Yelp Me If You Can: Online Reviews and the Future of Occupational Licensing

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Abstract. In the United States, occupational licensing has steadily increased since the 1970s, requiring government-issued licenses for various professions. Supporters argue it safeguards consumers, while critics contend it erects barriers to entry. This study focuses on personal care services, approximately 90% of the workforce in this occupation being female, to assess licensing's effect on service quality. Analyzing over 7,500 personal care businesses and 240,000 Yelp reviews, we explore how state-level licensing changes influence service quality. Leveraging advanced natural language processing techniques, we track shifts in consumer sentiment toward six distinct aspects of service. Our findings show that removing licensing enhances service quality. Notably, delicensing significantly benefits businesses in Black communities, highlighting how licensing practices can disproportionately burden minority business owners. Delicensing leads to a marked increase in both the number of businesses and employee sizes, with newcomers receiving significantly higher ratings than their existing counterparts. In contrast, introducing licensing appears to deteriorate service quality and reduce employee numbers. This research sheds light on the complex relationship between occupational licensing, quality, and economic opportunity, suggesting a need for careful reevaluation of licensing practices to balance consumer protection with fostering female-owned and operated business growth and equity.

Key words: Occupational licensing, Online reputation system, User-generated content, Natural language processing

1. Introduction and Background

In the United States, the significance of occupational licensing has been steadily growing since the 1970s, with an increasing number of professions mandating government-issued licenses for employment (Kleiner 2006). According to the US Census Bureau, Current Population Survey (CPS), 30% of employed individuals held active licenses in 2022, marking a substantial increase from only 4.5% reported in the 1950s. In fact, nearly one in every four American workers is required to obtain an official authorization document in order to lawfully engage in their chosen professions (NCSL, 2022). This trend means that many jobs in the US are accessible only to those who have time and resources to meet often extensive licensing requirements. Licensing is especially burdensome and prevalent in lower-income professions (The White House, 2016), affecting a diverse range of occupations including plumbers, auctioneers, and hair salon specialists.

While the primary aim of the occupational license is to protect public safety (Pancak and Sirmans 2004, Anderson et al. 2020), the practice often leads to misaligned requirements, considerable financial and time investments, and hurdles to job mobility and market entry (Greenberg 2021, Knepper et al. 2022), particu-

larly among racial minorities (Dorsey 1983, Sutherland et al. 2023)[1]. Interestingly, a striking contrast exists within the regulatory landscape: fewer than 60 occupations, such as doctors, dentists, and EMTs, require licensing across all states due to their inherently risky nature. However, over 1,100 are licensed in just *one* state (House 2015), showing a fragmented approach to regulating potential risks in various occupations.

Among these, personal care services emerge as one of the most widely and onerously regulated fields, particularly burdening lower-income and minority workers (Mindy et al. 2021). Women dominate this field, making up a large proportion of licensed professionals such as hairdressers, cosmetologists, and nail technicians. Looking at the licensing burden of personal care services shown in Figure 1, we observe that licensing requirements for personal care services vary significantly across states. The cost of cosmetology programs, based on licensing requirements, averaged over $16,000 during the 2022-2023 school year, with less than a third of cosmetology students graduating on time (IPEDS). Furthermore, the median income of personal care services workers is lower than that of occupations without burdensome state licensure or state-mandated education requirements, such as restaurant cooks and concierges (Bureau of Labor Statistics, 2022), further entrenching gender-based income disparities in a female-dominated field. The difficulty of entering an occupation often does not line up with the public health or safety risk it poses. For example, 66 occupations have greater average licensure burdens than emergency medical technicians. The average cosmetologist spends 372 days in training while the average EMT only takes 33 days (Carpenter et al. 2022). This points to the essential yet inconsistently regulated nature of many essential service-oriented jobs. However, the demand for personal care services is on the rise, with employment expected to grow by 8% from 2022 to 2032, outpacing the average for all occupations[2].

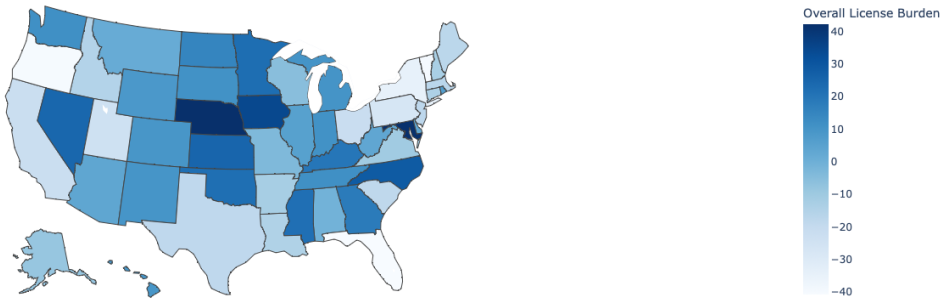


Figure 1 License Burden in Personal Care Services Sector

In this work, we focus on the inconsistently regulated and essential occupations in the personal care service sector. There exists a significant gap in understanding the need for licenses and their role in ensuring

[1] See more discussion in MIT Sloan Newsletter, Federal Reserve Bank of Minneapolis, and Foundation for Economic Education

[2] U.S. Bureau of Labor statistics, Occupational Outlook Handbook

safety, despite the ubiquitousness of online reputation systems that reduce information asymmetry (Tabarrok and Cowen 2015, Tadelis 2016) between consumers and providers. Empirical research on the quality of services in the personal care sector and consumer responses to changes in licensing remains limited, despite the increasing importance of these services and the increase in technology-mediated reputational mechanisms through which consumers can infer a service provider's quality without intervention from the government. We use novel, large-scale data and state-of-the-art Transformer models to understand latent quality from consumer reviews to address this question. Therefore, our research contributes to the ongoing debate on the impact of occupational licenses on service quality by addressing the following questions: (1)Does occupational licensing impact service quality? (2) What specific dimensions of quality are influenced by licensing change? (3) How do licensing regulations affect businesses in minority communities?

These questions are managerially important. Studies show that the rigorous process of obtaining a license drives up service costs (Kleiner 2015, Kleiner et al. 2016), limit job opportunities (Adams et al. 2002, Larsen 2015, Zapletal 2019), and reduce consumer welfare (Kleiner and Soltas 2023), without necessarily enhancing service quality. Our research thus focuses on occupations in the service sector, where the harm is not demonstrably high and yet in high demand. The biggest challenge in studying the service sector is the lack of reliable data to study quality. Other studies in occupational licensing exclusively study occupations such as health care (Anderson et al. 2020, Kleiner and Kudrle 2000) and education (Boyd et al. 2008, Larsen 2015) where the roles have high risk and outcomes are measurable though malpractice suits and mortality (for physicians and midwives), cavities (for dentists) and test scores (for teachers). Fortunately, the meteoric rise in user-generated content (UGC) platforms provides us with rich data on customer experiences in the service sector (Mejia et al. 2021, 2019). Further, occupations in the personal care service sector get licensed and de-licensed in different states at different times, which provides us with the exogenous variation to causally measure the impact of these changes on the quality outcomes using the review data and state-of-the-art advances in Natural Language Processing (NLP).

Our study finds that removing licensing requirements leads to enhanced service quality, as evidenced by increased ratings and positive consumer sentiment in Yelp reviews related to service elements, which are hospitality and style. This suggests that the elimination of licensing mandates does not necessarily lead to a deterioration in service quality. Interestingly, this improvement is particularly pronounced in Black communities, where the removal of licensing barriers allows more businesses to enter the market, in which newcomers are showing significantly higher service quality as measured by online ratings. Crucially, the removal of licensing barriers significantly increases the income of female workers, demonstrating the potential of de-licensing to promote a more inclusive and equitable market environment.

On the other hand, introducing licensing mandates results in a significant decline in online ratings and increased dissatisfaction to both guidelines and services, particularly in areas such as cleanliness and style, with the profession of manicurists specifically marking the negative drive in ratings. This adverse impact

is attributed to a substantial decrease in the workforce size of businesses, which, coupled with a relative spike in customer demand, leads to challenges in maintaining service quality. These findings suggest that the higher barriers to entry imposed by licensing may result in worker shortages and the exit of small, independent, or community-focused businesses from the market. As a result, the remaining businesses may struggle to maintain service quality while catering to relatively increased demand.

Our work contributes to the occupational licensing literature and the literature on the societal impact of user-generated platforms, demonstrating the value of leveraging user-generated content and advanced NLP techniques to gain a more nuanced understanding of service quality. By analyzing textual data from online reviews, we can uncover insights that may not be captured by traditional metrics such as numerical ratings. This approach enables policymakers and researchers to assess the multidimensional nature of service quality and make more informed decisions regarding occupational licensing reforms.

The paper begins by reviewing existing literature on the role of occupational licensingits impact on quality, and the potential of online reputation systems, as discussed in Section 2. Section 3 provides details on the dataset utilized in our study, while Section 4 outlines our research methodology and empirical findings. Further, we explore additional Natural Language Processing (NLP) results in Sections 5. The robustness checks are presented in Section 6. Finally, we conclude our study with a discussion of findings and implications in Section 7.

2. Related Literature

Occupational licensing, a regulatory practice integral to numerous professions, acts as a bridge between market needs and consumer protection. We review key studies that analyze the rationale underpinning the structure of occupational licensing and focus on empirical studies that examine the effects of licensing on service quality, public health, and safety standards. Finally, we review research centered on online review platforms, highlighting a gap indicating the potential for online reputation systems to reshape the consumer protection landscape and service assessment methodologies.

2.1. Role of Licensing

The purposes of occupational licensing are primarily discussed in two main streams within the existing literature, focusing on the perspectives of practitioners and policymakers.

From the standpoint of practitioners, occupational licensing often functions as a protective mechanism for workers in regulated professions. The foundational economic theory suggests that individuals within these occupations actively seek regulation to limit competition (Kleiner 2006). This limitation results in higher prices for their services, leading to increased incomes for practitioners (Stigler 2021). The drive for regulation becomes particularly pronounced when the demand for the service is inelastic, making consumers less responsive to price changes. For workers, the licensing framework provides a means to secure higher wages. Additionally, from a club model perspective, licensing serves as a signaling mechanism for

commitment and quality within the profession, enabling dedicated professionals to stand out in the market and safeguard their interests in a competitive landscape (Spence 1978, Iannaccone 1992).

On the other hand, policymakers are often motivated to regulate occupations through licensing as a means to address market failures and protect the public interest. The dominant public interest rationale suggests that occupations posing higher risks to the public are more likely to be regulated (Wheelan 2016). Policymakers may be driven by a desire to ensure public safety, with regulatory measures acting as a safeguard against potential harm (House 2015). The club model also presents a perspective wherein licensing becomes a tool for nonprofit organizations to engage in exclusive behavior, maintaining quality and commitment within the profession. Policymakers, guided by these perspectives, aim to strike a balance between fostering a competitive market and ensuring the well-being and safety of the public (House 2015). By implementing licensing requirements, policymakers seek to establish a framework that encourages high professional standards, ethical behavior, and ongoing education, contributing to a robust and responsible workforce.

