From Cold-Start to Warm Reception: Knowledge Contribution as a Signaling Mechanism

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Abstract

While reputation systems can be advantageous for well-established firms with a proven track record, they can pose new challenges for entrants who typically initiate operations without any pre-existing reputation, commonly referred to as "cold-start problem". Building on the theoretical underpinnings of signaling mechanisms, this paper examines how attorneys in the online legal services market can mitigate this challenge via strategic signaling decision of their inherent quality through knowledge contribution in Question & Answer sessions. Our finding reveals the positive impact of knowledge contribution on the reduction of the time needed to transact with the initial customer, and this benefit is exclusive to high-quality attorneys. Notably, we did not find any significant differences in the number of signals generated between high- and low-quality attorneys. Instead, most attorneys engage in actively signaling their quality in the absence of customer reviews. This behavior appears to stem from the notion that the marginal benefits of quality disclosure are particularly low when no other supplemental information is available to verify the disclosed quality.

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1 Introduction

Reputation and feedback systems have played a pivotal role in enhancing trust and mitigating information asymmetries between anonymous sellers and buyers in online marketplaces. A well-known mechanism is customer feedback; Amazon shows qualitative customer reviews and quantitative start ratings in 0.1 incremental out of 5: Taobao grants a distinctive medal icon beside the banner of a merchant who garners a certain number of positive reviews. A substantial size of economic literature confirms that sellers with higher user-generated review ratings experience several advantages, including price premiums (Jolivet et al., 2016; Moreno & Terwiesch, 2014; Jin & Kato, 2006; Resnick et al., 2006), increased revenues (Luca, 2016; Liu et al., 2016), and a higher likelihood of products sell-outs (Anderson & Magruder, 2012).

While reputation systems can benefit existing firms that have been able to build a track record, they can pose a new challenge for entrants who typically must start out without any established reputation. In fact, new sellers may opt to earn lower revenue or even accept initial losses in order to build a favorable reputation that will pay off in the long term (Shapiro, 1983; Holmström, 1999). This short-term loss in market performance could even jeopardize their long-term business survival prospects (Fan et al. (2016)). Consequently, while reputation systems have the potential to alleviate information asymmetries in anonymous transactions, they can create an entry barrier for qualified newcomers who have not yet established their reputations. This challenge is referred to as the "cold-start problem" (Li et al. (2020)).

In the context of the cold-start problem within the online legal consultation platform, this paper examines how the knowledge contribution of attorneys can help them smoothly pass through the cold-start period. A new entrant faces difficulty in establishing its reputation, as there is limited information available to buyers about the entrant's quality (Pallais (2014)). However, the professional service platform in this study allows lawyers to voluntarily participate in Question & Answer (Q&A) sessions, actively addressing potential clients' inquiries to attract them — customers post the lawsuits that they are involved, covering the detailed legal and circumstantial issues, followed by responses from attorneys. The primary purpose of providing answers is to signal to potential clients that the attorney has the necessary skills and knowledge to handle their legal matters. Attorneys aim to create a favorable impression that can lead to a client deciding to hire them. Given that these responses are accessible to anyone visiting the platform's website, lawyers have a strong incentive to leave answers for their future clients, emphasize their strengths, qualifications, and past successes in order to create a positive impression through these responses, especially when they lack prior reputation from the market, such as review ratings.

We employ a unique dataset to evaluate the impact of knowledge contribution as a quality signal on the early-stage market performance of professionals. Our dataset is sourced from the largest legal platform in the Republic of Korea, that contains comprehensive information about attorneys' signaling activities and changes in their reputation from the moment they join the platform until they exit the market. The market's administrative data allows us to distinguish the cold-start period into two phases: the first phase is the period during which attorneys were required to wait until they meet the first customer, and the second phase is the time after they have completed their first transaction but have yet to receive any market signal, that is, the first customer review.

In our empirical setting, we first explore whether new entrants act differently to undergo the early stage of their business than matured incumbents. The preliminary look of our data reveals that sellers in the cold period do behave differently compared to their mature period. Notably, during the cold period, attorneys tend to charge lower consulting fees, and suffer from lower sales volumes compared to the warm period. Furthermore, it's intriguing to find that the average number of signals left by attorneys during the cold period is more than double that of the warm period. This evidence not only aligns with the previous research highlighting the dynamic nature of sellers in managing their reputation (Cabral and Hortacsu (2010)), but also underscores that sellers have higher incentive to engage in knowledge contribution when there is limited information available to the market.

