Consumer Decision-making under Uncertainty on Digital Platforms*

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February 20, 2020

Abstract

Inspired by the ride-sharing market in New Zealand, with Uber and Zoomy offering respectively a fixed price and an estimated price range per ride, we ask ourselves if competitors in the digital economy could deliberately offer distinct pricing schemes aimed at serving consumers with different levels of ambiguity tolerance to gain market shares. Our results suggest that in spite of the realistic asymmetric distribution of ambiguity-loving versus ambiguity-averse consumers - calibrated with the distribution of the attitudes toward ambiguity obtained in a suitable preliminary laboratory experiment - in equilibrium both platforms offering respectively a fixed price and an estimated price range per ride can coexist in the market: Ambiguity-loving consumers are attracted toward the price range offers, whereas ambiguity averse consumers shy away from them.

Keywords: ambiguity, ride-sharing, digital platforms, experiments
JEL codes: C91, D11, D21, D43, D81, D9, L11

*For their suggestions and comments, we would like to thank Simon Anderson, Mark Armstrong, Francis Bloch, Hülya Eraslan, Simon Grant, Steffen Lippert, Addison Pan, John Panzar, Thomas Pfeiffer, Antonio Rosato, Matthew Ryan, Karl Schlag, Frank Staehler, James Tremewan, and Julian Wright, as well as participants in the 2019 Microeconomics Study Group Meeting in Auckland, the "Knowledge Science Theme: Centre for Mathematical Social Science Lightning Talks Event" in Auckland, the "Economic Theory Mini-Workshop" in Auckland, the 4th Asia-Pacific Industrial Organisation Conference in Tokyo, and the 38th Australasian Economic Theory Workshop in Adelaide. Any remaining errors are our own responsibility.

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1 Introduction

The past decade has seen the rise of ride-sharing platforms in the point-to-point transport industry. In 2018, the global uptake of ride-sharing services was around 11.8%, which translates to 858 million riders worldwide (Statista, 2019). The ride-sharing market has also contributed to the global digital economy, generating a total revenue of USD 153 billion in the same year. The user penetration rate is projected to reach 20% or 1,500 million riders in 2023, raking in an estimated revenue of USD 319 billion.

Ride-sharing platforms are known as digital platforms — two or multisided markets — that facilitate transactions between riders and drivers. In the ride-sharing context, consumers or riders could install ride-sharing apps on their phones for free; they could easily multihome with low switching costs. Through free-to-install apps, consumers could compare the prices of ride-sharing services across different platforms before requesting a ride on their chosen platform in any instance.

As ride-sharing services are relatively homogeneous in nature, pricing becomes an important factor in the consumers' decision-making process when they choose between competing platforms. Platform operators could segment the market by offering different pricing schemes to appeal to consumers with heterogeneous preferences. Rochet and Tirole (2003) explored asymmetric pricing between competing platforms to attract users from different sides of the market, whereas Belleflamme and Peitz (2019) looked into pricing mechanisms to overcome competitive bottlenecks, when users from one side of the market (but not the other) could multi-home. Note, however, that the latter is less relevant in the ride-sharing market, as both riders and drivers could multihome[1].

Ambiguity attitudes have been known to influence individual decision-making under unknown scenarios. Put simply, ambiguity can be defined as uncertainty that cannot be measured in an objective manner. For instance, a situation in which the probability distribution of events related to an agent's decision-making process is unknown could be a source of ambiguity. Faced with ambiguous information about an event, the decision-maker forms certain beliefs about the probabilities of the outcomes and chooses the associated action that maximises their expected utility. Based on a decision-maker's action, that individual could be categorised as an ambiguity averse, ambiguity neutral or ambiguity seeking agent in decision theory.

A platform could improve its competitiveness by implementing a pricing scheme which appeals to consumers with different ambiguity preferences. This strategy is not new. There is some anecdotal evidence on the exploitation of heterogeneity in consumer ambiguity attitudes in the marketplace. For instance, it is not uncommon for operators in the hospitality industry to adopt strategies to cater to ambiguity seeking consumers, ranging from Expedia's Secret Saver Hotels[2] to Air New Zealand's Mystery Breaks™. For the latter, the mystery destination is unknown to the consumer at the time of booking and is revealed to the buyer on the day prior to travelling. Here, the principal (seller)

[1] In many jurisdictions, drivers are recognised as independent contractors (not employees) of ride-sharing platforms. While the independent contract classification remains a contentious issue in labour law, it offers flexibility for drivers to work for multiple platforms simultaneously – a common feature in the gig economy.

[2] Currently discontinued.

capitalises on incomplete information, given that the exact characteristics of the good are known to the principal, but not fully known to the agent (buyer); this is known as the informed principal problem. Balestrieri and Izmalkov (2014) explored how buyers could be price discriminated based on their valuation for the seller's private information about the characteristics of the product.

In New Zealand, competing ride-sharing platforms — Uber and Zoomy — implement different pricing schemes that can attract consumers with varying levels of ambiguity tolerance. Uber offers upfront pricing for each ride, whereas rival platform Zoomy offers a price range estimate for the same ride to a consumer. Uber's upfront pricing provides certainty to the consumer on the final amount they would be charged for a ride, while Zoomy's price range estimate introduces ambiguity to the consumer's decision-making process, as the final price of the same ride is not explicitly determined beforehand.

As part of our research, we recreated the experience of a multihoming consumer in the New Zealand ride-sharing market. At 3:48pm on the 28th of August, 2019, we logged onto Uber and Zoomy to check the real-time prices of a ride on either platform – with a 30-second lapse – from the University of Auckland to Ponsonby Central. We received a fixed quote of NZD 10.54 from Uber and a price range estimate of NZD 10 – NZD 13 from Zoomy. Our anecdotal evidence suggests that Uber and Zoomy could be performing market segmentation based on the consumers' ambiguity attitudes to gain market share. In this context, a consumer who uses Zoomy's service does not know a priori the exact price of a ride, as the cost would vary according to factors such as real-time traffic conditions and the final route taken by the driver for the given trip. Faced with different pricing schemes, a consumer's ambiguity attitude could influence whether they choose to accept the service from Uber or Zoomy. Interestingly, Uber may be able to offer a fixed quote that is close to the maximum price of Zoomy's price range estimate. If Uber were to exercise this strategy, it could hint at the practise of imposing an ambiguity premium for each ride, as consumers who opt for Uber are more willing to pay a higher price for certainty in the final cost of a ride.

Drawing on Savage's (1954) Subjective Expected Utility (SEU) model, the sure-thing principle states that uncertainty should not change an agent's choice between two acts, if that uncertainty does not affect their preference over those two acts. A classic counterexample of the sure-thing principle is Ellsberg paradox (1961): a person prefers to bet in situations for which they know specific odds, rather than in situations with ambiguous odds. Ellsberg demonstrated the violation of sure-thing principle through the well-known two-colour urn thought experiment, and concluded that individuals may face situations where they do not obey the usual probability rules as described in the SEU model. Despite the shortcomings of Savage's SEU model, it could be adapted to represent the behaviour of ambiguity neutral agents, who act as if they attach subjective probabilities to the set of possible outcomes.

Other notable examples on utility representations under ambiguity in the literature include: MaxMin EU model (Gilboa & Schmeidler, 1989), MaxMax EU model (Gilboa & Schmeidler, 1989) and α-MaxMin EU model (Hurwicz, 1951). MaxMin EU model could be used to represent ambiguity aversion: the agent places a weight of one to the minimum expected utility and zero to the maximum expected utility. Under the

MaxMin EU model, we have an extremely pessimistic agent, who perceives Nature to be malevolent and maximises their expected utility from the worst case scenario. Next, we have the MaxMax EU model which illustrates the behaviour of ambiguity loving individuals: the agent places a weight of zero to the minimum expected utility and one to the maximum expected utility. Here, the MaxMax EU model represents the behaviour of an extremely optimistic agent, who assumes that Nature is benevolent and proceeds to maximise their expected utility from the best case scenario.

The convex combination of the former two — α-MaxMin EU model — is based on the Hurwicz Criterion (Hurwicz, 1951). The α-MaxMin EU model allows us to model an agent who selects the option that maximises their expected utility, based on the weighted average of the best and worst outcome for any given event. The parameter $\alpha \in [0, 1]$ denotes the relative degree of optimism and pessimism of the agent regarding the possible outcomes of an event. Our motivation to include the aforementioned models is supported by Hey, Lotito and Maffioletti (2010), who, in their study, found that relatively simple models, such as the MaxMin EU model, may offer better predictive power than more elegant theoretical frameworks in modelling decision-making under ambiguity.

Finally, we draw on Prospect Theory (Kahneman & Tversky, 1979) to model individual decision-making under pricing-related ambiguity. Specifically, we hypothesise that reference dependence and loss aversion may distort how an individual respond to ambiguity. The agent may perceive Uber's fixed price option as a reference point and form their decision based on the expected gains or losses with respect to the reference point, thus justifying Zoomy's pricing mechanism as a strategy to compete more effectively with Uber, in order to improve Zoomy's position in the ride-sharing market. In addition, assuming that an agent chooses between competing platforms to minimise the cost of a ride, the agent's ambiguity attitude in the loss domain could influence their decision-making process. In particular, we hypothesise that loss aversion, the over-weighing of certainty and status quo bias could be relevant to the decision-maker in the ride-sharing context. In fact, we may be able to draw parallels between decision-making under risk and ambiguity: an agent could be more ambiguity seeking in the domain of losses.

