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On Customer (Dis)honesty in Unobservable Queues: The Role of Lying Aversion

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Queues where people misreport their private information to access service faster are everywhere. Motivated by the prevalence of such behaviour in practice, we construct a queueing-game-theoretic model where customers make strategic claims to reduce their waiting time, and the Manager decides on the static scheduling policy based on those claims to minimize the expected delay cost in the system. We develop a lying aversion model where customers incur both delay and lying costs. We run controlled experiments to validate our modelling assumptions regarding customer misreporting behaviour. In particular, we find that people do incur lying costs, and that their misreporting behaviour does not depend on changes in waiting times, but rather on the scheduling parameters. Based on the validated lying aversion model, we study the equilibrium that arises in our game. We find that under certain conditions, the optimal policy is to use an *honor policy* where service priority is given according to customer claims. We also find that it may be optimal to *incentivize more honesty* by means of an *upgrading policy* where some customers who claim to not deserve priority are upgraded to the priority queue. We find that the upgrading policy deviates from the celebrated $c\mu$ rule.

Key words: Scheduling policy, priority queues, strategic customers, lying aversion, behaviour in queues.

1. Introduction

Queuing systems where people make dishonest claims in order to access service faster are everywhere. For example, in telephone triage systems, it is known that patients routinely exaggerate symptoms to get a doctor's appointment sooner (Kirton et al. 2020) or an ambulance faster (Jones 2020). In the United Kingdom, there have been reports of people lying about their symptoms (BBC 2020a) or their employment status (BBC 2020b) in order to receive COVID-19 tests faster at home. In this case, it was possible for people to be dishonest with impunity because the online booking system was explicit on its reliance on public honesty rather than employment checks (Weaver and Proctor 2020). This is similar to the honor policy used for the scheduling of COVID vaccinations in some countries; e.g., in the United States (NPR 2021a), where claims of eligibility are not verified since requiring additional checks would add barriers to access, and is therefore undesirable or logistically difficult to enforce (NPR 2021b). While some systems rely on unverifiable customer claims to schedule services (despite knowing that misreporting is prevalent), other systems opt to not rely on customer claims at all, due to such dishonesty. For example, a chat-bot symptom checker application was recently commissioned by the National Health Service (NHS) to aid in booking general practitioner (GP) appointments for patients. This initiative was dropped, after initial pilot trials, because patients admitted that they would exaggerate their symptoms (in the text exchange with the chat-bot symptom-checker) in order to see the GP faster (Heather 2017).

The above examples share similar characteristics. First, only customers know their private information, which gives rise to a clear incentive to misreport in order to begin service faster. As claims are not verified, it is difficult to punish or fine untruthful behaviour, which creates an opportunity to misreport with complete impunity. Second, queues in those settings are unobservable, i.e., customers make claims without seeing the other customers waiting, or directly observing other customers' claims. This is because the service requests themselves are made either online or through the phone. Third, those services typically involve a single (or rare) interaction with the queueing system, so there is a strong degree of anonymity for customers. Thus, reputation concerns do not play a role, and community enforcement of desirable behaviour, which may occur with physical queues, is not possible (Allon and Hanany 2012). Fourth, due to the nature of those settings, price discrimination, which is a standard operational control used to induce truthful incentive-compatible claims, is not possible. For example, healthcare services provided by the NHS are publicly funded and cannot be individually priced. Similarly, due to access concerns and the social nature of those systems, inspection and admission controls, which are also standard operational controls, may be undesirable. For example, during the COVID-19 pandemic in the United Kingdom, many supermarket chains implemented a groceries delivery service where priority slots were reserved for vulnerable people who were not able to leave their homes (Kaidan 2020). For this service, customer claims were actually verified against a list of vulnerable people provided by the government. However, recent reports have found that because of "poor data", it took too long to identify more than a third of the 2.2 million vulnerable people who were struggling to gain access to food (Syal 2021). Finally, while there is evidence of customer untruthfulness, clearly it remains that not everyone misreports. However, it is not clear what properties of the scheduling policy (i.e., the order in which to serve customers) drive customer misreporting behaviour, if at all, or help to mitigate it.

In settings like the ones described above, managers aim to make efficient scheduling decisions in order to minimize customer waiting, especially for those customers with the most urgent needs. However, it is not clear how customers will strategically respond to different scheduling decisions and, thus, how to use potentially false customer claims. Indeed, while the above examples share the same set of properties and presumably a similar objective, in practice different scheduling policies are observed, as illustrated above. This gives rise to our main research questions: (1) How should service systems make scheduling decisions in settings where customers may potentially make dishonest and unverifiable claims? (2) How does the misreporting behaviour of customers depend on the scheduling policy? (3) Can the Manager incentivize more honest claims by relying on a judicious scheduling policy?

To address those questions, we consider a priority queueing-game-theoretic model and run controlled experiments to validate our modelling assumptions regarding customer misreporting behaviour. In our game, the Manager's information about true customer types (either high or low) is based solely on customers' own claims. At the beginning of the game, the Manager defines and communicates a scheduling policy according to which customers will be served. We focus on scheduling policies where customers are routed probabilistically, based on their claims, to either a regular or to a priority queue. The Manager seeks to minimize the total expected delay cost in the system. Based on the scheduling policy and the expected waiting times in the system, customers decide on their individual claims. Customers have the incentive to misreport if doing so leads to a shorter expected waiting time. Finally, based on the scheduling policy and customer claims, customers wait in a queue and eventually receive service. We study the equilibrium that arises in the game and the optimal scheduling policy.

Contributions. To model misreporting behaviour in our game, we consider a lying aversion model in which customers incur lying costs when they misreport. To validate the existence of lying costs and to derive sensible modelling assumptions on customer misreporting behaviour, we run controlled experiments where people can misreport their private information in order to wait less in a virtual queue. In our experiment, we vary the waiting times and the scheduling parameters, and estimate the impact of those changes on the misreporting probability. To the best of our knowledge, we are the first to investigate misreporting behaviour when time is at stake, rather than money. Moreover, in our queueing setting, customers are routed probabilistically based on their claims, i.e., the outcomes are random. Studying the effect that uncertainty has on lying aversion is a key contribution of our paper. Indeed, very few papers in the literature investigate how the lying behaviour changes in uncertain environments and none of these papers consider a queueing setting as we do here. Importantly, we provide experimental evidence that the majority of explainable lying behaviour can be attributed to the scheduling parameters, rather than the waiting times themselves.

Based on our experimentally-validated lying-aversion model, we theoretically study the equilibrium that arises in the game and the optimal scheduling policy. We find that, as long as there is some level of honesty in the system, customer claims are informative in equilibrium. Thus, it is always optimal for the Manager to rely, in some way, on customer claims in scheduling. This gives support to our motivating examples above where customer claims are actively sought despite the fact that misreporting is possible. In particular, we find that if customers' lying behaviour is not sensitive enough to changes in the scheduling parameters (in a sense to be made more precise later), then the optimal scheduling policy, which arises at equilibrium, is to give priority to customers based on their claims. This provides support to *honor policies* commonly observed in practice.

Interestingly, we find that if lying behaviour is sensitive enough, then it is optimal to *incentivize more customer honesty* by means of an *upgrading policy* where some truthful customers who claim to not deserve priority, are randomly upgraded to a priority queue. Importantly, this *upgrading policy* deviates from the celebrated $c\mu$ rule, which prioritizes customers in decreasing order of their $c\mu$ index, where c denotes the delay cost and μ denotes the service rate. This is noteworthy because the $c\mu$ rule has been shown to be optimal with uncertain, yet exogenous, customer claims (Argon and Ziya 2009, Bren and Saghafian 2019).

The remainder of the paper is structured as follows. In §2, we review the relevant literature. In §3, we describe the model primitives and our queueing game. In §4, we describe the Manager's problem. In §5, we describe the customer's problem and present a lying-aversion model. In §6, we present an experimental study to validate several assumptions of the lying-aversion model. In §7, we derive the equilibrium in the game and describe the optimal scheduling policy. Finally, in §8, we draw conclusions.

2. Literature Review

This paper is related to four different streams of literature, which we describe below.

Queues with uncertain customer information. There is a rich queueing-theoretic literature which studies scheduling decisions in priority queues where true customer types are perfectly known to the Manager. In particular, the $c\mu$ rule has been shown to be optimal for delay cost minimization in various settings (Cox and Smith 1991, Van Mieghem 1995). In practice, the true customer types may not be perfectly known to the Manager. Van der Zee and Theil (1961) study how exogenous misclassification errors affect optimal scheduling decisions in the system. Argon and Ziya (2009) assume that the Manager receives a signal from each arriving customer, where the signal is the probability that the customer is of a certain type. Argon and Ziya (2009) show that the Highest Signal First (HSF) scheduling policy, which is consistent with the $c\mu$ rule, yields the lowest long-run average waiting cost among all finite-class priority policies. Bren and Saghafian (2019) consider the case in which the type of an arriving customer is known but the service rate for each type has to be dynamically learnt through a data-driven optimization approach. They also derive an optimal scheduling policy that is similar to the HSF policy. Singh et al. (2022) assume that customer signals are the output of a data-driven classifier, and propose an integrated approach where the classifier and the prioritization policy are jointly optimized. In line with this stream of literature, we also investigate scheduling decisions when customer true types are not known to the Manager. However, unlike those papers, we focus on settings where customers have private information about their own types, and where they strategically manipulate the signals (claims) that they send to the Manager.

Queues with strategic customers. There is a rich queueing-economics literature which focuses on settings where customer information is private and where market mechanisms such as pricing (Mendelson and Whang 1990, Afeche and Mendelson 2004), auctions (Kittsteiner and Moldovanu 2005), or bribing (Kleinrock 1967, Lui 1985) can be used to induce truthful reporting in the system; see Hassin and Haviv (2003) for a survey. Hu et al. (2021) investigate a setting where customers are strategic in deciding whether to disclose personal information to the service provider. Similar to this literature, we focus on modelling queues with strategic customers who are delay sensitive. However, contrary to those papers which resort to money transfers in order to differentiate customers, we study how lying aversion influences customers' strategic behaviour, and show how the Manager can differentiate between customers, to a certain extent, without the use of incentive-compatible pricing/auction mechanisms. Indeed, we focus on settings where money transfers are not applicable, and instead investigate how the scheduling policy helps to incentivize truthful reporting.

Several papers investigate how scheduling decisions affect strategic customer behaviour, as we do here (Afeche 2013, Afeche and Pavlin 2016, Yang et al. 2021, Yang 2021). In particular, some of these works find that giving partial priority, e.g., by means of reducing the gap between the expected waiting times of the different priority classes, may be useful to induce desirable customer behaviour. Our optimal scheduling policy is a partial priority policy as well. However, in our paper, this partial priority must be reached through upgrading low claims (and not by other means of manipulating the waiting times) because of customers' preferences for truth-telling.

Behavioural queues. Our work is broadly related to papers studying the behavioural foundations of queueing systems; see Allon and Kremer (2018) for background. Shunko et al. (2018) study the behavioural impact of queue design on worker productivity in service systems which involve human servers. Buell (2021) identifies the negative effects of last-place aversion in queues. Armony et al. (2021) develop a game-theoretic model to assess the performance of pooling when behavioural servers choose their capacities strategically. Kim et al. (2020) study admission decisions in queues using behavioural models and controlled experiments. Wang and Zhou (2018) study how the queue configuration affects human servers' service time in a field experiment. Ülkü et al. (2020) investigate the relationship between waiting time and subsequent purchase decisions. Luo et al. (2022) study how customers in observable queues form their completion costs based on their position in line, the number of people that have been served since they joined the line, and the service speed. Althenayyan et al. (2022) investigate how line-sitting and express lines affect customers' satisfaction and fairness perceptions.

While there is ample empirical evidence illustrating the important role of social norms and preferences in queueing systems, Allon and Hanany (2012) is, to the best of our knowledge, the only work that investigates queueing intrusions with a formal mathematical model. In particular, Allon and Hanany (2012) show that the common observation of "queue jumping" can be part of social norms and can be explained on rational individual grounds. We depart from Allon and Hanany (2012) in three fundamental ways. First, Allon and Hanany focus on service systems with observable queues where the Manager is not involved in the way in which the queue is managed. Thus customers, through community enforcement, regulate the queue. In contrast, we focus on unobservable queueing systems where the Manager is in charge of controlling the queue, and where customers do not see each other and are unable to prevent intrusions. Second, unlike Allon and Hanany (2012), we model customer aversion to being untruthful and study its operational implications. Third, our methodological approach is different, as we conduct controlled experiments to shed light on the untruthful behaviour of customers in queues.

Misreporting behaviour and lying costs. In recent years, a fast-growing literature across economics, psychology, and sociology has begun to study how people misreport their private information; see Rosenbaum et al. (2014) for a survey and Abeler et al. (2019) for a meta-analysis. Overall, the literature strongly shows that people exhibit lying aversion (Abeler et al. 2019) as not everyone misreports even under conditions of complete anonymity and impunity. In particular, the experimental paradigm in Fischbacher and Föllmi-Heusi (2013) is the most widely adopted in the literature to investigate misreporting behaviour. In this paradigm, participants privately observe the outcome of a random variable, report this outcome, and receive a monetary payoff proportional to their report. Similarly, we adopt this experimental paradigm to study how participants misreport in a queueing setting. However, in contrast to this literature which uses *money* to incentivize participants to misreport their private information, in our experimental investigation, people have the incentive to misreport in order to shorten their *waiting time* in queue. Also, the literature has almost exclusively focused on settings where outcomes are certain, and until recently the literature has been largely silent on how lying costs extend to uncertain environments. In contrast, in our experimental investigation, outcomes associated with lying or telling the truth may be uncertain due to the scheduling policy. Similar to our work where outcomes are uncertain, Celse et al. (2019), Dugar et al. (2019), Steinel et al. (2022) explore, under different risky environments, how lying changes when its consequences are not certain and they do not consider a queueing setting. Contrary to this, we investigate how lying changes when the consequences of truth-telling (due to the upgrading probability) are random. Finally, Özer et al. (2011) also models lying costs, however, their paper focuses on forecasting in supply chains, unlike our focus in this paper.

3. Model Primitives

We consider an $M/M/1$ queueing system where customers arrive according to a Poisson process with rate λ, and where service times are independent and identically distributed exponential random variables with parameter $1/\mu$. An arriving customer has type X, where X takes value H with probability p_H, and value L with probability $p_L = 1 - p_H$. Customers are delay sensitive, and a customer of type $X = x$ has a per-time-unit waiting cost c_x. We assume that $c_H > c_L$. The traffic intensity is $\rho = \lambda/\mu$, and we assume that the system is stable, i.e., that $\rho < 1$.