Our findings of the pre-transaction analysis suggest that attorneys who contributed their knowledge take, on average, one and a half months less to transact with the first customer than those who did not. This "shortening effect", however, was only existent for high-quality attorneys. We attribute this rationale primarily to the insight articulated by Tadelis and Zettelmeyer (2015), which suggests that the information disclosure about the quality of objects facilitates more matching between bidders and sellers when the information disclosed is surprising. In cases where the information disclosed aligns with prior expectations, it has no discernible effect. We hypothesize that only the answers provided by high-quality attorneys are positively surprising to the market, while the answers from low-quality attorneys are in alignment with their off-platform reputations. For robustness check, we test the potential concerns that attorneys might thoughtlessly scatter the similar answers to different questions to use answers simply as attention picking. If this is the case, the answer is not a credible signal representing the attorney's quality - but cheap talk. To check this possibility, we carefully matched the attorney's area of expertise and the subcategory of their answers to examine the actual content of those answers. The data shows that more than 90% of answers are concentrated on the attorney's area of expertise. About 80% of attorneys left their answers in their primary profession, meaning that separating equilibrium is sustained as the information attorneys send well represents the quality of attorneys.

This research makes several contributions to literature. First, we contribute to clear understanding of the cold-start problem in online marketplace by utilizing a unique dataset that spans from the inception of the online marketplace. As for the best of authors knowledge, ours is the first to examine the whole life-cycle behavior of the sellers in the massive online marketplace. We provide an in-depth analysis of how the cold-start problem manifests in the online labor market, even before sellers get the first transaction, challenging the applicability of traditional approaches. Second, we contribute to a more nuanced understanding of how professionals' contributions of knowledge can shape their early-stage success in the online marketplace. Specifically, we explore the impact of knowledge contribution, a distinctive attribute in credence goods market, on the early-stage performance of sellers. Differing from Liang et al. (2016), which advocated for the implementation of mandatory systems to monitor the workflow of individuals, we delve into the mechanisms through which sellers endogenously self-select, proactively addressing the challenge of no-reputation period. Third, our research empirically confirms the theoretical underpinnings echoed in Daley and Green (2014) that the presence of public reputation alters the signaling equilibrium. We investigate the intricate relationship between out-of-platform reputation (e.g., years of experience, college ranking, area of certificates, and location of the office, etc.) and quality signaling, and find out that knowledge contribution and public reputation are the substitutes for each other.

The rest of this paper is organized as follows: In Section 2, we review the relevant literature. Section 3 provides an overview of the data and institutional background. In Section 4, we present our analyses and the corresponding results. Finally, in Section 5, we conclude and discuss the implications of our findings.

2 Literature Review

An increasing body of economic literature delves into the discourse of reputation mechanisms and reputation management. Reputation mechanisms serve to mitigate inefficiencies in markets characterized by information asymmetry (Bar-Isaac et al. (2008)). It is well-established that sellers boasting higher ratings are afforded a premium within the market (Jin & Kato, 2006; Anderson & Magruder, 2012; Moreno & Terwiesch, 2014; Luca, 2016; Jolivet et al., 2016). Luca (2016) stands as a notable exemplar in the empirical evidence in this field, utilizing a regression discontinuity design to demonstrate that a one-star discrepancy in review ratings causes approximately a 9 percent increase in restaurant revenue. Applying the same discontinuous star rating system observed in the general practitioner ratings within England's healthcare market, Brown et al. (2023) illustrates that this dissemination of public information yields exclusive advantages for low-income patients, who generally considered to have less information than high-income patients. This phenomenon arises due to the fact that high-income patients already have access to prior private information regarding the quality of general practitioners, rendering public reputation systems ineffective in their decision-making process. Conversely, there are critiques that cast doubt on the informativeness of review ratings (Dellarocas & Wood, 2008; Mayzlin et al., 2014; Tadelis, 2016; He et al., 2022). They suggest that such ratings may be inflated by buyers (Dellarocas & Wood, 2008; Tadelis, 2016) or manipulated by competitive sellers (Mayzlin et al., 2014; He et al., 2022). Consequently, there arises a call for informative quality measures in online marketplaces (Nosko & Tadelis, 2015; Luca & Zervas, 2016).

This paper aligns with a substantial body of empirical literature that investigates the functioning of signaling mechanisms in diverse contexts characterized by asymmetric information. The foundational premise, rooted in the efficacy of signaling mechanisms in advertising as a signal, as postulated by Nelson in 1974, is underpinned by the notion that sellers of high-quality products is more likely to have incentive to invest in advertising. This incentive stems from the expectation that high-quality sellers stand to gain from repeated purchases by satisfied buyers, thus amplifying the benefits of their investments. The resonance of this principle reverberates throughout empirical research, validating the potency of signaling mechanisms across a spectrum of different market segments. These encompass domains such as product warranty (Boulding & Kirmani, 1993; Roberts, 2011), the role of advertising (Thomas et al., 1998; Horstmann & MacDonald, 2003; Tsui, 2012), money-back guarantees (Moorthy & Srinivasan, 1995), rebates for feedback (Li et al., 2020), charitable donation (Elfenbein et al., 2012), virtual roses in a dating market (Lee & Niederle, 2015), and information disclosures (Lewis, 2011; Tadelis & Zettelmeyer, 2015).