While many studies[3] have explored decision-making under ambiguity, little discussion has been around how individuals respond to ambiguity in competing pricing schemes. To the best of our knowledge, we are the first to look at the role of ambiguity attitudes in user multihoming, as well as competition between ride-sharing platforms. In our research, we aim to study: (i) how individuals form decisions when they face distinct pricing schemes from competing ride-sharing platforms; and (ii) whether platforms could offer distinct pricing schemes to serve consumers with different ambiguity attitudes and improve their position in the market.

We conduct a laboratory experiment to investigate how ambiguity attitudes and different types of utility representations affect individual decision-making under ambiguous pricing information. In particular, our objective is to test our theoretical model in a laboratory setting, to assess the degree to which our theoretical predictions align with

[3] Grant, Rich, and Stecher (2019) offer a generalisation of expected utility representations for decision-making under ambiguity which mirrors ordinal utility functions over commodities. Fabrizi, Lippert, Pan, and Ryan (2019) provide a theoretical and experimental approach to model collective decision-making in a voting game among ambiguity averse voters.

experimental evidence. The experimental data from our study can support firms in optimising their pricing models and improving their competitiveness in the digital economy. With our study, we could also gain insights on consumer welfare, and how it is affected by the offering of competing pricing schemes – both fixed price and price range options – that are offered to prospective consumers before they purchase ride-sharing services.

2 The Model

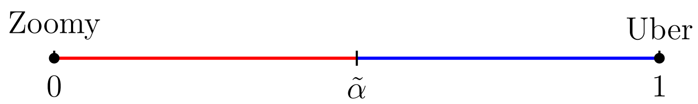
2.1 Model Setup

We represent our market via a modified Hotelling (1929) model. Suppose we have two ambiguity neutral platforms – Uber and Zoomy – operating in the same market. For simplicity, we normalise the mass of consumers in the market to 1. A consumer's valuation of a ride from either Zoomy or Uber is the same and equal to V. Each consumer perceives the price of a Zoomy ride as $\widetilde{p}_z \in [\,\underline{p}\,,\,\overline{p}\,]$.

We consider the ambiguity attitudes of consumers as locations along the Hotelling unit line and denote the parameter for the relative degree of optimism and pessimism of a consumer as $\alpha \in [0,1]$, which is drawn from a continuous distribution f(α). Following the α-MaxMin EU rule, each consumer places a weight of α on the best case scenario, $\underline{p}$ and $(1-\alpha)$ on the worst case scenario, $\overline{p}$. This gives us what each consumer perceives the price of a Zoomy ride to be, based on their ambiguity tolerance level, such that

$$\widetilde{p}_z = [\ \alpha\bar{p} \,+\, (1-\alpha)\underline{p}\ ]$$

Note that the degenerate cases $\widetilde{p}_z = \bar{p}$ and $\widetilde{p}_z = \underline{p}$ correspond to the MaxMin EU rule ($\alpha = 0$) and MaxMax EU rule ($\alpha = 1$) respectively. Since Uber offers a fixed price p_u and Zoomy offers a price range $[\,\underline{p}\,,\,\overline{p}\,]$ for the same ride, we place Uber on the right end of the Hotelling line. This is because Uber's fixed price offer would attract consumers who are more ambiguity averse. Following the same logic, we place Zoomy at the left extreme end, since Zoomy's pricing scheme would appeal to the more ambiguity loving consumers. We denote $\widetilde{\alpha}$ as the ambiguity attitude of the indifferent consumer, as shown below



The indifferent consumer will derive the same surplus from accepting a ride from either Uber or Zoomy. This is given by

$$V \,-\, \widetilde{p}_z \,=\, V \,-\, p_u$$

Plugging in the perceived price of a Zoomy ride by the indifferent consumer, we obtain

$$V - [\,\tilde{\alpha}\bar{p} + (1-\tilde{\alpha})\underline{p}\,] = V - p_u$$

$$\Rightarrow \tilde{\alpha} = \frac{p_u - \underline{p}}{\bar{p} - \underline{p}} = \frac{p_u - \underline{p}}{\triangle p} \tag{1}$$

Therefore, the *conditional expected price Zoomy can charge consumers* is equivalent to the conditional mean of the perceived price of those consumers who would be accepting a ride with Zoomy, that is those with ambiguity attitudes up to $\tilde{\alpha}$:

$$E[\tilde{p}_z|\alpha \leq \tilde{\alpha}] = \frac{1}{\int_0^{\tilde{\alpha}} f(\alpha)\, d\alpha} \int_0^{\tilde{\alpha}} [\,\alpha\bar{p} + (1-\alpha)\underline{p}\,]\, f(\alpha)\, d\alpha \tag{2}$$

Assumption 1 *The consumers' attitudes toward ambiguity follow a Beta distribution respectively with probability and cumulative density distributions satisfying*

$$f(\alpha; a=4, b=2) = 20\,\alpha^{a-1}\,(1-\alpha)^{b-1} = 20\,\alpha^3\,(1-\alpha)$$

and

$$F(\alpha; a=4, b=2) = 20\left(\frac{\alpha^4}{4} - \frac{\alpha^5}{5}\right)$$

Graphically:

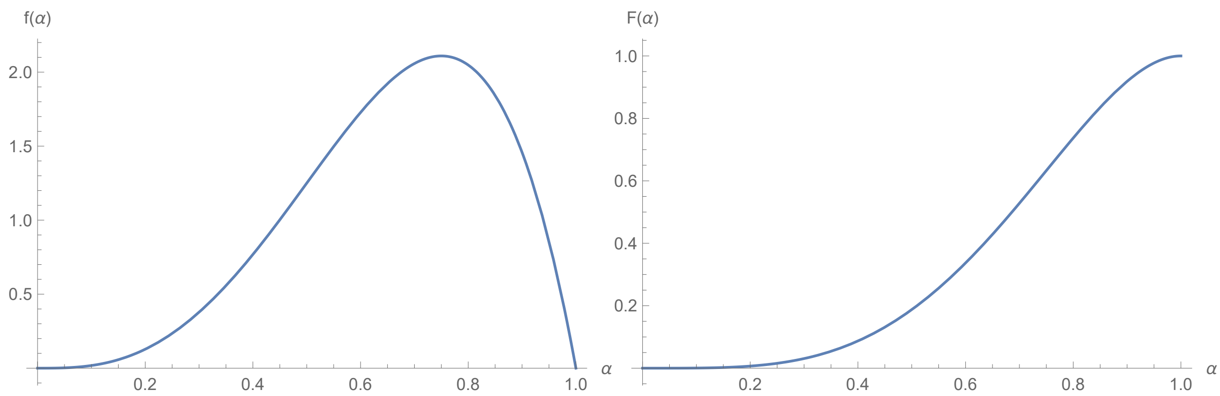


Figure 1: Beta distributions for the density, $f(\alpha; a=4, b=2)$, and cumulative, $F(\alpha; a=4, b=2)$, functions of consumers' attitudes toward ambiguity, α, with $0 \leq \alpha \leq 1$.

These are plausible distributions of consumers' attitudes toward ambiguity. They account for a minority of ambiguity-loving types relative to SEU/Neutral and ambiguity averse types in any given groups of individuals. This asymmetry closely captures typical distributions of attitudes toward ambiguity, and it is also consistent with the observed attitudes which were recently elicited in a series of experiments conducted in the DECIDE Lab at the University of Auckland. One of these experiments was conducted as a preliminary calibration exercise for this project, and another one as part of a related project on decision-making under ambiguity.[4] From those experiments, it emerged that

[4]See more on the experimental design used to elicit subjects' attitudes toward ambiguity in Section 3.2 of this study, and Fabrizi, Lippert, Pan and Ryan (2019) for a related experiment.

the proportion of ambiguity loving types, characterised by $\alpha < 1/2$, consistently ranged between 10% and 20%. Accordingly, the associated cumulative distribution function for this Beta distribution allows for a minority of ambiguity-loving types, totalling 18.75% of the entire population, which is well within the empirically observed range.[5]

Consequently, by using this Beta distribution the conditional expected price Zoomy can charge consumers can be rewritten as follows

$$E[\widetilde{p}_z|\alpha \leq \widetilde{\alpha}] = \frac{1}{\int_0^{\tilde{\alpha}} 20\,\alpha^3\,(1-\alpha)d\alpha} \int_0^{\tilde{\alpha}} [\ \alpha\bar{p}\ +\ (1-\alpha)\underline{p}\ ]\ 20\,\alpha^3\,(1-\alpha)\,d\alpha \tag{3}$$

We can next compute the corresponding profits for Zoomy and Uber respectively, and also based on their respective market shares – which are $F(\widetilde{\alpha})$ for Zoomy and $1-F(\widetilde{\alpha})$ for Uber – before solving for their profit-maximising problems, next, to finally characterise the equilibrium fixed price and price range that would allow both ride-sharing services to eventually co-exist.

