The Effects of Government Licensing on E-commerce: Evidence from Alibaba*

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Abstract

Inspired by Demsetz's (1982) call for assessing the broader implications of occupational licensing, we examine how the 2015 Food Safety Law (FSL) affects e-commerce in China. The FSL requires most food sellers on e-commerce platforms to obtain a valid, offline license for retail food handling. Based on its gradual rollout on the Alibaba platform, we find that larger and more reputable sellers tend to display an FSL license earlier, and buyers are more willing to transact with a seller with a license. Moreover, buyer response to the FSL license is stronger for younger and less reputable sellers, suggesting that the license provides useful information in addition to what consumers have observed on the platform. Market-wide, we find the average quality of surviving food sellers has improved and seller concentration has increased since the FSL. Meanwhile, the platform's gross merchandise value (GMV) on food did not decline, nor did the average sales price increase significantly one year into the full enforcement of the FSL. This suggests that the FSL does not hamper the long-term performance of the regulated market, probably because it has enhanced seller quality and made the market more transparent.

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1 Introduction

The Internet enables transactions anytime anywhere, but how to ensure product and service quality is a first-order question for all online platforms.

Platforms can set rules based on what they observe, and adopt mechanisms such as seller reputation[2], voluntary certification, platform warranty, buyer insurance, and internal policing.[3] However, a lot of information crucial to consumer welfare – for example, the supply chain that contributes to product quality and seller qualification – is not always available to the platform, especially when the information relates to offline operation and sellers may not report it truthfully. In the meantime, the government can impose occupational licensing or quality standards, and obtain key information hidden from the platform. But the government is often short of resources. It is difficult for a government intervention to take effect on a digital market until the platform tracks relevant data, detects potential violations, and enforces compliance. These pros and cons suggest that it is valuable to assess classical regulations in the new world of e-commerce.

In this paper, we evaluate a nationwide food safety regulation on Alibaba, China's largest e-commerce platform. In 2015, China introduced the Food Safety Law (FSL), requiring most food sellers on e-commerce platforms to obtain a valid, offline license for retail food handling. This licensing requirement is seller-specific but not product-specific. To be licensed, a food seller must have an offline production, packaging, and storage site that meets the local government's hygiene requirements. That site must have adequate facilities for disinfection and waste disposal, as well as adequate personnel for food safety and management. The cost of licensing can be non-trivial, especially for small, family-owned businesses in remote areas. To address this, China exempts sellers of raw, agricultural products from the FSL. In the meantime, some special food types—for example, alcoholic drinks—had already been subject to a separate licensing requirement before 2015. In light of this, we study how the 2015 FSL affects non-agricultural non-alcoholic (NANA) food on Alibaba's two e-commerce markets (Taobao and Tmall).

The FSL was rolled out progressively. In January 2015, Alibaba notified all food sellers of the forthcoming Food Safety Law. Meanwhile, Alibaba updated its user interface so that

[2]See Bajari and Hortacsu (2004) and Tadelis (2016) for reviews. The reputation system is imperfect, as buyer reviews may not be objective and independent (Dai et al., 2018), sellers may have an incentive to fake or game reviews (Mayzlin et al., 2014; Luca and Zervas, 2016), and the platform's review policy could encourage retaliation between users (Dellarocas, 2003).

[3]See Jin and Kato (2007); Lewis (2011); Roberts (2011); Cai et al. (2014); Hui et al. (2016) for examples, and Luca (2017); Tadelis (2016) for recent reviews.

licensed sellers could upload their local government license directly on the platform. In October 2015, Alibaba started to disallow unlicensed food sellers from creating new listings on Taobao and Tmall, while existing listings remained valid. Starting April 2016, Alibaba prohibited any unlicensed sellers from selling any food on its platform unless they were exempted by the FSL. Thus, starting January 2014, we observe periods of no regulation (January-December 2014), voluntary certification (VC, January-September 2015), partial licensing (PL, October 2015 – March 2016), and mandatory licensing (ML, April 2016 – June 2018). These changes were gradual, partly because some local governments delayed application approval, and partly because it is difficult to detect all violations immediately given the platform's size.

As argued by Friedman and Kuznets (1954) and Demsetz (1982) (see Section 2 for a full literature review), the trade off between voluntary certification and mandatory licensing is non-trivial, because they affect not only seller costs but also barriers to entry. For the same reason, certification and licensing tend to have different overall and distributional effects on the regulated market. The gradual rollout of the FSL – combined with the proprietary data of the whole Alibaba platform – provides a unique opportunity to study these issues.

Unfortunately, due to a missing-data problem (described in Section 4), we only observe the licensing status for a subset of NANA food sellers, and therefore cannot document the month-by-month licensing rate for the full sample. Conditional on sellers with valid licensing information, those that had a better online reputation and more online food sales before the FSL tend to display an FSL license earlier on the platform. This is not surprising, as larger and more reputable sellers may have a lower cost to meet the licensing requirement and expect more revenue loss if they have to exit the platform without a license. Moreover, within a seller, buyers are more willing to transact with the seller after she displays her FSL license. This positive response is stronger for younger and less reputable sellers, suggesting that license provides useful information in addition to what consumers have observed on the platform.

Market-wide, we identify the effect of the FSL via synthetic control matching between NANA food and non-food categories. This approach does not use any information on seller-specific license status, thus getting around the missing-data problem. Results suggest that the average quality of surviving sellers has improved after partial and mandatory licensing, partly because those who are unwilling to obtain the FSL license must exit the platform. As a result, seller concentration has increased. In the meantime, the platform's gross merchandise value (GMV) in NANA food did not decline post FSL, nor did the average sales price increase

significantly one year after the full enforcement of the FSL. This suggests that the FSL does not hamper the long-term performance of the regulated market, probably because it has enhanced seller quality and market transparency on the platform. Further analysis finds differential effects of the FSL by seller size and reputation.

The rest of the paper is organized as follows. Section 2 reviews the existing literature of certification and licensing. Section 3 describes the background. Section 4 presents the data we use. Section 5 documents how NANA food sellers respond to the FSL, in terms of licensing and exit. Section 6 turns to the demand side, showing how market sales respond to changes in a seller's licensing status. Section 7 presents market-wide results by comparing NANA food with other categories. Section 8 integrates all the empirical results in light of the existing literature. A brief conclusion is offered in Section 9.

2 Literature Review

Our work is related to the traditional literature on occupational licensing, which was originated from the classic study of Friedman and Kuznets (1954), and concisely summarized by Kleiner (2000). A common concern is that occupational licensing restricts supply and thereby drives up the price of services (Rottenberg, 1980). However, licensing can also generate benefits such as reducing information asymmetry (Akerlof, 1970), boosting overall demand, improving service quality (Arrow, 1971), protecting property rights, and encouraging investment/innovation (Demsetz, 1982). Our findings add new empirical evidence for the benefits and costs of licensing.

While the bulk of the traditional literature focuses on offline licensing, we extend the study of licensing from local offline markets to a nationwide online market. To our best knowledge, only two recent papers study the role of offline licensing in online markets. Farronato et al. (2020) study sellers' voluntary reporting of offline license on an online platform for professional services. They find that consumers pay little attention to (validated) licensing information, but respond vigilantly to online customer reviews. Hall et al. (2019) study local licensing and background screening requirements of Uber drivers. They find that occupational licensing often does not improve ride safety or ride quality outcomes. In the meantime, costly licensing and screening requirements tend to discourage Uber drivers' entry into local ride-sharing markets. Unlike both studies, we find that buyers respond positively and significantly to the FSL license, and this response is stronger for young and less reputable sellers. Our findings suggest that licensing provides new and useful information in

addition to the information already available on the platform.

Thanks to the gradual rollout of the FSL, we contribute to the literature that compares voluntary certification with mandatory licensing. Theorists often view certification and licensing as different tools to address the same information problem, but believe certification is more flexible because it allows sellers below the licensing standard to stay in the market (Leland, 1979; Shapiro, 1986). These low-quality sellers can serve consumers that prefer low-quality low-price products. In contrast, mandatory licensing is often advocated to eliminate poor-quality or unsafe products, but it could raise product price, limit entry, and reduce market competition.

Theoretical ambiguity could also arise from product differentiation. For example, licensing eliminates below-standard sellers, which mechanically improves the average quality available on the market (Leland, 1979). However, if competition is imperfect, it could motivate above-standard sellers to further improve quality, because product differentiation softens price competition (Ronnen, 1991). This prediction is sensitive to the number of firms in the market (Scarpa, 1998) and in some cases the incentive to differentiate could even lower the average quality on the market (Garella and Petrakis, 2008). When mandatory licensing is not fully enforced – as in our partial licensing period – low-quality sellers may choose to stay below standard, while high-quality sellers are better motivated to comply with the minimum quality standard (Chen and Serfes, 2012).[4]

Given the ambiguous theoretical predictions, it is not surprising that empirical evidence on the effect of certification and licensing is often mixed. For example, Law and Kim (2005) and Law and Marks (2009) find occupational licensing improved markets when it was hard to ascertain quality of professional services or quality of workers; Anderson et al. (2020) find that requiring midwives to be licensed reduced maternal and infant mortality during 1900-1940; Bhattacharya et al. (2019) show that fiduciary duty improved the overall performance of financial advisers by constraining low-quality advice; Larsen et al. (2020) find that stricter licensing requirements increased the left tail of the quality distribution of secondary school teachers and were effective at weeding out less-qualified candidates from the profession. In contrast, Kleiner and Kudrle (2000) find no improved dental outcomes but higher prices of basic dental services in places with stricter licensing; Adams III et al. (2003) find fewer births by midwifery upon more stringent licensing; and Kleiner and Todd (2009) find mortgage broker licensing had no impact on the number of foreclosures but led to higher price of mortgages.

[4]See Dranove and Jin (2010) for a literature review of quality disclosure and certification.

In Section 8, we articulate how the trade-off between certification and licensing manifests in our data, and to what extent our setting differs from the traditional contrast of certification vs. licensing.

3 Background

In 2015, the Chinese government announced a new Food Safety Law (FSL), which for the first time requires online e-commerce food distribution to comply with the same regulations as the traditional, offline distribution channels.

The new law introduces a licensing system for food production and trade, setting standards for food production, storage, equipment, personnel, and raw materials. For example, it requires the ownership of an offline production or storage site that is clean and tidy, and in a prescribed distance from pollution sources. It also requires the licensee have professional equipment or facilities suitable for food production, have qualified equipment for disinfection, disposal and garbage, and have adequate personnel for food safety and management. Online platforms have the responsibility to display the license to consumers. Also, different types of food have different exposure to the licensing system. Non-agricultural products face the most stringent standard. Any sales of non-agricultural products have to obtain a legal license. But raw, agricultural products, for example, seafood that had not been hyper-processed, are exempted from mandatory licensing. Also, alcoholic drinks have already been subject to a special licensing requirement before 2015 so the FSL does not apply to them.

Alibaba is the leading e-commerce provider in China. It owns two marketplaces, Taobao and Tmall. The new law affects seven level-one food groups on Taobao and Tmall, including snacks, fruits/vegetables/seafood and cooked food, oil/rice/noodle/seasoning, nutrition food, tea, coffee/oatmeal, milk/infant formula. We thus focus on the effect of the FSL on non-agricultural non-alcoholic (NANA) food, and pool all NANA food-related groups as one treatment category. All the other 134 level-one non-food groups form the control donor pool for the market-wide analysis in Section 7.

From January 2015 to March 2016, Alibaba has taken many actions to implement FSL licensing. Alibaba changed its user interface so that sellers can show their FSL licenses to consumers. Starting January 2015, Alibaba had notified all food producers and retailers, encouraging them to obtain a legal FSL license and disclose it online. Since October 2015, Alibaba prohibited any new listings from unlicensed sellers. Alibaba also started to clean up the existing food listings from unlicensed sellers and finished it by the end of March 2016.

