restaurants, but not their unique business identifiers. Hence, the information was incomplete on both sides.

To overcome the limitation, I purchased additional data from the Italian Business Registry containing names, addresses and VAT codes for all the restaurants in the Province. I then used the name and address (previously processed by Google API for text harmonization) to assign a VAT code to as many restaurants as possible in the Tripadvisor sample. For restaurants that could not be matched using the name and address, or for which the matching precision was low, I tried to manually collect the VAT codes from their websites or from the pictures of receipts posted by the clients on Tripadvisor/Google. This two-step matching procedure resulted in about 6,000 Tripadvisor restaurants with an associated VAT code. Of them, 80% were matched using the name and address of the firm, while the remaining 20% were matched manually.

Because of their high resolution, the Tripadvisor data could not be imported – as they were – in the servers of the data center. In fact, importing external records is subject to strict rules for confidentiality concerns, to avoid that researchers could identify individual firms from the data. To comply with this requirement, I selected only the most important Tripadvisor variables and simplified the majority of them through categorization (e.g., grouping continuous variables in a limited number of categories). Eventually, this simplified version of the Tripadvisor dataset could be imported in the INSP servers and matched with the social security archives through the previously associated VAT codes.²⁸ In particular, the

²⁷In compliance with the program requirements, most of the empirical analysis presented in the paper has been carried out at the data center in Rome, and no data has left the center except for the output tables and figures reported in the paper. Official information on the program is available here <https://www.inps.it/dati-ricerche-e-bilanci/attivita-di-ricerca/programma-visitinps-scholars>.

²⁸The main data import process took place in early 2019. For this reason, imported data on reviews, ratings and replies from Tripadvisor cover until December 2018.

final matched Tripadvisor-Social Security sample comprises 5,472 firms that operated in the industry at any point in time between 2015 and 2019.²⁹ This sample represents almost 53% of the total number of active businesses in that period and it is employed in the market-level analysis to assess how entry/exit dynamics shape the composition of the restaurant industry. Moreover, among the matched restaurants, 4,628 had a Tripadvisor profile with at least one review (and, therefore, a rating) in May 2017. I employ this sample in the firm-level analysis.

3.4 Summary statistics

Table 1: Summary of firm-level outcomes

	Firms	Period: Jan 2015 - Dec 2019						Pre-policy
		Obs	Mean	SD	Min	Median	Max	Mean
N. of monthly employees	4628	219835	5.69	5.50	0.0	4.0	29.0	5.55
Annual revenues (Thousand, €)	2043	6677	692.18	1065.00	5.0	394.0	8752.0	646.60
Monthly working days	4628	219835	92.13	102.04	0.0	58.2	1922.9	90.96
Working days per worker	4517	197194	15.66	5.84	0.1	15.6	185.9	15.86
1 if firm exits ($\times 100$)	4628	219835	0.41	6.36	0.0	0.0	100.0	0.33
1 if firm hires worker w/ previous experience in restaurants	4628	219835	0.08	0.28	0.0	0.0	1.0	0.08
1 if firm hires worker w/o previous experience in restaurants	4628	219835	0.06	0.23	0.0	0.0	1.0	0.06
Months of experience in restaurants of newly-hired employees	3550	30133	14.46	22.96	0.0	3.8	157.0	13.01
Months of experience in restaurants of quitting/fired employees	3584	30911	27.21	29.83	0.0	17.0	152.0	25.12
Average daily salary (€)	4558	200402	66.60	19.12	24.6	61.1	156.8	64.88
Average 5-month Tripadvisor rating	4373	147274	3.96	0.65	1.0	4.0	5.0	3.98
N. of 5-month replies to reviews	4377	146713	2.46	11.47	0.0	0.0	313.0	2.56
N. of monthly Tripadvisor reviews	4572	178425	5.70	12.51	0.0	3.0	1110.0	6.18

Each observation is a restaurant-month-year, with the exception of revenues, which are observed at the restaurant-year level up to 2018. Data on Tripadvisor reviews, rating and replies refer to the period between Jan 2015 and Dec 2018. Daily salary is adjusted for part-time workers so to reflect the full-time equivalent salary.

Table 1 shows descriptive statistics for the 4,628 matched restaurants with available Tripadvisor rating at the time of the roaming policy. For the main outcome variables, the table reports a series of statistics referring to the Jan 2015 - Dec 2019 period, as well as, for the sake of comparison, their mean in the pre-policy period (Jan 2015 - May 2017). The

²⁹To minimize the risk of measurement error due to misreporting in the social security data, before conducting the analysis I trimmed observations with a number of employees above the 98th percentile. The final sample does not include these observations.

figures indicate that the average restaurant in the sample is a small business, with less than 6 monthly employees and an annual revenue just below 700 Thousand Euros. Its employees work, on average, almost 16 days per month, and their adjusted full-time-equivalent gross salary is about €67 per day. During the period of interest, 8% of the times the average establishment hires a worker with previous experience in the restaurant industry and, when it does, the new employee has worked about 14.5 months in the sector. The 5-month rolling average rating that the typical restaurant obtains on Tripadvisor is almost 4, and the number of 5-month total replies to online reviews is 2.5.

To address concerns on the potential bias in the analysis introduced by the matching procedure, Appendix Table D1 compares the main descriptive statistics of the matched sample with those of the entire Tripadvisor and Social Security datasets, separately. While matched restaurants tend to be slightly larger in size, as well as closer and more exposed to tourist attractions than the average restaurant in the Province, they also appear to have similar Tripadvisor ratings and price categories, recruit equally-experienced workers, and pay comparable salaries. Overall, this evidence seems to discard the possibility that results could be systematically driven by sample selection.

3.5 The roaming policy and the use of Tripadvisor

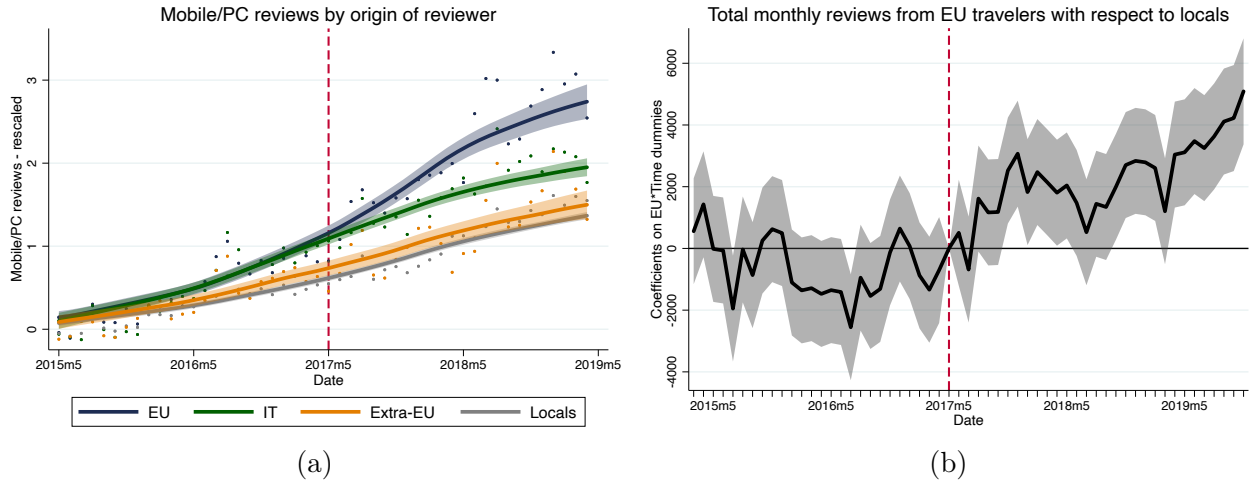
As the costs of mobile internet falls, its use is expected to increase. Consumers with free internet access have the possibility to search and verify products online before purchasing. Tripadvisor data allows to study the reviewers' behavior across types of device and nationality. Although Tripadvisor contributions reflect the supply of reviews and not necessarily their consumption, in the absence of better data on the demand side, I employ them here as a proxy for overall usage of the platform.³⁰

Panel (a) of Figure 2 shows the change in reviewers' behavior over time across device and origin of the reviewer, which is proxied by the language of the review. The picture points out a shift from PC- to mobile-based contributions following the implementation of the roaming policy (the red dashed line). Importantly, this effect is remarkably visible only for EU tourists but not for Italians, extra-EU travelers and locals, who were not deliberately targeted by the new regulation. Regression analysis confirms the visual results. Appendix Table D2 directly compares the posting behavior of EU, extra-EU and Italian travelers with that of the locals. After the policy, users from EU countries became 1.4 times more likely to post reviews on their mobile devices as opposed to PC, while no significant change occurred for extra-EU and

³⁰Reviewers are likely to be a subset of the total users (visitors) of Tripadvisor, as posting reviews entails an additional effort that not all users are willing to bear. Hence, finding evidence on changes in reviewers' posting behavior likely implies that similar changes hold, more generally, for the broader set of users.

Italian users. The table also shows that the absolute number of monthly reviews posted on mobile devices by EU travelers increased by approximately 500 reviews per month after the policy, compared to the locals.

Figure 2: The roaming policy and the use of Tripadvisor



Notes to Panel (a): Data on 14,146 restaurants with at least one review as of December 2019. Dots represent the monthly ratios, lines depict local polynomial fits with 95% confidence intervals. Values are re-scaled so that they are equal to 0 at the beginning of the period.

Notes to Panel (b): The graph reports estimated coefficients on the interactions between EU-dummy and time dummies, from a regression where each observation is a region of origin-month-year. The gray area reports 95% confidence intervals.

These patterns are not necessarily and exclusively driven by PC-to-mobile substitution. Panel (b) of Figure 2 shows event-study estimates for the total (mobile+PC) number of reviews posted by EU users compared to the locals. While before the policy total contributions from both categories displayed similar trends, the volume of monthly reviews from EU travelers significantly and steadily increased after May 2017. Importantly, as Appendix Table D3 and Figure C1 show, these results are unlikely to be driven by a discontinuous increase in international tourist flows toward Italy around the time of the policy. Overall, this evidence suggests that the new regulation provided an abrupt and arguably exogenous source of variation in the use of Tripadvisor services by EU travelers.

4 Empirical strategy

To estimate the demand and supply effects of increased access to information from online reviews, I combine the temporal variation induced by the policy with the spatial variation in restaurants' exposure to tourist clientele. The basic idea is that restaurants that more frequently cater to tourists are also more likely to be affected by the roaming regulation, as a larger share of their clientele experiences the decrease in mobile internet tariffs. For instance,

in the 2.5 years preceding the regulation, Tripadvisor reviews from EU travelers accounted for about 30% of the total volume in restaurants located in the most touristy areas of the Province, while for less than 1.5% in the least touristy ones.

4.1 Restaurants' exposure to tourists

I take advantage of the granularity of my data and construct two measures of exposure to tourist clientele that account for the intensity to which each restaurant is potentially affected by the policy. I then use such measures to identify the parameters of interest. In both cases, I rely on the location of a restaurant with respect to tourist attractions to predict the composition of its clientele.

The first measure aims to capture the probability that a tourist finds a restaurant while walking away from an attraction site. To build this measure, I consider the top-100 attractions in the Province of Rome, according to their total volume of Tripadvisor reviews. For each attraction, I identify the closest Tripadvisor restaurants around it, and then use the Google Maps API to construct the shortest walking route from the attraction site to each of these restaurants. The procedure generates the partial road network around every attraction. I then assume that tourists follow a *random walk* while they move away from the attraction site, which allows me to assign equal conditional probabilities to every road at a same junction. Finally, I compute the joint probability to find the restaurant(s) located at any point along the network as a product of the conditional probabilities attached to all the consecutive roads leading to that point. The procedure, which is described in details in Appendix B.1, provides a continuous probability measure $P(i) \in [0, 1]$ that reflects the chances that restaurant i is visited by tourists while they move randomly toward the periphery of the road network, starting from the attraction site. Hence, by construction, this quantity only depends on (1) the location of the restaurant with respect to its closest tourist attraction, and (2) the shape and density of the road network around it.³¹

Appendix B.2 shows that such probability is positively associated with the average share of reviews from tourists, while it is negatively correlated with the average Tripadvisor rating of restaurants, consistently with theories on asymmetric information, repeat purchases and product quality (Cooper and Ross 1984; Riordan 1986). Moreover, I investigate the robustness of my procedure to different data and assumptions. First, instead of focusing only on the shortest path, I also include all alternatives routes provided by the Google Maps API in the

³¹The advantage of this approach is that it relies exclusively on location parameters. Alternatively, one could use other information contained on Tripadvisor, such as the origin of reviewers, to determine the level of exposure to tourists for each restaurant. However, such information is the result of past consumption patterns and reviewers' behavior that might interplay with the policy, influencing future consumers' decisions on a restaurant regardless of its actual level of exposure to tourists.

computation process. Second, rather than imposing equal conditional probabilities (random walk assumption), I assume tourists form educated guesses on which path to follow, based on importance (frequency) of each road. These procedures are explained in Appendix B.1, and the resulting probability measures will be used in the analysis to conduct robustness checks.

The probability measure described above varies across restaurants, which is an attractive feature to study firm-level response. Such a granular level of variation, however, does not allow to identify the aggregate (market-level) effects of the policy on the industry composition. For this purpose, I focus on the ZIP codes in the province of Rome, and construct an alternative measure of exposure to tourists at that level. Particularly, I focus on the number of top-100 tourist attractions in each ZIP code. In turn, this measure reflects the potential exposure of all restaurants in a ZIP code to tourist clientele and, therefore, to the change in internet tariffs induced by the policy. Among the 127 ZIP codes in which I observe one or more restaurants of my sample, about 25% contain at least one tourist attraction, with the most touristy ZIP codes containing 25 sites.

4.2 Identification

The basic idea behind the identification strategy is to compare the evolution of firm-level and ZIP-level outcomes before and after the policy across firms/ZIP codes that are differentially exposed to tourists, and therefore to the change in the roaming tariffs.

4.2.1 Firm-level outcomes

The firm-level analysis employs the first measure of exposure to tourist clientele, i.e. the probability $P(i)$ previously defined. Appendix B.3 shows that – because of the composition of their clientele – only restaurants with a sufficiently high probability are potentially affected by the policy, as both the pre-policy shares of EU reviews and their change across devices (from PC to mobile) after the policy are significantly higher for restaurants with probability values above the median. Thus, the benchmark empirical specification of the paper relies on these facts to identify two equally sized groups of restaurants: the treatment group, composed of restaurants with a probability value above or equal to 0.17%,³² and the control group with the remaining restaurants. Specifically, I consider observations within a symmetric time-window around the policy (i.e., Jan 2015 - Dec 2019),³³ and estimate the following

³²This is the median in the sample of 4,628 matched restaurants used in the firm-level analysis. For the sub-sample of restaurants with available revenue data (N=2,043), I use the respective median of the probability measure in the sub-sample, which is 0.35%.

³³With the exception of financial and rating data, which are only available up to 2018.

Difference-in-Differences model:

$$y_{i,t} = \beta Tourist_i \times Post_t + \alpha_i + \gamma_t + \phi \mathbf{x}_i \times Post_t + \varepsilon_{i,t} \quad (19)$$

where i is the restaurant, and t is time. Depending on the outcome, the analysis is conducted at the monthly or yearly level. $Tourist_i$ is a binary variable taking value 1 if the measure of tourist exposure $P(i) \geq 0.17\%$ (or 0.35% in the sub-sample with available revenue data). $Post_t$ takes value 1 after the policy, that is for t after May 2017 when outcomes are observed at monthly frequencies, while for t after 2016 when outcomes are annual.³⁴

α_i and γ_t represent restaurant and time fixed effects, respectively. Their inclusion allows controlling for both time-invariant firm-level characteristics and aggregate trends (such as seasonality) that might affect the outcome $y_{i,t}$ while being simultaneously correlated with the main independent variable, $Tourist_i \times Post_t$. Nevertheless, there is still the possibility that some demand- and supply-side factors might influence the outcomes of interest over time, while being simultaneously correlated with the main independent variable. To account for such potential endogeneity issue, vector \mathbf{x}_i includes a series of time-invariant and predetermined restaurant-specific characteristics, which – once interacted with $Post_t$ – are allowed to have different impacts on the outcomes over time. In particular, in all regressions I control for the distance (in km) of the restaurant to its closest attraction to account for factors, other than the presence of tourists, that correlate with proximity and could affect restaurants' and consumers' decisions.³⁵ It is worth mentioning that, once I control for the proximity to the attraction, the probability measure $P(i)$ mainly captures the "visibility" of a restaurant, i.e. whether the place is easy or difficult to be discovered by a tourist due to the shape and density of the road network. Moreover, other controls include restaurant price categories, a dummy indicating whether its cuisine is Italian or not, indicators for the concentration of restaurants within a 400-meter radius (reflecting the level of competition), indicators for the volume of reviews to the closest attraction (capturing the popularity of the whole area, potential congestion and rental costs), the classification of the main economic activity of the restaurant (Ateco code) and its legal status (e.g., LLC vs sole proprietorship).³⁶ Appendix Table D4

³⁴In the yearly analysis, year 2017 is assumed to be fully treated even if the policy was effective in June. If anything, this should reduce the size of estimated coefficients, thus providing a lower-bound for the effect of the policy.

³⁵Examples include rent costs that tend to be higher closer to attraction sites, or congestion (in fact, restaurants in touristy areas can easily be overcrowded, thus leading to longer waiting times, more noise, and worse service).

³⁶Although most of the control variables were originally continuous (or categorical with many values), their simplified versions are used in the analysis. In fact, importing external rich data in the INPS servers was not allowed for confidentiality concerns, as the researcher could exploit the high-dimensionality of the dataset to identify specific firms and their records. Therefore, I had to re-categorize the original variables before

reports the list of independent and control variables along with their descriptive statistics. Finally, in all regressions, I also include ZIP-code linear time trends, as well indicators for the distance to Rome city-center, to account for potentially diverging patterns in the outcomes across areas of the Province that are subject to different exposure to tourist demand and municipal regulations.³⁷ I cluster the standard errors at municipality level (86 clusters) to account for serial and spatial dependence in the errors.³⁸

Theory described in section 2 posits a differential impact of a reduction in search costs on demand and production choices across restaurants selling *ex-ante* different qualities. While demand for higher-quality products is expected to increase more, firm exit and quality-upgrading should be more prevalent among lower-quality restaurants. To empirically analyze the changes in the outcomes along the quality gradient, I estimate model (28) on different samples. First, I study the overall impact focusing on all matched restaurants with available Tripadvisor rating at the time of the policy (N=4,628). Second, I use the tertiles of such average rating to split the sample in three sub-samples of equal size and estimate the model on each group, separately. Appendix figure C2 shows the overall rating distribution, and highlights the three subgroups of interest: low-rating restaurants, with rating < 3.85 ; mid-rating ones, with rating $\in [3.85, 4.25)$; high-rating ones, with rating ≥ 4.25 .³⁹ It is worth mentioning that Tripadvisor does not display the average rating of a restaurant, but rather its rounded value.⁴⁰ Therefore, these three groups contain restaurants whose displayed ratings are approximately below, around, and above 4, respectively.

By estimating (19) via OLS, the coefficient of interest β reflects the change in the outcomes before/after the policy that restaurant more exposed to tourists experience with respect to those with lower probability values. In order for β to have a causal interpretation, the identification assumption requires that changes in the outcomes across the two groups of restaurants would have been the same in the absence of the policy. This so-called parallel trends assumption entails that the two groups are, on average, comparable over time and that the policy is exogenous with respect to other factors, such as seasonality, tourist flows composition and anticipation effects. I conduct a number of placebo exercises to provide plausible evidence in support of this assumption. These include (i) event study estimates, where the dummy variable $Tourist_i$ is interacted with semester dummies, which allow to both

importing them. Importantly, being these controls, their simplification should not crucially affect the results.

³⁷In Italy, sanitary and hygienic regulations of the restaurants as well as their structural standards (such as capacity and equipment) are generally established by the municipal councils.

³⁸I provide robustness of the estimates to a different level of clustering, using ZIP codes.

³⁹In the sub-sample with available revenue data (N=2,043), the rating tertiles are 3.80 and 4.20.

⁴⁰In both Tripadvisor and Yelp the average rating is rounded at the nearest half integer. So for example, a 3.73 average rating would be rounded to 3.5. Some papers like [Farronato and Zervas \(2019\)](#) and [Luca \(2016\)](#) take explicit advantage of this feature in their identification strategy.

study the timing of the impacts after the policy, and check for the presence of differential trends in the outcomes in the pre-policy period; (ii) a series of permutation tests, where the effect of several placebo policy-dates between 2012-2016 is assessed; (iii) specific placebo policy-dates coinciding with the months of May in years 2013-2016 to explicitly test whether the start of the tourist season could explain the main results.

Finally, there is still the possibility that online information from mapping apps⁴¹ helps tourists navigate the streets around attractions, allowing them to discover less visible restaurants – e.g., those around the corner or in certain hidden alleys of the city center –, which would have not been visited otherwise (e.g., as suggested by Ghose et al. 2013 and Dall’orso et al. 2016). Thus, I take advantage of the granularity of my probability measure to study the potential reallocation of consumption over space, from highly visible establishments to more hidden restaurants that are nevertheless easy to reach (i.e., within walking distance) for tourists. To do so, I allow for (28) to take a more flexible form, where I use deciles/quantiles of $P(i)$ instead of the dummy variable $Tourist_i$, and interact them with $Post_t$. I display these results in a series a figures.

4.2.2 ZIP-level outcomes

To study the aggregate effects of the policy on the distribution of equilibrium qualities in the industry, I group establishments at the ZIP-code level and exploit the variation in the number of tourist attractions to proxy for exposure to tourist clientele (as described in 4.1). In this setting, a Diff-in-Diff approach would compare changes over time across ZIP codes with a higher and lower number of attractions. Particularly, I focus on the matched sample of restaurants irrespectively of their presence on Tripadvisor at the time of the policy (N=5,472)⁴² and, similarly as before, I consider observations between January 2015 and December 2019 and estimate the following equation:

$$y_{z,t} = \beta Attractions_z \times Post_t + \alpha_z + \gamma_t + \phi \mathbf{x}_z \times Post_t + \varepsilon_{z,t} \quad (20)$$

where z is the ZIP code, and t is time, measured in months. $Post_t$ takes value 1 after May 2017. $Attractions_z$ is a time-invariant variable containing the number of attractions located in z . α_z and γ_t are ZIP-code and month fixed-effects, respectively. To account for potentially diverging trends in the outcomes across different ZIP codes, I also include ZIP-level linear time trends. Moreover, in vector \mathbf{x}_z , I include categorical variables reflecting the average

⁴¹These include Tripadvisor, which has a "find-near-me" option, but also other popular apps such as Google Maps.