When considering the impact on consumers, the discussion revolves around two aspects: costs and benefits. On the one hand, licensing is intended to address asymmetric information (Leland 1979), overcome the lemons problem (Akerlof 1970), and ensure a certain level of service quality (Benham 1981). However, consumers may bear the costs associated with higher prices (Kleiner et al. 2016, Kleiner and Kudrle 2000) resulting from limited competition among practitioners (Buonanno and Pagliero 2018). The complexity and costs associated with understanding professional regulations can also create a barrier for consumers to actively participate in advocating for or against licensing (Cox and Foster 1990). Additionally, the "monopoly face" of licensing, where supply is restricted to increased prices, may lead to higher service costs and limited choice options for consumers (Kleiner 2006). On the positive side, regulatory requirements, such as continuing education and adherence to ethical standards, have the potential to contribute to a higher quality of service (Rottenberg 1980).

2.2. Effects of Licensing on Quality, Health, and Safety

The impact of occupational licensing on service quality, health, and safety has been extensively studied, covering a diverse range of occupations and quality measures.

The predominant body of research reveals null or adverse effects resulting from stringent licensing practices on service quality. Empirical studies cover across various professions, including dentistry (Carroll and Gaston 1981, Kleiner and Kudrle 2000), medicine (Kugler and Sauer 2005), electrical services (Carroll and Gaston 1981), contracting (Maurizi 1980), education (Kleiner and Petree 1988, Kane and Staiger 2005, Angrist and Guryan 2008, Kane et al. 2008, Larsen 2015, Klee 2013, Larsen 2015), real estate (Powell and Vorotnikov 2012), tour guiding (Erickson 2016), accounting (Klee 2013, Barrios 2022), floral services (Carpenter and Dick 2012), and ride-sharing with Uber drivers (Hall et al. 2019). The measurement of quality, health, and safety mostly relies on measurable metrics, such as test scores, complaint volumes, report records, and changes in insurance rates.

Studies that find the positive impact of occupational licensing on service quality are mainly concentrated in medical settings. Stringent entry requirements were linked to lower adverse outcomes, such as cavities and broken teeth (Holen 1977). Similarly, studies demonstrate that expanding nurses' independence enhances healthcare service quality (Timmons 2017, Traczynski and Udalova 2018) while licensing requirements for midwives reduce maternal mortality and decrease infant mortality (Anderson et al. 2020). Some notable exception lies in the educational sector, where positive effects on student achievement and narrow qualification gaps among instructors are associated with heightened stringency in the teaching profession (Boyd et al. 2008, Larsen 2015).

2.3. Opportunities in Online Reviews Platforms to Examine Quality

As technology continues to advance, Tabarrok and Cowen (2015) argues that the growing availability of online consumer information and various review platforms enables customers to access information on the service quality of practitioners or businesses. Moreover, a properly operating feedback system can function as a viable alternative for licensing, lessening the need for cumbersome and expensive upfront screening or quality certification procedures (Farronato and Zervas 2022, Friedman 1962, Shapiro 1986).

Online review platforms have emerged as an effective channel for providing information on consumer experiences, benefiting both potential customers and service providers. (Forman et al. 2008, Mudambi and Schuff 2010). With platforms like Yelp, Amazon, and TripAdvisor, online reviews have established themselves as influential reputation systems (Dellarocas 2003, Tabarrok and Cowen 2015, Farronato and Zervas 2022). According to BrightLocal's 2022 consumer surveys, 98% of U.S. consumers read online reviews for local businesses, with service-area businesses and tradespersons being the most top-selected focus. Notably, over half of U.S. consumers specifically rely on Yelp for reviews. This observation highlights the potential that these online platforms play in shaping consumer protection, emphasizing the transformative impact of online reviews on the dynamics of the consumer-service provider relationship.

From the business perspective, service providers prioritize acquiring informative online reviews and engaging with consumers online (Van Doorn et al. 2010). Research finds that customer reviews enhance product innovation (Bertschek and Kesler 2022), improve service-based firm operations (Ananthakrishnan et al. 2023), upgrade product and service quality (Tadelis 2016, Goldfarb and Tucker 2019, Donati 2022), and identify customer needs (Timoshenko and Hauser 2019). Moreover, Farronato et al. (2020) finds evidence that consumers prioritize review ratings and prices over the platform-verified licensing status of professionals. As online reviews and consumer information play a significant role in addressing information asymmetry, the evaluation of occupational licensing leans towards understanding whether existing legal remedies, consumer ratings, reputational mechanisms, and less burdensome regulatory approaches suffice to protect consumers (House 2015).

In summary, while existing research extensively covers the motives for occupational licensing from both practitioner and policymaker perspectives and its impacts on consumers, the specific effects on service

quality and public safety remain unclear. There is a notable gap in research exploring the multifaceted nature of service quality and consumer response to these variations. Recognizing that service quality is inherently multidimensional, this study aims to explore demand-side perceptions to better understand service quality across a broad spectrum of personal care occupations. Further, by leveraging AI-based NLP techniques, we provide a unique perspective in this debate by measuring quality, which has thus far been difficult to measure in the personal industry sector.

3. Data

We leverage the exogenous variation from licensing changes across various occupations within the personal service sector, occurring in different states and at different points in time as a natural shock to explore the impact on the quality outcomes. We first collect occupational licensing enforcement data and then hand-collect Yelp review data, combined with Historical Business Data, Data Axle and GPS-enabled foot traffic data, Safegraph data.

3.1. Occupational Licensing Enforcement

The National Conference of State Legislatures (NCSL) has established both sunset and sunrise processes within the framework of occupational licensing to assess the relevance and necessity of specific licenses or regulations. Sunrise processes involve comprehensive analyses of newly proposed licensing laws, addressing the question of whether a particular occupation should be subject to licensing while sunset processes enable policymakers to evaluate existing laws and regulations, determining whether ongoing licensing is warranted. In essence, sunset processes inquire whether occupations currently under licensing should continue to be regulated, while sunrise processes focus on whether a new occupation should be introduced into the realm of licensing (NCSL 2020).

We gather information concerning changes in licensing regulations, considering both sunrise and sunset perspectives, i.e., the introduction (licensed) and removal (delicensed) of licenses, combined with the findings documented by Knepper et al. (2022)) along with additional data collected from licensing boards in each state. After gathering the license enforcement change data, we identified the border states that have been consistently licensed and experienced no change in the licensing regulations as our control states. The comprehensive details of license changes are compiled in Table 1.

Subsequently, we collect user-generated content related to the identified occupation in the particular states from the major review site, Yelp.com.

3.2. Yelp.com

Yelp stands as a prominent review-centric website, serving as a comprehensive platform connecting individuals with local businesses spanning services, restaurants, contractors, retail, and more. As of 2023, the

Table 1 Licensing Regulation Change.

	Occupation	Year	Treated States	Control States
Delicesned	Hairstylist	2018	VA	MD
		2019	AZ	NM
		2020	MN	IA
		2021	UT	CO
		2021	AR	LA
	Makeup Artist	2020	FL	GA
		2020	MN	IA
		2021	MS	LA
	Shampooer	2017	TN	AL
		2020	WV	OH
		2021	MO	IA
		2022	NH	MA
Licesned	Manicurist	2021	CT	NY, MA
	Skincare Specialist	2020	CT	NY, MA
	Massage therapist	2021	VT	MA

site reports approximately 287 million reviews and approximately 32 million active devices on the Yelp platform each month (Yelp, 2023[3]).

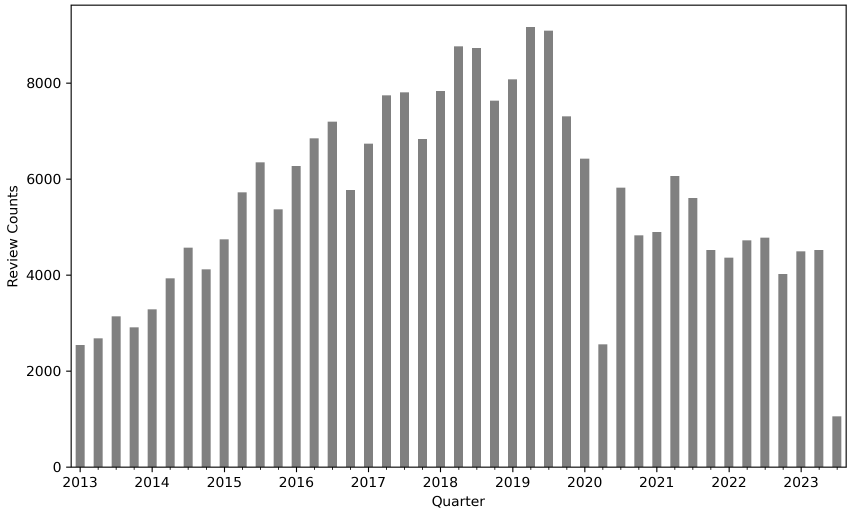
On Yelp, users can both read and write reviews, assigning ratings to businesses on a 1-5 star scale and providing detailed textual reviews and/or photos. Once a review is composed, it becomes accessible to anyone, whether or not the individual has an account on the platform. Users may access reviews based on query searches that involve business type, search location, and other filters. By offering trusted local business information, accompanied by photos and review content, Yelp serves as a comprehensive local platform, facilitating consumers in discovering, connecting, and interacting with local businesses.

In this study, we first identify the top ten most populous cities within each state that is compiled in Table 1. Following that, we collect all the reviews from the state cities as 'Location' and the associated occupations as the keyword search query. In other words, each review is associated with an occupation used as the search query keyword, such as "Hairstylist, Phoenix Arizona," "Hairstylist, Tucson, Arizona," "Hairstylist, Mesa, Arizona," and so forth. Our analysis includes all Yelp reviews written between 2013 and 2023. In total, our dataset comprises 239,859 reviews spanning 7,595 businesses in 23 states that span 6 occupations in personal care services, which are hairstylist, makeup artist, shampooer, massage therapist, skincare specialist, and manicurist. Figure 2 illustrates the quarterly review totals collected from Yelp.com.

We gather various types of information, including business details such as platform-verified license status, location, address, website, business labels, and available badges. Additionally, we collect customer-related data such as reviewer friend counts, post numbers, review locations, and uploaded photos. We also collect review-related information, such as review date, review context, and votes on usefulness, funniness, coolness, as well as owner responses.

[3]https://www.yelp-press.com/company/fast-facts/default.aspx

Figure 2 Yelp Review Counts by Quarter



3.3. Historical Business Data - Data Axle

We observe the market supply trends utilizing historical business data, Data Axle. Data Axle records various business-related details such as street addresses, phone numbers, number of employees, SIC codes, and more, organized in a state-year format. The data involve address-level data on US businesses and other organizations spanning from 1996 to 2022.

For our research scope, we focus on the personal care service industries, which are identified by NAICS Codes 812112 (Beauty Salons), 812113 (Nail Salons), and 812199 (Other Personal Care Services). By matching businesses collected from Yelp with the Data Axle dataset, we have identified a total of 5,197 businesses with 39,755 business-year observations.

3.4. Safegraph Data

To observe the customer demand change, we employ the SafeGraph dataset to identify the foot traffic. The SafeGraph dataset is comprised of three distinct subsets: Core Points of Interest (POI), Geometry, and Patterns, which collectively enable us to more accurately gauge market flow and dynamics.

