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Freshly Cooked or Factory-Prepared? Estimating Restaurants' Hidden Production Practices through Labor Market Signals

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Abstract

Many Chinese consumers worry about the use of prepared meals in restaurants. However, this production practice is usually unobservable. This study identifies a labor-market signal which may indicate the restaurants' reliance on prepared meals. We assemble an original restaurant-level dataset from 5 major cities in China by combining online recruitment postings, commercial-rent listings, chain size, location-based cooking constraints, and consumer reviews. A Multiple Indicators Multiple Causes (MIMIC) model uses the chef-to-server wage ratio and the share of negative reviews mentioning prepared meals as reflective indicators of latent prepared meal reliance. The estimation uses 311 complete restaurant observations. Results show that higher rent, greater chain size, and location in the interior of large commercial complexes are each associated with greater latent reliance. Consistent with the proposed mechanism, reliance is negatively reflected in the chef-to-server wage ratio and positively reflected in prepared-meal-related complaints. The study contributes to consumer-affairs research by offering consumers and regulators a practical means of mitigating information asymmetry and supporting more transparent disclosure of restaurant production practices. The study also point out that opaque production practices in one market may be inferred from observable traces in an adjacent market.

KEYWORDS

Prepared Meals, Consumers Right to Know, Labor-Market Signals, Restaurant Transparency, MIMIC model, China

1 | INTRODUCTION

1.1 | Prepared Meals & Controversy in China

The use of prepared meals has been a trend in catering industry during last few years. According to Deloitte's industry interviews, as compiled by Qianzhan Industry Research Institute (2023, p. 45), the food-service sector accounted for approximately 64% of China's prepared meals consumption in 2021. The shock of COVID-19 pandemic has further accelerated the development of prepared meals. The sales of prepared meal in 2021 were 16 times higher than in 2020 (Zhou 2021). From 2020 to 2025, China's prepared dishes market generally maintained year-on-year growth of approximately 20% or more. By 2025, the market had reached RMB 617.3 billion (iiMedia Research and Nanfang Rural News 2025).

However, this trend has raised the social concerns. These concerns originate from various aspects. China has a history of food safety issues, especially concerning food products manufactured through industrialized production processes: Melamine-Tainted Milk Scandal

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in 2008 [1], Gutter Oil Scandal from 2011 to 2012 [2], Preserved Vegetable and Pork Prepared-Dish Scandal in 2024 [3], and Lead-Contaminated Food Incident in 2025 [4]. These events often involved improper actions by the supervisory authorities, which have led to a lack of social trust. Though prepared meals are not necessarily unhealthy compared with fresh meals, Chinese consumers often associate prepared meals with past food safety scandals (Xue et al. 2025).

Another concern is the taste. Chinese dishes emphasize the freshness of ingredients and the skilled cooking. The Chinese term *Wok Hei* (the breathe of the *wok*[5]), which refers to “the energy a wok bestows upon a stir-fry, giving foods a unique smoky flavor and aroma” (López-Alt 2012), is an indispensable aspect of judging a Chinese dish’s taste. Chinese consumers regard *Wok Hei* as an important component of the dining-out experience. When restaurants serve prepared meals lacking *Wok Hei*, consumers may feel frustrated (Xue et al. 2025). Although double-blind experiments investigating consumers’ ability to distinguish the taste of prepared Chinese dishes remain limited, some consumers do claim that they can identify the inferior sensory qualities associated with prepared dishes[6]. In 2025, after dining at Xibei, Chinese businessman Luo Yonghao argued that the restaurant used prepared dishes and criticized their poor taste. Subsequent revelations and public discussions provided considerable support for his claim[7].

Criticism on prepared meals exploded after the government’s ‘prepared meals on campus’ promotion without substantial public debate. ‘The concept of prepared meals has emerged suddenly’, some remarked (Xue et al. 2025). This reflects the general distrust toward prepared meals. One way that government alleviating social anxiety is to take more narrow definition of prepared meals, and classified some as ‘central kitchen mode’ (Xue et al. 2025). Prepared food products vary in their degree of pre-processing. Some require only simple reheating at the restaurant, whereas others require further cooking. Prepared meals manufactured by food-processing firms and dishes supplied by central kitchens may substantially overlap in their processing technologies. Therefore, no clear technological boundary can be drawn between them solely on the basis of the degree of pre-processing. Under Chinese current regulatory framework, the distinction rests primarily on the organization of production and distribution: fresh-cut ingredients, semi-finished dishes, and finished dishes centrally prepared by a chain restaurant enterprise and distributed to its own outlets are regulated as central-kitchen outputs rather than classified as prepared dishes (State Administration for Market Regulation et al. 2024).

However, for consumers, the major concerns are safety, taste of *Wok Hei*, and the main economic mechanism of prepared meals and ‘central kitchen mode’ — the outsourcing of some cooking tasks — are the same. Therefore, this paper will not do further distinction between prepared meals and central kitchen mode to avoid confusion, and will use the term ‘prepared meals’ to refer to both.

Consumer information has an important role in making markets operate efficiently (Rothwell 2019). Unfortunately, there is no regulations that require restaurants to disclose whether they use prepared meals until July 2026. It is difficult for consumers to observe the production mode when stepping into a restaurant. Even when regulations require restaurants to explicitly disclose their use of prepared meals, the extent of such use remains difficult to measure. Restaurants may differ substantially in their degree of reliance: some use prepared components only in a small number of dishes or rely merely on pre-prepared sauces, whereas others depend heavily on prepared meals, leaving chefs to do little more than reheat. This cause an information asymmetry problem that consumers have little access to the extent which the restaurants rely on prepared meals.

[1] Melamine was illegally added to diluted milk to falsify protein-test results. See Reuters, “Factbox: What Is Melamine, and Why Add It to Milk?,” January 22, 2009, Reuters.

[2] Waste oil collected from restaurant grease traps, discarded animal products, and other unsanitary sources was illegally processed and resold as edible cooking oil through underground supply chains. See Reuters, “China Arrests 52 over Cooking Oil Scandal,” December 20, 2011, Reuters.

[3] Scandal directly related to prepared meals. See CCTV Finance, “Lymph Nodes and Glandular Tissue Clearly Visible: Disturbing Production Conditions behind Packaged *Meicai Kourou*,” March 15, 2024, CCTV News (in Chinese; title translated by the author).

[4] A kindergarten allegedly added non-food-grade coloring pigments containing high levels of lead to cakes and other foods. See Xinhua, “Kindergarten Staff Arrested after 247 Children Poisoned with Lead in NW China,” July 20, 2025, Xinhua.

[5] The term *wok* refers to a round-bottomed Chinese cooking pan traditionally used for stir-frying, deep-frying, steaming, braising, and other high-heat cooking techniques.

[6] See Zhang Shoukun, Wu Haozheng, “As Prepared Meals Gain Popularity Online and Offline, Should Restaurants Disclose Their Use of Them?” *Legal Daily*, Septempber 1, 2023

[7] See Xue Shasha, Zhu Xuan, Hong Yu, and Wu Qi, “On-site Investigation of Xibei’s Preparation of Luo Yonghao’s ‘Same Menu’: The Scallion-Flavored Grilled Fish Used Marinated Frozen Fish with an 18-Month Shelf Life,” *The Paper*, September 13, 2025, https://www.thepaper.cn/newsDetail_forward_31602252. See also Shao Bingyan, “Xibei Apologizes: It Will Move as Much Central-Kitchen Pre-Processing as Possible to In-Store Preparation,” *The Paper*, September 15, 2025, https://m.thepaper.cn/newsDetail_forward_31612841.

It is undeniable that prepared meals offer several important advantages. It can reduce the cost and increase the profit for single dish (Zhou 2021). It can also increase the turnover rate because many processes are finished in the factory or central kitchen (China Chain Store & Franchise Association and China Renaissance 2022). However, since a considerable proportion of Chinese consumers prefer fresh meals over prepared meals when dining out (iiMedia Research 2022), and that it is difficult for consumers to know the production mode, restaurants have incentive to conceal this information. Article 55 of the *Food Safety Law of the People's Republic of China* says 'It is advocated that food and beverage service providers make public manufacturing processes and publicly display information such as raw materials and the sources thereof' (Standing Committee of the National People's Congress of the People's Republic of China 2015). Though this is not a mandatory regulation, if production mode matters to consumers, the disclosure of this information can help consumers make choice based on their personal acceptance to prepared meals.

If information asymmetry regarding restaurant production mode persists, a market failure similar to Akerlof's (1970) 'market for lemons' may occur. When restaurants generally do not disclose their production methods, real fresh meals may be unable to obtain adequate market recognition, while lower-cost prepared meals may gain a competitive advantage and gradually crowd out freshly cokked meals. Such an outcome may not only deviate from social preferences for fresh meals but also reduce incentives for skilled culinary labor, potentially threatening the transmission of Chinese traditional culinary knowledge.

This argument does not imply that prepared meals are undesirable. For dishes whose sensory quality depends heavily on broths, sauces, marinades, or seasoning systems, prepared meals may achieve sensory performance comparable to, or in some cases better than, conventional cooking (Latoch et al. 2023, Rahman et al. 2023). However, without transparent labeling, these advantages cannot be fully appreciated by consumers whose preferences align with such products. Especially for some consumers who are angry with some restaurants that 'merely reheat them (the dishes)' but 'still charge the price of freshly cooked meals' (Xue et al. 2025, p. 12). This reflects that consumers may not resist prepared meals itself but the nontransparent use. If information asymmetry cannot be effectively mitigated, declining consumer trust and confidence in the restaurant industry may ultimately harm the broader development of the sector.