⁴²Note that this allows me to study the effects of the policy not only on the exit but also on the entry-type of new restaurants.

distance of restaurants in the ZIP code to Rome city-center, which I interact with $Post_t$ to control for factors, other than the presence of tourists, that correlate with proximity to the main city and might affect consumption and production choices over time. I cluster the standard errors at ZIP-code level (127 clusters) to account for serial correlation in the errors.

By estimating (20) via OLS, the coefficient of interest β reflects the change in the outcomes before and after the policy, across ZIP codes that are more and less exposed to tourist clientele. In order for β to have a causal interpretation, the identifying assumption requires that, in the absence of the policy, the outcomes of different ZIP codes would have changed similarly. To check the plausibility of this assumption, I perform a variety of event-study and placebo estimates similar to those described in the firm-level analysis of Section 4.2.1.

5 Results

This section presents the supply and demand effects of the reduction in consumer information costs from the estimation of the benchmark specifications (19) and (20). Section 6 discusses the plausibility of the identifying assumption for all the outcomes and Section 7 assesses the sensitivity of the main results to alternative specifications, clustering units and measurements.

5.1 Restaurant revenues and size

5.1.1 Main results

Theory presented in Section 2 predicts that higher-quality firms increase their output as a consequence of lower consumers search costs. To test this hypothesis in the absence of data on quantity, I first rely on restaurant revenues as a proxy for output, using the Tripadvisor rating at the time of the roaming policy to proxy for the baseline quality of the restaurant. Particularly, I consider the sample of restaurants with available annual financial information and estimate equation (19). Column (1) of Table 2 shows that, after the policy, sales in more touristy restaurants increased by almost 5% compared to less touristy ones. The estimated coefficient is robust to the inclusion of additional controls (column 2), such as the price category of the restaurant and the type of cuisine, which might be correlated with both revenues and the level of exposure to tourists. The most conservative estimates imply an annual average increase in restaurant revenues of approximately 32.5 Thousand Euros, considering that mean revenue in the pre-policy period was around 650 Thousand Euros.

Columns (3-5) of the table analyze differential effects of the policy across restaurants with *ex-ante* different ratings – i.e., low, mid and high rating –, estimating equation (19) on three sub-samples containing a similar number of restaurants. Coefficients suggest that the overall

Table 2: The impact of the roaming policy on restaurant revenues

	Y=log(annual revenues); years 2015-2018				
	(1) Full sample	(2) Full sample	(3) Low rating	(4) Mid rating	(5) High rating
Tourist*Post	0.047*** (0.012)	0.053*** (0.012)	-0.002 (0.026)	0.033** (0.015)	0.069*** (0.024)
Restaurant & Year FE	✓	✓	✓	✓	✓
ZIP-code*Year	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	6677	6652	2305	2299	2048
Restaurants	2043	2034	696	697	641
Clusters	57	56	39	40	41
Adj. R-squared	0.846	0.847	0.869	0.849	0.782
Mean Y pre-policy	646.6	648.8	977.4	558.0	360.7
DDD <i>p-value</i>				0.962	0.004

Post=1 if date is after 2016. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.80)$, $[3.80, 4.20)$, $[4.20, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-year. The sample includes observations between 2015 and 2018. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

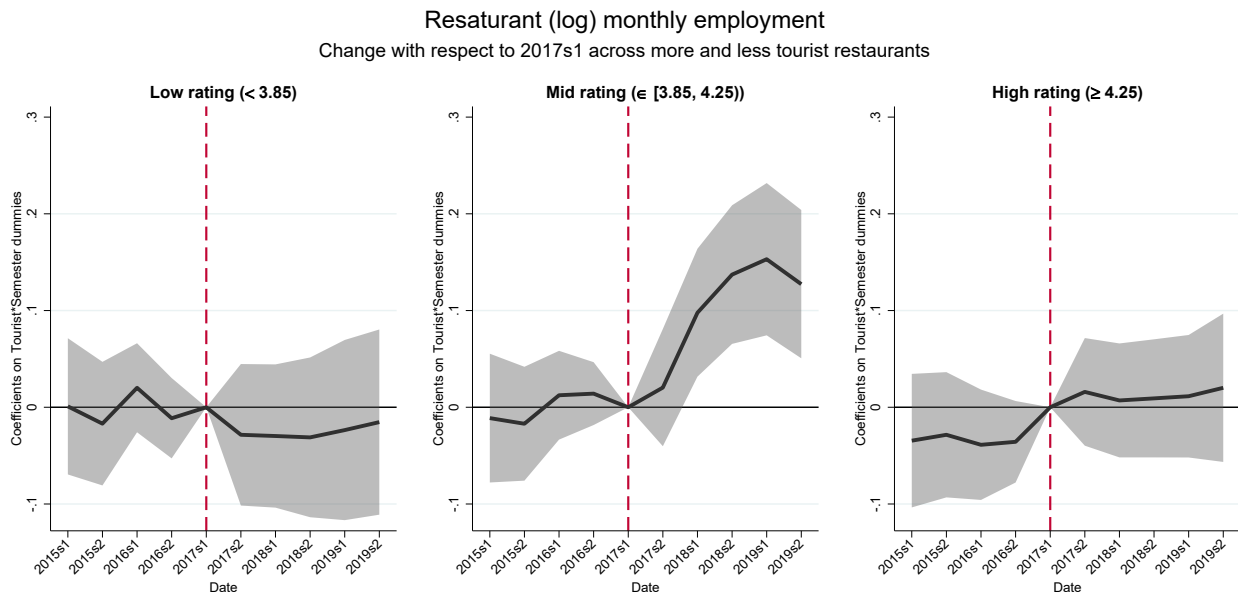
increase in revenues is mainly driven by high-rating restaurants, whose sales expanded by almost 7%. Revenues in the mid-rating category also improved but to a smaller extent, by approximately 3%. By contrast, the policy had no impact on sales in the low-rating category, for which the estimated coefficient is virtually zero and not statistically significant. To test whether the change in revenues in the mid- and high-rating groups is statistically different from the low-rating one, I perform a triple-difference estimation, where dummy variables for mid- and high-rating categories are interacted with $Tourist \times Post$. The last row of columns (4-5) report the p-values of these coefficients, which confirm a positive revenue gradient along the rating dimension, with the change in high-rating restaurants being significantly different than that in the low-rating ones.

Data on revenues might be subject to measurement error, for instance due to firms misreporting their sales in the attempt to pay lower taxes. Therefore, I complement the analysis of restaurant output using monthly employment records.⁴³ To some extent, changes over time in the number of employees – i.e., firm size – reflect the variation in the restaurant’s ability to attract clientele and fill-up the tables. However, the relationship between output and firm size is not necessarily linear (Basu and Fernald, 1997), especially when firms face capacity constraints, which likely imply decreasing returns to labor. In the case of restaurants,

⁴³Labor information is generally more difficult to cover up and misreport to the authorities compared to financial data.

such constraints arise because of the narrow time-windows to serve a meal (launches and dinners) and limited physical space. In practice, an additional worker would not be much productive when all the tables are already filled-up and clients have to wait in line outside of the restaurant for the next available seat. Conscious of this potential limitation of labor data, I estimate the effect of the policy on the (log) number of employees for all restaurants with available Tripadvisor rating at the time of the regulation. Figure 3 shows event-study estimates from separate regressions on the three sub-samples corresponding to the different rating categories previously defined. At the same time, Table 3 reports the regression output.

Figure 3: Event-study estimates for restaurant employment



Notes: The graph reports estimated coefficients on the interactions of Tourist*Semester dummies from three separate regressions where each observation is a restaurant-month-year. All controls and fixed-effects from the main analysis are included. The omitted semester is 2017s1. Tourist restaurants are those with a measure of exposure above the median. The sample includes observations between Jan 2015 and Dec 2019. Shaded areas depict 95% confidence intervals.

In line with findings on restaurant revenues, after the policy, total monthly employment expanded by approximately 4% in more touristy restaurants. The estimated coefficient does not change when additional controls are included in the regression (columns (1-2) of Table 3). Figure 3 reveals that the mid-rating category is mostly responsible for the overall increase. Here, on average, monthly employment grew by 10% after the policy, implying an average increase in the restaurant size by more than 0.5 workers, when compared to the pre-policy mean. The event-study estimates also suggest that such labor expansion did not take place immediately, but it rather happened around 6-12 months after the policy. This suggests some delay either in the consumer learning process or in the ability of restaurants to adjust their factors of productions when they experience boost in demand. Moreover, while revenues in the high-rating category expanded, labor did not change significantly. The estimated coefficient is

Table 3: The impact of the roaming policy on restaurant employment

Y=log(monthly employees); Jan 2015 - Dec 2019					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.043** (0.017)	0.042** (0.020)	-0.024 (0.019)	0.103*** (0.031)	0.041 (0.038)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	219835	217622	72133	76920	68569
Restaurants	4628	4576	1490	1571	1515
Clusters	86	86	59	71	71
Adj. R-squared	0.779	0.778	0.759	0.793	0.769
Mean Y pre-policy	5.5	5.6	6.9	5.7	4.0
DDD <i>p-value</i>				0.089	0.065

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

around 4%, yet it is not statistically different from zero at any conventional confidence level. This result can signal the presence of decreasing returns to labor in the restaurant industry. Particularly, high-rating restaurants were likely to be popular among Italian tourists and locals even before the roaming policy, and therefore were already producing at full capacity. The additional demand increase that they get from EU travelers translates into higher revenues, but not into more workers. Finally, and consistently with the revenue analysis, low-rating restaurants do not exhibit any significant change in their size. If anything, the sign of the estimated coefficient is negative (-2.5%) but not statistically different from zero. The last row of columns (4-5) also suggests that the positive trends in employment for mid- and high-rating restaurants are statistically different than those in the low-rating category.

5.1.2 Discussion and additional findings

The evidence on revenues and employment presented so far suggests that, because of the cheaper information available to consumers, restaurants with *ex-ante* a better online reputation on Tripadvisor – namely with a rating around 4 or above – attracted new clients and grew in size more than those with worse ratings (below 4). These findings are consistent with those from the previous literature (e.g., [Anderson and Magruder 2012](#); [Chevalier and Mayzlin 2006](#);

Lewis and Zervas 2019; Luca 2016),⁴⁴ and add to this existing work providing new empirical evidence on the general effects of online word-of-mouth on firm employment.

The fact that gains at the top of the rating distribution are not symmetrically compensated by losses at the bottom could be explained by several reasons. One is market expansion, which is consistent with the average increase in revenues/employment found on the entire sample (e.g., columns (1-2) of Tables 2 and 3). Aggregate demand expansion could occur, for example, if some consumers start substituting food from supermarkets with meals at the restaurants. However, such dynamic is unlikely to be the exclusive reason underlying the overall positive effects of the policy. Another possible explanation is demand substitution from restaurants with no Tripadvisor account (which are out of the sample and therefore not observed) to those with an active profile (in-sample). Nevertheless, even this type of substitution should not play a major role, as the greatest majority of the restaurants in the Province was already on Tripadvisor around the time of the policy.

Alternative explanations bring into play supply-side dynamics rather than market expansion. For example, firm exit (which is discussed in Section 5.2) might lead to a reduction in the total number of players in the market, leaving more clients – and therefore more revenues – to the surviving restaurants even if aggregate demand does not change. Moreover, upward price adjustments in high-rating restaurants could explain the overall larger revenues. This is in line with the evidence on profit margin reported in Appendix Table D5, which shows that profits increased after the policy only in the high-rating category. In fact, these restaurants could benefit from their online reputation to raise their market power – most likely, they had their tables already filled-up before the new regulation –, and eventually increase their markups without losing much of their clientele. Nevertheless, the remarkable growth in employment among mid-rating establishments clearly indicates that more than just a price adjustment is going on in this category, and some demand-side dynamics must be driving their expansion. Unfortunately, my data does not allow to disentangle the specific mechanism behind the overall positive effects of the policy, and all these hypotheses remain equally plausible. Regardless of which one prevails, my results speak in favor of the first theoretical prediction of the model: as a consequence of lower costs for consumers to learn about product quality, demand to better-quality producers increases.

So far, I relied on the extensive margins of employment – i.e., the total number of workers – to measure restaurant size and proxy for output. Table D6 in the Appendix presents the results using the (log) number of total working days, which also capture adjustments at the intensive

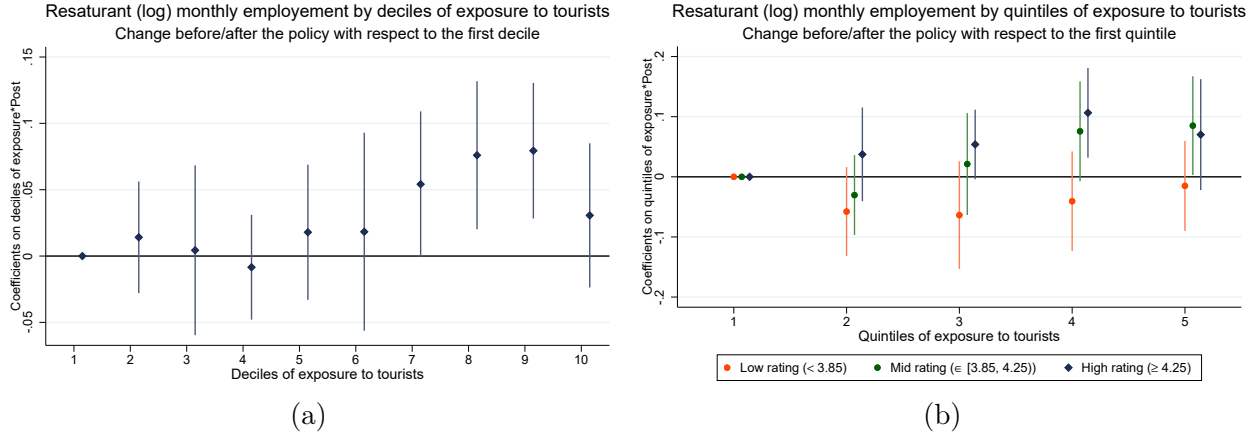
⁴⁴For example, using data on several online platforms such as Yelp, Tripadvisor, Expedia and Hotels.com, Lewis and Zervas (2019) and Luca (2016) have found that a one-star increase in rating leads to a 5-9 percent increase in restaurant/hotel revenues.

margins. Coefficients are in line with the previous ones, with some additional evidence suggesting negative and significant effects (at the 10% level) in low-rating restaurants, where the number of working days shrank by almost 7% after the policy. Such a reduction might be the result of a negative demand shock that these establishments experienced. Moreover, to isolate changes at the intensive margins only, I consider the number of monthly working days per worker. Appendix Table D7 reveals that, after the policy, each employee in high-rating restaurants worked, on average, 0.4 days more per month, while those in mid-rating ones worked almost half-a-day less. The first finding is consistent with the presence of capacity constraints in high-rating restaurants: rather than hiring additional employees and expand in size, these firms demanded more days of work to their current personnel. The second result is consistent with the view that lower-quality restaurants may attempt at improving their service quality through strategic employment choices, for instance by hiring new dining room staff while guaranteeing them better working conditions (e.g., shorter shifts). Such a mechanism will be covered in detail in Section 5.3.

Previous work (e.g., Lewis and Zervas 2019; Luca 2016) has found that online reputation is more important for independent restaurants, where asymmetric information is more severe compared to chains. My data lack information on resultants' affiliation, but they contain details on their price range (i.e., the market segment). In this respect, cheap (e.g., fast food) and fancy starred places are expected to gain less from the information provided by online reviews than those in the middle segment, even when their ratings are high. For instance, low and middle budget tourists (which represent the majority of visitors) are more willing to substitute a low-price restaurant with a medium-price one, once they are reassured about the good quality of the latter. Yet, at the same time, fine-dining restaurants would remain outside of their consideration set. Table D8 in the Appendix replicates the benchmark estimation for three different price categories and provides some evidence in support of this hypothesis. Particularly, it shows that high-rating mid-price restaurants expanded their total employment by approximately 10% after the policy, while the corresponding coefficients for low- and high-price restaurants are negative and not significant. By contrast, employment decreased in low-rating cheap and expensive restaurants after the policy.

The benchmark findings are robust to different specifications, measurements and samples. For instance, I examine whether my estimates are driven by the specific choice over the construction of the treatment variable *Tourist*. Particularly, rather than identifying just two groups of restaurants according to the median value of the probability measure, I consider its deciles and estimate a more flexible specification, interacting them with the dummy variable *Post*. Besides providing a robustness for my main results, this approach allows to study demand reallocation over space, e.g., from restaurants located in front of tourist attractions to

Figure 4: The impact on restaurant employment across levels of exposure to tourists



Notes to Panel (a): The graph reports estimates on the interactions of deciles of exposure*Post from a regression where each observation is a restaurant-month-year. The first decile is omitted. All controls and fixed-effects from the main analysis are included. Post takes value 1 after May 2017. The sample includes observations between Jan 2015 and Dec 2019. Heteroskedasticity-robust standard errors are clustered at municipality level. Bars depict 95% confidence intervals.

Notes to Panel (b): The graph reports estimates on the interactions of quintiles of exposure*Post from three separate regressions (low, mid, high-rating restaurants), where each observation is a restaurant-month-year. The first quintile is omitted. All controls and fixed-effects from the main analysis are included. Post takes value 1 after May 2017. The sample includes observations between Jan 2015 and Dec 2019. Heteroskedasticity-robust standard errors are clustered at municipality level. Bars depict 95% confidence intervals.

those "hidden" in the surrounding alleys. To some extent, Panel (a) of Figure 4 suggests that such a reallocation is likely to take place. The impact of the roaming policy on employment is not statistically significant for restaurants at the 10th decile of exposure to tourists (the most visible ones), while the coefficients on the 7-8-9th deciles are driving the overall positive results. Moreover, coefficients on lower deciles are remarkably smaller in size, and always insignificant. In a similar fashion, Panel (b) replicates the same exercise across both rating categories and quintiles of exposure to tourists.⁴⁵ Point estimates displayed in the figure are qualitatively consistent with those from the main analysis and confirm that more touristy higher-rating restaurants drive the overall results. A similar conclusion hold for revenues, as discussed in Section 7. This section also conducts additional sensitivity analysis, such as using different clustering units for the standard errors, focusing only on a balanced sample of restaurants that never exit the market after the policy, and using alternative measures of tourist exposures. My results are generally robust to these alternative specifications, reassuring about potential concerns on selection bias and measurement choices. Finally, placebo exercises carried out in Section 6 provide additional evidence in favor of the parallel trends assumption for restaurant revenues and employment.

⁴⁵In this case, I use quintiles in order to have a sufficient and representative number of observations within each pair (*quintile, rating category*).

5.2 Industry composition

The second set of hypotheses presented in Section 2 concerns the supply side, namely: (1) firms’ decisions to stay in the market or not and, conditional on staying, (2) their level of investment into quality. This section covers the former, while the latter will be discussed in Section 5.3. Firm dynamics represents one potential mechanism through which the cheaper access to information from online reviews could affect the overall quality levels in the industry. Theory predicts that when consumers face lower search costs, those firms producing the lowest-quality products are more likely to be pushed out of the market (i.e., a reduction in the adverse selection problem). To empirically test the effects of the roaming regulation on the industry composition and isolate the role of entry/exit dynamics (as opposed to quality upgrading), I track the presence of restaurants in the market over time by rating category. Particularly, I use the official date of registration and termination of the business as recorded by the INPS database to proxy for firm entry and exit, respectively. The analysis is conducted both at the firm and ZIP-code levels.

5.2.1 Firm exit

The firm-level framework described in equation (19) exploits the within-firm variation in the outcomes of interest over time, for the sample of firms with available Tripadvisor rating – and therefore operating in the market – at the time of the policy. As such, this setting only allows to study firm exit, and not entry.⁴⁶ Specifically, I construct a dummy variable that takes value 1 when a firm exits the market and 0 otherwise, and estimate (19) via OLS. Table 4 presents the estimation results of this linear probability model.

Columns (1-2) show that, after the policy, monthly exit rate among more touristy restaurants increased by 0.11-0.16 percentage points, with respect to less touristy ones. Comparing these coefficients with the average pre-policy exit rates (0.3%) reveals that the frequency at which firms leave the market went up by approximately 35-55% during the 30 months after the new regulation. Columns (3-5) decompose the effect across different rating categories, providing a direct test for the theoretical predictions. Column (3) shows that the overall increase in the exit rate is mainly driven by low-rating restaurants: their frequency to exit the market went up more than 0.30 percentage points, which corresponds to doubling the pre-policy average exit rate in this category. At the same time, exit rates in the mid- and high-rating groups were not significantly affected: the estimated coefficients in columns (4-5)

⁴⁶In equation (19), the coefficient of interest on $Tourist \times Post$ cannot be identified if firms’ outcomes are not observed both before and after the policy. Moreover, if a firm enters the market later on, its Tripadvisor rating at the time of the policy would not be available. For these reasons, firm entry will be studied in the aggregate analysis presented later.

Table 4: The impact of the roaming policy on restaurant exit

	Y=1 if firm exits the market; Jan 2015 - Dec 2019				
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.0011*	0.0016**	0.0031***	-0.0000	0.0015
	(0.0006)	(0.0006)	(0.0010)	(0.0009)	(0.0024)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	219835	217622	72133	76920	68569
Restaurants	4628	4576	1490	1571	1515
Clusters	86	86	59	71	71
Adj. R-squared	0.059	0.060	0.058	0.061	0.061
Mean Y pre-policy	0.003	0.003	0.003	0.003	0.004
DDD <i>p-value</i>				0.056	0.558

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

are much smaller in size, and they are not statistically different from zero at any conventional confidence level. Overall, this evidence supports the theoretical predictions of the model and points out that cheaper access to information for consumers, made possible through the access to review platforms, has the potential to push some of the lowest-quality providers out of the industry, alleviating the adverse selection problem in the experience goods market.⁴⁷

5.2.2 Aggregate effects

Does the above result hold in the aggregate, when firm entry is taken into account? To answer this question, I rely on the ZIP-level framework described in equation (20), which provides a more suitable setting to study changes in the industry composition. For each ZIP code/month, I consider the (log) count of active restaurants – of any rating, as well as in the three rating categories previously identified – and regress it on the number of attractions, which is a proxy for exposure to tourist clientele. As in the above analysis, I use the Tripadvisor rating at the time of the policy to proxy for the quality of the restaurant. In addition to that, to measure the quality of the entrants joining the market after the policy and assign them to one of the three rating categories, I use the most recent Tripadvisor rating.⁴⁸ Columns (1-4) of Table 5 present the results.

⁴⁷This result is in line with what Hui et al. (2018) finds to hold in online marketplaces (eBay).

⁴⁸I focus on the most recent rating so to have a sufficient number of underlying reviews to compute it.