2.2 Analysis

Profit maximisation

Without loss of generality, we normalise the marginal costs of providing a ride for both Zoomy and Uber to zero.

Zoomy Let us start with deriving Zoomy's profit, which is obtained by the product of the conditional expected price Zoomy can charge consumers for a ride and the mass of consumers served by Zoomy. This leads to

$$\pi_z\ =\ E[\widetilde{p}_z|\alpha \leq \widetilde{\alpha}]\,F(\widetilde{\alpha})$$

By Assumption 1 Zoomy's profit can be rewritten as follows

$$\pi_z\ =\ \frac{1}{\int_0^{\tilde{\alpha}} 20\,\alpha^3\,(1-\alpha)d\alpha} \int_0^{\tilde{\alpha}} [\ \alpha\bar{p}\ +\ (1-\alpha)\underline{p}\ ]\ 20\,\alpha^3\,(1-\alpha)\,d\alpha \int_0^{\tilde{\alpha}}\ 20\,\alpha^3\,(1-\alpha)d\alpha$$

Or, simply:

$$\pi_z\ =\ \int_0^{\tilde{\alpha}} [\ \alpha\bar{p}\ +\ (1-\alpha)\underline{p}\ ]\ 20\,\alpha^3\,(1-\alpha)\,d\alpha$$

When solving for this integral, Zoomy's profit can also be written as:

$$\pi_z = 20\left(\frac{\widetilde{\alpha}^5}{5}\bar{p} - \frac{\widetilde{\alpha}^6}{6}\bar{p} + \frac{\widetilde{\alpha}^4}{4}\underline{p} - \frac{2\widetilde{\alpha}^5}{5}\underline{p} + \frac{\widetilde{\alpha}^6}{6}\underline{p}\right)$$

[5] It is easy to derive $F(\alpha = 1/2; a = 4, b = 2)) = \int_0^{1/2}\ 20\,\alpha^3\,(1-\alpha)d\alpha = 20\left[\frac{\alpha^4}{4} - \frac{\alpha^5}{5}\right]_0^{1/2} = 0.1875$.

Finally, plugging the value of $\widetilde{\alpha}$ as per Eq. (1) into this profit, we obtain

$$\pi_z = 20\left(\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^5 \frac{1}{5}\bar{p} - \left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^6 \frac{1}{6}\bar{p} + \left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^4 \frac{1}{4}\underline{p} - \left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^5 \frac{2}{5}\underline{p} + \left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^6 \frac{1}{6}\underline{p}\right) \tag{4}$$

We will use Eq. (A) to obtain the first order conditions for Zoomy's profit with respect to its strategic variables $\underline{p}$ and $\bar{p}$, which are part of the conditions needed to derive the equilibrium in this ride-sharing market.

Uber Before doing so, we also need to determine how Uber's profit depends on the fixed price it charges and the mass of consumers it serves, which, in turn, is the result of the interplay of all prices set in this ride-sharing market.

Uber's profit function can be easily obtained by the product of the fixed price Uber offers to each consumer for a ride and the mass of consumers it serves. This leads to

$$\pi_u \;=\; p_u\,[\,1 \;-\; F(\widetilde{\alpha})\,] \tag{5}$$

By Assumption 1, we can rewrite Uber's profit as

$$\pi_u \;=\; p_u \;\left(1 - \int_0^{\widetilde{\alpha}}\; 20\,\alpha^3\,(1-\alpha)d\alpha\right)$$

Solving for the integral, this simplifies to

$$\pi_u \;=\; p_u \;\left(1 - 5\widetilde{\alpha}^4 + 4\widetilde{\alpha}^5\right)$$

By plugging the value of $\widetilde{\alpha}$ as per Eq. (1) into this profit, we obtain

$$\pi_u \;=\; p_u \;\left(1 - 5\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^4 + 4\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^5\right) \tag{6}$$

Eq. (6) can be used to derive the first order condition for Uber's profit-maximisation problem, which together with the other two first order conditions for the profit-maximisation for Zoomy, and the non-negativity constraints for the respective market shares of Zoomy and Uber, provide us with a system of equations the solution to which characterises the equilibrium pricing in the ride-sharing market.

We summarise those profit-maximisation problems and related conditions in the table below.

Zoomy	Uber
$\max_{\underline{p}\,,\bar{p}} \left[E[\widetilde{p}_z \vert \alpha \leq \widetilde{\alpha}]\, F(\widetilde{\alpha}) \right] \; s.t. \; \widetilde{\alpha}\,,\; \underline{p}\,,\; \bar{p} \;\geqslant\; 0$	$\max_{p_u} \left[p_u \left(1 \;-\; F(\widetilde{\alpha}) \right] \; s.t. \; \widetilde{\alpha}\,,\; p_u \;\geqslant\; 0$
$\frac{\partial \pi_z}{\partial \underline{p}} \;\geqslant\; 0 \quad and \quad \frac{\partial \pi_z}{\partial \bar{p}} \;\geqslant\; 0$	$\frac{\partial \pi_u}{\partial p_u} \;\geqslant\; 0$

The profit-maximising conditions, when taken together as a system, translate into the following relationship, which needs to hold for the system to provide a solution that is compatible with the co-existence of Zoomy and Uber in the ride-sharing market. This requires the solution to be consistent with $\underline{p}^* < p_u^* < \bar{p}^*$.[6]

$$1 - \left(\frac{p_u^* - \underline{p}^*}{\bar{p}^* - \underline{p}^*} \right)^4 + 20 p_u^* \left(\frac{1}{\bar{p}^* - \underline{p}^*} \right) \left(\frac{p_u^* - \underline{p}^*}{\bar{p}^* - \underline{p}^*} \right)^3 \left(\left(\frac{p_u^* - \underline{p}^*}{\bar{p}^* - \underline{p}^*} \right) - 1 \right) = 0 \tag{7}$$

As evidenced from Tables 1-3 below, the relationship highlighted by Eq. (7) gives us infinitely many combinations of $\underline{p}^*$, $\bar{p}^*$ and p_u^* consistent with $\underline{p}^* < p_u^* < \bar{p}^*$ where Uber and Zoomy coexist. However, depending for any exogenously set spread between $\underline{p}^*$ and $\bar{p}^*$, the induced cut-off for the ambiguity types accepting a ride from Zoomy decreases as the absolute level of the prices increases, as Tables 1 and 2 are demonstrating. The only combinations of $\underline{p}^*$ and $\bar{p}^*$ which consistently guarantee that all ambiguity loving types are captured by Zoomy, is for Zoomy to set them such that $\underline{p}^* = \frac{1}{5}\bar{p}^*$.

p_u^*	$\underline{p}^*$	$\bar{p}^*$	$\widetilde{\alpha}^*$
0.95	0.5	1.5	0.45
1.38	1	2	0.38
1.84	1.5	2.5	0.34
2.31	2	3	0.31
2.79	2.5	3.5	0.29

Table 1: Equilibrium cut-off for ambiguity loving types and associated optimal pricing in the ride-sharing market for $\bar{p}^* - \underline{p}^* = 1$

It appears that although there are infinitely many combinations for the prices Zoomy and Uber could set that are compatible with $\underline{p}^* < p_u^* < \bar{p}^*$ and that satisfy Eq. (7), it is only when $\underline{p}^* = \frac{1}{5}\bar{p}^*$ that the equilibrium cut-off for $\widetilde{\alpha}^*$ equals $\frac{1}{2}$, which corresponds with the threshold for ambiguity loving types in the market, which in turn guarantees the largest proportion of consumers susceptible to be attracted toward Zoomy.

Proposition 1 *Under Assumption 1 competing ride-sharing services exploiting heterogeneous ambiguity attitudes of consumers, could set their respective prices such that* $\underline{p}^* < p_u^* < \bar{p}^*$ *and* $\widetilde{\alpha}^* = \frac{1}{2}$*, which always holds for* $\frac{1}{5}\bar{p}^* = \underline{p}^* < p_u^* = \frac{1}{2}\underline{p}^* + \frac{1}{2}\bar{p}^* < \bar{p}^* = 5\underline{p}^*$.