Building on the values outlined above, this study explores signals in labor-market information that can indicate restaurants reliance on prepared meals, thereby helping consumers make more informed judgments and mitigating information asymmetry.

In contrast to prior work focusing on the benefits of adopting central kitchen production modes for restaurants (Deng 2023, Zhang 2025), or examining consumers' changing perceptions of prepared meals (Chen et al. 2026, Xue et al. 2025), our research introduces labor market signals — specifically, chef and server wages — into the estimation of prepared-meal usage. By combining the chef-to-server wage ratio with consumers' existing reviews on online review platforms, this approach provides consumers with a feasible method to estimate the extent to which restaurants rely on prepared meals.

Prepared meals, as an industrialized production mode, will lead to a transfer of the tasks for chef. When a restaurant apply prepared meals instead of fresh cooking, it essentially outsources some of the cooking tasks to upstream factories or central kitchens (Deng 2023). In extreme cases, the chef's role may be reduced to merely reheating prepared dishes and completing final plating before service, reducing restaurants incentives to offer wage premiums for culinary labor. On the other hand, although the tasks of servers are not as complex as chefs, they are hard to substitute and their tasks are impossible to be outsourced since face-to-face interaction with consumers is impossible to be replaced by central kitchen. Therefore, when a restaurant adopts a central kitchen production mode, the wage of servers might still be lower than the wage of chef, but more stable. Consequently, when a restaurant relies heavily on prepared meals, the requirement for being a chef will no longer higher than servers in the restaurants, leading to a smaller wage gap between chef and servers. Since the absolute wages of chefs and servers may be affected by factors such as regional economic conditions and restaurant market positioning, the wage ratio $\frac{ChefWage}{ServerWage}$ provides a more appropriate estimation on the prepared meals usage than chefs' wages alone.

Prior research demonstrates that online restaurant reviews serve as an important information source through which consumers infer unobservable restaurant attributes (Wu et al. 2015). Consumers' reviews, especially complaints on 'prepared meals-like taste', is also useful in offering information to consumers, though has the risk of being manipulated by the restaurants(Luca and Zervas 2016). Therefore, highly reliant on reviews on the consumer review website has the risk of being misled by unethical restaurants. However, in practice, consumers can easily get access to the wage ratio on recruitment platforms. Even if this method is applied generally, it is hard for restaurants to conceal their wages on recruitment platforms. Therefore, this paper provides consumers with a feasible method that uses online accessible information to estimate the extent of prepared meals usage in restaurants.

To examine whether labor-market information can reveal restaurants hidden reliance on prepared meals, we employ a two-stage empirical strategy that combines a Multiple Indicators Multiple Causes (MIMIC) model with an external validation exercise. The MIMIC model is estimated using the full restaurant sample (311 restaurants in five cities) rather than only restaurants whose production practices have been publicly disclosed, and we will discuss its mathematical mechanism in Research Method part (see section 4). This model allows us to evaluate whether the proposed wage-ratio indicator behaves consistently with a broader latent construct without treating restaurants lacking public disclosures as confirmed non-users. The external validation serves a distinct but complementary purpose. We compare the mean wage ratio of 53 restaurants with publicly documented use of prepared meals or central-kitchen production with that of restaurants for which no such disclosure was identified. Because public disclosure is selective, the known-positive group is not representative of all restaurants that use prepared meals and therefore cannot provide an unbiased estimate of prepared-meal reliance across the market. Nevertheless, it provides an external criterion for assessing whether the proposed wage-ratio indicator distinguishes restaurants with independently documented prepared-meal use from those without identified public disclosure. Accordingly, the MIMIC model establishes the internal coherence and construct validity of the indicator across the full sample, whereas the external validation examines whether the same indicator distinguishes restaurants independently known to use centralized or prepared-food production. Combining the two approaches reduces reliance on either correct substantive interpretation of the latent variable or selective corporate disclosure alone. Taken together, results from MIMIC model and external validation suggest that the wage ratio captures a systematic change in restaurants demand for on-site culinary skills and can therefore serve as a practical, publicly observable indicator of otherwise hidden production practices.

This study makes three contributions. First, it provides consumers with a low-cost, accessible, and practical signal for assessing restaurants' hidden reliance on prepared meals. Using publicly available recruitment wages, the chef-to-server wage ratio may help consumers avoid paying freshly cooked meals prices for meals produced through highly centralized or pre-prepared processes. Second, it contributes to research on information asymmetry and lemons markets by showing that opaque production practices in one market may be inferred from observable traces in an adjacent market, as illustrated by the labor-market signal developed in this study. Third, it shifts the perspective of task-based research. Whereas existing studies ask how observed offshoring affects relative wages, this study asks what observed wage structures can reveal about otherwise unobservable task reallocation, extending the framework to domestic outsourcing and centralized production.

2 | LITERATURE REVIEW AND THEORETICAL BACKGROUND

2.1 | Consumer Information Asymmetric

In the catering market, it is difficult for consumers to observe the production mode of the meals. Though we are not able to make such hasty conclusion that fresh meals are better in quality than prepared meals, Chinese consumers do prefer fresh meals to prepared meals and even considered the latter 'unhealthy' and 'inferior'. This gives rise to an information asymmetric problem – only restaurants know the production mode, but have incentive to hide this information.

The market for lemon theory is useful for illustrating the problem of asymmetric information in prepared meals. Akerlof (1970) first provided a canonical analysis of how asymmetric information in the quality of used cars may distort the market. When sellers have more information on the quality of a car, while buyers have to estimate the possible quality by statistics, buyers' valuation of the car based on the expected quality may not satisfy the sellers of good cars, which discourages "good sellers" but encourages "bad sellers". In the long run, this distortion in incentive drives the good products out of the market (Akerlof 1970).

The similar mechanism may appears in the catering market: since consumers have insufficient information to judge whether the restaurant serves prepared meals before eating, it may be unwilling to pay a full premium for genuinely fresh and skill-intensive cooking. This weakens the market reward for restaurants that persist serving fresh meals with higher costs. In the long run, this distortion in incentive will drive restaurants that persist fresh mode out of the market, which deviates from social preference for freshly cooked meals.

The asymmetric information in the catering market not only originates from nontransparent production, but also from the dishonest advertisement. News reports about restaurants that had advertised or implied freshness but were later reported to rely on prepared, or central-kitchen products have appeared repeatedly in recent years.[8]. Brand *T* responded to the public challenge of using prepared meals by separating "fresh-live" stores and others. This response is relatively effective in regaining market trust because this separation admitted limited but open use of prepared meals.[9] However, it is difficult to distinguish genuine disclosure from public relations strategies.

Akerlof's discussion of the costs of dishonesty further clarifies that the welfare loss from misleading and dishonest advertisement is not limited to the amount by which buyers are directly deceived. When prepared meals can be presented as fresh meals, dishonest sellers may undermine the viability of honest transactions and drive restaurants who persist fresh mode out of the market (Akerlof 1970).

Common remedies for lemons-market problems include signaling, screening, warranties, reputation-building, and third-party certification (Riley 2001, Dranove and Jin 2010). Voluntary disclosure of prepared meals usage faces credibility problem. The value of this research includes offering a signal of prepared meals reliance, which is open and accessible for Chinese consumers.

2.2 | The Impact of Production Model Change on Labor Structure

This study draws on the task-based view of production model change to explain why labor-market information may reveal hidden production practices in restaurants.

Acemoglu and Autor (2011) define task as a unit of work activity that produces output, and the output including both service and goods. Different from the canonical skill-based model, treating a job as a fixed bundle of skills, which is insufficiently nuanced to account for the rich relationships among skills, tasks and technologies, the task-based framework distinguishes between workers skills and the tasks they perform (Autor et al. 2003). Under task-based framework, workers apply their skill endowments to tasks in exchange for wages, and skills applied in tasks produce output (Acemoglu and Autor 2011). This distinction is important because technological or organizational change may not directly alter workers skills, but it can change which tasks remain inside the firm, which tasks are simplified, and which tasks are transferred to machines, suppliers, or external production sites. Sampson (2021) based on this task-based framework develops a professional task-automation framework that shows how individual tasks within a given job can be enhanced or disrupted by automation in very different ways, and Kanazawa et al. (2022)successfully applied the task-based model to micro-level productivity analysis through an empirical study of the taxi industry.

Acemoglu and Autors task-based framework is also especially useful for this study because it explains how production can be reorganized without being immediately visible to consumers. In task-based framework, the labor market are not only simply changed by the variation of productivity, but also changed by the varying allocation of tasks across different skill workers (Acemoglu and Autor 2011). Acemoglu and Autor (2011) assume that there are three types of skills – low, medium and high – and each worker is endowed with one of these types of skills. In this setting, intermediate tasks are often performed by medium-skilled workers and

[8] For representative media reports, see China News Service's financial outlet Zhongxin Jingwei, "Lengdong rouxian suan bu suan 'xianbao xianzhu'? Yuanji Yunjiao juanru yuzhicai fengbo" [Does frozen meat filling count as "freshly wrapped and freshly cooked"? Yuanji Yunjiao involved in a prepared-food controversy], September 28, 2023, https://www.jwview.com/jingwei/html/m/09-28/560291.shtml; *Beijing News*, "Xibei zhiqian bing xuanbu tiaozheng zhizuo gongyi, 'yuzhicai biaoqian' weihe tieshang nan sixia?" [Xibei apologizes and announces adjustments to its production process: why is the "prepared-food" label difficult to remove?], September 15, 2025, https://m.bjnews.com.cn/detail/1757929395168203.html; Xinhua News Agency, "Zhongxiao xie fabu 2023 nian shida xiaofei weiquan yuqing redian" [China Consumers Association releases the top ten consumer-rights public-opinion issues of 2023], March 15, 2024, https://www.news.cn/politics/20240315/3ee4d07c90c04bae9bc92cc425ef70ea/c.html; and *Workers' Daily*, republished by China News Service, "Gaojia xiyan jin qicheng shi yuzhicai, heyi lingren bushuang?" [Why is it frustrating that nearly 70 percent of an expensive wedding banquet consisted of prepared dishes?], June 7, 2023, https://www.chinanews.com.cn/cj/2023/06-07/10020459.shtml. Accessed July 6, 2026.