Table 5: The aggregate effects of the roaming policy on industry composition

Y=	log(N. of active establishments)				% of active establishments	
	(1) All	(2) Low rating	(3) Mid rating	(4) High rating	(5) Low rating	(6) Mid rating
N. of attractions * Post	-0.004** (0.002)	-0.006*** (0.002)	-0.003 (0.002)	0.001 (0.002)	-0.102** (0.049)	0.010 (0.096)
ZIP-code & Time FE	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓
Observations	7501	7501	7501	7501	7501	7501
ZIP-codes	127	127	127	127	127	127
Adj. R-squared	0.993	0.989	0.985	0.976	0.930	0.882
Mean Y pre-policy	29.90	10.43	10.31	9.16	32.76	34.65

Post=1 if date is after May 2017. Each observation is a ZIP-code-month-year. All regressions include the distance of the ZIP-code to Rome city center interacted with Post. The sample includes observations between Jan 2015 and Dec 2019. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85)$, $[3.85, 4.25)$, $[4.25, 5]$, respectively. If the restaurant entered the market after the policy, the most recent rating is considered. Heteroskedasticity-robust standard errors clustered at ZIP-code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 5: Event-study estimates for industry composition



Notes: The graph reports estimated coefficients on the interactions of N. of attractions * Semester dummies from three separate regressions where each observation is a ZIP-code-month-year. Controls and fixed-effects from the ZIP-code-level analysis are included. The omitted semester is 2017s1. The sample includes observations between Jan 2015 and Dec 2019. Shaded areas depict 95% confidence intervals. Rating is computed at the time of the policy. If the restaurant entered the market after the policy, the most recent rating is considered.

I find empirical support for the hypothesis that lower search costs – even when experienced by only a fraction of the total consumers – can make the industry more quality-oriented. Column (1) indicates that, after the policy, one additional tourist attraction in the ZIP code is associated with a reduction in the overall number of active restaurants by 0.4%. Notably, columns (2-4) show that low-rating restaurants are the main drivers of such effect: their number decreased by 0.6% after the policy, for any additional attraction in the ZIP code. By

contrast, the count of mid- and high-rating restaurants was not significantly altered. The latter result discards the presence of a "superstar effect" in this context, and challenges the view that cheaper access to information should reduce the number of high-demand firms, while increasing their market shares (Brynjolfsson et al., 2010). Most likely, this is due to the peculiarity of the restaurant industry: the presence of (physical) capacity constraints limits the expansion of their output above a certain threshold.

Furthermore, columns (5-6) of Table 5 consider the percentage (expressed in 0-100 points) of active restaurants in each rating category, and show that the percent of low-rating restaurants operating in markets more exposed to tourist clientele shrank after the policy. Column (5) suggests that the presence of one additional tourist attractions in the ZIP code made the proportion of low-rating restaurants decrease by more than 0.10 percentage points. Back-of-the-envelope calculations indicate that the share of low-rated restaurants operating in the most touristy neighborhoods (25 attractions) decreased by 2.5 percentage points after the policy, compared to non-touristy ZIP codes (0 attractions). Figure 5 plots the event-study estimates, which confirm the previous findings and show that the quality distribution changed for the better, with low-rating restaurants leaving room for high-rating ones. These patterns also provide visual evidence in favor of the parallel trends assumption, while additional placebo exercises are discussed in Section 6. Finally, Section 7 shows that the above estimates are robust to different specifications and measurements. All together, these findings suggests that the distribution of equilibrium qualities in the restaurant industry improved because some of the existing tourist traps (low-rating restaurants) were forced to leave the market. The next section examines restaurants' production choices as an additional mechanism for achieving better qualities.

5.3 Restaurant quality upgrading

The last prediction of the theoretical model presented in Section 2 states that reductions in consumer search costs affect restaurants' incentives to improve quality, and more so for lower-quality establishments (i.e., a reduction in the moral hazard problem). To test this hypothesis, I consider several proxies for both input and output quality. Producing high-quality outputs typically requires high-quality inputs (see, e.g., Bastos et al. 2018; Halpern et al. 2015; Hansman et al. 2020; Kugler and Verhoogen 2012). This relationship is also visible in the theoretical model, where at better output qualities correspond higher costs of productions (better inputs), holding firm productivity constant. Empirically, I consider restaurants' hiring decisions over workers with different experiences, as well as their wages, as

a proxy for changes in the service quality.⁴⁹ Moreover, following recent empirical literature (e.g., [Ananthakrishnan et al. 2019](#); [Chevalier et al. 2018](#); [Proserpio and Zervas 2017](#)), I use the online reputation of the restaurant as reflected by the average dynamic Tripadvisor rating to proxy for the quality of the output. While hiring decisions capture a more objective dimension of quality – i.e., that of the factors of productions and, specifically, labor –, online ratings reflect the subjective experience of the consumers with the good. Thus, to some extent, the two sources complement each other.

5.3.1 Hiring decisions and salaries

I take advantage of the employer-employee matched data and investigate if, in their attempt at improving service quality, restaurants are more likely to hire workers with better curricula, as measured by their previous experience in the restaurant sector.⁵⁰ First, I consider the full employment history of every newly-hired employee in my sample of restaurants, and construct dummy variables indicating whether, by the time of their appointment, they had previously worked in the restaurant sector or not.⁵¹ For each outcome, I estimate equation (19) on the entire sample of restaurants, as well as on the three sub-groups corresponding to the different rating categories.

In columns (1-4) of Table 6 the dependent variable is a dummy taking value 1 in months in which the restaurant hires a new employee who had previously worked in other restaurants, and 0 otherwise.⁵² Column (1) indicates that, overall, after the regulation, restaurants more exposed to tourist clientele became almost 1-percentage-point more likely to hire experienced employees, which corresponds to approximately a 10% increase in the pre-policy mean. Consistently with the theoretical prediction, columns (2-4) show that low- and mid-rating restaurants are the drivers of such a change. Their probability to hire workers with better curricula significantly went up by 0.9-1.1 percentage points, an increase of 9-16% with respect to the pre-policy mean. By contrast, the coefficient for high-rating restaurants is considerably smaller in magnitude, close to 0 and not statically significant.

These results could be due to the overall larger employee turnover in lower-rated restaurants,

⁴⁹Along similar lines, [Shin et al. \(2021\)](#) use labor market outcomes to study the impact of the gig economy (Uber and Lyft) on restaurant service quality.

⁵⁰I exclusively focus on the experience dimension of the worker’s curriculum. Unfortunately, other factors (such as education) are not available in the data. Nevertheless, this should not pose a critical obstacle to my analysis, since in the restaurant sector previous experience is likely to be more informative than education to signal the skills of waiters and other room staff.

⁵¹The restaurant sector is defined by firms with ATECO codes 56.10.11 (dine-in restaurants), 56.10.12 (agriturismi), 56.10.20 (take-away restaurants), 56.10.30 (bakeries).

⁵²To facilitate the interpretation of the coefficient estimates, I use a linear probability model (OLS) as the benchmark specification. Coefficients from a Logit model are qualitatively similar and are reported in Table D9 in the appendix.

Table 6: The impact of the roaming policy on hiring decisions (extensive margins)

Y=1 if firm hires worker	<i>with</i> previous experience in restaurants				<i>without</i> experience in restaurants		
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating	(5) Low rating	(6) Mid rating	(7) High rating
Tourist*Post	0.009*** (0.002)	0.009*** (0.003)	0.011*** (0.003)	0.002 (0.004)	-0.006** (0.002)	0.011** (0.004)	0.007** (0.003)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	217622	72133	76920	68569	72133	76920	68569
Restaurants	4576	1490	1571	1515	1490	1571	1515
Clusters	86	59	71	71	59	71	71
Adj. R-squared	0.124	0.143	0.104	0.116	0.049	0.043	0.037
Mean Y pre-policy	0.08	0.10	0.07	0.08	0.06	0.06	0.06
DDD <i>p-value</i>			0.259	0.047		0.000	0.002

The sample includes observations between Jan 2015 and Dec 2019. Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (3-4) and (6-7) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

rather than their recruiting strategy being intentionally targeted at more experienced workers. However, columns (5-6) of Table 6 indicate that this is unlikely to be the case. In fact, the probability of hiring workers with no experience in the industry significantly decreased by 10% after the policy among more touristy low-rating restaurants, while it increased for the mid- and high-rating ones by almost 18 and 12%, respectively, compared to their pre-policy values. All together, these estimates also suggest that while low- and high-rating restaurants seem to focus their recruiting efforts on distinct and opposite types of workers (experienced vs. inexperienced, respectively), mid-rating ones hire from a more heterogeneous pool of candidates.

While the above results assess the impact of the policy on the extensive margins of targeted recruiting strategies (i.e., whether or not restaurants hire experienced workers), consistent findings are obtained when considering the intensive margins of worker experience. In this case, I restrict the attention only to those months in which the restaurant hires/fires an employee, the contract terminates, or the employee voluntarily quits the job. I then measure the cumulative experience of such workers by counting the total number of months they have been employed in the restaurant sector in the past. This way, I can quantify the impact of the policy on the gain/loss in human capital that restaurants face.

Table 7 shows the results. Column (1) indicates that, after the policy, restaurants in

Table 7: The impact of the roaming policy on hiring decisions (intensive margins)

Y=Months of experience in restaurants of	newly-hired employees				quitting/fired employees		
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating	(5) Low rating	(6) Mid rating	(7) High rating
Tourist*Post	1.469* (0.834)	2.977*** (1.083)	0.789 (1.160)	0.465 (0.544)	0.177 (1.034)	-0.440 (1.192)	2.375** (1.181)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	30059	11318	10205	8536	12281	10395	8131
Restaurants	3531	1163	1220	1148	1197	1226	1136
Clusters	76	53	59	61	51	57	58
Adj. R-squared	0.117	0.109	0.117	0.127	0.190	0.170	0.183
Mean Y pre-policy	13.0	13.5	13.5	11.8	25.8	27.0	21.5
DDD <i>p-value</i>			0.034	0.000		0.598	0.460

The sample includes observations between Jan 2015 and Dec 2019. Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (3-4) and (6-7) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

more touristy areas hire workers with additional 1.5 months of previous experience in the industry, compared to less touristy ones. Importantly, columns (2-4) show that low-rating restaurants are the drivers of such a change: after the policy, they hire workers with 3 additional months of experience in the industry, corresponding to a 22% increase with respect to the pre-policy mean. The coefficients for the mid- and high-rating categories are positive but not statistically significant, suggesting that the accumulation of human capital mainly takes place in lower-rated restaurants. By contrast, high-rating establishments appear to loose human capital. Columns (5-7) consider the employment history of those workers who left the firm, either because they decided to quit, their contract expired or they got fired.⁵³ While no effect is detectable for low- and mid-rating establishments, employees that are let go by more touristy high-rating restaurants are, on average, 2.4 months more experienced compared to less touristy ones in the pre-policy period.

Changes in the composition of the labor input quality should be reflected in the firms' production costs. In a competitive labor market, firms must pay higher wages in order to attract employees with better skills. Figure 6 provides graphical evidence on the evolution of

⁵³Note that this definition is intentionally broad, for instance it also includes workers who reached their retirement age. This is done to capture the overall loss in human capital that restaurants experience, by looking at any worker who left the firm, irrespectively of the reason.

average gross daily salaries paid by the restaurants in the three rating categories.⁵⁴ Consistently with the evidence on workers experience presented so far, these event-study estimates point out an increase in the salaries paid to employees of more touristy low-rating restaurants by more than €1 a day. By contrast, salaries in high-rating restaurants decreased by a similar amount, on average, while they did not change in the mid-rating category. At the same time, the figures provide reassuring evidence on the absence of diverging trends in the outcome across more and less touristy restaurants in the pre-policy period. Regression estimates reported in Table 8 confirm the graphical analysis. Salaries in low-rating (high-rating) establishments grew (shrank) by almost 2% (1.8%) with respect to their pre-policy mean. By contrast, no significant change in average salaries is detected in the overall sample and in the mid-rating category.⁵⁵

Figure 6: Event-study estimates for restaurant daily salaries (€)



Notes: The graph reports estimated coefficients on the interactions of Tourist*Semester dummies from three separate regressions where each observation is a restaurant-month-year. Full-time equivalent salary is computed for part-time employees, according to the percentage of the part-time as reported in their contract. All controls and fixed-effects from the main analysis are included. The omitted semester is 2017s1. Tourist restaurants are those with a measure of exposure above the median. The sample includes observations between Jan 2015 and Dec 2019. Shaded areas depict 95% confidence intervals.

All together, these findings provide persuasive evidence that lower information costs for consumers can affect firms' incentives to upgrade product quality through strategic employee turnover, especially for those producers with the highest margins of improvement. In particular, restaurants with initially lower qualities targeted their hiring efforts at better skilled and experienced workers (both at the intensive and extensive margins) and ended-up paying higher

⁵⁴To make the salaries of full- and part-time employees comparable, I compute the full-time equivalent salary for part-time employees, using the percentage of the part-time as reported in their contract.

⁵⁵These results are robust to the use of a logarithmic scale of salaries, as shown in Appendix Table D10.

Table 8: The impact of the roaming policy on restaurant daily salaries

Y=Average daily salary (€); Jan 2015 - Dec 2019					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	-0.010 (0.245)	0.038 (0.257)	1.312*** (0.374)	-0.120 (0.440)	-1.125** (0.448)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	200402	199026	67507	70593	60926
Restaurants	4558	4512	1492	1538	1482
Clusters	86	86	59	71	70
Adj. R-squared	0.467	0.469	0.485	0.465	0.451
Mean Y pre-policy	64.9	64.9	66.0	65.0	63.5
DDD <i>p-value</i>				0.206	0.015

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

salaries. By contrast, restaurants that were already selling higher qualities took advantage of their established online reputation to divest in human capital and save in production costs. Evidence reported in Appendix Table D5 indicates that these decisions eventually impact on restaurants profitability, since – at least among restaurants with available financial records – the profit margin of high-rating establishments grew by 2.5 points after the policy. By contrast, profits in low- and mid-rating restaurants decreased. Finally, it is worth mentioning that these opposite recruiting strategies might also generate human capital flows from high- to low-rating establishments. As Table D11 in the Appendix shows, low- and mid-rating restaurants became more likely to hire workers previously employed in establishments with better Tripadvisor ratings. This evidence offers an optimistic assessment of the possibility of quality upgrading in *ex-ante* worse restaurants through human capital externalities from better producers. The next section provides additional evidence in support of this view.

5.3.2 Tripadvisor rating

In the absence of objective measures of restaurant output quality,⁵⁶ I rely on Tripadvisor rating as a proxy for its reputation dimension. In particular, I compute the moving average of the monthly Tripadvisor rating over dynamic 5-month windows for all the restaurants in

⁵⁶Previous work (e.g., Farronato and Zervas 2019; Jin and Leslie 2003) relied on health inspection scores to measure the hygiene dimension of quality. Unfortunately, these data are not available for Italy.

my sample.⁵⁷ Figure 7 displays event-study estimates across the three rating categories, and shows that restaurants in the low- and mid-rating groups received better ratings after the policy, with peaks reaching almost 0.11 and 0.09 points, respectively. Coefficient estimates of model (19) reported in Table 9 confirm these patterns. After the regulation, the 5-month Tripadvisor rating of more touristy restaurants improved by almost 0.05 points overall (i.e., a 1.3% increase with respect to the pre-policy mean), and by 0.09 points (2.5%) and 0.08 points (1.9%) in low- and mid-rating establishments, respectively. By contrast, the coefficient for the high-rating category is virtually zero and not statistically significant, indicating no change in the online reputation of those restaurants already at the top of the rating distribution.

Figure 7: Event-study estimates for restaurant Tripadvisor rating



Notes: The graph reports estimated coefficients on the interactions of Tourist*Semester dummies from three separate regressions where each observation is a restaurant-month-year. All controls and fixed-effects from the main analysis are included. The omitted semester is 2017s1. Tourist restaurants are those with a measure of exposure above the median. The sample includes observations between Jan 2015 and Dec 2018. Shaded areas depict 95% confidence intervals.

These findings confirm the theoretical predictions of the model and are generally consistent with the evidence on the hiring decisions presented above. Particularly, Appendix Table D12 shows that recruiting workers with previous experience in the restaurant sector is associated with more positive Tripadvisor reviews in the subsequent months. The correlation is even larger when the new employee comes from a higher-rating establishment. By contrast, hiring non-experienced employees has no impact on subsequent rating. These results corroborate the view that better online reputation can be achieved through labor market choices (as in Shin

⁵⁷Fake reviews could potentially represent a concern for measurement (e.g., He et al. 2022). However, the retrospective collection of information from the platform and the effort of Tripadvisor in detecting and removing fraudulent reviews in a timely manner (2021 Review Transparency Report) should minimize the risk of measurement error.

Table 9: The impact of the roaming policy on restaurant Tripadvisor rating

Y=Average 5-month Tripadvisor rating; Jan 2015 - Dec 2018					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.040*** (0.012)	0.049*** (0.012)	0.087*** (0.017)	0.077*** (0.019)	-0.003 (0.012)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	147274	146620	48577	53659	44384
Restaurants	4373	4330	1413	1499	1418
Clusters	86	86	59	70	70
Adj. R-squared	0.503	0.504	0.324	0.251	0.297
Mean Y pre-policy	3.98	3.98	3.51	4.05	4.43
DDD <i>p-value</i>				0.000	0.000

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

et al. 2021), which are, in turn, a consequence of the lower information costs for consumers.

Nevertheless, two facts might appear less obvious. First, both low- and mid-rating restaurants were successful at improving their online reputation by a similar amount despite their diverse recruiting strategies and salaries, which highlighted that low-rating restaurants more intensively targeted experienced workers. A potential explanation behind the rating improvement in the mid category might be the strategic use of management responses to consumer reviews as a way to obtain more positive feedback.⁵⁸ To assess this hypothesis, I construct the dynamic count of online replies over 5-month windows and analyze whether restaurants started interacting more frequently with their reviewers in the attempt to upgrade their subsequent online reputation. Appendix Table D13 shows a significant increase in these replies among restaurants in the mid-rating category, pointing out a potential reason for their reputation upgrading. Another possible explanation for their success is the growth in personnel (more employees) and improvements in working conditions (less working days per worker) discussed in Section 5.1, both of which could have positive effects on the service quality and, eventually, on the customer experience. Finally, a further possibility is that these restaurants started using better raw materials in their kitchens. Although the data do not allow me to test this explicitly, I find that the (log) annual net purchases increased in

⁵⁸For instance, Proserpio and Zervas 2017 find that after responding to reviews on Tripadvisor, hotels' ratings increase by 0.12 points, an effect that is comparable to my estimates.

mid-rating restaurants after the policy (Appendix Table D14), potentially indicating the use of higher-quality ingredients in preparing the recipes. On the other hand, purchases remained the same in the other two rating categories.⁵⁹

The second empirical fact that might be puzzling is the absence of a decline in the online reputation for high-rating restaurants, despite the documented loss in human capital. For them, replies to reviews, expansions in their personnel and the use of better ingredients are not plausible explanations.⁶⁰ An alternative reason, which is in line with the theoretical model, is that these establishments are very capable (efficient) at managing their factors of productions. This efficiency advantage allows them to employ less skilled workers, save in costs and increase profits without compromising output quality.

Finally, for all outcomes discussed above, Section 6 provides evidence in favor of the parallel trends assumption. Moreover, it is worth mentioning that all the above results are not driven by firm selection into exit: even larger coefficients are obtained when restricting the attention to restaurants that did not leave the market after the policy. These sensitivity checks are discussed in Section 7, which also shows that the previous estimates are robust to alternative specifications, clustering units and different measurements.

6 Placebos

This section carries out a series of placebo exercises to assess the plausibility of the identifying assumptions. The first set of exercises aims to address potential concerns about the correlation between seasonality and the timing of the policy. In fact, the new regulation was effective in June 2017, which coincides with the beginning of the tourist season in Italy. It might be that the corresponding change in the volumes and composition of tourist flows drives the above estimates, invalidating their interpretation. In order to investigate this possibility, I focus on the pre-policy period (between May 2012 and May 2017) and perform a variety of regressions using placebo policy-dates coinciding with the month of June – i.e., the same of the regulation – but in the four years preceding the roaming policy. In practice, I regress all the above outcomes on the *Tourist* dummy variable used throughout the paper, interacted here with these four placebo policy-dates, separately. For each policy-date, the sample includes observations within a 24-month window around the placebo policy.⁶¹ Moreover, to replicate

⁵⁹Net purchases reflect any expenditure in inputs other than labor. As such, the variable might also include the purchase of specialized services from online advertising and customer management companies.

⁶⁰Appendix Table D13 shows that, if anything, high-rating restaurants engaged less with reviewers, after the policy. Moreover, as discussed in section 5.1, these restaurants did not significantly employ more workers. Finally, as shown in Appendix Table D14, annual purchases remained the same.

⁶¹For revenues, which are observed annually, I consider 4-year windows around the placebo policy-years 2013, 2014 and 2015. In addition, for industry composition, I conduct the analysis at the ZIP-code level and

the results across different rating-categories, I consider the Tripadvisor rating of the restaurant at the time of the respective placebo policy-date. Table 10 shows an example of the output of this procedure for the (log) number of employees. The estimated coefficients in column (1) are generally small in magnitude and not statistically significant. Moreover, their signs across different rating categories reported in columns (2-4) do not exhibit any systematic and significant pattern. This evidence discards the possibility that results on employment are driven by seasonal peaks.