Because the FSL was implemented gradually, we have a unique opportunity to compare the effect of certification and licensing in the marketplace. We have four periods with different intensities of regulation. From January 2014 (the beginning of our sample period) to December 2014, all sellers did not have a license, indicating a period with no regulation and no license disclosure. From January 2015 to September 2015, some sellers had obtained and disclosed their license, while, unlicensed sellers had also been allowed to sell online, suggesting a period of voluntary certification (VC). From October 2015 to March 2016, sellers had to disclose their licenses before listing new products, but sellers who listed products before the regulation were still able to sell without a license, corresponding to a period of partial licensing (PL). From April 2016 to June 2018 (the end of our sample period), all sellers needed a license to sell food products, indicating a period of mandatory licensing (ML).

In the FSL context, enforcement is rather difficult for at least two reasons. First, some sellers may game the system by uploading wrong documents or posting regulated items as non-regulated listings. It takes time and resources to validate documents and listings. Since the FSL applies nationwide but licensing criteria and paperwork vary significantly across local governments, it is impossible for the platform to detect all violations immediately and precisely. Throughout the whole rollout period, Alibaba worked closely with the government and received only one small fine for a minor violation in FSL enforcement. Second, the FSL puts significant stress on local governments, which have to process a massive number of applications, send inspectors to inspect an applicant's physical facilities on site, and deal with all the idiosyncrasies of approval, appeal, reinspection, etc. We were told that lack of government resources had generated long delay between licensing application and licensing approval in some provinces. At times, the tension was so severe that Alibaba was allowed to acknowledge government receipt of licensing application as evidence of compliance and permit temporary selling without a final licensing approval. For these reasons, our data most likely reflects a gradual transition from VC to ML, rather than sudden regime shifts.

4 Data

We have access to aggregated, proprietary data from Alibaba Group for all listings in all categories. From January 2014 to June 2018, the data includes product information, seller information, price, quantity sold, and revenue.

Product information includes the specific title of a listing, a set of product characteristics, and the product classification the listing belongs to (as defined by Alibaba). Excluding digital

and service goods such as real estate, ticket booking and gift cards, Alibaba's classification has 141 level-one groups, 7 of which are food related.

Our data on food listings has a special indicator for alcoholic drinks, but it does not explicitly indicate whether a food item is agricultural or not. This presents a challenge, as only non-agricultural food is subject to the FSL. To address it, we use listing titles to infer whether an item is agricultural or non-agricultural, depending on whether the item on sale comes in an original retail package from the manufacturer. We were told that this feature is a strong indicator for non-agricultural food, although not having it does not necessarily imply the item must be agricultural. For example, dried fruits that are individually wrapped by the manufacturer is non-agricultural for sure, but if a seller sells the same product by weight and without the original retail package, it is hard to tell whether it is agricultural or not. Whenever we have doubts, we classify the food listing as "unknown." In doing so, we identify 2% of food listings as agricultural food or alcoholic drinks, 32% as non-agricultural non-alcoholic (NANA food), and the rest, 66%, as unknowns. Throughout the paper, we exclude all agricultural food, alcoholic drinks and the unknowns from the analysis. All results are robust if we include the unknowns.[5]

Below we summarize the data at the category level and the individual seller level.

4.1 Category-level data summary

At the category level, we take NANA food as one treated category and the 134 non-food level-one groups as control categories. Each category-month can be summarized by seller count, average sales price, average seller quality, and total GMV. By seller count, we mean the number of unique sellers that sold anything in category c and month t. If a seller has sold in multiple categories in that month, she is counted as active in each of these categories. For each category-month, we can count the number of unique listings that have positive revenue. Across all listings in a category-month, we can sum up the total revenue and total units sold. The ratio of the two yields average sales price.

We rely on Alibaba's consumer rating system and return records to measure seller quality. Alibaba displays seller-specific rating scores in three dimensions: product description, service, and shipping. Each score is the average for all reviews given by previous consumers who have purchased from the seller in the last six months. Across the three scores, we compute an average for each seller. Thus, the resulting average score is seller-month specific, indicating the overall product, shipping, and service quality of the seller in the past six months. An

[5]Results are available upon request.

average of the three average rating scores gives us one overall measure of average seller quality per category-month. Similarly, based on the return records, we compute "average percentage of returns due to quality problem per active seller" and "average percentage of returns due to counterfeit per active seller" as two other measures of average seller quality.

Though imperfect, these measures capture the type of product and seller quality that consumers could observe ex post. In Figure 1a, we present a few examples where consumers identify bad quality via the look of the package ("broken to pieces"), food taste ("greasy","spoiled"), and body reaction after consumption ("uncomfortable in stomach"). These types of feedback contrast the examples of positive feedback about food quality in Figure 1b, and will be reflected in the seller ratings of product description and service. Figure 1c further demonstrates a formal consumer complaint, which argues that the food tasted differently from the authentic version, the seller did not admit counterfeit, and the seller was only willing to refund for the unopened portion of the purchase. Such complaint would be counted in "average percentage of returns due to quality problem per active seller" and "average percentage of returns due to counterfeit per active seller."

Note that some, but not all, of these quality problems are directly related to inappropriate food handling. However, sellers that take a shortcut in food handling are also likely to cut corners in shipping and customer service, so the quality measures from Alibaba are more comprehensive than what the FSL attempts to regulate. For the same reason, the average seller ratings that Alibaba present to consumers are not as salient as an FSL license would be on the quality of food handling, leaving room for the license to add useful information to consumers. The resulting improvement in seller quality could be reflected in the quality measures from Alibaba, either because some measures are directly about appropriate food handling, or because the FSL requires dedicated personnel on food safety and therefore allows other personnel to focus on qualities unrelated to food safety.

Seller reputation is another important attribute of sellers, which may reflect a NANA seller's overall quality including but not limited to food handling practice. In particular, at time t, Alibaba defines a seller's reputation as her total count of positive consumer feedback minus total count of negative feedback. By definition, this measure is accumulative across time and across all categories since the seller's entry onto the platform. Seller reputation is important for both buyers and sellers because it is highly visible on the platform and Alibaba uses it to classify sellers into stars and crowns. However, because it is cumulative and negative feedback is rare on average, seller reputation is more related to the seller's age and overall trading volume on the platform, than to the seller's product or service quality

per transaction. That said, being able to survive for a long period and for many transactions could in itself be interpreted as a signal of seller quality.

Across the four periods (no regulation, VC, PL, and ML), Table 1 summarizes our category-level data for NANA food. To avoid revealing Alibaba's business secrets, we normalize the summary statistics by deducting the platform-level mean and dividing the difference by the platform-level standard deviation in each month. The table thus shows the category-level variations in NANA food relative to platform-wide average.

Panels A and B document market structure changes in NANA food. According to Panel A, in the no-regulation period, the number of NANA food sellers was 0.112 standard deviation above the platform average, which further increased to 0.687 and 0.697 during VC and PL, but dropped below that of no-regulation (-0.021) after ML started. This suggests that many food sellers may have entered the market under VC, but exited under ML. Consistently, Panel B shows that the Herfindahl index (HHI) of NANA food increased over time, especially after ML started.

Panels C, D, E and F focus on quality measures. As shown in Panel C, average rating score per active seller declined from no-regulation to VC, and then increased during PL and ML. Panel D summarizes average reputation per active seller. It was below platform average during no regulation, VC and PL, but rose above platform average during ML. Panels E and F summarize average percentage of return due to quality problems or counterfeits per active seller. Both metrics were extraordinarily high for NANA food in the no-regulation period, but they decreased steadily throughout VC, PL and ML. These patterns suggest that the average seller quality of NANA food may have improved over time, especially as the FSL became more binding in ML.

Finally, in Panels G and H, average sales price (per unit sold) increased for NANA food, but GMV fluctuated.

4.2 Seller-level data summary

Category-level comparison helps to describe the big picture, but it ignores many heterogeneities within a category. As a supplement, we extract a random sample of 1,926 NANA food sellers from those that had NANA food sales for at least three months in 2014 (roughly 1%). For the drawn sellers, we keep all their NANA food listings from January 2014 to June 2018, and aggregate the listings by seller-month. For each seller-month, we compute total revenue, total number of NANA food listings that have any sales, and average sales price (total revenue divided by total units sold).

By definition, such sampling is limited to incumbent sellers who had sales during the no regulation period. Because new entrants have no pre-FSL period, they are not included in the individual-seller sample. Towards the end of the paper, we will present statistics on the NANA food sellers that entered the platform post 2014.

Table 2 summarizes the sample of 1,926 NANA food sellers. A seller is defined as exiting the platform at month t if t is the last month she had positive NANA food sales and t is not the last month of our data. By this definition, 1,613 (83.7%) of the 1,926 sellers have exited by the end of our sample period. The high exit rate is not unique to NANA food, as the whole platform features high entries and exits, and sellers often jump categories over time. Over time, we observe a smaller number of exits in no-regulation and VC periods (292 and 387) than in PL and ML (419 and 828). The higher exit rate during PL and ML could be driven by tighter enforcement of FSL licensing in these two periods.

There is a missing data problem that could potentially bias our description of licensing progress between 2014 and 2018. In particular, for some sellers, the historical FSL licensing data was overwritten by their recent licensing status after the end of our data period, and thus we cannot recover their full history of FSL licensing. For example, we do not know whether they never displayed any FSL license before June 2018 or they had done so but the historical record is missing. For other sellers, we know exactly when they first obtained and displayed the FSL license on the platform. This information is cumulative, as no sellers switched from being licensed to no license unless they exit the NANA food category or the platform as a whole. Either way, we were told that a seller that had any NANA food sales post the start of ML must have a valid FSL license or present a reasonable excuse to be temporarily exempted from the delisting enforcement (e.g. local government has a technical delay processing the seller's FSL application).

Out of the 1,926 NANA food sellers, we observe that 335 (17.4%) display an FSL license by June 2018. As lack of license could be driven by missing data or by sellers not obtaining the FSL license, we zoom into the 901 sellers that had positive sales post ML. In theory, they should have all displayed the FSL license by the end of our data if the delay of local government approval is not too severe. Among them, 303 (33.7% of 901) have displayed an FSL license sometime, while the other 598 did not. In contrast, only 32 (3.1%) of the 1,296 sellers that did not sell any NANA food post ML have any FSL licensing data. This suggests that the vast majority of those exiting before ML did not bother to get licensed, while some that continued to sell post ML may suffer a missing data problem.

Conditional on the sellers that had positive NANA food sales post ML, Table 3 compares

them by whether their license data is missing. As shown in the first two columns, those with valid FSL licensing data were older, bigger and more reputable before the FSL than the ones without FSL licensing history. However, post ML, those without the FSL licensing history have a higher monthly GMV, although they are on average active for fewer months. To further examine the missing pattern, the last two columns of Table 3 zoom into the 382 sellers that sold any NANA food in 2018 (the last six months of our data). If local government delay is one important reason for missing licensing data, we should observe less missing in this subgroup. Indeed, only 35.2% (135 out of 382) of them miss licensing history, which is much lower than the percent of missing (66.3%) among those that sold anything post ML. The two subgroups—with and without licensing history—are also more similar to each other once we condition on having sales in 2018. Above all, we conclude that data overwriting accounts for some of the missing data, but it is also possible that license approval was delayed in some local governments when ML started and such delay was alleviated over time. Unable to tell the exact reason for each missing data point, our comparison between licensed and unlicensed sellers will likely underestimate the real difference, as the unlicensed group would include some that actually got the license.