[9] See *National Business Daily*, September 16, 2025; *Beijing News*, "Shuaixian shixian zhengcan quan caidan touminghua, 'baogai' hou de Tai Er ruhe chongsu canyin xincheng?" [After its revamp, how does Tai Er rebuild restaurant trust through full-menu transparency?], December 19, 2025; and Tai Er official website, "Brand Story."

are more susceptible to automation or relocation than many low-end in-person service tasks and high-end managerial tasks. (Acemoglu and Autor 2011).

This logic can be applied to restaurant production. A restaurant does not produce meals through a single homogeneous task, but through a series of differentiated tasks, including food preparation, cooking, plating, serving, cleaning (Göde and Ekergil 2020).

According to Blinder (2007) and Blinder and Krueger (2008), any job that does not need to be done in person (i.e., face-to-face) can ultimately be outsourced, regardless of whether its primary tasks are abstract, routine, or manual. For customer-service-related tasks, although they do not require highly specialized skills, they do require situational adaptability, visual and linguistic recognition, and face-to-face interaction during execution, which makes them non-transferable outside the restaurant setting (Acemoglu and Autor 2011). For tasks such as cooking or preparation procedures, can be centralized in central kitchens or food processing factories. Once semi-finished or finished food products are produced, they are distributed to restaurants, where the remaining on-site culinary tasks may be reduced to reheating, plating, or final-stage cooking (Deng 2023).

Therefore, the usage of prepared food or central kitchen production can be interpreted as a form of task reallocation. In a traditional freshly cooked model, a substantial share of intermediate tasks is performed in the restaurant kitchen. Chefs are required to perform cooking-related tasks on site, including preparation, timing, heat control, flavor adjustment, and quality stabilization(China Cuisine Association and Shuhai Supply Chain and Baichuan Research Institute 2023). These tasks generate demand for culinary labor, especially for chefs with medium skill level who are directly involved in dish production.

However, when a restaurant relies more heavily on prepared food or centralized production, part of culinary tasks are transferred away from the on-site kitchen. The restaurant may still provide similar dishes to consumers, but the task allocation behind those dishes has secretly changed. A chef may retain the same culinary ability, but if fewer valuable cooking tasks remain inside the restaurant, the restaurant has less incentive to pay a high wage premium for that ability. In contrary, the tasks for server will probably remain same after the adoption of prepared meals or central kitchen production mode, so their will likely remain stable, leading to a smaller wage difference between server and chef.

3 | OBSERVABLE INDICATORS AND THEORETICAL DETERMINANTS OF PREPARED-MEAL RELIANCE

3.1 | Indicator Deduction

3.1.1 | Chef-to-server Wage Ratio

The following adaptation is intended to formalize the intuition underlying the proposed wage-ratio indicator rather than validate the reliability of chef-to-server wage-ratio. To formalize this mechanism of the impact of production model change on labor structure, we adapt the task-based offshoring framework in Acemoglu and Autor (2011) to the restaurant context. Let the unit interval $i \in [0,1]$ represent the full set of production tasks in a restaurant, ordered by increasing complexity. If the i is closer to 0, the tasks are closer to low complexity tasks such as serving the table, plating, reheating. If the i becomes higher, the tasks become more complex, for instance, preparation, timing, heat control, flavor adjustment, and quality stabilization. And finally, when the i is closer to 1, the tasks become the high complexity task in the restaurant, such as managing, developing new cuisines.

As the result, the final product of the restaurants is not a single task, but a combination of a series of tasks.

$$Y_r = \exp\left[\int_0^1 \ln y_r(i)\,\mathrm{d}i\right]$$

In this formula, r represents restaurant, Y_r is the complete dining service that the restaurants provide to customers, and $y(i)$ is the output of task i. And for each single task $y(i)$, the production function is:

$$y(i) = A_L\alpha_L(i)L(i) + A_M\alpha_M(i)M(i) + A_H\alpha_H(i)H(i)$$

In this formula, L is low skill workers, represents the server in the restaurants, M is medium skill workers, represents chef, especially the middle-level chef, in responsible for dishes cooking directly. H is high skill workers, mainly represents the management layer in a restaurant.

A_L $A_M A_H$ represent factor-augmenting technology of different skill workers, while $\alpha_L(i)$ $\alpha_M(i)$ $\alpha_H(i)$ represent productivity of different skill group on $y(i)$, and $L(i)$ $M(i)$ $H(i)$ are number of different skill workers that needs to be assigned to this task.

According to Acemoglu and Autor (2011) Assumption 2, $\dfrac{\alpha_L(i)}{\alpha_M(i)}$ and $\dfrac{\alpha_M(i)}{\alpha_H(i)}$ will decrease as i increases, because the more complex the task, the more comparative advantage will be gained from the high-skilled workers compared to the medium-skilled worker, the medium-skilled workers compared to the low-skilled workers.

As the result, there will be two threshold value I_L I_H , which divides the tasks interval into three part: $[0, I_L)$ conducted by low skill workers (servers), (I_L, I_H) conducted by medium skill workers (middle-level chef), $(I_H, 1]$ conducted by high skill workers.

Firms maximize profit by hiring labor until the market wage equals the value of the marginal product of labor (Lumen Learning 2024). And now, we define $p(i)$ is the price of $y(i)$, and the wage for server, middle-level chef and management layer can be represented as follow:

$$w_L = p(i)A_L\alpha_L(i)$$
$$w_M = p(i)A_M\alpha_M(i)$$
$$w_H = p(i)A_H\alpha_H(i)$$

According to law of one price for skills in Acemoglu and Autor (2011), even though workers of the same skill level are performing different tasks, in equilibrium they will receive the same wage, because if there is a wage difference for different tasks for labor in a same skill group, the firm cannot hire labor for the task with a lower wage in a long term. For all tasks actually performed by the same skill group, the no-arbitrage condition requires them to earn the same wage. Consequently, $p(i)\alpha(i)$ is equalized across the range of tasks assigned to that skill group in equilibrium. So now we define $P_L = p(i)\alpha_L(i)$, $P_M = p(i)\alpha_M(i)$ and $P_H = p(i)\alpha_H(i)$, and rewrite the wage as follow:

$$w_L = A_L P_L$$
$$w_M = A_M P_M$$
$$w_H = A_H P_H$$

The Cobb-Douglas technology implies that the 'expenditure' in all tasks should be equalized (Acemoglu and Autor 2011). So we get:

$$p(i)y(i) = Y \qquad \forall\, i \in [0, 1] \tag{1}$$

The Cobb-Douglas technology let different tasks have the same expenditure, while the wages are equalized in the task interval for the same skill group, the distribution of workers with the same skill level is uniform in their own task interval.

Let us define l, m, h, to be the supply of server, middle-level chef and management layer, so we get $L(i) = l/I_L$, $M(i) = m/(I_H - I_L)$, $H(i) = h/(1 - I_H)$.

As we have already discussed equation (1), the 'expenditures' across all tasks are equalized:

$$Y = P_M A_M \frac{m}{I_H - I_L} = P_L A_L \frac{l}{I_L}$$
$$\Rightarrow \frac{P_M}{P_L} = \frac{I_H - I_L}{A_M m} \cdot \frac{A_L l}{I_l}$$

When calculating the wage ratio:

$$\frac{w_M}{w_L} = \frac{A_M P_M}{A_L P_L} = \frac{(I_H - I_L)l}{I_L m} = \left(\frac{I_H - I_L}{m}\right) \Big/ \left(\frac{I_L}{l}\right)$$

Now consider the usage of prepared meals or the adoption of a central kitchen production model that allows the externalization of a subset of intermediate culinary tasks through centralized kitchens or food processing facilities. Specifically, a task interval $[I', I''] \subset (I_L, I_H)$ can be relocated outside the restaurant. This generates a new task structure in which the effective set of in-house production tasks becomes segmented.

After externalization, the allocation of tasks is given by:

$$T(i) = \begin{cases} L, & i \in [0, I_L), \\ M, & i \in [I_L, I') \cup [I'', I_H), \\ H, & i \in [I_H, 1]. \end{cases}$$

Accordingly, the distribution with the same skill level adjusts to the reduced task:

$$L(i) = \frac{l}{I_L}, \quad M(i) = \frac{m}{(I' - I_L) + (I_H - I'')}, \quad H(i) = \frac{h}{1 - I_H}.$$

This implies that the reallocation of standardized culinary tasks to centralized production facilities reduces the tasks of chefs. As a result, the relative wage structure is affected as follows:

$$WageRatio = \frac{w_M}{w_L} \downarrow \tag{2}$$

In equation (2), w_M represents the wage of middle-level chef and w_L represents the wage of server. This mechanism is consistent with Acemoglu and Autor (2011) implications of offshoring on the structure of wages, providing a structural interpretation for why the chef-to-server wage ratio can decline even in the absence of changes in individual skill distributions, as it reflects a contraction in the set of tasks performed by chefs rather than a change in their underlying ability. However, this model just provides the directional prediction used to construct the indicator; the empirical validity of the indicator is subsequently assessed in section 5.