Table 10: Placebo policies and restaurant employment

Y=log(monthly employees)				
	(1)	(2)	(3)	(4)
	Full sample	Low rating	Mid rating	High rating
Tourist*Post May2013	-0.007 (0.014)	-0.029 (0.018)	0.040 (0.050)	-0.006 (0.025)
Observations	38862	16647	12921	9294
Tourist*Post May2014	0.015 (0.020)	0.030 (0.029)	0.011 (0.017)	0.006 (0.029)
Observations	48795	19572	16664	12559
Tourist*Post May2015	-0.013 (0.011)	0.007 (0.015)	-0.024 (0.015)	-0.023 (0.030)
Observations	58028	22394	19658	15976
Tourist*Post May2016	0.005 (0.015)	-0.018 (0.017)	0.007 (0.019)	0.044 (0.028)
Observations	59571	21195	20219	18157

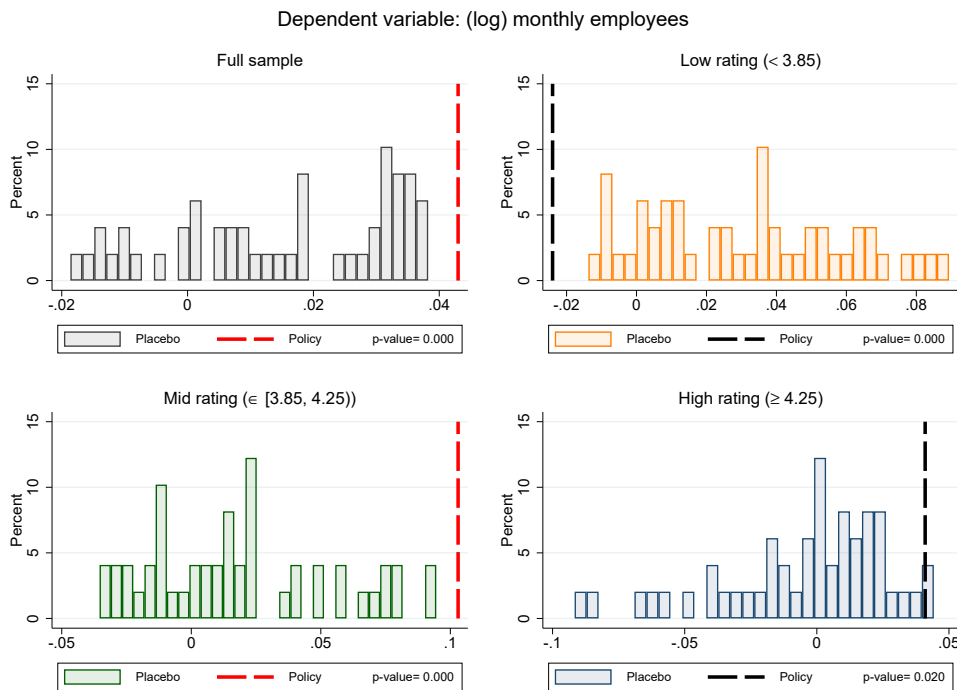
Every row/column is the output of a separate regression where each observation is a restaurant-month-year. Post May $year=1$ if date is after May of the respective $year$. Tourist restaurants are those with a measure of exposure above the median. Heteroskedasticity-robust standard errors clustered at municipality level. Each regression includes all controls and fixed effects from the main analysis. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the placebo policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Tables D15 to D21 replicate the same exercise for the other outcomes, namely, restaurant revenues, exit, industry composition, hiring decisions, salaries and rating. For them, the estimated coefficients on the entire sample of restaurants are generally small and insignificant. The same is true for coefficients in the three rating categories, although there are a few exceptions with some estimates resulting statistically different from zero. However, the signs of significant coefficients have consistently opposite directions with respect to those estimated in the main analysis. Overall, this evidence rules out the possibility that tourism seasonality could drive the main results and corroborates their interpretation as the consequence of lower information costs induced by the policy.

The second set of placebo exercises consists of a series of policy-permutation tests conducted in the period before the roaming regulation (Jan 2012 - Dec 2016) to assess its exogeneity with respect to other potential factors or existing pre-trends in the outcomes that might explain use the number of tourist attractions in the ZIP code to proxy for exposure to tourists.

the observed results. In practice, I replicate the previous exercises for all placebo policy-dates between May 2012 and May 2016 – for a total of 49 regressions for each outcome –, following the approach used to carry out randomization inference in experiments (e.g., [Gerber and Green 2012](#)).⁶² Then, I plot the histograms of all estimated placebo coefficients for the whole sample of restaurants, as well as for the three different rating categories considered in the main analysis.⁶³ For instance, Figure 8 reports the results for restaurant employment, where the vertical dashed lines depict the respective policy coefficient estimated in Section 5.1. Red (black) lines indicate that the coefficient was significant (insignificant).

Figure 8: Permutation test for restaurant employment



Notes: Each panel plots the distribution of coefficients on $\text{Tourist} \times \text{Post-Month}$, where Month is between May 2012 and May 2016, estimated on a sample of observations between Jan 2012 and Dec 2016. Tripadvisor rating and the respective category are calculated in each month. The vertical dashed lines report the actual policy coefficients, as estimated in the main analysis. The line is red when the respective coefficient is significant at least at the 10% confidence level, and black otherwise.

The comparison of the distribution of placebo coefficients with the policy point estimate would speak in favor of the identifying assumption if the policy estimates lie at the extremes of the distributions of placebo coefficients. More formally, I compute the p-value of the permutation test by counting the number of times the placebo coefficients are more extreme than the policy estimate, and dividing it by the total number of coefficients. In this context, low p-values imply that, most of the times, the policy estimates are larger in magnitude than the placebos, alleviating concerns on the endogeneity of the roaming regulation. For example,

⁶²In this case, rather than varying the composition of the control group, I modify the time dummy *Post*.

⁶³I consider the Tripadvisor rating of the restaurant at the time of the respective placebo policy-date.

in each subplot of Figure 8 the p-value is always lower than the conventional 5% level. This means that the estimated 4.2% increase in overall restaurant employment and the 10% effect found in the mid-rating category can be plausibly attributed to the roaming regulation.

I summarize the results for the other outcomes in a series of figures reported in the Appendix (Figures C3 to C8). When the policy estimates are significant, they are always at the extremes of the distribution of placebo coefficients. The associated p-values are consistently small and always below the conventional 5% level, implying that only in very few cases the placebos are larger in magnitude than the estimated policy coefficients.

Finally, additional placebo exercises are reported in the event-study estimates. These graphs can be used to investigate the presence of potentially diverging trends in the outcomes of interest before the regulation was effective. As a result, they provide some evidence on the plausibility of the parallel-trend assumption underlying the empirical strategy of the paper. Figures 3, 5, 6, and 7 reported in the text suggest that this assumption is likely to hold for restaurant employment, industry composition, salaries and rating, respectively. Additional figures reported in the Appendix (C9 to C12) confirm that similar conclusions generally hold for restaurant revenues, exit and hiring decisions, although in some cases these graphs are less clear because of the nature of certain outcomes (e.g., binary variables for exit and hiring decisions). Nevertheless, all together, the above placebo exercises corroborate the identifying assumptions and validate the use of the Difference-in-Differences strategy in this context.

7 Robustness

This section carries out a series of additional estimations to investigate the sensitivity of the main results to different measurements, samples and clustering units. First, a potential concern with the firm-level estimates is that they might be driven by both (1) the definition of the binary variable *Tourist* and (2) the construction of the underlying measure of exposure to tourist clientele $P(i)$, defined in Section 4. To address the first point, I replicate the baseline estimation using a more flexible specification, in which I consider dummies for quintiles of exposure to tourists – rather than the median value – interacted with the variable *Post*. This procedure generalizes the results to study the effects of the policy along a more continuous gradient of exposure and, at the same time, guarantees that estimates remain easy to interpret. Particularly, I show the results using a series of figures, reporting the effects at each quintile (with respect to the first one, which is the omitted category) as well as across the three rating categories. Panel (b) of Figure 4 already discussed in Section 5.1 presents the results for restaurant employment. Consistently with the main analysis, better-rated restaurants at the higher quintiles of the tourist-exposure distribution are the drivers of employment growth.

Appendix Figures C13 to C18 show that similar conclusions hold for restaurant revenues, exit, hiring decisions, salaries and rating, with point estimates being consistently larger for the highest quintiles. This evidence corroborates the benchmark specification and alleviates the concern that the main results are driven by the specific definition of the binary variable *Tourist*.

Moreover, the procedure I adopted to construct the probability measure $P(i)$ could also influence the firm-level outcomes. To address this concern, I study the sensitivity of the main analysis to the use of alternative measures of tourist exposures, which rely on different data and assumptions as explained in Appendix B.1. First, instead of focusing only on the shortest path, I also include all alternative routes provided by the Google Maps API in the computation process. Second, rather than imposing equal conditional probabilities (random walk assumption), I assume tourists form educated guesses on which path to follow, based on importance (frequency) of each road. I then replicate the main estimations using newly-defined *Tourist* dummy variables based on these two alternative measures (as in the main analysis, I use the median value to create the binary treatment indicator). Tables D22 to D33 in the Appendix show that in both cases estimated coefficients are always qualitatively, and often quantitatively, similar to those from the benchmark specification.

In addition, another potential concern is that sorting of restaurants into exit might bias the baseline estimates. In fact, the latter are based on a sample that includes the approximately 560 firms that, at some point after the policy, ceased their operations and left the market. Hence, I replicate the estimations on the sample of restaurants that survived throughout the whole 30-month period after the roaming regulation. Appendix Tables D34 to D39 show that coefficients are very similar to those from the main analysis. Certain effects – such as the hiring of experienced workers and improvements in ratings for low-rating restaurants – are even more remarked, suggesting that, if anything, the presence of exiting firms might attenuate the results.

Finally, my estimates are generally robust to different clustering units. Appendix Tables D40 to D46 use the 127 ZIP codes (that are smaller than municipalities) to cluster the standard errors, and show that – with the exception of restaurant revenues, which are observed at annual frequencies – the significance of the coefficients is not remarkably altered.

8 Economy-wide effects of Tripadvisor

The goal of this section is to recover the economy-wide effects of increasing access to information from Tripadvisor in the experience goods market. In fact, the Diff-in-Diff estimation provides only reduced-form evidence on the impact of the roaming policy on restaurants in the Province

of Rome. On the one hand, the regression coefficients represent intent-to-treat effects of the provision of information, because in the treatment group (identified by the *Tourist* binary variable) only a fraction of the clientele – namely, the EU users – benefited of the cheaper internet costs. Therefore, recovering the treatment-on-the-treated effect is the first step to assess the importance of expanding the access to Tripadvisor for the whole customer base. On the other hand, the benchmark estimation was conducted only on a sample of restaurants, which poses a limit to the generalization of the effects. Thus, re-weighting the estimates is needed to contextualize their magnitudes in the entire Italian restaurant industry.

The procedure requires three additional assumptions:

1. Among *Tourist* restaurants, take-up of the policy was 23%, which corresponds to the percent of Tripadvisor reviews from EU travelers in the post-policy period.
2. Non-tourist restaurants are not affected by the policy.
3. The share of tourist restaurants in Italy is 8%, which corresponds to the fraction of establishments located in ZIP-codes with at least one top-tourist attraction.

Assumption (1) relies on Tripadvisor contributions from Europeans to proxy for their usage of the platform in the post-policy period.⁶⁴ Although a gap between demand and supply of reviews plausibly exists, it is unlikely that it depends on the origin of the reviewers. Hence, the ratio EU/Total contributions should provide a reasonable approximation for the relative usage among Europeans. Moreover, assumption (2) requires that outcomes in the control group (i.e., non-tourist restaurants) do not change after the policy. This assumption is likely to hold for at least two reasons. First, estimates of the policy by deciles/quintiles of exposure to tourists show that effects are generally driven by restaurants at higher levels of exposure. Second, as shown in Appendix Figure C19, de-trended average employment in non-tourist restaurants remains stable after the roaming regulation. Regarding assumption (3), I collect information from Tripadvisor on the top-100 tourist attractions in Italy (based on their total volume of reviews) and then compute the fraction of Italian restaurants that are located in the ZIP-codes with at least one of such attractions.

Finally, I consider the most conservative estimates of the policy on revenues, employment and exit as reported in columns (1-2) of Tables 2, 3 and 4. I divide these coefficients by 0.23 and multiply them by 0.08, and compare them with the aggregate trends in the industry. Results are reported in Table 11, and suggest that promoting access to review platforms has relevant economy-wide consequences on the whole Italian restaurant industry. Back-of-the-envelope calculations point out that reducing the costs for consumers to access Tripadvisor

⁶⁴Disaggregated Tripadvisor usage statistics are not available.

leads to an overall increase in restaurant revenues, employment and exit rate by 1.6%, 1.5% and 0.5 pp, respectively. The first two figures correspond to about 12% and 5% of the overall growth in revenue and employment experienced by restaurants between 2016 and 2019, respectively. While the last figure corresponds to almost 3% of the exit rate faced by the industry during the first year of the Covid-19 pandemic. All together, these results indicate that lower consumer information costs due to review platforms can have real effects on the performance and composition of firms operating in industries generally affected by asymmetric information.

Table 11: Economy-wide effects of Tripadvisor

	Adjusted effect of Tripadvisor	2016-2019 growth rate	Percent of growth explained by Tripadvisor
Annual revenues	1.6%	13.2%	12.1%
Monthly employment	1.5%	29.7%	5.1%
	Adjusted effect of Tripadvisor	Exit rate in Covid year 2019-2020	Percent of exit rate explained by Tripadvisor
Annual exit rate	0.46 pp	15.7%	2.9%

Notes: Revenue growth rate refers to the 2016-2018 period.

9 Conclusions

The digital era has changed the way consumers get and share information. Yet, it is not (fully) clear what are consequences of this phenomenon for markets with information asymmetries, such as the service sector. While there is general optimism around the possibility for online review platforms to create reputation and feedback mechanisms that attenuate adverse selection and moral hazard on the producer side, empirical evidence is scarce. This paper shows that lower information frictions for consumers - caused by an exogenous abolition of internet tariffs - have the potential to change how firms in these markets operate and make the service industry more quality oriented.

First, I built a model in which consumers with heterogeneous search costs engage in sequential search to buy one unit of a vertically differentiated product, while firms with heterogeneous abilities endogenously select into production and compete in quality. The model predicts that lower search costs positively affect the equilibrium quality levels but have differing effects across businesses. In fact, some of the lowest-quality firms exit the market while the surviving ones increase their effort to upgrade product quality.

To test these hypotheses, I focused on the restaurant industry in the province of Rome and assembled a unique dataset which combines restaurants' information from Tripadvisor

with rich administrative establishment-level data. I took advantage of a plausibly exogenous reduction in the costs of mobile internet - caused by the abolition of roaming charges for tourists in the European Union - to identify the effects of lower search costs on consumers' behavior, restaurants' incentives to upgrade their quality, as well as changes in the industry composition.

Using a Difference-in-Differences strategy, I compared the variation (before/after policy) in the outcomes across restaurants that are differentially exposed to tourist clientele. I estimated the model on the whole sample of restaurants with available Tripadvisor rating at the time of the policy, as well as on three sub-samples containing restaurants with different ratings: namely, low, mid and high rating.

I showed that, after the policy, revenues increased in mid- and high-rating restaurants, while employment grew only in the mid-rating category, suggesting that high-rating establishments were already producing at full capacity. I then analyzed the supply side. First, I showed that for low-rating restaurants, the probability to exit the market double after the policy compared to the pre-policy period. Moreover, by aggregating observations at the ZIP-code level, I found that the share of low-rating firms operating in the most touristy neighborhoods decreased by 2.5 pp after the policy, compared to non-touristy ZIP codes. Then, I analyzed the behavior of surviving firms. In particular, I showed that low-rating restaurants focused their recruiting efforts on workers with previous experience in the restaurant industry and ended-up paying higher salaries. Eventually, low- and mid-rating improved their online reputation, as their dynamic Tripadvisor rating increased after the policy.

All together, my findings indicate that lower information costs for consumers create the conditions that push some low-quality providers out of the market and encourage others to produce higher-quality goods. These results offer an optimistic assessment of the possibilities of quality-upgrading in the restaurant industry through policies that reduce information costs for consumers and facilitate the use of review platforms. More generally, these results imply that ICT policies can improve welfare by reducing asymmetric information problems.

Appendices

A Model

Derivation of equation (4): Let $g(r)$ be the pdf of the reservation quality. Then, using equation (2), the corresponding cdf can be expressed as:

$$G(r) = 1 - Z[\rho^{-1}(r)] = 1 - Z \left[\int_r^\infty [1 - F(q)] dq \right]$$

Taking the derivative of $G(r)$ with respect to r yields:

$$G'(r) = g(r) = -z \left[\int_r^\infty [1 - F(q)] dq \right] [F(r) - 1] = z[\rho^{-1}(r)] [1 - F(r)]$$

Finally, replacing $g(r)$ into equation (3) yields equation (4).

Proof of Property 1: Applying the Implicit Function Theorem to the first-order condition (6) yields:

$$\begin{aligned} \frac{\partial q(\lambda)}{\partial \lambda} &= - \frac{x''_{qq}[q(\lambda)] q'_\lambda(\lambda) - C''_{q\lambda}[q(\lambda), \lambda] - C''_{qq}[q(\lambda), \lambda] q'_\lambda(\lambda)}{x''_{qq}[q(\lambda)] - C''_{qq}[q(\lambda), \lambda]} \\ &= -q'_\lambda(\lambda) + \frac{C''_{q\lambda}[q(\lambda), \lambda]}{x''_{qq}[q(\lambda)] - C''_{qq}[q(\lambda), \lambda]} \\ &\iff q'_\lambda(\lambda) = \frac{1}{2} \frac{C''_{q\lambda}[q(\lambda), \lambda]}{x''_{qq}[q(\lambda)] - C''_{qq}[q(\lambda), \lambda]} > 0 \end{aligned}$$

The latter inequality holds because the numerator is negative by assumption, while the denominator is negative by the second-order condition (7). ■

Proof of Property 2:

$$\frac{\partial x[q(\lambda)]}{\partial \lambda} = x'_q[q(\lambda)] q'_\lambda(\lambda) > 0$$

The latter inequality holds because $x'_q > 0$ as the demand function is upward sloping in quality, and $q'_\lambda > 0$ by Property 1. ■

Proof of Property 3: Applying the Envelope Theorem to the profit function (5) yields:

$$\frac{\partial \pi[q(\lambda), \lambda]}{\partial \lambda} = -C'_\lambda(q, \lambda) > 0$$

The latter inequality holds because of the assumption on the cost function. ■

Proof of Lemma 1: Replacing the equilibrium profit schedule (17) into the entry condition (9) yields the following identity

$$\Theta(\rho, L; a) \equiv \int_{\lambda(a)}^{\infty} \left[\frac{1}{\lambda} - 2\sqrt{\frac{1}{aL\lambda}} + \frac{1}{aL}(1 - \rho) \right] \gamma(\lambda) d\lambda - \kappa = 0, \quad (21)$$

where both ρ and L are functions of a , and $\lambda(a) = aL(1 - \rho)^{-2}$. Implicitly differentiating the identity with respect to a yields

$$\Theta'_a + \Theta'_\rho \frac{\partial \rho(a)}{\partial a} + \Theta'_L \frac{\partial L(a)}{\partial a} = 0. \quad (22)$$

These partial derivatives are

$$\begin{aligned} \Theta'_a &= \int_{\lambda(a)}^{\infty} \frac{1}{a^2} \left[\sqrt{\frac{a}{L\lambda}} - \frac{(1 - \rho)}{L} \right] \gamma(\lambda) d\lambda < 0; \\ \Theta'_\rho &= \int_{\lambda(a)}^{\infty} -\frac{1}{aL} \gamma(\lambda) d\lambda < 0; \\ \Theta'_L &= \int_{\lambda(a)}^{\infty} \frac{1}{L^2} \left[\sqrt{\frac{L}{a\lambda}} - \frac{(1 - \rho)}{a} \right] \gamma(\lambda) d\lambda = \frac{a}{L} \Theta'_a < 0. \end{aligned}$$

The latter equality together with equation (22) yields

$$\frac{\partial \rho}{\partial a} = -\frac{1}{\Theta'_\rho} \left[\Theta'_a + \frac{\partial L}{\partial a} \Theta'_L \right] = -\frac{\Theta'_a}{\Theta'_\rho} \left[1 + \frac{a}{L} \frac{\partial L}{\partial a} \right]. \quad (23)$$

Since $\rho'_a < 0$ from equation (2), $\Theta'_a < 0$ and $\Theta'_\rho < 0$, then (23) implies that

$$1 + \frac{a}{L} \frac{\partial L}{\partial a} > 0 \iff a \frac{\partial L}{\partial a} + L > 0 \implies \delta'_a > 0. \quad \blacksquare$$

Proof of Lemma 2: Taking the derivative of the equilibrium profit function (17) with

respect to a yields

$$\pi'_a(\lambda; a) = \frac{1}{\delta(a)} \left[\frac{\delta'_a(a)}{\sqrt{\delta(a)}} \frac{1}{\sqrt{\lambda}} - \frac{(1-\rho)}{\delta(a)} - \frac{\partial \rho(a)}{\partial a} \right].$$

Thus, the sign of $\pi'_a(\lambda; a)$ depends on the sign of the term in brackets. Since $\delta'_a > 0$ by Lemma 1, this term is decreasing in λ . This implies that, if the term is negative for $\lambda_0 \geq \lambda$, then it will also be negative $\forall \lambda > \lambda_0$. ■

Proof of Proposition 1: Lemma 1 implies that

$$q'_a(\lambda; a) = - \left[\frac{\delta'_a(a)}{2\sqrt{\delta(a)\lambda}} \right] < 0. \quad (24)$$

Moreover, taking the derivative of (24) with respect to λ , yields

$$q''_{a\lambda}(\lambda; a) = \frac{1}{4} \frac{\delta'_a(a)}{\sqrt{\delta(a)}} \lambda^{-3/2} > 0.$$

That is, the negative change in quality predicted by (24) becomes smaller (i.e., closer to zero) for larger values of λ . ■

Proof of Proposition 2: Lemma 1 implies that

$$C'_a(\lambda; a) = - \frac{1}{2\sqrt{\lambda}} \delta(a)^{-3/2} \delta'_a(a) < 0. \quad (25)$$

Moreover, taking the derivative of (25) with respect to λ , yields

$$C''_{a\lambda}(\lambda; a) = \frac{1}{4} [\lambda \delta(a)]^{-3/2} \delta'_a(a) > 0.$$

That is, the negative change in costs predicted by (25) becomes smaller (i.e., closer to zero) for larger values of λ . ■

Proof of Proposition 3: Consider the entry condition

$$\int_{\lambda(a)}^{\infty} \pi(\lambda; a) \gamma(\lambda) d\lambda = \kappa.$$

Differentiating this with respect to a , yields

$$\int_{\underline{\lambda}(a)}^{\infty} \pi'_a(\lambda; a) \gamma(\lambda) d\lambda = 0. \quad (26)$$

Together with Lemma 2, this implies that $\pi'_a[\underline{\lambda}(a); a] > 0$, otherwise the integrand in (26) would be negative $\forall \lambda > \underline{\lambda}$ (by Lemma 2), which would contradict (26). To see how the ability threshold $\underline{\lambda}(a)$ changes as search costs decreases, consider a shift in a : a_1 to $a_2 < a_1$. Then

$$\pi[\underline{\lambda}(a_2), a_2] = 0 = \pi[\underline{\lambda}(a_1), a_1] > \pi[\underline{\lambda}(a_1), a_2],$$

where the two equalities follow from the definition of $\underline{\lambda}$, and the inequality follows from $\pi'_a[\underline{\lambda}(a); a] > 0$. Since (by Property 3) $\pi'_\lambda > 0 \forall \lambda$, it follows that $\underline{\lambda}(a_2) > \underline{\lambda}(a_1)$. ■

Proof of Corollary 1: Taking the derivative of $x(\lambda; a)$ with respect to a , yields

$$x'_a(\lambda; a) = \frac{1}{\delta(a)} \left[\frac{\delta'_a(\rho - 1)}{\delta(a)} + \frac{\delta'_a}{2\sqrt{\lambda\delta(a)}} - \rho'_a \right]. \quad (27)$$

The sign of (27) equals the sign of the expression in brackets. In particular, the expression is negative for sufficiently high values of λ , that is

$$x'_a(\lambda; a) < 0 \iff \lambda > \frac{\delta(a)}{4 \left[1 - \rho + \frac{\delta(a)\rho'_a}{\delta'_a} \right]^2}.$$

Hence, there exists a $\hat{\lambda} > \underline{\lambda}$ such that $x'_a(\hat{\lambda}; a) < 0$. Since from (27) it is clear that x'_a is decreasing in λ (as $\delta'_a > 0$ by Lemma 1), this implies that $x'_a(\lambda; a) < 0 \forall \lambda > \hat{\lambda}$. ■

B Measurements

B.1 Defining exposure to tourists

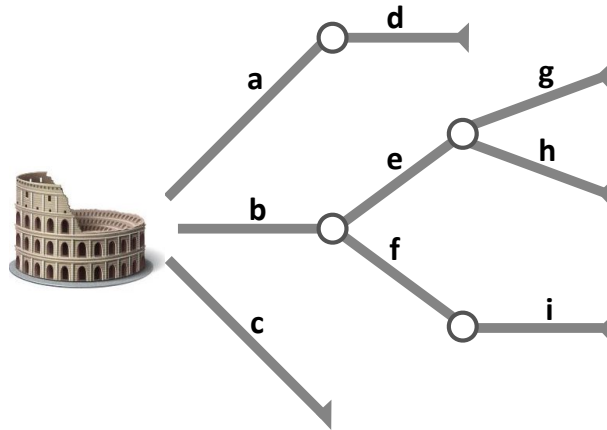
I assume that search is sequential over space and bounded by the structure of the road network around a tourist site. In particular, the probability of coming across a restaurant is equal to the probability of ending up on the street where the restaurant is, taking into account the previous path. Hence, two or more restaurants located on the same street have the same probability of being found, but this probability depends on the path to their location. Tourists start inspecting high-visible places around them - such as those in front of a tourist attraction - and then move to other less visible places until the marginal expected cost (time and fatigue

of walking) becomes larger than the marginal expected benefit of finding a good deal.