The Core POI dataset contains information on over 390,000 Points of Interest (POIs) for businesses in personal care services in the US. It includes details such as the business name, placekey, address, brand association, opening hours, etc. The Geometry dataset provides the polygon representation of businesses, outlining their physical locations. Finally, the Patterns dataset describes visitation patterns of each unique POI, including monthly aggregated visitation numbers, dwell times, popularity of the brand, etc. SafeGraph utilizes mobile device GPS locations and machine learning to attribute visits to POIs

To understand the foot traffic trend, we match the business data collected from Yelp with the SafeGraph data, resulting in approximately 7,412 businesses. We then aggregate the monthly visit counts per business to average quarterly visit counts. To ensure data quality, we exclude businesses with irregularly low foot

traffic, defined as consecutive three months with no or only one visit recorded and all quarters having less than 5 visits. Additionally, businesses with no visits recorded in the past year are classified as closed, leaving us with 5,400 businesses of 102,864 business-quarter observations.

3.5. Census Bureau

To have a better understanding regarding the demographics profile in the local communities, we leverage The American Community Survey (ACS) and the Decennial Census data. The ACS provides annual estimates on a wide range of population, housing, social, and economic characteristics across specific occupations at the individual level while the Decennial Census data provides detailed demographic and housing information Together, these datasets enable a comprehensive understanding of demographic trends and shifts.

The overall demographic composition in the personal care services industry is detailed in Table 2. This industry is predominantly female and features significant minority representation. Hairdressers and shampooers make up the largest proportion of the workforce, with notable representation from Black, Asian, and Hispanic communities, accounting for about 30% of the workforce. Massage therapists and skincare specialists also show significant Asian and Hispanic representation. Manicurists and pedicurists are predominantly Asian, with over 70% of the workforce belonging to this group. Overall, this industry is characterized by a predominantly female workforce and substantial participation from minority racial groups.

Table 2 Proportions of Various Personal Care Services Demographic Profile.

Occupation	Obs Proportion	Female pct	White pct	Black pct	Asian pct	Hispanic pct
Hairdressers and shampooers	0.6372	91.86%	80.07%	9.91%	6.49%	13.17%
Massage therapists	0.1479	82.42%	81.74%	5.88%	10.59%	10.12%
Manicurists and pedicurists	0.0901	83.50%	21.53%	2.50%	73.43%	9.76%
Skincare specialists	0.0304	98.75%	79.30%	6.58%	11.43%	15.62%
Other personal appearance workers	0.0110	91.75%	69.03%	12.54%	12.60%	22.33%

The statistics is from the ACS between 2013-2022 via IPUMS.

4. Models and Results

As rating is viewed as a credible metric for service quality (Bardach et al. 2012, Farronato et al. 2020, Hall and Porteus 2000), our study starts by investigating the overall influence of occupational license changes on review ratings within the market. We employ a Difference in Differences (DiD) framework to analyze the impact at the market level, where we define the market boundaries by county. The model is specified as follows:

$$\text{Avg Review Rating}_{cot} = \beta \cdot \text{After Delicense}_{ocst} \setminus \text{After License}_{ocst} + \gamma X'_{ct} + \mu_c + \delta_o + \tau_t + \epsilon \qquad (1)$$

Here, $\text{After Delicense}_{ocst}$ and $\text{After License}_{ocst}$ are the treatment indicators, taking a value of 1 if occupation o in county c, state s during quarter t is delicensed or licensed, and 0 otherwise. For control counties, the

treatment indicator remains 0 across all quarters. μ_c, δ_o, τ_t represent fixed effects for county, occupation, and quarter respectively. X'_{ct} includes additional controls for reviewer-related characteristics, including metrics of the average reviewer's number of friends, posts, and uploaded photos during the quarter t in county c and market-related characteristics, including the number of business, logarithm of the average cumulative number of reviews and the average cumulative rating in county c up to quarter t - 1. The coefficient of interest, β, captures the average impact of occupational licensing on service quality in personal care services. Standard errors are clustered at the state-occupation level.

We validate the parallel trends assumption using the event study by employing a four-quarter pre-period before the license change event and a four-quarter post-period window. The model is specified as follows:

$$\text{Avg Review Rating}_{ct} = \sum_{j=-4}^{4} \beta_j \cdot \mathbb{1}[t - e_{ocs} = j] + \gamma X'_{ct} + \mu_c + \delta_o + \tau_t + \epsilon \tag{2}$$

The indicator variable, $\mathbb{1}[t - e_{ocs} = j]$, represents event-time that takes the value of 1 when the policy changes (i.e., delicense or license) of occupation o in quarter t are j periods away for county c in state s. The baseline period is -1, which represents that the average change in review ratings in the treatment group compared to the review ratings in the control group is measured relative to the difference in review ratings in the control group one quarter before the license change.

We start by presenting model-free evidence on the impact of occupational licensing across both treated and control groups. We calculate the average review ratings for these groups, as illustrated in Figure 3. This figure shows that in counties where licensing was removed, the average review ratings for the treated groups were generally slightly higher than those for the control groups. Conversely, in counties that introduced licensing mandates, the average review ratings for the treated groups showed a decrease compared to the control groups.

Figure 3 Average Rating Change

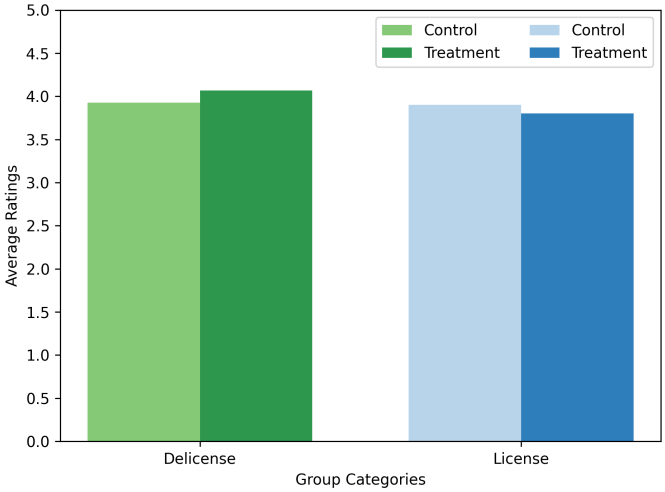


Table 3 Review Ratings - Delicensed & Licensed.

	Delicense	License
DV: Avg Review Rating	(1)	(2)
Post Treat	0.0733*	-0.1051***
	(0.0380)	(0.0210)
Market Size$_q$	0.0044***	0.0018
	(0.0014)	(0.0020)
Log Avg Num Review$_{q-1}$	-0.0352*	-0.0454**
	(0.0174)	(0.0149)
Avg Review Rating$_{q-1}$	0.1941***	0.1662**
	(0.0452)	(0.0682)
Avg Num Friend By Reviewer	0.0008***	0.0009***
	(0.0001)	(0.0002)
Avg Num Post By Reviewer	0.0004**	8.07E-5
	(0.0002)	(0.0004)
Avg Num Photos By Reviewer	8.68E-5**	5.13E-5
	(3.13E-5)	(0.0001)
County FE	Yes	Yes
Quarter FE	Yes	Yes
Occupation FE	Yes	Yes
Observations	6,953	2,515
R^2	0.13128	0.33206

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To address potential confounding factors such as seasonality or business-specific influences, we employ a Difference-in-Difference (DiD) model, as presented in Equation 1. This method enables us to provide a causal estimate of the impact of occupational licensing on review ratings. We present the estimates in Table 3. Column (1) shows the results for the delicensed group, while Column (2) presents the outcomes for the licensed group. Our analysis shows that the elimination of occupational licensing regulations has a marginally positive impact on average review ratings. Conversely, the imposition of licensing regulations on the occupation demonstrates a significant negative effect on review ratings. This observation aligns with our findings from the model-free evidence.

Figure 4 presents the event study estimates over a time window that extends six quarters before and ten quarters after a licensing change, as specified in equation 2. During the pre-period, we observe no significant trends, thereby supporting the parallel trends assumption for both the delicensed and licensed groups. Subsequently, in the delicensed group, we notice an increasing trend of the review ratings in the long term. Conversely, the licensed group experiences an immediate decline in review ratings after the license mandate.

As we previously observed personal care services is characterized by a substantial participation of minority racial groups and numerous studies have highlighted, occupational licensing disproportionately affects

communities of color (Dorsey 1983, Sutherland et al. 2023)[4] and for immigrants (Gomez et al. 2015, Drange and Helland 2019) [5], we aim to uncover this differential impact in the personal care services sector.

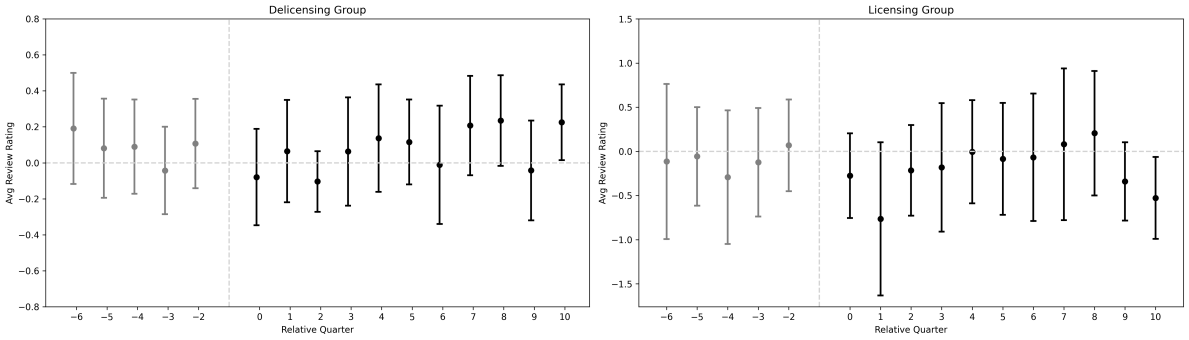
To understand the impact of occupational licensing on service quality in communities of different population compositions, our study introduced a geographical layer to the dataset. First, we extracted business addresses from Yelp reviews and manually mapped these locations to their respective census tracts using the United States Census Bureau Geocoder. Subsequently, we match our dataset with demographic data from the Decennial Census and American Community Survey Data, linking the demographic profile to each county. We calculated the median percentage of four different population types across all counties: non-white, Black, Asian, and Hispanic.

Next, we compared each racial type percentage in each county to the median, categorizing counties as having a higher or lower than median minority population percentage. This categorization resulted in four indicators: higher non-white ("Non-white County"), higher Black ("Black County"), higher Asian ("Asian County"), and higher Hispanic ("Hispanic County").

The immigrants are defined as the "foreign-born" workers, which includes all individuals born outside the United States and its territories, regardless of their naturalization status. We also computed the median percentage of the foreign-born population across all counties and established the indicator "High Immigrant" based on whether the county has a higher-than-median or lower-than-median foreign-born population percentage. The statistics of county characteristics are compiled in Table 4.

We observe that in counties classified as lower-than-median, the percentage of minority populations is significantly less—at least half—compared to those classified as higher-than-median. Generally, the percentage of minority populations in higher-than-median counties is four to five times greater than in lower-than-median counties.

