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The Impact of Platform Protection Insurance on Buyers and Sellers in the Sharing Economy: A Natural Experiment

Xueming Luo, Siliang Tong, Zhijie Lin, and Cheng Zhang

Abstract

The sharing economy has radically reshaped marketing thought and practice, and research has yet to examine whether and how platform-level buyer protection insurance (PPI) affects buyers and sellers in this economy. The authors exploit a natural experiment involving an unexpected system glitch during a PPI launch and estimate difference-in-differences models using over 5.4 million data points from a food sharing platform. Results suggest that PPI significantly increases buyer spending and seller revenue, affirming the benefits of this platform-level insurance in the sharing economy. The authors also uncover multifaceted buyer-side and seller-side responses that enable such benefits. PPI increases buyer spending by boosting product orders and variety-seeking behavior. Furthermore, it enhances seller revenue by increasing customer retention and acquisition. This work contributes to the literature by (1) putting a spotlight on the topic of PPI, a platform governance policy that reduces consumer risks and improves the efficacy of sharing platforms; (2) accounting for how PPI alters buyer and seller behaviors on a platform; (3) addressing what types of buyers and sellers benefit more or less from PPI; and (4) offering guidance for managers to improve platform reputation, marketplace efficiency, and consumer welfare in the context of the sharing economy.

Keywords

consumer protection insurance, customer retention and acquisition, peer-to-peer, platform regulation, sharing economy

The rise of the sharing economy has dramatically reshaped marketing thought and practice. In a comprehensive review, Eckhardt et al. (2019) delineate that the sharing economy has altered the traditional marketing views of consumers, firms, and marketplace governance. Indeed, the projected revenue from sharing accommodation and transportation alone will surpass $335 billion in 2025 (Tabcum 2019). The recent initial public offerings of Uber and Lyft exemplify this remarkable growth (Franklin 2019).

However, consumers continue to face high transaction uncertainty and purchase risks on sharing platforms, which host unbranded individual sellers who offer products of mixed quality (Eckhardt et al. 2019; Lamberton and Rose 2012). Although most sharing platforms have implemented review-based reputation systems, these systems are insufficient for fully eliminating consumer risks because of review bias, inflation, and manipulation on the platform (Ert, Fleischer, and Magen 2016; Fradkin et al. 2015; Sunder, Kim, and Yorkston 2019).

Therefore, major sharing economy players have adopted platform-level buyer protection insurance (PPI), which refers to a blanket safeguard program that provides buyers with insurance protection against product quality failures caused by sellers on the platform. For example, Uber, Airbnb, and TaskRabbit have implemented a myriad of insurance policies to reduce consumer risks in the sharing economy (see Web Appendix A).

Despite its widespread use in industry practice, PPI has been neglected in the extant academic literature. As summarized in Table 1, Panel A, there is a nascent stream of research on the sharing economy. Theoretically, Perren and Kozinets (2018)

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Table 1. Summary of Relevant Literature on the Sharing Economy and Consumer Protection Programs.

A: Sharing Economy

	Platform	Focus	Data	Model	Key Findings
Perren and Kozinets (2018)	–	Conceptualization	–	–	Understanding peer-to-peer, sharing, and access-based markets through consociality and platform intermediation.
Eckhardt et al. (2019)	–	Conceptualization	–	–	The sharing economy will radically change marketing's institutions, processes, and value creation.
Guda and Subramanian (2019)	Uber	Surge pricing	–	Analytical	Surge pricing can be effective in zones where supply exceeds demand.
Lamberton and Rose (2012)	–	Risk perception	MTurks and lab	OLS	Perceived risk reduces consumers' propensity to participate in commercial sharing.
Zhang et al. (2016)	Airbnb	Professional photos	Natural experiment	DID	High image quality of verified photos increases hosts' revenue.
Zervas, Proserpio, and Byers (2017)	Airbnb	Platform entry	Natural experiment	DID	The entry of Airbnb has reduced hotel revenue, especially among lower-tier hotels.
Edelman, Luca, and Svirsky (2017)	Airbnb	Racial discrimination	Field experiment	OLS	Guests with African American names are less likely to be accepted by hosts.
Costello and Reczek (2020)	Borrow'd	Marketing communications	Field experiment and lab	OLS	A provider-focused (vs. platform-focused) marketing message has a positive impact on customer purchase.
Cui, Li, and Zhang (2020)	Airbnb	Reviews and racial discrimination	Field experiment	OLS	Positive reviews reduce the racial discrimination against African American–sounding names.

B: Consumer Protection Programs

	Platform	Protection Type	Pledge Party	Cost of Protection	Data	Model	Seller-Side Outcomes	Buyer-Side Outcomes	Key Findings
Roberts (2011)	Online auction (eBay type)	Product guarantee	Own-platform	Default-contingent	Observation	OLS	Price and sales likelihood	–	A "guaranteed or money back" promise does not affect sellers' prices and sales likelihood and does not substitute for reputation.
Cai et al. (2013)	EachNet (eBay type)	Product guarantee	Own-platform	Default-contingent	Observation	OLS	Review rating and warning	–	Buyer protection increases negative feedback toward sellers, induces sellers to charge higher prices, and reduces the marketplace size.
Hui et al. (2016)	eBay	Product guarantee	Own-platform	Default-contingent	Observation	RDD	Price and sales likelihood	–	Buyer protection increases sellers' prices but substitutes for the premium of reputation badges.
This study	Food sharing economy	Insurance	Third-party insurer	Default-independent and default-contingent	Natural experiment	DID	Sales revenue, number of orders, price, customer acquisition, retention, and opportunistic behavior	Spending, order value, number of purchases, variety seeking, and adverse selection	PPI increases buyer spending by boosting product orders and variety-seeking behavior. Also, PPI boosts seller revenue by improving customer retention and acquisition.

Notes: OLS = Ordinary least square regression, DID = difference-in-differences modeling, and RDD = regression discontinuity design.

conceptualize the differences between peer-to-peer, sharing, and access-based markets through consociality and platform intermediation. Eckhardt et al. (2019) conceptualize that the sharing economy will radically change marketing's institutions, processes, and value creation. In an analytical study, Guda and Subramanian (2019) find that surge pricing can be effective in zones where supply exceeds demand. Empirically, Lamberton and Rose (2012) find that beyond cost-related benefits, consumers' perceived risk reduces their propensity to participate in commercial sharing. Zhang et al. (2016) show that the quality of professional photos has a positive impact on the revenue growth of Airbnb hosts. Also, Zervas, Proserpio, and Byers (2017) conclude that the entry of Airbnb has had a negative impact on the revenue of traditional hotels, especially lower-tier ones. Furthermore, Airbnb hosts racially discriminate against guests with African American–sounding names (Edelman, Luca, and Svirsky 2017), but this discrimination is reduced by positive reviews (Cui, Li, and Zhang 2020). Extending these theoretical and empirical studies, we focus on PPI, a prevalent yet underresearched governance policy that may reduce consumer risk and improve the efficacy of online sharing platforms. Because there is a dire need to explore effective platform governance that lowers transaction uncertainty and improves consumer welfare in the sharing economy (Eckhardt et al. 2019; Perren and Kozinets 2018), PPI is a timely and important topic that offers opportunities for generating theoretical and managerial insights for the sharing economy.

Also, as shown in Table 1, Panel B, prior platform literature on consumer protection programs has focused on product guarantees but has found mixed results. Roberts (2011) notes that a product guarantee with a money-back promise has an insignificant impact on selling prices and sales probability and does not substitute for the value of feedback in the form of reviews. Cai et al. (2013) find that product guarantees even negatively affect sellers' subsequent review ratings because they induce dishonest behaviors and attract entries of opportunistic sellers. At the same time, Hui et al. (2016) report that product guarantees increase marketplace efficiency and can substitute for the value of reputation badges. Extending these studies, we put a spotlight on PPI and examine how it affects the sharing economy not only through buyer-side and seller-side responses but also through heterogeneous effects across different types of buyers and sellers. Theoretically, PPI differs from product guarantees in two key aspects. (1) PPI is endorsed by a third-party insurer outside the platform. The officially certified insurance seal acts as a reputable pledge to nurture institution-based trust among consumers and thus reduce consumer risk (Luo 2002; Özpolat et al. 2013). By contrast, product guarantees are own-platform policies. Essentially, they involve promises pledged by the platform with its own reputation to lower consumer risks. (2) PPI sends a comprehensive quality signal to consumers because the platform bears not only upfront insurance costs ex ante (default-independent) but also additional costs for default incidences ex post (default-contingent) to safeguard consumers' potential losses. Thus, consumers could see the third-party insurer as a stronger quality signal, especially when the sharing platform is a new business without a well-established reputation. By contrast, in product guarantee policies, the platform may bear the costs for default incidences ex post only, not ex ante (Kirmani and Rao 2000; Price and Dawar 2002).

Although prior literature has noted the general benefits of insurance in B2C retail settings (Chu and Chintagunta 2011; Eisner and Strotz 1961), the impact of insurance in C2C sharing platform settings has been neglected and could be rather different. Unlike retail insurance, in which some customers self-select to participate but others do not, PPI is a blanket protection wherein platforms adopt the insurance policy to protect all consumers and reduce purchase risk for the whole platform. Furthermore, unlike traditional retailers that directly control the quality of their product offerings, sharing platforms do not have such direct control because they only act as an intermediator or matchmaker. This makes buyer-side and seller-side responses to insurance more nuanced in the sharing economy context. Indeed, in B2C settings, customers pay insurance costs. By contrast, sharing platforms pay the costs of PPI, which might lead buyers (reassured that they are well-protected by free blanket insurance) to purchase goods from low-quality sellers—an adverse selection problem among buyers on the platform. Also, dodgy individual sellers on sharing platforms might take advantage of the free blanket insurance to opportunistically raise their prices and/or lower their service quality, likely jeopardizing consumer welfare in the sharing economy (Eckhardt et al. 2019).

Therefore, prior research has yet to systematically examine whether and how PPI affects the buyers and sellers in the sharing economy. To fill this gap in the literature, our goal is to (1) quantify the impact of PPI in the sharing economy, (2) reveal the multifaceted buyer-side and seller-side responses to PPI, and (3) explore the moderating role of the prior experiences of buyers and sellers.