Conditional on the 335 sellers with valid licensing information in our data, the second panel of Table 2 describes the distribution of the timing of their license display: only 96 of them (28.7%) obtained and displayed their FSL license in the VC period, while 129 (38.5%) got licensed in PL and the other 110 (32.8%) in ML. This pattern suggests that the tighter enforcement of PL and ML may have given sellers an extra motivation to acquire and display an FSL license.

The next block of Table 2 summarizes GMV, number of orders, number of unique buyers, and total quantity sold per active seller-month. By active seller-month, we mean each seller that has positive sales in a specific month. In total, there are 41,272 active seller-months in our sample. To capture potential skewness, we show mean, median and standard deviation for each measure. It is obvious that all these sales measures are highly skewed, with the mean much higher than the median.

The last two blocks of Table 2 classify the 1,926 NANA food sellers by their reputation and age on the platform. Among all active seller-months, the average seller reputation is 21,932, and the median is 2,419. If we classify the 1,926 sellers by their average reputation in the no-regulation period, 669 (34.7%) had a reputation no higher than 250. We refer to them as "low-reputation" sellers, and the rest as "high-reputation" sellers.

Seller age is defined as the number of months since the seller opened her first store in

Alibaba marketplaces. Across the whole sample of individual NANA food sellers, the average seller age (per active seller-month) is 21.89 months and the median is 10. If we classify the 1,926 sellers by their average age in the no-regulation period, 641 of them (33.3%) were less than 12 months old. We refer to them as "young" sellers and the rest as "old."

5 Supply Response: Who Obtains an FSL License and Who Exits?

Despite the missing data problem, the observed licensing data may still tell us something about who got the FSL license and when.

Figure 2 plots the hazard rate of licensing for all NANA food sellers (before we sample individual sellers). Each point represents the fraction of sellers that started to display the FSL license during time t if they had not been FSL-licensed by the beginning of t. The three vertical lines indicate the start of VC, PL, and ML respectively. Because sellers without licensing data are counted as never licensed in this figure, the absolute hazard rate will underestimate the actual hazard rate, but relative change of hazard rate is still informative if the missing data problem is random. Consistent with Table 2, Figure 2 shows that unlicensed sellers are more likely to obtain an FSL license right before PL and ML, probably because of the threat of more stringent enforcement from the platform. During ML, there is another spike of licensing hazard rate near the end of 2016, which may reflect batch approvals from some local governments.

Figure 3 plots the exit hazard rate for NANA food sellers. Recall that exit is defined by a seller's last sales record in our data, which does not suffer any missing data problem. Generally speaking, the exit hazard increased from no-regulation to VC, peaked during PL, and declined in ML. There was a small rise of exit rate at the start of VC and PL, likely reflecting the (perceived) tightening in platform enforcement.

To further understand seller behavior, we apply a duration model with Cox proportional hazard to the sample of 1,926 individual NANA food sellers. In particular, we assume the hazard of seller i uploading the FSL license at month t is as follows, conditional on her not displaying such license by $t-1$:

$$\lambda(discloselicense_t|X_{it}) = \lambda_0(t) \times exp(X_{it}\beta), \tag{1}$$

where X_{it} includes the interactions between the dummies of VC, PL and ML periods and a

seller's pre-FSL GMV and reputation (both in log). Because sellers could not upload the FSL license until VC started in January 2015, the estimation sample excludes the no-regulation period. By definition, every seller in our individual seller sample had positive sales in at least three months before the FSL, so we compute her pre-FSL GMV and pre-FSL reputation as the monthly average during no-regulation. The stand-alone terms of pre-FSL GMV and pre-FSL reputation are dropped, because a period post the FSL must be VC, PL or ML, and we already include their interactions with VC, PL and FL respectively.

Table 4 presents the results in two columns. The first column uses all of the 1,926 NANA food sellers in our random sample; the second column is conditional on the 335 sampled sellers that have some FSL licensing data. Obviously, the second column is a highly selected sample because sellers that intended to exit before ML may not bother to seek the FSL license. However, because we cannot distinguish them from those that got the FSL license but have missing value in our data, a focus on the licensed ones would at least tell us who tends to get the FSL license earlier than others. In comparison, the first column is subject to the missing data problem and may underestimate the baseline hazard rate and the impact of observable factors.

As shown in Column 1 of Table 4, the hazard ratio of log(pre-FSL GMV) is significantly higher than one in the VC and PL (1.356 and 1.180), but lower than one in the ML (0.783). Results are qualitatively similar in Column 2 (but with smaller magnitudes), suggesting that sellers with higher sales before the FSL are more likely to obtain and upload an FSL license early, rather than wait until the platform adopted the tightest enforcement in the ML. This is not surprising, as sellers of higher pre-FSL sales should have more resources to pay for the licensing cost and would face more revenue loss if they had to exit the platform without a license. In comparison, the hazard ratio on log(pre-FSL reputation) follows a similar pattern: it is significantly higher than one in the VC and PL (1.353 and 1.145) but not distinguishable from one in the ML (1.011). Results are qualitatively similar in Column 2, suggesting that the pattern is unlikely driven by the missing data problem.

We run a similar duration model for seller exit. For seller i, we code her as exiting in month t if t is the last month we observe her positive sales in NANA food and t is not the last month of our data (June 2018). This definition may over-count exit if some sellers only sell seasonal NANA food that has high demand in May but little demand in June.

Table 5 reports the duration results on seller exit. Although we could compute the hazard rate of exit during no-regulation, we choose to exclude the no-regulation period from the estimation sample, because the sellers are sampled conditional on sales before the FSL

and our key variables – pre-FSL GMV and pre-FSL seller reputation – are computed from the seller's whole history during no-regulation. As we do not have any missing data problem for sales and exit, we report the results for the full sample of 1,926 NANA food sellers.

Consistent with the hazard of licensing, Table 5 shows that sellers of higher pre-FSL reputation are significantly less likely to exit in VC and PL periods. This makes sense, as more reputable sellers are more likely to obtain an FSL license during VC and PL, thus having less need to exit. In comparison, conditional on survival at the beginning of the ML, they are more likely to exit during ML, probably because the platform has tightened the FSL enforcement during ML and those that chose to be unlicensed have to exit. Surprisingly, those that had a higher pre-FSL GMV are more likely to exit during VC and PL, which is opposite the effects of VC and PL on those that had a higher pre-FSL reputation. As pre-FSL GMV and pre-FSL reputation are positively correlated, we do not have a good explanation. One possibility is that the FSL triggered multiple types of reactions: some were motivated to obtain an FSL license early and remain active post-FSL; others may try to clear out all food items before the FSL became binding. Both types could involve big or small sellers. In the Appendix, we will use synthetic control matching for each individual seller, to better understand how the FSL affects the distribution of NANA food sellers.

6 Demand Response: How Sales Relate to a Seller's FSL License?

Whether a seller is motivated to seek an FSL license depends on how consumers respond to the display of the license. To gauge consumer response, we use the monthly records of the same 1,926 NANA sellers as in Tables 4 and 5. If we condition on active sellers (i.e. with positive sales in a month), the panel consists of 41,272 observations by seller-month. We refer to this sample as the active selling sample. If we include those who have not exited but made zero sales in a month, there are 56,364 seller-months. We refer to this sample as the potential selling sample.

Our econometric specification is:

$$y_{it} = \gamma_1 1_{\{FSLlicense,it\}} \cdot 1_{\{VC\}} + \gamma_2 1_{\{FSLlicense,it\}} \cdot 1_{\{PL\}} + \gamma_3 1_{\{FSLlicense,it\}} \cdot 1_{\{ML\}} + \chi_i + \mu_t + \epsilon_{it} \quad (2)$$

where i denotes the seller, t is month, χ_i is seller fixed effects, and μ_t is year-month fixed effects. When we use the potential selling sample, the dependent variable y_{it} is the dummy

of whether seller i makes any NANA food sales in month t. Conditional on the active selling sample, the dependent variables are the seller's monthly GMV, number of orders, number of buyers, and quantities sold.

Our main independent variables are the interaction between the seller's license status ($1_{\{FSLlicense,it\}}$) and the dummies of VC, PL and ML. Again, because no license is available until the VC started, the stand-alone term of $1_{\{FSLlicense,it\}}$ is dropped due to collinearity. All regressions include seller fixed effects, thus $\{\gamma_1, \gamma_2, \gamma_3\}$ measure how y_{it} changes within the same seller after she displayed the FSL license on the platform. We do not include seller reputation, quality, or average sales price on the right-hand side, because seller fixed effects already absorb each seller's pre-FSL characteristics, and any concurrent change in reputation, quality or price can be equilibrium outcomes post the FSL.

For this reason, $\{\gamma_1, \gamma_2, \gamma_3\}$ should not be interpreted as the causal effect of randomly assigning an FSL license to an incumbent NANA seller. Rather, they capture the average within-seller change of sales likelihood and sales amount when the seller switches from no license to having an FSL license in a particular post-FSL period. Licensed sellers could be a selected group, and the licensing dummy reflects whatever factors that drive the seller's licensing decision.

Table 6 shows the estimation results for the full sample of 1,926 NANA food sellers. According to Column (5), displaying an FSL license during the VC period is related to a 14.1% higher probability to make any sales, relative to the no regulation period. The boosting effect of licensing in the PL and ML are even higher 31% and 32.3%. Conditional on making sales, Column (1) shows that, displaying an FSL license in VC is associated with 30.4% more GMV within the same seller, as compared to pre-FSL. Positive effects also occur in PL (53.8%) and ML (69.7%). Similar patterns appear in other sales measures. In short, consumers' positive response to FSL licensing is consistent with the fact that some sellers sought licensing even when the mandate was not fully in effect.

Tables 7 and 8 rerun the same specification by subsamples, according to whether a seller was more than 12 months old before FSL and whether a seller's pre-FSL reputation was over 250. Comparing young and old sellers in Table 7, we find 13 out of all 15 coefficients are higher for young sellers. A similar pattern occurs in Table 8, where all 15 coefficients are higher for low-reputation sellers than high-reputation sellers (although the 4 coefficients on low-reputation sellers in the VC are not significant from zero due to insufficient data variations). Some of the found effects may not be fully attributable to FSL licensing as we do not control the full information set of consumers. But the pattern suggests that an

FSL license helps consumers to trust younger and less reputation sellers on the platform, probably because the license provides useful information in addition to what consumers can observe on the platform.

The above results are based on the full sample of the 1,926 NANA food sellers, which could be biased due to the missing data problem in licensing history. To the extent that the unlicensed sellers in our data could have obtained an FSL license in reality, these results could under-estimate the true effect of FSL license display. Because of this caveat, these results should not be interpreted as the causal effects of the FSL. Later on, we will identify the market-wide effect of the FSL via synthetic control matching, which does not depend on any seller's licensing status.

7 Market-wide Effects of the FSL

So far, we have documented supply and demand changes after the FSL within NANA sellers. However, these descriptive statistics do not control for what else was happening on the platform at the same time, and are subject to missing values in some sellers' licensing history. In this section, we pursue the causal effects of the FSL on market-wide performance, by comparing NANA food with non-food categories via synthetic control matching.

Synthetic control matching is developed for case studies with one outcome variable (Abadie and Gardeazabal, 2003; Abadie et al., 2010), but we need to consider multiple outcome variables including seller count, average price, seller quality, etc. Ideally, we want the synthetic control unit to be the same as the treated across all outcome variables. But when we try to match all variables jointly, the pre-treatment matching quality is uneven across outcome variables.[6] Ex ante, it is difficult to judge which outcome variable should receive more weight in the overall quality of joint matching. In light of this, we apply synthetic control matching to each outcome variable independently.