This paper is also in alignment with research investigating the early-stage performance of newcomers as they navigate through the initial, no-reputation phase. Early contributions in the reputation literature highlighted the potential challenges associated with the cold-start problem. Resnick et al. (2006) argued that buyers tend to be willing to pay more to sellers with established reputations, as compared to those without established reputations. Fan et al. (2016) demonstrated that new sellers frequently resort to lowering their prices to stimulate sales volume. A select group of studies has taken a direct approach to tackling the cold-start problem, particularly within the context of vast online labor marketplaces. For example, Liang et al. (2016) examined the impact of monitoring systems on improving the employment of inexperienced workers in an online labor market, wherein employers post project descriptions and required skills, and workers bid for projects. A similar line of inquiry was undertaken by Pallais (2014), who revealed that simply providing workers with an initial job and disseminating information about them to the market can benefit these workers by enhancing the market's awareness of their abilities.

Our study bears strong similarity to the work of Li et al. (2020) and Hui et al. (2020). Our data corroborates their findings, confirming that the responses offered in Q&A sessions within the professional service market align with the theoretical underpinnings of signaling mechanisms. However, our study distinguishes it from the previous research in several significant ways. While it is true that we are within the sphere of signaling mechanisms, our study is positioned on a distinct context – the professional service market, which has its own intricate dynamics and challenges. Previous studies have predominantly focused on product-oriented markets, such as retail, restaurant, and online dating, where the nature of signaling and quality measurement may differ considerably.

Our examination of the cold-start problem unfolds within the context of a professional platform that permits lawyers to voluntarily engage in Question & Answer (Q&A) sessions. This unique setting introduces a novel dimension to the study of signaling mechanisms in the online marketplaces, as the responses provided in these sessions are not only signals of quality but can be disseminated without relying on pre-existing market reputation, helping attorneys go through the cold period smoothly. The implications of such responses extend beyond traditional product markets, as they directly impact the choice of legal counsel, making our findings particularly relevant to the realm of professional services. Furthermore, our study stands out as one of the first to provide a comprehensive analysis of the entire life cycle of sellers within a massive online marketplace. This approach allows us to delve deeper into the manifestation of the cold-start issues and its implications, even before sellers secure their first transaction. Our research also challenges the applicability of traditional approaches and brings to light the nuances of the problem that may vary across different stages of a seller's journey in the online marketplace.

3 Data and Institutional Background

We sourced the proprietary administrative dataet used in our primary analysis from LawTalk, the largest online legal service platform in South Korea[1]. LawTalk operates as a two-sided online marketplace, where they connect individuals who seek legal advisers and ultimately want to hire attorneys, and attorneys who are interested in advertising their services online. In the U.S., the online legal service platforms take various forms; for instance, LegalZoom assists clients in creating legal documents without the need for hiring a lawyer, and Incfile provides specialized legal services to business owners. Lawtalk's business model is most analogous to Avvo, which provides consumers access to a database of local lawyer profiles and generates revenue by selling advertisements to lawyers.

At LawTalk, consumers have the option to purchase either 15 minutes, 30 minutes, or 60 minutes of video consultation with an attorney regarding their legal concerns. Unfortunately, we cannot access the specific content of these consultations due to the non-disclosure agreements between the attorneys and clients; neither do we have the data indicating whether a client ultimately hired the attorney to represent them in court. What we have access to is data on the transacted consultations that were completed between clients and attorneys. Given that more than 97% of transactions involve 15-minute consultations, we omitted samples involving consultations exceeding this duration. The dataset comprises a total of 139,102 number of transactions between lawyers and clients. A unique aspect of our data is its coverage from the time when the company starts its operation up to the most recent data available. This timeframe enables us to track the complete history of attorneys who engaged in the consultations on the platform during our sample period. To conduct our analysis, we transformed the raw data into an attorney-week panel, allowing us to evaluate an attorney's market performance (e.g., sales volume) at a specific point in time. We defined the "week" as our time unit. Because, on average, it takes 5.82 days (with a standard deviation of 1.4) for attorney's last response to be shown for a given client's question, and we assume that clients may wish to receive as many responses as possible from attorneys before deciding to purchase

[1]During our discussions with a legal consultation industry expert, we learned that LawTalk held approximately 90% of the market share in the online legal consulting service industry within our sample period. As a result, we have not factored in the competitive nature typical of oligopolistic platforms within this market. For insights into how competition between two-sided markets influences market outcomes, see, for example, Filistrucchi et al. (2012) for mergers and Belleflamme and Peitz (2019) for multihoming.

an attorney's counsel. This panel setup provides us with 25,269 samples involving 789 unique attorneys. Additionally, we observe various attorney characteristics that may influence consumers' choices when they are choosing which attorney to engage with.