This implication also explains why this study uses the chef-to-server wage ratio rather than the absolute chef wage. The adoption of prepared meals or central-kitchen production mode has two conceptually distinct effects. On the one hand, it externalizes part of the in-house culinary task interval previously performed by middle-skill chefs. On the other hand, it may also operate as a productivity-enhancing technology, since standardized upstream production can reduce unit costs, increase operational efficiency, and raise the effective productivity of restaurant production (China Cuisine Association and Shuhai Supply Chain and Baichuan Research Institute 2023). Therefore, the direction of the absolute chef wage is theoretically ambiguous. If the productivity effect is sufficiently large, the wage of chefs may remain unchanged or even increase despite the contraction of in-house culinary tasks.

By contrast, the chef-to-server wage ratio is more directly linked to the relative task structure inside the restaurant. When prepared meals relocate a substantial part of cooking, seasoning, heat control, and food-preparation tasks to central kitchens or upstream suppliers, the remaining in-store culinary work becomes closer to simple finishing, reheating, and plating. In the limiting case, the task requirements of in-store kitchen workers become increasingly similar to those of low-skill restaurant workers. According to the law of one price for skills Acemoglu and Autor (2011), workers performing tasks with similar skill requirements should receive similar wages in equilibrium. Hence, as the in-house chef task set contracts and becomes less distinct from low-skill restaurant tasks, the chef-to-server wage ratio should move closer to one.

The wage ratio also reduces the influence of local labor-market and demand-side conditions. Absolute chef wages may vary substantially across cities, neighborhoods, and restaurant segments because of differences in local income levels, consumption capacity, rent, and general wage levels (Combes et al. 2008). A given chef wage level therefore cannot by itself identify whether a restaurant relies heavily on prepared meals. The chef-to-server wage ratio normalizes chef wages by the wage of another occupation within the same local restaurant labor market, making it a more appropriate proxy for changes in the relative demand for in-house culinary skills.

3.1.2 | Comment Ratio

In order to build up the MIMIC model to test the validity of chef-to-server wage ratio, we need to design another indicator, as MIMIC model needs at least two reflective indicators (Jöreskog and Goldberger 1975). For most of the consumers, the common way to avoid restaurants that secretly use prepared meals is to look up existing comments of these restaurants. Although no scientific experiments can prove that consumers can accurately determine the difference between prepared meals and freshly cooked meals, some studies have shown that consumers who have already dined in the restaurant before can infer whether this restaurant uses prepared meals secretly by using the degree of processing (Hässig et al. 2023), sensory perception of food (Bai et al. 2019) or unusual serving speed (Xue et al. 2025) as signals.

However,Luca and Zervas (2016) state that there exists erroneous judgments of consumers, some restaurants may even commit review fraud by leaving negative reviews for their competitors, so it is unreasonable to determine a restaurant is using or relying on prepared meals if it receives any reviews related to prepared meal. And for some popular restaurants, they tend to receive more reviews than other restaurants, as the results, we cannot simply believe that more reviews related to prepared meals manifesting that this company more relying on prepared meals.

We therefore define the *CommentRatio* for restaurant as

$$CommentRatio = \frac{N^{PM}}{N} \tag{3}$$

In equation (3), N^{PM} denotes the number of negative reviews that explicitly mention prepared meals or related production practices (Central Kitchen), and N denotes the total number of negative reviews received by the restaurant. A higher Comment Ratio is consequently expected to reflect greater reliance on prepared meals and should load positively on the latent prepared-meal-reliance construct.

This construction measures the proportion of consumer dissatisfaction that is specifically attributed to prepared-meal production. It has three advantages over a raw review count. First, it normalizes for differences in restaurant popularity and total review exposure. Second, it distinguishes prepared-meal-related dissatisfaction from general dissatisfaction caused by service, price, sanitation, waiting time, or the dining environment. Third, because the numerator is a subset of the negative-review denominator, both are exposed to more comparable review-generation, fraud-detection, complaint, and moderation processes. The ratio may therefore partially absorb restaurant-level differences in the visibility and retention of negative reviews. Moreover, as noted by Jöreskog and Goldberger (1975), in MIMIC model, indicators are conditionally independent given the latent variable. Because the origin of *WageRatio* and *CommentRatio* stem from two distinct perspectives, they serve as suitable indicator variables to be incorporated into the MIMIC framework.

Nevertheless, the indicator is not a direct verification of production practices. Consumer misclassifications and fraudulent reviews may still generate measurement error. We therefore use the *CommentRatio* only as an auxiliary reflective indicator rather than as a stand-alone classification criterion. In the robustness analysis, we additionally impose minimum-review thresholds to reduce instability arising from small denominators and change *CommentRatio* into other form to show that the validity of *WageRatio* does not hinge exclusively on its specific formulation from the consumers' perspective.

3.2 | Determinants Analysis

3.2.1 | Determinant 1: Rent-Driven Reliance on Prepared Meals

Unlike many other retail businesses, restaurant operations are commonly divided into front-of-house (FOH) and back-of-house (BOH) areas(ONeill et al. 2024). The front-of-house area primarily comprises the dining room and other customer-contact spaces, whereas the back-of-house area centers on the kitchen and food-production activities, including storage, preparation, and cooking.

Higher commercial rent increases the opportunity cost of allocating floor space to back-of-house operations. Additional front-of-house space can often be monetized relatively directly by accommodating more tables and customers, whereas back-of-house space contributes to revenue indirectly by supporting food production. This does not imply that kitchen space does not create value. Rather, compared with dining space, kitchen space cannot usually expand customer capacity simply by accommodating additional seats. This spatial trade-off is particularly important in the restaurant industry because customer demand is often concentrated within relatively short meal periods. During peak dining hours, seating capacity and operational throughput therefore become especially valuable.

Traditional freshly cooked production requires restaurants to maintain sufficient and functionally differentiated back-of-house space for storing ingredients, handling unprocessed raw materials, preparing and cooking food, separating finished products from production waste, and preventing interference or contamination across different production processes (Flessas et al. 2015). By contrast, restaurants that use prepared meals or adopt central-kitchen production can relocate some of these activities to upstream production facilities. Consequently, the space requirements of the store will be reduced, these restaurants may enjoy a lower rental costs or increase revenue by reallocating part of the released back-of-house area to dining areas (Deng 2023). Industry evidence illustrates the potential magnitude of this cost-saving mechanism. According to Zhou (2021), the rental cost of a typical dish allocated to each order decreased by approximately 40% when on-site cooking was replaced with prepared meals (see table A1). Therefore, when a restaurants is facing a high rental cost, it will have a high incentive to cut the cost by using prepared meal or adopting central kitchen production mode.

[Insert table A1 here]

Accordingly, commercial rent is incorporated into the MIMIC model as a theoretically motivated cause of latent prepared-meal reliance. The hypothesis is stated in terms of a systematic association:

Hypothesis 1. *Holding other observed determinants constant, higher local commercial rent is positively associated with a restaurant's latent reliance on prepared meals or central-kitchen production.*

3.2.2 | Determinant 2 (Chain-Driven):

For large chain restaurants, the core challenge is maintaining consistency while expanding geographically (Bradach 1998). As the result, compared to individual restaurants, large chain restaurants has greater pressure to ensure their consistency and replicability for further expansion. Zhang (2025) states that after introducing central kitchen production mode, firms can improve quality consistency across outlets. According to China Chain Store & Franchise Association and China Renaissance (2022), the trend toward restaurant chain expansion further promotes the application of prepared meals and drives the maturity of the entire supply chain for the central kitchen, and the usage of prepared meals in chain restaurants is already an openly known secret within the catering industry.

Consequently, the central kitchen model meets restaurant chains' cost reduction and efficiency improvement needs (Deng 2023). Therefore, compared to restaurants with fewer stores or independent restaurants, large restaurant chains have a stronger incentive to use prepared meals.

Accordingly, number of chain stores is incorporated into the MIMIC model as a theoretically motivated cause of latent prepared-meal reliance. The hypothesis is stated in terms of a systematic association:

Hypothesis 2. *Holding other observed determinants constant, the number of chain stores is positively associated with a restaurant's latent reliance on prepared meals or central-kitchen production.*

3.2.3 | Determinant 3 (Regulation-Driven):

According to the regulations for catering areas in large commercial complexes (Ministry of Emergency Management of the People's Republic of China 2023, Section 9.2b), restaurants located underground or inside large commercial complexes face stricter fire-safety and facility-layout constraints, catering establishments shall not use liquefied petroleum gas (LPG) or Class A or Class B liquid fuels. Additionally, kitchen areas using open fire should be arranged against the exterior wall (Ministry of Emergency Management of the People's Republic of China 2023, Section 9.2e). As a result, for restaurants located in large commercial complexes in the interior, whose kitchen area is impossible to be arranged against the exterior wall, using open fire for cooking is impossible.