At the beginning of the game, the Manager commits to and communicates a claim-based scheduling policy according to which customers will be served. Customers have private information about their type X and, upon arrival, make a claim $Y = y \in \{H, L\}$ about their type. Because the Manager does not know the true customer types, and because the scheduling of customers depends on their claims, customers may be untruthful in their claims, i.e., we may have $X \neq Y$. While the Manager cannot observe individual customer types, he can correctly anticipate the customers' aggregate claiming behaviour for a given scheduling policy. Finally, based on the scheduling policy and on customer claims, customers wait in queue and, eventually, receive service. Waiting times in the system depend on customer claims and on the scheduling policy, which must be chosen optimally based on those claims. In turn, customer claims are, themselves, based on the scheduling policy which is announced by the Manager a priori. That is, the dependence between waiting times, customer claims, and the scheduling policy is endogenously determined.

4. The Manager's Problem

The Manager commits to a scheduling policy according to which customers will be served. The Manager's objective is to minimize the expected waiting cost in the system. We investigate static work-conserving two-class priority policies, where customers are assigned to a priority class with expected waiting time W_y (not including service time) based on their claims $y \in \{H, L\}$.

To find the optimal scheduling policy, it is customary to use the *operationally achievable* method (Coffman Jr and Mitrani 1980), which focuses on identifying the optimal waiting times, W_y, factoring in customer decisions, while abstracting away from specific scheduling policies that induce those waiting times. Once the optimal W_y are identified, one can consider different policy implementations and calibrate the relevant parameters consistently. This implicitly assumes that customer decisions are only driven by W_y, irrespective of the actual scheduling policy implementation - a reasonable assumption with rational customers.

However, when behavioural factors are considered, as we do here, different scheduling policy implementations may lead to different customer behaviours. That is, having the same expected waiting times does not guarantee that customer behaviour will be the same in *all* policy implementations. In particular, misreporting behaviour has been found to be insensitive to changes in the benefits associated with dishonesty, but highly conditional and susceptible to contextual factors (Rosenbaum et al. 2014, Abeler et al. 2014), e.g., factors that increase the salience of honesty standards, factors that allow for moral justifications, or factors that allow for reactions and interpretations to objective risk (Dugar et al. 2019). This is particularly relevant in our investigation of optimal scheduling policies as different implementations may vary in their contextual factors. For example, policies that schedule the service probabilistically based on customers' decisions (Yang et al. 2021) allow for different customer interpretations of objective risk, while policies that schedule the service deterministically (Yang 2021) do not. Based on this, to derive managerial prescriptions that take into account customer behaviour, we focus on a specific class of scheduling policies.

4.1. Scheduling Policy Implementation

We consider the non-preemptive version of the α-*policy* (Yang et al. 2021), since preemptive policies are difficult to implement in practice. Based on customer claims, the Manager assigns customers to a queue $K = k \in \{1, 2\}$ with expected waiting times W_1 (priority queue) and W_2 (regular queue). These waiting times arise endogenously and are given by

$$W_1 = \frac{\lambda}{\mu(\mu - \lambda_1)} \quad \text{and} \quad W_2 = \frac{W_1}{1 - \lambda/\mu},$$

where λ_1 is the rate of arrivals of customers who are assigned to the priority queue at equilibrium. Customers are served in a first-come-first-served (FCFS) fashion within each queue, and customers in the priority queue are given non-preemptive priority over customers in the regular queue. In particular, based on customer claims, the α-policy assigns customers to the priority queue with probabilities $\alpha_y = \mathbb{P}(K = 1 | Y = y)$. That is, upon arrival, customers who claim H (L) are assigned to the priority queue with probability α_H (α_L), and to the regular queue with probability $1 - \alpha_H$

$(1-\alpha_L)$. Thus, the Manager's problem is to select the *routing probabilities* $\boldsymbol{\alpha} = (\alpha_H, \alpha_L)$ in order to minimize the total expected steady-state waiting cost in the system:

$$\underset{\boldsymbol{\alpha}}{Min} \sum_{k\in\{1,2\}} \sum_{x\in\{H,L\}} \lambda_{k,x} c_x W_k, \tag{1}$$

where $\lambda_{k,x}$ is the equilibrium rate of arrivals of customers of true type x who are assigned to priority queue k. The Manager cannot observe the true type x of each customer, but can determine $\lambda_{k,x}$ based on the known equilibrium customer behaviour. Specifically, the arrival rate $\lambda_{k,x}$ is obtained by conditioning on customer claims as follows for $x \in \{H,L\}$ and $k \in \{1,2\}$:

$$\lambda_{k,x} = \lambda \cdot \mathbb{P}(X=x) \cdot \sum_{y\in\{H,L\}} \mathbb{P}(K=k|X=x, Y=y)\mathbb{P}(Y=y|X=x),$$

where $\mathbb{P}(K=k|X=x,Y=y) = \mathbb{P}(K=k|Y=y)$ since the assignment of claims to priority queues is independent of $X=x$, conditional on $Y=y$. Also, $\mathbb{P}(Y=y|X=x)$ captures a typical x type customer's equilibrium claiming behaviour. In §7, we describe the customer claiming behaviour and the optimal scheduling policy that arise in equilibrium.

We note that the α-policy is general in the sense that different parametrizations lead to conceptually different policies. For example, $(\alpha_H = 1, \alpha_L = 0)$ corresponds to a policy where customers with H claims are given *full priority*[1]. In general, $(1 \geq \alpha_H > \alpha_L \geq 0)$ correspond to policies that give *partial priority* to customers with H claims. For example, $(1 > \alpha_H > \alpha_L = 0)$ corresponds to a policy where customers with H claims are given partial priority by means of *downgrading* some H claims to the regular queue. Also, $(1 = \alpha_H > \alpha_L > 0)$ corresponds to a policy where customers with H claims are given partial priority, albeit by means of *upgrading* some L claims to the priority queue. Finally, $(\alpha_H = 1, \alpha_L = 1)$ corresponds to the FCFS policy. Note that, as above, we can also let $\alpha_L > \alpha_H$ to give full or partial priority to customers with L claims.

[1] With the α-policy, expected waiting times based on claims are given by $W_y = \alpha_y W_1 + (1-\alpha_y)W_2$. Formally, customers who claim H are given full priority whenever $W_H = \frac{\lambda}{\mu(\mu-\lambda_H)}$ and $W_H < W_L$. Also, customers who claim H are given partial priority whenever $W_H > \frac{\lambda}{\mu(\mu-\lambda_H)}$ and $W_H < W_L$. The same logic applies for L claims.

5. Customer Problem: A Lying Aversion Model

It is well established in the literature that when dishonesty is not sanctioned or remains anonymous, the decision of whether or not to lie poses a conflict between self-interest and self-concept (Fischbacher and Föllmi-Heusi 2013, Rosenbaum et al. 2014, Abeler et al. 2019). That is, people have an incentive to lie to obtain a material gain (e.g., reducing their waiting cost) but they, concurrently, incur a lying cost because misreporting is intrinsically costly. To capture this tension, we model the behavioural process which leads to individual customer claims as follows. A customer of true type $x \in \{H, L\}$ makes a claim $y \in \{H, L\}$ to minimize a total expected cost equal to the sum of the expected delay cost and the intrinsic lying cost:

$$\underset{y \in \{H,L\}}{Min} \; c_x W_y + \theta \ell(x, y, \boldsymbol{\alpha}, \mathbf{W}), \tag{2}$$

where $c_x W_y = c_x(\alpha_y W_1 + (1-\alpha_y)W_2)$ is the expected waiting cost for customers of type x who claim y and $\theta \ell(x, y, \boldsymbol{\alpha}, \mathbf{W})$ is the expected lying cost of a misreporting customer, for $\boldsymbol{\alpha} = (\alpha_H, \alpha_L)$ and $\mathbf{W} = (W_1, W_2)$. Because customers are delay sensitive, they have the incentive to misreport their types if doing so leads to a shorter expected waiting time. However, a growing body of research has consistently found that people present lying aversion (Gneezy et al. 2013): People often refrain from misreporting their private information, even when they can do so anonymously and with complete impunity (Rosenbaum et al. 2014). Such lying aversion coalesces from a myriad of idiosyncratic factors such as moral or religious reasons, self-image concerns, or unwillingness to deviate from socially-acceptable behaviour (Abeler et al. 2014, Gibson et al. 2013).

To model intrinsic lying costs, we assume that customers experience no lying cost when they claim their true types, i.e., $\ell(x, y, \boldsymbol{\alpha}, \mathbf{W}) = 0$ for $y = x$, and incur a non-negative lying cost whenever they misreport, i.e., $\ell(x, y, \boldsymbol{\alpha}, \mathbf{W}) \geq 0$ for $y \neq x$, where such lying cost is a function of (potentially) the routing probabilities and waiting times. In §5.1, we present several sensible specifications for the lying cost, based on the extant literature. Consistent with empirical research which suggests that individuals exhibit heterogeneous lying costs (Gibson et al. 2013, Rosenbaum et al. 2014, Abeler et al. 2014, 2019), we assume that customers are endowed with a lying aversion, Θ, which is random. Each customer draws a random variate, $\Theta = \theta$, which represents their individual lying aversion, where θ is independently drawn from a distribution Φ with density ϕ over some interval $[0, \bar{\theta}]$. While individual θ values are private information to customers, we assume that the Manager knows the distribution of Θ. We assume that the lying aversion distribution is an *increasing failure rate* (IFR) distribution: the failure rate of Θ is given by $h(z) = \phi(z)/(1 - \Phi(z))$, and the random variable Θ is said to have an increasing failure rate if $h(z)$ is weakly increasing in z for $\Phi(z) < 1$; see Lariviere and Porteus (2001). We note that the assumption that the lying aversion Θ is IFR is not restrictive because it captures many common distributions, e.g., uniform, exponential, half normal, among others (Banciu and Mirchandani 2013). Also, the IFR assumption leads to a unimodal Manager's objective function and thus to a unique equilibrium in the game.

Finally, we emphasize that, as per our motivating examples in the introduction, we focus on unobservable queueing settings, where there are no reputation concerns and where the service involves an anonymous, one-shot, interaction with the Manager. Since the queue is unobservable, customers do not see others making false claims and jumping the queue. We envision that, with observable queues, directly observing the behaviour of others may shape a customer's lying cost, i.e., we may have reputation-based lying costs[2]. We defer the study of lying behaviour in observable queueing setting to future research.

5.1. Sensible Lying-Cost Specifications

In the extant literature, there are two main approaches to model the intrinsic lying cost[3]: (1) A fixed lying cost (DellaVigna et al. 2016, Khalmetski and Sliwka 2019), and (2) a lying cost which

[2] For example Dufwenberg and Dufwenberg (2018) present a model where people derive disutility in proportion to the amount by which they are perceived to misreport, even if they are actually honest. That is, in observable queues, our assumption that $\ell(x, y, \boldsymbol{\alpha}, \mathbf{W}) = 0$ for $y = x$ does not necessarily hold.

[3] The other prominent classes of models found in literature that do not focus on intrinsic lying costs are: social norms models, where lying costs depend on the perception of how others behave, e.g., Abeler et al. (2019); and reputation models, where lying costs depend on what others think about the honesty of the individual, e.g., Gneezy et al. (2018), Dufwenberg and Dufwenberg (2018), Khalmetski and Sliwka (2019). See Abeler et al. (2019) for a survey on variations within each class: for example, the social norms class includes models based on conformity and inequality aversion; and the reputation class includes models based on reputation for honesty and reputation for not being greedy.

increases in the linear (or strictly convex) *material benefit* derived from misreporting (Duch et al. 2021, Gneezy et al. 2018, Kartik 2009). In our setting, a fixed lying cost would be $\ell(x, y, \boldsymbol{\alpha}, \mathbf{W}) = d$ for $y \neq x$, where d is some constant. A lying cost which increases in the convex *material benefit* derived from misreporting would be $\ell(x, y, \boldsymbol{\alpha}, \mathbf{W}) = (c_x(W_x - W_y)^+)^r$, for $r \geq 1$. This expression captures the material benefit as the difference between expected waiting costs given a claim. We note that, in the operations management literature, Özer et al. (2011) propose a linear size of the lie specification in terms of the extent to which information is misreported. Ultimately, our objective is to identify to what extent the predictions under those sensible lying-cost specifications, hold with human decision-makers.

5.2. Misreporting Behaviour

Individual customer types and lying costs are *not observable*, and only the aggregate misreporting probability can be determined by the Manager. This is consistent with our motivating examples where individual customer misreporting cannot be directly observed. In such settings, studying how the misreporting probability depends on a given set of *fixed* values for the waiting times and routing probabilities, i.e., deriving the *best-response* misreporting probability function, allows us to identify which lying-cost specification, from the ones introduced above, is most consistent with experimental data. Thus, we will focus our experimental efforts here on investigating the best-response misreporting probability function. This circumvents many experimental complexities associated with studying queueing steady-state equilibria (Allon and Kremer 2018).

Consider a tagged x type customer with lying aversion parameter θ' who faces, upon arrival, claim-based expected waiting times W_y and routing probabilities α_y. Based on (2), the expected cost of that tagged customer is $c_x W_x$ for a honest claim $y = x$ and $c_x W_y + \theta' \ell(x, y, \boldsymbol{\alpha}, \mathbf{W})$ for a dishonest claim $y \neq x$. That tagged customer selects the claim y which minimizes her expected cost. First, we note that the tagged customer will never misreport if there is no incentive, specifically when $W_x < W_y$ for $y \neq x$, since $c_x W_x < c_x W_y + \theta' \ell(x, y, \boldsymbol{\alpha}, \mathbf{W})$. For the case of no incentive where $W_x = W_y$ for $y \neq x$, it is possible that customers will be indifferent between claims and misreport with arbitrary probability in equilibrium. This happens when $\ell(x, y, \boldsymbol{\alpha}, \mathbf{W}) = 0$ for $y \neq x$, e.g., in the *material benefit* specification above. We note that the misreporting behaviour in this particular case is inconsequential since, for $W_x = W_y$, the expected delay cost in the system is equivalent to the one achieved under a FCFS scheme irrespective of the actual misreporting probability. Finally, if there is an incentive to misreport, $W_x > W_y$ for $y \neq x$, the tagged customer misreports whenever her lying aversion parameter θ' is sufficiently small[4]:

$$\theta' \leq \frac{c_x(W_x - W_y)}{\ell(x, y, \boldsymbol{\alpha}, \mathbf{W})} = \frac{c_x(\alpha_y - \alpha_x)(W_2 - W_1)}{\ell(x, y, \boldsymbol{\alpha}, \mathbf{W})} \quad \text{for} \quad y \neq x.$$

Since individual lying aversions, i.e., specific θ values, are not observable, it follows that a typical x type customer misreports with probability:

$$\mathbb{P}(Y = y | X = x) = \Phi\left(\frac{c_x(\alpha_y - \alpha_x)(W_2 - W_1)}{\ell(x, y, \boldsymbol{\alpha}, \mathbf{W})}\right) \quad \text{for} \quad y \neq x, \tag{3}$$

where we recall that Φ is the CDF of the lying aversion Θ. The best-response misreporting probability is given by (3). This expression motivates our experimental design. In §6, we run controlled experiments to investigate how changes in pre-specified values for the waiting times and routing probabilities affect the misreporting probability in (3). The misreporting probability is readily measurable in a controlled experimental environment where subjects face an individual decision task. Based on the aforementioned potential lying-cost specifications, i.e., fixed cost, linear cost in the material benefit, and strictly convex cost in the material benefit, the best-response misreporting probability is, respectively, given by:

$$[\text{fixed}] \quad \mathbb{P}(Y = y | X = x) = \Phi\left(\frac{c_x(\alpha_y - \alpha_x)(W_2 - W_1)}{d}\right) \quad \text{for} \quad y \neq x, \tag{4}$$

$$[\text{linear}] \quad \mathbb{P}(Y = y | X = x) = \Phi\big(1\big) \quad \text{for} \quad y \neq x, \tag{5}$$

$$[\text{strictly convex}] \quad \mathbb{P}(Y = y | X = x) = \Phi\left(\frac{1}{(c_x(\alpha_y - \alpha_x)(W_2 - W_1))^{r-1}}\right), \text{with } r > 1, \quad \text{for} \quad y \neq x. \tag{6}$$

Based on these expressions, to assess which lying-cost model, if any, is consistent with the data, we experimentally investigate in §6 how changes in both $\Delta\alpha = \alpha_y - \alpha_x$ and $\Delta W = W_2 - W_1$ affect the probability to misreport.