In practice, I use information from Google Maps and construct the partial road network that leads to the Tripadvisor restaurants around each attraction, and eventually compute the probabilities to find them while walking away from the attraction. The procedure works as follows. First, for each restaurant i , I consider its closest (shortest distance) tourist attraction t . Then, for each identified pair (t, i) , I use the Google Maps API to find the directions (street names) of all the paths that lead from t to i on foot. In case more than one path is suggested by Google, I consider the shortest distance path to build the benchmark measure, while I also provide robustness to the use of all alternative paths. Then, I construct the partial road network around attraction t using the street names from Google Maps and, for each i , I compute the conditional probabilities of being in any of the roads that form the path from t to i (taking into account competing roads). Finally, I multiply them and compute the probability of finding i . In the process, I assume that all roads are equally weighted. Figure B1 shows a simplified example of this calculation.

Figure B1: Example of partial road network

Segments represent roads, circles represent junctions



Assuming equal conditional probabilities:

$$p(a) = p(b) = p(c) = 1/3$$

$$p(e|b) = p(f|b) = p(g|e) = p(h|e) = 1/2 \Rightarrow p(e) = p(f) = 1/6 \text{ and } p(g) = p(h) = 1/12$$

$$p(d|a) = p(i|f) = 1 \Rightarrow p(d) = 1/3 \text{ and } p(i) = 1/6$$

More formally, the probability that a tourist moving away from attraction t comes across restaurant i is equal to the joint probability of traveling the path defined by a vector of streets

(s_1, \dots, s_{N_i}) connecting t to i . Hence,

$$P(i) = P(s_1 \& s_2 \& \dots \& s_{N_i}) = P(s_1|t) \prod_{j=2}^{N_i} P(s_j|s_{j-1}) \quad (28)$$

This probability measure reflects the chances that a restaurant is visited by a tourist and thereby the extent to which it is exposed to the policy. In particular, this measure not only reflects the "visibility" of restaurant i from attraction t , but also the effect of proximity of i to t . In fact, an increasing number of streets compete in the road network as the radius enlarges by moving farther away from the attraction, and this naturally drives down the estimated probability. Hence, any observed differential impact of the policy along the probability measure could be in part explained by factors - other than the presence of tourists - that correlate with proximity and affect restaurants' decisions.⁶⁵ For this reason, in the empirical analysis, I always control for the distance to the attraction and the distance to Rome city center.

I use equation 28 and compute this probability for all restaurants in the Tripadvisor sample.⁶⁶ The empirical distribution of the probability measure is right-skewed. About 50% of the restaurants have roughly a 0 probability of being found by the tourists (specifically, $P(i) < 0.17\%$, which is the median). Most likely, distance to the attraction explains the fact. Because these establishments are usually located too far from tourist paths, their chance of being affected by the policy is very limited: even if tourists were aware of their existence, they would not visit them as the cost to reach them is too high. For this reason, I consider them as a control group in the baseline specification. Among the remaining 50%, the top 10% most visible restaurants have a probability larger than 12.5%, meaning that about 40% of the restaurants are left with a probability between 0.17% and 12.5%.

Finally, I also use an alternative approach to measure tourist exposure that lifts the assumption of equal conditional probabilities and instead allows for weighting roads based on their "importance". Particularly, weights reflect the number of times that a road appears on every (sub)path over the total number of (sub)paths. For instance, considering the example reported on figure B1, I get:

$$\begin{aligned} p(a) &= 2/9, p(b) = 6/9, p(c) = 1/9 \\ p(e|b) &= 3/5, p(f|b) = 2/5 \\ p(g|e) &= p(h|e) = 1/2 \end{aligned}$$

⁶⁵Examples include rent costs that tend to be higher closer to attraction sites, or congestion - restaurants near touristic locations can easily be overcrowded, thus leading to longer waiting times, more noise, and worse service.

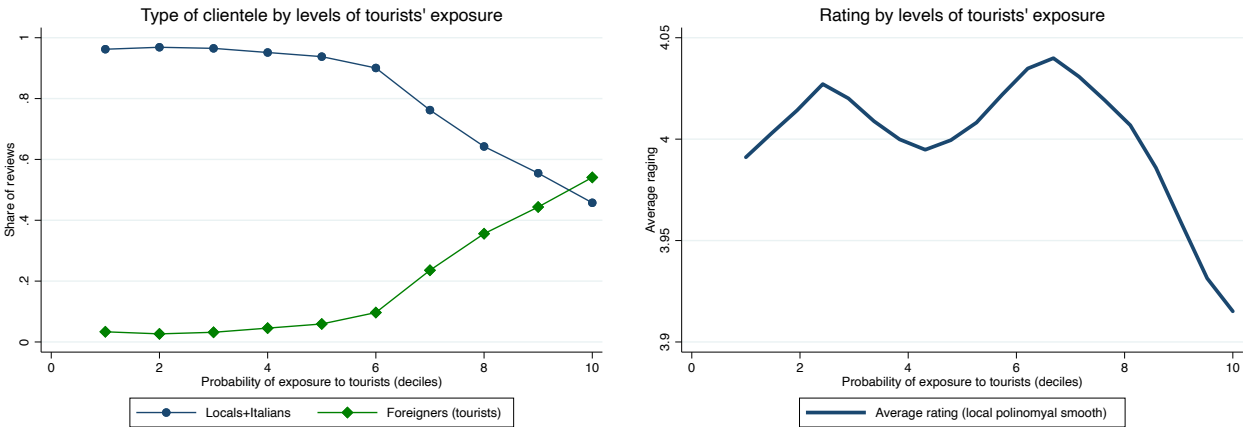
⁶⁶Note that this measure could not be computed for the entire universe of restaurants in the Social Security database, as their exact location remains unknown to the researcher for confidentiality reasons.

$$p(d|a) = p(i|f) = 1$$

B.2 Exposure to tourists, clientele and rating

Using the probability measure defined above, I examine how restaurants' type of clientele and ratings vary with the restaurant potential exposure to tourist demand. This exercise helps me to both validate the constructed measure as well as provide a description of the restaurant's industry. The left panel of figure B2 exploits the origin of the reviewers to distinguish them between locals and tourists. I identify as foreign tourists all those reviewers writing in a language different than Italian. This means that the green line in the graph is probably under-reporting the share of total tourists, as Italian travelers are not accounted.⁶⁷ However, since the roaming policy did not affect Italians directly, excluding them from this group provides a more conservative picture of the potential effect of the policy across different levels of exposure to tourists. Particularly, for restaurants whose probability is below or equal to the median, the share of foreign clientele remains quite stable and below 10%. By contrast, this increases rapidly afterwards, and reaches almost 60% for restaurants at the top probability-decile.

Figure B2: Type of clientele and rating by exposure to tourists



The right panel of figure B2 shows how Tripadvisor rating varies across levels of exposure to tourists. For each decile of probability, it reports the mean of all restaurants' average rating at the time of the policy. Restaurants more exposed to tourist demand have, on average, poorer Tripadvisor ratings, in the order of 0.10-0.15 on a scale from 1 to 5. In line with the theory,

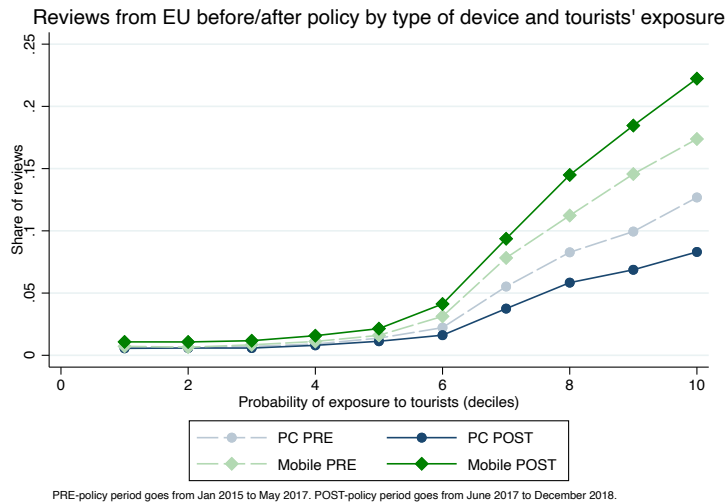
⁶⁷The main problem here is that, among Italians, I can identify the "locals" only for a subset of reviewers who explicitly indicate their town in their profile. The rest of Italians can either be tourists or locals, yet it is impossible to distinguish them.

restaurants that rely more on repeated and informed clientele sell higher quality meals.⁶⁸ The explanation is two-fold. First, locals are more likely to be informed. Restaurants located in areas where the share of informed consumers is higher (e.g. those with a lower probability measure), have incentive to provide a better quality product/service to stay in the market (Cooper and Ross, 1984). Second, locals exert control over quality through repeated purchases. Then, quality provision becomes a way to establish reputation in the market (Riordan, 1986).

B.3 The roaming policy and exposure to tourists

Does the roaming policy affect the composition of demand across restaurants based on their level of exposure to tourists? To answer this question, in figure B3, I plot the share of reviews from Europeans by different type of device across deciles of probability, before and after the policy. The graph shows that, after the policy, the share of mobile (PC) reviews from Europeans increased (decreased). However, all the largest change took place in restaurants with higher exposure to tourists, namely, those with a probability above the median, while virtually nothing happened for other restaurants.

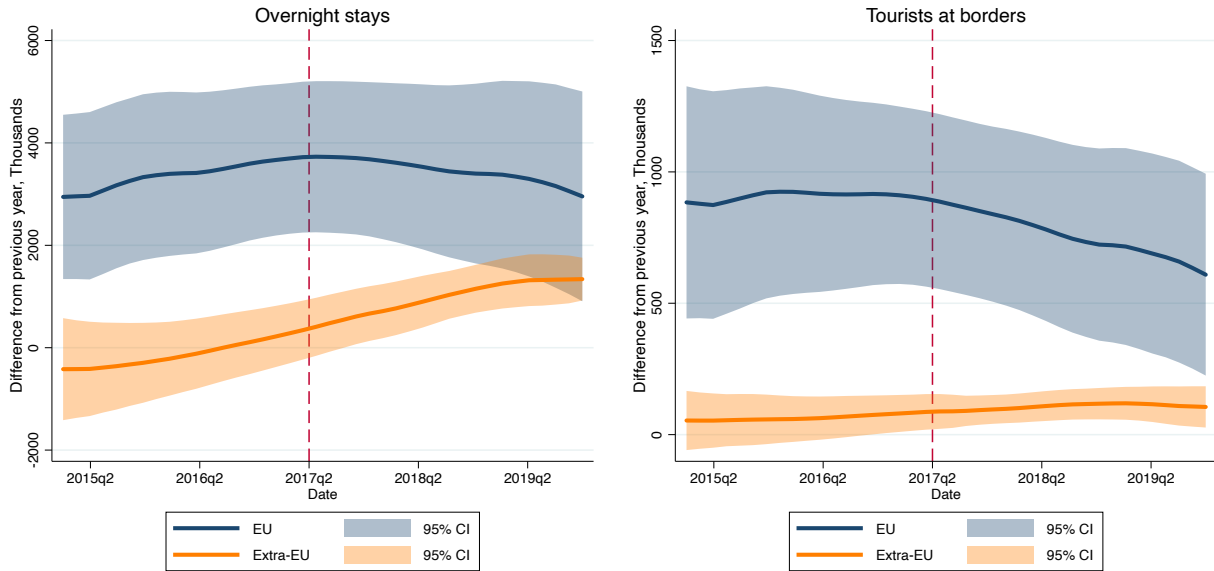
Figure B3: Roaming and reviews from Europeans



⁶⁸These results are in line with those of Dall’orso et al. (2016), who provide evidence on the existence of quality differential across more and less visible restaurants using data from Yelp on 10 large cities in Europe and North America. In particular, they show that restaurants with higher visibility from tourists - i.e. those located at street intersections - consistently exhibit a lower Yelp rating.

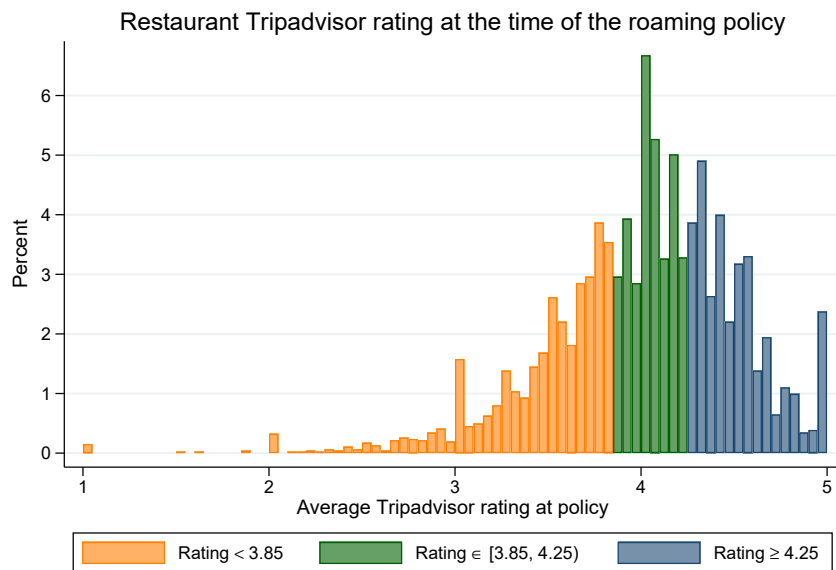
C Figures

Figure C1: International travelers to Italy (Δ from previous year, Thousands)



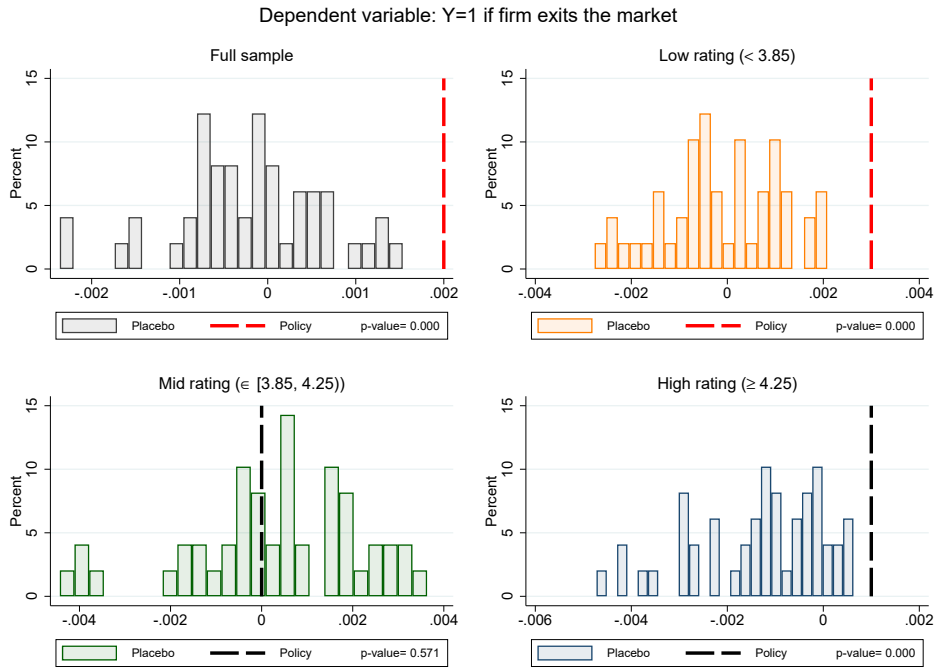
The data report international tourists traveling to Italy from different regions/countries of the world, in Thousands. The lines depict local polynomial fits of quarterly observations reporting the difference from the quarter of the previous year. EU refer to tourists from a EU country, and Extra-EU refer to all other tourists. Source: Bank of Italy.

Figure C2: Distribution of Tripadvisor average rating



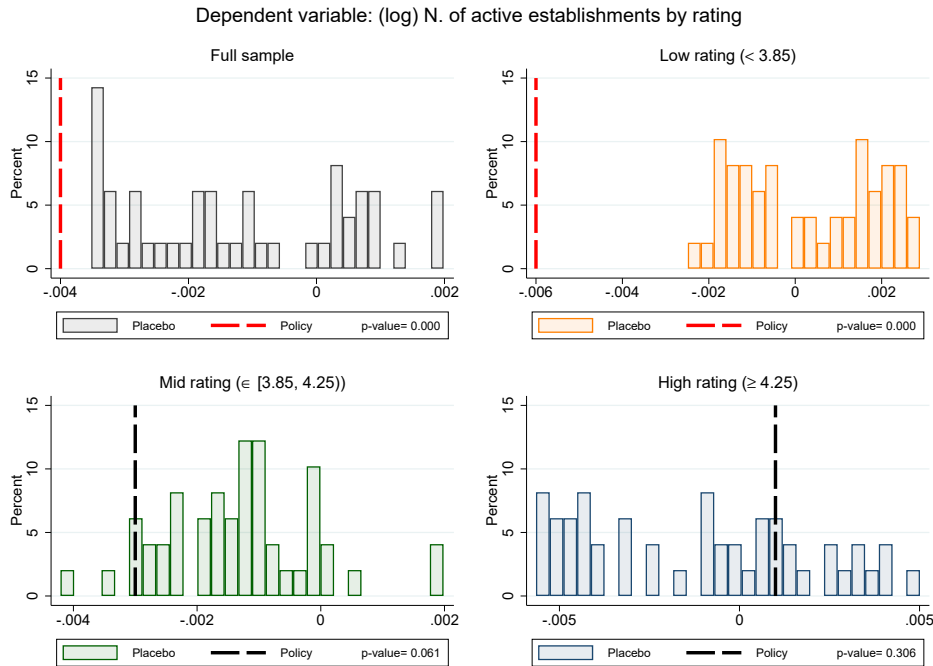
The figure shows the histogram of Tripadvisor average ratings of restaurants at the time of the policy, for the 4,628 matched restaurants with available information. Different colors split the overall sample in subgroups based on tertiles of ratings. In the sub-sample with available revenue data ($N=2,043$), the rating tertiles are 3.80 and 4.20.

Figure C3: Permutation test for restaurant exit



Notes: Each panel plots the distribution of coefficients on $Tourist * Post - Month$, where $Month$ is between May 2012 and May 2016, estimated on a sample of observations between Jan 2012 and Dec 2016. Tripadvisor rating and the respective category are calculated in each month. The vertical dashed lines report the actual policy coefficients, as estimated in the main analysis. The line is red when the respective coefficient is significant at least at the 10% confidence level, and black otherwise.

Figure C4: Permutation test for industry composition



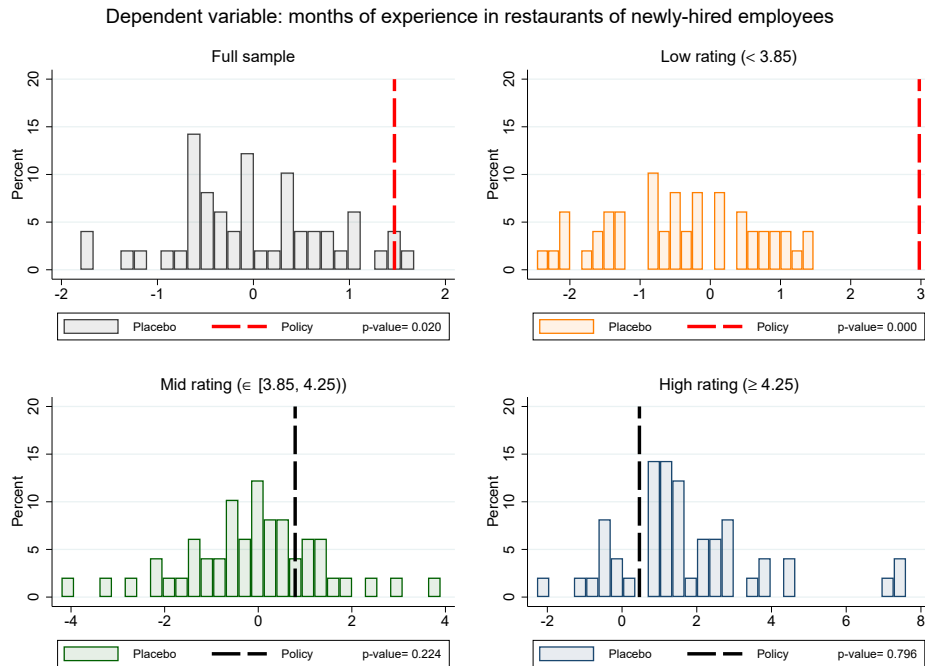
Notes: Each panel plots the distribution of coefficients on $Tourist * Post - Month$, where $Month$ is between May 2012 and May 2016, estimated on a sample of observations between Jan 2012 and Dec 2016. Tripadvisor rating and the respective category are calculated in each month. The vertical dashed lines report the actual policy coefficients, as estimated in the main analysis. The line is red when the respective coefficient is significant at least at the 10% confidence level, and black otherwise.