As mentioned before, Chinese dishes emphasize on *Wok Hei*, which to some extent relies on open-fire cooking. Relevant research suggest that the formation of *Wok Hei* is closely associate with the browning enabled by the Maillard reaction (MR) (Ko and Hu 2020). MR is an important mechanism through which volatile flavor compounds are generated (Liu et al. 2022). MR are highly dependent on surface temperature and moisture conditions. Traditional high-temperature dry-heat cooking methods, such as open-flame cooking, may be more conducive to surface dehydration, temperature increase, and browning (Purlis 2010). By contrast, studies on microwave suggest that insufficient browning and flavor development are typical limitations of microwave heating (Sumnu 2001, Dong et al. 2022). These may be the reasons why some Chinese consumers claims that prepared meals that simply reheated by microwave taste inferior to fresh meals. On the other hand, studies on braised pork show that traditional open-fire cooking can generate a richer profile of characteristic aroma compounds than induction cooking (Wang et al. 2024). Mechanistic accounts of *wok hei* further suggest that open-flame wok cooking is more conducive to smoky and charred sensory notes, as well as aromas associated with lipid oxidation, thermal degradation, and the partial combustion of aerosolized oil (Ko and Hu 2020, Chin 2019). Therefore, the good taste of *Wok Hei* needs to be delivered by open-flame cooking, not just the freshness of ingredients.

Despite open-flame, the packaging, transportation, storage, and reheating of prepared meals may compromise flavor preservation. This is because volatile aroma compounds can be absorbed by packaging materials, while storage and reheating can promote lipid oxidation, protein degradation, and the formation of warmed-over flavor (Sajilata et al. 2007, Chen et al. 2024). Cold-chain temperature fluctuations may further accelerate the loss of desirable volatile compounds and the production of off-flavor compounds (Yu et al. 2020).

Complaints on 'gas stove ban' by Chinese chefs occur frequently because they think techniques like 'stir-frying' need open flame for rapid and high-intensity heat [10].

Therefore, it is reasonable to make such inference that if gas is banned in large commercial complexes, and if induction cooking cannot provide satisfactory flavor, restaurants may rather use prepared meals to cut the expense on skilled chefs since their skills no longer generate much value for consumer. Incidents in which restaurants adopted prepared dishes and dismissed chefs due to fire-safety regulations have indeed been reported by Chinese media[11].

Accordingly, whether there is open fire regulation is incorporated into the MIMIC model as a theoretically motivated cause of latent prepared-meal reliance. The hypothesis is stated in terms of a systematic association:

Hypothesis 3. *Holding other observed determinants constant, open fire ban for restaurants located in large commercial complexes in the interior is positively associated with a restaurant's latent reliance on prepared meals or central-kitchen production.*

[10] For media reports, see Jenn Harris, "The End of Korean BBQ in L.A.? What the Gas Stove Ban Means for Your Fave Restaurants," *Los Angeles Times*, June 2, 2022, https://www.latimes.com/food/story/2022-06-02/gas-stove-ban-chinese-korean-bbq-electric-new-buildings-restaurants-future; Naoki Nitta, "Would Giving Up Gas Stoves Threaten the Art of Chinese Cooking?," *San Francisco Chronicle*, January 30, 2023, https://www.sfchronicle.com/food/article/gas-stove-wok-chinese-17742332.php; These reports quote Chinese or Asian-restaurant chefs and owners who argue that gas and open flame is important for wok cooking, high-heat stir-frying, and the production of wok hei or smoky flavor.
[11] See Hu Kefei, "The Chef Disappears from the Back Kitchen," *China Newsweek*, January 10, 2022, https://www.inewsweek.cn/viewpoint/2022-01-10/14884.shtml.

4 | RESEARCH METHOD

Our objective is to identify a reliable indicator of restaurants hidden reliance on prepared meals, rather than to estimate the causal effect of prepared-meal adoption on restaurant wage structures. We therefore adopt a latent-variable approach, treating reliance on prepared meals as an unobserved construct that cannot be measured directly. In a MIMIC model, latent constructs are inferred from the systematic relationships among observable variables, even though the constructs themselves remain unobserved (Jöreskog and Goldberger 1975). The model jointly estimates a set of structural and measurement equations in which the latent variable is linked to both its observed determinants and its observable indicators (Frey and Weck-Hanneman 1984).

In our setting, the latent construct is a restaurants degree of reliance on prepared meals. It is modeled as being influenced by a set of theoretically motivated determinants and reflected in observable indicators. The MIMIC framework is therefore appropriate because it allows us to assess whether the indicator derived from our task-based framework behaves consistently with an underlying construct whose variation is systematically associated with the proposed determinants.

The MIMIC model consists two sets of equation:

$$\mathbf{y} = \lambda\eta + \varepsilon \tag{4}$$

$$\eta = \gamma'\mathbf{x} + \zeta \tag{5}$$

where equation (4) is the measurement model for the latent variable η and equation (5) is the structural equation equation for the latent variable η. And in our study, $\mathbf{y}$ is a column vector of 2 indicators of the single latent variable, and $\mathbf{x}$ is a vector of 3 determinants of η. In the equation (5), the latent performance is assumed to be caused by the vector of explanatory variable $\mathbf{x}$. ε refers to a vector of zero mean (2×1) measurement error variables associated with the indicators, while ζ is a zero mean scalar structural error that captures unmodeled variables affecting η and the measurement error associated with it. It is assumed that ζ and all the elements of ε are mutually uncorrelated. And the mechanism of the MIMIC model is visualized in figure B1.

[Insert figure B1 here]

According to Jöreskog and Goldberger (1975), for a standard scalar MIMIC model, identification requires at least two reflective indicators with uncorrelated measurement errors and at least one observed causal variable. In our MIMIC model, we have 3 determinants (observed causal variable) and 2 reflective indicators, which lives up to its identification requirements.

In this study, we assume restaurant's reliance on prepared meals or central kitchen production mode is manifested through labor market signal and consumers' experience. We use *WageRatio* in equation (2) and *CommentRatio* in equation (3)as indicators of reliance on prepared meals or central kitchen production mode ($\mathbf{y}$) in equation (4).

$$\begin{aligned} WageRatio_i &= \lambda_1\eta_i + \nu_{1i}, \quad \lambda_1 < 0 \\ CommentRatio_i &= \lambda_2\eta_i + \nu_{2i}, \quad \lambda_2 > 0 \end{aligned} \tag{6}$$

We include *Rent*, *Chain* and *Regulation* as the vector of exogenous causal variables (Determinants) as $\mathbf{x}$ in equation (5).

$$\eta_i = \alpha_1 Rent_i + \alpha_2 Chain_i + \alpha_3 Regulation_i + \zeta_i \tag{7}$$

where *Rent* is the daily rent per square meter of restaurant *i*, *Chain* is the log of the number of outlets of the brand associated with restaurant *i*, to account for the potential non-linear relationship between brand scale and its reliance on prepared meal, and *Regulation* is a dummy variable, if the location of restaurant *i* makes its usage of open fire become illegal, $Regulation_i = 1$, if not, $Regulation_i = 0$.

All the determinant and indicator variables used in our analysis along with their descriptions are summarized in table A2.

[Insert table A2 here]

The aim of using the MIMIC model is to cope with the selection bias of external validation in section 5.2.4, as the external validation based on publicly disclosed central-kitchen adoption is subject to a potential disclosure-selection problem. Restaurants that publicly report the use of central kitchens are unlikely to constitute a random sample of all restaurants using prepared meals. In particular, non-disclosing restaurants may still rely on prepared meals, implying that the comparison group should be interpreted as an unknown group rather than as confirmed non-users.

To address this limitation, the MIMIC model is not built on the publicly disclosed central-kitchen sample. Instead, it uses the full restaurant sample to examine whether the proposed wage-ratio indicator is systematically linked to a latent construct predicted by theoretically motivated economic and regulatory causes. The known-positive central-kitchen sample is therefore used only as an external criterion-validity check, rather than as the primary basis for identifying prepared-meal reliance.

5 | DATA AND EMPIRICAL RESULTS

5.1 | Data

This analysis uses data collected in 2026, our original data set contains the wage information of 352 different restaurants in five major cities in China: Guangzhou, Shenzhen, Beijing, Shanghai, and Hangzhou. The initial sample was obtained from BOSS Zhipin, one of Chinas major online recruitment platforms (Tang 2016). By using a web-scraping program, we collected restaurant job postings in which the same restaurant simultaneously recruited both front-of-house servers and back-of-house kitchen workers. After removing duplicated postings, non-restaurant businesses, the final labor-market sample contains 352 restaurants.

For each restaurant, we recorded the advertised server wage and the advertised kitchen-worker wage. According to Audoly et al. (2024), for job advertisements providing pay-related information, most of them explicitly revealing the actual salary information. Unlike countries with established tipping systems such as the United States, restaurant servers in China generally do not receive gratuities as a systematic component of compensation (Liu 2003). Therefore, posted wages provide a closer approximation of their labor-market returns.

Because kitchen jobs differ substantially in skill content, we manually classified chef-related positions into three categories based on job titles and stated job requirements. Junior kitchen positions include tasks such as cutting, dish washing, and other auxiliary back-kitchen work. Middle-level chef positions refer to jobs directly responsible for cooking and dish preparation. Senior chef positions include managerial or administrative responsibilities, such as executive chef, and kitchen-management roles. The empirical analysis uses the wage of middle-level chefs to construct the wage ratio, because this category is most directly exposed to substitution by prepared meals or central-kitchen production, similar to Acemoglu and Autor (2011) definition of medium skill workers. Junior kitchen workers do not fully represent skilled cooking labor, while senior chefs often combine culinary work with management functions. Middle-level chef wages therefore provide the cleanest measure of the labor-market value of restaurant-level cooking skills. For job postings reported wage intervals rather than point wages, we used the midpoint of the advertised wage range. This procedure was applied consistently to both server and chef positions.

Following the approach of Boeing and Waddell (2017), who utilized web-scraped online rental listings to construct fine-grained spatial measures of local market conditions, we collect commercial rental information from Anjuke, one of the largest online real estate platforms in China that provides extensive listings of commercial properties. A web-scraping program was used to obtain rental prices and geographic coordinates of commercial spaces. These rental observations were then geographically matched with restaurants identified from BOSS Zhipin to construct a restaurant-level measure of rental cost pressure.