[4] Recall that $W_y = \alpha_y W_1 + (1 - \alpha_y) W_2$ for $y \in \{H, L\}$. Therefore, the difference in expected waiting times given a claim is $W_x - W_y = (\alpha_y - \alpha_x)(W_2 - W_1)$ for $y \neq x$.

6. Experimental Investigation

In this section, we experimentally study the direction of changes in human decisions along the two dimensions of the scheduling policy environment: The routing probabilities and the waiting times. In particular, we study how changes in both $\Delta\alpha$ and ΔW affect the best-response misreporting probabilities associated with subject decisions. This study is based on the well-known experimental procedure proposed by Fischbacher and Föllmi-Heusi (2013) to investigate the extent to which people misreport their private information, hereafter referred to as the FFH paradigm. In the FFH paradigm, participants *privately* observe the outcome of a random variable, e.g., the roll of a die. They are then asked to report that outcome and, subsequently, receive a payoff depending on their reported claims. While dishonesty cannot be verified at the individual participant level (because the true outcome is unknown to the experimenter), one can make inferences about aggregate participant lying behaviour, because the probability distribution of the random variable in the experiment is known to the experimenter. Importantly, participants can misreport their privately observed outcomes with absolute impunity and anonymity, making this design appropriate for investigating intrinsic lying costs - it allows to mitigate the effect of other confounding factors, such as reputation costs, negative externality towards others, perception by others, or fear of getting caught. The FFH paradigm is the most widely adopted in the literature: it has been used in over 90 studies involving more than 44,000 subjects across 47 countries (Abeler et al. 2019). Finally, several studies have found that the observed behaviour in the FFH paradigm represents a good metric for honesty as it correlates strongly with real-life behaviour (Gächter and Schulz 2016, Dai et al. 2018).

6.1. Experimental Procedure

To study intrinsic lying costs and to further mitigate confounding factors, such as reputation and image concerns, we decide to run an online experiment. We conduct an online virtual queueing experiment in Qualtrics, that represents a one-shot individual decision-making situation where participants are told the waiting times in two queues and the routing probabilities to these two queues, depending on their claims. In other words, scheduling is in accordance with the α-policy. We note that our decision to run a virtual queue experiment is in line with our motivating examples where service requests are commonly made online. In our experiment, participants are randomly assigned to one of nine different experimental conditions in a between-subject fashion (see Table 1) where we vary the differences in the routing probabilities, $\Delta\alpha$, and the waiting times between queues, ΔW. Consistent with our unobservable queueing setting and motivating examples in the introduction, participants cannot observe the dynamic state of the queue, i.e., the number of participants in line, or the real-time behaviour of other participants. They only have information about the waiting times in each queue and the routing probabilities.

Based on the FFH paradigm, participants are asked to privately roll a six-sided die and to record the outcome on a piece of paper. To avoid potential confounding factors, participants are instructed to roll a die at home or, alternatively, to use Google's virtual die[5]. Indeed, as described above, to study intrinsic lying costs it is important that the experimenters do not observe the die rolls. After participants roll the die and write down the outcome on a piece of paper, they are presented with the waiting times and routing probabilities according to their randomly assigned condition. Participants are instructed that those who claim the number 5 will wait in the Short queue with probability α_H, and those who claim any other number will wait in the Short queue with probability α_L. We set $\alpha_H > \alpha_L$ in all experimental conditions, so that participants have the incentive to claim the number 5 to reduce their expected waiting time. Before participants roll the die and report any number, they are placed in a practice queue for 2 minutes. This ensures that participants understand what it feels like to wait in the Short virtual queue (in all our experimental conditions, the waiting time of the Short queue is 2 min). After participants report a number, they are assigned to a queue based on the α-policy, wait in queue, and finally answer two simple questions related to their experience in the queue, which concludes the experiment. Throughout the experiment, there is no mention of lying, honesty, or any related concepts.

[5] At the following link `https://www.google.com/search?q=dice+roller`.

Table 1 Experimental conditions.

Condition	$\Delta\alpha$	ΔW	α_H	α_L	W_2	W_1	Sample
1	1	3 min	1	0	5 min	2 min	226
2	1	8 min	1	0	10 min	2 min	220
3	1	13 min	1	0	15 min	2 min	217
4	0.5	3 min	1	0.5	5 min	2 min	222
5	0.5	8 min	1	0.5	10 min	2 min	227
6	0.5	13 min	1	0.5	15 min	2 min	222
7	0.1	3 min	1	0.9	5 min	2 min	220
8	0.1	8 min	1	0.9	10 min	2 min	233
9	0.1	13 min	1	0.9	15 min	2 min	234

Participants and exclusions. We recruited participants from the Amazon Mechanical Turk (MTurk) platform. Participants were instructed that they must wait in a virtual queue, then answered a two-question survey in exchange for a 1 US dollar payment (the payment is independent of the wait time in queue). Participants were informed that the experiment could take up to 30 minutes. To ensure high-quality data, participants with at least 0.95 HIT approval ratio (proportion of completed tasks) were recruited, and we incorporated reCAPTCHA directly in our study. Participants were also asked, as part of the instructions for the experiment, several questions related to the α-policy implementation. Participants were able to finish the instructions section only if they typed the correct answers. We excluded participants that did not complete the experiment. Moreover, while waiting in the virtual queue, and to ensure that participants experienced the wait, they were asked to click a button that appeared every 60 seconds in order to move ahead in the queue. The remaining waiting time for participants in a given queue stopped from elapsing until they clicked that button. We recorded the time that participants took to click each button and excluded participants that, on average, took longer than 30 seconds to click those buttons once they appeared.

We set the target sample size for the experiment and our analysis plans a priori[6]. A total of 2,373 participants (44.33% female, mean age $M_{age} = 37.97$, standard deviation $SD_{age} = 11.70$) were recruited. In our experiment we have a completion rate of 95%. From our original sample, 90% of participants took, on average, less than 30 seconds to click the buttons, and the mean and median average click time was 14 seconds and 4 seconds, respectively. After exclusions, we are left with a sample of 2,021 participants (45.47% female, mean age $M_{age} = 38.23$, standard deviation $SD_{age} = 11.99$). Results are unchanged by the aforementioned exclusions.

6.2. Hypotheses

The existence of intrinsic lying costs underpins our lying-aversion model. Indeed, without lying costs as a behavioural extension in the customer problem (2), our queueing game becomes trivial: We can clearly see that if $\ell(x, y, \boldsymbol{\alpha}, \mathbf{W}) = 0$ for $y \neq x$, then all customers misreport with probability 1. In other words, the existence of intrinsic lying costs is a necessary condition to retrieve any level of honesty, given our experimental design which precludes any other type of lying-related costs. This leads to our first hypothesis:

H1. The proportion of participants who misreport their private information in order to wait in the Short queue is bounded away from 1.

Moreover, as described before, and motivated by the expressions for the misreporting probabilities under the sensible lying-cost specifications in §5.2, we are interested in investigating the effects of $\Delta\alpha$ and ΔW on misreporting. We see in (4) that, with a fixed lying cost, misreporting is predicted to increase in both the difference in routing probabilities, $\Delta\alpha$, and in the difference in waiting times between queues, ΔW. Formally:

H2a. Increasing the difference in the waiting times between the two queues *increases* the proportion of participants who misreport.

H3a. Increasing the difference in the routing probabilities *increases* the proportion of participants who misreport.

[6] The pre-registration document can be found at: `https://aspredicted.org/blind.php?x=7u6ar3`.

In contrast, in (5), we see that with a lying cost that increases linearly in the material benefit, changes in $\Delta\alpha$ and ΔW are predicted to not affect misreporting. Formally:

H2b. Changing the difference in the waiting times between the two queues *does not have an effect* on the proportion of participants who misreport.

H3b. Changing the difference in the routing probabilities *does not have an effect* on the proportion of participants who misreport.

Finally, in (6), if the lying cost increases convexly in the material benefit for $r > 1$, then the probability of misreporting is predicted to decrease in both $\Delta\alpha$ and ΔW. Formally:

H2c. Increasing the difference in the waiting times between the two queues *decreases* the proportion of participants who misreport.

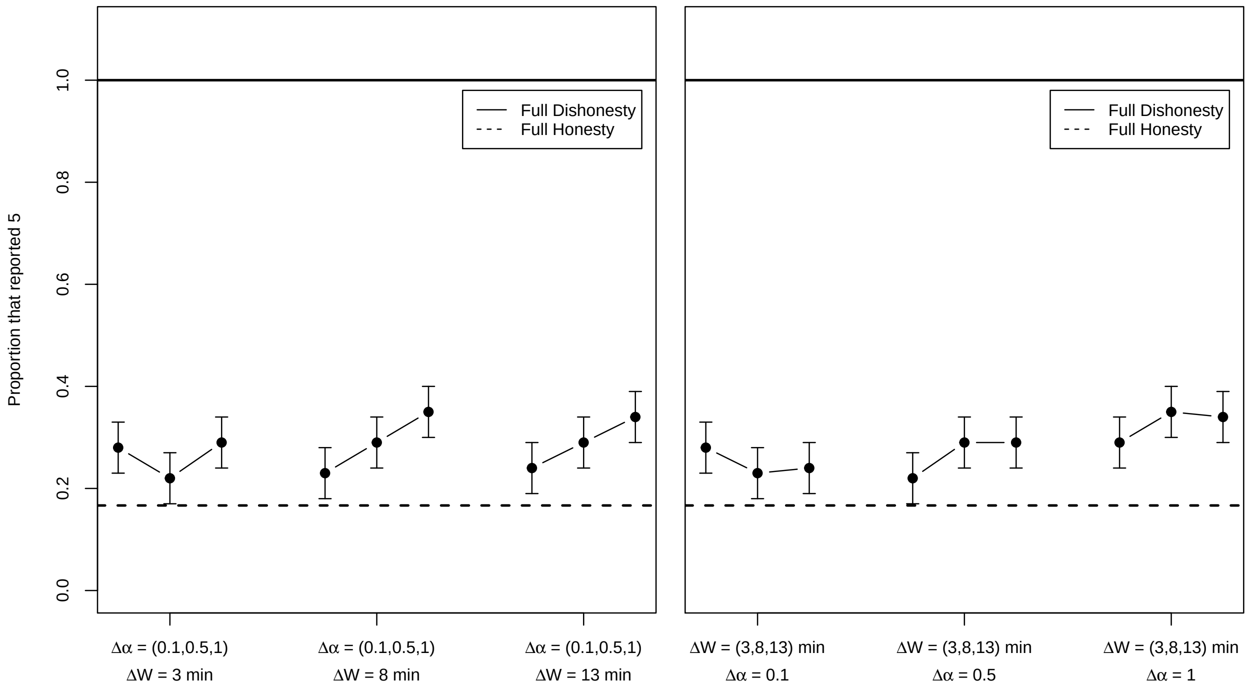
H3c. Increasing the difference in the routing probabilities *decreases* the proportion of participants who misreport.

6.3. Experimental Results

We now describe our experimental results. In the FFH experimental design, since it is not possible to observe individual die outcomes, predictions regarding the misreporting behaviour of participants are tested by conducting statistical analyses on participants' reported outcomes; this is a standard procedure, see e.g., Abeler et al. (2019), Fischbacher and Föllmi-Heusi (2013). Indeed, under the assumption that there is no down-reporting (i.e., participants lying to their disadvantage), and since die outcomes are generated by a discrete uniform distribution in every experimental condition, differences in reporting behaviour between conditions can be attributed to differences in lying behaviour, and differences between the distribution of reports and the uniform distribution represent evidence for lying (Fries and Parra 2021, Fries et al. 2021). As a robustness check, in Appendix B.3.3 we conduct a simulation analysis where we investigate the effect of the sampling variation of the die outcome. Our simulation results show that for the sample sizes that we work with in the present experiment, we can confidently conclude that differences in reporting behaviour are indeed attributed to differences in lying behaviour, and not to sampling variation.

In Figure 1, we plot the proportions of participants who reported the number 5 across all experimental conditions. In Appendix B.1, we present corresponding proportions in Table 2. Recall that participants have the incentive to report the number 5 to reduce their waiting time in the queue.

Figure 1 Proportions of participants who reported the number 5 across experimental conditions.



Human misreporting behaviour demonstrates the existence of lying costs. We run exact binomial tests for the proportion of participants who reported the number 5 in each condition compared to the proportion that would have reported the number 5 under full honesty i.e., 1/6, (p-values < 0.05). This means that participants misreported in all conditions, which can be readily seen in Figure 1, where the black horizontal dashed line represents the expected proportion of customers who would have reported the number 5 under the assumption of full honesty. Any value above the dashed line is based on untruthfulness, in expectation. Importantly, we find that participants misreport little across all experimental conditions. It is clear from Figure 1 that the proportion of participants who reported the number 5 is far from 1, i.e., the full-dishonesty black horizontal solid line in the figure. Since the FFH paradigm focuses on intrinsic costs and, by design, controls for other confounding costs, any reluctance to lie can be attributed to intrinsic lying costs. This result strongly supports the existence of lying costs, as per our model in (2), i.e., we find support for H1.

Impact of changes in waiting times. To test the effects of changes in waiting times, we run logistic regressions for the probability to claim the number 5, where we control for age and gender (see Table 3 in Appendix B.2 for details). We find that the coefficient for the difference in waiting times is not significant and close to 0 in all of the regression specifications. This provides strong evidence to support the claim that changes in waiting times affect very little (if at all) misreporting behaviour. In Appendix B.3, we present several non-parametric tests as robustness checks to further support our conclusions. We note that this finding provides support to H2b, but not to H2a and H2c. That is, this result is consistent with the prediction of the linear lying-cost model, but not with the predictions of the fixed and strictly convex lying-cost models.