Figure 4 Event Study Plots - Treatment Effects on Avg Review Rating



(a) Delicensed Group (b) Licensed Group

[4]See more discussion in MIT Sloan Newsletter, Federal Reserve Bank of Minneapolis, and Foundation for Economic Education

[5]See more discussion in Migration Policy Institute, NCSL Report, and Center on Budget and Policy Priorities

Table 4 County Characteristics - Delicensed & Licensed.

	Type	High - Population Pct (%)	Low - Population Pct (%)
Delicense	Non-white	51.26%	21.69%
	Black	25.6%	4.13%
	Asian	6.77%	1.83%
	Hispanic	18.28%	5.13%
	Immigrants	14.31%	4.39%
License	Non-white	49.98%	24.44%
	Black	13.02%	3.35%
	Asian	11.00%	3.25%
	Hispanic	25.12%	8.72%
	Immigrants	25.5%	10.5%

We introduced the interactive term to each of the indicators, which are Post Treat × Non-white County, Post Treat × Black County, Post Treat × Asian County, Post Treat × Hispanic County and Post Treat × High Immigrants to Specification 1 respectively and present the results in Table 5.

First, looking at the results in the delicensed counties, we observe that overall ratings marginally increased in non-white counties and significantly increased in Black counties, suggesting an improvement in service quality in these areas. In contrast, for licensed counties, we observe a marginally negative decline in review ratings is observed in high immigrant counties compared to non-high immigrant counties and a general decline in the overall post-licensing period. This explains the negative consequences observed in the licensed counties.

This discrepancy could be attributed to two potential explanations. First, the removal of licensing regulations had a more pronounced effect on service quality in Black communities. This could be due to a greater proportion of service providers in Black communities being previously excluded from the market due to licensing barriers. The elimination of these barriers may have allowed skilled workers to re-enter the market, leading to an improvement in overall service quality and, consequently, higher review ratings. Second, the restriction of labor supply with the enforcement of licensing(Kleiner and Soltas 2023) leads to reduced market fluidity(Davis et al. 2014). As licensing often requires significant investment in terms of time and money, individuals from lower socioeconomic backgrounds, who are disproportionately represented in Black communities, might find these requirements particularly prohibitive. Thus, while the removal of licensing facilitates market entry and possibly improves service standards, the reintroduction or tightening of these regulations could have the opposite effect, cementing barriers that were previously mitigated and adversely affecting the service quality perceived by consumers. In particular, immigrants may face additional challenges when licensing requirements are stringent. Language barriers, recognition of foreign credentials, and unfamiliarity with complex bureaucratic processes can exacerbate the difficulties faced by immigrant service providers. In other words, immigrants face a Catch-22: their experience is not recognized as credit toward a license, but they can't get a job to gain U.S. experience without a license. Therefore, strict licensing may not only restrict their market entry but also marginalize a segment of the community that

Table 5 Review Ratings - Delicensed & Licensed.

Delicense					
DV: Avg Review Rating	(1)	(2)	(3)	(4)	(5)
Post Treat	-0.0159	-0.0789	0.0634	0.1002*	0.0446
	(0.0603)	(0.0657)	(0.0605)	(0.0490)	(0.0684)
Post Treat × Non-white County	0.1346*				
	(0.0733)				
Post Treat × Black County		0.2478**			
		(0.0966)			
Post Treat × Asian County			0.0346		
			(0.0644)		
Post Treat × Hispanic County				-0.0602	
				(0.0645)	
Post Treat × High Immigrants					0.0004
					(0.0745)
County FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
Observations	6,543	6,543	6,953	6,953	6,543
R^2	0.13690	0.13813	0.13347	0.13556	0.13924
License					
Post Treat	0.0281	0.0264	-0.1034*	0.0320	0.1596
	(0.1332)	(0.1335)	(0.0514)	(0.1018)	(0.1093)
Post Treat × Non-white County	-0.1996				
	(0.1577)				
Post Treat × Black County		-0.1988			
		(0.1580)			
Post Treat × Asian County			0.1490		
			(0.0949)		
Post Treat × Hispanic County				-0.2823	
				(0.1706)	
Post Treat × High Immigrants					-0.3322*
					(0.1600)
County FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
Observations	2,515	2,515	2,515	2,515	2,401
R^2	0.33302	0.33258	0.33624	0.33363	0.35266

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

could potentially offer unique services and perspectives. Therefore, businesses may encounter an unstable supply despite relatively increased customer demand, reflected in the overall decreased service quality.

4.1. Consumer Demand and Market Supply

To assess shifts in customer demand and market dynamics of new business entry, we utilized foot traffic as a proxy for customer demand and both the employee size and business count to gauge market dynamics.

First, we use the Safegraph foot traffic data to understand the customer demand shift. We utilize the aggregated quarterly visit counts per business and aggregated quarterly visitor counts per business as our dependent variable outlined in Equation 1. The results are detailed in Table 6.

Our results show that the average demand of visits and visitors per business did not significantly change after removing the license mandates. However, we observe a significant increase in both visits and visitors per business after introducing the licensing requirements. This signals that there is a significantly higher consumer demand shift after the licensing mandate faced by the businesses, verifying our previous hypothesis of the relatively higher customer demand.

Table 6 Customer Demand Dynamics.

	Delicense		**License**	
DV:	Average Visits	Average Visitors	Average Visits	Average Visitors
	(1)	(2)	(3)	(4)
Post Treat	-38.29	-21.92	39.56**	15.48*
	(25.44)	(18.78)	(16.10)	(7.006)
County FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Observations	3,849	3,849	1,292	1,292
R^2	0.23085	0.23711	0.32010	0.33604

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We now gauge the supply dynamics after the license change using the Data Axle historical business dataset. Noted that this dataset records data at the business-year level, we, therefore, aggregate the annual average employee size and the annual business count within each county as our dependent variables and again estimate the change before and after the license alteration. We control for county, year, occupation, and state-year fixed effects. The results are detailed in Table 7.

We observe that after removing the license requirement, both the average employee size and the number of businesses increased. In particular, there is a significant increase in businesses observed in the Black Counties. Conversely, for the licensed group, the average employee size significantly decreased and the business count significantly decreased in Black Counties. This supports our hypothesis that licensing acts as an entry barrier, potentially leading to reduced market participation and diminished economic dynamism. By imposing licensing requirements, regions may inadvertently stifle growth and prevent potential workers from entering their chosen professions. This suggests that while intended to maintain standards, licensing can also act as a significant impediment to economic and job market fluidity.

Table 7 Market Supply Dynamics.

Delicense						
	Avg Employee Size			**Business Count**		
	All	Black County	Non-Black County	All	Black County	Non-Black County
	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat	18.82*	20.43	13.51	6.969**	5.783**	5.726
	(11.00)	(18.56)	(15.70)	(3.123)	(2.580)	(5.301)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,001	1,018	983	2,001	1,018	983
R^2	0.71695	0.71924	0.86866	0.79389	0.75736	0.92392
License						
	Avg Employee Size			**Business Count**		
	All	Black County	Non-Black County	All	Black County	Non-Black County
	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat	-25.85**	-30.49*	-12.54	-3.635	-9.687**	6.414
	(10.72)	(12.59)	(15.90)	(3.921)	(2.623)	(5.762)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	572	310	262	572	310	262
R^2	0.54051	0.52537	0.58415	0.60865	0.57250	0.70233

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.2. Performance Disparity: New Entrants vs. Established Businesses

With the observed influx of new businesses and the dynamic rating changed resulted from removing the license, especially prominent in the Black Counties, it becomes natural to examine the performance of the new entrants relative to that of established entities. This analysis will provide valuable insights into the practitioners who drive service quality improvement.

To do so, we compute the unemployment rate of each county. Then we derive an indicator, *High Unemployment*, which takes the value of 1 if the county has an unemployment rate higher than the median before the enforcement of licensing changes and 0 otherwise. The rationale behind this indicator is twofold. Firstly, higher unemployment rates tend to exist in areas with higher barriers to entry. In this sense, the removal of such barriers is likely to facilitate a larger influx of new businesses or workers. Secondly, regions with higher unemployment may indicate a higher unmet demand, thereby attracting more newcomers. Consequently, this indicator may signal areas likely to experience a higher influx of workforce participation after the removal of licensing restrictions. We run the model specified in Equation 1 and introduce the interactive term Post Treat $\times$ High Unemployed, controlling for the same market and reviewer characteristics as specified in Section 3. The results are reported in Table 8.

Table 8 Performance Results.

	Delicensed	Licensed
Post Treat	-0.0134	-0.1107***
	(0.0546)	(0.0264)
Post Treat × High Unemployed	0.1280**	0.0336
	(0.0548)	(0.0234)
Market Size$_q$	-0.0010	0.0005
	(0.0015)	(0.0015)
Log Avg Num Review$_{q-1}$	0.0464**	-0.0656**
	(0.0202)	(0.0246)
Avg Review Rating$_{q-1}$	-0.1551***	0.2374*
	(0.0491)	(0.1054)
Avg Num Friend By Reviewer	0.0006***	0.0009***
	(0.0001)	(0.0002)
Avg Num Post By Reviewer	0.0004**	-1.38E-5
	(0.0002)	(0.0005)
Avg Num Photos By Reviewer	-7.4E-5**	-7.14E-5
	(2.82E-5)	(0.0001)
County FE	Yes	Yes
Quarter FE	Yes	Yes
Occupation FE	Yes	Yes
Observations	6,953	2,515
R^2	0.21970	0.34305

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

From the table, we observe a significant increase in review ratings in areas with higher unemployment compared to areas with lower unemployment after removing the license requirement. This observation suggests that the newcomers entering the market following the removal of occupational licensing demonstrate an ability to provide satisfactory service.

4.3. Income

As discussed in Section 3, personal care services are predominantly staffed by women, with approximately 90% of the workforce in this occupation being female. To assess the income status of women in this sector, we utilized ACS data collected from IPUMS. We focus specifically on women subgroups to examine changes in female individual income before and after the change in licensing mandates. We use total personal income as the dependent variable. Due to the annual granularity of the dataset, we control for county, year, occupation, and state-year fixed effects. The findings are reported in Table 9.

We observe that female workers show a significant increase in income after the removal of the licensing mandate, whereas the introduction of licensing does not have a significant impact on income. The lack of significant impact from licensing may be attributed to workers leaving the market, resulting in their incomes no longer being observed in the dataset.

Therefore, combined with the previous findings, we observe that the deregulation of licensing not only enhances market accessibility for new entrants but also potentially improves overall service quality. Addi-

Table 9 Female Income Results.

	Delicensed	Licensed
Post Treat	2,113.2**	627.3
	(1,018.9)	(6,399.9)
County FE	Yes	Yes
Year FE	Yes	Yes
Occupation FE	Yes	Yes
States-Year FE	Yes	Yes
Observations	24,406	2,038
R^2	0.02597	0.04361

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

tionally, there is a notable increase in female income, indicating that deregulation may provide economic benefits to women in the personal care services sector. These dynamics are especially pronounced in regions previously characterized by high unemployment and economic stagnation, suggesting that deregulation can be particularly beneficial in underserved and economically disadvantaged communities. The removal of licensing barriers appears to foster a more inclusive and thriving marketplace, offering new opportunities for economic advancement and improved service standards in areas that need them most.