However, it is difficult to accomplish this goal due to formidable challenges such as the lack of fine-grained field data and causal evidence. Few researchers have access to granular transaction data, as sharing platforms are a fairly recent phenomenon. Although researchers can use web scraping to collect front-end data on sellers' business performance (Zervas, Proserpio, and Byers 2017), the back-end granular transaction records of individual buyers associated with each seller only exist in the private databanks of platform companies. At the same time, such private data are needed to uncover the multifaceted buyer-side and seller-side responses to PPI and heterogeneous effects of PPI for different types of buyers and sellers. In addition, it is notoriously difficult to scientifically identify the causal impact of PPI because randomized field experiments, which protect some buyers through insurance while excluding others, are unethical in the real world.

Fortunately, we acquired rich, proprietary field data from a major food-sharing mobile app platform. Leveraging a natural experiment with over 5.4 million data points, we were able to quantify the causal impact of PPI with difference-in-differences (DID) models. The natural experiment was based on an unexpected system glitch during the PPI launch that excluded the visibility of PPI information to those buyers who did not update the app. Thus, it allowed us to construct a control group with buyers who were not aware of PPI because they had an older app version, as well as a treatment group with buyers who had the latest app version and thus were aware of PPI. Our panel data contained detailed records of buyer–seller pairing transactions both before the PPI launch and after the glitch was fixed. We then applied DID models to estimate the causal impact of PPI by comparing the differences between the treatment and the control groups across pre- and post-PPI periods.

We find that PPI significantly increases buyer spending and seller revenue, affirming the benefits of this platform-level insurance in the sharing economy. We also uncover multifaceted buyer-side and seller-side responses that enable such benefits. In particular, PPI boosts buyer spending by way of increasing product orders and variety-seeking behavior among buyers, who seek out different products and sellers on the sharing platform. Moreover, PPI boosts seller revenue by increasing customer retention and acquisition. Additional preliminary findings show that PPI does not increase adverse selection among buyers (i.e., buyers do not purchase more items from lower-quality sellers) or opportunistic behaviors among sellers (i.e., sellers do not raise their prices or receive more consumer complaints) in the short run. Furthermore, the insurance benefits are amplified for buyers with worse prior experience and sellers with shorter tenure experience on the platform, suggesting that PPI acts as a reputable quality signal to reduce transaction uncertainty and purchase risk on the sharing platform.

Our research makes three main contributions to the literature: (1) To the best of our knowledge, it is the first to examine the platform governance policy of PPI that can reduce consumer risk and improve the efficacy of online sharing platforms. Extending the nascent literature on the sharing economy (Costello and Reczek 2020; Eckhardt et al. 2019; Lamberton and Rose 2012; Zervas, Proserpio, and Byers 2017), we put a spotlight on PPI, which is crucially important because a core challenge in the sharing economy is how to reduce purchase risk and safeguard consumer welfare. (2) Extending the literature on buyer protection programs (Cai et al. 2013; Hui et al. 2016; Roberts 2011), our work reveals that PPI engenders beneficial buyer-side and seller-side responses and that the benefits of PPI are amplified for more (vs. less) vulnerable buyers and sellers. This is nontrivial because platforms are challenged to simultaneously protect consumers and regulate sellers who may behave opportunistically. (3) Our work contributes to the literature on insurance. Although ample research has noted the benefits of insurance in the context of retailing (Chu and Chintagunta 2011; Heal 1977; Johnson et al. 1993), we extend the literature by focusing on platform insurance in the context of the sharing economy, examining multiside responses to platform insurance, exploring the heterogeneous effects across buyers and sellers, and quantifying the magnitude of the effects through a rigorous research design with causality inference and large sample sizes.

Managerially, our research suggests that platforms can use PPI to affect buyer and seller behaviors and subsequent business performance. Our findings on the multifaceted buyer-side and seller-side behavioral responses suggest that PPI may help empower platform managers to build a trusting relationship with both internal and external stakeholders in the ecosystem. Furthermore, platform managers can craft more targeted communications for different user segments to earn higher returns on PPI. Our DID modeling with natural experiment methods provides managers with a scientific toolbox that empowers them to gauge the causal impact of platform insurance and other governance policies in the sharing economy.

Propositions for the Impact of PPI in the Sharing Economy

A striking challenge in the C2C sharing economy is how to reduce purchase risk (Lamberton and Rose 2012) and safeguard consumer welfare (Eckhardt et al. 2019). In the sharing economy, consumers typically face high levels of transaction uncertainty and purchase risk because the sharing platforms host unbranded individual sellers whose product credibility may be questionable (Koopman, Mitchell, and Thierer 2014). Indeed, researchers have alerted that "because platforms do not typically produce offerings, they cannot control quality or guarantee consistency" (Eckhardt et al. 2019, p. 10). Also, because individual sellers lack the necessary resources to build a brand reputation for trustworthiness, consumers face substantial ambiguity and perceived risk when they estimate the likelihood of possible negative consequences before the transaction (Kahn and Sarin 1988; Lamberton and Rose 2012). Furthermore, after the transaction, product failures of unbranded sellers might result in potential financial losses and physical suffering, which also reduces the benefits customers derive from purchases on the sharing platform (Johnson et al. 1993; Sugden 2003).

Therefore, we propose PPI as a platform-wide insurance policy that tackles this challenge and boosts the efficacy of online platforms. Figure 1 illustrates our propositions: PPI affects buyer spending and seller revenue, and these effects are driven by multifaceted, different buyer-side and seller-side responses. Furthermore, the prior experiences of buyers and sellers play a moderating role in the impact of PPI in the sharing economy.

Effects of PPI on Buyer Spending and Buyer-Side Responses

Our propositions are grounded in the consumer utility theory. According to the utility model, customers decide to purchase from sellers on the sharing platform when the transaction offers more benefits than costs and risks (Hennig-Thurau, Henning, and Sattler 2007; Lamberton and Rose 2012). Prior literature on decision making suggests that customers will compare the expected benefits with transactional costs and related risks (Lamberton and Rose 2012). Also, consumers incorporate the

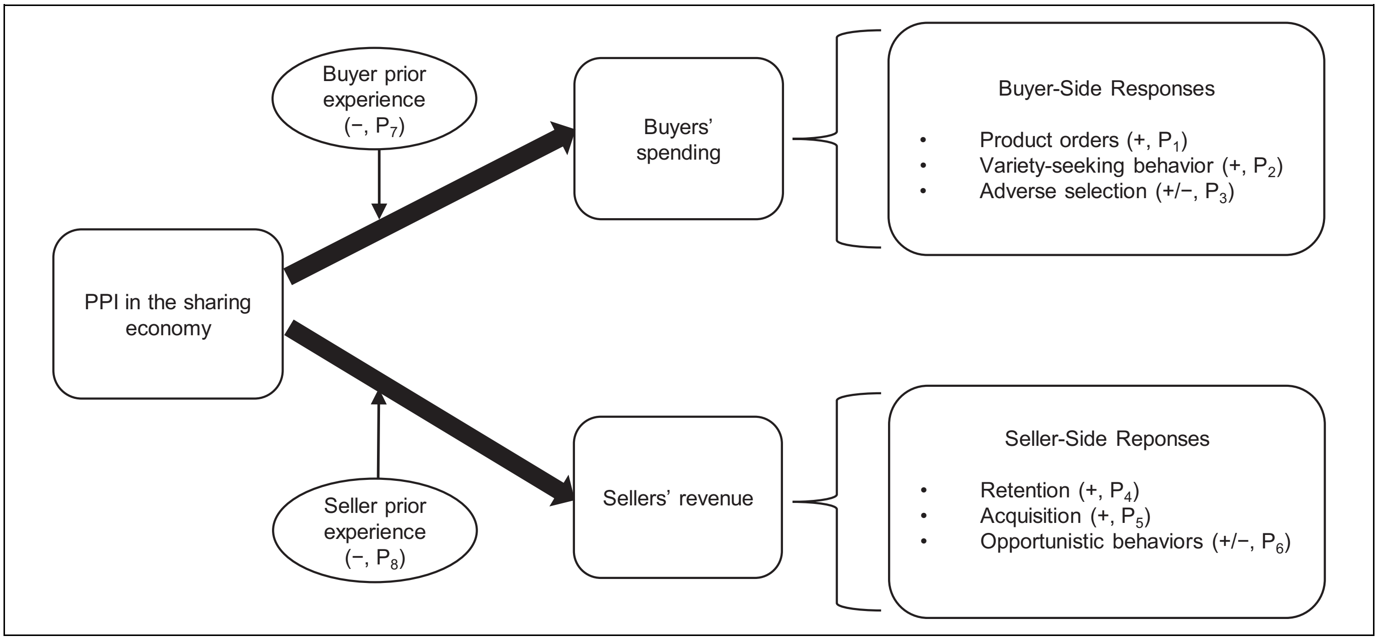

Figure 1. The multifaceted effects of PPI.

possibility of default incidences (i.e., product failure) that diminish the expected utility (Disatnik and Steinhart 2015; Fishburn 1981).

It is conceivable that PPI can increase buyers' total utility by reducing product-level transaction uncertainty and purchase risk related to the intangible features of a product and the ambiguous ex post performance of products that cannot be fully assessed by customers ex ante (Kim and Krishnan 2015). More specifically, such product uncertainty and risk can be reduced by PPI in two key ways. First, before the transaction, PPI's officially certified seal from a reputable third-party insurer sends a quality signal and fosters institution-based trust among consumers (Hsu, Lai, and Chen 2007; Luo 2002) that can improve the trustworthiness of insured products and thus lower consumer risk. By paying the insurance costs to safeguard all buyers up front, the platform also signals its dedication to high product quality and low product failure (Sporleder and Goldsmith 2001). Second, even after the transaction, PPI offers financial indemnification in the event of plausible product failure through insurance claims (Eisner and Strotz 1961; Johnson et al. 1993), thus further lowering consumer risk. Therefore, to the extent that PPI reduces buyers' product-level purchase risk with higher total utility (Lamberton and Rose 2012), it likely boosts buyer spending by eliciting favorable buyer-side responses to PPI (i.e., more product orders and larger order sizes). In other words, PPI may induce buyers to not only place more product orders but also increase their order amounts, thus positively affecting buyer spending on the sharing platform.