Figure C5: Permutation test for restaurant hiring decisions (extensive margins)



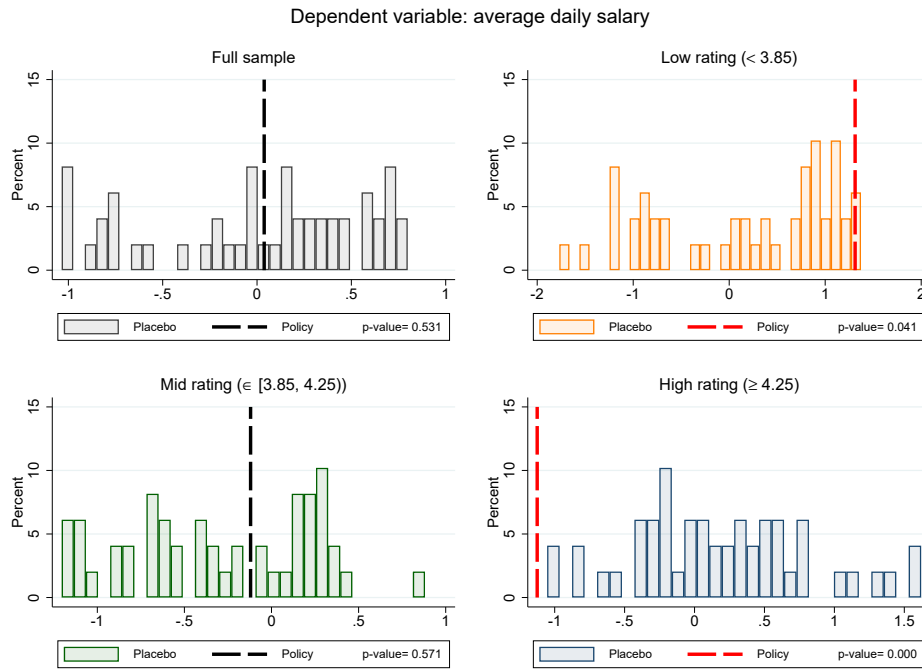
Notes: Each panel plots the distribution of coefficients on $Tourist * Post - Month$, where $Month$ is between May 2012 and May 2016, estimated on a sample of observations between Jan 2012 and Dec 2016. Tripadvisor rating and the respective category are calculated in each month. The vertical dashed lines report the actual policy coefficients, as estimated in the main analysis. The line is red when the respective coefficient is significant at least at the 10% confidence level, and black otherwise.

Figure C6: Permutation test for restaurant hiring decisions (intensive margins)



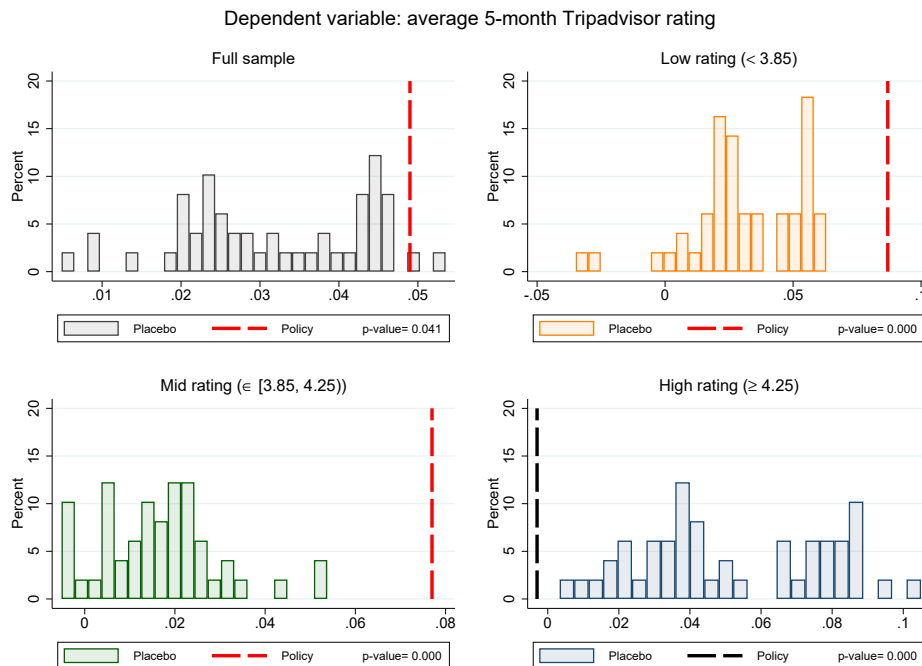
Notes: Each panel plots the distribution of coefficients on $Tourist * Post - Month$, where $Month$ is between May 2012 and May 2016, estimated on a sample of observations between Jan 2012 and Dec 2016. Tripadvisor rating and the respective category are calculated in each month. The vertical dashed lines report the actual policy coefficients, as estimated in the main analysis. The line is red when the respective coefficient is significant at least at the 10% confidence level, and black otherwise.

Figure C7: Permutation test for restaurant daily salaries



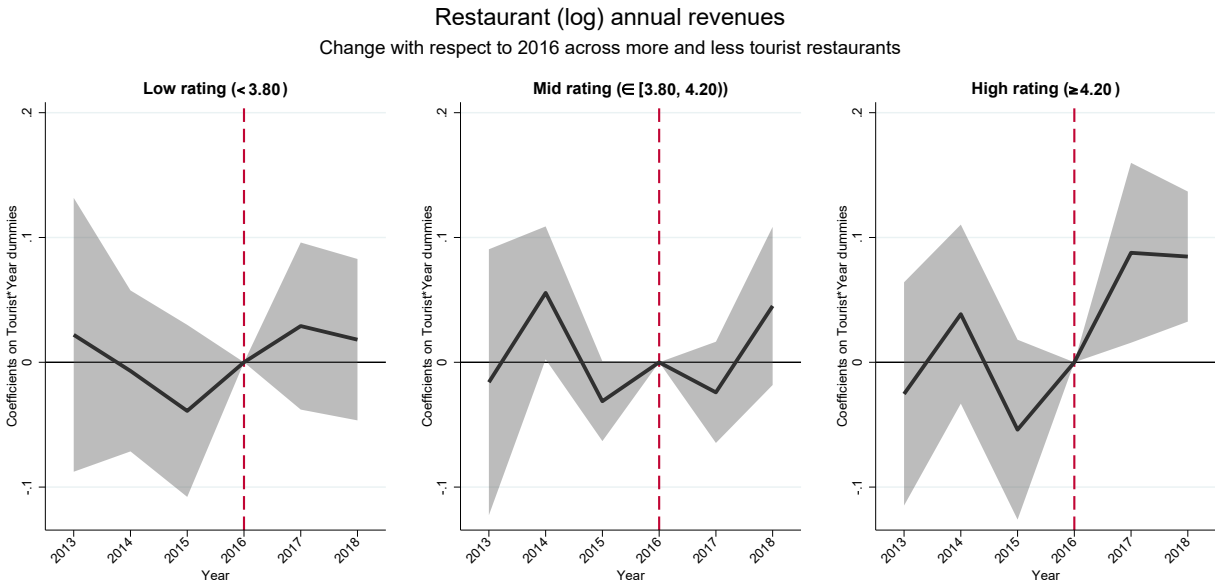
Notes: Each panel plots the distribution of coefficients on $\text{Tourist} \times \text{Post-Month}$, where Month is between May 2012 and May 2016, estimated on a sample of observations between Jan 2012 and Dec 2016. Tripadvisor rating and the respective category are calculated in each month. The vertical dashed lines report the actual policy coefficients, as estimated in the main analysis. The line is red when the respective coefficient is significant at least at the 10% confidence level, and black otherwise.

Figure C8: Permutation test for restaurant Tripadvisor rating



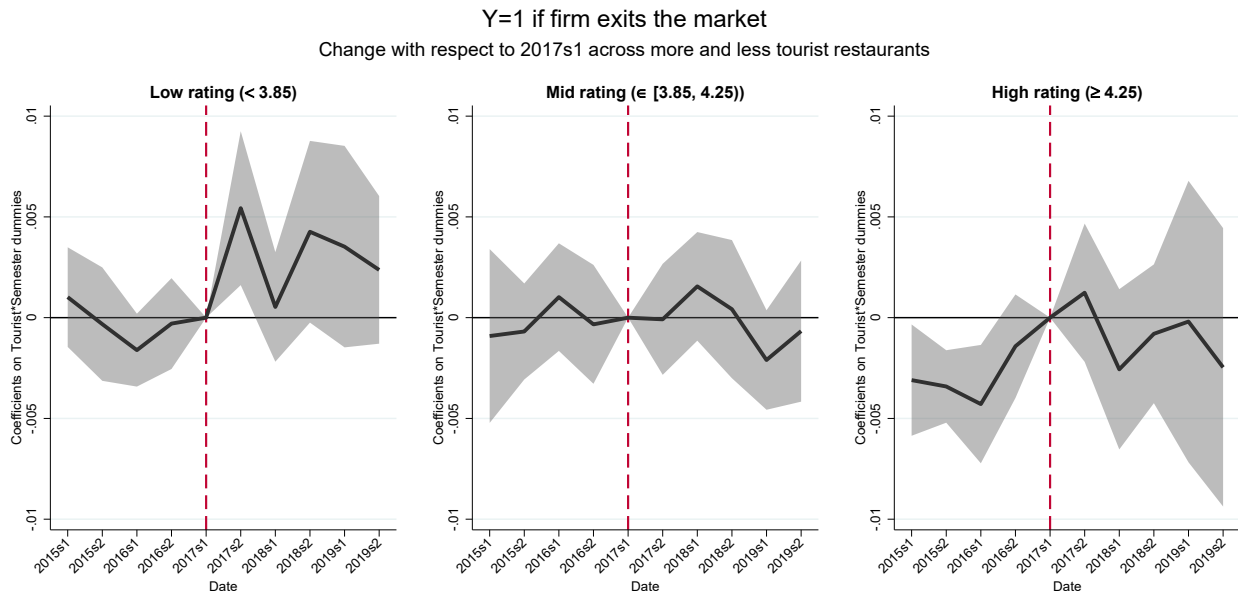
Notes: Each panel plots the distribution of coefficients on $\text{Tourist} \times \text{Post-Month}$, where Month is between May 2012 and May 2016, estimated on a sample of observations between Jan 2012 and Dec 2016. Tripadvisor rating and the respective category are calculated in each month. The vertical dashed lines report the actual policy coefficients, as estimated in the main analysis. The line is red when the respective coefficient is significant at least at the 10% confidence level, and black otherwise.

Figure C9: Event-study estimates for restaurant revenues



Notes: The graph reports estimated coefficients on the interactions of Tourist*Year dummies from three separate regressions where each observation is a restaurant-year. All controls and fixed-effects from the main analysis are included. The omitted year is 2016. Tourist restaurants are those with a measure of exposure above the median. The sample includes observations between 2013 and 2018. Shaded areas depict 95% confidence intervals.

Figure C10: Event-study estimates for restaurant exit



Notes: The graph reports estimated coefficients on the interactions of Tourist*Semester dummies from three separate regressions where each observation is a restaurant-month-year. All controls and fixed-effects from the main analysis are included. The omitted semester is 2017s1. Tourist restaurants are those with a measure of exposure above the median. The sample includes observations between Jan 2015 and Dec 2018. Shaded areas depict 95% confidence intervals.

Figure C11: Event-study estimates for hiring decisions (extensive margins)



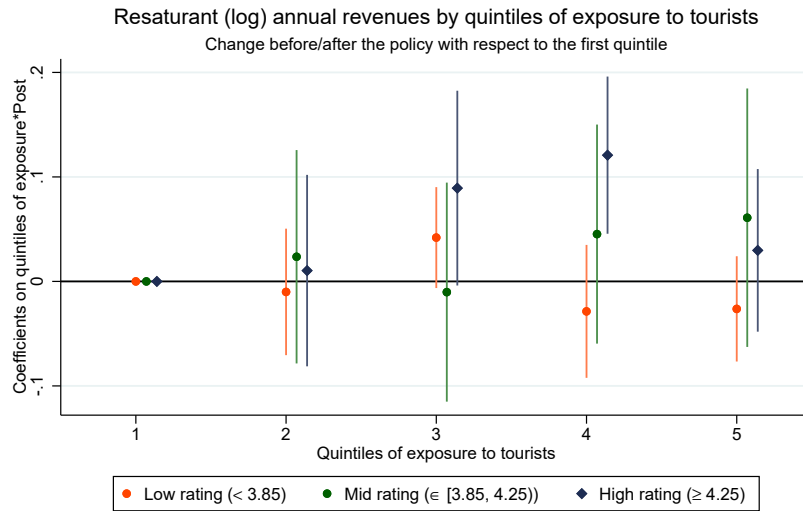
Notes: The graph reports estimated coefficients on the interactions of Tourist*Semester dummies from three separate regressions where each observation is a restaurant-month-year. All controls and fixed-effects from the main analysis are included. The omitted semester is 2017s1. Tourist restaurants are those with a measure of exposure above the median. The sample includes observations between Jan 2015 and Dec 2018. Shaded areas depict 95% confidence intervals.

Figure C12: Event-study estimates for hiring decisions (intensive margins)



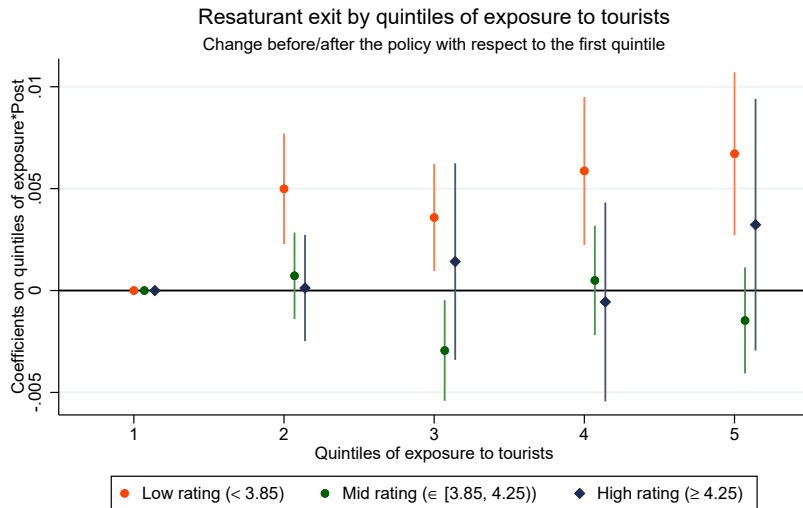
Notes: The graph reports estimated coefficients on the interactions of Tourist*Semester dummies from three separate regressions where each observation is a restaurant-month-year. All controls and fixed-effects from the main analysis are included. The omitted semester is 2017s1. Tourist restaurants are those with a measure of exposure above the median. The sample includes observations between Jan 2015 and Dec 2018. Shaded areas depict 95% confidence intervals.

Figure C13: The impact on restaurant revenues across quintiles of exposure



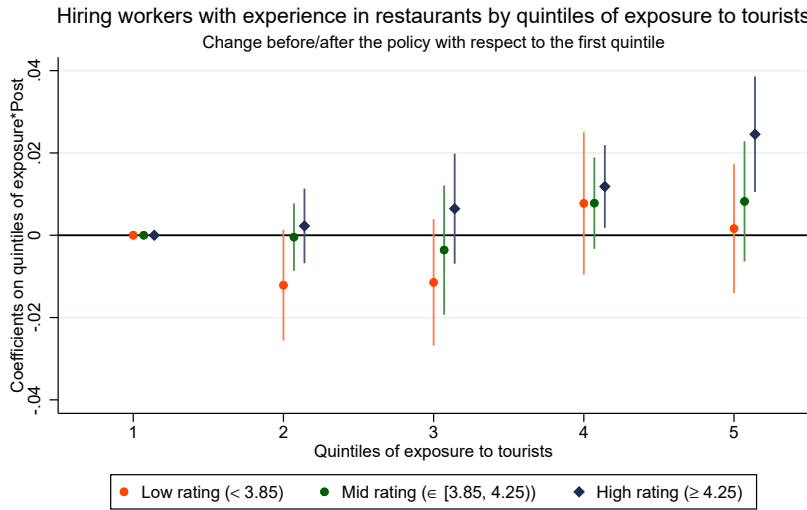
Notes: The graph reports estimates on the interactions of quintiles of exposure*Post from three separate regressions (low, mid, high-rating restaurants), where each observation is a restaurant-year. The first quintile is omitted. All controls and fixed-effects from the main analysis are included. Post takes value 1 after 2016. The sample includes observations between 2015 and 2018. Heteroskedasticity-robust standard errors are clustered at municipality level. Bars depict 95% confidence intervals.

Figure C14: The impact on restaurant exit across quintiles of exposure



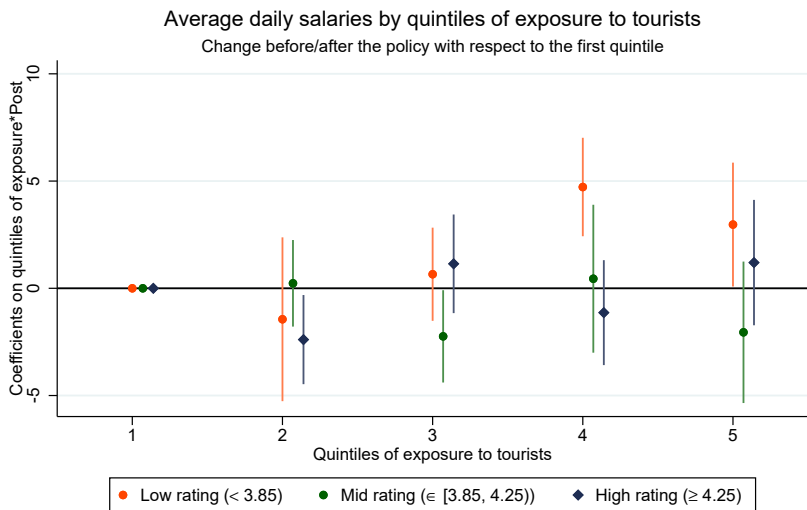
Notes: The graph reports estimates on the interactions of quintiles of exposure*Post from three separate regressions (low, mid, high-rating restaurants), where each observation is a restaurant-month-year. The first quintile is omitted. All controls and fixed-effects from the main analysis are included. Post takes value 1 after May 2017. The sample includes observations between Jan 2015 and Dec 2019. Heteroskedasticity-robust standard errors are clustered at municipality level. Bars depict 95% confidence intervals.

Figure C15: The impact on hiring decisions (extensive margins) across quintiles of exposure



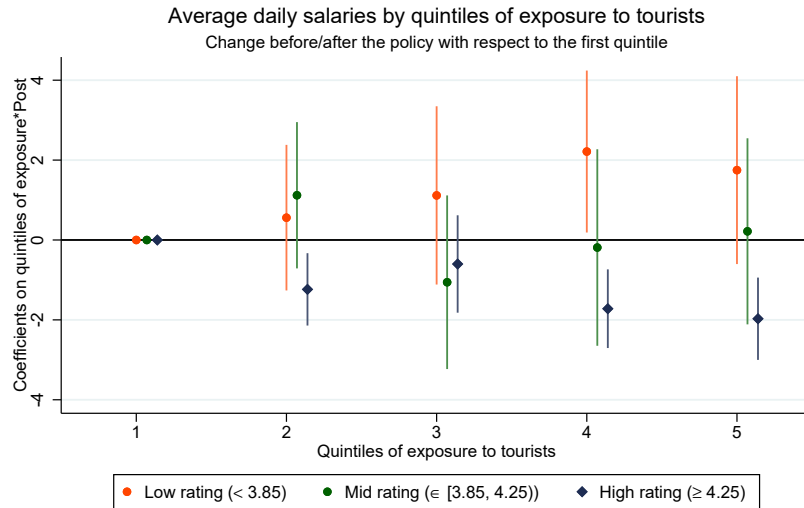
Notes: The graph reports estimates on the interactions of quintiles of exposure*Post from three separate regressions (low, mid, high-rating restaurants), where each observation is a restaurant-month-year. The first quintile is omitted. All controls and fixed-effects from the main analysis are included. Post takes value 1 after May 2017. The sample includes observations between Jan 2015 and Dec 2019. Heteroskedasticity-robust standard errors are clustered at municipality level. Bars depict 95% confidence intervals.

Figure C16: The impact on hiring decisions (intensive margins) across quintiles of exposure



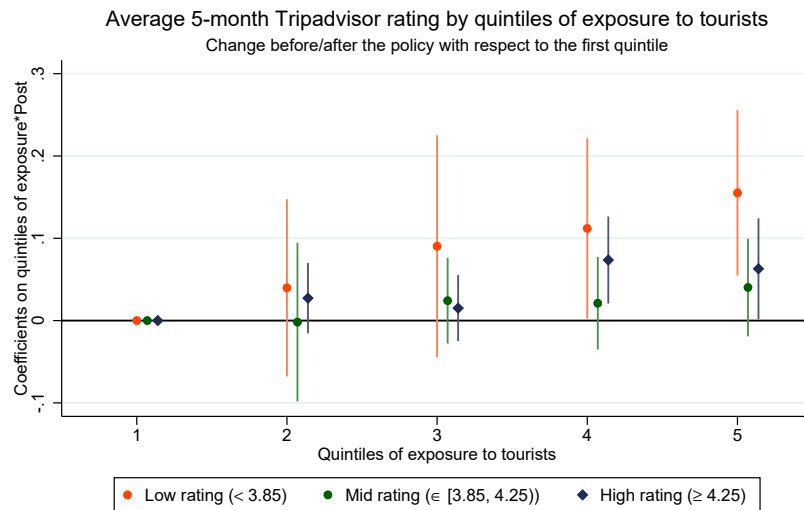
Notes: The graph reports estimates on the interactions of quintiles of exposure*Post from three separate regressions (low, mid, high-rating restaurants), where each observation is a restaurant-month-year. The first quintile is omitted. All controls and fixed-effects from the main analysis are included. Post takes value 1 after May 2017. The sample includes observations between Jan 2015 and Dec 2019. Heteroskedasticity-robust standard errors are clustered at municipality level. Bars depict 95% confidence intervals.