[6]For a complete derivation of this condition, see Appendix A.

p_u^*	$\underline{p}^*$	$\bar{p}^*$	$\widetilde{\alpha}^*$
1.5	0.5	2.5	0.50
1.90	1	3	0.45
2.33	1.5	3.5	0.415
2.77	2	4	0.385
3.23	2.5	4.5	0.365

Table 2: Optimal pricing in the ride-sharing market for $\bar{p}^* - \underline{p}^* = 2$

p_u^*	$\underline{p}^*$	$\bar{p}^*$	$\widetilde{\alpha}^*$
3	1	5	0.50
4.5	1.5	7.5	0.50
6	2	10	0.50
7.5	2.5	12.5	0.50
9	3	15	0.50

Table 3: Optimal pricing in the ride-sharing market for $\underline{p}^* = \frac{1}{5}\bar{p}^*$

Next, we can use Proposition 1 to derive the induced optimal conditional expected price offered by Zoomy, as follows

$$E\left[\widetilde{p}_z^*|\alpha \leq \widetilde{\alpha}^* = \frac{1}{2}\right] = \frac{1}{\int_0^{\frac{1}{2}} 20\,\alpha^3\,(1-\alpha)d\alpha} \int_0^{\frac{1}{2}} [\ \alpha\bar{p}^* \ + \ (1-\alpha)\underline{p}^*\ ]\ 20\,\alpha^3\,(1-\alpha)\,d\alpha$$

Given that whenever $\widetilde{\alpha}^* = \frac{1}{2}$, we also have that $\bar{p}^* = \frac{5}{3}p_u^*$ and $\underline{p}^* = \frac{1}{3}p_u^*$, we can rewrite the optimal conditional expected price offered by Zoomy, as follows

$$E\left[\widetilde{p}_z^*|\alpha \leq \widetilde{\alpha} = \frac{1}{2}\right] = \frac{1}{\int_0^{\frac{1}{2}} 20\,\alpha^3\,(1-\alpha)d\alpha} \int_0^{\frac{1}{2}} \left[\ \frac{5}{3}p_u^*\alpha \ + \ \frac{1}{3}p_u^*(1-\alpha)\ \right]\ 20\,\alpha^3\,(1-\alpha)\,d\alpha$$

This simplifies to

$$E\left[\widetilde{p}_z^*|\alpha \leq \widetilde{\alpha} = \frac{1}{2}\right] = p_u^*\frac{23}{27}$$

Corollary 1 *Under Assumption 1, for* $\widetilde{\alpha}^* = \frac{1}{2}$ *the optimal prices in the ride-sharing market lead to* $\widetilde{p}_z^* \in \left[\frac{1}{3}p_u^*, \frac{5}{3}p_u^*\right]$*, with* $E\left[\widetilde{p}_z^*|\alpha \leq \widetilde{\alpha}^* = \frac{1}{2}\right] = p_u^*\frac{23}{27}$.

Corollary 2 *Under Assumption 1, for* $\widetilde{\alpha}^* = \frac{1}{2}$ *the corresponding market shares of competing ride-sharing services are respectively equal to* $F(\widetilde{\alpha}) = 0.1875$ *and* $(1 - F(\widetilde{\alpha})) = 0.8125$.

We draw on *Proposition 1* and Corollaries 1–2 to inform our experimental calibrations. This is elaborated in *Section 3 The Experiment*.

Consumer surplus

Using the optimal conditional expected perceived price that Zoomy could charge the mass of consumers they serve, the aggregate expected consumer surplus for the mass of consumers served by Zoomy can be computed as follows

$$CS_z = (V - E[\widetilde{p}_z^*|\alpha \leq \widetilde{\alpha}^*])\, F(\widetilde{\alpha}^*) \tag{8}$$

Conversely, the consumer surplus for the mass of consumers served by Uber consists of

$$CS_u = (V - p_u^*)(1 - F(\widetilde{\alpha}^*)) \tag{9}$$

In the market for homogeneous ride-sharing services, fierce competition between platforms would benefit consumers but not the firms; a platform would undercut their rival's pricing, driving profits down to zero. By introducing pricing schemes that would attract consumers with different ambiguity attitudes, each platform could separate the market by ambiguity types to maintain their market share at a positive profit. Price discrimination by ambiguity attitudes provides a channel that allows competing platforms to coexist in the market and extract rents from consumers to maximise profits. In this context, Zoomy could attract consumers who are more ambiguity loving by offering a price range estimate for each ride, whereas Uber would appeal to those who are more ambiguity averse through their fixed price offer.

Our model offers a glimpse into how ride-sharing platforms could implement different pricing schemes to compete in the market more effectively. In the era of big data, the growing adoption of Artificial Intelligence and learning algorithms could enhance price discrimination strategies. Through repeated data collection, a platform may be able to fine tune their pricing algorithms to devise prices that appeal to a consumer's ambiguity tolerance level, so that the platform could extract more rents from each consumer. In our static model, we do not preclude the possibility of personalised pricing, which, in its extreme form, would depict the best case scenario for Zoomy and Uber (and worst case scenario for consumers), where both platforms could extract all of the consumer surplus to maximise profits.

3 The Experiment

3.1 Price Calibrations

Based on our model, we calibrated the experimental parameters to assess the validity of our theoretical predictions. Proposition 1 and Corollaries 1–2 provide us with the unique relationship between the three strategic variables, $\underline{p}^*$, $\bar{p}^*$ and p_u^*, that sustain $\widetilde{\alpha}^* = \frac{1}{2}$. As such, we can readily obtain infinitely many prices that satisfy this relationship. Given the multiplicity of equilibria, we calibrated the experimental parameters based on two criteria: we have chosen what we perceived to be reasonable fares of a ride in the ride-sharing market; but we have also selected the prices such that the total payoffs to subjects would meet our research budget constraint.

We selected twenty-one combinations of $\underline{p}$, $\bar{p}$ and p_u for our experiment, as shown in Table 3.1. In the experiment, all subjects are presented with these scenarios, each characterised by two pricing options: the fixed price option p_u and the price range option $[\underline{p}, \bar{p}]$. The realised price, when chosing the price range, is not revealed to the subjects during the experiment. Subjects are informed about the price that applies to the computer-chosen round that contributes to their final payoff – be it the fixed price or the price range, depending on their choice in that round – only at the end of the experiment.

Table 3.1: Experimental calibrations

Scenarios	p_u^*	$\underline{p}^*$	$\bar{p}^*$	$E\left[\widetilde{p}_z^* \mid \alpha \leq \widetilde{\alpha} = \frac{1}{2}\right] = p_u^* \frac{23}{27}$
1	3	1	5	$3(\frac{23}{27})$
2	3.30	1.10	5.50	$3.30(\frac{23}{27})$
3	3.60	1.20	6	$3.60(\frac{23}{27})$
4	3.90	1.30	6.5	$3.90(\frac{23}{27})$
5	4.20	1.40	7	$4.20(\frac{23}{27})$
6	4.50	1.50	7.5	$4.50(\frac{23}{27})$
7	4.80	1.60	8	$4.80(\frac{23}{27})$
8	5.10	1.70	8.5	$5.10(\frac{23}{27})$
9	5.40	1.80	9	$5.40(\frac{23}{27})$
10	5.70	1.90	9.5	$5.70(\frac{23}{27})$
11	6	2	10	$6(\frac{23}{27})$
12	6.30	2.10	10.5	$6.30(\frac{23}{27})$
13	6.60	2.20	11	$6.60(\frac{23}{27})$
14	6.90	2.30	11.5	$6.90(\frac{23}{27})$
15	7.20	2.40	12	$7.20(\frac{23}{27})$
16	7.50	2.50	12.5	$7.50(\frac{23}{27})$
17	7.80	2.60	13	$7.80(\frac{23}{27})$
18	8.10	2.70	13.5	$8.10(\frac{23}{27})$
19	8.40	2.80	14	$8.40(\frac{23}{27})$
20	8.70	2.90	14.5	$8.70(\frac{23}{27})$
21	9	3	15	$9(\frac{23}{27})$

Furthermore, notice that as a result of the unique relationship between the three strategic variables, the bandwidth of the price range option increases with prices - this is analogous to the increase in stakes as prices increase. For instance, scenario 1 involves low-stake options, where the bandwidth of the price range option is also relatively narrow. On the flip side, scenario 21 depicts high-stake options, as illustrated by the wide bandwidth of the price range option.

3.2 Experimental Design

Our experiment involves three stages of individual decision-making tasks that were implemented via Zurich Toolbox for Ready-made Economic Experiments (z-Tree). In Stage 1, we employ a variation of the Ellsberg urn routine to elicit a subject's ambiguity attitude. In Stage 2 and 3, we ask subjects to choose between two options: a fixed price and a price range. In both stages, subjects are presented with different prices which are calibrated based on the theoretical predictions of our model. Our design allows us to observe how subjects choose between the two options as the stakes increase in both stages. In contrast, the difference between Stage 2 and 3 is the representation of the price range option. Specifically, the price range option in each round is displayed in its numerical form in Stage 2, whereas it is presented in a written form in Stage 3. This allows us to assess whether numerical and verbal framing could influence the subjects' decision-making process.

We implement a *within-subject design* to assess the effects of: (i) the size of the stakes; (ii) the pricing representations on individual decision-making; and (iii) the salience of fixed price versus price range offers, depending on whether they are presented in dollar amounts or verbally. A within-subject design allows us to control for heterogeneity in individual preferences and thus achieve greater statistical power. The details of each stage are as follows.

In **Stage 1**, we implement a computerised version of the modified Ellsberg three-colour urn game à la Cohen, Gilboa, Jaffray, and Schmeidler (2000) with real financial incentives. Subjects are asked to place three consecutive bets on the colours of a randomly selected ball from a standard three-colour Ellsberg urn, which is aimed at eliciting each participant's ambiguity attitude. Subjects are informed about the composition of the balls in the urn; of the 90 balls in the urn, 30 are white, and the remainder 60 are either black or yellow balls. The true composition of the Ellsberg urn is randomly selected by the computer and not revealed to the subjects. Then, the computer randomly chooses a ball from the urn with replacement until a white or black ball is chosen. This chosen ball is not revealed to the subjects until the end of the experiment. Subjects are then invited to place three bets. There are four options in each bet.