A challenge in the study of the cold-start period, as noted in prior literature, stems from the arbitrary selection of specific time intervals, primarily due to the unavailability of early-stage dataset or identifiable exogenous changes occurring during the platform's operational period (Li et al., 2020; Liang et al., 2016; Hui et al., 2020; Qiu et al., 2016). Our dataset, on the other hand, affords us the capability to discern critical temporal milestones in an attorney's journey on the platform. This includes the attorney's initial sign-up date, the date of their first transaction with a client, the date of the first client review, and the date of the attorney's exit from the platform. Leveraging this comprehensive information, we are able to meticulously trace an attorney's reputation throughout their life cycle, distinguish various signaling behaviors in the early, middle, and late stages of their online businesses, and evaluate their offline reputation as a professional.

3.1 Variable Definition and Descriptive Statistics

The variables utilized in our empirical analysis are presented in Table 1. Descriptive statistics for attorney-level variables are provided in Panel A of Table 1, while those for attorney-week-level variables are provided in Panel B of Table 1. The dependent variable under consideration in the attorney-level analysis, is the time elapsed from an attorney's initial sign-up to their first transaction. Notably, the average duration for attorneys to secure their inaugural client is substantial, with an average wait time of 8.5 months. This protracted waiting period can be predominantly attributed to the fact that all transactions within LawTalk's marketplace represent additional revenue streams. Prior to the establishment of LawTalk, the prevailing method for seeking legal services primarily involved in-person visits to attorneys' offline offices. Attorneys were still able to sustain their practice and livelihood through offline clientele, making the acquisition of additional online revenue sources considerably more attractive in light of the relatively high marginal benefit they offered, outweighing the associated waiting costs. The average total number of responses by attorneys throughout their tenure on the platform is 356, albeit with substantial variance among individual attorneys. The cumulative number of consultations from attorneys amounts to 176. According to the LawTalk's internal user satisfaction survey, approximately one out of three consumers engage attorneys for the cases they have discussed, which shows that attorneys are retained for legal proceedings approximately 53 times on average.

We observe various important attributes of the attorneys in our dataset. The "years of experience" variable is defined as the difference in years between the date attorneys obtained their bar certificates and the date of the transaction. Given the high asymmetry of information characterizing the professional services market, the Korean Bar Association (KBA) bestows "area of expertise" certifications upon attorneys who meet specific criteria. These criteria include (i) having a minimum of 3 years of experience, (ii) having handled over 30 lawsuits within a specific area in the past

Table 1: Summary Statistics for each Panel

Panel A. Attorney level	N	Mean	Std.	10%	Median	90%
Time elapsed singup to 1st transaction	789					
Number of answers (total)	789	356	1,262	0	45	697
Number of answers (before first tran)	789					
Quantity sold	789	176	369	3	55	466
Revenue ($)	789	4,711	10,184	80	1,400	12,010
Ad fee ($)	789	8,965	13,816	0	3,620	24,016
Years of experience	789	7.42	6.21	1.67	5.58	15.5
KBA Certified expertise	789	0.47	0.5	0	0	1
Prof. license except attorney	789	0.4	0.49	0	0	1
Office rent ($/	789	17.55	5.87	7.4	20.4	23.3
College ranking	789	10.85	11.61	1	8	24

Panel B. Attorney-week level	N	Mean	Std.	10%	Median	90%
Number of answers	25,269	11.121	46.258	0	0	25
=1 if answered	25,269	0.425	0.494	0	0	1
Quantity sold	25,269	5.505	5.938	1	4	12
Price ($)	25,269	26.984	10.67	20	25	39.167
Revenue ($)	25,269	147.091	175.247	20	100	310
Ad fee ($)	25,269	279.936	315.054	0	252.083	618.75
=1 if advertised	25,269	0.745	0.436	0	1	1

three years, and (iii) successfully completing the educational requirements provided by the KBA. Attorneys are permitted to hold a maximum of two KBA-certified expertise areas, and this number may be adjusted based on their evolving areas of expertise. Our dataset reveals that approximately 47% of the attorneys in our sample possess such certified expertise in distinct legal domains. Beyond their legal qualifications, attorneys can also hold professional licenses in other fields, such as accounting, real estate, or medicine. Notably, around 40% of the attorneys in our sample possess professional licenses in addition to their legal credentials. The geographical location of attorneys' offices can also serve as a signal of their inherent quality to clients. Clients often associate attorney's quality with the geographical location of attorneys' office in the sense that attorneys with offices situated in downtown New York, for example, can afford the substantial rent associated with prime urban locations. Our dataset provides specific office addresses, enabling us to link this information with monthly rent fee data from the Korea Real Estate Association. Furthermore, we ascertain the educational backgrounds of attorneys, including the name of the college from which they graduated, categorizing these institutions into five tiers based on their ranking.