Figure C17: The impact on salaries across quintiles of exposure



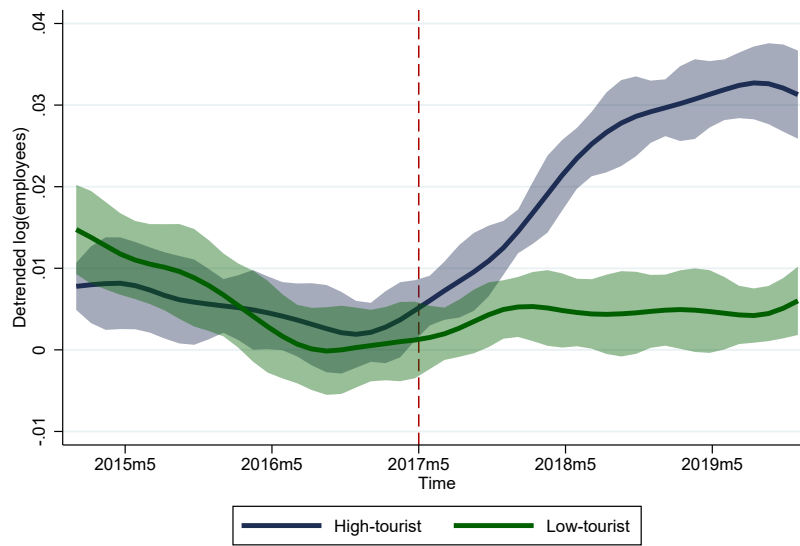
Notes: The graph reports estimates on the interactions of quintiles of exposure*Post from three separate regressions (low, mid, high-rating restaurants), where each observation is a restaurant-month-year. The first quintile is omitted. All controls and fixed-effects from the main analysis are included. Post takes value 1 after May 2017. The sample includes observations between Jan 2015 and Dec 2019. Heteroskedasticity-robust standard errors are clustered at municipality level. Bars depict 95% confidence intervals.

Figure C18: The impact on Tripadvisor rating across quintiles of exposure



Notes: The graph reports estimates on the interactions of quintiles of exposure*Post from three separate regressions (low, mid, high-rating restaurants), where each observation is a restaurant-month-year. The first quintile is omitted. All controls and fixed-effects from the main analysis are included. Post takes value 1 after May 2017. The sample includes observations between Jan 2015 and Dec 2019. Heteroskedasticity-robust standard errors are clustered at municipality level. Bars depict 95% confidence intervals.

Figure C19: The impact of the roaming policy on de-trended monthly employment



Notes: High-tourist restaurants are those for which the binary variable *Tourist*=1, while *Tourist*=0 for low-tourist restaurants.

D Tables

Table D1: Comparison of main statistics across samples

	Tripadvisor sample	Matched sample	INPS sample
	Mean/(SD)	Mean/(SD)	Mean/(SD)
N. of tourist attractions in the ZIP code	3.01 (6.65)	3.10 (6.59)	2.59 (6.13)
Probability of exposure to tourists	0.04 (0.12)	0.04 (0.10)	
Distance (km) from closest attraction	9.02 (11.14)	8.19 (10.71)	
Average 5-month Tripadvisor rating	3.97 (0.65)	4.00 (0.56)	
Average N. of 5-month replies to reviews	1.79 (8.98)	2.38 (9.58)	
Total Tripadvisor reviews	134.62 (320.06)	174.46 (297.80)	
Price €	0.25 (0.43)	0.25 (0.43)	
Price €€- €€€	0.71 (0.45)	0.71 (0.45)	
Price €€€€	0.04 (0.20)	0.04 (0.19)	
Average N. of monthly employees		5.24 (5.02)	4.31 (4.60)
1 if firm exits market in Jan2015-Dec2019		0.21 (0.41)	0.29 (0.45)
1 if firm exits after policy (Jun2017-Dec2019)		0.13 (0.34)	0.15 (0.36)
1 if firm enters market in Jan2015-Dec2019		0.41 (0.49)	0.44 (0.50)
1 if firm enters after policy (Jun2017-Dec2019)		0.15 (0.36)	0.17 (0.38)
1 if firm hires workers w/ experience in restaurants at least once in Jan2015-Dec2019		0.76 (0.43)	0.69 (0.46)
Average months of experience of newly-hired employees		13.64 (14.55)	12.72 (14.45)
Average daily salaries (€)		65.98 (10.48)	65.88 (11.41)
Observations	14146	5472	10391

Each observation is a restaurant. Data refer to the period between Jan 2015 - Dec 2019, unless otherwise specified. Data on Tripadvisor reviews, rating and replies refer to the period between Jan 2015 and Dec 2018. The matches sample is used in the market-level analysis.

Table D2: The roaming policy and the use of Tripadvisor by nationality of the reviewer

	Ratio Mobile/PC monthly reviews			Total monthly reviews from Mobile devices		
	(1)	(2)	(3)	(4)	(5)	(6)
EU	0.33*** (0.08)			-2301.21*** (111.86)		
EU*Post	0.47*** (0.12)			496.37*** (155.62)		
Extra-EU		0.18*** (0.06)			-2916.72*** (141.85)	
Extra-EU*Post		-0.12 (0.09)			129.76 (197.34)	
IT			0.99*** (0.11)			5617.90*** (300.21)
IT*Post			0.02 (0.15)			-714.22* (417.65)
Month*Year FE	✓	✓	✓	✓	✓	✓
Observations	120	120	120	120	120	120
Adj. R-squared	0.840	0.824	0.764	0.923	0.908	0.880
Mean EU pre-policy	1.14			3162.97		
Mean Extra-EU pre-policy		1.00			2547.45	
Mean IT pre-policy			1.80			11082.07

Post takes value 1 after May 2017. Each observation is a region of origin-month-year. The regions of origin are EU, Extra-EU, IT and locals, which is the comparison (omitted) category in every column. The panel includes observations between 2015 and 2019. Standalone Post is absorbed by the Month*Year FE. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D3: The roaming policy and international travelers to Italy

	Δ from previous year, Thousands					
	Overnight stays			Tourists at borders		
	(1)	(2)	(3)	(4)	(5)	(6)
EU	506.212*** (83.752)	530.153*** (118.615)		126.723*** (17.343)	133.083*** (24.561)	
Post	154.244* (81.093)	172.200* (102.724)	310.167 (204.811)	0.800 (16.793)	5.570 (21.270)	55.051 (41.994)
EU*Post		-47.883 (167.747)	-47.883 (161.642)		-12.720 (34.734)	-12.720 (33.143)
Origin FE			✓			✓
Year and quarter FE			✓			✓
Observations	320	320	320	320	320	320
Adj. R-squared	0.107	0.104	0.168	0.139	0.136	0.214

The data contain the number of international tourists traveling to Italy from different regions/countries of the world, in Thousands. Each observation is a region of origin-year-quarter. The panel includes observations between 2015 and 2019. EU takes value 1 when the region of origin of the tourists is a EU country, and 0 otherwise. Post takes value 1 after 2017q2. Source: Bank of Italy. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D4: Summary statistics of independent and control variables

	Firms	Mean	SD	Min	Median	Max
Probability of exposure to tourists ($\times 100$)	4628	4.21	10.27	0.0	0.17	100.0
1 if tourist restaurant	4628	0.49	0.50	0.0	0.00	1.0
Tripadvisor rating at policy	4628	4.01	0.51	1.0	4.05	5.0
1 if low-rating ($\in [1, 3.85)$)	4628	0.33	0.47	0.0	0.00	1.0
1 if mid-rating ($\in [3.85, 4.25)$)	4628	0.34	0.47	0.0	0.00	1.0
1 if high-rating ($\in [4.25, 5]$)	4628	0.33	0.47	0.0	0.00	1.0
1 if restaurant is LLC	4628	0.56	0.50	0.0	1.00	1.0
1 if sole proprietorship	4628	0.23	0.42	0.0	0.00	1.0
1 if dine-in restaurant/bar	4628	0.86	0.34	0.0	1.00	1.0
1 if food truck	4628	0.04	0.19	0.0	0.00	1.0
1 if take-away only	4628	0.07	0.25	0.0	0.00	1.0
Distance (km) from closest attraction	4628	8.10	10.71	0.0	3.00	55.0
1 if distance to Rome city center < 6 km	4628	0.49	0.50	0.0	0.00	1.0
1 if distance to Rome city center 6-15 km	4628	0.20	0.40	0.0	0.00	1.0
1 if distance to Rome city center > 15 km	4628	0.32	0.47	0.0	0.00	1.0
1 if price is €	4576	0.26	0.44	0.0	0.00	1.0
1 if price is €€- €€€	4576	0.70	0.46	0.0	1.00	1.0
1 if price is €€€€	4576	0.04	0.19	0.0	0.00	1.0
1 if cuisine is Italian	4628	0.76	0.43	0.0	1.00	1.0
1 if no other restaurant in 400 m radius	4628	0.05	0.23	0.0	0.00	1.0
1 if 1-10 restaurants in 400 m radius	4628	0.25	0.43	0.0	0.00	1.0
1 if 11-30 restaurants in 400 m radius	4628	0.19	0.39	0.0	0.00	1.0
1 if more than 30 restaurants in 400 m radius	4628	0.51	0.50	0.0	1.00	1.0
1 if closest attraction has $< 1,000$ reviews	4628	0.37	0.48	0.0	0.00	1.0
1 if closest attraction has 1,000-5,000 reviews	4628	0.36	0.48	0.0	0.00	1.0
1 if closest attraction has $> 5,000$ reviews	4628	0.26	0.44	0.0	0.00	1.0

Each observation is a restaurant.

Additional results

Table D5: The impact of the roaming policy on restaurant profit margin

Y=Annual profit margin; years 2015-2018					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	-0.013*** (0.004)	-0.013*** (0.004)	-0.017*** (0.006)	-0.031*** (0.009)	0.025** (0.010)
Restaurant & Year FE	✓	✓	✓	✓	✓
ZIP-code*Year	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	6614	6591	2291	2283	2017
Restaurants	2026	2018	693	693	632
Clusters	57	56	39	40	41
Adj. R-squared	0.345	0.349	0.326	0.352	0.363
DDD <i>p-value</i>				0.061	0.096

Post=1 if date is after 2016. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.80)$, $[3.80, 4.20)$, $[4.20, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-year. The sample includes observations between 2015 and 2018. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D6: The impact of the roaming policy on total working days

Y=log(monthly working days); Jan 2015 - Dec 2019					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.087*** (0.031)	0.081** (0.035)	-0.066* (0.039)	0.188*** (0.055)	0.100 (0.098)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	219835	217622	72133	76920	68569
Restaurants	4628	4576	1490	1571	1515
Clusters	86	86	59	71	71
Adj. R-squared	0.714	0.713	0.701	0.728	0.700
Mean Y pre-policy	91.0	91.7	113.8	95.4	63.0
DDD <i>p-value</i>				0.034	0.104

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85)$, $[3.85, 4.25)$, $[4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D7: The impact of the roaming policy on working days per worker

Y=N. of working days per worker; Jan 2015 - Dec 2019					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.085 (0.094)	0.008 (0.092)	0.038 (0.133)	-0.466*** (0.142)	0.371** (0.159)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	196749	195348	64454	70021	60873
Restaurants	4517	4471	1454	1537	1480
Clusters	86	86	59	71	70
Adj. R-squared	0.727	0.727	0.741	0.742	0.695
Mean Y pre-policy	15.8	15.8	16.0	16.2	15.2
DDD <i>p-value</i>				0.263	0.294

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D8: The impact of the roaming policy on restaurant employment by price category

Y=log(monthly employees); Jan 2015 - Dec 2019									
	Low price (€)			Medium price (€€- €€€)			High price (€€€€)		
	(1) Low rating	(2) Mid rating	(3) High rating	(4) Low rating	(5) Mid rating	(6) High rating	(7) Low rating	(8) Mid rating	(9) High rating
Tourist*Post	-0.057** (0.027)	0.088** (0.034)	-0.025 (0.032)	-0.008 (0.026)	0.117*** (0.036)	0.103** (0.046)	-0.361*** (0.074)	0.113 (0.071)	-0.015 (0.110)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	16919	17819	22560	54187	56170	42228	1027	2931	3781
Restaurants	337	365	493	1130	1149	935	23	57	87
Clusters	29	33	45	55	64	66	6	12	17
Adj. R-squared	0.762	0.781	0.769	0.754	0.792	0.756	0.801	0.806	0.791
Mean Y pre-policy	5.4	4.7	3.2	7.4	5.8	4.2	8.5	9.6	7.3

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D9: Logit estimates: the impact of the roaming policy on hiring decisions

Y=1 if firm hires worker	<i>with</i> previous experience in restaurants				<i>without</i> experience in restaurants		
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating	(5) Low rating	(6) Mid rating	(7) High rating
Tourist*Post	0.175*** (0.048)	0.150** (0.074)	0.235*** (0.087)	0.032 (0.095)	-0.028 (0.084)	0.227** (0.093)	0.160 (0.100)
Restaurant FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	176898	61956	62097	52845	61361	63352	55925
Restaurants	3568	1229	1221	1118	1178	1221	1157
Pseudo R-squared	0.014	0.017	0.015	0.018	0.013	0.014	0.012
Mean Y pre-policy	0.12	0.14	0.10	0.11	0.14	0.08	0.07
DDD <i>p-value</i>			0.376	0.013		0.409	0.378

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (3-4) and (6-7) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D10: The impact of the roaming policy on restaurant daily salaries

	Y=log(average daily salary (€)); Jan 2015 - Dec 2019				
	(1) Full sample	(2) Full sample	(3) Low rating	(4) Mid rating	(5) High rating
Tourist*Post	-0.000 (0.003)	0.000 (0.003)	0.016** (0.006)	-0.001 (0.006)	-0.014** (0.005)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	200402	199026	67507	70593	60926
Restaurants	4558	4512	1492	1538	1482
Clusters	86	86	59	71	70
Adj. R-squared	0.495	0.496	0.511	0.491	0.482
Mean Y pre-policy	64.9	64.9	66.0	65.0	63.5
DDD <i>p-value</i>				0.477	0.102

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D11: The impact of the roaming policy on hiring from Tripadvisor restaurants

Y=1 if firm hires worker from	Tripadvisor restaurants with any rating				Tripadvisor restaurants with mid/high rating			
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating	(5) Full sample	(6) Low rating	(7) Mid rating	(8) High rating
Tourist*Post	0.004*** (0.002)	0.004 (0.003)	0.006** (0.003)	-0.001 (0.002)	0.006*** (0.002)	0.008*** (0.003)	0.005** (0.003)	0.001 (0.001)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	217622	72133	76920	68569	217622	72133	76920	68569
Restaurants	4576	1490	1571	1515	4576	1490	1571	1515
Clusters	86	59	71	71	86	59	71	71
Adj. R-squared	0.086	0.102	0.071	0.082	0.067	0.076	0.054	0.070
Mean Y pre-policy	0.04	0.05	0.04	0.04	0.03	0.03	0.03	0.03
DDD <i>p-value</i>			0.142	0.184			0.649	0.004

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (3-4) and (7-8) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D12: Correlation between Tripadvisor rating and restaurant hiring decisions

	Y=Average 5-month Tripadvisor rating; Jan 2012 - Dec 2018					
	(1)	(2)	(3)	(4)	(5)	(6)
Hire worker w/ experience in restaurants	0.0116*** (0.002)	0.0116*** (0.002)	0.0112*** (0.002)	0.0054* (0.003)	0.0097*** (0.002)	
Hire worker w/o experience in restaurants		-0.0002 (0.003)	0.0001 (0.003)	0.0001 (0.003)	-0.0013 (0.003)	
Hire worker from higher-rating restaurant				0.0162*** (0.003)		
log(monthly employees)					0.0061** (0.003)	
Years of experience in restaurants						0.0043*** (0.001)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓
Controls			✓	✓	✓	✓
Observations	223494	223494	222405	222405	222405	30015
Restaurants	5147	5147	5089	5089	5089	3737
Clusters	89	89	89	89	89	76
Adj. R-squared	0.480	0.480	0.482	0.482	0.482	0.557
Mean Y	3.95	3.95	3.95	3.95	3.95	3.91

Each observation is a restaurant-month-year. The sample includes observations between Jan 2012 and Dec 2018. Heteroskedasticity-robust standard errors clustered at municipality level. Controls include distance (km) to closest attraction and indicators for distance to Rome city center, restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D13: The impact of the roaming policy on restaurant replies to Tripadvisor reviews

	Y=N. of 5-month replies to reviews; Jan 2015 - Dec 2018				
	(1) Full sample	(2) Full sample	(3) Low rating	(4) Mid rating	(5) High rating
Tourist*Post	0.156* (0.083)	0.308*** (0.094)	0.008 (0.247)	1.013** (0.442)	-0.444* (0.258)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	146713	145085	48937	52172	43976
Restaurants	4377	4328	1412	1499	1417
Clusters	86	86	59	70	70
Adj. R-squared	0.704	0.704	0.663	0.647	0.752
Mean Y pre-policy	2.56	2.59	1.58	2.51	3.90
DDD <i>p-value</i>				0.006	0.000

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D14: The impact of the roaming policy on restaurant net purchases

	Y=log(annual net purchases); years 2015-2018				
	(1) Full sample	(2) Full sample	(3) Low rating	(4) Mid rating	(5) High rating
Tourist*Post	0.056*** (0.012)	0.060*** (0.010)	-0.034 (0.029)	0.115*** (0.041)	0.019 (0.026)
Restaurant & Year FE	✓	✓	✓	✓	✓
ZIP-code*Year	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	6677	6652	2305	2299	2048
Restaurants	2043	2034	696	697	641
Clusters	57	56	39	40	41
Adj. R-squared	0.858	0.859	0.882	0.865	0.801
Mean Y pre-policy	255.9	256.8	369.1	228.9	154.7
DDD <i>p-value</i>				0.839	0.027

Post=1 if date is after 2016. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85)$, $[3.85, 4.25)$, $[4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-year. The sample includes observations between 2015 and 2018. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Placebo policy-dates

Table D15: Placebo policies and restaurant revenues

	Y=log(annual revenues)			
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) high rating
Tourist*Post 2013	0.010 (0.023)	-0.037 (0.030)	0.047 (0.038)	-0.028 (0.023)
Observations	4173	1763	1393	1017
Tourist*Post 2014	-0.003 (0.016)	0.010 (0.020)	-0.025 (0.027)	-0.024 (0.043)
Observations	5029	2040	1662	1327
Tourist*Post 2015	0.026 (0.019)	0.077 (0.046)	-0.022 (0.015)	0.003 (0.048)
Observations	4351	1706	1397	1248

Every row/column is the output of a separate regression where each observation is a restaurant-year. Post *year*=1 if date is after *year*. Tourist restaurants are those with a measure of exposure above the median. Heteroskedasticity-robust standard errors clustered at municipality level. Each regression includes all controls and fixed effects from the main analysis. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the placebo policy $\in [1, 3.80)$, $[3.80, 4.20)$, $[4.20, 5]$, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D16: Placebo policies and restaurant exit

	Y=1 if firm exits the market			
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating
Tourist*Post May2013	-0.001 (0.001)	0.002 (0.001)	-0.003*** (0.001)	-0.006*** (0.002)
Observations	39012	16693	12963	9356
Tourist*Post May2014	0.001 (0.001)	0.002 (0.002)	0.001 (0.002)	-0.001 (0.003)
Observations	48795	19572	16664	12559
Tourist*Post May2015	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	0.001 (0.002)
Observations	58028	22394	19658	15976
Tourist*Post May2016	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	-0.000 (0.002)
Observations	58893	21014	20066	17813

Every row/column is the output of a separate regression where each observation is a restaurant-month-year. Post May $year=1$ if date is after May of the respective $year$. Tourist restaurants are those with a measure of exposure above the median. Heteroskedasticity-robust standard errors clustered at municipality level. Each regression includes all controls and fixed effects from the main analysis. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the placebo policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D17: Placebo policies and industry composition

	Y=log(N. of active establishments)			
	(1) All	(2) Low rating	(3) Mid rating	(4) High rating
N. of attractions*Post May2013	0.001 (0.001)	0.001 (0.001)	-0.001 (0.001)	0.003 (0.002)
Observations	2712	2712	2712	2712
N. of attractions*Post May2014	-0.001 (0.001)	0.000 (0.001)	-0.001 (0.002)	-0.001 (0.002)
Observations	2841	2841	2841	2841
N. of attractions*Post May2015	-0.002** (0.001)	-0.001 (0.002)	-0.001 (0.001)	-0.002 (0.001)
Observations	2881	2881	2881	2881
N. of attractions*Post May2016	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.002)
Observations	2240	2240	2240	2240

Every row/column is the output of a separate regression where each observation is a ZIP code-month-year. Post May $year=1$ if date is after May of the respective $year$. Heteroskedasticity-robust standard errors clustered at ZIP-code level. Each regression includes all controls and fixed effects from the main analysis. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the placebo policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. If the restaurant entered the market after the placebo policy-date, the most recent rating is considered. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D18: Placebo policies and restaurant hiring decisions (extensive margins)

Y=1 if firm hires worker with previous experience in restaurants				
	(1)	(2)	(3)	(4)
	Full sample	Low rating	Mid rating	High rating
Tourist*Post May2013	0.006 (0.004)	0.014 (0.008)	-0.009 (0.008)	0.015 (0.016)
Observations	38862	16647	12921	9294
Tourist*Post May2014	-0.001 (0.004)	-0.005 (0.004)	0.002 (0.006)	-0.003 (0.010)
Observations	48795	19572	16664	12559
Tourist*Post May2015	0.003 (0.003)	-0.001 (0.005)	-0.004 (0.004)	0.019*** (0.004)
Observations	58028	22394	19658	15976
Tourist*Post May2016	0.005 (0.003)	-0.009 (0.006)	-0.001 (0.004)	0.026*** (0.005)
Observations	60147	21359	20354	18434

Every row/column is the output of a separate regression where each observation is a restaurant-month-year. Post May $year=1$ if date is after May of the respective $year$. Tourist restaurants are those with a measure of exposure above the median. Heteroskedasticity-robust standard errors clustered at municipality level. Each regression includes all controls and fixed effects from the main analysis. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the placebo policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D19: Placebo policies and restaurant hiring decisions (intensive margins)

Y=Months of experience in restaurants of newly-hired employees				
	(1)	(2)	(3)	(4)
	Full sample	Low rating	Mid rating	High rating
Tourist*Post May2013	1.391 (1.080)	0.054 (1.314)	1.884 (1.924)	3.791* (2.147)
Observations	6270	3028	2001	1241
Tourist*Post May2014	-0.842 (0.574)	-2.531*** (0.919)	-0.085 (0.984)	-0.562 (1.409)
Observations	7431	3499	2338	1594
Tourist*Post May2015	-0.547 (0.578)	0.425 (0.921)	-2.142 (1.643)	-1.574 (2.583)
Observations	10770	4922	3351	2497
Tourist*Post May2016	0.652 (0.458)	-0.631 (0.545)	0.799 (1.390)	3.394*** (0.967)
Observations	11592	4957	3579	3056

Every row/column is the output of a separate regression where each observation is a restaurant-month-year. Post May $year=1$ if date is after May of the respective $year$. Tourist restaurants are those with a measure of exposure above the median. Heteroskedasticity-robust standard errors clustered at municipality level. Each regression includes all controls and fixed effects from the main analysis. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the placebo policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D20: Placebo policies and restaurant daily salaries