Following prior research that measures restaurant chain scale using publicly available outlet information (e.g., company disclosures and franchise records), we constructed a chain-size measure based on the number of outlets operated by each restaurant brand (China Chain Store & Franchise Association and China Renaissance 2022)(Zhang 2025). Because outlet information is not uniformly disclosed across Chinese restaurant brands, we adopted a hierarchical manual search procedure. Specifically, we first collected outlet numbers from official brand websites. When such information was unavailable, we relied on Jiamengxing, a Chinese franchise-information platform. Finally, for brands lacking both sources, we manually retrieved store counts from Dianping.

In addition to labor-market and operating-environment data, we manually collected consumer-review information and restaurant consumption per capita from Dianping, one of the largest Chinese online restaurant review platforms, providing user-generated reviews and restaurant information that have been widely used in empirical studies of restaurant markets (Wu et al. 2015). As Dianping explicitly restricts automated scraping, this part of the dataset was collected manually. For each restaurant labor-market sample, we recorded per-capita consumption, the total number of reviews, the total number of negative reviews, and the number of negative reviews that explicitly criticized prepared meals, semi-finished dishes, reheated food, central-kitchen production, or similar standardized food-preparation practices. In total, we collected 24,615 negative reviews, among which 1,339 were identified as involving prepared-meal-related criticism. To reduce measurement error, Dianping reviews were independently collected by three researchers and reevaluated if detected any difference.

After excluding restaurants with missing or unreliable information on rental costs, customer reviews, outlet numbers, or consumption levels, we obtained a final dataset comprising 311 restaurants. This sample size is considered adequate for estimating the parsimonious MIMIC model employed in this study. With two reflective indicators and three observed causes, the reduced-form coefficient matrix is a 2×3 matrix constrained to have rank one, generating $(2-1) \times (3-1)$ testable restrictions and rendering the model overidentified (Jöreskog and Goldberger 1975). Given the five observed variables and the two degrees of freedom, a full mean-and-covariance formulation implies approximately 18 freely estimated parameters, corresponding to an observation-to-parameter ratio of 17.3 : 1. This ratio is substantially above the conventional minimum of approximately five observations per estimated parameter, while the total sample also exceeds the general benchmark of 150–200 observations recommended for structural equation models (Jöreskog and Goldberger 1975). Moreover, previous applied MIMIC studies have estimated models with 2 or 3 indicators using samples of 288 (Lafuente-Ruiz-de Sabando et al. 2019)and 200 (Barrales-Molina et al. 2013). Therefore, a sample size of more than 300 observations is considered adequate for the estimation of the model.

To conduct the external validation, we identified 21 restaurant brands that had publicly disclosed their use of prepared meals or central-kitchen production, either directly or through authoritative media reports. These brands yielded a validation sample of 53 restaurant outlets.

5.2 | Results

This Section is divided into four parts: section 5.2.1 reports the descriptive statistics, section 5.2.2 reports the results for the MIMIC model, and the robustness results are reported in section 5.2.3. In section 5.2.4, we using restaurants which has already disclosed its central kitchen production mode or restaurants which were disclosed by authority medias that are using prepared meals secretly.

5.2.1 | Descriptive statistics

In table A3, we report the summary statistics of the wages, determinants, and indicators used in the analysis. Comparing the wages of servers and chefs, the sample mean wage of chefs is higher than that of servers, which is consistent with the traditional division of labor in restaurants where cooking tasks generally require more specialized skills. Meanwhile, the standard deviation of chef wages is substantially larger than that of server wages.

This pattern is consistent with our theoretical expectation that the adoption of prepared meals may affect different restaurant tasks asymmetrically. While service tasks remain highly dependent on in-person interaction and are relatively difficult to substitute, some cooking tasks, particularly standardized and repetitive preparation tasks, can potentially be replaced by prepared meals or centralized production. As a result, restaurants relying more heavily on prepared meals may exhibit greater heterogeneity in their demand for cooking skills, leading to wider dispersion in chef wages.

In addition, the descriptive statistics of the determinants provide preliminary evidence on the heterogeneity of restaurants in terms of operational scale, local cost pressure, and regulatory constraints. These variables are subsequently incorporated into the MIMIC model to examine the factors associated with restaurants' reliance on prepared meals.

[Insert table A3 here]

5.2.2 | Results from the MIMIC model

We present the estimates from the MIMIC model in table A4. Results from three model are presented. The results indicate that all the determinants have expected signs. As shown in table A4, the coefficients of rent, chain scale, and regulation are all positive and statistically significant at 1 percent level, indicating that higher rents, greater chain scale, and open-fire cooking restrictions are positively associated with restaurants reliance on prepared meals.

[Insert table A4 here]

We also report the diagnostic statistics of the estimated MIMIC model in table A4. A necessary condition for model identification is: $(p \times q + 1/2(p)(p+1) - 2p -$

$q) \geq 0$ where p denotes the number of indicator variables and q is the number of causal variables. According to Jöreskog and Goldberger (1975), the likelihood-ratio test jointly examines whether the reduced-form coefficient matrix satisfies the rank-one restriction implied by the MIMIC model and whether the residual covariance matrix is consistent with a common latent factor and indicator-specific measurement errors. Under the null hypothesis this test statistic is distributed as a χ^2 with $q(p-1)+\frac{1}{2}p(p-3)$ degrees of freedom. In our model, $p = 2$ and $q = 3$, yielding two degrees of freedom. The second row of diagnostic statistics in table A4 reports the result from the over-identification test. Rejection of the null hypothesis would suggest the estimated model is mis-specified. Our result, as stated row 2 of table A4 clearly indicate that the estimated model is not mis-specified. Given this evidence, we then provide a series of model fit diagnostics to render the estimated model statically adequate. We use five different statistics: the coefficient of determination (CD), the comparative fit index (CFI), the Trucker-Lewis index (TLI), the root mean square of approximation (RMSEA) and the standardized root mean square of residual (SRMR). All these statistics indicate a measure of overall good-fit of our estimated model.

5.2.3 | Robustness check

Since the reliability of indicator *CommentRatio* may be compromised for restaurants with only a small number of reviews, we exclude restaurants with fewer than 100 total reviews and re-estimate the model using the restricted sample. The results of this model is depicted by table A5. The results remain qualitatively unchanged.

[Insert table A5 here]

However, the reliability of *CommentRatio* may be affected by its dependence on the total number of negative reviews. For example, a restaurant with 20 prepared-meal-related reviews out of 40 negative reviews and a restaurant with only 1 such review out of 2 negative reviews would both have a *CommentRatio* of 0.5. Nevertheless, the former provides substantially stronger evidence of reliance on prepared meals because the indicator is supported by a much larger number of relevant observations. To address this limitation, we replace *CommentRatio* in equation (6) with N^{PM} which denotes the absolute number of negative reviews that explicitly mention prepared meals, central-kitchen production, or related production practices. And the result of this model is depicted by table A6.

[Insert table A6 here]

The alternative specification remains excellent model fit, and the signs and statistical significance of the measurement and structural coefficients remained consistent with those of the baseline model.

To address potential heterogeneity across restaurant formats, we conduct an additional robustness check by excluding fast-food and hotpot restaurants. These two categories may exhibit inherently different production structures: fast-food restaurants often rely on standardized production systems, while hotpot restaurants require relatively limited cooking labor (China Cuisine Association and Shuhai Supply Chain and Baichuan Research Institute 2023). Therefore, including them may mechanically reduce the *WageRatio* independent of prepared-meal reliance. After exclusion, the estimated relationships remain stable. According to table A7, the model remains acceptable after excluding fast-food and hotpot restaurants, with the likelihood-ratio test failing to reject the model specification. All the determinants remain positively associated with latent reliance on prepared meals, while *WageRatio* remains a significant negative indicator loading. Moreover, most of the diagnostics statistics continue to perform well. Although RMSEA increases to 0.100, this measure can be unstable in models with low degrees of freedom and small sample (Jöreskog and Goldberger 1975).

[Insert table A7 here]

One potential concern is that the wage ratio may simply reflect differences in restaurants' market positioning or price levels. A potential alternative explanation is that high-end restaurants pay relatively higher wages to front-of-house servers because they require more intensive service, more formal dining procedures, and better customer interaction. Under this interpretation, a lower chef-to-server wage ratio may simply reflect higher server wages in expensive restaurants, rather than a reduction in skilled back-kitchen labor caused by prepared-meal adoption.

To address this concern, we use restaurant-level consumption per capita as a placebo outcome. If the wage ratio primarily reflects restaurant quality, luxury positioning, or high-end service intensity, it should be systematically associated with consumption per capita. In particular, if expensive restaurants have relatively higher server wages, then the chef-to-server wage ratio should be negatively associated with consumption per capita. By contrast, if the wage ratio captures back-kitchen deskilling associated with prepared-meal reliance, rather than general restaurant price level, its relationship with consumption per capita should be weak or statistically insignificant.

Formally, we estimate the following placebo outcome regression:

$$ConsumptionPerCapita_i = \theta_0 + \theta_1 WageRatio_i + \varepsilon_i,$$

where $ConsumptionPerCapita_i$ denotes the average spending per customer at restaurant *i*.

As reported in table A8, the estimated coefficient of Wage Ratio is statistically insignificant ($p = 0.592$), proving that the plausibility that the indicator simply reflects restaurant tier rather than differences in production practices is reduced.