5. Mining Service Qualities from Reviews

Thus far, our analysis has primarily relied on numerical ratings from reviews to gauge changes in business quality following the implementation or removal of licensing regulations. While these quantitative metrics offer readily available insights, they lack the depth and granularity inherent in raw, unstructured text data. Given that the primary aim of occupational licensing is to safeguard consumer health and safety, it becomes important to delve deeper into the nuanced effects of license changes on various aspects of service quality. This includes examining both guideline-related elements such as public health and safety and other service-related elements such as professional, consumer experience, or stylistic considerations.

5.1. Reviews as Indicators of Service Quality and Safety

We begin by addressing a crucial question: Is the online reputation system adequate for informing customers about service quality and protecting them from potential health and safety risks? To explore this, we review the licensing curricula mandated by the State Board of Cosmetology since all our occupations in personal care services fall under cosmetology regulation. We have compiled the topics regulated across different states, and the summary of these topics is presented in Table 10. For a detailed breakdown of the curricula in each state, please refer to Appendix A. Additionally, we examine whether these aspects are mentioned in customer reviews. If reviews reflect all aspects covered by regulation and can even identify adverse outcomes, then the online reputation system may sufficiently serve as a direct indicator, revealing service quality and alerting potential harm to the customers.

Table 10 State Board of Cosmetology Licensing Curricula Summary.

Main Topics	Dimensions	BERTopic in Reviews
General cosmetology skills	shampooing, hair shaping, hairstyling, skin care, scalp treatment, and facial makeup	['hair', 'haircut', 'skin','styling', 'treatment', 'blow', 'scalp', 'layers', 'facial','shampoo', 'makeup']
Specialized cosmetology skills	permanent waving, hair coloring, hair straightening, nail technology	['hair', 'roots', 'highlights', 'dye', 'color', 'bleach', 'nail', 'tech', 'perm', 'machine', 'coat']
Business and Ethics	law, business practices, ethics, theory and professional attitude	['care', 'rude', 'customer', 'service', 'owner', 'unprofessional', 'business', 'price', 'appointment', 'certificate', 'loyal', 'process']
Hygiene and Sanitation	sanitation, infection control, working environments control, first aid	['infection', 'fingers', 'scalp', 'cut', 'cuticle', 'bleed', 'tools', 'sterilizes', 'equipment', 'room', 'unsanitary']
Science	esthethics and skin science, massage skills, general science	['chemical', 'skin', 'peeling', 'extractions', 'face', 'esthetician', 'pressure', 'beautiology', 'relaxation', 'salicyclic', 'follicles']

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We observe that the licensing curricula cover general skill training, business management perspectives, and health and safety training. To understand whether these perspectives are discussed in reviews, we leverage large-scale textual data extracted from reviews and employ machine learning-based natural language processing (NLP) techniques. This approach enables us to explore a broader spectrum of quality dimensions beyond numerical ratings, providing insights into how licensing reforms impact different facets of service quality.

5.2. BERTopic Modeling

We employ BERTopic (Grootendorst 2022) modeling techniques to decipher the subjects discussed in customer reviews. Followed by that, we show that all the aspects covered in the licensing curricula are discussed in the reviews. The relevant topics discussed are compiled in Table 10.

As the main purpose of the occupational license is to protect public health and safety and ensure service quality, after identifying the validity of reviews in embodying all aspects of regulation, we categorize the different focal points regarding guidelines and service-related elements that contribute to different spectrum of quality and safety issues. The results are compiled in Table 11. There are some subject matters more relevant related to public health and safety, including cleanliness, facility requirements, chemical handling, and safety while others are more associated with general service perspective, including style, hospitality, and customization.

5.3. Aspect-Based Sentiment Analysis (ABSA)

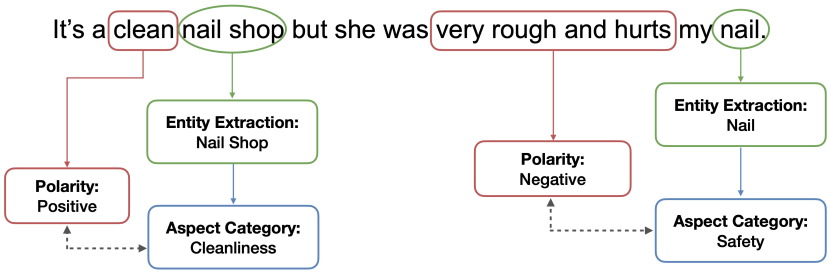
After identifying the pertinent aspects of service quality, we employ Aspect-Based Sentiment Analysis (ABSA) as our analytical approach. ABSA (Pontiki et al. 2016) involves three tasks, as depicted in Figure

Table 11 BERTopic Modeling Results.

Type	Aspect	Content	BERTopic Keywords Example
Public Health and Safety	Cleanliness Sanitation	hygienic practices and environments	['clean', 'tools', 'sterilized', 'filthy', 'unsanited', 'dust', 'dirty', 'personal', 'tidy']
	Chemical Handling	using, storing, or disposing of chemicals	['smell', 'chemical', 'toxic', 'chemicals', 'odors', 'dispose', 'dilute']
	Safety	infection control, equipment and client safety	['bleeding', 'cuticles', 'infection', 'cut', 'skin', 'painful', 'fungus', 'fungal', 'doctor']
	Facility Requirements	physical and operational standards	['room', 'locker', 'ventilation', 'handwashing', 'robe', 'shielding', 'workstation']
Service	Style	aesthetic and design	['ochoa', 'trendy', 'cut', 'color', 'stylist', 'fashion', 'straight', 'look', 'natural']
	Hospitality	personalized advice, service, product selection	['nice', 'help', 'employee', 'advice', 'register', 'personalized', 'care', 'need', 'custom']

5: Name Entity Extraction (NER), Aspect Category Detection (ACD), and Sentiment Polarity (SP). NER focuses on extracting entities, ACD identifies associated attributes, and SP predicts sentiment on the valence.

Figure 5 Three tasks of ABSA in a sample review.



To perform NER and ACD on reviews, we initially sample 2,000 reviews randomly from our dataset for manual annotation. This involves labeling entities listed in Table 11, resulting in six distinct labels: cleanliness, facility requirements, chemical handling, safety, style, and hospitality. Next, we fine-tune a pre-trained Transformer NER model using these annotated reviews. Using this customized NER model, we process all collected reviews, generating a dataset of extracted entity-valence observations. Subsequently, we randomly select 2,000 entity-valence observations for a second round of manual annotation, where we assign three labels: negative, neutral, and positive. With this annotated dataset, we train a sentiment analysis model. Finally, we use this model to predict sentiment analysis for all extracted entity-valence observations, yielding the final dataset containing entities and associated sentiment scores. The numbers of the extracted entities are compiled in Table 12.

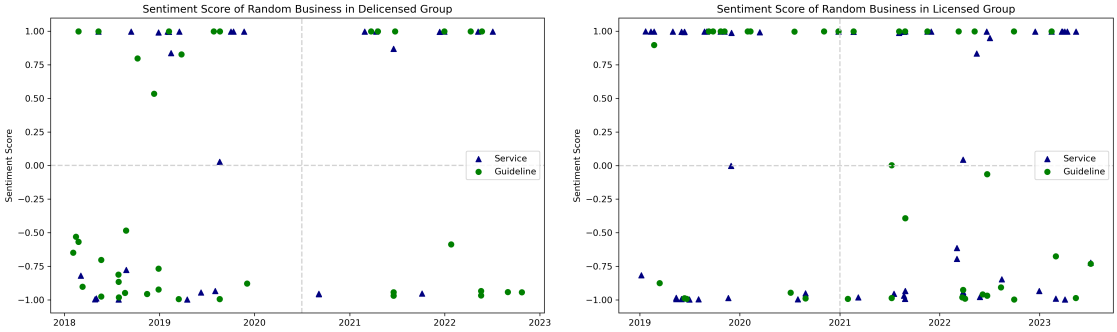
We visualize the sentiment associated with service and guidance for a random sample of businesses across both delicensed and licensed groups. By plotting sentiment scores related to these two dimensions in Figure 6, we observe shifts in sentiment density under varying licensing conditions. The model-free visualization shows a decrease in negative sentiment regarding both service and guidance following the

Table 12 Number of Extracted Entities

Extracted Entities	Count
HOSPITALITY	47,489
CLEANLINESS	37,847
STYLE	29,171
SAFETY	21,117
FACILITY_REQUIREMENT	2,720
CHEMICAL_HANDLING	2,358

removal of licensing requirements, while the introduction of such requirements shows a shift from positive to negative sentiment toward both aspects. This highlights the dynamic nature of customer perceptions and service quality in response to changes in licensing regulations.

Figure 6 Sentiment Dynamics toward Service and Guideline Aspect



(a) Delicensed Group (b) Licensed Group

As looking at the random textual examples from the Yelp review dataset compiled in Table 13, we observe the sentiment dynamics surrounding the services offered, marked by shifts in both positive and negative directions. Moreover, the entities and sentiments extracted from the reviews paint a diverse picture of customer experiences, enabling an evaluation of multiple facets of the service performance. Following this, we explore sentiment changes over time to quantify the impact of licensing alterations on service quality through the lens of customer voices.

In formalizing this analysis within a regression framework, we must address reviews that do not mention the focal entity [6]. However, the absence of entity mention can be informative, indicating that certain aspect wasn't a concern for the customer. Hence, to address whether an entity is mentioned or not, we assign a neutral score of zero to any review that doesn't mention the focal entity.

We employ Specification 1 and utilize the average sentiment score of each focal entity as our dependent variable. We summarize these findings in Table 14. Our analysis shows that the removal of licensing leads to marginally increased satisfaction in general service aspects including styling and hospitality. Meanwhile,

[6]Within our dataset, 36% of reviews do not mention the Service Aspect Entity and 53% of reviews do not mention the Guideline Aspect Entity.

Table 13 Examples of Entities and Sentiment Before/After License Change.

Review Text	Entity and Sentiment
Example 1 - Delicensed Group	
The haircut is fine, but my experience was disappointing. The hairstylist barely spoke to me the whole time. She had the nozzle of the blow dryer so close to my scalp a couple of times that it actually hurt and felt like she was going to burn me. My scalp now has a sore, itchy spot that it didn't have before.	haircut (0.0), experience (-0.90), blow dryer (-0.95), scalp (-0.93)
Wonderful salon. Clean, friendly, and well decorated. They don't push services unnecessarily; it's nice going somewhere you can trust have your best interests in mind. I had my very-long-hair cut and she handled it very well. I was adoring my cut for weeks.	salon (0.88), clean (0.92), service (0.85), cut (0.97)
Example 2 - Licensed Group	
The staff is so sweet and the facilities are very clean and refreshing. No toxic smell, plenty of space, clean clean clean. My nail tech was efficient and did a beautiful job.	staff (0.97), facilities (0.90), smell (0.87), clean (0.77), nail tech (0.88), job (0.69)
It is a clean relaxing atmosphere but I'm not impressed. My nail tech was more interested in all that was going on around her than servicing me her client? My pedicure was rushed, the exfoliating was so fast it did absolutely nothing and the polish I can see right through.	atmosphere (0.75), service (-0.91), pedicure (-0.93), exfoliating (-0.92), polish (-0.95)

all the aspects related to public health and safety remain the same level of satisfaction. Nevertheless, introducing licensing requirements results in a marginal increase in negative sentiment related to both general services and public health and safety dimensions, which are styling and cleanliness.