	Y=Average daily salary (€)			
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating
Tourist*Post May2013	-0.747 (0.456)	-0.730 (0.457)	-0.465 (0.944)	-0.466 (0.870)
Observations	35759	15321	11943	8495
Tourist*Post May2014	0.336 (0.440)	0.761 (0.759)	0.145 (0.429)	0.031 (0.453)
Observations	44362	18103	15201	11058
Tourist*Post May2015	0.322 (0.306)	0.486 (0.396)	0.480 (0.421)	-0.515 (0.492)
Observations	52527	20429	17934	14164
Tourist*Post May2016	0.167 (0.338)	0.690 (0.564)	-0.233 (0.364)	0.072 (0.630)
Observations	53148	18996	18298	15854

Every row/column is the output of a separate regression where each observation is a restaurant-month-year. Post May $year=1$ if date is after May of the respective $year$. Tourist restaurants are those with a measure of exposure above the median. Heteroskedasticity-robust standard errors clustered at municipality level. Each regression includes all controls and fixed effects from the main analysis. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the placebo policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D21: Placebo policies and restaurant Tripadvisor rating

	Y=Average 5-month Tripadvisor rating			
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating
Tourist*Post May2013	0.016 (0.024)	0.005 (0.051)	0.040 (0.025)	0.008 (0.040)
Observations	36043	15470	12016	8557
Tourist*Post May2014	0.005 (0.022)	0.001 (0.026)	-0.006 (0.018)	0.007 (0.037)
Observations	47105	18979	16161	11965
Tourist*Post May2015	0.010 (0.011)	0.004 (0.026)	0.009 (0.026)	0.008 (0.016)
Observations	56176	21665	19262	15249
Tourist*Post May2016	0.007 (0.010)	-0.028 (0.018)	0.026 (0.022)	0.034** (0.015)
Observations	56540	20096	19572	16872

Every row/column is the output of a separate regression where each observation is a restaurant-month-year. Post May $year=1$ if date is after May of the respective $year$. Tourist restaurants are those with a measure of exposure above the median. Heteroskedasticity-robust standard errors clustered at municipality level. Each regression includes all controls and fixed effects from the main analysis. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the placebo policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Robustness: exposure to tourist including alternative routes

Table D22: The impact of the roaming policy on restaurant revenues

	Y=log(annual revenues); years 2015-2018				
	(1) Full sample	(2) Full sample	(3) Low rating	(4) Mid rating	(5) High rating
Tourist*Post	0.048*** (0.011)	0.057*** (0.011)	0.010 (0.022)	0.001 (0.016)	0.063** (0.026)
Restaurant & Year FE	✓	✓	✓	✓	✓
ZIP-code*Year	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	6677	6652	2305	2299	2048
Restaurants	2043	2034	696	697	641
Clusters	57	56	39	40	41
Adj. R-squared	0.846	0.847	0.869	0.849	0.782
Mean Y pre-policy	646.6	648.8	977.4	558.0	360.7
DDD <i>p-value</i>				0.669	0.020

Post=1 if date is after 2016. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.80)$, $[3.80, 4.20)$, $[4.20, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-year. The sample includes observations between 2015 and 2018. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D23: The impact of the roaming policy on restaurant employment

	Y=log(monthly employees); Jan 2015 - Dec 2019				
	(1) Full sample	(2) Full sample	(3) Low rating	(4) Mid rating	(5) High rating
Tourist*Post	0.041*** (0.012)	0.042*** (0.015)	-0.008 (0.019)	0.069*** (0.024)	0.052* (0.030)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	219835	217622	72133	76920	68569
Restaurants	4628	4576	1490	1571	1515
Clusters	86	86	59	71	71
Adj. R-squared	0.779	0.778	0.759	0.793	0.769
Mean Y pre-policy	5.5	5.6	6.9	5.7	4.0
DDD <i>p-value</i>				0.100	0.026

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85)$, $[3.85, 4.25)$, $[4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D24: The impact of the roaming policy on hiring decisions (extensive margins)

Y=1 if firm hires worker	<i>with</i> previous experience in restaurants				<i>without</i> experience in restaurants		
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating	(5) Low rating	(6) Mid rating	(7) High rating
Tourist*Post	0.007*** (0.002)	0.009*** (0.003)	0.004 (0.003)	0.005 (0.003)	-0.006** (0.002)	0.006 (0.004)	0.006** (0.003)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	217622	72133	76920	68569	72133	76920	68569
Restaurants	4576	1490	1571	1515	1490	1571	1515
Clusters	86	59	71	71	59	71	71
Adj. R-squared	0.124	0.143	0.104	0.116	0.049	0.043	0.037
Mean Y pre-policy	0.08	0.10	0.07	0.08	0.06	0.06	0.06
DDD <i>p-value</i>			0.985	0.113		0.006	0.013

The sample includes observations between Jan 2015 and Dec 2019. Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (3-4) and (6-7) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D25: The impact of the roaming policy on hiring decisions (intensive margins)

Y=Months of experience in restaurants of	newly-hired employees				quitting/fired employees		
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating	(5) Low rating	(6) Mid rating	(7) High rating
Tourist*Post	0.678 (0.851)	2.478*** (0.802)	0.060 (1.264)	-0.780 (0.656)	-0.424 (1.389)	-0.051 (1.113)	1.412 (1.855)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	30059	11318	10205	8536	12281	10395	8131
Restaurants	3531	1163	1220	1148	1197	1226	1136
Clusters	76	53	59	61	51	57	58
Adj. R-squared	0.117	0.109	0.117	0.127	0.190	0.170	0.183
Mean Y pre-policy	13.0	13.5	13.5	11.8	25.8	27.0	21.5
DDD <i>p-value</i>			0.038	0.000		0.976	0.428

The sample includes observations between Jan 2015 and Dec 2019. Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (3-4) and (6-7) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D26: The impact of the roaming policy on restaurant daily salaries

Y=Average daily salary (€); Jan 2015 - Dec 2019					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	-0.121 (0.232)	-0.116 (0.259)	0.930*** (0.343)	-0.657 (0.680)	-0.680 (0.431)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	200402	199026	67507	70593	60926
Restaurants	4558	4512	1492	1538	1482
Clusters	86	86	59	71	70
Adj. R-squared	0.467	0.469	0.485	0.465	0.451
Mean Y pre-policy	64.9	64.9	66.0	65.0	63.5
DDD <i>p-value</i>				0.181	0.095

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D27: The impact of the roaming policy on restaurant Tripadvisor rating

Y=Average 5-month Tripadvisor rating; Jan 2015 - Dec 2018					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.040*** (0.009)	0.040*** (0.010)	0.036* (0.019)	0.076*** (0.017)	0.009 (0.011)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	147274	146620	48577	53659	44384
Restaurants	4373	4330	1413	1499	1418
Clusters	86	86	59	70	70
Adj. R-squared	0.503	0.504	0.324	0.251	0.297
Mean Y pre-policy	3.98	3.98	3.51	4.05	4.43
DDD <i>p-value</i>				0.007	0.000

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Robustness: exposure to tourist weighted by road importance

Table D28: The impact of the roaming policy on restaurant revenues

Y=log(annual revenues); years 2015-2018					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.052*** (0.008)	0.054*** (0.008)	-0.003 (0.017)	0.025 (0.021)	0.061** (0.026)
Restaurant & Year FE	✓	✓	✓	✓	✓
ZIP-code*Year	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	6677	6652	2305	2299	2048
Restaurants	2043	2034	696	697	641
Clusters	57	56	39	40	41
Adj. R-squared	0.846	0.847	0.869	0.849	0.782
Mean Y pre-policy	646.6	648.8	977.4	558.0	360.7
DDD <i>p-value</i>				0.862	0.005

Post=1 if date is after 2016. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.80)$, $[3.80, 4.20)$, $[4.20, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-year. The sample includes observations between 2015 and 2018. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D29: The impact of the roaming policy on restaurant employment

Y=log(monthly employees); Jan 2015 - Dec 2019					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.030*** (0.010)	0.035*** (0.011)	-0.002 (0.018)	0.058** (0.023)	0.044 (0.027)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	219835	217622	72133	76920	68569
Restaurants	4628	4576	1490	1571	1515
Clusters	86	86	59	71	71
Adj. R-squared	0.779	0.778	0.759	0.793	0.769
Mean Y pre-policy	5.5	5.6	6.9	5.7	4.0
DDD <i>p-value</i>				0.153	0.056

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85)$, $[3.85, 4.25)$, $[4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D30: The impact of the roaming policy on hiring decisions (extensive margins)

Y=1 if firm hires worker	<i>with</i> previous experience in restaurants				<i>without</i> experience in restaurants		
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating	(5) Low rating	(6) Mid rating	(7) High rating
Tourist*Post	0.006** (0.002)	0.007** (0.003)	0.002 (0.003)	0.006 (0.003)	-0.002 (0.003)	0.011*** (0.004)	0.005** (0.002)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	217622	72133	76920	68569	72133	76920	68569
Restaurants	4576	1490	1571	1515	1490	1571	1515
Clusters	86	59	71	71	59	71	71
Adj. R-squared	0.124	0.143	0.104	0.116	0.049	0.043	0.037
Mean Y pre-policy	0.08	0.10	0.07	0.08	0.06	0.06	0.06
DDD <i>p-value</i>			0.954	0.330		0.005	0.085

The sample includes observations between Jan 2015 and Dec 2019. Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (3-4) and (6-7) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D31: The impact of the roaming policy on hiring decisions (intensive margins)

Y=Months of experience in restaurants of	newly-hired employees				quitting/fired employees		
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating	(5) Low rating	(6) Mid rating	(7) High rating
Tourist*Post	0.339 (0.661)	2.313*** (0.571)	-0.880 (1.296)	-0.295 (0.516)	0.280 (1.272)	2.240 (1.749)	3.064** (1.333)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	30059	11318	10205	8536	12281	10395	8131
Restaurants	3531	1163	1220	1148	1197	1226	1136
Clusters	76	53	59	61	51	57	58
Adj. R-squared	0.117	0.109	0.117	0.127	0.190	0.170	0.183
Mean Y pre-policy	13.0	13.5	13.5	11.8	25.8	27.0	21.5
DDD <i>p-value</i>			0.011	0.000		0.345	0.564

The sample includes observations between Jan 2015 and Dec 2019. Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (3-4) and (6-7) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D32: The impact of the roaming policy on restaurant daily salaries

Y=Average daily salary (€); Jan 2015 - Dec 2019					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	-0.153 (0.269)	-0.128 (0.269)	1.036** (0.439)	-0.623 (0.621)	-1.023* (0.561)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	200402	199026	67507	70593	60926
Restaurants	4558	4512	1492	1538	1482
Clusters	86	86	59	71	70
Adj. R-squared	0.467	0.469	0.485	0.465	0.451
Mean Y pre-policy	64.9	64.9	66.0	65.0	63.5
DDD <i>p-value</i>				0.224	0.114

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D33: The impact of the roaming policy on restaurant Tripadvisor rating

Y=Average 5-month Tripadvisor rating; Jan 2015 - Dec 2018					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.055*** (0.019)	0.064*** (0.018)	0.087*** (0.020)	0.065** (0.030)	0.044*** (0.014)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	147274	146620	48577	53659	44384
Restaurants	4373	4330	1413	1499	1418
Clusters	86	86	59	70	70
Adj. R-squared	0.503	0.504	0.324	0.251	0.297
Mean Y pre-policy	3.98	3.98	3.51	4.05	4.43
DDD <i>p-value</i>				0.000	0.000

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Robustness: excluding firms that exited the market after the policy

Table D34: The impact of the roaming policy on restaurant revenues

Y=log(annual revenues); years 2015-2018					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.068*** (0.016)	0.067*** (0.017)	0.033 (0.030)	0.043** (0.016)	0.074** (0.030)
Restaurant & Year FE	✓	✓	✓	✓	✓
ZIP-code*Year	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	6176	6158	2148	2130	1880
Restaurants	1872	1865	642	637	586
Clusters	56	55	35	38	39
Adj. R-squared	0.852	0.853	0.871	0.858	0.790
Mean Y pre-policy	664.8	666.7	1011.7	563.7	366.1
DDD <i>p-value</i>				0.830	0.024

Post=1 if date is after 2016. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.80)$, $[3.80, 4.20)$, $[4.20, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-year. The sample includes observations between 2015 and 2018. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D35: The impact of the roaming policy on restaurant employment

Y=log(monthly employees); Jan 2015 - Dec 2019					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.050** (0.022)	0.047* (0.026)	-0.017 (0.020)	0.101*** (0.034)	0.047 (0.051)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	199012	197346	65432	70772	61142
Restaurants	4071	4033	1315	1413	1305
Clusters	85	85	58	71	70
Adj. R-squared	0.784	0.783	0.764	0.797	0.777
Mean Y pre-policy	5.7	5.7	7.1	5.8	4.1
DDD <i>p-value</i>				0.099	0.063

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85)$, $[3.85, 4.25)$, $[4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D36: The impact of the roaming policy on hiring decisions (extensive margins)

Y=1 if firm hires worker	<i>with</i> previous experience in restaurants				<i>without</i> experience in restaurants		
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating	(5) Low rating	(6) Mid rating	(7) High rating
Tourist*Post	0.009*** (0.002)	0.010*** (0.003)	0.008** (0.004)	0.002 (0.003)	-0.005** (0.002)	0.010* (0.005)	0.009*** (0.003)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	197346	65432	70772	61142	65432	70772	61142
Restaurants	4033	1315	1413	1305	1315	1413	1305
Clusters	85	58	71	70	58	71	70
Adj. R-squared	0.125	0.144	0.107	0.118	0.050	0.043	0.038
Mean Y pre-policy	0.08	0.10	0.07	0.07	0.06	0.06	0.06
DDD <i>p-value</i>			0.598	0.073		0.021	0.008

The sample includes observations between Jan 2015 and Dec 2019. Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (3-4) and (6-7) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D37: The impact of the roaming policy on hiring decisions (intensive margins)

Y=Months of experience in restaurants of	newly-hired employees				quitting/fired employees		
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating	(5) Low rating	(6) Mid rating	(7) High rating
Tourist*Post	1.677* (0.911)	3.294*** (1.156)	1.252 (1.270)	0.174 (0.612)	0.409 (1.034)	0.142 (1.195)	2.561** (1.103)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	27448	10396	9414	7638	11228	9436	7171
Restaurants	3129	1035	1098	996	1056	1093	975
Clusters	74	53	57	59	51	56	55
Adj. R-squared	0.116	0.105	0.122	0.122	0.181	0.169	0.182
Mean Y pre-policy	13.1	13.7	13.4	11.8	26.0	27.4	21.8
DDD <i>p-value</i>			0.115	0.000		0.866	0.362

The sample includes observations between Jan 2015 and Dec 2019. Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (3-4) and (6-7) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D38: The impact of the roaming policy on restaurant daily salaries

Y=Average daily salary (€); Jan 2015 - Dec 2019					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	-0.007 (0.256)	-0.014 (0.274)	1.022** (0.387)	-0.033 (0.404)	-1.025* (0.516)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	181903	180953	61649	64930	54374
Restaurants	4011	3979	1319	1384	1276
Clusters	85	85	58	71	69
Adj. R-squared	0.474	0.475	0.489	0.475	0.458
Mean Y pre-policy	64.8	64.9	65.9	65.0	63.5
DDD <i>p-value</i>				0.375	0.061

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D39: The impact of the roaming policy on restaurant Tripadvisor rating

Y=Average 5-month Tripadvisor rating; Jan 2015 - Dec 2018					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.053*** (0.012)	0.063*** (0.012)	0.112*** (0.018)	0.091*** (0.022)	0.011 (0.013)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	131302	130941	43522	48710	38709
Restaurants	3849	3818	1248	1351	1219
Clusters	85	85	58	70	69
Adj. R-squared	0.503	0.504	0.324	0.252	0.300
Mean Y pre-policy	3.97	3.97	3.51	4.05	4.43
DDD <i>p-value</i>				0.000	0.000

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at municipality level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Robustness: clustering standard errors at the ZIP-code level

Table D40: The impact of the roaming policy on restaurant revenues

	Y=log(annual revenues); years 2015-2018				
	(1) Full sample	(2) Full sample	(3) Low rating	(4) Mid rating	(5) High rating
Tourist*Post	0.047 (0.030)	0.053 (0.033)	-0.002 (0.075)	0.033 (0.052)	0.069 (0.071)
Restaurant & Year FE	✓	✓	✓	✓	✓
ZIP-code*Year	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	6677	6652	2305	2299	2048
Restaurants	2043	2034	696	697	641
Clusters	113	113	101	98	99
Adj. R-squared	0.846	0.847	0.869	0.849	0.782
Mean Y pre-policy	646.6	648.8	977.4	558.0	360.7
DDD <i>p-value</i>				0.965	0.419

Post=1 if date is after 2016. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.80)$, $[3.80, 4.20)$, $[4.20, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at ZIP-code level. Each observation is a restaurant-year. The sample includes observations between 2015 and 2018. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D41: The impact of the roaming policy on restaurant employment

	Y=log(monthly employees); Jan 2015 - Dec 2019				
	(1) Full sample	(2) Full sample	(3) Low rating	(4) Mid rating	(5) High rating
Tourist*Post	0.043** (0.021)	0.042* (0.022)	-0.024 (0.043)	0.103*** (0.036)	0.041 (0.033)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	219835	217622	72133	76920	68569
Restaurants	4628	4576	1490	1571	1515
Clusters	127	127	115	119	119
Adj. R-squared	0.779	0.778	0.759	0.793	0.769
Mean Y pre-policy	5.5	5.6	6.9	5.7	4.0
DDD <i>p-value</i>				0.078	0.051

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85)$, $[3.85, 4.25)$, $[4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at ZIP-code level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D42: The impact of the roaming policy on restaurant exit

Y=1 if firm exits the market; Jan 2015 - Dec 2019					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.0011 (0.0008)	0.0016* (0.0008)	0.0031** (0.0015)	-0.0000 (0.0012)	0.0015 (0.0018)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	219835	217622	72133	76920	68569
Restaurants	4628	4576	1490	1571	1515
Clusters	127	127	115	119	119
Adj. R-squared	0.059	0.060	0.058	0.061	0.061
Mean Y pre-policy	0.003	0.003	0.003	0.003	0.004
DDD <i>p-value</i>				0.365	0.621

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at ZIP-code level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D43: The impact of the roaming policy on hiring decisions (extensive margins)

Y=1 if firm hires worker	<i>with</i> previous experience in restaurants				<i>without</i> experience in restaurants		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full sample	Low rating	Mid rating	High rating	Low rating	Mid rating	High rating
Tourist*Post	0.009** (0.004)	0.009 (0.007)	0.011** (0.005)	0.002 (0.007)	-0.006 (0.006)	0.011* (0.006)	0.007 (0.006)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	217622	72133	76920	68569	72133	76920	68569
Restaurants	4576	1490	1571	1515	1490	1571	1515
Clusters	127	115	119	119	115	119	119
Adj. R-squared	0.124	0.143	0.104	0.116	0.049	0.043	0.037
Mean Y pre-policy	0.08	0.10	0.07	0.08	0.06	0.06	0.06
DDD <i>p-value</i>			0.538	0.363		0.047	0.115

The sample includes observations between Jan 2015 and Dec 2019. Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at ZIP-code level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (3-4) and (6-7) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D44: The impact of the roaming policy on hiring decisions (intensive margins)

Y=Months of experience in restaurants of	newly-hired employees				quitting/fired employees		
	(1) Full sample	(2) Low rating	(3) Mid rating	(4) High rating	(5) Low rating	(6) Mid rating	(7) High rating
Tourist*Post	1.469 (0.924)	2.977** (1.149)	0.789 (1.584)	0.465 (1.680)	0.177 (1.548)	-0.440 (1.928)	2.375 (2.135)
Restaurant & Time FE	✓	✓	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	30059	11318	10205	8536	12281	10395	8131
Restaurants	3531	1163	1220	1148	1197	1226	1136
Clusters	121	108	111	114	107	110	113
Adj. R-squared	0.117	0.109	0.117	0.127	0.190	0.170	0.183
Mean Y pre-policy	13.0	13.5	13.5	11.8	25.8	27.0	21.5
DDD <i>p-value</i>			0.031	0.000		0.434	0.466

The sample includes observations between Jan 2015 and Dec 2019. Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85)$, $[3.85, 4.25)$, $[4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at ZIP-code level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (3-4) and (6-7) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D45: The impact of the roaming policy on restaurant daily salaries

	Y=Average daily salary (€); Jan 2015 - Dec 2019				
	(1) Full sample	(2) Full sample	(3) Low rating	(4) Mid rating	(5) High rating
Tourist*Post	-0.010 (0.384)	0.038 (0.376)	1.312** (0.555)	-0.120 (0.528)	-1.125* (0.638)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	200402	199026	67507	70593	60926
Restaurants	4558	4512	1492	1538	1482
Clusters	125	125	114	118	118
Adj. R-squared	0.467	0.469	0.485	0.465	0.451
Mean Y pre-policy	64.9	64.9	66.0	65.0	63.5
DDD <i>p-value</i>				0.346	0.079

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85)$, $[3.85, 4.25)$, $[4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at ZIP-code level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D46: The impact of the roaming policy on restaurant Tripadvisor rating

Y=Average 5-month Tripadvisor rating; Jan 2015 - Dec 2018					
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Low rating	Mid rating	High rating
Tourist*Post	0.040*	0.049**	0.087**	0.077**	-0.003
	(0.021)	(0.020)	(0.040)	(0.030)	(0.035)
Restaurant & Time FE	✓	✓	✓	✓	✓
ZIP-code*Time	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Observations	147274	146620	48577	53659	44384
Restaurants	4373	4330	1413	1499	1418
Clusters	127	127	115	119	119
Adj. R-squared	0.503	0.504	0.324	0.251	0.297
Mean Y pre-policy	3.98	3.98	3.51	4.05	4.43
DDD <i>p-value</i>				0.128	0.015

Post=1 if date is after May 2017. Tourist restaurants are those with a measure of exposure above the median. Restaurants in low, mid and high categories had their Tripadvisor rating at the time of the policy $\in [1, 3.85), [3.85, 4.25), [4.25, 5]$, respectively. Heteroskedasticity-robust standard errors clustered at ZIP-code level. Each observation is a restaurant-month-year. Distance (km) to closest attraction and indicators for distance to Rome city center interacted with Post are included in all regressions. Controls include indicators for restaurant price category, Italian cuisine, concentration of restaurants in 400m radius, n. of reviews to closest attraction, type of economic activity and legal status of the firm, all interacted with Post. Columns (4) and (5) report the p-values from a triple-difference estimation testing whether the DDD coefficients for mid and high ratings are equal to low rating. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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