The summary statistics at the attorney-week level, as presented in Panel B, indicate that attorneys provide an average of 11 answers per week. This implies that, on average, an attorney remains active on the platform for approximately 32 weeks, calculated as the total number of transactions (356) divided by the average number of answers (11.121). Next, when we convert the attorney responses from a continuous level to an indicator variable, we observe that, in a given week, attorneys contribute knowledge approximately 42.5% of the time. In accordance with this observation, we

Table 2: Descriptive Statistics for Various Quality Metrics

	N	Mean	Std.	10%	Median	90%
Quality Measures						
Review rating (total satisfaction)	25,269	4.787	0.779	4.7	5	5
Review rating (average) (average of four metrics)	25,269	4.205	1.515	1.225	4.95	5
Percent Review (PR) (=cum. reviews / cum. sales)	25,269	0.344	0.152	0.163	0.344	0.533
Percent Positive (PP) (=cum. pos. reviews / cum. reviews)	24,267	0.700	0.356	0.054	0.884	1
Effective Percent Positive (EPP) (=cum. pos. reviews / cum. sales)	25,269	0.244	0.182	0.008	0.234	0.5

have shown, in Table #, that attorneys tend to transmit more signals during the cold-start period.

To disentangle the influence of knowledge contribution from other quality-related metrics, it became necessary to establish reliable measures of attorney reputation. Table 2 presents a weekly-level assessment of attorney quality across various quality metrics. One of the quality metrics is the ”review rating” (total satisfaction), which represents the unadulterated customer review ratings visible to all users on the platform. However, it is worth noting that, as documented in previous literature (Dellarocas & Wood, 2008; Tadelis, 2016), review ratings can be unreliable in cases where they are inflated by buyers or manipulated by sellers. Tadelis (2016) illustrates that feedback reviews on platforms like eBay can be skewed, as consumers tend to leave reviews when they are either extremely satisfied with a transaction or highly dissatisfied with the service. Similar to the dynamics in commodity markets, the professional consulting market also exhibited a similar pattern, with the mean review rating at 4.78 out of 5 and a median of 5 out of 5. Despite breaking down the review rating into four subcategories of consumer satisfaction to mitigate these issues, the median value remained at 4.95.

As an alternative approach for evaluating attorney quality, we introduce three additional metrics: Percent Review (PR), Percent Positive (PP), and Efficient Percent Positive (EPP). Of these, we adopt EPP as our primary measure of attorney quality, following its application in Nosko and Tadelis (2015) as a relatively exogenous quality measure. EPP is calculated by dividing the cumulative positive reviews by the cumulative sales. Since the total sales of attorneys are not directly observable by clients or other platform users, this metric remains concealed and can be considered exogenous to other public reputations. Moreover, EPP declines as sales volumes increase, suggesting that higher transaction volumes do not necessarily imply higher quality among attorneys.

3.2 The Source of Cold-Start Problem

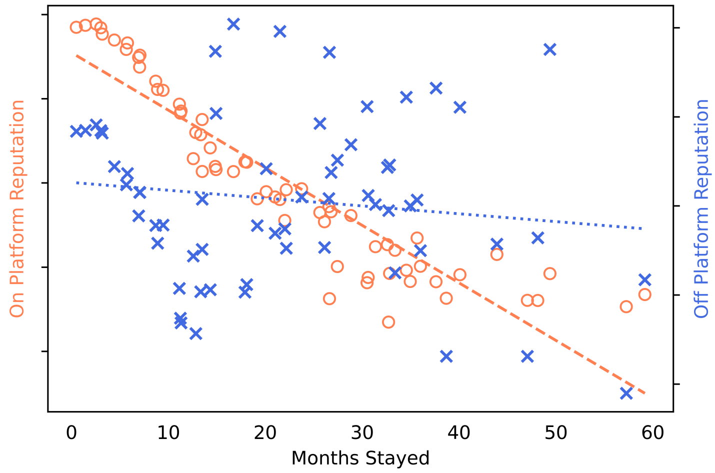
In this section, we explore the practical manifestations of the cold-start problem and seek to identify where the underlying sources of early-stage struggle come from. The cold-start problem hinges on the pivotal role of the reputation metrics publicly observable to platform users, or the established track record of existing participants, as a barrier to online labor market entry for newcomers ((Pallais, 2014)). However, the term "reputation" necessitates a precise definition within this context. To address this, we categorize the reputation of incumbents into two distinct types. The first category encompasses various types of reputation that attorneys have cultivated before their participation in the platform. This includes factors like their years of experience as attorneys, the reputation of their law firm, and the location of their office, among others. A noteworthy metric within this category is the university ranking from which an attorney graduated. We draw on the concept of education as a signal, as outlined in Spence (1974), which posits that education level, in this case, college ranking serves as a costly yet credible signal of professional's quality. In Korea context, it is widely acknowledged that the top three universities hold a privileged status, commonly referred to as "SKY" universities, distinguishing them from "ground" universities . The second category involves the reputation that attorneys begin to establish after they join the platform, which includes their contributions to Q&A sessions and the accumulation of user reviews. Consider A_{-it} as the set of active attorneys, excluding attorney i, at the time of her platform registration at time t. We denote $Reviews_i t$ and $Answers_i t$ as the number of reviews obtained and answers provided by attorney i until month t, respectively. We then compute the competitiveness index (CI), represented as $CI_i t$, in the online legal service market, according to the formula:

$$CI_{it} = \sum_{j \in A_{-it}} (Reviews_{jt} \times Rating_{jt}) \times Answers_{jt} \times \frac{1}{n(\mathcal{A}_{-it})} \tag{1}$$