The increased dissatisfaction within the general services and public health and safety dimensions suggests that as barriers to entry become higher due to the costs and requirements associated with obtaining and maintaining a license, businesses may lose workers in the workplace or even cause some small, independent, or community-focused businesses to exit the market. The consequences of increased relative demand per business are observed and discussed in 4. Consequently, the supply becomes vulnerable and unstable while catering to the uptick in demand. Practitioners may become sloppy, resulting in increased dissatisfaction in the aspects of cleanliness.

Here are some evidence from the reviews:

– This is the most disgusting place I've been to, they do not clean their products and they try to rush to get you out of there. They gave me a nail infection. Don't ever go here if you care about your health.

– Waited 1/2 hour even with an appointment. Sloppy pedicure. Nails were ok. Towels used for the pedicure looked dirty. I will not be back.

5.4. Adverse Events in Customer Reviews

We have observed that issues related to public health and safety have emerged following the implementation of licensing mandates, despite the primary objective of licensing being to safeguard public health and safety. To gain a deeper understanding of licensing's effectiveness, we aim to scrutinize these safety issues further. Our approach involves first identifying whether serious adverse events have been reported by customers, and secondly, exploring any improvements in these outcomes since the licensing mandates were enacted.

Table 14 Sentiment Change of Different Aspects of Service Quality.

Delicensed						
	Hospitality	Style	Cleanliness	Safety	Chemical Handling	Facility Requirements
	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat	0.0034*	0.0124*	-0.0009	-0.0009	0.0005	0.0005
	(0.0018)	(0.0075)	(0.0094)	(0.0065)	(0.0028)	(0.0028)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,143	47,817	47,240	47,365	46,244	46,209
R^2	0.00447	0.01029	0.01585	0.02370	0.01350	0.00859
Licensed						
	Hospitality	Style	Cleanliness	Safety	Chemical Handling	Facility Requirements
	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat	-0.0025	-0.0111*	-0.0400*	0.0165	0.0030	-0.0040
	(0.0129)	(0.0057)	(0.0233)	(0.0091)	(0.0048)	(0.0021)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,868	53,001	56,506	56,534	52,076	52,059
R^2	0.01129	0.00635	0.01093	0.01989	0.00266	0.00163

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To achieve this, we zoom in to the 'safety' entities, which capture the safety issues reported in the reviews and we compiled the relevant serious adverse outcomes in Table 15 of each occupation.

Table 15 Adverse Outcomes.

Occupation	Adverse Outcomes
Hairstylist	Allergic reactions, Bald spots, Red and irritated scalp, Chemical burns, Scissor pokes leading to bleeding, Infections, Heat damage
Makeup Artist	Severe burns leading to eyes shutting, Scars, Eye infections, Skin irritation
Shampooer	Bumping ear with great force, Exposure to harmful chemicals, Broken hair, Hair damage
Manicurist	Fungal infections, Large dents, Skin peeling, Cauterized infections, Sharp jabs, Cuticle cuts leading to bleeding
Massage Therapist	Back pain, Forceful hits on bones, Beating on the back, Muscle pain, Bruised neck and shoulders, Numb muscles
Skincare Specialist	Allergic reactions, Facial swelling, Burned capillaries, Darkened skin, Platysma strain, Skin burns

We observe that reviews effectively identify serious adverse outcomes. Customers also upload photographic evidence, significantly highlighting the risks associated with specific service providers. Examples of this are shown in Figure 7.

Figure 7 Photos of Adverse Outcomes by Reviewers.



(a) Chemical Burn/Scar (b) Cauterized infections (c) Burned capillaries

To quantify the effectiveness of licensing in protecting public safety, we developed an adverse event measurement, *Neg Safety*. The metric is calculated based on the proportion of 1-star reviews that mention severe safety issues, relative to the total count of reviews. This measurement captures the occurrence probability of severe adverse outcomes. We employ this variable as our dependent variable in the model outlined in Specification 1 to assess the impact of changes in licensing on safeguarding public health. The findings are detailed in Table 16.

Table 16 Adverse Events Outcome.

	Delicense			**License**		
DV: Neg Safety	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat	-0.0180*	-0.0147	-0.0334	-0.0173	-0.0581	-0.0355
	(0.0106)	(0.0110)	(0.0243)	(0.0112)	(0.0434)	(0.0214)
Post Treat × Black County		-0.0063			0.0551	
		(0.0122)			(0.0482)	
Post Treat × High Immigrants			0.0244			0.0316
			(0.0255)			(0.0279)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,640	6,640	6,640	3,542	3,542	3,542
R^2	0.03209	0.03212	0.03475	0.05333	0.05482	0.05433

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Our result shows that removing licensing requirements results in a marginal decrease in the probability of severe adverse outcomes occurring. In Black County, although the findings are not statistically significant, we observe a downward trend in the incidence of severe adverse outcomes. However, the introduction of licensing requirements does not significantly reduce the likelihood of adverse outcome occurrences. This finding iterates the benefits of removing unnecessary burdensome licensing requirement that allows qualified practitioners to enter the market, potentially increasing competition and service quality that drives down the occurrence likelihood of the severe adverse outcome.

6. Robustness Check

6.1. Sub-group Analysis

We validate the observed effect on review ratings by conducting sub-group analysis. Referring to Table 1, several border-pair states experienced differential treatment timing of license change. To conduct the sub-experiment for each border-pair state, we utilize the Stacked Difference-in-Difference (Stacked DiD) method (Cengiz et al. 2019, Deshpande and Li 2019, Butters et al. 2022) to stack each pair-border as the same event time to build the single dataset. We study each sub-experiment specified as in Equation 3:

$$Y^d_{ocst} = \sum_{j=-\kappa_a}^{\kappa_b} \beta^d_j \cdot \mathbb{1}[E_{td} = j] + \sum_{m=-\kappa_a}^{\kappa_b} \delta^d_j(\text{Treat}_{ocsd} \cdot \mathbb{1}[E_{td} = j]) + \theta^d_c + \gamma^d_q + \tau^d_o + \epsilon^d_{cst} \tag{3}$$

Here, Y^d_{ocst} represents the average review rating of occupation o in county c state s during quarter t of sub-experiment d. The θ^d_c are county fixed effects, γ^d_q are quarter fixed effects, and τ_o are occupation fixed effects of sub-experiment d. The variable Treated_{ocsd} is an indicator equal to 1 if occupation o in county c state s is a treated unit of sub-experiment d and 0 otherwise. E_{td} is indicators equal to 1 if quarter t is in the post period in sub-experiment d and 0 otherwise. We cluster standard errors at the state-occupation level. The coefficients of interest are the δ^d_j; they represent the difference between pair-wise treated and controlled business in border-states in review rating. We report the results in Table 17.

Table 17 Stacked DiD Results.

	Delicense			**License**		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat	0.0993*	0.0044	0.0850	-0.2887**	-0.1740	-0.0541
	(0.0550)	(0.0939)	(0.0611)	(0.0825)	(0.1525)	(0.1231)
Post Treat × Black County		0.1719*			-0.1665	
		(0.1088)			(0.2711)	
Post Treat × High Immigrants			0.0247			-0.4122*
			(0.0525)			(0.2390)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,953	6,953	6,953	2,515	2,515	2,515
R^2	0.04782	0.04881	0.04922	0.19811	0.19884	0.21785

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Overall, the findings align with previous research, showing that removing licensing mandates leads to an increase in review ratings, predominantly in communities of color, while the introduction of licensing significantly drives a decrease in review ratings, primarily in districts with higher immigrant populations.

6.2. Sentiment Shifts with Licensing Changes

We previously observed that the proportion of severe adverse outcomes declined and satisfaction with general service aspects increased after the removal of the licensing requirement. In contrast, when licensing was added, there was no significant improvement in severe adverse outcomes, and we observed a decrease in satisfaction with general services and cleanliness. To verify this trend, we computed the fraction of entities showing negative sentiment in two areas: (1) general services: hospitality and styling, and (2) public health and safety: cleanliness, chemical handling, facilities, and safety. Consequently, we have two dependent variables: the fraction of negative public health and safety mentions and the fraction of negative general service mentions. We applied the model specified in 1. The results are presented in Table 18. We also conducted the same analysis for positive mentions in these two aspects, with the results reported in Appendix B.

Table 18 Results of Negative Mentions.

Negative Mentions of Public Health and Safety Issues						
	Delicense			**License**		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat	-0.0130**	-0.0094	-0.0210*	-0.0164	-0.0332	-0.0276
	(0.0048)	(0.0073)	(0.0116)	(0.0120)	(0.0296)	(0.0176)
Post Treat × Black County		-0.0063			0.0222	
		(0.0085)			(0.0351)	
Post Treat × High Immigrants			0.0128			0.0184
			(0.0127)			(0.0177)
County FE	Yes	Yes	Yes	Yes		
Quarter FE	Yes	Yes	Yes	Yes		
Occupation FE	Yes	Yes	Yes	Yes		
Observations	19,086	19,086	19,086	10,952	10,952	10,952
R^2	0.01954	0.01979	0.02123	0.02104	0.02115	0.02125
Negative Mentions of General Services						
	Delicense			**License**		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat	-0.0027	0.0064	0.0038	0.0110**	0.0098	0.0102
	(0.0054)	(0.0076)	(0.0080)	(0.0045)	(0.0135)	(0.0125)
Post Treat × Black County		-0.0163*			0.0015	
		(0.0093)			(0.0137)	
Post Treat × High Immigrants			-0.0065			0.0013
			(0.0089)			(0.0139)
County FE	Yes	Yes	Yes	Yes		
Quarter FE	Yes	Yes	Yes	Yes		
Occupation FE	Yes	Yes	Yes	Yes		
Observations	19,086	19,086	19,086	10,952	10,952	10,952
R^2	0.02254	0.02328	0.02441	0.02715	0.02736	0.02755

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

If our previous findings hold true, we should expect to see a significant decrease in mentions related to public health and safety issues, along with fewer complaints about general services, especially in the Black

counties. Conversely, under licensing, we anticipate an increase in negative mentions regarding general services. The results from the table support these findings: there is a significant decline in negative mentions related to public health and safety in the delicensed group. Additionally, negative mentions of general services have decreased in Black counties. However, there is a notable increase in negative mentions of general services overall.

6.3. Assessing Licensing Removal on Incumbent Businesses

As we observe that both the employee size and the number of new businesses increase after the removal of licensing, with newcomers demonstrating higher service quality — which in turn drives the higher review ratings in the delicensed group — we now seek to validate this observation by exclusively calculating the average ratings of incumbent businesses. Specifically, we exclude ratings from businesses that entered after the licensing change. Thus, we focus on assessing the impact of increased employee size on established businesses. If our hypothesis that newcomers deliver superior service quality holds true, we should similarly expect to observe a significant increase in the average review ratings among these incumbents as there are new workforce joining the incumbents. We use the average review ratings of the incumbents as our dependent variables and run the model specified in 1. The results are presented in Table 19.