We start with the seven outcome variables listed in Table 1. For each outcome variable, we look for a synthetic control unit from the donor pool of the 134 non-food categories. We match the outcome variables during no regulation and keep the weights unchanged for the periods of VC, PL and ML.

We do not have a balanced panel for average sales price if a seller has zero sales in a month, because we calculate sellers' average sales price from the GMV and quantities sold.

[6] Robbins et al. (2017) proposed a micro-synthetic control method for multiple outcome variables and a `RStudio` package `microsynth.R`. We have tried the new method jointly matching all outcome variables.

To deal with it, we aggregate the seller-month-level prices to seller-quarter-level prices and drop sellers who still have unbalanced quarterly prices during no regulation. Also, we observe missing rating scores if a seller has no sales in a month. We impute the missing value as the seller's non-missing average rating score in the latest previous month with positive sales, because the rating score is mechanically calculated based on purchases in the last six months according to the platform. Therefore, the results for sellers' monthly GMV, average rating score, and the number of active listings are all unconditional on seller survival, but the result for average sales price is conditional on seller survival.

Figure 4 presents the effects of the FSL on NANA food over three treated periods (VC, PL and ML). To protect Alibaba's business secrets, we only display the relative difference between the treated unit and the synthetic control rather than their actual values.

Table 9 displays the treatment effects of the FSL on NANA food in the first month of each treatment period. The P-values are computed using bootstrapping. In particular, we conduct the synthetic control for each of the control categories while using all categories except for itself as the donor pool. This gives us a distribution of treatment effects under the null hypothesis of zero effect. We use the distribution to calculate p-values. For a positive (negative) treatment effect, its one-sided p-value is the probability that placebo effects are above (below) the treatment effect.

Consistent with data summary in Table 1, seller count in NANA food has a 15.4% increase in the first month of VC but a 1.4% drop in the first month of ML, all relative to no regulation. Most times, the effect on seller count is not statistically different from zero. The HHI increase in NANA food started in VC, but became statistically significant in PL and ML. Average rating score per seller was on the upper end of the confidence interval during VC, PL and the first half of ML, and eventually became significantly positive in the second half of ML.[7] In the meantime, the percentage of returns due to quality and counterfeit problems dropped significantly. For these two variables, the quality of synthetic control matching is not as good as other outcome variables, partly because they are designed to capture small probability events, and partly because their values for NANA food were extraordinarily high in part

[7]The abnormal dip towards the end of VC was driven by Alibaba's algorithm change on rating score. Since late 2015, Alibaba's rating system no longer includes transactions in which the final transaction price is extremely low (<5 RMB, equivalent to 80cents in US$). This policy applies to historical cumulative ratings and affects different categories differently depending on the price distribution specific to each category. Because food items are more likely to be of low price, this algorithm causes the average rating score to drop significantly in late 2015. However, average rating score is a 6-month moving average, so the impact of this change attenuates over time. To the extent that it remains to affect food more than other categories, our synthetic control estimate may under-estimate the effect of the FSL on sellers' rating score.

of 2014 (Table 1). The synthetic matching results also suggest that these two variables improved significantly even before the beginning of VC. We don't know the exact reason. If Alibaba had started to target the food category for quality issues before the official start of the FSL, the large improvement post FSL may not be fully attributable to the adoption of FSL. Overall, the three quality measures suggest that average seller quality has improved post the FSL. As for average sales price, the point estimate is positive but rarely significant. Similarly, the effect of the FSL on the platform's total GMV in NANA food was always within the 95% confidence interval. This suggests that the FSL does not hamper the long-term performance of the regulated market, probably because it has enhanced seller quality and market transparency on the platform.

8 Discussion

In this section, we integrate the empirical findings and discuss how our findings relate to the literature on certification and licensing.

As reviewed in Section 2, occupational licensing could have a positive effect on the market, because it reduces the information asymmetry facing consumers, and eliminates below standard quality. In the meantime, it could also have a negative effect in terms of higher price, more barriers to entry, and lack of low-quality products to satisfy diverse demand.

Our findings support both sides of the argument. On the positive side, we show that average seller quality in NANA food, relative to other non-food categories, has increased post the FSL, partly because sellers of high quality are more likely to seek licensing and survive, and partly because sellers of low quality are more likely to exit without an FSL license. Meanwhile, a NANA food seller that obtains an FSL license tends to see her sales grow, suggesting that consumers do appreciate the information conveyed by an FSL license.

On the negative side, we find an increase of seller concentration in NANA food, suggesting that the FSL may have raised the barrier to entry. In theory, seller concentration may have mixed impacts on the platform's total revenue. On the one hand, fewer sellers on the platform may reduce the number of transactions and drive away certain consumers. On the other hand, the surviving ones may be able to charge a higher price either because their product quality has improved or because of less competition on the platform. It is also possible that licensing boosts consumer confidence in the platform and encourages more quality conscious consumers to buy on the platform. With all these possibilities, it is difficult to predict whether seller concentration would result in more or less GMV for the platform.

Empirically, we observe higher seller concentration but no significant change in the average price or platform GMV. Since GMV is proportional to average price times total quantity, these results suggest that the surviving sellers (and new entrants under the FSL) quickly filled the quantity gap left by exiting sellers, and they did so without raising the transaction price on average. Combined with the improvement in average seller quality, there is reason to believe that consumers that trade on the platform are better off post the FSL.

However, these results are silent on the sellers and buyers that stop trading on the platform. If the exiting sellers are small family-owned businesses, the FSL may have narrowed their retail channels or made them switch to less regulated markets. Similarly, low-income consumers that prefer below-standard products may face a smaller choice set on the platform, and could potentially be worse off. Unfortunately, we do not have data on trade out of the Alibaba platform, and thus cannot support or rule out this classical concern of licensing. That being said, we find quality improvement without a significant rise of average price, suggesting that some low-income consumers may choose to stay in the market because the FSL enables them to receive better quality on the same budget.

Out of the same concern, economists often believe certification is a better tool to address the information asymmetry regarding product quality, because it does not shut down the market for below-standard products. We find at least two differences between certification and licensing in the FSL setting.

First, the hazard rate of seeking an FSL license spiked right before the beginning of PL and the beginning of ML (Figure 2). This finding defies the classical unraveling results, which argues that all sellers with above-standard quality should voluntarily seek certification without any mandate. It is hard to pin down the exact reason for the failure of unraveling: one possibility is that the cost of getting an FSL license is significant for sellers. Some sellers may have a high discount rate and therefore be unwilling to invest early in such a cost. Another possibility is that sellers didn't know exactly when Alibaba would strictly enforce the licensing requirement. It was also hard to predict when the local government would approve the licensing application quickly. Given these uncertainties, consumers did not necessarily interpret no-FSL license as a signal of worse quality, which undermines the unraveling theory and gives the sellers a reason to wait. A third possibility is endogenous product differentiation. Knowing that mandatory licensing would eliminate the below-standard products, some sellers may intentionally target consumers that would prefer below-standard products during the certification period, and then cater to the consumers in the above-standard market if they end up staying on the platform after mandatory licensing. The classical literature does

not capture this dynamic, because it often focuses on the equilibrium in a certification-only or licensing-only world. In our setting, the gradual transition from certification to licensing makes the dynamic differentiation feasible.

Moreover, we find that different types of sellers respond to certification and licensing differently. In particular, larger and more reputable sellers are more willing to get an FSL license during VC (Table 4), although early licensing could bring greater benefits (in terms of percentage of GMV and probability of any sale) to younger and less reputable sellers should they choose to get licensed early (Table 7, Table 8). These findings could be reconciled if FSL licensing is more costly for younger and less reputable sellers. This is quite plausible, as younger sellers that have not established a strong reputation on Alibaba may need to invest more in order to satisfy the FSL requirement and they may face more resource constraints to do so.

To further understand the heterogeneous effects of the FSL, we use synthetic control matching to compare the random sample of 1,926 NANA food sellers with a random sample of 5,721 sellers in seven "household" categories. We were told that these household categories – covering household items such as kitchen products, decorations, cleansers, gifts and festival products, household goods (lamp), and storage boxes – are most similar to NANA food in terms of seller composition, demand diversity, and market-wide performance. Appendix Table A.1 compares the sampled sellers in NANA food and household categories.

The Appendix describes how we use synthetic control matching on individual sellers. Results are shown in Appendix Tables A.2, A.3 and Figures A.1, A.2. In short, we find that NANA food sellers in the top decile of pre-FSL GMV (or pre-FSL reputation) are more able to survive, grow GMV, and expand number of listings in the ML period than sellers in all the other deciles. However, market dynamics are complicated, as many sellers in the top decile had a significant drop in GMV while some sellers in other deciles enjoyed GMV growth post the FSL. This suggests that the FSL has triggered some reshuffling within NANA food, and such reshuffling is not necessarily monotone to the pre-FSL GMV or reputation.

The results presented above are incomplete, because a NANA food seller cannot appear in our random sample unless she already sold some NANA food during the no-regulation period. By construction, this sampling misses entries post the FSL. To get a sense of market entry, Figure 5 compares new entrants in NANA food with new entrants in the seven household categories. A seller is counted new in month t if she opened the store on Alibaba after January 2014 and still has sales on or after month t. By this definition, the new seller count

is cumulative since January 2014, conditional on survival at the study time.[8]

Over time, Figure 5a displays the percentage of new sellers among all surviving sellers in NANA food, relative to household categories. For example, if at month t, x% of all sellers active in the household categories are new since January 2014 and (x+1)% of NANA food sellers are new, then the graph plots 1% for month t. The three straight lines indicate the start of VC, PL and ML respectively. In short, Figure 5a finds relatively fewer new sellers in NANA food after the beginning of ML, although more entries occurred in NANA food during VC and PL. The latter could happen if VC and PL prompted new non-licensable sellers to take the last opportunity to sell NANA food without a license. The drop of entry post the ML is consistent with the common concern that mandatory licensing tends to raise barriers to entry.

Figure 5b plots the new entrants' average rating score after 3 months post entry, in NANA food relative to the household categories. Throughout the whole sample period (January 2014 to June 2018), new entrants in NANA food tend to have higher average rating score than similar entries into household categories, at an average of 0.035. This gap became somewhat smaller in the first half of ML and larger in the second half of ML. Recall from the category-level analysis that FSL has a positive effect on seller quality, especially during PL and ML. Figure 5 suggests that such quality improvement is unlikely driven by new entrants, as NANA food saw fewer new entrants than household categories in the ML period and the quality gap of the new entrants in NANA food and household categories did not rise significantly during PL and ML. Put another way, the market-wide improvement in NANA food seller quality is more likely driven by weeding out low-quality incumbents rather than attracting high-quality entries.

9 Conclusion

We examine how the 2015 Food Safety Law (FSL) affects e-commerce in China. Because the FSL was rolled out progressively, we have a rare opportunity to observe a gradual transition from voluntary certification to partial licensing and mandatory licensing.

We find that FSL licensing provides an opportunity for younger and less reputable sellers to stand out as quality food sellers, and consumers respond positively to the display of the FSL license on the platform. In addition, as compared to non-food categories, it seems that

[8]Figure 5 is limited to NANA food and household categories, because we do not have individual seller data to track seller entry time in other categories. For the same reason, we do not have enough non-food categories to construct category-level synthetic control for the pattern of seller entry.

the FSL has improved average seller quality in the regulated food category without driving down its overall GMV or raising its average sales price one year post the full enforcement of the FSL. These findings suggest that the FSL may have brought substantial benefits to the market.