For Bet 1, subjects could choose (i) to bet that the selected ball is white; (ii) to bet that the selected ball is black; (iii) to be indifferent between betting on either white or black, and delegating the betting task to the computer, which would choose either white or black with equal probabilities; or (iv) to not bet at all, thus foregoing the opportunity to receive a positive payoff from a correct bet. For Bet 2, subjects could choose (i) to bet that the selected ball is white or yellow; (ii) to bet that the selected ball is black or yellow; (iii) to be indifferent between betting on either of the former two options, and delegating the betting task to the computer, which would then select one of the first two options with equal probabilities; or (iv) to not bet at all, thus foregoing the opportunity to receive a positive payoff from a correct bet. Bets 1 and 2 are modified versions of the

Ellsberg three-colour urn experiment, given that they have included the two additional options (iii) and (iv), where subjects could choose to be indifferent between the first two options or renounce the opportunity to bet. After Bet 2, subjects would be informed that the ball selected for Bets 1 and 2 was not yellow and that it was returned to the urn. Finally, the computer draws another ball, where the colour of the ball is not disclosed to the subjects until the end of the experiment. Then, subjects are offered the same options as in Bet 1 and have to select an option for Bet 3.

Subjects receive NZD 2.00 for each correct bet. They do not receive any prize for making the wrong bet or choosing not to bet. Also, subjects do not receive any feedback about the outcome of their bets until the end of the experiment; this is implemented to control for wealth effects.

In **Stage 2**, subjects choose between binary pricing options for twenty-one subsequent rounds. This design emulates the decision-making process of a multihoming individual in the ride-sharing market. Subjects are given an endowment of NZD 15.00 for each round and are faced with different scenarios, which all have in common the choice they need to make between two pricing options: (a) a fixed price; and (b) a price range. The options in each of the twenty-one rounds can be found under *Section 3.1 Price Calibrations*. To address order effects, we shuffle the sequence in which the scenarios are presented to the subjects for each experimental session. Subjects are required to select one of the two options presented to them. If a subject were to select the fixed price option, their earnings for that round would be NZD 15.00 minus the fixed price. On the other hand, if a subject were to select the price range option, the corresponding charged price would correspond to its associated optimal conditional expected price as predicted on our theoretical model. Then, their earnings in that round would be NZD 15.00 minus the associated conditional expected price for that round. At the end of the experiment, one of the twenty-one rounds is randomly and independently selected by the computer to count towards the subjects' final payoff. Subjects are informed about their decision in the selected round and the realised price for the price range option (if they selected the price range) at the end of the experiment.

In **Stage 3**, five scenarios that are drawn from Table 3 are proposed to subjects to assess the effects of framing on the individual's decision-making under pricing-related ambiguity. In particular, we selected scenarios 1, 6, 11, 16 and 21, listed in Table 3.1, which consist of the fixed price options NZD 3, NZD 4.50, NZD 6, NZD 7.50 and NZD 9, respectively, so that we could directly compare the subjects' choices in this stage – when they are offered price range options in written form – with their decisions in Stage 2, in which they are presented with numerical alternatives. These five decision-making rounds also count towards the subjects' payoffs. In each round, subjects are given an endowment of NZD 15.00 and they have to choose between two pricing options: (a) a fixed price; and (b) written description of a price range, expressed as the maximum value of a potential discount and the corresponding price cap, namely "*up to 2/3 cheaper and at most 2/3 more expensive than the fixed price*". Only one of those five scenarios is then selected at random at the end of Stage 3 to determine subjects' payoffs in this stage.

At the end of the experiment, subjects receive feedback about their choices in each stage in the form of an overall summary, with the breakdown of their earnings, stage by stage, based on which round in each of Stages 2 and 3 were chosen at random for such payments. Each subject is paid a show-up fee of NZD 10.00, as well as NZD 2.00 for each correct bet, for a maximum of NZD 6.00 in Stage 1. In Stage 2, a subject could earn up to approximately NZD 12, similarly to the maximum amount they could earn in Stage 3. Overall, the minimum and maximum payments each subject can receive in a session are NZD 10.00 and approximately NZD 40 respectively.

3.3 Ambiguity Types

Table 3.3: Ambiguity attitudes

		Bet 1			
		White	Black	Indifferent	Do not bet
Bet 2	White or yellow	SEU	$\alpha < 1/2$	Inconsistent	Inconsistent
	Black or yellow	$\alpha > 1/2$	SEU	Inconsistent	Inconsistent
	Indifferent	Inconsistent	Inconsistent	SEU or $\alpha = 1/2$	Inconsistent
	Do not bet	Inconsistent	Inconsistent	Inconsistent	Inconsistent

Table 3.3 summarises all possible combinations of the eight options for Bet 1 and 2 in Stage 1, and the corresponding ambiguity attitudes that could be revealed through a subject's choices. Below we demonstrate how each subject's choices relate to their ambiguity attitudes[7].

Let us begin with a subject who adheres to the sure-thing principle. The subject would display either of the two preferences: they would select (i) the "white" option in Bet 1 and "white or yellow" in Bet 2; or (ii) the "black" option in Bet 1 and "black or yellow" in Bet 2. The subject's choices across the two bets align with the sure-thing principle, because the introduction of uncertainty in the betting options – the opportunity to bet on the yellow ball with unknown distribution in the urn – has not changed their preference for white (or black) balls across the two bets. Both preferences are consistent with the SEU model. We identify subjects who exhibit such preferences as ambiguity neutral individuals.

However, if a subject were to change the preference ordering for the white and black balls when they moved from Bet 1 to Bet 2, the subject's preference could be represented by the α-MaxMin model. This model allows us to capture ambiguity attitudes as a continuum from 0 to 1, consistent with the Hurwicz Criterion. For a subject who chooses the "white" option in Bet 1 and "black or yellow" in Bet 2, their behaviour suggests a violation of the sure-thing principle: they prefer "white" over "black" in the first bet but prefer "black or yellow" to "white or yellow" in the second bet. Subjects who display such preferences are known to be ambiguity averse, which is associated with the relative degree of pessimism $\alpha > 1/2$. Conversely, a subject who chooses the "black" option in Bet 1 and "white or yellow" in the second bet is known to be ambiguity loving, with the corresponding degree of optimism $\alpha < 1/2$.

[7] Bet 3 relates to Bayesian Updating. As it does not relate to the objectives of our study, we shall take the liberty to skip this segment in our discussion.

Lastly, for a subject who is indifferent between betting on the white and black balls, regardless of whether pricing uncertainty is present, their preferences could be represented by either SEU or $\alpha = 1/2$. The remaining combinations across the two bets indicate preference patterns that are inconsistent. As such, we cannot classify the ambiguity attitudes of subjects who exhibit such behaviour.

3.4 Experimental Data

We conducted a preliminary experiment at the University of Auckland Laboratory for Business Decision Making (DECIDE) from the 12th to 27th of August 2019 to elicit a typical distribution of subjects' attitudes toward ambiguity, for us to then use to calibrate our model. We then conducted some initial sessions for our full fledged experiments using the predictions so obtained and as described in the previous sessions, by repeating Stages 1–3 with more subjects, recruited starting from January 2020. For all experimental sessions, we recruited subjects via the Online Recruitment Software for Economic Experiments (ORSEE). Overall, a total of 113 subjects took part across six experimental sessions in the first wave of our experiment (in 2019). We then continued with our experiment, by recruiting further subjects to the lab and we are currently still conducting additional experimental sessions, to complete this project (we will have collected all necessary data by May 2020). We consistently provide detailed instructions to subjects at the beginning of each session and at the start of each stage, as described in *Section 3.2 Experimental Design*. Each subject's total earnings is composed of the show-up fee and the payoffs they had received from Stage 1 and 2.

3.4.1 Descriptive Statistics and Data Analysis

With the data from Stage 1, from the experimental sessions conducted in 2019, we were able to identify the ambiguity attitudes of 110 out of 113 subjects. For three subjects who did not bet in Stage 1, we were unable to identify for certain their ambiguity types, given their inconsistent preferences. Hence, we excluded their observations in our subsequent analysis.

Based on the subjects' choices in Stage 1, they are categorised into one of three groups: either ambiguity averse, Subjective Expected Utility (SEU), or ambiguity loving individuals. We find that 41.8% of the subjects are ambiguity averse, another 41.8% display SEU preferences, and the remaining 16.4% are ambiguity loving individuals.

As already discussed, we use this stylised evidence to calibrate our model and predict behaviour of consumers whose attitudes toward ambiguity is skewed toward ambiguity aversion.

When repeating our experiment, to include also Stages 2 and 3, and letting subjects choose between a fixed price and a price range option, the experimental data inform us as to the average probability of selecting the price range option, relative to the fixed price option. We can label these incidences of choosing a price range over a fixed price as *"Choices"*, which we use as our continuous dependent variable. As the value of this mean probability approaches 0, subjects are more likely to select the fixed price option.

On the other end of the spectrum, subjects are more inclined to select the price range option as the value of the mean probability approaches 1. When the mean probability is exactly 0.5, the subjects are indifferent between the two options. Our experiment will allow us to present our findings for the subject population and three ambiguity types.