Table 19 Ratings of Incumbents

	Delicense		
DV: Avg Review Ratings	(1)	(2)	(3)
Post Treat	0.1323**	0.0139	0.1023
	(0.0625)	(0.0901)	(0.1070)
Post Treat × Black County		0.2247**	
		(0.1032)	
Post Treat × High Immigrants			0.0357
			(0.0943)
County FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes
Observations	6,789	6,789	6,789
R^2	0.13295	0.13464	0.13506

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Based on the results, we find that the removal of licensing significantly increases the average review ratings, particularly prominent in Black counties. This finding confirms our previous observations about the benefits of reducing entry barriers for communities of color and also highlights the potential for such policy changes to foster greater economic inclusion and service quality improvements. These results suggest that deregulation may not only enhance business performance but also contribute to leveling the playing field in historically underserved areas.

7. Discussion and Conclusion

Our study explores the nuanced impact of occupational licensing regulations on service quality within the personal care sector. This question is critical as it intersects with broader issues of economic opportunity, market inclusivity, and consumer welfare. By leveraging novel, large-scale data and advanced Natural Language Processing (NLP) techniques, our research provides new insights into how online reputation systems can elucidate the effects of licensing on service quality and measure the broader societal impacts of such regulations. Ultimately, we demonstrate that online reputation systems can serve as a viable alternative for understanding service quality that mitigates the potential downsides of stringent licensing requirements.

Our findings reveal important insights into the impact of occupational licensing on service quality within the personal care services sector. Contrary to the common rationale that licensing is necessary to ensure high-quality services and protect public safety, our results suggest that the removal of licensing requirements can lead to improved service quality. This improvement is particularly evident in increased consumer satisfaction as captured by higher online ratings and more positive sentiments expressed in reviews.

First, we observe the impact of de-licensing on minority communities, where removing licensing barriers facilitate increased market entry for businesses. This, in turn, enhances competition and improves service quality. This finding is crucial, as it highlights how occupational licensing can disproportionately affect minority communities, not only by restricting economic opportunities but also by limiting access to higher-quality services. The evidence suggests that de-licensing may promote both economic inclusivity and service quality in underserved areas.

Second, we explore the gendered impacts of licensing regulations, especially in an industry like personal care services, which is predominantly staffed by women. The removal of licensing requirements has led to a significant increase in income for female workers, suggesting that these regulations may have been a barrier to higher earnings. This outcome underscores the potential of de-licensing to foster a more equitable labor market, where women can achieve greater economic success without the hindrance of unnecessary regulatory constraints.

Conversely, our analysis indicates that the introduction of licensing requirements can have detrimental effects on service quality. Specifically, we observed a decline in online ratings and an increase in consumer dissatisfaction in areas including styling and cleanliness. This decline is attributed to a significant decrease in business size and workforce, resulting in difficulties in meeting customer demand and maintain service quality. These findings suggest that licensing, rather than protecting consumers, may instead reduce the availability of high-quality services by imposing barriers that limit the number of service providers in the market.

We introduce a novel methodological approach that integrates user-generated content and machine learning to analyze service quality. This approach provides empirical evidence challenging traditional beliefs

about the benefits of occupational licensing and demonstrates the effectiveness of online reputation mechanisms in protecting the public from potential risks. The presence of robust online review platforms like Yelp seems to mitigate the need for strict licensing by enabling consumers to directly assess service quality, aligning with previous literature suggesting that online reputation systems can effectively reduce information asymmetry between consumers and providers, serving as an alternative mechanism for ensuring quality in the absence of burdensome regulation.

Our research holds significant implications for researchers, policymakers, and the personal care services industry. For researchers, we offer a novel methodological framework that utilizes user-generated content and advanced natural language processing techniques to measure various dimensions of service quality. Policymakers are encouraged to reconsider the efficacy and impact of stringent occupational licensing, as our study highlights its potential adverse effects on service quality and market inclusivity, particularly in minority communities. These insights suggest that policies need careful evaluation to ensure they do not inadvertently hinder market entry or exacerbate socio-economic disparities but consider the societechnical impact of online reputation systems. For businesses and workers, our findings implies that delicensing might foster a more competitive market environment, enhancing service quality and increasing business formation, especially in underserved areas. Managers and business owners in the personal care industry can leverage the insight to adjust business strategies to thrive in more open market conditions.

Our study also contributes to academic and policy debates by introducing a robust empirical framework for analyzing the impact of occupational licensing. One of the biggest challenges in studying the service sector is the lack of reliable data to measure quality. However, we demonstrate that the meteoric rise in user-generated content (UGC) on online platforms provides rich data on customer experiences in the service sector. By leveraging advanced NLP techniques, we can uncover insights that may not be captured by traditional metrics such as numerical ratings. This approach enables policymakers and researchers to assess the multidimensional nature of service quality and make more informed decisions regarding policy and managerial practices.

Moreover, our study contributes to industry insights by uncovering nuanced effects of licensing on different community segments, offering valuable information for businesses in licensed professions. These businesses could benefit from advocating for and adapting to less stringent regulatory environments to enhance competitiveness and service diversity.

However, our research has limitations. Primarily focused on the personal care services industry, the findings may not be universally applicable across different regions or sectors, particularly where online reputations are not yet maturely established. Additionally, the granularity of our study stands at business and customer perspectives, rather than individual workers, which means we might not fully capture worker behavior during changes in licensing mandates.

Overall, the study provides a comprehensive view of the intricate interplay between occupational licensing regulations and service quality, advocating for balanced regulatory frameworks that prioritize consumer protections while mitigating undue burdens on workers and businesses.

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Appendices

A. Detailed Licensing Curricula

We provide a detailed report on the licensing curricula across different states used in our analysis. The data were compiled from licensing boards and referenced from Greenberg (2021) and Knepper et al. (2022).

Table 20: Licensing Curricula.

Occupation	States	Curriculum	Hrs. Req	Total Hours
Hairstylist, Makeup Artist, Shampooer, Skincare Specialist, Massage Therapist	AL	Shampooing	57.5	1500
		Scalp & Hair Treatments	22.5	
		Manicure	26.5	
		Hair Shaping	75	
		Hair Styling	415	
		Permanent Waving	140	
		Chemical Relaxing	22.5	
		Hair Coloring	182.5	
		Skin Care	87.5	
		Brow and Lash Care	16	
		Science and Related Services	107.5	
	AR	Hygiene and Sanitation	80	1500
		Related Science	120	
		Arkansas Hairdressing	1000	
		Manicuring	100	
		Aesthetics	100	
		Salesmanship / Management / Law	50	
		Courtesy/Neatness/Attitude	50	
	AZ	No Subfield Hourly Requirements		1600
	CO	Scalp Care (Shampooing / Rinsing / Conditioning)	50	1500
		Hair Coloring/Tinting/Bleaching	200	
		Haircutting	200	
		Hairstyling	175	
		Chemical Texture Services	100	
		Manicuring / Pedicuring	175	
		Application of Artificial Nails	125	
		Facials/Skin Care	175	
		Facial Makeup	25	
		Hair Removal	75	
		Law, Rules, and Regulations	25	
		Management, Ethics, Interpersonal Skills	25	
		Disinfection/Cleaning/Safety	150	
	FL	FL Education Requirements	21	1200
		Electricity	8	
		Facials	66	
		Product Chemistry	8	
		Hair Removal	2.5	

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Table 20 – continued from previous page

Occupation	States	Curriculum	Hrs. Req	Total Hours
		Makeup	2	
		Skin	85	
		Law, Rules, and Regulations	47.29	
		Sanitation and Disinfection	47.29	
		Facial Services	10	
		Hair-Shaping Services	56.25	
		Scalp Services	7.5	
		Shampoo Services	16.67	
		Hairstyling Services	450	
		Haircoloring Services	157.5	
		Waving/Relaxing Services	195	
		Manicure/Pedicure Services	20	
	GA	GA Theory	40	1500
		Permanent Waving	45	
		Hair Coloring	45	
		Hair and Scalp Treatments and Conditioning	20	
		Hair Cutting	25	
		Shampooing	15	
		Hairdressing	35	
		Nail Care and Skin Care	25	
		Theory	100	
		Social Skills	50	
		Laboratory	50	
		Hairdressing/Shampoo	255	
		Haircutting/Shaping	124.5	
		Permanent Wave	150	
		Hair Relaxing	139	
		Hair Coloring	155	
		Scalp and Hair Treatment	49	
		Facials/Makeup/Hair Removal	52.5	
		Hair Removal	30	
		Sanitizing and Disinfection	5	
		Manicures/Pedicures	90	
	IA	IA Cosmetology Theory (Multiple Subfields)	615	2100
		IA Applied Practical Instruction	1335	
		Core Life Sciences	150	
	LA	No Subfield Hourly Requirements		1500
	MA	Manicuring	50	1500
		Waving/Straightening Hair	250	
		Shampoo	25	
		Finger Waving	50	
		Marcelling/Iron Curls	45	
		Skin/Facial Grooming	80	
		Wiggery/Scalp Treatments	50	
		Dyes/Bleaching	150	
		Haircut	125	

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Table 20 – continued from previous page

Occupation	States	Curriculum	Hrs. Req	Total Hours
		Sterilization/Hygiene/Anatomy	125	
		Sanitation	25	
		Ethics/Salesmanship/Courtesy	25	
	MN	Shampoo	50	1550
		Hair/Scalp	80	
		Hair Shaping	150	
		Chemical Hair Control	200	
		Hair Coloring	100	
		Hair Styling	200	
		Facials/Makeup	200	
		Manicures (Incl. Artificial Nails)	150	
		MN Theory/Lecture	420	
	UT	No Subfield Hourly Requirements		1600
	VA	No Subfield Hourly Requirements		1500
	MD	Orientation	4	1500
		Professional Image	3	
		Bacteriology/Aids Awareness	8.5	
		Sterilization/Sanitation	60.5	
		Hair and Scalp	38.5	
		Draping	28.5	
		Shampooing,Rinsing, and Conditioning	57	
		Hair Shaping	154.5	
		Finger Waving	84.5	
		Wet HairStyling	109.5	
		Thermal Hairstyling	130.5	
		Thermal Straightening	79.5	
		Permanent Wave	184.5	
		Hair Color	159	
		Permanent/Relaxing	124.5	
		Artificial Hair	23.5	
		Manicuring/Pedicuring	54.5	
		Nail Disorders	8.5	
		Massage	20	
		Facials	24.5	
		Makeup	34.5	
		Skin and Skin Disorders	8.5	
		Hair Removal	19	
		Anatomy and Physiology	35.5	
		Electricity and Light Therapy	16	
		Chemistry	16.5	
		Business	8.5	
		First Aid	2	
		Interview/Employment/Taxes	2	
	MO	Shampoo	40	1500
		Hair Coloring	130	
		Haircutting	130	
		Waving/Relaxing	125	