> **P_1**: The launch of PPI has a positive impact on buyer spending by boosting product orders (i.e., more product orders and larger order sizes) on the sharing platform.

Furthermore, buyers experience seller-level uncertainty and purchase risk: the degree to which an individual seller is not capable of or trustworthy in selling their products and services (Eckhardt et al. 2019; Purohit and Srivastava 2001). Thus, buyers tend to avoid seeking out new sellers or new products offered by the same seller, which typically incur higher purchase risk than repeated transactions with the same sellers and products (Kahn 1995; Sajeesh and Raju 2010; Zhang 2011). However, by providing blanket insurance protection through the official insurance seal for all products offered by all individual sellers, PPI ameliorates such purchase risk and increases consumers' expected utility to seek out and explore a larger variety of different sellers and products for the first time (Kahn 1995; Weathers, Sharma, and Wood 2007). If so, PPI likely increases buyer spending by also boosting variety-seeking behavior (i.e., consumers seeking more first-time transactions with new sellers and products) on the sharing platform.

> **P_2**: The launch of PPI has a positive impact on buyer spending by increasing variety-seeking behavior (i.e., consumers seeking more first-time transactions with new sellers and products) on the sharing platform.

Despite its overall positive impact on buyer spending, it is debatable whether PPI increases or decreases adverse selection among buyers (i.e., transacting with low-quality sellers). On the one hand, following PPI, customers who feel they are well-protected by the official insurance seal may pay less attention to purchase risk and thus transact more with low-quality sellers (i.e., with low review ratings), likely increasing adverse selection among buyers (Cai et al. 2013; Caillaud and Jullien 2003; Lamberton and Rose 2012). On the other hand, because PPI signals that a platform still relies on the insurance seal to govern the overall quality, it reminds buyers of the risk of purchasing from low-quality sellers (Eckhardt et al. 2019; Edelman and Geradin 2018) and thus leads them to spend less with low-quality sellers, likely reducing adverse selection among buyers. This suggests the following competing propositions:

> **P_3**: The launch of PPI increases adverse selection among buyers (i.e., customers buy more from lower-quality sellers) on the sharing platform.

> **$P_{3\_competing}$**: The launch of PPI decreases adverse selection among buyers (i.e., customers buy less from lower-quality sellers) on the sharing platform.

Effects of PPI on Seller Revenue and Seller-Side Responses

Although PPI insures buyers, it may also affect sellers on the platform and induce seller-side responses. Specifically, as buyers derive higher total utility from PPI and make more purchases on the platform, all sellers' customer lifetime value will be boosted on average (Eckhardt et al. 2019; Gupta et al. 2006). The more PPI lowers transaction risk and increases customer purchases (Chu and Chintagunta 2011; Heal 1977), the more the sellers may benefit from the booming purchase activities and higher customer equity (Kumar, Lahiri, and Dogan 2018). Indeed, PPI may increase seller revenue in two main ways. First, sellers' retention of current customers is improved. As customers derive more utility from transactions involving PPI, they will have a higher propensity to keep using and buying from the same sellers on the platform (Lamberton and Rose 2012), providing sellers with the benefit of better current-customer retention (Meyer-Waarden and Benavent 2006). In addition, sellers' acquisition of new customers is strengthened. As customers derive more utility from seeking out new sellers and purchasing from them under the protection of PPI (Eckhardt et al. 2019; Kahn 1995), sellers are then poised to acquire more new customers on the platform. Thus, PPI also benefits sellers with more purchases from new buyers (i.e., better new-customer acquisition), positively impacting seller revenue on the sharing platform.

> **P_4**: The launch of PPI has a positive impact on seller revenue by way of improving current-customer retention on the sharing platform.

> **P_5**: The launch of PPI has a positive impact on seller revenue by way of improving new-customer acquisition on the sharing platform.

Furthermore, Eckhardt et al. (2019, p. 10) explicate a dark side of the sharing economy: "individual service providers have high levels of agency and may use the platform opportunistically." In this context, it is debatable whether PPI increases or decreases sellers' opportunistic behaviors on the platform. On the one hand, the fact that the costs of PPI are covered by the platform, not the sellers, may cause an agency problem. That is, because sellers do not have to bear the insurance costs in the case of default, a plausible unintended consequence is that PPI seems to protect sellers from their product failures (Eisner and Strotz 1961). Crooked sellers then may take advantage of this blanket insurance protection and the induced surge in demand by engaging in more opportunistic behaviors (i.e., raising prices and cutting corners to fulfill the increasing orders at the expense of quality) (Cai et al. 2013; Cooper and Ross 1985). If so, PPI likely increases opportunistic behaviors by sellers on the platform. On the other hand, the platform's decision to invest in PPI and bear the insurance costs up front may strongly signal its dedication to safeguarding overall reputation and quality so as to govern a trustworthy ecosystem on the platform (Eckhardt et al. 2019). This platform governance PPI policy then reduces dodgy sellers' propensity to engage in opportunistic behaviors because such behaviors will capture more attention by the platform along with possible punitive reactions (Hui et al. 2016). If so, PPI will decrease opportunistic behaviors by sellers on the platform.

> **P_6**: The launch of PPI increases opportunistic behaviors by sellers on the sharing platform.

> **$P_{6\_competing}$**: The launch of PPI decreases opportunistic behaviors by sellers on the sharing platform.

Moderating Role of Buyers' and Sellers' Prior Experience

It is feasible that the positive impact of PPI on buyer spending is amplified for buyers with worse (vs. better) prior experiences. Buyers with more favorable pre-PPI experiences are already likely to have more utility and lower risk given their prior purchases (Moorman, Deshpandé, and Zaltman 1993; Nelson 1970). Customers' positive prior experience reinforces their confidence in and familiarity with the sellers and the platform, which helps lessen their purchase uncertainty and risk (Kim and Krishnan 2015; Lamberton and Rose 2012). By contrast, customers with relatively poor pre-PPI experiences are more likely to perceive purchases as risky because previous product failures violated their trust. Thus, buyers with worse prior experiences derive more total utility from PPI to make purchases on the platform.

Similarly, the positive impact of PPI on seller revenue is likely amplified for sellers with less (vs. more) prior experience on the sharing platform. Tenure can be an indicator of sellers' experience and quality on the sharing platform (Eckhardt et al. 2019; Luca and Zervas 2016). Sellers with a shorter tenure, then, are often perceived by consumers to have less credibility and quality reputation with higher purchase risk (Chu and Chintagunta 2011; Lamberton and Rose 2012). Therefore, sellers with less prior experience may derive more total utility from PPI to attain sales revenue on the sharing platform.

> **P_7**: The positive impact of PPI on buyer spending is amplified for buyers with worse prior experience on the sharing platform.

> **P_8**: The positive impact of PPI on seller revenue is amplified for sellers with less prior experience on the sharing platform.

Setting, Data, and Models

Institutional Setting

The empirical setting is a major food sharing platform (the company wishes to remain anonymous) that was founded in Beijing, China, in October 2014. At the time of our research, the company had more than two million registered users and was the dominant C2C food sharing platform. Essentially, it is a C2C food sharing platform that connects individual sellers (entrepreneurs cooking meals in their home kitchens) with individual buyers (customers purchasing meals) on a mobile app. The app matches buyers with nearby sellers on the basis of location proximity, captured by mobile GPS. Sellers set up virtual kitchens with descriptions that include the price, ingredients, and images of the dishes for sale. They then take orders and cook meals for buyers on the platform. There are several steps for completing a transaction on the app. First, as indicated in Web Appendix B, when a buyer opens the app, the platform automatically detects her location through mobile geofencing technology and lists nearby sellers. Second, the buyer browses the listed sellers, selects a seller, and adds desired meals to a shopping cart. Third, the buyer places an order and pays through the app. Once the ordered meals are cooked, the platform arranges for food to be delivered to the buyer.

Due to the risk of foodborne illnesses and poisoning, buyers are concerned about food quality when ordering meals from unbranded individual sellers (Buckley and Wu 2016). Poor product quality in the food sector can have dire consequences, causing nausea, vomiting, diarrhea, and even death. Indeed, consumers in local markets have significant concerns about food quality issues, ranging from contaminated gutter (recycled) cooking oil, poisonous poultry, toxic condiments, tainted fish and seafood, and unclean vegetables, to human hair in food (Barfblog 2016; Brookings 2016; Buckley and Wu 2016). Unlike B2C food ordering platforms, wherein professional restaurants are required to conform to government hygiene regulations, C2C food-sharing platforms are exempt from these government regulations and are thus riskier for customers. For this reason, food-sharing platforms enforce self-regulation to signal product quality and reduce consumer risk. For example, they strictly require each seller to obtain a health certificate and to wear a cooking uniform with a chef's hat and mouth-covering mask (Fullerton 2015). Despite these efforts, though, consumer review feedback on the platform included many concerns and complaints about food quality (see Web Appendix B). This unique feature of the food-sharing platform provides an ideal setting for testing the effects of PPI in the sharing economy.

PPI on the Platform

The platform cooperated with an official trusted third party, the People's Insurance Company of China (PICC), to provide an insurance policy using food quality assurance seals. The authoritative PICC insurance seal is highly credible and trusted by all sellers and buyers in the local market. This PPI policy, which took effect on January 15, 2016, covered all transactions on the platform. It provided blanket protection for every buyer, with the cost (RMB 1 per transaction) being borne by the platform. Under this policy, a buyer who suffered from a poor food quality–related illness could file an insurance claim for compensation of up to RMB 300,000. This official third-party insurance seal fostered institution-based trust (Luo 2002; Özpolat et al. 2013), acting as a trusted pledge of platform quality control efforts to mitigate consumer risk. (The platform revamped its PPI terms and imposed a mandatory insurance charge on buyers for all transactions in September 2016, but this change would not confound our results because it occurred seven months after our data period.)