Impact of changes in the routing probabilities. In our logistic regressions, based on the Akaike Information Criterion (AIC), we find that the most appropriate model specification among the ones considered, is Model (2a) which includes an intercept, demographic covariates (insignificant in our data), and the $\Delta\alpha$ covariate (see Table 3 in Appendix B.2). We observe that the coefficient for $\Delta\alpha$ is significant and positive, indicating that the misreporting probability increases in $\Delta\alpha$. The other specifications included the ΔW covariate, and the interaction term $\Delta\alpha * \Delta W$. We note that in Model (4a) the coefficient for the interaction term $\Delta\alpha * \Delta W$ is not significant and close to 0. Since such interaction term represents the difference in expected waiting times between the priority classes $W_L - W_H$, this latter result provides support to our claim in §4 that customers deviate from the rationality assumption where their decisions would be only driven by expected waiting times W_y. Overall, we find sufficient statistical evidence in our data to support the claim that changes in $\Delta\alpha$ affect misreporting behaviour. In Appendix B.3, we present several non-parametric tests as robustness checks to further support our conclusions. We note that this finding provides support to H3a, but not to H3b and H3c. That is, this result is consistent with the prediction of the fixed lying-cost model, but not with the predictions of the linear and strictly convex lying-cost models.

6.4. Modelling Implications

The results of our experimental study show that not everyone misreports, which strongly supports the existence of lying costs, as per our model in (2). Moreover, the results indicate that the great majority of explainable lying behaviour can be attributed to $\Delta\alpha$, while only a very small portion (if at all) can be attributed to the expected waiting times ΔW. We note that none of the considered sensible models in §5.1 are consistent with *both findings*, i.e., their predictions for the best-response misreporting probabilities do not exhibit the same directional patterns as our experimental results along the two dimensions of the scheduling policy environment: the routing probabilities and the waiting times. This indicates that we require to revise our assumptions to better capture the direction of changes in the observed decisions in our data. To do so, we highlight the fact that the considered lying-cost models above are based on the extant literature which has mainly focused on settings where the consequences of the reporting behaviour are certain. In contrast, in our queueing setting, due to the routing probabilities, the outcomes of both telling the truth and misreporting may be uncertain. Importantly, we highlight that for our experimental conditions 1-3, where outcomes are certain (since $\alpha_H = 1$ and $\alpha_L = 0$), the linear lying cost specification i.e., $\ell(x, y, \boldsymbol{\alpha}, \mathbf{W}) = c_x(W_x - W_y)^+$, is the only one which is consistent with our experimental results, as it is the only one where changes in the waiting times do not affect misreporting. This finding is consistent with the evidence in the literature that the average amount of lying does not change in the difference in monetary payoffs, even when they are increased from a few cents to 50 USD, a 500-fold increase (Abeler et al. 2019).

We now propose a model which is consistent with our experimental data, i.e., which leads, simultaneously, to a misreporting probability which is insensitive to the waiting times yet sensitive to changes in the routing probabilities. In Appendix F, we provide a numerical analysis where we study the optimal policies that arise when the misreporting probability is indeed sensitive to waiting times. This allows us to better understand the impact of capturing wait-time insensitivity. To guarantee insensitivity to waiting times, it is sufficient to assume that the lying cost, $\ell(x, y, \boldsymbol{\alpha}, \mathbf{W})$, is proportional to the material gain from lying, i.e., proportional to $c_x(W_x - W_y)^+$. This explanation is commonly made in the literature (Kajackaite and Gneezy 2017) to justify the insensitivity of the misreporting probability to changes in the material incentives. As such, we ensure that the lying cost balances out the incentive to misreport, so that indeed varying the difference in waiting times does not affect the probability of misreporting.

To capture the dependence of the misreporting probability on the routing parameters, we allow for the routing probabilities to affect the lying aversion, θ, directly. We note that this assumption is informed by the literature which argues that the lying aversion of individuals is malleable (Rosenbaum et al. 2014, Abeler et al. 2014), and can be directly shaped by factors that affect the *justifiability* of the lie such as *outcome uncertainty* (Celse et al. 2019, Dugar et al. 2019). This latter point is important since outcome uncertainty in our setting stems from the usage of routing probabilities for the scheduling of customers. In particular, a higher justifiability to lie creates a sort of "psychological distance" from misreporting, which allows people to further relax their moral standards (Dugar et al. 2019).

Based on the above, we assume that a customer of true type $x \in \{H, L\}$ makes a claim $y \in \{H, L\}$ to minimize a total expected cost equal to the sum of the expected delay cost and the intrinsic lying cost:

$$\underset{y\in\{H,L\}}{Min}\; c_x W_y + \theta(\boldsymbol{\alpha}) c_x (W_x - W_y)^+, \tag{7}$$

where $\theta(\boldsymbol{\alpha}) = \theta$ for customers without an incentive to lie (i.e., for whom $W_x \leq W_y$ or, equivalently, $\alpha_y \leq \alpha_x$ for $y \neq x$), and $\theta(\boldsymbol{\alpha}) = \theta/\tau(\Delta\alpha)$ for customers with an incentive to lie (i.e., $W_x > W_y$ or, equivalently, $\alpha_y > \alpha_x$ for $y \neq x$). In this case, the lying aversion θ is shaped by a function $\tau(\Delta\alpha) > 0$. Based on (7) for $y \neq x$, as in §5.2, a type x customer for which $W_x < W_y$ never misreports. A type x customer for which $W_x = W_y$ misreports with arbitrary probability in equilibrium. Finally, a type x customer for which $W_x > W_y$ misreports with probability:

$$\mathbb{P}(Y = y | X = x) = \Phi\big(\tau(\Delta\alpha)\big) \quad \text{for} \quad y \neq x, \tag{8}$$

where we recall that Φ is the CDF of the lying aversion Θ. Note that the expression in (8) is consistent with our experimental results where we saw that participant lying behavior is influenced by changes in routing probabilities $\Delta\alpha$, rather than in the waiting times.

6.4.1. Properties of $\tau(\Delta\alpha)$. We make assumptions on $\tau(\Delta\alpha)$ to capture changes in the misreporting probability which are consistent with our experimental data. In what follows we write $f'(t)$ and $f''(t)$ to denote, respectively, the first and second derivative of a function f with respect to its argument t.

ASSUMPTION 1. We assume that $\tau(\Delta\alpha)$ satisfies $\tau'(\Delta\alpha) \geq 0$ and $\tau(1) < \bar{\theta}$.

The assumption, $\tau'(\Delta\alpha) \geq 0$, implies that the lying aversion decreases in $\Delta\alpha$, which is consistent with our experimental observation that misreporting increases in $\Delta\alpha$ (see Table 3 in Appendix B.2 for details). This can be interpreted as follows. Lower (higher) values of $\Delta\alpha$ provide less (more) justification to misreport, such that customers experience a higher (lower) lying aversion. For example, in our experimental study, we observed that in the conditions with a higher probability to gain priority by *means of truth-telling* (i.e., which reduces $\Delta\alpha$), the misreporting prevalence was indeed lower. In this case, people arguably have less justification to misreport since they are presented with the chance to obtain priority without the need to misreport. The assumption, $\tau(1) < \bar{\theta}$, ensures that not everyone misreports, which is consistent with our experimental results, the extant literature, and our motivating examples. To see this, recall that $\bar{\theta}$ represents the upper bound of the support for the lying aversion distribution. Since $\tau(\Delta\alpha)$ increases in $\Delta\alpha$, if $\tau(1) < \bar{\theta}$ then it follows that $\Phi(\tau(\Delta\alpha)) < 1$, that is, that not everyone misreports.

We will see in Proposition 1 that the *semi-elasticity* (Wooldridge 2015) of misreporting behaviour, $\mathcal{S}$, arises naturally in the characterization of the optimal policy:

$$\mathcal{S}(\Delta\alpha) = \frac{\partial(1-\Phi(\tau(\Delta\alpha)))/\partial\Delta\alpha}{1-\Phi(\tau(\Delta\alpha))} = \frac{\tau'(\Delta\alpha)\phi(\tau(\Delta\alpha))}{1-\Phi(\tau(\Delta\alpha))} = -\tau'(\Delta\alpha)h(\tau(\Delta\alpha)) \leq 0, \tag{9}$$

where $h(\cdot)$ is the failure rate of the lying-aversion distribution. This metric measures the percentage change in the proportion of honest claims (from L types) in terms of a change in $\Delta\alpha$. Intuitively, it measures how sensitive the misreporting behaviour of customers is to changes in the routing probabilities $\Delta\alpha$. Based on this, we further make an assumption on $\tau(\Delta\alpha)$ to ensure the unimodality of the waiting cost; see Appendix A.2.

ASSUMPTION 2. We assume that $\tau''(\Delta\alpha)$ satisfies $\Delta\alpha\mathcal{S}'(\Delta\alpha)-\mathcal{S}(\Delta\alpha)>0$.

This assumption is not restrictive since it allows the misreporting probability to change in $\Delta\alpha$ in a strictly convex, strictly concave, or in a linear fashion.

Overall, our lying aversion model in (7) captures the fact that while customers have a higher incentive to lie when the difference in waiting times between the queues is increased, they also feel worse about lying because the stakes are higher. Thus, variations in waiting times do not affect misreporting. At the same time, changes in the probability to get priority affect customer misreporting behaviour as it shapes customers' lying aversion directly according to $\tau(\Delta\alpha)$. Finally, in Appendix B.4, we conduct a structural estimation analysis where we propose a specification for $\tau(\Delta\alpha)$ as per our Assumptions 1 and 2 that achieves a better fit to the experimental data and a better predictive ability in comparison to the described sensible lying costs specifications.

7. Optimal Scheduling Policy

Based on problems (1) and (7), and under Assumptions 1 and 2, in this section, we derive the optimal routing probabilities, α_H^* and α_L^*, which minimize the expected waiting cost in the system, at equilibrium. In Appendix D, we derive sufficient conditions for which our results hold under more general specifications for customers misreporting probability or under different formalizations for the customer problem.

7.1. Over and Under-Prioritization Trade-Off

We begin by elaborating on the main trade-off that the Manager faces, to build intuition. In the Manager's problem (1), there is an underlying cost asymmetry between the cost that arises from under-prioritization (i.e., H type customers who are placed in the regular queue), and from over-prioritization (i.e., L type customers who are placed in the priority queue). To see this, we let $\delta_H =$

$\mathbb{P}(K=2|X=H)$ be the steady-state under-prioritization probability and $\delta_L = \mathbb{P}(K=1|X=L)$ be the steady-state over-prioritization probability, given by:

$$\delta_H = (1-\alpha_H)\mathbb{P}(Y=H|X=H) + (1-\alpha_L)\mathbb{P}(Y=L|X=H), \tag{10}$$

$$\delta_L = \alpha_H \mathbb{P}(Y=H|X=L) + \alpha_L \mathbb{P}(Y=L|X=L). \tag{11}$$

For any given customer reporting behaviour $\mathbb{P}(Y=y|X=x)$, we study, in the following lemma, the monotonicity of the expected waiting cost as a function of those prioritization errors.

LEMMA 1. *The expected waiting cost in the system $\mathcal{C}$ in (1) is increasing in both δ_H and δ_L. Moreover, it is more sensitive to δ_H than δ_L, i.e., $\frac{\partial \mathcal{C}}{\partial \delta_H} > \frac{\partial \mathcal{C}}{\partial \delta_L} > 0$ if, and only if, $\delta_H + \delta_L < 1$. The additional sensitivity to δ_H over δ_L, i.e., $\frac{\partial \mathcal{C}}{\partial \delta_H} - \frac{\partial \mathcal{C}}{\partial \delta_L}$, increases in ρ.*

Lemma (1) is similar to Proposition 7 in Singh et al. (2022) and Proposition 2 in Argon and Ziya (2009). We repeat this result here to draw parallels between our setting, where customers are strategic in their claims, and the models in those papers where customers do not have the ability to influence their priority classifications. Consistent with intuition, Lemma 1 shows that the waiting cost increases strictly in the prioritization errors δ_H and δ_L under a condition which, we will see, is satisfied at optimum; see Proposition 1 in the next section. Importantly, Lemma 1 demonstrates the asymmetric impact of under-prioritization versus over-prioritization errors, particularly in congested systems: Under-prioritization is more costly than over-prioritization. Given this asymmetry in the Manager's trade-off, we will see that the optimal policy allows to eliminate the under-prioritization error, while minimizing the over-prioritization error.

7.2. Game Equilibrium

Recalling from equation 9 that $\mathcal{S}(\Delta\alpha)$ represents a measure of how sensitive the misreporting/honest behaviour of customers is to changes in $\Delta\alpha$, we now present the equilibrium that arises in the game.

PROPOSITION 1. *Based on problems (1) and (7), under Assumptions 1 and 2, there exists a unique equilibrium which arises in the game between the customers and the Manager:*

(a) All customers with true type $X = H$ make a truthful claim $Y = H$.

(b) A fraction $\Phi(\tau(\alpha_H^* - \alpha_L^*)) < 1$ of customers with true type $X = L$ are dishonest i.e., claim $Y = H$.

(c) The optimal routing policy is to assign high priority to all high-claim customers, i.e., $\alpha_H^* = 1$, and to assign high priority to low-claim customers with probability α_L^*. We have that $\alpha_L^* = 0$ if, and only if, $-\mathcal{S}(1) \leq 1$, and $\alpha_L^* \in (0,1)$ as the unique solution to $1 + (1-\alpha_L^*)\mathcal{S}(1-\alpha_L^*) = 0$, otherwise.

Consistent with intuition, part (a) of Proposition 1 shows that customers of type $X = H$ always claim their true type. Part (b) shows that only a proportion (bounded away from 1) of $X = L$ type customers misreport. This result is consistent with the extant literature and with our motivating examples. Finally, part (c) shows that the optimal policy is not FCFS (which corresponds to $\alpha_H = \alpha_L = 1$). Indeed, as long as there is some level of honesty in the system, the Manager is able to extract, at equilibrium, some information from customer claims about the true customer types:

$$\begin{aligned}
\mathbb{P}^*(X = H | Y = H) &= \frac{p_H}{p_H + p_L \Phi(\tau(\alpha_H^* - \alpha_L^*))} > p_H, \\
\mathbb{P}^*(X = L | Y = L) &= 1 > p_L,
\end{aligned}$$

where we recall that p_H and p_L are the proportions of true H and L types. This shows that due to customers' lying aversion, the Manager can still extract some information from the customers' own claims, despite the prevalence of misreporting. This is a useful insight for managers. For example, in one of our motivating examples, the National Health Service, anticipating dishonest claims from patients, dropped a chat-bot symptom checker application designed to aid in booking appointments (Heather 2017). Our theoretical results provide insight into when this may, or may not, be a good decision.