Continued on next page

Table 20 – continued from previous page

Occupation	States	Curriculum	Hrs. Req	Total Hours
		Styling/Thermal Hairstyling	225	
		Hairstyling	105	
		Hair/Scalp	30	
		Facials	40	
		Manicure/Massage/Nails	110	
		Chemistry	25	
		Salesmanship/Management	10	
		Sanitation/Sterilization	30	
		Anatomy	20	
		Law	10	
		Curriculum to Be Determined by School	470	
	MS	No Subfield Hourly Requirements		1500
	NH	No Subfield Hourly Requirements		1500
	TN	Sterilization, Anatomy, Ethics, Law	300	1500
		Chemical Waves, Relaxers, Color, Nails	600	
		Physical Shampoo, Scalp Care	600	
	NM	NM Theory	75	1600
		Sterilization/Sanitation	75	
		Shampoo/Scalp Treatments	75	
		Permanents/Chemical Treatments	200	
		Hairstyling	150	
		Haircoloring	125	
		Haircutting	200	
		Facials	175	
		Manicuring/Pedicuring	175	
		Business/Retail	50	
		Miscellaneous/Unassigned	300	
	OH	OH Infection Control	60	1500
		Hair and Scalp	120	
		Hairstyling / Thermal Styling / Haircutting / Wiggery	460	
		Hair Waving/Relaxing/Coloring	480	
		Manicure / Pedicure / Nail Enhancements / Massage	120	
		Skin/Facials/Electricity	120	
		Management/Communication	120	
		Laws and Rules	20	
Manicurist	CT	No Subfield Hourly Requirements		100
	MA	Safety and Sanitation	10	100
		Artificial Nails	25	
		First Aid	2.5	
		Manicuring and Massage	40	
		Ethics/Mgmt/Law	12.5	
		Hygiene and Anatomy	10	
	NY	NY Orientation	4	
		Safety and Health	8	

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Table 20 – continued from previous page

Occupation	States	Curriculum	Hrs. Req	Total Hours
		Bacteria / Diseases / Disorders	10	250
		Infection Control	10	
		Client Consultation	10	
		Manicuring/Massage	4	
		Pedicuring	20	
		Tip Application/Design	15	
		Business/Retail	12	
		Nail Wraps	25	
		Liquid and Powder Nail Extensions	50	
		Gel Nails	20	
		Nail Art	4	
		Retailing Techniques	6	
		Business Practices	8	
		Job Skills	6	
		Miscellaneous/Unassigned	38	

B. Positive Sentiment Shifts with Licensing Changes

We perform the exercise of computing the fraction of entities showing positive sentiment in three dimensions: (1) safety entities (2) general services: hospitality and styling, and (3) public health and safety: cleanliness, chemical handling, facilities, and safety. Consequently, we have three dependent variables: the fraction of positive safety mentions, the fraction of positive general service mentions and the fraction of positive public health and safety mentions. We applied the model specified in 1. The results are presented in Table 21, Table 23, and Table 22 respectively.

Table 21 Positive Safety Entities.

	Delicense			License		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat	-0.0049	-0.0092	-0.0114	0.0073	0.0096	0.0085
	(0.0049)	(0.0078)	(0.0099)	(0.0070)	(0.0076)	(0.0084)
Post Treat × Black County		0.0083			-0.0031	
		(0.0097)			(0.0096)	
Post Treat × High Immigrants			0.0093			-0.0022
			(0.0108)			(0.0046)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,052	6,052	6,052	3,220	3,220	3,220
R^2	0.06551	0.06585	0.06567	0.06629	0.06720	0.06637

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Aligned with our previous findings, we observed no significant change in the fraction of positive safety-related mentions for both the delicensing and licensing groups.

Table 22 Positive Entities related to Public Health and Safety

	Delicense			License		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat	-0.0052	-0.0069	0.0109	-0.0147*	-0.0006	-0.0040
	(0.0056)	(0.0083)	(0.0086)	(0.0077)	(0.0220)	(0.0185)
Post Treat × Black County		0.0031			-0.0187	
		(0.0088)			(0.0252)	
Post Treat × High Immigrants			-0.0194*			-0.0177
			(0.0096)			(0.0200)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,086	19,086	19,086	10,952	10,952	10,952
R^2	0.02652	0.02760	0.02793	0.01927	0.01965	0.01943

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Our results support previous findings that shows a significant increase in negative sentiment regarding cleanliness, which is part of the public health and safety category. Here, we observed a significant decrease in positive mentions related to public health and safety, which confirms a downward trend in satisfaction in this aspect. Additionally, our analysis of positive mentions in general services yielded no significant results. However, the positive coefficient observed in Black Counties aligns with prior observations that removing licensing leads to increased satisfaction with general services. Conversely, the negative coefficient observed in areas with a high immigrant population aligns with our previous findings that licensing tends to decrease sentiment towards general services, particularly in regions with larger immigrant communities.

Table 23 Positive Entities related to General Services.

	Delicense			License		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat	-0.0076	-0.0159	0.0029	0.0200	0.0594	0.0384
	(0.0092)	(0.0151)	(0.0196)	(0.0192)	(0.0485)	(0.0401)
Post Treat × Black County		0.0145			-0.0525	
		(0.0154)			(0.0474)	
Post Treat × High Immigrants			-0.0092			-0.0300
			(0.0210)			(0.0385)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,086	19,086	19,086	10,952	10,952	10,952
R^2	0.02783	0.03211	0.03041	0.03835	0.03886	0.03880

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

C. Heterogeneity in Occupations

Given the varying levels of public health and safety risk associated with different occupations, we applied the model specified in Equation 1 across subsamples of each profession, which are hairstylists, shampooers,

makeup artists, skincare specialists, manicurists, and massage therapists, to assess the differential impacts of licensing. The result is detailed in Table 24.

Our analysis finds that all the occupations undergoing de-licensure, namely hairstylist, shampooer, and makeup artist, exhibited no significant alteration in review ratings. Conversely, for the professions introducing the license requirement, including manicurists, massage therapists, and skincare specialists, manicurists show a significant decline in review ratings after the introduction of licensing. This trend thus mainly drives the decrease in review rating after licensing enforcement that we observed in Table 24.

Table 24 Review Ratings By Occupation.

	Delicense			**License**		
DV: Avg Review Rating	Hairstylist	Shampooer	Makeup Artist	Manicurist	Skincare	Massage Therapist
	(1)	(2)	(3)	(4)	(5)	(6)
Post Treat	0.1077	0.0979	-8.3E-5	-0.0357**	-0.0322	0.0040
	(0.0970)	(0.1409)	(0.0821)	(0.0078)	(0.0487)	(0.0225)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,675	2,525	1,753	1,060	965	490
R^2	0.16068	0.16653	0.19547	0.36423	0.27389	0.25766

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

D. Analysis by Minority Subgroups within Occupations

We performed an analysis focusing on the largest minority subgroup within each occupation. Using ACS data collected from IPUMS, we may identify the largest minority subgroup based on the statistics reported in Table 2. Since the occupation categories in the ACS are not as detailed as those in our analysis, we combined occupations based on the ACS occupation categories or if the occupations share the same largest minority population. Specifically, we grouped hairdressers and shampooers together as they are categorized in the same occupation category in ACS and both share the Hispanic population subgroup as the largest minority group. Makeup artists also have the Hispanic population subgroup but fall under the ”Other personal appearance workers” category, so they were analyzed in a separate subgroup. For licensed occupations, we combined manicurists and massage therapists as they both have the Asian population as the largest minority group. Finally, skincare specialists have the Hispanic population as the largest minority. The results are reported in Table 25.

Based on the results, we observe that delicensing shows a significant increase in review ratings for the occupation of hairstylists and shampooers. Makeup artists did not show a significant impact. On the other hand, Asian counties with manicurists and massage therapists show a marginal increase in review ratings after licensing. In contrast, there is a significant overall increase in review ratings for Hispanic counties, but a significant decrease in review ratings in Hispanic counties compared to non-Hispanic counties. This

Table 25 Review Ratings By Minority Subgroups.

	Delicense		License	
	Hairstylists & Shampooers	Makeup Artist	Manicurists & Massage Therapists	Skincare Specialists
Post Treat	0.1122**	-0.0855	-0.0153	0.3898**
	(0.0524)	(0.1617)	(0.0164)	(0.0891)
Post Treat × Hispanic County	-0.1144	0.0635		-0.6914**
	(0.0811)	(0.1481)		(0.0771)
Post Treat × Asian County			0.0331*	
			(0.0129)	
County FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Observations	5,200	1,753	1,550	965
R^2	0.15124	0.19929	0.40706	0.27993

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

contradictory trend between the two minority communities can be explained by the composition of the workforce. For manicurists and massage therapists combined, Asian counties comprise the majority of the workforce, with over 70% of the workforce being Asian. In contrast, Hispanic counties make up approximately 16% of the workforce in skincare specialists. Therefore, as licensing barriers are introduced, the unstable supply of workers in Hispanic counties is more likely to be reflected in the ratings, as they face relatively higher fluctuations in demand.

E. Continuous Measurement of Racial Population Impact

We include the results using a continuous measurement of the racial population, where we interact with the percentage of each minority race population. The results are reported in Table 26.

For the delicensed group, there is overall no significant impact on review ratings when considering the continuous measurement of racial population percentages. However, the coefficient of non-white and black counties are positive, aligning with our previous findings.

In contrast, for the licensed group, a significant decrease in ratings is observed in high-immigrant counties compared to low-immigrant counties. This indicates that licensing may negatively impact service quality in areas with a higher concentration of immigrant populations. The significant decrease in ratings in high immigrant counties could be due to increased barriers to entry for immigrant workers, leading to a reduced supply of services and potentially lower quality as competition decreases.

This trend is consistent with our main findings reported in Section 4, where we also observed that licensing has a more pronounced negative effect in high immigrant areas. These results highlight the importance of considering demographic factors when assessing the impact of occupational licensing on service quality.

Table 26 Review Ratings By Race.

			Delicense			
Post Treat	0.1421	0.0345	0.0167	0.0787	0.0922*	0.0383
	(0.1135)	(0.0862)	(0.0641)	(0.0566)	(0.0512)	(0.0594)
Post Treat × Pct of Non-White Pop.		0.1076				
		(0.1860)				
Post Treat × Pct of Black Pop.			0.3106			
			(0.3501)			
Post Treat × Pct of Asian Pop.				-0.1810		
				(0.7375)		
Post Treat × Pct of Hispanic Pop.					-0.1662	
					(0.2888)	
Post Treat × Pct of Immigrants						-0.0992
						(0.2833)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,953	6,953	6,953	6,953	6,953	6,543
R^2	0.13136	0.13136	0.13391	0.13466	0.13252	0.14293
			License			
Post Treat	-0.4111	0.0389	-0.0220	-0.0626	0.0394	0.5269**
	(0.3994)	(0.2226)	(0.1275)	(0.2752)	(0.1905)	(0.2142)
Post Treat × Pct of Non-White Pop.		-0.4500				
		(0.6194)				
Post Treat × Pct of Black Pop.			-1.019			
			(1.306)			
Post Treat × Pct of Asian Pop.				-0.7711		
				(6.565)		
Post Treat × Pct of Hispanic Pop.					-0.9755	
					(1.080)	
Post Treat × Pct of Immigrants						-3.317**
						(1.256)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,515	2,515	2,515	2,515	2,515	2,401
R^2	0.33230	0.33230	0.33230	0.33622	0.33257	0.35257

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$