TO BE COMPLETED————————

4 Analysis of Experimental Data

TO BE COMPLETED————————

5 Limitations and Future Directions

First of all, similar to other attempts to model complex human behaviour, ours require a number of simplifying assumptions for pragmatic reasons, one of which is to calibrate the experimental parameters. The price calibrations in the experiment are based on the theoretical assumptions that the consumers' ambiguity types in the market follow a Beta distribution, skewed towards ambiguity-averse types. This is a convenient, yet realistic, assumption to impose on our model.

Secondly, the statistical power of our data will depend on the number of observations we will be able to gather from the subject population. In particular, based on Stage 1 findings, a substantially smaller proportion of our subjects were identified as ambiguity loving individuals, compared to the other two ambiguity types. This restricts our ability to infer results from the available data, particularly for the ambiguity loving subjects, when having an overall population for the second wave of subjects who will participate in our experiment below a certain threshold (*we aim at having at least 100 subjects taking part in the second wave of experimentation – so far, we have collected data from a little more than 30 subjects and we plan to run extra experimental sessions in the coming weeks and months, to complement this number to reach a satisfactory sample size for us to perform our desired econometric analysis of our data*).

As an extension of this study, we could direct our attention to the other side of the ride-sharing platform, by modelling the behaviour of multihoming drivers. This area is worthy of further exploration, given that in reality, drivers are independent contractors who could legally work for multiple platforms simultaneously. Moreover, platforms rely heavily on having a large user base, not solely in the rider side of the market, but also the driver side to cement their position in the market. Retaining a huge driver pool would allow the platform to attract more riders to their networks, otherwise known as cross-side network effects. Similar to market segmentation in the rider side of the platform by ambiguity types, an operator could replicate this strategy in the driver side of the market, by separating the drivers according to the same classification to improve the platform's market share.

Altering our existing theoretical model to accommodate this context could be a worthwhile exercise. This would require some adjustments to the model and also tweaks with the derivation of consumer surplus. To portray the aforementioned scenario, we could obtain the expected driver surplus for the mass of drivers served by Zoomy, by taking the product of the conditional expected price that Zoomy would pay drivers and the mass of drivers served by Zoomy. Similar logic applies for the analysis of Uber drivers. Aside from driver surplus, the theoretical predictions of our model should remain the same for identical distributions of ambiguity types.

The adaptation of the driver scenario to suit the experiment, however, could lead to less trivial differences in the experimental design and outcome. This is because our experiment was designed to study individual decision-making in the loss domain. To emulate the decision of a driver in the ride-sharing market, we have to modify the experimental design such that it reflects decision-making in the gain domain. In addition, if we were to draw on Prospect Theory, which posits that losses and gains are valued differently, this distinction could affect attitudes towards uncertainty. Therefore, results may vary between the two experiments.

6 Conclusion

We explore individual decision-making under ambiguous pricing information in the ride-sharing market from a theoretical and experimental approach. To pursue our investigation, we extract the predictions from our model to calibrate the parameters in our experiment and we also use preliminary experimental data to help us in our modelling choice related to the distribution of consumers' attitudes toward ambiguity. In turn, by introducing explicit ambiguity in the laboratory, we obtain experimental evidence to assess the predictions of our theoretical model, on how ambiguity attitudes and different types of utility representations over ambiguous outcomes affect individual decision-making under ambiguity.

Our model tells us that Uber and Zoomy could co-exist in the market, with Uber serving a higher fraction of the market compared to Zoomy, and that the pricing strategies adopted by both platforms should be each platform's best response to their rival's prices. On the other hand, our experimental design could still accommodate scenarios in which subjects randomise their choices between the two pricing options over multiple scenarios, regardless of their ambiguity types; this may be analogous to user multihoming in the ride-sharing market. However, on average, we expect subjects to be more likely to select the fixed price over the price range option when stakes are higher. Moreover, the introduction of verbal framing for the price range option could counteract the negative effects of an increase in stakes on the average probability of selecting the price range. And, we expect these findings to be most pronounced among ambiguity averse subjects.

With our work, we contribute to filling the gap in the study of how individuals form decisions when they are faced with ambiguity in competing pricing schemes. Furthermore, we add to the literature by analysing the implications of pricing-related ambiguity on user multihoming, and the subsequent impact of pricing strategies on competition in the digital economy.

References

Balestrieri, F., & Izmalkov, S. (2014, January). Informed seller in a Hotelling market. *SSRN Electronic Journal*.

Belleflamme, P., & Peitz, M. (2019, October). Platform competition: Who benefits from multihoming? *International Journal of Industrial Organization*, *41*(64), 1–26.

Cohen, M., Gilboa, I., Jaffray, J., & Schmeidler, D. (2000). An experimental study of updating ambiguous beliefs. *Risk, Decision and Policy*, *5*(2), 123–133.

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, *75*(4), 643–669.

Fabrizi, S., Lippert, S., Pan, A., & Ryan, M. (2019). Unanimous jury voting with an ambiguous likelihood. *University of Auckland: Auckland, New Zealand*.

Fellner, G., & Maciejovsky, B. (2007). Risk attitude and market behavior: Evidence from experimental asset markets. *Journal of Economic Psychology*, *28*(3), 338–350.

Gilboa, I., & Schmeidler, D. (1989). Maxmin expected utility with non-unique prior. *Journal of Mathematical Economics*, *18*(2), 141–153.

Grant, S., Rich, P., & Stecher, J. D. (2019). An ordinal theory of worst-and best-case expected utility. *Available at SSRN 3369078*.

Hagiu, A. (2007). Merchant or two-sided platform? *Review of Network Economics*, *6*(2), 1-19.

Harrison, G. W., Lau, M. I., & Rutström, E. E. (2007). Estimating risk attitudes in Denmark: A field experiment. *The Scandinavian Journal of Economics*, *109*(2), 341-368.

Hey, J. D., Lotito, G., & Maffioletti, A. (2010, October). The descriptive and predictive adequacy of theories of decision making under uncertainty/ambiguity. *Journal of Risk and Uncertainty*, *41*(2), 81–111.

Hotelling, H. (1929). Stability in competition. *Economic Journal*, *39*(153), 41–57.

Hurwicz, L. (1951). Optimality criteria for decision making under ignorance. Cowles Commun. *Discuss. Paper, Stat*(370).

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–291.

Ma, W., Luo, X., & Jiang, Y. (2017, Jan). An ambiguity aversion model for decision making under ambiguity. *Proceedings of the 31st AAAI Conference on Artificial Intelligence*, San Francisco.

Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy*, *78*(2), 311–329.

Pacheco Pires, C. (2002, September). A rule for updating ambiguous beliefs. *Theory and Decision*, *53*(2), 137–152.

Rochet, J.-C., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, *1*(4), 990–1029.

Statista. (2019). *Ride hailing.* Retrieved from `https://www.statista.com/outlook/368/100/ride-hailing/worldwidemarket-revenue`

Stecher, J., Shields, T., & Dickhaut, J. (2011). Generating ambiguity in the laboratory. *Management Science*, *57*(4), 705–712.

A Mathematical derivations

Profit maximisation for Zoomy

$$\pi_z \;=\; E[\widetilde{p}_z|\alpha \leq \widetilde{\alpha}]\, F(\widetilde{\alpha}) \;\; s.t. \; \widetilde{\alpha},\, \underline{p},\, \bar{p} \;\geqslant\; 0$$

$$\pi_z \;=\; \tfrac{1}{\int_0^{\tilde{\alpha}} 20\alpha^3(1-\alpha)d\alpha} \int_0^{\tilde{\alpha}} [\alpha\bar{p} + (1-\alpha)\underline{p}] 20\alpha^3(1-\alpha)d\alpha \int_0^{\tilde{\alpha}} 20\alpha^3(1-\alpha)d\alpha$$

$$\pi_z \;=\; \int_0^{\tilde{\alpha}} [\alpha\bar{p} + (1-\alpha)\underline{p}] 20\alpha^3(1-\alpha)d\alpha$$

$$\pi_z \;=\; 20\int_0^{\tilde{\alpha}} [\alpha^4\bar{p} - \alpha^5\bar{p} + \alpha^3\underline{p} - \, 2\,\alpha^4\underline{p} + \alpha^5\underline{p}]d\alpha$$

$$\pi_z = 20\left(\frac{\widetilde{\alpha}^5}{5}\bar{p} - \frac{\widetilde{\alpha}^6}{6}\bar{p} + \frac{\widetilde{\alpha}^4}{4}\underline{p} - \frac{2\widetilde{\alpha}^5}{5}\underline{p} + \frac{\widetilde{\alpha}^6}{6}\underline{p}\right)$$

By substituting $\widetilde{\alpha} = \frac{p_u - \underline{p}}{\bar{p} - \underline{p}}$ as per Eq. (1) into this profit, we obtain

$$\pi_z = 20\left(\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^5 \frac{1}{5}\bar{p} - \left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^6 \frac{1}{6}\bar{p} + \left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^4 \frac{1}{4}\underline{p} - \left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^5 \frac{2}{5}\underline{p} + \left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^6 \frac{1}{6}\underline{p}\right)$$