[Insert table A8 here]

5.2.4 | External Validation of the Wage-Ratio Indicator

Although the MIMIC model provides internal construct-validity evidence that the *WageRatio* behaves consistently with the latent reliance on prepared meals, the interpretation of this indicator can be further strengthened through external validation. The purpose of this section is not to prove a causal effect of central-kitchen adoption on restaurant wage structures. Rather, it examines whether restaurants that actively or passively admit their the use of prepared meals or central kitchen exhibit the theoretically expected wage-structure pattern.

We construct a validation group based on restaurants' official website or authoritative media's report. A restaurant is classified into the known-positive group if official websites, franchise documents, prospectuses, annual reports, media interviews, or other public materials explicitly disclose that the restaurant adopts a central-kitchen production system, uses standardized semi-finished products, or relies on centrally prepared meal components.

Let $\mathcal{C}$ denote the set of restaurants that publicly disclose the use of central-kitchen or prepared-meal production. We define:

$$CentralKitchen_i = \begin{cases} 1, & i \in \mathcal{C} \\ 0, & i \notin \mathcal{C} \end{cases}$$

It should be emphasized that $CentralKitchen_i = 0$ does not imply that restaurant *i* does not use prepared meals or centralized production. It only indicates that no public disclosure is available. Therefore, the validation sample should be interpreted conservatively: restaurants with $CentralKitchen_i = 1$ serve as a known-positive group, while the remaining restaurants are not treated as confirmed non-users.

[Insert figure B3 here]
[Insert table A9 here]

As shown in table A9, group $\mathcal{C}$ has a significantly lower mean *WageRatio* than the no-public-disclosure group. The difference is both statistically significant ($p < 0.001$) and large in magnitude (Cohen's $d = -1.097$), providing external support for the validity of the wage-ratio indicator.

6 | DISCUSSION AND CONCLUSIONS

The findings of this study should be interpreted as a cumulative validation of a theory-derived indicator rather than as a single-model proof or a binary classification exercise. Drawing on the task-based offshoring framework, we first formalize the economic intuition that transferring medium-skill culinary tasks away from individual restaurant outlets compresses the wage premium of middle-level chefs over servers, causing *WageRatio* to decline toward wage parity. The MIMIC model does not generate this indicator ex post; rather, it examines whether the theoretically derived *WageRatio* behaves consistently with a latent construct predicted by theoretically relevant economic and regulatory factors, while *CommentRatio* only serves as an auxiliary reflective indicator, but not a highly reliable indicator to manifest restaurants reliance on prepared meals. The stability of the negative loading of *WageRatio* across alternative constructions of the review-based indicator and alternative sample restrictions demonstrates that the result is not driven by any particular measurement of consumer comments. The placebo test further finds no systematic association between *WageRatio* and restaurant consumption level, weakening other competing explanations. Finally, the substantially lower wage ratios observed among independently documented known-positive restaurants provide external evidence that the indicator corresponds to concrete production practices. Taken together, these results support *WageRatio* as a continuous screening indicator of restaurants' reliance on prepared meals: ratios approaching wage parity indicate greater reliance risk.

6.1 | Contribution to Practice

Typical consumers have very limited access to the kitchen and have little information on whether restaurants use prepared meals. As mentioned above, this information asymmetry may cause a similar market distortion as the lemon market: Most consumers give high valuation to fresh meals, but lack of information stops them from paying sufficient price for restaurants genuinely persisting fresh cooking, which drives these restaurants out of the market.

These findings could have significant implications for the catering market. As with other indicators or signals, measuring restaurants reliance on prepared meals is ambagious and unreliable. Restaurants do not have the incentive to actively disclose their reliance on prepared meals. However, with chef-to-server wage ratio, consumers can identify restaurants which may rely on prepared meals conveniently. Though this study makes no more accusations on any restaurant, we believe that consumers can refer to wage ratio as an estimation if they do mind having prepared meals in restaurants. Even if this indicator becomes widely used in the future, restaurants would have limited scope to conceal or strategically manipulate their recruitment information, as such information must remain sufficiently credible to attract job applicants.

At the same time, with respect to possible future disclosure policy implemented by the government, the method proposed in this study can also help regulators form rough estimates and conduct more targeted supervision of restaurants suspected of concealing their use of prepared meals or false advertising of freshly cooked. This study uses the recruitment wage as an accessible approximation to the real wage, but governments with taxation records may use more precise wage data to regulate restaurants. For those catering enterprises that have not actively declared the use of prepared meals but whose wage ratios that approach 1, precise targeted spot checks can be implemented. It should be noted that the present analysis does not establish a universal numerical threshold above which a restaurant can be conclusively classified as using prepared meals. Accordingly, the indicator should be interpreted as a screening tool rather than definitive proof, and any determination of deliberate consumer deception would require additional corroborating evidence.

6.2 | Contributions to Research

This study contributes to research on information asymmetry by showing that hidden information in production practice may be revealed by labor structure. Existing studies on information asymmetry in catering industry mainly focused on voluntary disclosure, mandatory disclosure, or government supervision. This study offers a new perspective on information asymmetry by showing that, even when production practices are not directly observable or are deliberately concealed, the production process may still leave observable traces in adjacent markets—in this case, the labor market. By examining these market signals, consumers and regulators may infer otherwise hidden production arrangements and make better-informed assessments of product value. In this way, labor-market information can help mitigate the information asymmetry problem underlying the market for lemons.

Moreover, this study extends the task-based framework proposed by Acemoglu and Autor (2011). Most applications of this model stressed on explaining or predicting the change in relative wage or inequity of income under the impact of technological and offshoring impact. This study reversely uses the relative wage change to identify change in the production organization, when the latter is unobservable or concealed deliberately. This extends the application of task-based model and can be generalized to other sectors.

6.3 | Limitations and Future Research

To our knowledge, this is the first study to develop a quantitative measure of restaurants reliance on prepared meals. The chef-to-server wage ratio introduced in this study provides future researchers with a potentially useful micro-level identification measure for estimating the penetration of prepared meals in Chinas catering industry.

However, a potential limitation of this study is that, when the method of referring to wage ratio becomes widespread among consumers, even though catering enterprises cannot conceal this information, but they can take some measures to make the wage information more ambiguous. Although directly modifying the recruitment wage may disturb the recruitment, we cannot completely exclude the possibility. Restaurants may set a wide range of advertising wages for both chefs and servers in order to prevent consumers from getting useful information.

It also should be emphasized that this study does not claim that restaurants with a wage ratio below a particular threshold necessarily use prepared meals. A restaurants reliance on prepared meals cannot be determined solely from its wage ratio, because the ratio may also be affected by other factors. Instead, the wage ratio should be interpreted as a screening signal available to consumers and regulators. Consumers may use it as supplementary information when making dining decisions, depending on their own acceptance of prepared meals.

Due to data availability constraints, we rely on cross-sectional data collected within a single period rather than panel data tracking restaurants over time. Although the cross-sectional design allows us to identify systematic differences across restaurants, it cannot fully capture changes in restaurants production practices or establish dynamic relationships between operational factors and reliance on prepared meals. Future research could construct panel datasets by continuously tracking restaurants labor-market signals, review information, and operational characteristics over multiple periods. Such longitudinal data would enable researchers to identify appropriate classification thresholds, evaluate the sensitivity and specificity of the proposed indicator, and examine how restaurants reliance on prepared meals evolves over time, thereby enhancing its practical applicability.

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Eric Wu: Conceptualization; Methodology; Formal analysis; Investigation; Data curation; Writing – original draft.
Vincent Lau: Conceptualization; Methodology; Investigation; Visualization; Data curation; Writing – original draft.
Colin Sheng: Investigation; Data curation; Validation; Writing – review and editing.
Uchenna Cyril EZE: Supervision; Methodology; Validation; Project administration; Writing – review and editing.

All authors reviewed and approved the final version of the manuscript.

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None reported.

CONFLICT OF INTEREST

The authors declare no potential conflict of interests.

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APPENDIX

A TABLES

TABLE A1 Cost & Profit Comparison of a Typical Chinese Dish

Category	Freshly Cooked	Prepared Meals	Percentage Change
Packaging cost	¥ 2.00	¥ 2.00	
Platform promotional fees	2.40	2.40	
Platform commission	5.20	5.20	
Ingredient cost	6.50	7.50	+ 15.38%
Labor cost	1.60	0.80	– 50.00%
Rental cost	1.00	0.60	– 40.00%
Utilities and miscellaneous expenses	0.40	0.20	– 50.00%
Selling price per serving	20.00	20.00	
Profit per serving	0.90	1.30	+ 44.44%

Note: Percentage change is calculated as (Prepared Meals – Freshly Cooked) / Freshly Cooked.
Source: Authors' compilation based on Zhou (2021).

TABLE A2 Definitions of Variables

Variable	Definition
Indicators	
WageRatio	Ratio of the wage offered to a mid-level chef to that offered to a server at the same restaurant.
CommentRatio	Number of negative reviews explicitly mentioning prepared meals, central-kitchen production, or related production practices, divided by the total number of negative reviews.
Determinants	
Chain	Natural logarithm of the total number of outlets operated by the restaurant chain.
Rent	Daily commercial rent per square meter in the restaurant's local area.
Regulation	Dummy variable, equals to 1 if the use of open flames is prohibited at the restaurant's location, and 0 otherwise.