Note that the platform launched PPI to support its long-term sustainable growth, not as a strategic response to market changes or competition (the company began negotiating with the PICC almost one year before the PPI launch date). Also, the introduction of PPI was exogenous to sellers and buyers because the platform did not announce it to sellers or buyers ex ante. After implementation, the PPI insurance seal was highly visible to buyers. It was clearly displayed on the app's landing and checkout pages (see Web Appendix B screenshots). The platform manager confirmed that the company did not communicate with buyers about the insurance through any other channels during this period, and there was no social network function on the app that buyers could use to share information at the time. No other C2C food sharing platforms introduced this type of insurance during the research period either (Chen 2017).

Identification Strategy with an Unexpected System Glitch

Buyer-side identification. We leveraged a natural experiment in which an unexpected system glitch exogenously affected the visibility of PPI information for one group of buyers only. Specifically, PPI took effect at 8:00 A.M. on January 15, 2016, and covered all transactions thereafter. Due to an unexpected system glitch involving coding conflicts between the updated (2.4.6) version and older (2.4.4 or 2.4.5) versions, the PPI information was visible only to buyers with the updated app. It was not visible to buyers with older app versions (who would not see the insurance banner or coverage terms on the checkout page). This glitch took the IT team 20 days to fix, and the PPI information became visible to all buyers at midnight on February 4, 2016. By the PPI launch date, about 89% of buyers had the updated 2.4.6 app, whereas 11% of buyers continued to use older versions. In other words, during the 20 days, the former group was aware of PPI coverage, whereas the latter group was not, despite still being protected by the insurance policy. Because the platform did not announce PPI to buyers ex ante, and buyers did not foresee that their app versions would affect the visibility of PPI, the PPI implementation was exogenous to buyers' app update decisions. The system glitch thus enabled us to identify a valid control group (buyers with older app versions, unaware of PPI), as well as a treatment group (buyers with the latest app version, aware of PPI). As shown in

Web Appendix D, users in the treatment group were relatively more active than those in the control group before the launch of PPI. We then applied DID models to estimate the causal effects of PPI on buyer-side outcomes in the treatment group relative to the control group before and after the PPI launch (Narang and Shankar 2019; Proserpio and Zervas 2017).

Seller-side identification. To identify the causal effects of PPI on the seller side, we first constructed an eligible customer base for each seller using location data. Specifically, each seller/kitchen was asked to choose a delivery–distance parameter (1–5 kilometers) when setting up a kitchen page on the platform, and this parameter was unchangeable once chosen. When buyers logged on, they only saw sellers with a delivery distance that covered their location. By leveraging the detailed location data on sellers and buyers, we determined the eligible buyers aware of PPI (treated buyers) and those not so (control buyers) for a given seller. Then, we calculated the percentage of each seller's buyers who were aware of PPI and labeled it as the "PPI treatment dosage level" (see Web Appendix C). This is a continuous variable that gauges each seller's degree of PPI treatment, akin to the drug treatment dosage levels used in clinical trials. Because the sellers' choices of the delivery radius and location were exogenous to PPI, this treatment dosage level allowed us to identify the causal effects of PPI on seller-side outcomes.

Data

The platform provided a granular data set of more than 530,000 transactions between January 1, 2016, and February 13, 2016. The data recorded all purchase activities between buyers who registered an account and sellers who built a kitchen page on the platform. Each transaction included customer ID (buyer), kitchen ID (seller), transaction date, transaction amount, customer app version, the longitude and latitude of the delivery start point (seller location), and the longitude and latitude of the delivery end point (buyer location). To construct the estimation dataset for buyers, we first aggregated their transactions on the basis of user ID and transaction date. Then, to ensure treatment assignment compliance, we removed any buyers who had updated their apps to the new version after the PPI launch. (Noncompliance was low, with less than 120 customers.) The resulting buyer–day panel data included 5,403,552 observations on 122,808 individual buyers over the 44 days. Similarly, to construct the estimation dataset for sellers, we aggregated transactions on the basis of kitchen ID and transaction date. The resulting seller–day panel data consisted of 135,036 observations on 3,069 individual sellers. Note that our data sample was based on transactions among a fixed group of buyers and sellers. Each buyer made at least one purchase during the observational period, and each kitchen received at least one order. We used this sample selection procedure to rule out alternative explanations (e.g., the entry of new buyers and new sellers on the sharing platform).

Table 2 provides descriptive statistics of our data. On the buyer side, an average buyer placed 1.17 orders and spent RMB 40.468 on the app before PPI implementation (these statistics are conditional on buyer purchases, and the unconditional statistics are reported in Web Appendix D). Buyers gave kitchens an overall average rating of 4.589 out of 5 stars, suggesting that ratings were positively skewed, which is in line with the literature (Dellarocas and Narayan 2006; Li and Hitt 2008). As profile information was optional rather than compulsory for buyers, a relatively low proportion of buyer profiles were complete. On average, only 18% of buyers had avatar photos, 33.6% had nicknames, 26.2% chose to reveal their gender, and 24.1% reported their age. On the seller side, the average kitchen received 7.510 orders and generated RMB 260.245 in sales revenue each day on average. Sellers received an average of 4.827 review rating stars, mirroring the positively skewed customer review ratings. On average, each seller had 10.435 listed dishes with an average price of RMB 33.887 and maintained a 13.632 stock level for each dish, reflecting the small scale of these single-person businesses on the platform. In addition, 73.4% of the sellers were female, with an average age of 43.464. These statistics make sense given the nature of the food-sharing platform, in which most sellers are middle-aged women with enough time to sell home-cooked meals.

Econometric Models

In our econometric models, we adopted the DID with two-way fixed effects, which is widely applied in natural experimental settings (Narang and Shankar 2019 Proserpio and Zervas 2017). Our DID with two-way fixed effects effectively addressed the empirical challenge wherein the treated and control groups had some pretreatment systematic differences because it compared the changes in the outcomes between these two groups after explicitly accounting for the pretreatment systematic difference. In addition, it accounted for time-variant, individual-invariant confounds (e.g., demand shocks in holiday seasons) due to the inclusion of time fixed effects, and it controlled for individual-variant, time-invariant confounds (e.g., gender of the buyers and sellers on the sharing platform) because of the inclusion of individual fixed effects.

DID model for the effect of PPI on buyer spending. On the buyer side, we specified our two–fixed effects DID model as follows:

$$\begin{aligned}\mathrm{Buyer}_{it} = \alpha_{10} &+ \alpha_{11}\,\mathrm{TreatmentGroup}_{i} \times \mathrm{AfterPPI}_{t} \\ &+ \alpha_{12}\,\mathrm{Buyer}_{it-1} + \alpha_{13}\,\mathrm{X}_{it-1} + \theta_{i} + \tau_{t} + \varepsilon_{1it},\end{aligned} \tag{1}$$

where Buyer_{it} is the total amount of spending by the focal buyer i on day t. $\mathrm{TreatmentGroup}_{i}$ equals 1 for the treated group (buyers with the latest app version) and 0 for the control group (buyers with an older app version). Again, the unexpected exogenous system glitch made it possible to construct treatment and control groups. $\mathrm{AfterPPI}_{t}$ is a time indicator that equals 1 for the time period within the 20 days after PPI was launched (i.e., from

Table 2. Summary Statistics.

A: Buyers	Spending (RMB)	Number of Orders	Average Review Rating	Profile Avatar	Profile Nickname	Profile Gender	Profile Age	Number of New Sellers	Number of New Products
Mean	40.468	1.170	4.589	.180	.336	.262	.241	.715	1.041
Standard deviation	30.920	.481	.8201	.384	.473	.440	.428	.570	.211
Minimum	11	1	0	0	0	0	0	1	0
Maximum	997	33	5	1	1	1	1	17	23

Notes: Spending is a continuous variable measuring buyers' daily spending on the platform; Number of Orders is a count variable for buyers' daily transactions on the platform; Average Review Rating is a continuous variable (from 1 to 5) reflecting the cumulative review rating posted by each buyer; Profile Avatar, Profile Nickname, Profile Gender, and Profile Age are binary dummy variables indicating whether the buyer completes the respective profile information; Number of New Sellers is a count variable indicating the number of new sellers (kitchens) the buyer purchases from per day; and Number of New Products is a count variable indicating how many new products (dish cuisines) the buyer purchases on the sharing platform.

B: Sellers	Revenue (RMB)	Number of Orders	Average Review Rating	Dish Prices	Dish Stock Level	Number of Listed Dishes	Gender	Age	Daily New Users	Number of Negative Comments
Mean	260.245	7.510	4.827	33.887	13.632	10.435	.734	43.464	3.511	.061
Standard deviation	278.3251	7.590	.294	13.636	13.861	7.339	.442	11.807	4.052	1.977
Minimum	25	1	0	5.909	1	1	0	20	0	0
Maximum	3,288	86	5	188	99	29	1	60	74	97

Notes: Revenue is a continuous variable measuring sellers' daily business on the platform; Number of Orders is a count variable for sellers' daily transactions on the platform; Average Review Rating is a continuous variable (from 1 to 5) reflecting the cumulative review rating received for each seller; Dish Prices is a continuous variable for the average dish price of each kitchen; Dish Stock Level is a count variable measuring the number of stock for each dish the seller provides; Number of Listed Dishes is a count variable for dishes listed by each seller; Gender is a binary dummy variable (1 = "female," and 0 = "male"); Age is a continuous variable for seller age; Daily New Users is a count variable for the daily number of new customers who purchased from the focal seller; and Number of Negative Comments is a count variable for the number of negative comments received by the focal seller on the sharing platform.

the date of PPI [January 15, 2016] to the date when the glitch was fixed [February 4, 2016]) and 0 for the time period before the PPI launch date (14 days before PPI implementation). Because the treatment indicator (TreatmentGroup_i) is colinear with the individual buyer fixed effects (θ_i) and the time indicator (AfterPPI_t) is colinear with the daily level time fixed effects (τ_t), these two indicators are omitted in the estimated results. ε_{1it} is the standard error clustered at the individual buyer level to account for within-group serial correlation, and Buyer_{it-1} is the lagged dependent variable accounting for potential time-variant and individual-variant omitted factors (Chen et al. 2019). X_{it-1} includes the lagged time-variant buyer-level variables (average review rating and cumulative purchase incidences) to control for the effects of buyers' past purchase experience and frequency. The coefficient α_{11} gauges the causal effect of PPI on buyer spending through the difference between the treatment and control groups before and after the PPI launch. (The other buyer-side dependent variables in the subsequent analyses use the same Equation 1.)