7.3. Honor Policy and Upgrading Policy

From Proposition 1, we can see that $\mathbb{P}^*(Y = H | X = H) = 1$ and $\mathbb{P}^*(Y = H | X = L) = \Phi(\tau(\alpha_H - \alpha_L)) < 1$. Thus, at equilibrium, from (10) and (11), we can see that the Manager faces the following prioritization errors:

$$\delta_H = 1 - \alpha_H, \tag{12}$$

$$\delta_L = \alpha_H \Phi(\tau(\alpha_H - \alpha_L)) + \alpha_L(1 - \Phi(\tau(\alpha_H - \alpha_L))). \tag{13}$$

In part (c) of Proposition 1, we see that, on one hand, the system Manager should always set $\alpha_H^* = 1$, i.e., to *eliminate* the under-prioritization error δ_H; see (12), even if this allows more misreporting customers to jump the queue; see (13). This is driven by the asymmetry between the costs of under-prioritization and over-prioritization in Lemma 1. This shows that Managers should exert caution when adopting strategies to mitigate misreporting at the expense of under-prioritizing. For example, this was the case in the groceries delivery services example of the introduction, where it took too long to verify the vulnerability status of people in order to give them priority slots to gain access to food (Syal 2021).

On the other hand, in part (c) of Proposition 1, we see that, the Manager uses $\alpha_L^* \geq 0$ in order to *minimize* the over-prioritization error δ_L. From (13), we find two effects for increasing α_L. First, increasing α_L leads to an increase in the second part of δ_L due to a higher proportion of honest L customers $(1 - \Phi(\tau(\alpha_H - \alpha_L)))$ being *upgraded* to the high-priority queue. Second, increasing α_L leads to a decrease in the first part of δ_L since it allows to *incentivize more honesty*: A lower proportion of L customers $\Phi(\tau(\alpha_H - \alpha_L))$ misreport due to their lying aversion. Therefore, to minimize the over-prioritization error δ_L, the Manager should balance that tension optimally by deciding *when to incentivize more honesty* from customers.

In part (c) of Proposition 1, we see that upgrading is optimal whenever $-\mathcal{S}(1) > 1$, which intuitively means that customers' responsiveness for upgrading is sufficiently strong so that it manages to decrease the overall cost. Finally, if the population under analysis does not respond to the upgrading control sufficiently, that is whenever $-\mathcal{S}(1) \leq 1$, Proposition 1 prescribes an honor policy, where priorities are given according to customer claims. This provides support to the honor-based scheduling policies observed in practice. For example, the UK used an online booking system to get access to COVID-19 tests at home, which relied on public honesty in claiming their employment status (Weaver and Proctor 2020).

7.4. Upgrading as a Deviation from the cμ Rule

It is well known that when customer types are fully known, the celebrated $c\mu$ rule minimizes the expected cost in the system. In our game, the true priority level of an arriving customer (equivalently, the true index $c\mu$) is unknown to the system Manager. Based on customer claims, in equilibrium, the system Manager can infer the expected $c\mu$ customer index, $I(y) = c_H\mu\mathbb{P}(X = H|Y = y) + c_L\mu\mathbb{P}(X = L|Y = y)$. It is easy to see that $I(H) > I(L)$ if, and only if, $c_H > c_L$, which is our assumption throughout this paper. When the uncertainty in customer types is exogenous, Argon and Ziya (2009) argue that customers should be prioritized in decreasing order of the expected $c\mu$ indices. In our model, upgrading is optimal because customer claims are *endogenous*: By allowing for some L claim customers to be in the priority queue (i.e., by deviating from the $c\mu$ rule), the Manager incites customers to be more honest in their reporting, which ultimately benefits the system as a whole.

7.5. Performance of Optimal Scheduling Policy

We see that the optimal α-policy is never a FCFS policy. Due to customers' lying costs, the Manager can always extract some information from customer claims, and use it to assign service priority. Indeed, the FCFS policy would have been optimal in a setting where all L type customers misreport their types. Yet, we still do not know how much better the optimal α-policy performs relative to the FCFS policy. We also do not know how well it performs relative to the First-Best (FB) policy. In our game, the FB policy is the one that minimizes the system's expected delay cost if the Manager *can* observe the actual customer types. It is well known that for $M/M/1$ systems, the $c\mu$ priority rule (i.e., H-type customers receive absolute priority over L type customers) is the FB. In our problem, since the Manager *cannot* observe customer types, we have that the optimal α-policy would be FB only if all L type customers are fully honest.

In Appendix E, to gain insight into the performance of the optimal α-policy, we study the *percentage cost increase* that it yields over the FB policy. We characterize several properties of that metric in Proposition 3 there. We also present a numerical analysis that characterizes its relation with customer misreporting behaviour. We find that the optimal α-policy performs well, and that its performance does not vary much as system parameters change. We also observe that the optimal policy performs increasingly better than a FCFS policy as congestion increases. We find that when customers are sufficiently honest, the Manager can guarantee very good system performance by using an honor policy. Importantly, we find that if the Manager faces a sufficiently dishonest population, an upgrading policy is well warranted to improve performance. This highlights the importance of leveraging customers' lying aversion in scheduling decisions.

7.6. Practical Considerations

In the lying aversion literature, considerable differences in lying proportions, across studies, are commonly observed (Janezic 2020). In Appendix C, we discuss such lying heterogeneity and present an additional experiment with a highly honest cohort of participants. Our model is sufficiently general to capture such variability in the prevalence of misreporting across different customer populations which differ in their lying aversion characteristics (e.g., lying aversion distribution and parametrizations). Indeed, in Proposition 1, the prescribed optimal policy is contingent on lying-aversion properties (subsumed by the semi-elasticity of honest behaviour metric) which would be specific to each customer population. In practice, such lying aversion properties may be unknown or not directly observable to the Manager. Moreover, easy-to-measure variables such as age, gender, country or social preferences have been found to have only limited predictive power for lying behaviour (Abeler et al. 2019, Janezic 2020). It is then natural to ask: In practice, how can the Manager determine the optimal policy based, e.g., on customer claim data alone?

We answer that question in Appendix G: We study how the Manager can determine the optimal upgrading policy by relying solely on customer claim data. In particular, we propose different data-driven heuristics to determine the optimal upgrading policy, and we conduct an extensive simulation analysis to illustrate their respective performances. We find that without knowledge of the true misreporting probability function, the proposed heuristics are indeed able to implement upgrading policies whose performances are very close to that of the true optimal policy. We defer the reader to Appendix G for further details, where we discuss and compare the proposed heuristics, and point to further steps that Managers can take to improve the observed performance in the analysis.

8. Conclusions

We studied the extent to which people misreport their private information in a two-class priority queueing system, where priorities are assigned according to customer claims, and where these claims are not verifiable nor punishable. Although standard economic theory predicts that all customers will claim that they should be given high priority, we showed, through the analysis of a theoretical queueing model and controlled experiments, that human behaviour deviates far from this prediction. We theorized and experimentally tested the intrinsic costs that people incur when they lie. We studied the consequences of uncertainty (probabilistic routing) on lying, and found that the scheduling policy, rather than the waiting times themselves, significantly impacts lying behaviour.

Priority systems which rely on customer claims are prevalent in practice. Our results highlight the informative value of those claims, even in systems where customers can lie with total impunity. Thus, we provided theoretical and experimental evidence that customer claims should be sought by the system Manager. This is particularly relevant to priority settings where market mechanisms, e.g., pricing the relevant services, are not applicable. In particular, we found theoretical evidence that supports the current honor scheduling system (routing customers according to their claims) which is in place in many real settings. Additionally, we found that, when the lying aversion cost is sufficiently elastic, a different prioritization rule, which deviates from the celebrated $c\mu$ rule, is optimal. Essentially, this rule prescribes upgrading some low-priority claims to the high-priority class in order to incentivize honesty in the system as a whole. We highlight that there is no guarantee, with other scheduling-policy implementations, to be able to identify operational controls that incentivize more honesty. One contribution of our work is, therefore, that we both experimentally and theoretically show that the considered α-policy provides a useful operational control (i.e., probabilistic routing) to mitigate dishonesty.

Limitations and future research. The study of untruthfulness in queues is rich and strongly motivated by practice. We hope that our work will spark more interest in this domain. Our experimental results are based on simple two-priority queueing settings. We advocate conducting more experimental work to further understand the role of intrinsic preferences for truth-telling in the reporting behaviour of people in more complicated queueing settings. Future work can, for example, investigate the extent to which people report untruthfully in a multi-priority queueing system, and unveil the relevant determinants in that case. While we foresee that some people will be honest and others will be untruthful, it is not clear, a priori, how customer claims will be distributed across the multiple priority queues: For example, will there be partial lying in this case?

In this paper, we focused on priority settings where the dynamic state of the queue is unobservable to customers, i.e., the length of the queue and the real-time behaviour of other customers. We also assumed the absence of reputation concerns since the service setting involves an anonymous, one-shot, type of interaction with the Manager. These properties are common features shared by many priority queueing settings, but certainly not all systems. Future research could focus on understanding customer untruthfulness in priority queues where the dynamic state of the queue is observable, e.g., in emergency departments where patients may exaggerate their own symptoms at the triage stage to receive medical service faster. In such settings, where customers observe each other, reputation and negative externality concerns may play a major role. Also, as mentioned above, this work is limited to settings where customers have a rare or one-shot interaction with the service system, like the ones in our motivating examples. We advocate that future research studies the effect of repeated interactions, where we envision that other behavioural factors may play an important role in the misreporting behaviour.

Finally, we believe that the study of lying behaviour under different scheduling policies is an interesting and important future research direction. In this work, we have restricted attention to the class of α-policies and proposed a lying cost model tied to such class of policies. More generally, different policy implementations that tap into different behavioural factors, may be considered, and more general lying cost models that accommodate different implementations can be investigated. For instance, in this work, we have observed that outcome uncertainty affects customer misreporting behaviour. Thus, one might explore different risk-conscious utility specifications (e.g., mean-standard deviation utility, cumulative prospect theory) that capture risk aversion not necessarily tied to a particular policy implementation. An alternative approach, based on our proposed lying-cost model, is to investigate a more general lying cost formula $\theta(\boldsymbol{\varrho})c_x(W_x - W_y)^+$, where $\boldsymbol{\varrho}$ represents the specific policy parameters under consideration (in our study, $\boldsymbol{\varrho} = \boldsymbol{\alpha}$). For instance, based on Coffman Jr and Mitrani (1980)'s proposed implementation, the Manager would define switching periods of time under which certain claims are prioritized. In this case, future research can examine how misreporting behaviour is affected by the likelihood of arriving when a specific claim type is prioritized.

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Appendix A: Technical Proofs

A.1. Lemma 1

Proof. Recall that, by assumption, we have that $c_H > c_L$. We can write the expected waiting cost in the system (1) as:

$$\mathcal{C}(\delta_H, \delta_L) = g(\rho) f(\delta_H, \delta_L),$$

where

$$g(\rho) = \left(\frac{\rho^2}{1-\rho}\right),$$

$$f(\delta_H, \delta_L) = \frac{p_H c_H (1-\rho(1-\delta_H)) + p_L c_L (1-\rho\delta_L)}{p_H(1-\rho(1-\delta_H)) + p_L(1-\rho\delta_L)}.$$

After some algebraic manipulations we find:

$$\frac{\partial f}{\partial \delta_H} = \frac{\rho p_H p_L (c_H - c_L)(1-\rho\delta_L)}{(p_H(1-\rho(1-\delta_H)) + p_L(1-\rho\delta_L))^2},$$

$$\frac{\partial f}{\partial \delta_L} = \frac{\rho p_H p_L (c_H - c_L)(1-\rho(1-\delta_H))}{(p_H(1-\rho(1-\delta_H)) + p_L(1-\rho\delta_L))^2}.$$

Since $\rho \in (0,1)$ and $\delta_L, \delta_H \in [0,1]$, it follows that $\frac{\partial \mathcal{C}}{\partial \delta_H} = g(\rho)\frac{\partial f}{\partial \delta_H} > 0$ and $\frac{\partial \mathcal{C}}{\partial \delta_L} = g(\rho)\frac{\partial f}{\partial \delta_L} > 0$.

We define $\Delta f' \doteq \frac{\partial f}{\partial \delta_H} - \frac{\partial f}{\partial \delta_L}$. After some algebraic manipulations we find:

$$\Delta f' = \frac{p_H p_L (c_H - c_L)\rho^2 (1-\delta_H-\delta_L)}{(p_H(1-\rho(1-\delta_H)) + p_L(1-\rho\delta_L))^2}.$$

Since $\rho \in (0,1)$ we have that $\Delta\mathcal{C}' = \frac{\partial \mathcal{C}}{\partial \delta_H} - \frac{\partial \mathcal{C}}{\partial \delta_L} = g(\rho)\Delta f' > 0$ if and only if $\delta_H + \delta_L < 1$.

Finally, taking the following derivatives:

$$\frac{\partial g(\rho)}{\partial \rho} = \frac{2-\rho}{(1-\rho)\rho} g(\rho),$$

$$\frac{\partial \Delta f'}{\partial \rho} = \frac{2 p_H p_L (c_H - c_L)\rho(1-\delta_H-\delta_L)}{(p_H(1-\rho(1-\delta_H)) + p_L(1-\rho\delta_L))^3},$$

and recalling that $\Delta\mathcal{C}' = \frac{\partial \mathcal{C}}{\partial \delta_H} - \frac{\partial \mathcal{C}}{\partial \delta_L} = g(\rho)\Delta f'$, we have that

$$\frac{\partial \Delta\mathcal{C}'}{\partial \rho} = \frac{\partial g(\rho)}{\partial \rho}\Delta f' + g(\rho)\frac{\partial \Delta f'}{\partial \rho}.$$

Since $\rho \in (0,1)$, we have that $g(\rho) > 0$ and $\frac{\partial g(\rho)}{\partial \rho} > 0$. Moreover, notice that the sign of both $\frac{\partial \Delta f'}{\partial \rho}, \Delta f$ is dictated by the sign of $1-\delta_H-\delta_L$. It follows that $\frac{\partial \Delta\mathcal{C}'}{\partial \rho} > 0$ if and only if $\frac{\partial \Delta f'}{\partial \rho}, \Delta f' > 0 \iff \delta_H + \delta_L < 1$. ■

A.2. Proposition 1

PROOF. There are 3 different cases to analyse: (1) when $\alpha_H < \alpha_L$, (2) when $\alpha_H = \alpha_L$, and (3) when $\alpha_H > \alpha_L$. Based on customers problem (7) it is easy to see that in the first case since $W_L < W_H$, all L type customers report their type and a proportion $\Phi(\tau(\alpha_L - \alpha_H)) < 1$ of H type customers misreport (note that here α_H represents the probability to get a benefit through honest means). For any $\alpha_H < \alpha_L$, L type customers are given priority over H type customers, recall that $c_H > c_L$ thus the waiting cost in the system is higher than in a FCFS policy. Also, for the second case since $W_L = W_H$, irrespective of customer claiming behaviour, the waiting cost in the system is equal to a FCFS policy. We now investigate the third case in detail.