In the meantime, anecdotes suggest that enforcement and compliance costs are non-trivial. Because the FSL is an offline licensing requirement for online sellers, enforcement entails both offline resources from local governments and online resources from the platform. Besides enforcement costs, the cost of compliance is likely non-trivial for at least some food sellers, which may explain why larger and reputable sellers are more likely to obtain the FSL license despite the fact that consumers respond more positively to the licensing of younger and less reputable sellers. Another cost of the FSL may be reflected in the increased seller concentration. In our sample period, the higher concentration has not led to detectable price increase, but we do observe fewer new entrants into NANA food in the ML period, as compared to entrants in the household categories. It remains to be seen whether the higher barrier to entry due to the FSL would generate more costs for market competition in the future.

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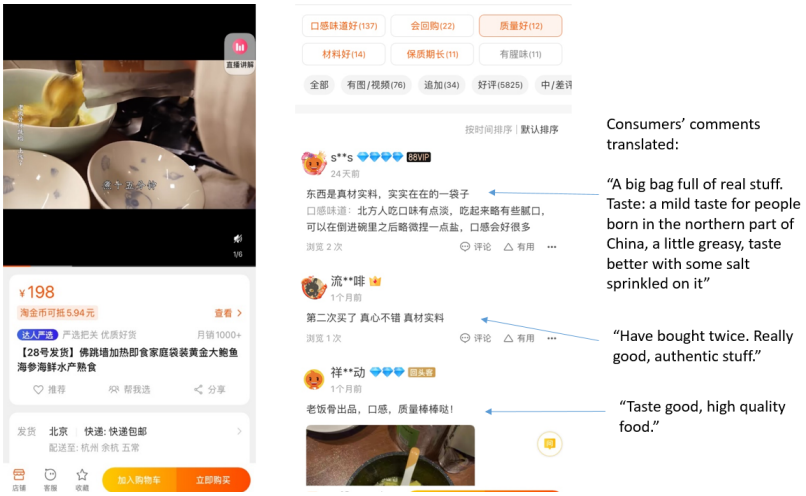
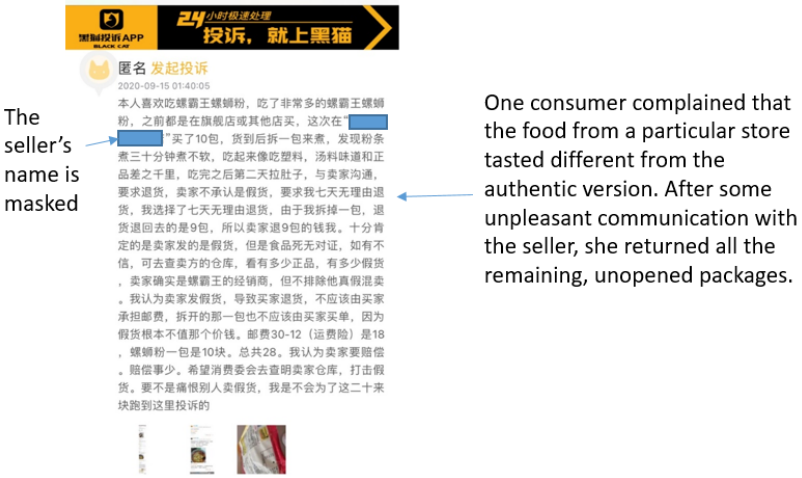
Figure 1: Examples of Consumer Feedback and Complaints in NANA Food

(a) Examples of negative consumer feedback about food quality

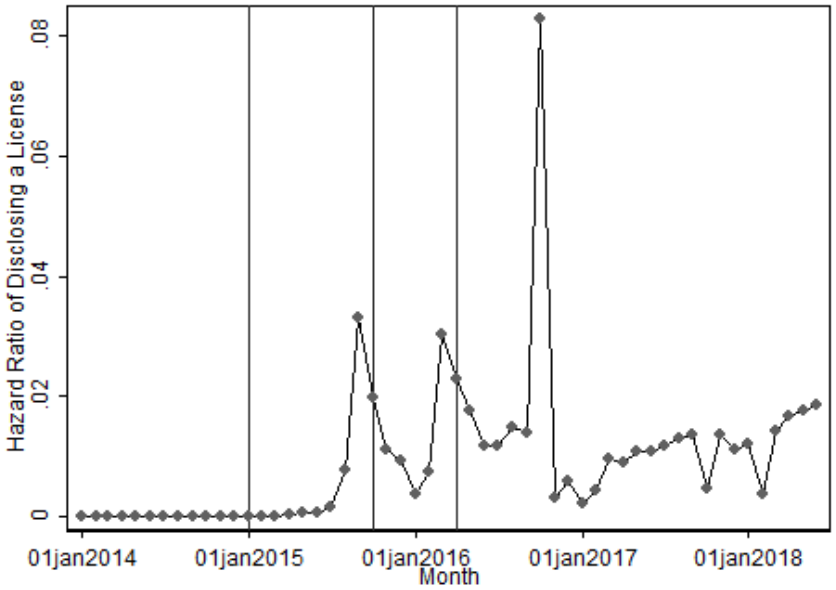


(b) Examples of positive consumer feedback about food quality



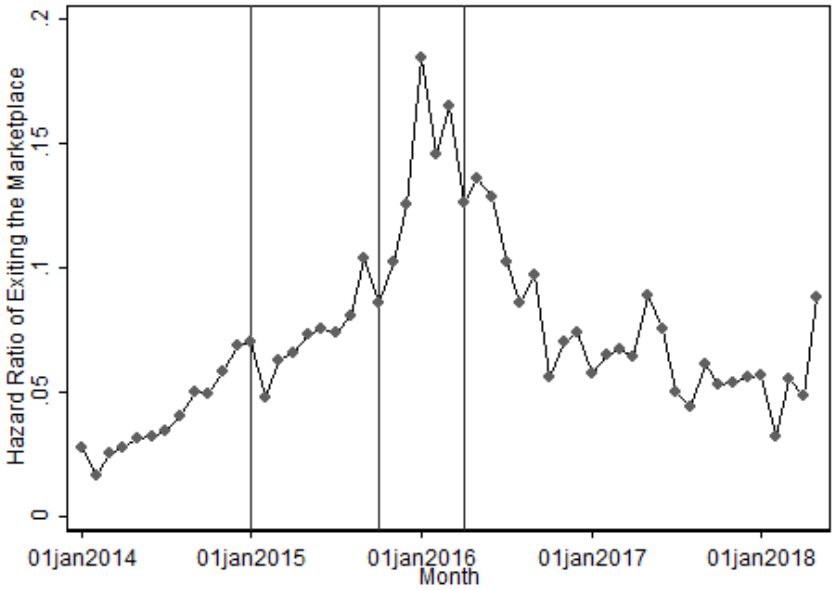
(c) An example of consumer complaint of non-authentic food

Figure 2: Hazard Ratio of NANA Food Sellers Displaying an FSL License



Notes: This figure presents the hazard rate of NANA food sellers displaying an FSL license in period t conditional on surviving and not-licensed yet at the beginning of period t. The three lines are the start time of voluntary certification, partial licensing, and mandatory licensing, respectively.

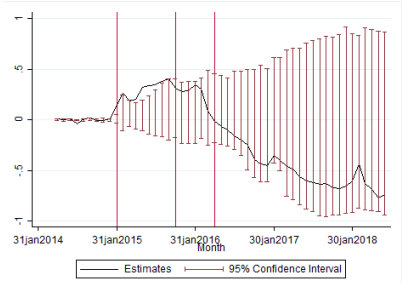
Figure 3: Hazard Ratio of NANA Food Sellers Exiting the Market



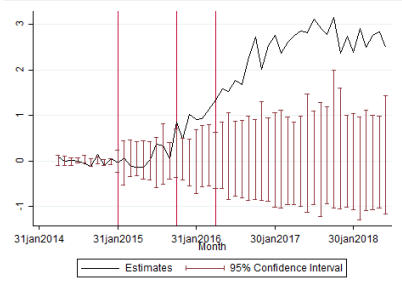
Notes: This figure presents the hazard rate of NANA food sellers exiting the market at the end of period t conditional on surviving at the beginning of period t. The three lines are the start time of voluntary disclosing, partial licensing, and mandatory licensing, respectively. A seller is defined as exiting the market at t if t is the last month we observe her positive sales in NANA food and t is the not the last month of our data (June 2018).

Figure 4: Synthetic Control: Treatment Effects of the FSL on NANA Food

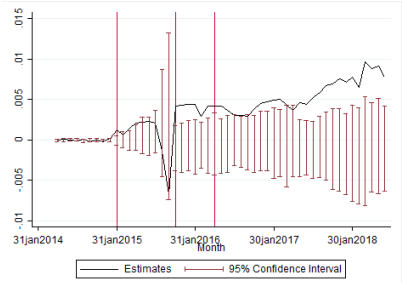
(a) Log of Total Number of Unique Active Sellers



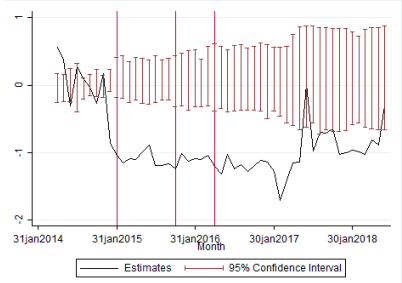
(b) Log of Category HHI



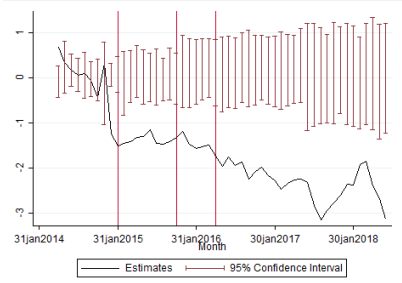
(c) Log of Avg. Rating Score per Active Seller



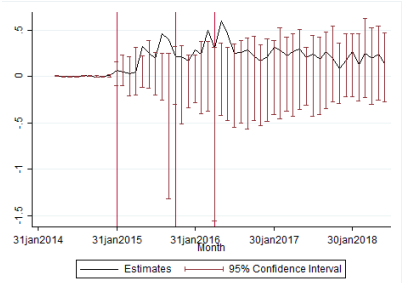
(d) Log of (1+Avg. %Returns due to Quality Problem per Active Seller)



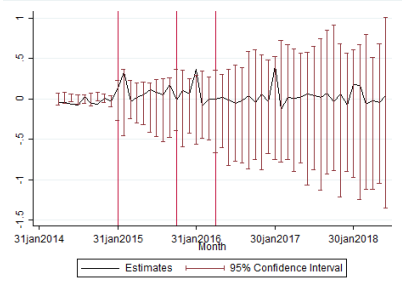
(e) Log of (1+Avg. %Returns due to Counterfeits per Active Seller)