DID model for the effects of PPI on seller revenues. We estimated the causal impact of PPI on seller revenue using the following two-way fixed effects DID model:

$$\text{Seller}_{jt} = \beta_{10} + \beta_{11}\,\text{PPI Dosage}_j \times \text{AfterPPI}_t + \beta_{12}\,\text{Seller}_{jt-1} + \beta_{13}\,Q_{jt-1} + \gamma_j + \tau_t + \mu_{1jt} \quad (2)$$

where Seller_{jt} is the total amount of sales revenue for the focal seller j on day t. Furthermore, PPI Dosage_j is the degree of PPI treatment for Seller j. We included individual fixed effects for each seller (γ_j), as well as daily time fixed effect (τ_t). In addition, μ_{1jt} is the standard error clustered at the individual seller level to account for within-group serial correlation, and Seller_{jt-1} is the lagged dependent variable, accounting for omitted time-variant and individual-variant factors. Q_{jt-1} includes seller-level lagged time-variant variables (average review rating and the cumulative number of reviews), which control for the effects of seller quality and popularity on the platform. The coefficient β_{11} estimates the causal effect of PPI on seller revenue through the difference in PPI treatment dosage levels before and after the PPI launch. (The other seller-side dependent variables in the subsequent analyses use the same Equation 2.)

Results

Model-Free Evidence

Figure 2, Panel A compares buyer spending across the treatment and control groups. On the x-axis, Day 0 is the PPI launch date and Day 20 is when the unexpected system glitch was fixed. The whole time period totals 44 days (i.e., 14 days in the pre-PPI launch period, 20 days in the post-PPI period before the glitch was fixed, and 10 days after the glitch was fixed). As this figure shows, buyer spending in the treatment (dashed line) and control (solid line) groups appears to follow a parallel trend before the PPI launch (this parallel trend is tested and supported). Then, these trends diverge on the day of the PPI launch: the treatment group has higher spending than the control group, visually suggesting a consistent gap (we test this gap's statistical significance with DID models subsequently). Thus, this provides model-free evidence of the positive impact of PPI on buyer spending (Web Appendix E presents model-free evidence for other outcome variables). Note that buyers in both treatment and control groups first increased then decreased their spending during the 20 days post-PPI period. Platform managers confirmed that this pattern could be caused by the Chinese New Year Holiday: consumers in both the treatment and control groups ordered more meals on the platform to celebrate the holiday season in the city during the first several days (thus, we first observe a large spike in spending for both groups with a peak around Day 4), but they then traveled from the focal city to rural hometowns for family reunions during the rest of the holiday season (thus, we then observe subsequent decreases in spending in the treatment period).

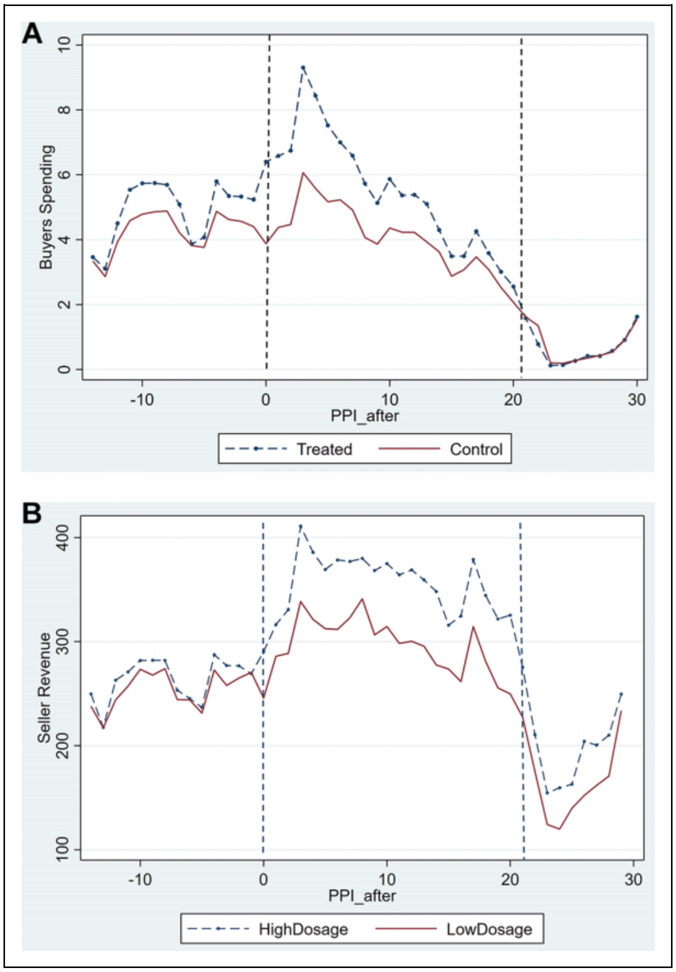

Figure 2. Model-free evidence for PPI effects on buyer spending (Panel A) and model-free evidence for PPI effects on seller revenue (Panel B).

Furthermore, over the same time period, Figure 2, Panel B suggests seller revenue in the high (dashed line) and low (solid line) PPI dosage groups, based on a median split, indeed

Table 3. Results for PPI Effects on Buyer Spending.

	1 Daily Spending Amount	2 Log (Daily Spending Amount)	3 Daily Spending Amount	4 Log (Daily Spending Amount)
TreatmentGroup × AfterPPI	1.158***	.115***	1.102***	.111***
	(.296)	(.007)	(.299)	(.007)
Average review rating	.377***	.030***	.357***	.030***
	(.045)	(.003)	(.042)	(.003)
Cumulative purchase incidences	−.556**	−.047***	−.624**	−.056***
	(.232)	(.005)	(.284)	(.006)
Lagged DV			−.042***	−.000***
			(.000)	(.000)
Individual fixed effect	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y
Buyers	122,808	122,808	122,808	122,808
Observations	4,175,472	4,175,472	4,175,472	4,175,472
R squared	.049	.012	.621	.465

Notes: Clustered standard errors at the individual buyer level are in parentheses.
*$p < .10$.
**$p < .05$.
***$p < .01$.

Table 4. Results for PPI Effects on Seller Revenue.

	1 Daily Revenue	2 Log (Daily Revenue)	3 Daily Revenue	4 Log (Daily Revenue)
PPI Dosage × AfterPPI	672.962*	4.658***	543.017*	3.991***
	(321.327)	(1.336)	(245.519)	(1.095)
Average review rating	−.001	.001***	.058	.001***
	(.074)	(.000)	(.063)	(.000)
Cumulative reviews	.002***	−.000***	.001**	−.000***
	(.000)	(.000)	(.000)	(.000)
Lagged DV			.184***	.000***
			(.013)	(.000)
Individual seller fixed effect	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y
Kitchens	3,069	3,069	3,069	3,069
Observations	104,346	104,346	104,346	104,346
R squared	.050	.024	.451	.225

Notes: Clustered standard errors at the individual seller level are in parentheses.
*$p < .10$.
**$p < .05$.
***$p < .01$.

follows a parallel trend before the PPI launch. Then, seller revenue diverges at the PPI launch date. The high PPI dosage group had higher seller revenue than the low PPI dosage group, and there was a consistent gap between them during the treatment period. The figure provides model-free evidence of the effects of PPI on seller revenue. Next, we present the model-based results.

Results for the Effects of PPI on Buyer Spending

Table 3 presents the results for the effects of PPI on buyer spending with and without log transformation. Columns 1 and 2 exclude the lagged dependent variable, whereas Columns 3 and 4 include it. We find that coefficients of the interaction term TreatmentGroup × AfterPPI are positive and significant ($p < .01$) across all columns, suggesting that the PPI launch indeed increased buyer spending. Also, the coefficient magnitude is reduced after the lagged dependent variable is included, downwardly adjusting the effect size after accounting for unobserved time-variant factors (Chen et al. 2019). The coefficient of TreatmentGroup × AfterPPI is .111 in Column 4 with log transformation of the dependent variable. The result suggests that buyers in the treatment group spent 11.74% ($= 100 \times [e^{.111} - 1]$) more than those in the control group after the platform implemented PPI, on average. This effect size of PPI is reasonable because Haley and Van Scyoc (2010) document that eBay buyer protection program lifts buyers' bidding price by 8.11%,

Table 5. Results for the Buyer-Side Responses to PPI.

Proposition	1 Daily Orders P_1: +	2 Log (Daily Orders) P_1: +	3 Order Value P_1: +	4 Log (Order Value) P_1: +	5 Number of New Sellers P_2: +	6 Log (Number of New Sellers) P_2: +	7 Number of New Products P_2: +	8 Log (Number of New Products) P_2: +
TreatmentGroup × AfterPPI	.040***	.024***	1.012***	.107***	.027***	.018***	.019***	.013***
	(.002)	(.002)	(.077)	(.007)	(.002)	(.001)	(.004)	(.003)
Average review rating	.010***	.007***	.296***	.029***	.004***	.002***	−.024***	−.017***
	(.001)	(.001)	(.033)	(.003)	(.001)	(.001)	(.003)	(.002)
Cumulative purchase incidences	−.023***	−.013***	−.513***	−.053***	−.019***	−.012***	−.002**	−.001**
	(.001)	(.001)	(.059)	(.006)	(.005)	(.003)	(.001)	(.001)
Lagged DV	.116***	.060***	2.178***	.244***	.026***	.016***	−.042***	−.026***
	(.012)	(.003)	(.208)	(.015)	(.005)	(.003)	(.005)	(.003)
Individual fixed effect(s)	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effect(s)	Y	Y	Y	Y	Y	Y	Y	Y
Buyers	122,808	122,808	122,808	122,808	122,808	122,808	122,808	122,808
N	4,175,472	4,175,472	4,175,472	4,175,472	4,175,472	4,175,472	4,175,472	4,175,472
R squared	.621	.465	.201	.329	.357	.348	.125	.126

Notes: Clustered standard errors at the individual buyer level are in parentheses. Coefficients in the first row of the estimation results provide empirical support for our P_1 and P_2.
*$p < .10$.
**$p < .05$.
***$p < .01$.

and Elfenbein, Fisman, and McManus (2012) find that enrolling in a charity giving program lifts eBay sellers' transaction probability by 30% on average.