For $\alpha_H > \alpha_L$ we have that all H type customers report their type and a proportion $\Phi(\tau(\Delta\alpha)) < 1$ of L type customers misreport in equilibrium, where $\Delta\alpha = \alpha_H - \alpha_L$. This comes from the fact that the misreporting probability (8) does not depend on waiting times (otherwise the customer equilibrium would come from the solution of a fixed point problem). This result is intuitive since customers can affect each other only through the waiting times. Since waiting times do not affect customer misreporting behaviour, customers make their decisions irrespective of how others behave. Based on the above, the Manager anticipates the following prioritization error probabilities:

$$\delta_H(\alpha_H, \alpha_L) = 1 - \alpha_H,$$

$$\delta_L(\alpha_H, \alpha_L) = \alpha_L + \Delta\alpha\Phi(\tau(\Delta\alpha)).$$

In this proof, for any function $q(\cdot)$, we use $q'_z(\cdot)$ and $q''_z(\cdot)$ to denote, respectively, the first and second partial derivative of $q(\cdot)$ with respect to z. Also, in this proof using the chain rule, we express the partial derivative $\frac{\partial\Phi(\tau(\Delta\alpha))}{\partial\alpha_H}$ as $\phi(\tau(\Delta\alpha))\tau'_{\Delta\alpha}(\Delta\alpha)$, and $\frac{\partial\Phi(\tau(\Delta\alpha))}{\partial\alpha_L}$ as $-\phi(\tau(\Delta\alpha))\tau'_{\Delta\alpha}(\Delta\alpha)$.

The Manager defines the routing probabilities $\alpha_H, \alpha_L \in [0,1]$ in order to minimize the expected waiting cost $\mathcal{C}$ in the system which can be written as:

$$\mathcal{C} = c \cdot f(\alpha_H, \alpha_L),$$

where

$$c = \left(\frac{\rho^2}{1-\rho}\right) > 0,$$

$$f(\alpha_H, \alpha_L) = \frac{p_H c_H (1 - \rho(1 - \delta_H(\alpha_H, \alpha_L))) + p_L c_L (1 - \rho\delta_L(\alpha_H, \alpha_L))}{p_H (1 - \rho(1 - \delta_H(\alpha_H, \alpha_L))) + p_L (1 - \rho\delta_L(\alpha_H, \alpha_L))},$$

$$f'_{\alpha_H}(\alpha_H,\alpha_L) = \frac{d(\alpha_H,\alpha_L)\gamma(\alpha_H,\alpha_L)}{g(\alpha_H,\alpha_L)},$$
$$f'_{\alpha_L}(\alpha_H,\alpha_L) = \frac{d(\alpha_H,\alpha_L)(1-\rho\alpha_H)\kappa(\alpha_H,\alpha_L)}{g(\alpha_H,\alpha_L)},$$
$$d(\alpha_H,\alpha_L) = p_H p_L \rho(c_H - c_L)(1-\Phi(\tau(\Delta\alpha))) > 0,$$
$$g(\alpha_H,\alpha_L) = (p_H(1-\rho(1-\delta_H(\alpha_H,\alpha_L))) + p_L(1-\rho\delta_L(\alpha_H,\alpha_L)))^2 > 0,$$
$$\gamma(\alpha_H,\alpha_L) = -(1-\rho\alpha_L) + (1-\rho\alpha_H)\Delta\alpha\tau'_{\Delta\alpha}(\Delta\alpha)h(\tau(\Delta\alpha)),$$
$$\kappa(\alpha_H,\alpha_L) = 1 - \Delta\alpha\tau'_{\Delta\alpha}(\Delta\alpha)h(\tau(\Delta\alpha)),$$
$$\kappa'_{\alpha_L}(\alpha_H,\alpha_L) = \Delta\alpha h'_{\tau(\Delta\alpha)}(\tau(\Delta\alpha))(\tau'_{\Delta\alpha}(\Delta\alpha))^2 + h(\tau(\Delta\alpha))(\tau'_{\Delta\alpha}(\Delta\alpha) + \Delta\alpha\tau''_{\Delta\alpha}(\Delta\alpha)) \geq 0,$$
$$h(\tau(\Delta\alpha)) = \frac{\phi(\tau(\Delta\alpha))}{1-\Phi(\tau(\Delta\alpha))}.$$

We want to solve the problem: $Min \;\; c\cdot f(\alpha_H,\alpha_L)$, subject to the constraints: $\alpha_L \geq 0 \iff -\alpha_L \leq 0; \alpha_L \leq \alpha_H \iff \alpha_L - \alpha_H \leq 0$; and $\alpha_H \leq 1 \iff \alpha_H - 1 \leq 0$. For this, we construct the lagrangian: $\mathcal{L} = cf(\alpha_H,\alpha_L) - \mu_1(\alpha_L) + \mu_2(\alpha_L - \alpha_H) + \mu_3(\alpha_H - 1)$, and derive the KKT conditions:

Stationarity: $\mathcal{L}'_{\alpha_H} = cf'_{\alpha_H^*} - \mu_2 + \mu_3 = 0$; $\mathcal{L}'_{\alpha_L} = cf'_{\alpha_L^*} - \mu_1 + \mu_2 = 0$.

Complementary Slackness: $\mu_1(-\alpha_L^*) = 0$; $\mu_2(\alpha_L^* - \alpha_H^*) = 0$; $\mu_3(\alpha_H^* - 1) = 0$.

Dual Feasibility: $\mu_1, \mu_2, \mu_3 \geq 0$.

Primal Feasibility: $\alpha_L^* \geq 0$; $\alpha_L^* \leq \alpha_H^*$; $\alpha_H^* \leq 1$.

Potential Candidate 1: $(\alpha_H^* = 1, \alpha_L^* = 0)$.

Complementary Slackness: $\mu_1 \neq 0 \Rightarrow \alpha_L^* = 0$; $\mu_2 = 0$; $\mu_3 \neq 0 \Rightarrow \alpha_H^* = 1$.

Stationarity: $\mu_3 = -cf'_{\alpha_H^*} = -\frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = -\frac{cd(1,0)\gamma(1,0)}{g(1,0)}$; $\mu_1 = cf'_{\alpha_L^*} = \frac{cd(\alpha_H^*,\alpha_L^*)(1-\rho\alpha_H^*)\kappa(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = \frac{cd(1,0)(1-\rho)\kappa(1,0)}{g(1,0)}$.

Dual Feasibility: $\mu_3 \geq 0 \iff \frac{cd(1,0)\gamma(1,0)}{g(1,0)} \leq 0 \iff \gamma(1,0) \leq 0 \iff \tau'_{\Delta\alpha}(1)h(\tau(1)) \leq 1/(1-\rho)$; $\mu_1 \geq 0 \iff \frac{cd(1,0)(1-\rho)\kappa(1,0)}{g(1,0)} \geq 0 \iff \kappa(1,0) \geq 0 \iff \tau'_{\Delta\alpha}(1)h(\tau(1)) \leq 1$.

Primal Feasibility: $\alpha_L^* \geq 0$; $\alpha_L^* \leq \alpha_H^*$; $\alpha_H^* \leq 1$.

Potential Candidate 2: $(\alpha_H^* = 1, \alpha_L^* \in (0,1))$.

Complementary Slackness: $\mu_1 = 0$; $\mu_2 = 0$; $\mu_3 \neq 0 \Rightarrow \alpha_H^* = 1$.

Stationarity: $cf'_{\alpha_L^*} = 0 \iff \frac{cd(\alpha_H^*,\alpha_L^*)(1-\rho\alpha_H^*)\kappa(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = \frac{cd(1,\alpha_L^*)(1-\rho)\kappa(1,\alpha_L^*)}{g(1,\alpha_L^*)} = 0 \iff \kappa(1,\alpha_L^*) = 0 \iff 1-(1-\alpha_L^*)\tau'_{\Delta\alpha}(1-\alpha_L^*)h(\tau(1-\alpha_L^*)) = 0$; $\mu_3 = -cf'_{\alpha_H^*} = -\frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = -\frac{cd(1,\alpha_L^*)\gamma(1,\alpha_L^*)}{g(1,\alpha_L^*)}$. We can see that $\kappa(1,1) > 0$ and that $\kappa(1,0) < 0$ whenever $\tau'_{\Delta\alpha}(1)h(\tau(1)) > 1$. In this case, since $\kappa(\alpha_L)$ is continuous and strictly increasing in α_L, it follows that there is a unique $\alpha_L^* \in (0,1)$ such that $\kappa(1,\alpha_L^*) = 0$.

Dual Feasibility: $\mu_3 \geq 0 \iff \frac{cd(1,\alpha_L^*)\gamma(1,\alpha_L^*)}{g(1,\alpha_L^*)} \leq 0 \iff \gamma(1,\alpha_L^*) \leq 0 \iff -\rho(1-\alpha_L^*) \leq 0$.

Primal Feasibility: $\alpha_L^* > 0 \iff \tau'_{\Delta\alpha}(1)h(\tau(1)) > 1$; $\alpha_L^* \leq \alpha_H^*$; $\alpha_H^* \leq 1$.

Potential Candidate 3: $(\alpha_H^* \in (\alpha_L^*, 1), \alpha_L^* = 0)$.

Complementary Slackness: $\mu_1 \neq 0 \Rightarrow \alpha_L^* = 0$; $\mu_2 = 0$; $\mu_3 = 0$.

Stationarity: $cf'_{\alpha_H^*} = 0 \iff \frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = 0 \iff \frac{cd(\alpha_H^*,0)\gamma(\alpha_H^*,0)}{g(\alpha_H^*,0)} = 0 \iff \gamma(\alpha_H^*,0) = 0 \iff \tau'_{\Delta\alpha}(\alpha_H^*)h(\tau(\alpha_H^*)) = 1/(\alpha_H^*(1-\rho\alpha_H^*))$; $\mu_1 = cf'_{\alpha_L^*} = \frac{cd(\alpha_H^*,\alpha_L^*)(1-\rho\alpha_H^*)\kappa(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = \frac{cd(\alpha_H^*,0)(1-\rho\alpha_H^*)\kappa(\alpha_H^*,0)}{g(\alpha_H^*,0)}$.

Dual Feasibility: $\mu_1 \geq 0 \iff \frac{cd(\alpha_H^*,0)(1-\rho\alpha_H^*)\kappa(\alpha_H^*,0)}{g(\alpha_H^*,0)} \geq 0 \iff \kappa(\alpha_H^*,0) \geq 0 \iff \tau'_{\Delta\alpha}(\alpha_H^*)h(\tau(\alpha_H^*)) \leq 1/\alpha_H^*$, which is never the case since $\tau'_{\Delta\alpha}(\alpha_H^*)h(\tau(\alpha_H^*)) = 1/(\alpha_H^*(1-\rho\alpha_H^*))$ and $\rho \in (0,1)$ and $\alpha_H^* \in (0,1)$.

Potential Candidate 4: $(\alpha_H^* \in (\alpha_L^*, 1), \alpha_L^* \in (0, \alpha_H^*))$.

Complementary Slackness: $\mu_1 = 0$; $\mu_2 = 0$; $\mu_3 = 0$.

Stationarity: $cf'_{\alpha_L^*} = 0 \iff \frac{cd(\alpha_H^*,\alpha_L^*)(1-\rho\alpha_H^*)\kappa(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = 0 \iff \kappa(\alpha_H^*,\alpha_L^*) = 0 \iff (\alpha_H^*-\alpha_L^*)\tau'_{\Delta\alpha}(\alpha_H^*-\alpha_L^*)h(\tau(\alpha_H^*-\alpha_L^*)) = 1$; $cf'_{\alpha_H^*} = 0 \iff \frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = 0 \iff \frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = 0 \iff \gamma(\alpha_H^*,\alpha_L^*) = 0(\alpha_H^*-\alpha_L^*)\tau'_{\Delta\alpha}(\alpha_H^*-\alpha_L^*)h(\tau(\alpha_H^*-\alpha_L^*)) = \frac{1-\rho\alpha_L^*}{1-\rho\alpha_H^*} \neq 1$.

Potential Candidate 5: $(\alpha_H^* = \alpha_L^* \in (0,1))$.

Complementary Slackness: $\mu_1 = 0$; $\mu_2 \neq 0 \Rightarrow \alpha_H^* = \alpha_L^*$; $\mu_3 = 0$.

Stationarity: $\mu_2 = cf'_{\alpha_H^*} = \frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = -\frac{cd(\alpha_H^*,\alpha_L^*)(1-\rho\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)}$.

Dual Feasibility: $\mu_2 \geq 0 \iff -\frac{cd(\alpha_H^*,\alpha_L^*)(1-\rho\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} \geq 0 \iff -(1-\rho\alpha_L^*) \geq 0$ which is never the case.

Potential Candidate 6: $(\alpha_H^* = \alpha_L^* = 0)$.

Complementary Slackness: $\mu_1 \neq 0 \Rightarrow \alpha_L^* = 0$; $\mu_2 \neq 0 \Rightarrow \alpha_H^* = \alpha_L^*$; $\mu_3 = 0$.

Stationarity: $\mu_2 = cf'_{\alpha_H^*} = \frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = -\frac{cd(0,0)}{g(0,0)}$.

Dual Feasibility: $\mu_2 \geq 0 \iff -\frac{cd(0,0)}{g(0,0)} \geq 0$ which is never the case.

Potential Candidate 7: ($\alpha_H^* = \alpha_L^* = 1$).

Complementary Slackness: $\mu_1 = 0$; $\mu_2 \neq 0 \Rightarrow \alpha_H^* = \alpha_L^*$; $\mu_3 \neq 0 \Rightarrow \alpha_H^* = 1$.

Stationarity: $\mu_2 = -cf'_{\alpha_L^*} = -\frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = -\frac{cd(1,1)(1-\rho)}{g(1,1)}$.

Dual Feasibility: $\mu_2 \geq 0 \iff -\frac{cd(1,1)(1-\rho)}{g(1,1)} = -(1-\rho) \geq 0$ which is never the case.

We can see that only candidates 1 and 2 comply with the KKT necessary conditions and that both candidates are mutually exclusive: candidate 1 (i.e., $\alpha_H^* = 1, \alpha_L^* = 0$) holds whenever $\tau'_{\Delta\alpha}(1)h(\tau(1)) \leq 1$ whereas candidate 2 (i.e., $\alpha_H^* = 1, \alpha_L^* \in (0,1)$ such that $1-(1-\alpha_L^*)\tau'_{\Delta\alpha}(1-\alpha_L^*)h(\tau(1-\alpha_L^*)) = 0$) holds whenever $\tau'_{\Delta\alpha}(1)h(\tau(1)) > 1$. We can see that in both candidates we have that $\alpha_H^* = 1$, which minimizes the under-prioritization error δ_H. Also, based on this, we can see that $\alpha_L^* = 0$ minimizes the over-prioritization error δ_L whenever $\tau'_{\Delta\alpha}(1)h(\tau(1)) \leq 1$, and $\alpha_L^* \in (0,1)$ as above minimizes the over-prioritization error δ_L whenever $\tau'_{\Delta\alpha}(1)h(\tau(1)) > 1$. From Lemma 1 we know that the waiting cost strictly increases in both δ_H and δ_L, which shows that the identified candidates minimize the delay cost in the system.