(f) Log of Avg. Price per Active Listing



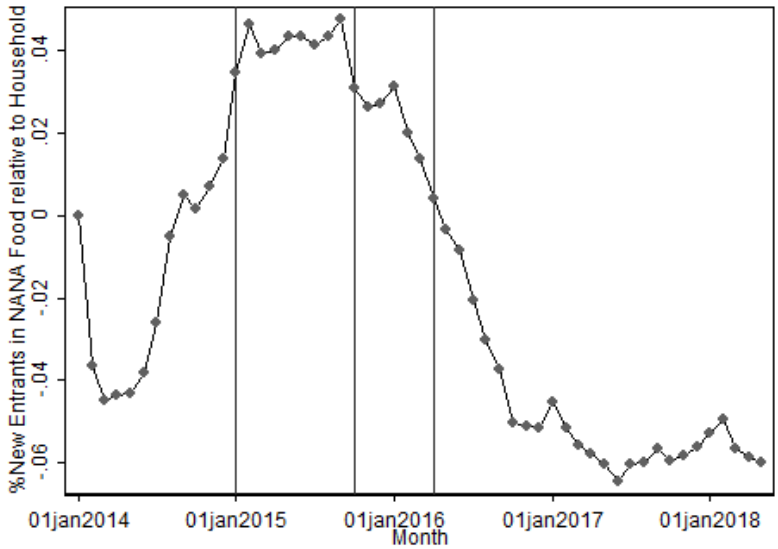
(g) Log of Total GMV



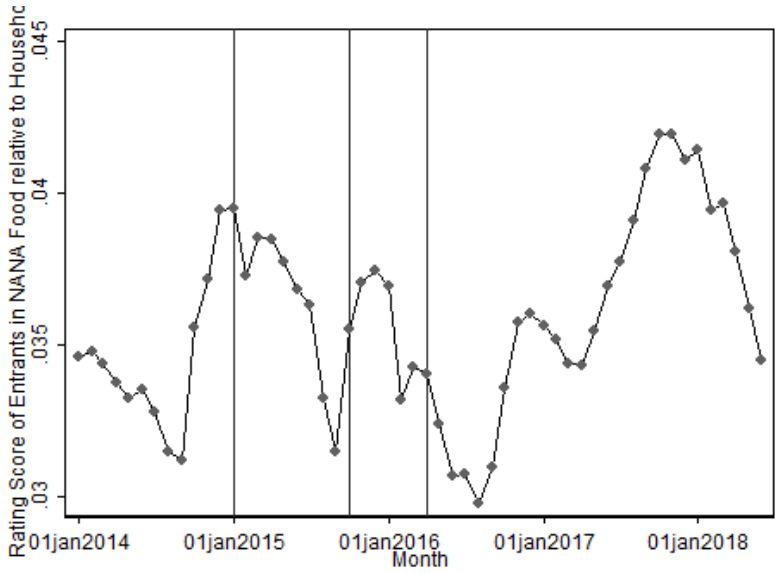
Notes: This figure shows the treatment effects of the FSL on the NANA food category. To avoid revealing Alibaba's business secrets, we only display the difference between the treated category and the synthetic control unit rather than their actual trends. The three vertical red lines are the beginning of voluntary disclosing, partial licensing, and mandatory licensing.

Figure 5: New Sellers: NANA Food Category v.s. Household Category

(a) Percentage of New Sellers to All Sellers



(b) New Sellers' Average Rating Score after 3 months post entry



Notes: The upper figure shows the difference in percent of new sellers in all sellers between NANA food and household categories. The lower figure shows the difference in new sellers' average rating score after three months post-entry between the NANA food and household categories. The three straight lines indicate the start of voluntary certification, partial licensing, and mandatory licensing. A new seller is counted new in month t if she first shows up in the data after January 2014 and still has sales on or after month t. By this definition, the new seller count is cumulative since January 2014, conditional on survival at the study time.

Table 1: Summary Statistics of NANA Food as a Category

	No Regulation	Voluntary Certification	Partial Licensing	Mandatory Licensing
A: Total of unique active sellers	0.112	0.687	0.697	-0.021
B: Category Herfindahl Index (HHI)	-0.356	-0.188	0.265	1.886
C: Avg. seller rating score per active seller	0.885	0.586	1.495	1.337
D: Avg. seller reputation per active seller	-0.127	-0.227	-0.125	0.218
E: Avg. %returns due to quality problem per active seller	2.036	-0.645	-0.782	-1.520
F: Avg. %returns due to counterfeits per active seller	4.719	-0.221	-0.431	-1.183
G: Avg. transaction price per active listing	-0.329	-0.327	-0.317	-0.311
H: Category total GMV	-0.282	-0.352	-0.339	-0.313

Notes: All statistics are average over months. To avoid revealing Alibaba's business secrets, all numbers are normalized by the platform-level mean and standard deviation. For example, 0.112 in row A means that the number of sellers in the NANA food category is 0.112 standard deviation above the platform-wide mean during no-regulation.

Table 2: Summary Statistics for A Random Sample of NANA Food Sellers

	Mean	Median	Std. Dev.
No. of Sellers	1,926	-	-
#Seller-Month Observations	41,272	-	-
#Sellers obtaining a license	335	-	-
#Sellers obtaining a license during VC	96	-	-
#Sellers obtaining a license during PL	129	-	-
#Sellers obtaining a license during ML	110	-	-
#Sellers exiting the market	1,613	-	-
#Sellers exiting the market during Non-regulation	292	-	-
#Sellers exiting the market during VC	387	-	-
#Sellers exiting the market during PL	419	-	-
#Sellers exiting the market during ML	828	-	-
Seller Monthly GMV ($)	4,929	268	42,177
Seller Monthly No. of Orders	393	12	2,724
Seller Monthly No. of Buyers	437	13	3,034
Seller Monthly Quantities	1,376	46	11,091
Sellers' Reputation	21,932	2,419	81,070
#Low Reputation Sellers (<=250 Pos. Ratings)	669	-	-
#High Reputation Sellers (>250 Pos. Ratings)	1,257	-	-
Sellers' Age (Months)	21.89	10	27.55
#Young (Pre-treat Age<=12 Months)	641	-	-
#Old sellers (Pre-treat Age>12 Months)	1,284	-	-

Notes: This table summarizes the random sample of 1,926 individual sellers who have sales in NANA food for at least three months during no regulation. A seller's reputation is defined by Alibaba as her total count of positive consumer feedback minus total count of negative feedback. GMV is translated from China RMB to US dollars using the exchange rate of 6.

Table 3: Comparing NANA food sellers with and without licensing information

	Sellers with Sales Post ML		Sellers with Sales in 2018	
	no License Data	with License Data	no License Data	with License Data
No. of Sellers	598	303	135	247
Pre-FSL Monthly GMV ($)	2502.25	4523.71	6565.82	5137.24
Pre-FSL Monthly Reputation	6315.19	18146.22	12221.09	19380.29
Pre-FSL Avg. Age (Months)	276.17	400.78	306.89	416.63
Monthly GMV ($)	7803.13	7066.75	18263.28	7815.51
Monthly No. of Buyers	386.89	678.55	956.34	761.24
Monthly No. of Orders	425.329	762.25	1051.54	856.30
Monthly Quantities	1081.003	2511.21	2032.633	2829.15
No. of Active Months	29.59	44.42	45.51	46.39
Post-ML Monthly GMV ($)	15294.48	8054.57	26887.98	8640.94
Post-ML Monthly No. of Buyers	688.29	741.54	1262.79	798.94
Post-ML Monthly No. of Orders	763.05	850.65	1398.74	917.22
Post-ML Monthly Quantities	1582.52	2331.55	2485.84	2515.97
Post-ML No. of Active Months	13.71	23.50	24.68	25.40

Notes: This table presents the average pre-FSL attributes and the average outcome variables by sellers with and without FSL license information, conditional on having NANA food sales post mandatory licensing (ML) or post 2018. As we miss the licensing record of some sellers, those that have sales post ML but no license is subject to a missing data problem. Pre-FSL GMV and pre-FSL reputation are computed as monthly average during no-regulation taking into account inactive months. During inactive months, the GMV is imputed with zero and the reputation is imputed with the latest reputation up to that inactive month. GMV is translated from China RMB to US dollars using the exchange rate of 6.

Table 4: Duration Model Result for NANA Food Sellers Displaying an FSL License

Covariates	Full Sample		Sellers with Valid Licensing Data Only	
	Hazard Ratio	Std. Err.	Hazard Ratio	Std. Err.
Log of pre-FSL GMV×Voluntary Certification	1.356***	(0.098)	1.192**	(0.082)
×Partially Licensing	1.180***	(0.051)	1.032	(0.048)
×Mandatory Licensing	0.783***	(0.039)	0.841	(0.042)
Log of pre-FSL Reputation×Voluntary Certification	1.353***	(0.102)	1.236**	(0.091)
×Partially Licensing	1.145*	(0.052)	1.087	(0.057)
×Mandatory Licensing	1.011	(0.053)	0.925	(0.044)
No. of Subjects	1,631		331	
No. of Observations	26,453		4,491	
Log-likelihood	-1664.183		-1289.506	

Notes: This table presents the Cox proportional hazard regression results for NANA food sellers' propensity of displaying a license. The pre-FSL GMV and the pre-FSL reputation are both monthly average including inactive months in 2014. For each inactive month, we impute the seller's GMV with zero and impute her reputation with her latest reputation up to that month. Standard errors in parentheses, "* p<0.05 ** p<0.01 *** p<0.001". The estimation drops 3 sellers with missing reputation measures in 2014.

Table 5: Duration Model Result for NANA Food Sellers Exiting the Market

Covariates	Hazard Ratio	Std. Err.
Log of pre-FSL GMV×Voluntary Certification	1.508***	(0.031)
×Partially Licensing	1.063**	(0.019)
×Mandatory Licensing	0.695***	(0.012)
Log of pre-FSL Reputation×Voluntary Certification	0.765***	(0.020)
×Partially Licensing	0.943*	(0.022)
×Mandatory Licensing	1.047*	(0.022)
No. of Subjects	1,631	
No. of Observations	34,028	
Log-likelihood	-7835.657	

Notes: This table presents the Cox proportional hazard regression results for NANA food sellers' behavior of exiting the marketplace. The pre-FSL GMV and the pre-FSL reputation are both the monthly average including inactive months in 2014. For each inactive month, we impute the seller's GMV with zero and impute her reputation with her latest reputation up to that month. Standard errors in parentheses, "* p<0.05 ** p<0.01 *** p<0.001". The estimation drops 3 sellers with missing reputation measures in 2014.

Table 6: Demand Responses to NANA Food Sellers' License Status

	Dependent Variable				
		Log of Sellers'			Dummy of
	GMV	#Orders	#Buyers	Quantities	Pos. Sales
	(1)	(2)	(3)	(4)	(5)
Disclosing a License					
×Voluntary Certification	0.304***	0.272***	0.276***	0.331***	0.141***
	(0.088)	(0.077)	(0.076)	(0.089)	(0.021)
×Partially Licensing	0.538***	0.561***	0.559***	0.522***	0.310***
	(0.054)	(0.047)	(0.046)	(0.055)	(0.013)
×Mandatory Licensing	0.697***	0.680***	0.665***	0.618***	0.323***
	(0.033)	(0.029)	(0.029)	(0.034)	(0.007)
No. of Observations	41,272	41,272	41,272	41,272	56,364

Notes: This table presents consumers' demand responses to NANA food sellers' license status. All columns display the OLS estimates from a linear model with seller-level fixed effects and monthly dummies. Columns (1) to (4) use active seller-month observations, and column (5) includes inactive months. Standard errors in parentheses, "* p<0.05 ** p<0.01 *** p<0.001".

Table 7: Demand Responses to NANA Food Sellers' License Status: By Age

	Dependent Variable				
		Log of Sellers'			Dummy of
	GMV	#Orders	#Buyers	Quantities	Pos. Sales
	(1)	(2)	(3)	(4)	(5)
	Panel A: Young Sellers				
Disclosing a License					
×Voluntary Certification	0.498*	0.429*	0.437*	0.558*	0.183**
	(0.225)	(0.196)	(0.193)	(0.228)	(0.056)
×Partially Licensing	0.867***	0.866***	0.867***	0.905***	0.293***
	(0.136)	(0.118)	(0.116)	(0.137)	(0.032)
×Mandatory Licensing	1.014***	1.099***	1.084***	1.028***	0.274***
	(0.078)	(0.068)	(0.067)	(0.079)	(0.017)
No. of Observations	10,736	10,736	10,736	10,736	16,399
	Panel B: Old Sellers				
Disclosing a License					
×Voluntary Certification	0.284**	0.241**	0.245**	0.294**	0.121***
	(0.095)	(0.083)	(0.082)	(0.096)	(0.022)
×Partially Licensing	0.485***	0.500***	0.498***	0.456***	0.293***
	(0.059)	(0.051)	(0.050)	(0.059)	(0.013)
×Mandatory Licensing	0.679***	0.627***	0.613***	0.564***	0.318***
	(0.037)	(0.032)	(0.032)	(0.038)	(0.008)
No. of Observations	30,536	30,536	30,536	30,536	39,965

Notes: This table presents heterogeneous demand responses to NANA food sellers' license status, by young and old sellers. All columns display the estimates from a linear model with seller-level fixed effects and monthly dummies. Columns (1) to (4) use the sample of active seller-month observations, and column (5) includes inactive months. Young sellers are defined as those who have opened a store in the marketplace for less than 12 months until December 2014, and old sellers are those who have opened a store in the marketplace more than 12 months until December 2014. Standard errors in parentheses, "* p<0.05 ** p<0.01 *** p<0.001".