Results for the Effects of PPI on Seller Revenues

As shown in Table 4, the coefficients of PPI Dosage × AfterPPI are positive and significant ($p < .01$) across four columns, affirming that PPI has a positive impact on seller revenue. The coefficient of PPI Dosage × AfterPPI is 3.991 in Column 4, suggesting that a one-percentage-point increase in seller PPI dosage level would lead to a 4.07% (= 100 × [$e^{.0399}$ − 1]) growth in seller revenue.

Results for Buyer-Side Responses to PPI

First, we replaced the dependent variable in Equation 1 with the total number of purchase orders and average order value. As reported in Table 5, the positive and significant coefficients ($p < .01$) of TreatmentGroup × AfterPPI across columns 1 through 4 support P_1.

Furthermore, we tested variety-seeking behavior among buyers by replacing the dependent variable in Equation 1 with the number of new sellers (kitchens) who transacted with the focal buyer, as well as the number of new products (dishes) the focal buyer purchased. When listing a dish on the platform, sellers need to choose the origins of the dish (i.e., Beijing, Northeast China, Northern China, Northwest China, Cantonese, and Sichuan), dish types (i.e., appetizer, main course, soup, and rice), main ingredients (i.e., pork, beef, poultry, vegetable, and seafood), and flavor (i.e., soy sauce, spicy, and dry pot). The platform offers over 400 dishes based on this categorization. A new dish is one that buyer i has never consumed by day t in our data, and a new seller is one with which the focal buyer had never previously transacted in our data period (i.e., the seller is new to the focal buyer rather than the platform). As shown in columns 5 thorough 8, the coefficients of TreatmentGroup × AfterPPI are consistently positive and significant ($p < .01$), thus supporting P_2.

Table 6. Results for PPI Effects on Adverse Selection Among Buyers.

Proposition	1 Spending with Low-Rating Sellers P_3: +/−	2 Average Review Rating
TreatmentGroup × AfterPPI	.277	.004
	(.166)	(.004)
Average review rating	.134*	N/A
	(.069)	
Cumulative purchase incidences	−.013	.001***
	(.008)	(.000)
Individual fixed effect(s)	Y	Y
Time fixed effect(s)	Y	Y
Buyers	122,808	122,808
N	4,175,472	4,175,472
R squared	.000	.035

Notes: Clustered standard errors at the individual buyer level are in parentheses. Coefficients in the first row of the estimation results do not support our P_3 or $P_{3\_competing}$.
*$p < .10$.
**$p < .05$.
***$p < .01$.

Table 7. Results for the Seller-Side Responses to PPI.

Proposition	1 Number of Orders P_4: +	2 Log (Number of Orders) P_4: +	3 Revenue: Existing Customers P_4: +	4 Log (Revenue: Existing Customers) P_4: +	5 Orders: Existing Customers P_4: +	6 Log (Orders: Existing Customers) P_4: +	7 Daily New Customers P_5: +	8 Log (Daily New Customers) P_5: +
PPI Dosage × AfterPPI	15.154**	2.758***	205.524**	4.358***	5.341**	1.448***	10.611*	2.725**
	(6.617)	(.799)	(101.372)	(1.587)	(2.501)	(.521)	(5.603)	(.948)
Average review rating	.001	.001***	(.051)	.001**	(.002)	.001***	.002	.001**
	(.003)	(.000)	(.055)	(.001)	(.001)	(.000)	(.001)	(.000)
Cumulative reviews	.000	−.000***	.001***	−.000***	.000**	−.000***	.000	−.000***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Lagged DV	.240***	.015***	.093***	.000***	.124***	.013***	.152***	.019***
	(.008)	(.001)	(.011)	(.000)	(.009)	(.001)	(.005)	(.001)
Individual seller fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Kitchens	3,069	3,069	3,069	3,069	3,069	3,069	3,069	3,069
Observations	104,346	104,346	104,346	104,346	104,346	104,346	104,346	104,346
R squared	.543	.328	.381	.278	.493	.280	.314	.165

Notes: Clustered standard errors at the individual seller level are in parentheses. Coefficients in the first row of the estimation results provide empirical support for our P_4 and P_5.
*$p < .10$.
**$p < .05$.
***$p < .01$.

Moreover, to test buyers' adverse selection, we replaced the dependent variable in Equation 1 with the amount they spent with low-quality sellers. (Seller quality is measured by consumer review ratings, and low-quality sellers are those whose average review rating is below 4 stars. Because the review ratings are positively skewed, after consulting with the management team, we defined the low-quality sellers as those with an accumulated review rating of below 4 out of 5.) The results are shown in Table 6, column 1. The coefficient of TreatmentGroup × AfterPPI is statistically insignificant, indicating that our data do not support either P_3 or $P_{3\_competing}$ in the short run (i.e., 20 days before the glitch was fixed).

Results for Seller-Side Responses to PPI

We replaced the dependent variable in Equation 2 with the total number of orders received by the focal seller, revenue received from existing customers, the number of orders placed by existing customers, and the number of new customers acquired. As shown in Table 7, columns 1 and 2, coefficients of PPI Dosage × AfterPPI are positive and significant ($p < .05$) for total orders. The positive and significant coefficients ($p < .05$) of PPI Dosage × AfterPPI in columns 3 through 6 show that PPI helps sellers retain more current customers through increased revenue and orders from existing customers. The positive and significant coefficients of PPI Dosage × AfterPPI in columns 7 through 8 indicate that PPI also enables sellers to acquire more new customers. Thus, both P_4 and P_5 are supported.

We then tested opportunistic behaviors among sellers by replacing the dependent variable in Equation 2 with the number of negative comments the seller j received on day t (see Web Appendix B for examples) and sellers' product prices. As shown in Table 8, columns 1 through 3, the statistically insignificant coefficients of PPI Dosage × AfterPPI suggest that sellers do not receive more negative review comments or raise their selling prices after PPI is implemented.

Table 8. Results for PPI Effects on Sellers' Opportunistic Behaviors.

Proposition	1 Number of Negative Comments P_6: +/−	2 Dish Prices P_6: +/−	3 Log (Dish Prices) P_6: +/−	4 Average Review Rating P_6: +/−
PPI Dosage × AfterPPI	20.397	−20.167	−.084	.400
	(11.545)	(18.616)	(.228)	(.323)
Average review rating	.017	(.002)	.000	.000
	(.065)	(.009)	(.000)	(.000)
Cumulative reviews	.000	.000	.000	.000**
	(.001)	(.000)	(.000)	(.000)
Individual seller fixed effect	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y
Observations	3,069	3,069	3,069	3,069
	104,346	104,346	104,346	104,346
R squared	.001	.127	.030	.002

Notes: Clustered standard errors at the individual seller level are in parentheses. Coefficients in the first row of the estimation results do not support our P_6 or $P_{6\_competing}$.
*$p < .10$.
**$p < .05$.
***$p < .01$.

Table 9. Moderating Results for PPI Effects on Buyer Spending.

Proposition	1 Daily Spending Amount P_7: −	2 Log (Daily Spending Amount) P_7: −	3 Daily Orders P_7: −	4 Log (Daily Orders) P_7: −	5 Order Value P_7: −	6 Log (Order Value) P_7: −
TreatmentGroup × AfterPPI × Prior Review Rating	−.177***	−.012***	−.004***	−.003***	−.066*	−.006*
	(.056)	(.002)	(.001)	(.000)	(.036)	(.003)
TreatmentGroup × AfterPPI	1.570***	.143***	.050***	.031***	1.242***	.127***
	(.198)	(.008)	(.002)	(.002)	(.094)	(.008)
Prior Review Rating × AfterPPI	.352***	.027***	.010***	.006***	.015	.003**
	(.052)	(.002)	.000	(.001)	(.015)	(.001)
Average review rating	.163***	.015***	.004***	.003***	−.028	−.003
	(.054)	(.003)	(.001)	(.001)	(.036)	(.004)
Cumulative purchase incidences	−.670**	−.060***	−.025***	−.014***	−.499***	−.052***
	(.290)	(.007)	(.001)	(.001)	(.087)	(.009)
Lagged DV	−.042***	.000	.117***	.060***	2.179***	.245***
	(.000)	(.000)	(.012)	(.003)	(.215)	(.016)
Individual fixed effect	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y
Buyers	122,808	122,808	122,808	122,808	122,808	122,808
Observations	4,175,472	4,175,472	4,175,472	4,175,472	4,175,472	4,175,472
R squared	.404	.388	.627	.475	.374	.605

Notes: Clustered standard errors at the individual buyer level are in parentheses. Coefficients in the first row of the estimation results provide empirical support for our P_7.
*$p < .10$.
**$p < .05$.
***$p < .01$.

Thus, our data do not support either P_6 or $P_{6\_competing}$ in the short run. It is important to note several critical caveats here: (1) Our analysis is based on a relatively short period with only 20 days before the glitch was fixed. Although we find a significant impact of PPI on seller revenue and buyer spending in the same short time frame, sellers' opportunistic behaviors (and buyers' adverse selection) may take a longer time to observe. (2) Our results are based on the current buyers and sellers in a fixed panel dataset, excluding new entries. PPI may induce especially more opportunistic behaviors among new sellers (Cai et al. 2013; Roberts 2011), which is beyond the scope of data samples. Finally, (3) the insignificant results of sellers' opportunistic behaviors may also be explained by the possibility that sellers simply did not know about the glitch that delayed the PPI for some buyers (and thus did not directly observe the PPI dosage) and therefore did not act on it opportunistically.