Notice that in this case, we have that all high type customers claim their type and that a proportion equal to $\Phi(\tau(1-\alpha_L^*)) < 1$ of low type customers misreport. When the Manager sets the routing prioritization policy $\alpha_H^* = 1, \alpha_L^* \in [0,1)$ the prioritization error probabilities are $\delta_H^* = 0$ and $\delta_L^* = \alpha_L^* + (1-\alpha_L^*)\Phi(\tau(1-\alpha_L^*)) < 1$. It is easy to see from Lemma 1, that this performs better than a FCFS discipline: for a FCFS ($\alpha_H = \alpha_L = 1$) we have that $\delta_H = 0$ and $\delta_L = 1$. Finally, since the routing policies in cases 1 (i.e., $\alpha_H < \alpha_L$) and 2 (i.e., $\alpha_H = \alpha_L$) perform respectively worse/same as a FCFS policy, thus we conclude that the routing policy in this case 3 performs better, and thus arises in equilibrium. ■

Appendix B: Further Details for Experimental Investigation

B.1. Experimental Results per Condition

Table 2 Proportions and half widths of 95% confidence intervals of participants who reported the die roll 5 across experimental conditions.

Condition	$\mathbb{P}$(Claim 5)
1	0.29 ± 0.06
2	0.35 ± 0.06
3	0.34 ± 0.06
4	0.22 ± 0.05
5	0.29 ± 0.06
6	0.29 ± 0.06
7	0.28 ± 0.06
8	0.23 ± 0.05
9	0.24 ± 0.05

B.2. Logistic Regressions

We run logistic regressions where we control for age and gender. We estimate the effects on the probability to claim the number 5 (see Table 3). We conduct likelihood ratio tests between Model (2a) and Model (3a) ($\chi^2 = 0.98$, $df = 1$, p-value $= 0.32$), and Model (2a) and Model (4a) ($\chi^2 = 2.8$, $df = 2$, p-value $= 0.24$) which show that the fit of Model (2a) does not significantly improve by adding the ΔW predictor in Model (3a) and the interaction term in Model (4a). Finally, the likelihood ratio test between Model (2a) and the null model including only an intercept term ($\chi^2 = 13.37$, $df = 3$, p-value 0.004) shows that the fit of Model (2a) is significantly better.

Table 3 Logistic Regressions

	$\mathbb{P}$(Claim 5)			
	(1a)	(2a)	(3a)	(4a)
(Intercept)	-1.03***	-1.19***	-1.29***	-1.09***
	(0.21)	(0.20)	(0.22)	(0.27)
Age	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
GenderM	0.13	0.13	0.13	0.14
	(0.10)	(0.10)	(0.10)	(0.10)
ΔW	0.01	-	0.01	-0.01
	(0.01)	-	(0.01)	(0.02)
$\Delta\alpha$	-	0.45***	0.45***	0.09
	-	(0.13)	(0.13)	(0.30)
$\Delta\alpha * \Delta W$	-	-	-	0.04
	-	-	-	(0.03)
N	2021	2021	2021	2021
AIC	2398.17	2387.79	2388.81	2388.99
Pseudo R^2	0.00	0.01	0.01	0.01
Pseudo R^2 †	0.01	0.23	0.25	0.25

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

† We compute McFadden's pseudo R^2 at the aggregate experimental condition level. Binary individual responses are grouped at the experimental condition $j \in \{0, \cdots, 9\}$ level with sample size n_j, such that the number of participants that claim the number 5 is captured by a binomial random variable k_j, and the log likelihood is given by $\sum_j log\big(\binom{n_j}{k_j} p_j^{k_j}(1-p_j)^{n_j-k_j}\big)$.

We also run logistic regressions with the covariate α_L instead of $\Delta\alpha$. We are able to do this because $\alpha_H = 1$ was fixed across all experimental conditions such that $\Delta\alpha = 1 - \alpha_L$. The results are presented in Table 4.

Table 4 Logistic Regressions

	$\mathbb{P}$(Claim 5)			
	(1a)	(2a)	(3a)	(4a)
(Intercept)	-1.03***	-0.73***	-0.84***	-1.00***
	(0.21)	(0.19)	(0.22)	(0.25)
Age	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
GenderM	0.13	0.13	0.13	0.14
	(0.10)	(0.10)	(0.10)	(0.10)
ΔW	0.01	-	0.01	0.03
	(0.01)	-	(0.01)	(0.02)
α_L	-	-0.45***	-0.45***	-0.09
	-	(0.13)	(0.13)	(0.30)
$\alpha_L * \Delta W$	-	-	-	-0.04
	-	-	-	(0.03)
N	2021	2021	2021	2021
AIC	2398.17	2387.79	2388.81	2388.99
Pseudo R^2	0.00	0.01	0.01	0.01
Pseudo R^2 †	0.01	0.23	0.25	0.25

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

† We compute McFadden's pseudo R^2 at the aggregate experimental condition level. Binary individual responses are grouped at the experimental condition $j \in \{0, \cdots, 9\}$ level with sample size n_j, such that the number of participants that claim the number 5 is captured by a binomial random variable k_j, and the log likelihood is given by $\sum_j log\big(\binom{n_j}{k_j} p_j^{k_j} (1 - p_j)^{n_j - k_j}\big)$.

Finally, we also run regressions with the covariate $W_L = \alpha_L W_1 + (1 - \alpha_L) W_2$, where recall that $W_1 = 2$ min was fixed. In Table 5 we present the results:

Table 5 Logistic Regressions

	$\mathbb{P}$(Claim 5)				
	(1a)	(2a)	(3a)	(4a)	(5a)
(Intercept)	-0.73***	-0.86***	-1.23***	-1.11***	-1.03***
	(0.19)	(0.23)	(0.20)	(0.22)	(0.27)
Age	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GenderM	0.13	0.13	0.14	0.14	0.14
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
α_L	-0.45***	-0.45***	-	-	-0.22
	(0.13)	(0.13)	-	-	(0.20)
W_2	-	0.01	-	-0.02	-
	-	(0.01)	-	(0.01)	-
W_L	-	-	0.04***	0.05***	0.03
	-	-	(0.01)	(0.01)	(0.02)
N	2021	2021	2021	2021	2021
AIC	2387.79	2388.81	2386.53	2387.09	2387.32
BIC	2410.24	2416.87	2408.98	2415.15	2415.38
Pseudo R^2	0.00	0.01	0.01	0.01	0.01
Pseudo R^2 †	0.23	0.25	0.22	0.23	0.24

$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

† We compute McFadden's pseudo R^2 at the aggregate experimental condition level. Binary individual responses are grouped at the experimental condition $j \in \{0, \cdots, 9\}$ level with sample size n_j, such that the number of participants that claim the number 5 is captured by a binomial random variable k_j, and the log likelihood is given by $\sum_j log\big(\binom{n_j}{k_j} p_i^{k_j}(1-p_j)^{n_j-k_j}\big)$.

First, we notice that the W_L covariate is significant, which is intuitive since it is a function of the upgrading probability, α_L. We notice that in model (4a), where we control for the waiting time in the long queue W_2, the coefficient for such W_2 is negative, close to 0, and not significant. Importantly, since $W_L = 2\alpha_L + (1-\alpha_L)W_2$, the fact that W_2 does not influence misreporting shows that the majority of explainable lying behaviour can be attributed to the upgrading probability. Now, we observe that the AIC and BIC of model (3a) are lower than that of model (1a), which is consistent with intuition since both models capture the effect of the upgrading probability, but model (3a) in addition captures the effect of the waiting time (even though it is a very small effect). Importantly, we run a Voung test between models (1a) and (3a) for the hypothesis that model (3a) fits the data better than model (1a) ($z = -0.254$, p-value $= 0.4$), which is similar to a Likelihood ratio test but for non-nested models (Vuong 1989) - the 95% confidence intervals for the AIC and BIC difference between models are given by ($-8.462 < AICdiff < 10.982$) and ($-8.462 < BICdiff < 10.982$). This result shows that we cannot reject the null hypothesis that both model fits are equal. Finally, a likelihood ratio test between model (1a) and (5a) ($\chi^2 = 2.47$, $df = 1$, p-value $= 0.12$) shows that the fit of Model (1a) does not significantly improve by adding the W_L predictor. Overall this provides further support for the claim that the great majority of explainable lying behaviour can be attributed to the upgrading probability.

Finally, we have seen that the difference in waiting times ΔW does not affect misreporting behaviour. The fact that the coefficient for W_2 is not significant and close to 0 shows that the waiting time in the Long Queue does not present an absolute effect on misreporting behaviour neither. Related to this, we want to highlight that our experimental data does not allow to test whether the waiting time in the Short Queue W_1 presents an absolute effect on misreporting since we kept W_1 fixed in our experimental conditions. This is noteworthy since in our proposed model, we make the assumption that W_1 does not affect misreporting. Based on this, to test the implications of this assumption, in Appendix F we conduct a numerical analysis where we identify the optimal α-policy that arises in a setting where the lying probability is a function of $\Delta W = \frac{\rho}{1-\rho} W_1$, and compare it with our current policy (that does not include the waiting time effect on misreporting).

B.3. Robustness Checks

B.3.1. Non-parametric tests: The effect of waiting times. We run a Generalized Cochran-Mantel-Haenszel test (Agresti 2003) for the conditional association between the proportion of participants that reported the number 5 and the ΔW condition, conditional on the levels of the $\Delta\alpha$ condition. We find that the conditional association is not significant ($M^2 = 1.36$, $df = 2$, p-value = 0.51). We also run a Chi-square test for the marginal association between the proportion of participants that reported the number 5 and the ΔW condition. We find that the marginal association is not significant ($\chi^2 = 1.22$, $df = 2$, p-value =

0.54). Moreover, for each $\Delta\alpha$ level (i.e., 0.1, 0.5, 1), we run Jonckheere–Terpstra tests for an order, both ascending and descending. We find that the proportion of participants that claim the number 5 does not significantly increase monotonically (p-values $= 0.78, 0.11, 0.20$), nor decrease monotonically (p-values $= 0.22, 0.89, 0.79$) as ΔW increases in each of the respective $\Delta\alpha$ levels. Also, by aggregating the data (ignoring the $\Delta\alpha$ levels), both the ascending (p-value $= 0.24$) and descending (p-value 0.75) trends are not significant in the Jonckheere–Terpstra test.

B.3.2. Non-parametric tests: The effect of routing probabilities. We run a Generalized Cochran-Mantel-Haenszel test for the conditional association between the proportion of participants that reported the number 5 and the $\Delta\alpha$ condition, conditional on the levels of ΔW. We find that the conditional association is significant ($M^2 = 12.16$, $df = 2$, p-value $= 0.002$). We also run a Chi-square test for the marginal association between the proportion of participants that reported the number 5 and the $\Delta\alpha$ condition. We find that the marginal association is significant ($\chi^2 = 12.03$, $df = 2$, p-value $= 0.002$). For each ΔW level (i.e., 3 min, 8 min, 13 min), we run Jonckheere–Terpstra tests for an order, both ascending and descending. We find that the proportion of participants who claim the number 5 does not significantly decrease monotonically (p-values $= 0.61, 0.99, 0.97$) as the $\Delta\alpha$ increases in any of the respective ΔW levels. Moreover, while that proportion does not significantly increase monotonically for the $2-5$ min level (p-value $= 0.39$), it does significantly decrease monotonically in the higher wait-time conditions, i.e., $2-10$ min (p-value $= 0.009$) and $2-15$ min (p-value $= 0.03$). Also, by aggregating the data (ignoring the ΔW levels), the proportion of participants that claim 5 significantly increases monotonically as the $\Delta\alpha$ increases (p-value 0.005).

B.3.3. Simulations. In our logistic regressions, we study the reporting behaviour of participants (i.e., whether they report a number 5) in order to derive conclusions about their misreporting behaviour. We found a significant $\Delta\alpha$ effect on the reporting behaviour. We concluded that this is attributed to changes in the lying behaviour. Since we do not observe individual die outcomes in the experiment, the noise in the realizations of the die rolls may lead to a wrong conclusion that $\Delta\alpha$ has an effect on lying behaviour, when in fact there is no effect, i.e., there may be a type 1 error with respect to the $\Delta\alpha$ condition.

To understand the impact of the sampling variation of the die outcome on the type 1 error probability of the $\Delta\alpha$ condition, we conduct a simulation analysis, where for each of the $j = 9$ experimental conditions (with sample size N_j), we simulate N_j independent Bernoulli(1/6) rolls. This captures the fact that participants get a number 5 with probability 1/6, and any other number with probability 5/6. Then, based on the actual die outcome, we simulate participants reports in the following way: If the actual die outcome is 5 we simulate a report equal to 5 with probability 1, and if the actual die outcome is not 5 we simulate a report equal to 5 with probability $\mathbb{P}(misreport)$, where we select different values of $\mathbb{P}(misreport)$ as a further robustness check. Importantly, to investigate the type 1 error, we assume that the lying probability in our simulations does not depend on the experimental conditions. We consider $\mathbb{P}(misreport) = 0$, $\mathbb{P}(misreport) = 0.14$, which is the average lying rate in our data set (we use the method proposed in Hugh-Jones (2019) to estimate lying rates in binary lying games, which estimates the excess number of 5s reports to what would be expected under full honesty based on a bayesian approach), and $\mathbb{P}(misreport) = 0.35$ (which is the maximum possible lying rate in our data set, and assumes that no participant actually rolled a number 5). Finally, once a data set is generated based on the aforementioned process, we fit a logistic regression with linear predictor $\beta_0 + \beta_1 \Delta W + \beta_2 \Delta\alpha$. For a total of 10,000 simulation runs, we use the p-values associated with the coefficient β_2 to compute the proportion of runs where such a coefficient is significant at different levels (i.e., $0.01, 0.05, 0.01, 0.001$), that is, where there is a type 1 error. The following table shows the results of our simulation analysis.

Table 6 Simulation Results: Type 1 error probability

Significance	$\mathbb{P}(misreport)$		
level	0	0.14	0.35
0.1	0.1019	0.0973	0.0969
0.05	0.0501	0.0508	0.0508
0.01	0.0097	0.0094	0.0087
0.001	0.0006	0.0007	0.0017

Overall, based on our simulation results we corroborate that the probability of a type 1 error is very close to the considered significance levels. Thus, we can confidently conclude that the observed differences in the reporting behaviour can be attributed to differences in the lying behaviour, and not to sampling variation. Finally, we want to mention that, in a related exercise, Fries et al. (2021) run a similar analysis in which they compare the frequency of reported 5s with the expected probability of success of 16.66% using binomial tests. They also corroborate that the type 1 error is close to the considered significance levels. Similarly, Fries and Parra (2021) show that frequentist methods in the die roll game produce accurate confidence intervals for the average die roll when the sample is about 100 observations or more.