Table 8: Demand Responses to NANA Food Sellers' License Status: By Reputation

	Dependent Variable				
		Log of Sellers'			Dummy of
	GMV	#Orders	#Buyers	Quantities	Pos. Sales
	(1)	(2)	(3)	(4)	(5)
	Panel A: Low Reputation				
Disclosing a License					
×Voluntary Certification	0.634	0.439	0.479	0.661	0.230*
	(0.384)	(0.301)	(0.293)	(0.383)	(0.106)
×Partially Licensing	0.715***	0.655***	0.656***	0.674***	0.313***
	(0.202)	(0.158)	(0.154)	(0.201)	(0.051)
×Mandatory Licensing	1.311***	1.480***	1.502***	1.311***	0.444***
	(0.112)	(0.088)	(0.085)	(0.111)	(0.026)
No. of Observations	7,966	7,966	7,966	7,966	14,775
	Panel B: High Reputation				
Disclosing a License					
×Voluntary Certification	0.282**	0.253**	0.254**	0.305***	0.098***
	(0.091)	(0.081)	(0.080)	(0.092)	(0.020)
×Partially Licensing	0.548***	0.564***	0.564***	0.537***	0.252***
	(0.057)	(0.050)	(0.050)	(0.057)	(0.012)
×Mandatory Licensing	0.675***	0.640***	0.622***	0.593***	0.261***
	(0.035)	(0.031)	(0.031)	(0.036)	(0.007)
No. of Observations	33306	33306	33306	33306	41,598

Notes: This table presents heterogeneous demand responses to NANA food sellers' license status, by low- and high-reputation sellers. All columns display the estimates from a linear model with seller-level fixed effects and monthly dummies. Columns (1) to (4) use active seller-month observations, and column (5) includes inactive months. Low-reputation sellers are defined as those with the lowest level of stars granted by Alibaba during the no-regulation period, and the high-reputation sellers are those above the lowest level of stars during the no-regulation period. Standard errors in parentheses, "* p<0.05 ** p<0.01 *** p<0.001".

Table 9: Synthetic Control: Treatment Effects of the FSL on NANA Food

	Log of Total No. of Unique Active Sellers	Log of Category HHI	Log of Avg. Rating Score per Active Seller	Log of Avg. %Returns due to Quality Problem per Active Seller	Log of Avg. %Returns due to Counterfeits per Active Seller	Log of Avg. Price per Active Listing	Log of Category Total GMV
Voluntary	0.154	-0.046	0.001	-1.038	-1.493	0.067	0.137
Certification	(0.000)	(0.426)	(0.066)	(0.000)	(0.000)	(0.213)	(0.180)
Partial	0.313	0.861	0.004	-1.241	-1.316	0.208	-0.013
Licensing	(0.115)	(0.049)	(0.131)	(0.000)	(0.000)	(0.311)	(0.508)
Mandatory	-0.014	1.337	0.004	-1.206	-1.730	0.302	-0.002
Licensing	(0.393)	(0.016)	(0.098)	(0.000)	(0.000)	(0.148)	(0.557)

Notes: This table displays the treatment effect $\alpha_t = x_t - \hat{x}_t$ and its p-value on the NANA food category at the start of voluntary certification, partial licensing and mandatory licensing, respectively, where x_t is the treatment and $\hat{x}_t = \sum_j \hat{w}_j x_{jt}$ is the synthetic control for the treated unit. P-values are calculated through bootstrap. We run the placebo test for each control unit j while using all of other control units as the donor pool. Then, for each control unit and each month t, we obtain a distribution of placebo effects $\{\alpha_{jt}\}_{j=1}^{1000}$. Comparing the distribution and α_t, we compute the one-sided p-value: $Pr(\alpha_t > \alpha_{jt})$ for $\alpha_t > 0$ and $Pr(\alpha_t < \alpha_{jt})$ for $\alpha_t < 0$.

Appendix: Heterogeneous effects of the FSL at the seller level

This appendix describes how we use synthetic control matching to identify the effect of the FSL on different types of sellers. For each of the 1,926 randomly drawn NANA food sellers, we use synthetic control matching to find the comparable control from the sample of 5,721 randomly drawn household sellers. This is done for each of the four outcomes separately (i.e., monthly GMV, average rating score, average sales price conditional on sales, and number of unique active listings). In total, we obtain a treatment effect for each NANA food seller in each outcome.

Appendix Figure A.1 presents the heterogeneous effects by sellers' pre-FSL GMV. We classify sellers into 10 groups based on the quantiles of their pre-FSL GMV in no-regulation. The x-axis shows the 10 groups from low to high. For each group, we show the distribution of the treatment effect with a whisker box plot. The bottom, middle, and top lines of the box show the 25th, 50th, and 75th percentiles. The two caps show the upper and lower adjacent values, which are the 25th (75th) percentile plus (minus) the 1.5 times the interquartile range. Values within the caps and out of the box are mild outliers, and the dotted values outside the caps are extreme values. This graph is drawn for each of the four outcomes separately.

Appendix Figure A.2 presents the heterogeneous effects of the FSL by sellers' pre-FSL reputation. As before, we classify the sampled sellers into 11 groups according to sellers' pre-FSL reputation based on Alibaba's definition for stars, crowns, and diamonds. For each group, we show the 25th, 50th, and 75th percentiles with the whisker box, the upper and lower adjacent values with two caps, and extreme outliers with dots.

Appendix Tables A.2 and A.3 show the point estimates for the median and 75th percentile of the individual treatment effects for each seller group, with p-value. The inference is drawn from bootstrapping. In particular, we randomly draw 30% (1,716) sellers from the 5,721 individual household sellers, and regard them as a hypothetical treatment group. We then compute the placebo treatment effect for each seller and each outcome, and group these "treated" placebo sellers into 10 groups by their pre-FSL GMV (or 11 groups by pre-FSL reputation). For each group, we can compute the placebo median effect and the placebo 75th percentile effect. Repeating this 100 times, we compute the one-sided p-value for the treatment median effect and the treatment 75th percentile effect. For the positive treatment effect, its one-sided p-value is the probability that placebo effects are above the treatment

effect. For the negative treatment effect, its one-sided p-value is the probability that placebo effects are below the treatment effect.

Among the multiple treatment periods, we only show the results in ML because that is the period with the most dramatic changes according to our category analysis. Results suggest that sellers in the top decile of pre-FSL GMV are more able to survive and grow their GMV in the ML period than sellers in all the other deciles; they are also more able to expand the number of listings in ML than other sellers. That being said, even the top decile sellers suffer from a large, significant drop in GMV at median and 75th percentile, suggesting that the true dynamics is more complicated than just that the largest survive and grow. As shown in Figure 4, each decile has some outlier sellers enjoying a significant GMV growth post-FSL, which in combination drives the significant increase of HHI in NANA food (Figure 4). As for average rating and price, sellers of all groups have positive median effects, and there is no obvious relationship between the magnitude of these effects and pre-FSL GMV. This suggests that ML could encourage higher seller quality and allow higher price regardless of the seller's pre-treatment size, if they can survive. When we group sellers by their pre-FSL reputation, the heterogeneity is similar.

Table A.1: Summary Statistics of NANA Food and Household Seller Samples

	NANA Food Sellers	Household Sellers
	Panel A: Seller Revenue	
No Regulation	0.115	-0.039
Voluntary Certification	0.089	-0.035
Partially Licensing	0.161	-0.058
Mandatory Licensing	0.187	-0.046
	Panel B: Seller Rating Score	
No Regulation	0.207	-0.070
Voluntary Certification	0.170	-0.067
Partially Licensing	0.126	-0.046
Mandatory Licensing	0.118	-0.030
	Panel C: Sellers' Price	
No Regulation	0.079	-0.027
Voluntary Certification	0.090	-0.035
Partially Licensing	0.152	-0.055
Mandatory Licensing	0.114	-0.028
	Panel D: Number of Active Listings	
No Regulation	-0.005	0.002
Voluntary Certification	-0.022	0.009
Partially Licensing	0.083	-0.030
Mandatory Licensing	0.117	-0.029

Notes:This table presents the average outcome variables per active seller-month for the 1,926 NANA food sellers and 5,721 household sellers. To avoid revealing Alibaba's business secrets, all numbers are normalized by the sample mean and sample standard deviation in each month.

Table A.2: Synthetic Control: Heterogeneous Effects of Mandatory Licensing on NANA Food Sellers by Pre-FSL GMV

Pre-FSL GMV Group	Median	P-value	75th Perc.	P-value	Median	P-value	75th Perc.	P-value
	Panel A: Sellers' GMV				Panel B: Sellers' Rating Score			
1	-1.000	0.000	-1.000	0.000	0.004	0.000	0.011	0.000
2	-1.000	0.000	-1.000	0.000	0.002	0.300	0.012	0.060
3	-1.000	0.000	-0.974	0.110	0.002	0.290	0.012	0.160
4	-1.000	0.000	-0.954	0.350	0.006	0.000	0.015	0.000
5	-1.000	0.000	-0.965	0.000	0.004	0.000	0.013	0.010
6	-1.000	0.000	-0.988	0.000	0.003	0.010	0.014	0.040
7	-0.999	0.000	-0.924	0.000	0.005	0.000	0.015	0.010
8	-0.997	0.000	-0.816	0.150	0.004	0.000	0.013	0.080
9	-0.976	0.000	-0.783	0.000	0.004	0.150	0.012	0.560
10	-0.948	0.000	-0.679	0.000	0.005	0.000	0.011	0.170
	Panel C: Sellers' Price Conditional on Survival				Panel D: #Unique Active Listings per Seller			
1	-0.049	0.000	0.045	0.990	-1.000	0.000	-1.000	0.000
2	-0.165	0.000	0.007	0.990	-1.000	0.000	-1.000	0.000
3	-0.144	0.110	0.084	0.860	-1.000	0.000	-0.766	0.020
4	-0.181	0.050	0.018	1.000	-1.000	0.000	-0.855	0.000
5	-0.267	0.010	0.021	0.970	-1.000	0.000	-0.834	0.000
6	-0.175	0.110	0.341	0.010	-1.000	0.000	-0.861	0.000
7	-0.106	0.580	0.543	0.010	-0.965	0.050	-0.185	0.370
8	-0.059	0.960	0.768	0.000	-0.949	0.000	-0.179	0.140
9	-0.182	0.040	0.695	0.100	-0.655	0.710	0.282	0.310
10	-0.200	0.210	0.897	0.000	0.309	0.000	1.851	0.000