First order conditions

$$\begin{aligned}\frac{\partial \pi_z}{\partial \bar{p}} \;=\; & 20\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^4 \Bigg[-\bar{p}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)\left(\frac{1}{\bar{p} - \underline{p}}\right) + \frac{1}{5}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{z}}\right) + \bar{p}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^2\left(\frac{1}{\bar{p} - \underline{p}}\right) \\ & -\frac{1}{6}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^2 - \underline{p}\left(\frac{1}{\bar{p} - \underline{p}}\right) + 2\underline{p}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)\left(\frac{1}{\bar{p} - \underline{p}}\right) - \underline{p}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^2\left(\frac{1}{\bar{p} - \underline{p}}\right)\Bigg] \geqslant 0\end{aligned}$$

$$\begin{aligned}\frac{\partial \pi_z}{\partial \underline{p}} \;=\; & 20\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^3 \Bigg[\bar{p}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)\left(-\frac{1}{\bar{p} - \underline{p}} + \frac{p_u - \underline{p}}{(\bar{p} - \underline{p})^2}\right) \\ & -\bar{p}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^2\left(-\frac{1}{\bar{p} - \underline{p}} + \frac{p_u - \underline{p}}{(\bar{p} - \underline{p})^2}\right) + \underline{p}\left(-\frac{1}{\bar{p} - \underline{p}} + \frac{p_u - \underline{p}}{(\bar{p} - \underline{p})^2}\right) \\ & + \frac{1}{4}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right) - 2\underline{p}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)\left(-\frac{1}{\bar{p} - \underline{p}} + \frac{p_u - \underline{p}}{(\bar{p} - \underline{p})^2}\right) \\ & - \frac{2}{5}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^2) + \underline{p}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^2\left(-\frac{1}{\bar{p} - \underline{p}} + \frac{p_u - \underline{p}}{(\bar{p} - \underline{p})^2}\right) + \frac{1}{6}\left(\frac{p_u - \underline{p}}{\bar{p} - \underline{p}}\right)^3\Bigg] \geqslant 0\end{aligned}$$

Profit maximisation for Uber

$$\pi_u \;=\; p_u\,[\,1\;-\;F(\widetilde{\alpha})\,]\;s.t.\;\widetilde{\alpha},\,p_u\;\geqslant\;0$$

$$\pi_u \;=\; [1-20\int_0^{\widetilde{\alpha}}20\alpha^3(1-\alpha)d\alpha]$$

$$\pi_u \;=\; [1-5\widetilde{\alpha}^4+4\widetilde{\alpha}^5]$$

Plugging in $\widetilde{\alpha}=\frac{p_u-\underline{p}}{\bar{p}-\underline{p}}$ as per Eq. (1) into this profit, we obtain

$$\pi_u \;=\; [1-5\left(\tfrac{p_u-\underline{p}}{\bar{p}-\underline{p}}\right)^4+4\left(\tfrac{p_u-\underline{p}}{\bar{p}-\underline{p}}\right)^5]$$

First order condition

$$\begin{aligned}\frac{\partial\pi_u}{\partial p_u} \;=\; & \left[1-5\left(\frac{p_u-\underline{p}}{\bar{p}-\underline{p}}\right)^4+4\left(\frac{p_u-\underline{p}}{\bar{p}-\underline{p}}\right)^5\right]\\ +\,p_u & \left[-20\left(\frac{p_u-\underline{p}}{\bar{p}-\underline{p}}\right)^3\left(\frac{1}{\bar{p}-\underline{p}}\right)+20\left(\frac{p_u-\underline{p}}{\bar{p}-\underline{p}}\right)^3\left(\frac{1}{\bar{p}-\underline{p}}\right)\right]\;\geqslant\;0\end{aligned}$$

The resulting equilibrium conditions for both Uber and Zoomy to coexist in the market are as follows

$$20\widetilde{\alpha}^4\left[\left(\frac{1}{\bar{p}-\underline{p}}\right)\left(-\bar{p}\widetilde{\alpha}+\bar{p}\widetilde{\alpha}^2-\underline{p}+2\underline{p}\widetilde{\alpha}-\underline{p}\widetilde{\alpha}^2\right)+\frac{1}{5}\widetilde{\alpha}-\frac{1}{6}\widetilde{\alpha}^2\right]\geqslant 0$$

$$20\widetilde{\alpha}^3\left[\left(-\frac{1}{\bar{p}-\underline{p}}+\frac{p_u-\underline{p}}{(\bar{p}-\underline{p})^2}\right)(-1)\left(-\bar{p}\widetilde{\alpha}+\bar{p}\widetilde{\alpha}^2-\underline{p}+2\underline{p}\widetilde{\alpha}-\underline{p}\widetilde{\alpha}^2\right)+\frac{1}{4}\widetilde{\alpha}-\frac{2}{5}\widetilde{\alpha}^2+\frac{1}{6}\widetilde{\alpha}^3\right]\geqslant 0$$

$$1-5\widetilde{\alpha}^4+4\widetilde{\alpha}^5+20p_u\widetilde{\alpha}^3\left(\frac{1}{\bar{p}-\underline{p}}\right)(\widetilde{\alpha}-1)\geqslant 0$$

Let $W=-\bar{p}\widetilde{\alpha}+\bar{p}\widetilde{\alpha}^2-\underline{p}+2\underline{p}\widetilde{\alpha}-\underline{p}\widetilde{\alpha}^2$

Zoomy's first order conditions can be rewritten as

$$20\widetilde{\alpha}^4\left[\left(\frac{1}{\bar{p}-\underline{p}}\right)(W)+\frac{1}{5}\widetilde{\alpha}-\frac{1}{6}\widetilde{\alpha}^2\right]=0\Rightarrow W=\left(-\frac{1}{6}\widetilde{\alpha}^2-\frac{1}{5}\widetilde{\alpha}\right)(\bar{p}-\underline{p})$$

$$20\widetilde{\alpha}^3\left[\left(-\frac{1}{\bar{p}-\underline{p}}+\frac{p_u-\underline{p}}{(\bar{p}-\underline{p})^2}\right)(-W)+\frac{1}{4}\widetilde{\alpha}-\frac{2}{5}\widetilde{\alpha}^2+\frac{1}{6}\widetilde{\alpha}^3\right]=0$$

$$\Rightarrow\left(-\frac{1}{\bar{p}-\underline{p}}+\frac{p_u-\underline{p}}{(\bar{p}-\underline{p})^2}\right)(-W)+\frac{1}{4}\widetilde{\alpha}-\frac{2}{5}\widetilde{\alpha}^2+\frac{1}{6}\widetilde{\alpha}^3=0$$

Plugging in $W = \left(-\frac{1}{6}\widetilde{\alpha}^2 - \frac{1}{5}\widetilde{\alpha}\right)\left(\bar{p} - \underline{p}\right)$

$$\left(-\frac{1}{\bar{p}-\underline{p}} + \frac{p_u - \underline{p}}{\left(\bar{p}-\underline{p}\right)^2}\right)(-1)\left(-\frac{1}{6}\widetilde{\alpha}^2 - \frac{1}{5}\widetilde{\alpha}\right)\left(\bar{p}-\underline{p}\right) + \frac{1}{4}\widetilde{\alpha} - \frac{2}{5}\widetilde{\alpha}^2 + \frac{1}{6}\widetilde{\alpha}^3 = 0$$

$$(-1+\widetilde{\alpha})\left(-\frac{1}{6}\widetilde{\alpha}^2 - \frac{1}{5}\widetilde{\alpha}\right) + \frac{1}{4}\widetilde{\alpha} - \frac{2}{5}\widetilde{\alpha}^2 + \frac{1}{6}\widetilde{\alpha}^3 = 0$$

$$\frac{1}{6}\widetilde{\alpha}^2 - \frac{1}{5}\widetilde{\alpha} + \frac{1}{5}\widetilde{\alpha}^2 + \frac{1}{4}\widetilde{\alpha} - \frac{2}{5}\widetilde{\alpha}^2 = 0$$

$$-2\widetilde{\alpha}^2 + 3\widetilde{\alpha} = 0$$

$$-4\widetilde{\alpha}^5 + 6\widetilde{\alpha}^4 = 0$$

Solving the resulting equilibrium conditions for both Uber and Zoomy to coexist in the market simultaneously, we obtain

$$1 - \widetilde{\alpha}^4 + 20p_u\widetilde{\alpha}^3\left(\frac{1}{\bar{p}-\underline{p}}\right)(\widetilde{\alpha}-1) = 0$$