TABLE A3 Descriptive Statistics

Variable	Mean	Median	Standard Deviation
Chef Wage	7.079	7.000	1.500
Server Wage	5.423	5.500	0.921
Indicators			
Wage Ratio	1.335	1.273	0.320
Comment Ratio	0.082	0.039	0.122
Determinants			
Chain	2.277	1.386	2.338
Rent	6.417	4.67	5.534
Regulation	0.277	-	-

Note: Wage variables are measured in thousand RMB per month, but Rent is measured in RMB/m^2/*day*

TABLE A4 Results from MIMIC Model

Variable	Unstandardized Coefficient	Standard Error	P	Standardized Coefficient	95% CI
Indicators					
Comment Ratio	1(constrained)	-	-	0.575	-
Wage Ratio	–3.408***	0.419	0.000	-0.744	[–4.229, –2.586]
Determinants					
Rent	0.004***	0.000	0.000	0.373	[0.003, 0.006]
Chain	0.011***	0.002	0.000	0.381	[0.007, 0.015]
Regulation	0.063***	0.011	0.000	0.408	[0.041, 0.086]
Diagnostic statistics	**Value**				
Observations	311				
χ^2 [p-value]	3.307 [0.191]				
CD	0.611				
CFI	0.994				
TLI	0.978				
RMSEA	0.046				
SRMR	0.018				

Note:
** Denotes significance at 5 percent level.
*** Denotes significance at 1 percent level.

TABLE A5 Results from MIMIC model excluding all the restaurants with reviews less than 100

Variable	Unstandardized Coefficient	Standard Error	P	Standardized Coefficient	95% CI
Indicators					
Comment Ratio	1(constrained)	-	-	0.615	-
Wage Ratio	–3.750***	0.505	0.000	-0.730	[–4.741, –2.760]
Determinants					
Rent	0.004***	0.000	0.000	0.333	[0.002, 0.006]
Chain	0.010***	0.002	0.000	0.392	[0.006, 0.015]
Regulation	0.058***	0.011	0.000	0.437	[0.037, 0.080]
Diagnostic statistics	**Value**				
Observations	234				
χ^2 [p-value]	3.888 [0.143]				
CD	0.608				
CFI	0.989				
TLI	0.960				
RMSEA	0.064				
SRMR	0.022				

Note:
** Denotes significance at 5 percent level.
*** Denotes significance at 1 percent level.

TABLE A6 Robustness Check: Numbers of Comments mentioned Prepared Meals

Variable	Unstandardized Coefficient	Standard Error	P	Standardized Coefficient	95% CI
Indicators					
N^{PM}	1(constrained)	-	-	0.597	-
Wage Ratio	–0.057***	0.006	0.000	-0.639	[–0.070, –0.045]
Determinants					
Rent	0.294***	0.040	0.000	0.454	[0.215, 0.373]
Chain	0.738***	0.106	0.000	0.481	[0.530, 0.946]
Regulation	3.397***	0.529	0.000	0.425	[2.360, 4.434]
Diagnostic statistics	**Value**				
Observations	311				
χ^2 [p-value]	1.110 [0.574]				
CD	0.828				
CFI	1.000				
TLI	1.013				
RMSEA	0.000				
SRMR	0.010				

Note:
** Denotes significance at 5 percent level.
*** Denotes significance at 1 percent level.

TABLE A7 Robustness Check: MIMIC Model Excluding Fast-Food and Hot-Pot Restaurants

Variable	Unstandardized Coefficient	Standard Error	*P*	Standardized Coefficient	95% CI
Indicators					
Comment Ratio	1(constrained)	-	-	0.652	-
Wage Ratio	–3.588***	0.512	0.000	-0.694	[–4.592, –2.583]
Determinants					
Rent	0.0039***	0.0008	0.000	0.336	[0.002, 0.006]
Chain	0.0112***	0.0024	0.000	0.405	[0.006, 0.016]
Regulation	0.0611***	0.0117	0.000	0.447	[0.038, 0.084]
Diagnostic statistics	**Value**				
Observations	196				
χ^2 [p-value]	5.939 [0.051]				
CD	0.638				
CFI	0.973				
TLI	0.904				
RMSEA	0.100				
SRMR	0.030				

Note:
** Denotes significance at 5 percent level.
*** Denotes significance at 1 percent level.

TABLE A8 Placebo Test: Wage Ratio and Consumption Level

Variable		Coefficient	Standard Error	*P*	95% CI
Wage Ratio		12.314	22.923	0.592	[–32.790, 57.419]
Constant		97.172	31.459	0.002	[35.271, 159.074]
Diagnostic Statistics	Observations	R^2	Adjusted R^2	F-statistics	p-value
Value	311	0.001	–0.002	0.29	0.592

Note: Standard errors are reported in parentheses. The dependent variable is consumption per capita.

TABLE A9 External Validation of the Wage-Ratio Indicator

Group	Observations	Mean	Standard Deviation	Standard Error
Known-positive group (*CentralKitchen* = 1)	53	1.027	0.069	0.009
No-public-disclosure group (*CentralKitchen* = 0)	346	1.347	0.311	0.017
Between-group comparison	**Value**			
Mean difference	-0.319			
Welch's t	-16.635			
Degrees of freedom	358.912			
p-value	< 0.001			
95% CI	[–0.357, –0.282]			
Cohen's d	-1.097			
95% CI for Cohen's d	[–1.395, –0.797]			

Note: The original dataset consists of 352 restaurants. Among them, six restaurants were identified as the Known-positive group based on publicly disclosed information regarding central kitchen or prepared-meal usage. The remaining 346 restaurants constitute the no-public-disclosure group. Mean differences are calculated as *CentralKitchen* = 1 minus *CentralKitchen* = 0. Welchs t-test is reported because Levenes test rejects the equal-variance assumption (F=48.202,p<0.001).

B FIGURES

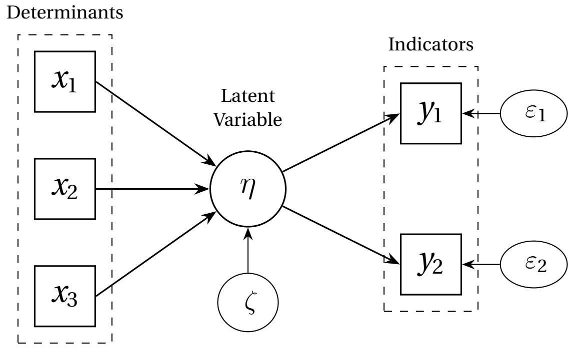
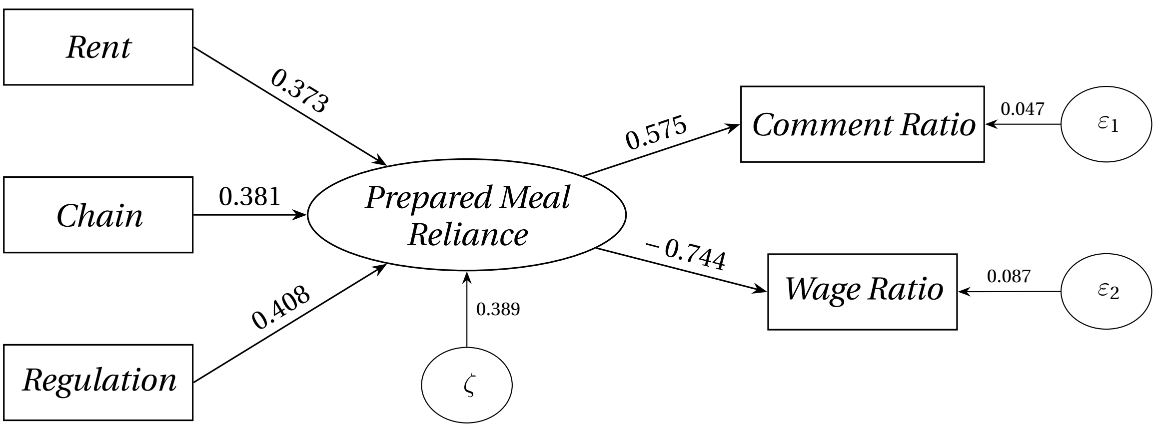
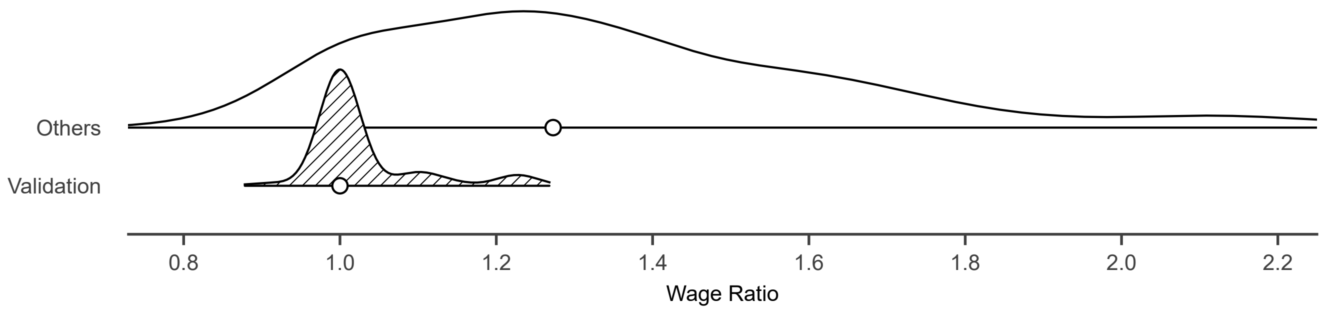


FIGURE B1 Path Diagram



Note: Standardized coefficients are reported. The values associated with the disturbance terms represent standardized residual variances.

FIGURE B2 Standardized Solution of the MIMIC Model



Note: Validation is the set of restaurants which are disclosed high reliance on prepared meals. Circle stands for median.

FIGURE B3 Distribution of Wage Ratio