Results for the Moderating Role of Buyers' and Sellers' Prior Experiences

We measured buyers' prior experience using their review ratings before PPI implementation (the higher the prior review ratings posted, the better the prior experience). To explore how the effect of PPI varies across buyers with different prior experiences, we used a difference-in-difference-in-differences (DDD) model, as shown in the following:

$$\begin{aligned}\text{Buyer}_{\text{it}} = {} & \alpha_{20} + \alpha_{21}\,\text{TreatmentGroup}_{\text{i}} \times \text{AfterPPI}_{\text{t}} \\ & \times \text{Prior Review Rating}_{\text{i}} + \alpha_{22}\,\text{TreatmentGroup}_{\text{i}} \\ & \times \text{AfterPPI}_{\text{t}} + \alpha_{23}\,\text{Prior Review Rating}_{\text{i}} \times \text{AfterPPI}_{\text{t}} \\ & + \alpha_{24}\,\text{Buyer}_{\text{it}-1} + \alpha_{25}\,\text{X}_{\text{it}-1} + \theta_{\text{i}} \\ & + \tau_{\text{t}} + \varepsilon_{2\text{it},}\end{aligned} \tag{3}$$

where $\text{Prior Review Rating}_{\text{i}}$ is a continuous variable on buyer i's averaged cumulative review ratings posted before PPI implementation. As shown in Table 9, the coefficient of the three-way interaction term is negative and significant ($p < .1$) in columns 1 through 6. We also conducted a floodlight analysis (Spiller et al. 2013). As shown in Web Appendix F, the results suggest that, within our data range, there is no Johnson–Neyman point in the downward slope. In other words, the effect of PPI on buyer spending is highly robust and fully observed across the whole data range of review ratings (from 1 to 5 stars). Thus, we find support for P_7: the positive effect of PPI on buyer spending is amplified for buyers with worse (rather than better) prior experiences (Web Appendix G reports similar moderating results for other outcome variables.)

In addition, we measured sellers' prior experience using their tenure on the platform. We estimated PPI effects across sellers with different prior experience with the following DDD model:

Table 10. Moderating Results for PPI Effects on Seller Revenue.

Proposition	1 Daily Revenue P_8: −	2 Log (Daily Revenue) P_8: −	3 Number of Orders P_8: −	4 Log (Number of Orders) P_8: −
PPI Dosage × AfterPPI × Tenure	−4.565**	−.023***	−.125**	−.017***
	(1.788)	(.005)	(.044)	(.004)
PPI Dosage × AfterPPI	537.455***	3.979***	16.355***	2.835***
	(128.041)	(.658)	(3.504)	(.450)
Tenure × AfterPPI	.505**	.002***	.014***	.002***
	(.174)	(.001)	(.004)	(.000)
Average review rating	.113	.001***	.002	.001***
	(.076)	(.000)	(.002)	(.000)
Cumulative reviews	.000	−.000***	.000*	−.000***
	(.000)	(.000)	(.000)	(.000)
Lagged DV	.183***	.000***	.238***	.015***
	(.012)	(.000)	(.008)	(.001)
Individual seller fixed effect	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y
Kitchens	3,069	3,069	3,069	3,069
Observations	104,346	104,346	104,346	104,346
R squared	.449	.222	.542	.326

Notes: Clustered standard errors at the individual seller level are in parentheses. Coefficients in the first row of the estimation results provide empirical support for our P_8.
*$p < .10$.
**$p < .05$.
***$p < .01$.

$$\begin{aligned}\text{Seller}_{jt} = {} & \beta_{20} + \beta_{21}\,\text{PPI Dosage}_j \times \text{AfterPPI}_t \times \text{Tenure}_j \\ & + \beta_{22}\,\text{PPI Dosage}_j \times \text{AfterPPI}_t + \beta_{23}\,\text{Tenure}_j \\ & \times \text{AfterPPI}_t + \beta_{24}\,\text{Seller}_{jt-1} + \beta_{25}\,Q_{jt-1} + \gamma_j \\ & + \tau_t + \mu_{2jt,}\end{aligned} \tag{4}$$

where Tenure_j is a continuous measure for seller j's length of operation (in months) on the platform before PPI implementation. As reported in Table 10, columns 1 through 4, the coefficient of the three-way interaction term is negative and significant ($p < .05$), supporting P_8: The positive effects of PPI on seller revenue are amplified for sellers with shorter (vs. longer) prior experience.

Additional Results with Heckman Correction for Unobservable Factors

Note that because the PPI launch was exogenous to the buyers' app update decision, the control group of buyers with the outdated app version is valid in our DID models. However, the nonrandomness of the app update decision could have resulted in a nonrandom assignment of the treatment in our data. To mitigate the endogeneity concern regarding unobserved factors, we applied a two-stage Heckman correction procedure (Heckman 1979; Narang and Shankar 2019). In the first stage, we modeled the endogenous app update decision using buyer profile information. The buyer's decision to provide profile information may have directly affected their decision to update the app (satisfying the inclusion rule), and this profile information does not directly influence buyer purchase activities (satisfying the exclusion rule) (Proserpio and Zervas 2017; Zhang et al. 2016). By using a vector of the buyer profile variables listed in Table 2, Panel A, we fit a probit model in the first stage to estimate the buyer's probability of updating the app. Then, to account for any unobservable factors related to the buyer's app update decision, we computed the inverse Mills ratio (IMR) in the first stage and augmented IMR as an additional variable in Equation 2 in the second stage to test the PPI effects. The results of the first-stage self-selection probit model of the app update decision are reported in Web Appendix H, Table A. As expected, a more complete buyer profile is associated with a higher probability of app update. Also, Web Appendix H, Table B, shows the model estimations with IMR as an additional control variable. The coefficient of IMR accounts for potential self-selection bias affecting the outcome variables. Our results show that the coefficient of IMR is negative and significant ($p < .01$), suggesting that the selection correction term adjusts the identified effects downwardly. Still, all results for the effects of PPI on buyer spending and seller revenue are robust to accounting for self-selection bias in the Heckman correction model.

Additional Results Accounting for Seller Spatial Correlations

One assumption in Equation 2 is that the error term is independent across sellers. However, two sellers close to each other may have similar PPI dosage levels, resulting in cross-seller dependence in the error term. To address this concern, we

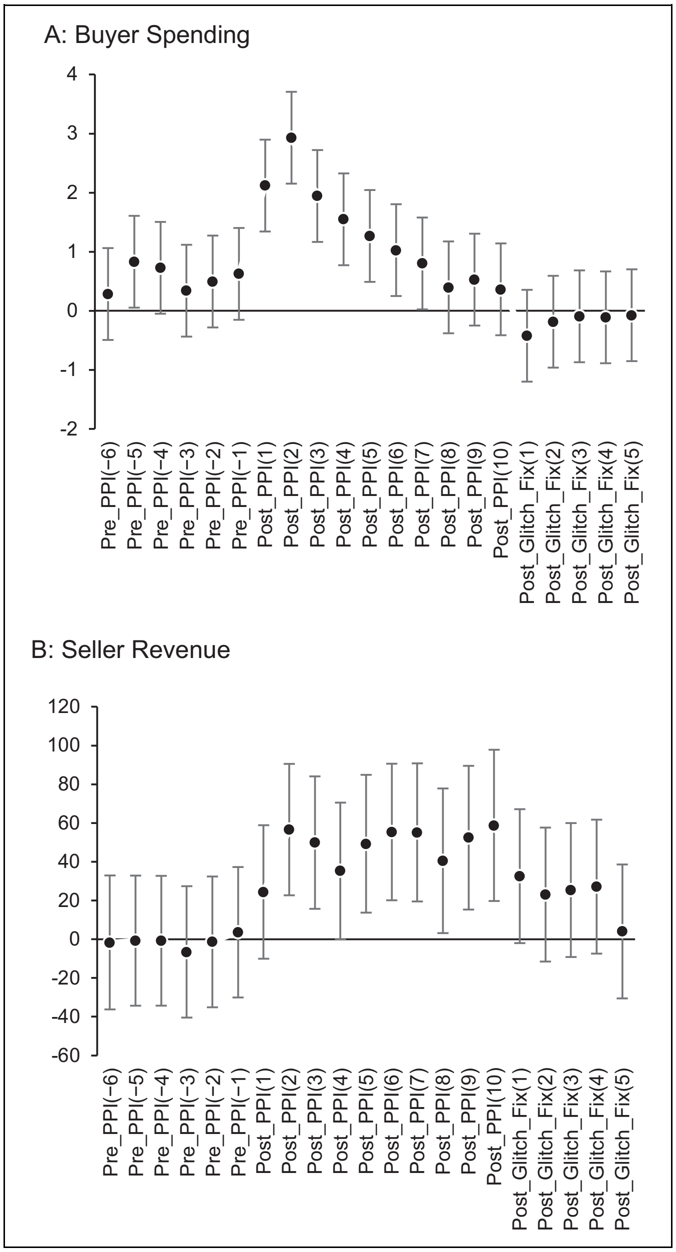

Figure 3. Results for the parallel trend.

Notes: The x-axis lists a two-day time interval before and after the PPI launch, and the y-axis displays the relative effect size of PPI.

applied a spatial autoregressive (SAR) approach that included spatial lags of dependent variables with SAR errors (Pesaran and Tosetti 2011). This approach allowed us to estimate the effect of PPI on seller revenue under the condition that outcomes in one specific region may be correlated with outcomes of nearby sellers. Using the location information of each seller, we constructed the spectral-normalized inverse-distance spatial weighting matrix W to correct for this spatial correlation concern. We implemented the SAR model for panel data using the Stata 16.0 spxtregress package and report the results in Web Appendix I. We find that coefficients of PPI Dosage × After-PPI remain positive and significant after spatial correlation is accounted for, thus adding more robust evidence for the positive effect of PPI on seller revenue.