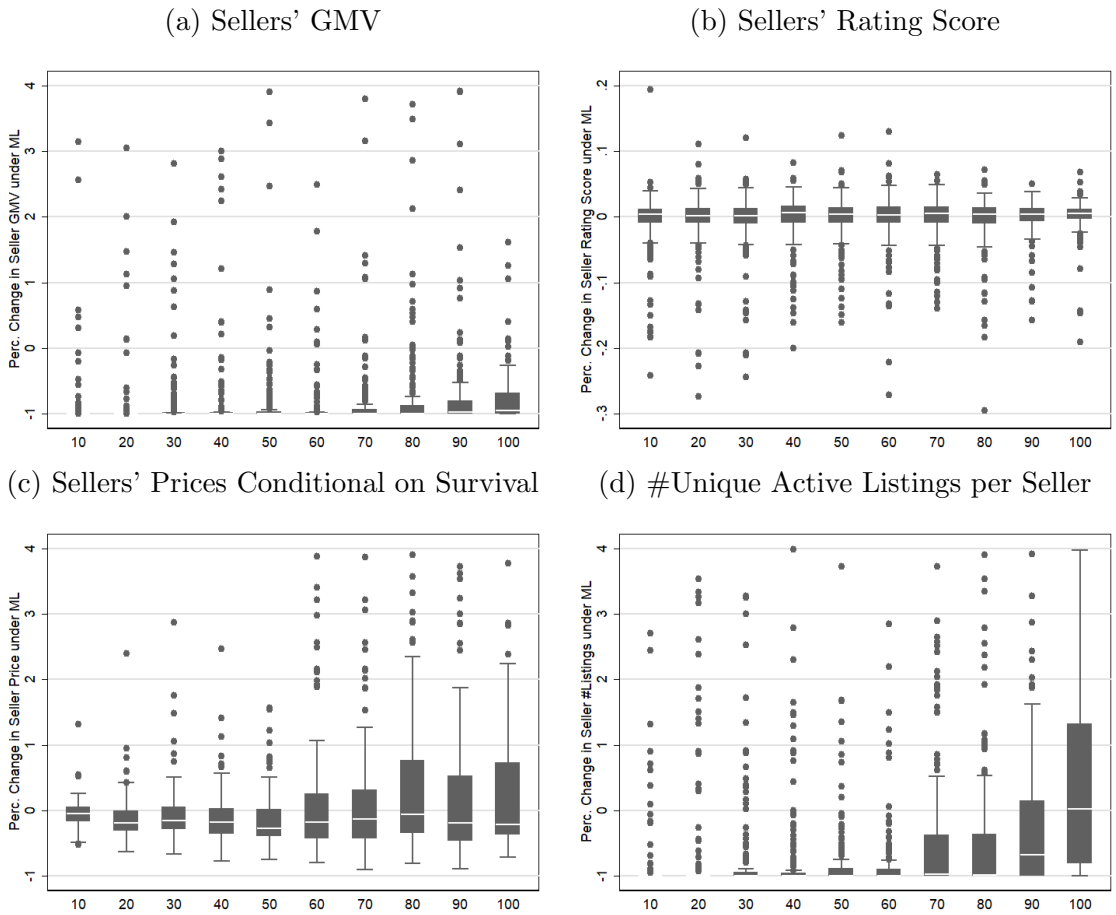
Notes: This table presents the median and 75th percentile of the effect of mandatory licensing, and their one-sided p-values for sellers in different percentiles of pre-FSL GMV. The pre-FSL GMV is computed as the monthly average during the no-regulation period taking into account sellers' inactive months, where a seller's missing GMV is imputed with zero. Each group contains 10 percent of sellers. The p-value is calculated by bootstrapping.

Table A.3: Synthetic Control: Heterogeneous Effects of Mandatory Licensing on NANA Food Sellers by Pre-FSL Reputation

Pre-FSL Reputation Group	Median	P-value	75th Perc.	P-value	Median	P-value	75th Perc.	P-value
	Panel A: Sellers' GMV				Panel B: Sellers' Rating Score			
1	-1.000	0.000	-1.000	0.000	-0.009	0.940	0.004	0.110
2	-1.000	0.000	-1.000	0.000	-0.009	0.840	0.011	0.000
3	-1.000	0.000	-0.999	0.000	-0.007	0.030	0.011	0.400
4	-1.000	0.000	-0.998	0.000	-0.001	0.950	0.014	0.000
5	-1.000	0.000	-0.953	0.000	0.005	0.010	0.015	0.170
6	-1.000	0.000	-0.962	0.000	0.008	0.000	0.015	0.040
7	-1.000	0.000	-0.956	0.000	0.005	0.240	0.015	0.240
8	-0.998	0.010	-0.907	0.040	0.005	0.060	0.014	0.260
9	-0.987	0.130	-0.773	0.090	0.006	0.000	0.014	0.040
10	-0.978	0.020	-0.608	0.230	0.006	0.000	0.013	0.000
11	-0.951	0.370	-0.587	0.200	0.006	0.000	0.010	0.070
	Panel C: Sellers' Price Conditional on Survival				Panel D: #Unique Active Listings Panel D: per Seller			
1	-0.230	0.160	-0.097	0.040	-1.000	0.000	-1.000	0.000
2	-0.247	0.020	-0.019	0.000	-1.000	0.000	-1.000	0.000
3	-0.109	0.270	0.034	0.980	-1.000	0.000	-0.950	0.000
4	-0.248	0.000	-0.089	0.000	-1.000	0.000	-0.972	0.000
5	-0.105	0.040	0.076	0.960	-1.000	0.000	-0.531	0.040
6	-0.087	0.380	0.668	0.010	-1.000	0.000	-0.406	0.080
7	-0.147	0.020	0.174	0.790	-1.000	0.000	-0.533	0.000
8	-0.054	0.730	0.456	0.000	-0.941	0.190	-0.162	0.800
9	-0.145	0.140	0.320	0.000	-0.806	0.590	0.373	0.000
10	-0.137	0.390	0.146	0.780	-0.689	0.330	0.717	0.010
11	-0.217	0.590	0.075	0.900	-0.084	1.000	1.313	0.000

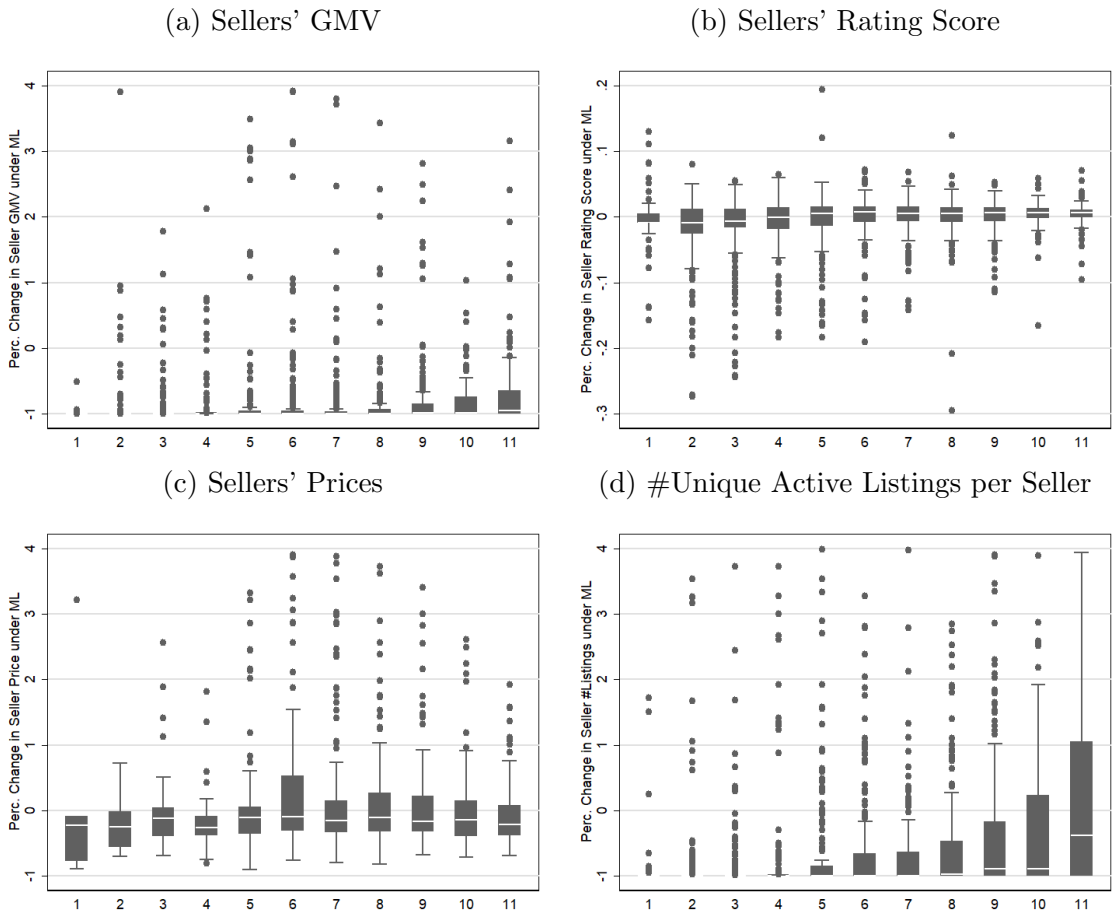
Notes: This table presents the median and 75th percentile of the effect of mandatory licensing, and their one-sided p-values for sellers in different groups of pre-FSL reputation. Pre-FSL reputation is computed as monthly average of seller reputation during no-regulation taking into account sellers' inactive months, where the missing seller reputation is imputed with the seller's latest reputation up to that month. Sellers are then classified into 11 groups according to seller's pre-FSL reputation based on Alibaba's classification for stars, crowns, and diamonds. The p-value is calculated by bootstrapping.

Figure A.1: Synthetic Control: Heterogenous Effects of the FSL by NANA Food Sellers' Pre-FSL GMV



Notes: This figure displays the distribution of treatment effects of mandatory licensing on NANA food sellers by different bins of pre-FSL GMV. Using a random sample of 1,926 NANA food sellers and 5,721 individual sellers in the household categories, we estimate the treatment effect of the FSL for each NANA food seller with synthetic control. We match the pre-FSL monthly trend for the outcome variables of GMV, quality and number of listings, and match the quarterly trend for average sales price due to missing values in inactive months. We then evenly divide NANA food sellers to 10 groups according to their pre-FSL GMV. The pre-FSL GMV is computed as the monthly average during the no-regulation period taking into account sellers' inactive months, where a seller's missing GMV is imputed with zero. Each box indicates the 25%, 50%, and 75% percentiles of the treatment effects for a group. The upper cap and the lower caps indicate the range of mild outliers, while the dots indicate extreme outliers. Mild and extreme outliers are defined according to the upper and lower adjacent values, which are the 25%/75% percentile plus/minus the 1.5 times of the difference between 75% and 25% percentiles.

Figure A.2: Synthetic Control: Heterogenous Effects of the FSL by NANA Food Sellers' pre-FSL Reputation



Notes: This figure displays the distribution of treatment effects of mandatory licensing on NANA food sellers in different bins of pre-FSL reputation. Using a random sample of 1,926 NANA food sellers and 5,721 individual sellers in the household categories, we estimate the treatment effect of the FSL for each NANA food seller with synthetic control. We match the pre-FSL monthly trend for the outcome variables of GMV, quality and number of listings, and match the quarterly trend for average sales price due to missing values in inactive months. We then divide food sellers to 11 groups according to sellers' pre-FSL reputation based on Alibaba's classification of stars, crowns, and diamonds. Pre-FSL reputation is computed as monthly average of seller reputation during no-regulation taking into account sellers' inactive months, where the missing seller reputation is imputed with the seller's latest reputation up to that month. Each box shows the 25%, 50%, and 75% percentiles of the treatment effects for a group. The upper cap and the lower cap indicate the range of mild outliers, and the dots indicate extreme outliers. Mild and extreme outliers are defined according to the upper and lower adjacent values, which are the 25%/75% percentile plus/minus the 1.5 times of the difference between 75% and 25% percentiles.