Here, $n(\mathcal{A}_{-it})$ displays the total number of attorneys in $\mathcal{A}_{-it}$, and its inclusion is to normalize the index by penalizing the presence of numerous competitors, similar to the methodology applied to college competitiveness. It's noteworthy that CI_{it} diminishes in instances of large number of competitors when attorney i initiates their platform engagement, or rises when other attorneys have substantially bolstered their reputation within the platform. We take the monthly average to this index as well.

As Figure 1 suggests, the prior-platform reputation (i.e., ratio of top 3 graduate) was not valid to properly predict the duration of months a new attorney stayed. It is the platform-specific reputation that is strongly related with the cold-start problem. It's noteworthy that both indexes are meaningful indicators when the average stayed months are less than 20. What makes a difference is the long-time stayers, especially those that need platform's help to have interaction with consumers. They are not affected much even if there are lots of high-ranked university graduates. But strongly impacted by attorneys who have strong platform-specific reputations. This can be one evidence that legal consumers care more about active reputation measures such as answers in Q&A sessions, not that much in the traditional sense of reputation.

Figure 1: Platform vs. Non-Platform Reputation on Stayed Duration of Attorneys



4 Empirical Results

4.1 Pre-Transaction Analysis

The Impact of Knowledge Contribution on Cold-Start Problem — In this section, we focus on the period preceding attorneys' first transactions and examine how signaling dynamics evolve during this initial phase. Our approach to estimate the effects of quality signaling on the cold-start problem involves a regression model formulated as follows:

$$y_i = \beta_0 + \beta_1 High_i + \beta_2 Answer_i + X_i\gamma + \varepsilon_i \tag{2}$$

In this model, the outcome variable, y_i, represents the time (measured in months) elapsed from an attorney's sign-up date to their first transaction date. For example, if an attorney registered on March 5, 2020, and completed their first transaction on May 10, 2020, it took them 66 days (excluding May 10, 2020) to have their first transaction. We convert this duration into months by dividing it by 30.5, resulting in approximately 2.164 months to acquire their first customer.

To categorize the attorneys into two distinct groups, namely high and low, we computed the Ultimate Effective Percent Positive (UEPP) for each attorney, denoted as $UEPP_i$. The $UEPP_i$ is derived from an attorney's Effective Percent Positive (EPP) at the time of their exit from the market or at the last period's EPP metric. Therefore, the concept of $UEPP_i$ implies that we employ ex-post measure of attorney quality to evaluate ex-ante outcome. Building on this rationale, we define the variable $High_i$ as an indicator variable that equals to 1 if $UEPP_i$ is higher than the median value. And $Answer_i$ is an indicator variable equal to 1 if attorney i has participated in Q&A sessions by providing answers prior to their first transaction. X_i' is a vector of various attorney characteristics such as the monthly rent fee of their office, years of experience as attorney, possession of any certificates granted by the Korean Bar Association, and college rankings. To mitigate the potential

Table 3: The Effects of Knowledge Contribution on the Time to the First Transaction

	Dependent variable:		
	Months sign-up date to the 1st trans.		
	(1)	(2)	(3)
High	-2.701***	-2.043**	-1.997*
	[0.767]	[1.031]	[1.038]
Signal	-1.448*		
	[0.739]		
High × Signal		-2.169**	-1.933*
		[1.056]	[1.059]
Low × Signal		-0.751	-0.376
		[1.039]	[1.047]
Rent fee			-0.160**
			[0.065]
Years of exp.			0.07
			[0.062]
KBA certificates			0.414
			[0.447]
College ranking			
(Base: Tier1)			
Tier 2			0.798
			[1.149]
Tier 3			1.597
			[1.260]
Tier 4			0.902
			[1.184]
Tier 5			1.593
			[1.876]
Year fixed effects	Yes	Yes	Yes
Observations	789	789	789
R-squared	0.496	0.496	0.504

influence of platform-specific factors, the model also includes year dummy variables representing the year of an attorney's sign-up. This inclusion aims to account for any network effects associated with the platform itself.

Table 3 presents the results of the regression model. The baseline specification in column (1) reveals that attorneys categorized as high type take an average of 2.7 months (equivalent to 82 days) less to complete their first transaction compared to their low type counterparts. This consistent positive effect of high-quality attorneys holds across all specifications in columns (1) through (4), indicating that our quality metric, $UEPP_i$, effectively captures the inherent quality of attorneys, aligning with the findings of Nosko and Tadelis (2015) and Li et al. (2020).