More Robustness Checks

First, we formally tested the parallel trend assumption of DID models. Following the extant literature (Proserpio and Zervas 2017; Wang and Goldfarb 2017; Zhang et al. 2016), we tested the parallel trend assumption of DID using the following models:

$$\begin{aligned}\text{Buyer}_{it} = {} & \alpha_{30} + \alpha_{31}\,\text{TreatmentGroup}_i \times \text{TimeInterval}_t \\ & + \theta_i + \tau_t + \alpha_{32}\,X_{it-1} + \varepsilon_{3it}\end{aligned} \tag{5}$$

$$\begin{aligned}\text{Seller}_{jt} = {} & \beta_{30} + \beta_{31}\,\text{PPI Dosage}_j \times \text{TimeInterval}_t + \gamma_j \\ & + \tau_t + \beta_{32}\,Q_{jt-1} + \mu_{3jt},\end{aligned} \tag{6}$$

where TimeInterval_t is the partitioned time around the PPI launch date: we have a total of 22 time intervals for the 44 days in our data (on a two-day interval scale), and the first interval is the reference baseline. We estimated the models and plotted the values of α_{31} and β_{31} together with their 95% confidence intervals. Figure 3 supports that α_{31} and β_{31} are indeed not statistically different from zero during the period of Pre_PPI (-6) to Pre_PPI (-1), confirming the parallel trend in our DID models. (We also find similar parallel trend results for other buyer- and seller-side outcome variables in Web Appendix J.)

We also conducted falsification tests. Specifically, if the effects of PPI due to the unexpected system glitch were indeed causal, we expected the identified effects to vanish after the glitch was fixed. To test this, we constructed a placebo PPI date on the fifth day after the glitch was fixed. In other words, we established a five-day period before and a five-day period after this placebo date. We then reestimated Equations 1 and 2. The results are reported in Web Appendix K. We found that coefficients of the interaction term were no longer significant for buyer spending and seller revenue, as expected. Indeed, Figure 3 also supports that α_{31} and β_{31} are not statistically different from zero in the period of Post_Glitch_Fix (1) to Post_Glitch_Fix (5): this was also expected because the glitch had been fixed. These insignificant coefficients are also consistent with the model-free evidence shown in Figure 2. As a result, our data pass the falsification tests.

Ruling out Alternative Explanations

This section rules out several alternative explanations. First, PPI may increase buyer spending because the financial compensation of insurance has an economic value. However, archival records from the platform company suggest that the actual insurance claim rate is very low: less than one out of a million transactions. This suggests that our findings on the effects of PPI are not driven by the economic value of insurance but rather by the signaling value of PPI on the sharing platform (which is good news for the platform because high claim rates would mean high financial costs).

Second, the effects of PPI may be driven by the entry of new buyers and sellers (i.e., more social influence and network effects). However, this alternative explanation can be ruled out because our data samples were based on a fixed group of buyers and sellers—there were no new buyers or sellers on the platform in our data.

Third, the results may be driven by other confounds. For example, PPI can put pressure on sellers to improve their product quality. Thus, we tested whether sellers altered their product quality by replacing the dependent variable in Equation 2 with sellers' average review ratings. The results in Table 8, column 4, show that coefficients of TreatmentGroup × After-PPI are statistically insignificant, suggesting that there was no significant change in seller quality after PPI implementation. (Also, the insignificant coefficient of TreatmentGroup × After-PPI in Table 6, column 2, adds corroborating evidence because buyers' review ratings of the sellers did not change after PPI implementation either.)

Discussion

On the basis of a natural experiment with more than 5.4 million data points, our study quantifies the magnitude of the causal impact of PPI in the sharing economy and finds that PPI significantly increases buyer spending and seller revenue. It also uncovers nuanced buyer-side and seller-side responses that enable these benefits. We find that PPI boosts buyer spending by increasing product orders and variety-seeking behavior. In addition, PPI enhances seller revenue by increasing customer acquisition and retention. Furthermore, the effects of PPI are amplified for buyers with worse prior experience and sellers with shorter tenure experience on the platform. These findings make several contributions to research and have broad implications for practice.

Research Contributions

This study makes several contributions to the literature. To the best of our knowledge, this is the first study in the nascent sharing economy literature that focuses on the platform governance policy of PPI. Prior studies merely conceptualize the sharing economy's role in marketing (Eckhardt et al. 2019; Perren and Kozinets 2018) and address platform governance by examining review reputation systems and product designs (Cui, Li, and Zhang 2020; Zervas, Proserpio, and Byers 2017). Extending this burgeoning literature, we put the spotlight on a different platform-level governance: PPI. The topic of PPI is critically important because a core challenge in the sharing economy is how to reduce purchase risk and safeguard the welfare of consumers who are connected to unbranded individual sellers, an issue of great importance to policy makers (Federal Trade Commission 2016; PwC 2016). Indeed, research has urgently called for empirical work to develop ways of reducing consumer risk on sharing platforms (Eckhardt et al. 2019). Our research responds directly to this call: we propose that PPI may lower consumers' perceived risk and boost their total utility by providing a trustworthy quality signal through an official third-party seal before the transaction and potential loss coverage after it. Furthermore, Lamberton and Rose (2012, p. 122) note that "[consumers'] perceived risk of product scarcity is a major driver of sharing propensity in commercial sharing systems." Extending their study, we not only reveal that PPI is a platform governance policy that may lower consumer risks and improve the efficacy of sharing platforms, but also account for both how PPI alters buyer and seller behaviors and what types of buyers and sellers benefit more or less from it in the sharing economy.

Moreover, our work complements and extends the literature on buyer protection policies. Prior studies have focused on buyer protection with product guarantee and documented mixed results: Roberts (2011) finds an insignificant impact, whereas Cai et al. (2013) note a negative effect, and Hui et al. (2016) report a positive impact. Indeed, product guarantee can be ineffective in restoring consumer trust and thus fails to boost the efficacy of online platforms, especially when dodgy sellers do not face a penalty (Cai et al. 2013; Roberts 2011). Extending this stream of research, our work is the first to identify the efficacy of an alternative buyer protection program of PPI. This is nontrivial because platforms are challenged to simultaneously protect consumers and regulate sellers who may behave opportunistically. Eckhardt et al. (2019, p. 10) note that "platforms do not typically produce offerings, they cannot control quality or guarantee consistency.... Individual service providers have high levels of agency ... a dark side of the sharing economy." We agree and add that PPI helps overcome this challenge by engendering significantly beneficial buyer-side and seller-side responses. Also, we reveal another new insight overlooked in the literature: the protection benefits of PPI are amplified for more vulnerable players (i.e., buyers with worse prior experience and sellers with less prior experience on the platform).

Furthermore, our work contributes to the literature on insurance. Although ample research has noted the benefits of insurance in the context of retailing (Chu and Chintagunta 2011; Heal 1977; Johnson et al. 1993; Kunreuther 2006; Skogh 1989), we extend the literature by (1) focusing on platform insurance in the context of the sharing economy, (2) examining multiside responses to platform insurance, (3) exploring the heterogeneous effects across buyers and sellers, and (4) quantifying the magnitude of the insurance benefits through a rigorous research design with causality inference and large sample sizes. These extensions are pivotal because they enrich our understanding of how insurance works in the broad economy. Both the multifaceted buyer-side and seller-side responses to PPI and the heterogeneous effects of PPI across different buyers and sellers are crucial for a comprehensive portrait of the economic value of insurance, yet they remain hidden in the literature. In other words, we extend the insurance literature by uncovering the far-reaching roles platform insurance could play for the sharing economy.

Our research methods based on a large-scale natural experiment can measure the causal impact of PPI in a way that is both valid (glitch-based) and reliable (large-sample based). Such scientific methods are useful for marketing research: In situations where a randomized field experiment is unethical or infeasible, researchers can rely on natural experiment methods to estimate causal effects after accounting for endogeneity and unobserved confounds. Future work may use natural experiment designs as a way of identifying the causal impact of other sharing platform policy and design changes (Eckhardt et al. 2019; Ramaswamy and Ozcan 2018). For example, scholars can use unexpected shocks to identify the causal effects of Airbnb Superhosts and Upwork Rising Talent, a pivotal but underresearched platform feature in the sharing economy.

Managerial Implications

Our research also offers some useful and actionable implications for platform managers. First, managers can use PPI to affect buyer and seller behaviors and subsequent business performance. Our findings on the multifaceted buyer-side and seller-side behavioral responses suggest that PPI may empower platforms to nurture trust among consumers and boost sales transactions for sellers, which will improve the business performance of sharing platforms. Our results on whether and how PPI affects the efficacy of sharing platforms also enable platform managers to better communicate and build trusting relationships with external stakeholders to gain more institutional legitimacy from public policy makers, raise funding from venture capital and stock markets, and boost platform reputation in news and social media. Building a trusting relationship with both internal and external stakeholders in the ecosystem is crucially important for the long-term survival and success of the sharing economy (Eckhardt et al. 2019; Perren and Kozinets 2018).

Furthermore, platform managers may craft more targeted communication strategies across different user segments to earn higher returns on PPI. For example, PPI has a stronger beneficial impact for buyers with worse prior experience and for sellers with less experience on the platform. Thus, for these customers who are more vulnerable and are in dire need of protection in the marketplace, a targeted marketing message that emphasizes the risk-reduction benefit of PPI might offer a more effective signal to boost their purchase confidence on the sharing platform (Eckhardt et al. 2019; Lamberton and Rose 2012).

Moreover, to justify sharing platforms' investment in PPI, platform managers are often challenged to scientifically quantify the causal impact because randomized field experiments that protect some buyers through insurance but exclude others are unethical in the real world. Our DID modelling with two-way fixed effects based on a natural experiment, which can mitigate the endogeneity concerns, provides managers with a viable solution or toolbox to scientifically gauge the causal impact of insurance and other platform governance policies in the sharing economy.

Limitations and Future Research

Our study has several limitations, which serve as opportunities for future research. First, our data are limited to the food-sharing platform context. It would be worthwhile for future research to examine whether our findings are generalizable to sharing platforms in other settings and industries. Second, our analyses are based on a relatively short time window. A clear limitation in our study is that our data cannot measure the possible long-term opportunistic behaviors of sellers and adverse selection of buyers in the wake of PPI. Thus, future studies with appropriate data could extend our results by examining the long-term impact of PPI. Third, our sample selection procedures ensured that buyers and sellers had at least one transaction to rule out alternative explanations. Thus, our results capture the intensive margin with a fixed set of current buyers and sellers. Future studies may examine the extensive margin regarding the effects of PPI on attracting new entries of buyers and sellers in the sharing economy.

In conclusion, this study is an initial step in exploring the causal impact of PPI on a sharing platform. We hope that it will stimulate more scholarly works on platform governance and consumer protection in the sharing economy.

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