B Experiment user interface

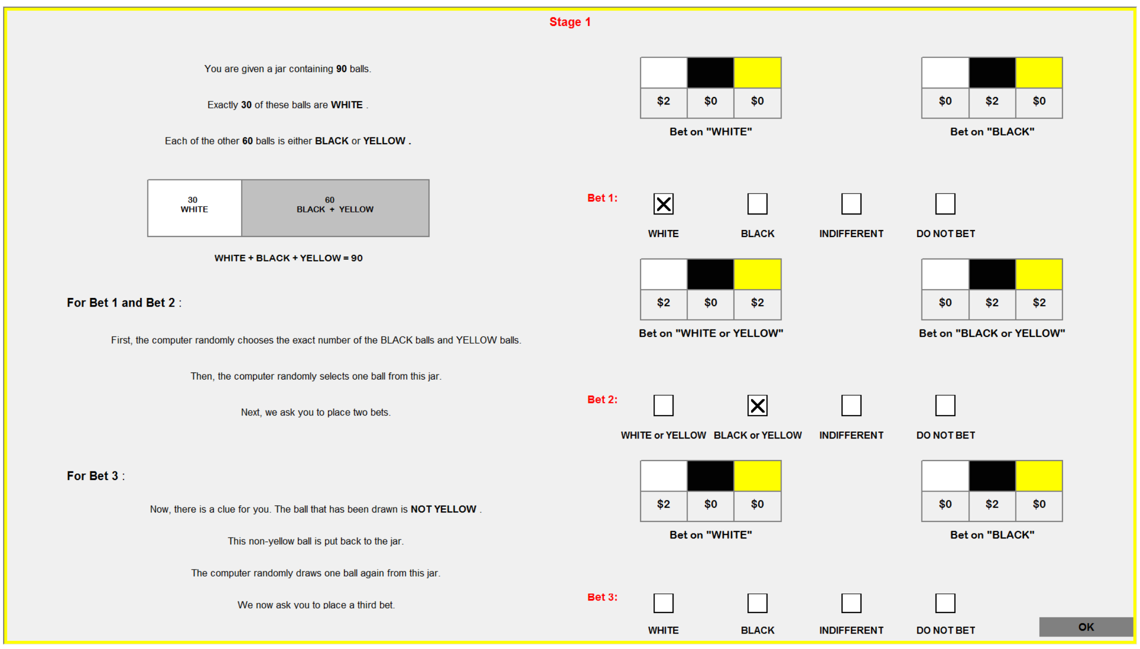


Figure 2: Modified Ellsberg three-colour urn game in Stage 1.

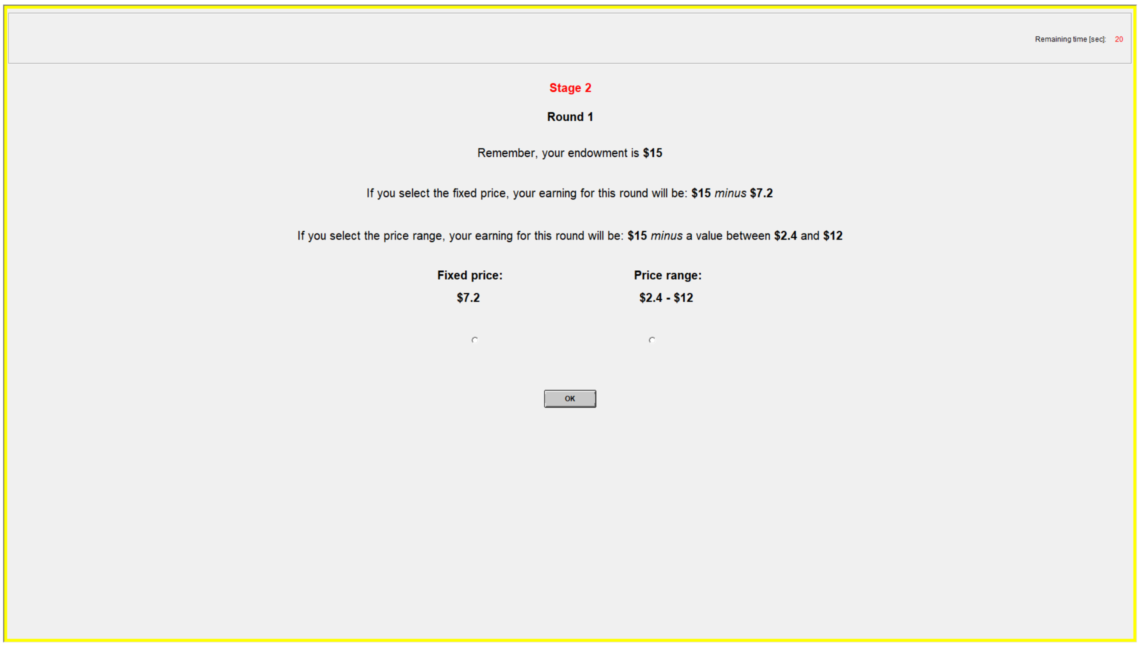


Figure 3: Example of choices faced by subjects in Stage 2.

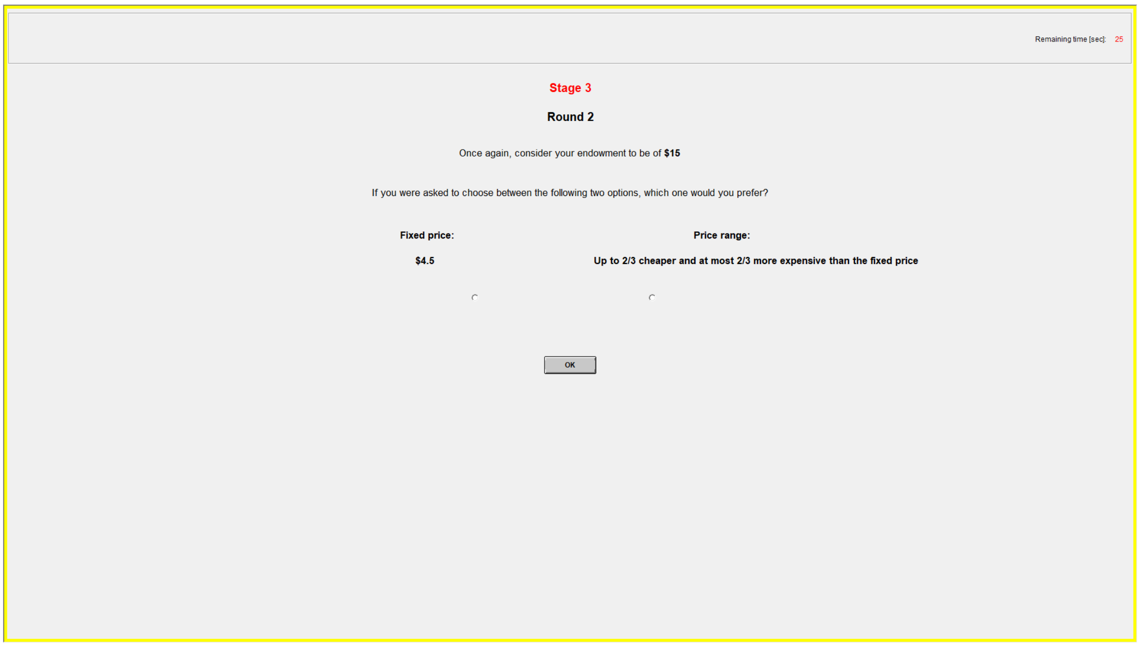


Figure 4: Example of choices faced by subjects in Stage 3.

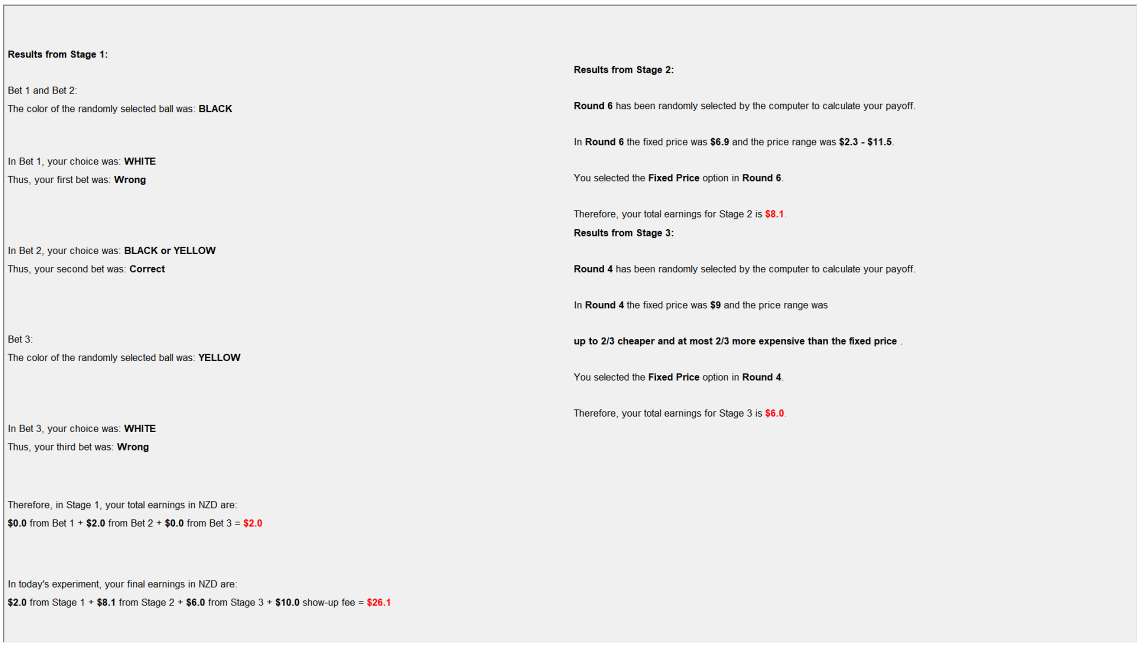


Figure 5: Display of a subject's final payoffs at the end of the experiment.