When examining the heterogeneous effects of knowledge contribution on the time required to complete the first transaction, it becomes evident that this shortening effect is predominantly observed among high-quality attorneys, rather than the low-quality attorneys, as seen in columns (2) through (4). We attribute this phenomenon to the perspective advanced by Tadelis and Zettelmeyer (2015), which suggests that information disclosure pertaining to the quality of items fosters improved alignment between prospective buyers and sellers when the revealed information deviates from their prior expectations, thereby enhancing market outcomes. Conversely, when the disclosed information corresponds with existing expectations, it does not yield a noticeable impact. Our conjecture is that solely the responses offered by high-quality attorneys elicit a positive surprise within the market, whereas the answers provided by low-quality attorneys align with the expectations derived from their off-platform reputations.

4.2 Post-Transaction Analysis

Our focus shifts to the decision-making processes of attorneys regarding signaling, revenue, and the dynamics of their reputation after they secure their first transaction but before they receive the first market signal, specifically the first customer review. Before delving into the regression analysis, we commence with a comparative examination of attorneys' behaviors during what we refer to as the cold and warm periods. The findings, presented in Table 4, illuminate intriguing insights. It is evident that sellers within the online legal marketplace experience notably lower revenue and reduced quantities sold during the cold period, which is characterized by the absence of a well-established reputation to showcase to potential buyers on the platform. What proves particularly interesting is the strategies employed by these sellers to navigate this period - they tend to adjust their pricing by offering lower rates, coupled with intensified signaling efforts to make their presence known to the market. Simultaneously, they actively engage in providing answers in Q&A sessions, with the goal of increasing the probability of matching with potential clients. This, in turn, lays the foundation for them to accumulate favorable review ratings on the platform.

Answers as a Credible Signaling Mechanism — Next, we proceed to examine whether the answers provided in Q&A sessions serve as credible signaling mechanisms, aligning with the expectations set forth in the signaling theory literature. Our regression model for testing this hypothesis is structured as follows:

$$Signal_{i,t} = \beta EPP_{i,t} + X_{i,t}\gamma + \mu_i + \tau_t + \varepsilon_{i,t} \tag{3}$$

where $Signal_(i, t+1)$ is the number of answers attorney i leaves at time t+1. $EPP_(i, t)$ is the effective positive percentage as defined in Section 3.1. $X_(i, t)$ is a vector of control variables that include the advertising status of attorney i at time t, the domestic ranking of college from which an attorney graduated, the number of certificates granted by the Korean Bar Association, the number of professional licenses other than that of a lawyer, and an attorney's years of experience. Our variable of interest is β, which measures whether an attorney's quality is positively associated with the frequency of attorney signaling. Given that the Effective Positive Percentage (EPP) can be indicative of an attorney's unobserved private quality, high-quality attorneys are likely to be more skillful and knowledgeable, thus it will positively affect the frequency of signals. Results are in Table 5 and consistent with the theoretical implications — higher quality sellers send more signals. And based on the full specification of column (6) of Table 5, we can see that in the cold period, attorneys send significantly more number of signals.

Table 4: Separating Equilibrium in EPP measure on Signaling Decision

	Dependent variable: frequency of answers at $t+1$					
	(1)	(2)	(3)	(4)	(5)	(6)
EPP	26.268***	26.301***	9.728*	10.418**	12.035**	13.617***
	[2.002]	[2.004]	[5.637]	[5.193]	[5.284]	[4.718]
Cold: review=0	4.918***	5.763***	3.968	4.132*	6.473***	7.122***
	[1.291]	[1.297]	[2.436]	[2.322]	[2.350]	[2.052]
Review rating	0.092	0.094	-0.288	-0.298	0.068	0.081
	[0.287]	[0.287]	[0.470]	[0.480]	[0.464]	[0.459]
Control Variables						
Advertisement	-9.002***	-8.733***	-5.682**	-5.642**	-4.558*	-4.569*
	[1.202]	[1.204]	[2.416]	[2.455]	[2.731]	[2.753]
Cum. # of reviews		0.009***		-0.008		-0.009
		[0.001]		[0.012]		[0.013]
Experience	0.289***	0.315***	-0.231	-0.166		
	[0.052]	[0.052]	[0.400]	[0.375]		
Certified expertise	-3.305***	-3.439***	-3.499	-3.116		
	[0.421]	[0.419]	[2.672]	[2.881]		
Other license	1.469***	1.326***	5.947	6.008		
	[0.433]	[0.430]	[4.164]	[4.225]		
Rent ($\$/m^2$)	0.415***	0.390***	-0.478	-0.382		
	[0.048]	[0.048]	[0.330]	[0.404]		
College ranking	0.521***	0.526***	0.318	0.342		
	[0.044]	[0.044]	[0.263]	[0.260]		
Constant	-22.604***	-23.087***	-37.727	-39.552	-44.749	-45.506
	[3.921]	[3.988]	[30.544]	[30.603]	[31.297]	[31.197]
Law firm fixed effects	No		Yes		No	
Attorney fixed effects	No		No		Yes	
Week fixed effects	Yes		Yes		Yes	
Std. errors clustering	Attorney		Law firm		Attorney	
Number of law firms	551	551	551	551	551	551
Number of attorneys	741	741	741	741	741	741
Observations	24,480	24,480	24,480	24,480	24,480	24,480
Adj. R-squared	0.056	0.057	0.384	0.385	0.421	0.421

Table 5: The Effects of Knowledge Contribution on Revenue

	Dependent variable: log of revenue at $t + 1$			
	(1)	(2)	(3)	(4)
Cold: review=0	-0.512***	-0.511***	-0.341***	-0.346***
	[0.057]	[0.057]	[0.060]	[0.061]
Answers (10s)	0.165***	0.207***	0.146***	0.255***
	[0.034]	[0.053]	[0.024]	[0.044]
EPP	0.624***	0.715***	0.527***	0.814***
	[0.136]	[0.168]	[0.154]	[0.187]
Answers (10s) $\times$ EPP		0.320**		0.756***
		[0.145]		[0.214]
Control Variables				
Advertisement	0.352***	0.350***	0.171***	0.170***
	[0.052]	[0.053]	[0.049]	[0.048]
Review rating	0.011	0.012	-0.016	-0.016
	[0.012]	[0.012]	[0.013]	[0.013]
Number of reviews	0.230***	0.230***	0.041	0.039
	[0.024]	[0.024]	[0.026]	[0.025]
Experience	-0.001	-0.001		
	[0.004]	[0.004]		
Certified expertise	-0.045	-0.048		
	[0.049]	[0.049]		
Other license	-0.018	-0.018		
	[0.049]	[0.049]		
Rent ($/m2)	0.014***	0.014***		
	[0.004]	[0.005]		
College ranking	-0.003	-0.003		
	[0.002]	[0.002]		
Constant	10.191***	10.148***	10.895***	10.807***
	[0.205]	[0.203]	[0.100]	[0.093]
Attorney fixed effects	No	No	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Std. errors clustering	Attorney	Attorney	Attorney	Attorney
Number of attorneys	741	741	741	741
Observations	24,480	24,480	24,480	24,480
Adj. R-squared	0.262	0.262	0.533	0.534

The Effect of Signaling on Revenue - Will more answers lead to higher revenue of attorneys? To check this possibility in the after-transaction period, we estimate the following regression model:

$$log(Revenue)_{i,t+1} = \beta_0 + \beta_1 Signal_{i,t} \times EPP_{i,t} + X_{i,t}\gamma + \alpha_i + \tau_t + \varepsilon_{i,t} \quad (4)$$

The variable of our interest is β_1 where it measures the extent to which the signals lead to the increased revenue. And if so, β_2 measures whether if there's any differences of marginal benefits of signaling across different quality of attorneys. The results are in Table 6 and they confirm that higher answers lead to higher revenue, and that effect is specifically strong for the higher quality attorneys (i.e., attorneys who have high EPP).

Notably, in column (4) of Table 5, we can see that as soon as the sellers obtain the first review, which means they overcome the cold-start period, they get 34.6% more revenue on average in the warm period. The emphasis on the first review was emphasized in Pallais (2014) that simply giving workers a first review benefits them by providing the market with information about their abilities.

5 Conclusion

In this study, we examined the intricate dynamics of reputation systems in online marketplaces, with a specific focus on the challenges faced by new entrants in overcoming the ”cold-start problem.” New entrants may need to tolerate initial losses to build a favorable reputation for future success, potentially jeopardizing their long-term survival prospects. We investigated how attorneys in the online legal consultation platform utilize knowledge contribution in Question & Answer (Q&A) sessions to navigate through this initial phase and establish their reputation. We explored the realm of online legal consultation and how attorneys, especially those without prior reputation, engage in knowledge contribution as a signaling mechanism to attract potential clients. Our findings shed light on several key aspects of this complex issue. First, we find distinctive behaviors of attorneys during the cold-start period, such as lower consulting fees, lower sales volumes, and a significantly higher number of signals left by attorneys. Second, our finding suggests that knowledge contribution positively impacted the time needed to transact with the first customer, primarily benefiting high-quality attorneys. Lastly, we delve into the idea that information disclosure regarding attorney quality is most impactful when it surprises consumers, rather than aligning with their prior expectations. For further research, our study sets the stage for several opportunities. First, it would be valuable to explore how reputation systems and knowledge contribution affect long-term performance, client retention, and the development of attorneys’ reputation on the platform. Additionally, examining the impact of reputation systems and knowledge contribution in other professional service markets, such as physicians, could provide insights into their broader applicability. Future research could also delve into the interplay between different signaling mechanisms and how they influence consumer decisions.

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