B.4. Structural Estimation

In this section, we conduct a structural estimation analysis with our experimental data to investigate the fit and the predictive ability of different lying aversion distributions and lying cost specifications. In particular, we consider an exponential lying aversion distribution with density $\phi(\theta) = \gamma e^{-\gamma\theta}$, a uniform distribution with density $\phi(\theta) = 1/\bar{\theta}$, a half-normal distribution with density $\phi(\theta) = \frac{2\sigma}{\pi_\alpha} e^{-\frac{(\theta\sigma)^2}{\pi_\alpha}}$, and a half-logistic distribution with density $\phi(\theta) = \frac{2e^{\theta/\sigma_l}}{\sigma_l(1+e^{\theta/\sigma_l})^2}$. Moreover, based on our discussion in §5.1, we consider a fixed lying cost that predicts a misreporting probability $\Phi((\alpha_H - \alpha_L)(W_2 - W_1))$ (see §5.2 where we describe how to derive the misreporting probability function), a linear in material benefit lying cost that predicts a misreporting probability $\Phi(1)$, and a quadratic in material benefit lying cost that predicts a misreporting probability $\Phi(1/(\alpha_H - \alpha_L)(W_2 - W_1))$. Recall that Φ represents the cumulative distribution function of the lying aversion.

In particular, in this analysis we are interested in showing that a lying cost specification, as per our proposed model in §6.4 and developed assumptions in §6.4.1, can achieve a better fit and out-of-sample predictive ability in comparison to the aforementioned lying costs specifications. Based on §6.4 and §6.4.1 we propose $\tau(\Delta\alpha) = (\Delta\alpha)^\varphi = (1 - \alpha_L)^\varphi$ where we recall that $\alpha_H = 1$ is fixed in all experimental conditions. We let $\varphi > 0$, which corresponds to a misreporting probability $\Phi((1 - \alpha_L)^\varphi)$. We propose such specification as it is flexible, i.e., it allows to capture linearity, concavity and convexity on α_L through the parameter φ.

We let $\mathbf{X} = \{y_j^i, \alpha_L^j, W_2^j\}$ represent our experimental data set, where y_j^i denotes the observed indicator random variate for participant i ($y_j^i = 1$ if participant i reports 5), in an experimental condition j with upgrading probability α_L^j and waiting time in the long queue W_2^j. We recall that $\alpha_H = 1$ and $W_1 = 2$ in all experimental conditions. We assume that Y_j^i are mutually independent across participants. We define $p_j := \mathbb{P}(Y_j^i = 1)$ which depends on the actual die roll. Assuming that there is no down-reporting, we have that $\mathbb{P}(Y_j^i = 1|\text{actual die outcome} = 5) = 1$ and $\mathbb{P}(Y_j^i = 1|\text{actual die outcome} \neq 5) = \Phi(f(\boldsymbol{\alpha}, \mathbf{W}))$ where $f(\boldsymbol{\alpha}, \mathbf{W})$ is some function that depends on the considered lying cost specification as described above.

We let $\boldsymbol{\beta}$ represent the relevant parameters to estimate. Given the experimental design, and under the assumption that participants roll a fair die, we obtain that: $p_j(\boldsymbol{\beta}) = \mathrm{P}(\mathrm{Y}_j^i = 1) = \frac{1}{6}\mathbb{P}(Y_j^i = 1|\text{actual die outcome} = 5) + \frac{5}{6}\mathbb{P}(Y_j^i = 1|\text{actual die outcome} \neq 5) = \frac{1}{6} + \frac{5}{6}\Phi(f(\boldsymbol{\alpha}, \mathbf{W}))$. Also, for our estimation, we group binary individual responses at the experimental condition $j \in \{0, \cdots, 9\}$ level with sample size n_j, such that the number of participants who claim the number 5 is captured by a binomial random variate k_j, and the log-likelihood is given by:

$$\mathcal{L}(\boldsymbol{\beta}|\mathbf{X}) = \sum_j log\Big(\binom{n_j}{k_j} p_j^{k_j}(\boldsymbol{\beta})(1-p_j(\boldsymbol{\beta}))^{n_j-k_j}\Big). \tag{14}$$

We estimate the relevant parameters that maximize $\mathcal{L}$ for all the aforementioned lying aversion distributions and lying cost specifications. To study the out-of-sample predictive ability of such specifications, we carry out the following procedure:

1. For a given lying aversion distribution and lying cost specification, we withhold a focal experimental condition and estimate the relevant parameters on the remaining 8 conditions.
2. Based on such estimates, we compute the predicted probability $\hat{\mathbb{P}}(Y=1)$ for the focal condition and calculate the absolute error with respect to the actual probability $\mathbb{P}(Y=1)$.
3. Once we do this for all experimental conditions, we compute the Mean Absolute Error (MAE) across the 9 focal conditions.

Table 7 summarizes the results of this analysis, and Tables 8 and 9 present further details. From Table 7, based on the AIC values, we can see that the proposed specification for $\tau(\Delta\alpha)$ as per our proposed model in §6.4 achieves a better fit in comparison to the sensible lying costs specifications from the literature. We note that this holds for all the considered lying aversion distributions. Indeed, we observe that the AIC values of a given lying cost specification do not vary much across lying aversion distributions. Moreover, based on the MAE values, we can see that our proposed specification provides the best out-of-sample predictive ability. We note that this holds for all the considered lying aversion distributions. Indeed, we observe that the MAE values of a given lying cost specification do not vary much across lying aversion distributions. Finally, we observe that the linear in material benefit lying cost presents the closest performance to our proposed specification. This is intuitive since our proposed specification, as described in §6.4, is based on a lying cost model that is proportional to the material benefit. The observed improvement of our proposed model in terms of AIC and MAE comes from the fact that it not only captures the insensitivity to the difference in waiting times (as the linear in material benefit model), but it also captures the sensitivity to changes in routing probabilities from the specification of $\tau(\Delta\alpha)$.

Table 7 Summary results: structural estimation and out-of-sample prediction ability

Lying Cost Specification	$\Theta \sim Exp(\gamma)$				$\Theta \sim Unif(0, \bar{\theta})$			
	Parameter estimate†		AIC	MAE	Parameter estimate†		AIC	MAE
	γ	φ			$\bar{\theta}$	φ		
Fixed	0.03*** (0.003)	-	84.88	0.06	43.04*** (4.063)	-	89.03	0.06
Linear	0.14*** (0.014)	-	71.93	0.04	7.41*** (0.658)	-	71.93	0.04
Quadratic	0.07*** (0.013)	-	180.48	0.11	15.73*** (2.514)	-	183.01	0.11
Proposed	0.2*** (0.023)	0.34* (0.124)	64.19	0.03	5.61*** (0.613)	0.32* (0.117)	64.12	0.03
Lying Cost Specification	$\Theta \sim HalfNormal(\sigma)$				$\Theta \sim HalfLogis(\sigma_l)$			
	Parameter estimate†		AIC	MAE	Parameter estimate†		AIC	MAE
	σ	φ			σ_l	φ		
Fixed	33.5*** (3.272)	-	88.25	0.06	20.82*** (2.047)	-	88.04	0.06
Linear	5.89*** (0.528)	-	71.93	0.04	3.68*** (0.331)	-	71.93	0.04
Quadratic	12.31*** (2.01)	-	182.74	0.11	7.67*** (1.257)	-	182.66	0.11
Proposed	4.44*** (0.493)	0.33* (0.118)	64.14	0.03	2.78*** (0.309)	0.33* (0.118)	64.14	0.03

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

† Values shown are the Maximum Likelihood Estimate with associated (standard error).

MAEs are rounded to two decimal places. For a given lying cost specification and lying aversion distribution, MAEs are computed by averaging the corresponding absolute errors across focal experimental conditions from Tables 8 and 9.

AIC $= 2b - 2\mathcal{L}(\hat{\boldsymbol{\beta}})$, where b is the number of estimated parameters. For a given lying cost specification and lying aversion distribution, AICs are computed from the estimation of the relevant parameters considering all 9 experimental conditions.

Table 8 Structural estimation and out-of-sample prediction ability (Exponential and Uniform distributions)

Focal Experimental Condition†	Observed $\mathbb{P}(Y=1)$	Lying Cost Specification	$\Theta \sim Exp(\gamma)$					$\Theta \sim Unif(0,\bar{\theta})$				
			Parameter estimate†		AIC	Predicted	Absolute	Parameter estimate†		AIC	Predicted	Absolute
			γ	φ		$\hat{\mathbb{P}}(Y=1)$	Error	$\bar{\theta}$	φ		$\hat{\mathbb{P}}(Y=1)$	Error
1	0.29	Fixed	0.03*** (0.003)	-	74.62	0.23	0.06	45.18*** (4.547)	-	77.59	0.22	0.07
		Linear	0.14*** (0.015)	-	66.04	0.28	0.01	7.52*** (0.718)	-	66.04	0.28	0.01
		Quadratic	0.07*** (0.013)	-	159.97	0.19	0.11	16.97*** (2.91)	-	161.69	0.18	0.11
		Proposed	0.21*** (0.028)	0.38* (0.135)	57.76	0.32	0.03	5.29*** (0.655)	0.36* (0.128)	57.65	0.32	0.03
2	0.35	Fixed	0.03*** (0.003)	-	78.35	0.32	0.03	45.75*** (5.175)	-	81.88	0.31	0.04
		Linear	0.13*** (0.014)	-	59.47	0.27	0.08	8.08*** (0.819)	-	59.47	0.27	0.08
		Quadratic	0.07*** (0.013)	-	133.82	0.17	0.18	16.5*** (2.748)	-	135.78	0.17	0.18
		Proposed	0.17*** (0.026)	0.28* (0.13)	56.28	0.30	0.05	6.2*** (0.844)	0.26* (0.123)	56.25	0.30	0.05
3	0.34	Fixed	0.04*** (0.004)	-	69.37	0.47	0.14	32.23*** (3.366)	-	71.15	0.50	0.17
		Linear	0.14*** (0.014)	-	62.37	0.27	0.06	7.9*** (0.784)	-	62.37	0.27	0.06
		Quadratic	0.07*** (0.013)	-	140.24	0.17	0.16	16.16*** (2.644)	-	142.43	0.17	0.17
		Proposed	0.18*** (0.027)	0.31* (0.131)	57.84	0.31	0.03	5.91*** (0.779)	0.29* (0.124)	57.80	0.31	0.03
4	0.22	Fixed	0.03*** (0.003)	-	78.81	0.20	0.02	43.45*** (4.157)	-	82.68	0.20	0.02
		Linear	0.16*** (0.015)	-	62.05	0.29	0.07	6.97*** (0.621)	-	62.05	0.29	0.07
		Quadratic	0.07*** (0.013)	-	174.73	0.21	0.01	16.12*** (2.693)	-	177.03	0.20	0.02
		Proposed	0.21*** (0.025)	0.33* (0.112)	53.25	0.29	0.07	5.28*** (0.556)	0.31* (0.105)	53.24	0.29	0.07
5	0.29	Fixed	0.03*** (0.003)	-	77.76	0.25	0.04	44.77*** (4.535)	-	81.08	0.24	0.04
		Linear	0.14*** (0.015)	-	66.19	0.28	0.01	7.47*** (0.709)	-	66.19	0.28	0.01
		Quadratic	0.07*** (0.013)	-	159.95	0.18	0.10	16.64*** (2.798)	-	161.84	0.18	0.11
		Proposed	0.2*** (0.024)	0.34* (0.124)	58.51	0.29	0.00	5.61*** (0.633) 0.32*	(0.118)	58.44	0.29	0.00
6	0.29	Fixed	0.03*** (0.003)	-	78.97	0.31	0.02	42.79*** (4.359)	-	83.35	0.29	0.00
		Linear	0.14*** (0.015)	-	66.17	0.28	0.01	7.49*** (0.711)	-	66.17	0.28	0.01
		Quadratic	0.07*** (0.013)	-	157.94	0.18	0.11	16.32*** (2.694)	-	160.02	0.17	0.11
		Proposed	0.2*** (0.024)	0.34* (0.125)	58.53	0.29	0.00	5.62*** (0.635)	0.32* (0.118)	58.45	0.29	0.00
7	0.28	Fixed	0.03*** (0.003)	-	64.70	0.17	0.10	43.41*** (4.127)	-	68.53	0.17	0.10
		Linear	0.14*** (0.015)	-	66.30	0.28	0.00	7.4*** (0.694)	-	66.30	0.28	0.00
		Quadratic	0.16*** (0.026)	-	158.11	0.50	0.23	7.3*** (1.152)	-	160.46	0.55	0.27
		Proposed	0.2*** (0.024)	0.48* (0.168)	55.87	0.22	0.06	5.44*** (0.599)	0.45* (0.159)	55.79	0.22	0.06
8	0.23	Fixed	0.03*** (0.003)	-	76.63	0.18	0.04	43.48*** (4.147)	-	80.44	0.18	0.04
		Linear	0.15*** (0.015)	-	62.76	0.29	0.06	7*** (0.627)	-	62.76	0.29	0.06
		Quadratic	0.08*** (0.015)	-	174.64	0.24	0.02	15.51*** (2.65)	-	177.41	0.24	0.01
		Proposed	0.19*** (0.024)	0.31* (0.141)	58.46	0.24	0.01	5.65*** (0.628)	0.29* (0.133)	58.39	0.24	0.01
9	0.24	Fixed	0.03*** (0.003)	-	77.08	0.20	0.04	43.69*** (4.196)	-	80.75	0.19	0.04
		Linear	0.15*** (0.015)	-	63.72	0.28	0.05	7.05*** (0.637)	-	63.72	0.28	0.05
		Quadratic	0.07*** (0.013)	-	174.19	0.21	0.02	16.45*** (2.823)	-	176.31	0.21	0.03
		Proposed	0.2*** (0.024)	0.34* (0.145)	58.60	0.24	0.00	5.62*** (0.623)	0.32* (0.137)	58.53	0.24	0.00

$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

Presented predicted probabilities, observed probabilities and absolute errors are rounded to two decimal places.

AIC $=2b-2\mathcal{L}(\hat{\boldsymbol{\beta}})$, where b is the number of estimated parameters.

† Values shown are the Maximum Likelihood Estimate with associated (standard error).

†In each row we withhold a focal experimental condition and estimate the relevant parameters on the remaining conditions. Based on such estimates, we compute the predicted probability $\hat{\mathbb{P}}(Y=1)$ for the focal condition and calculate the absolute error with respect to the actual probability $\mathbb{P}(Y=1)$.

Table 9 Structural estimation and out-of-sample prediction ability (Half-Normal and Half-Logistic distributions)

Focal Experimental Condition[†]	Observed $\mathbb{P}(Y=1)$	Lying Cost Specification	$\Theta \sim HalfNormal(\sigma)$ Parameter estimate[†] σ	φ	AIC	Predicted $\hat{\mathbb{P}}(Y=1)$	Absolute Error	$\Theta \sim HalfLogis(\sigma_l)$ Parameter estimate[†] σ_l	φ	AIC	Predicted $\hat{\mathbb{P}}(Y=1)$	Absolute Error
1	0.29	Fixed	35.2*** (3.646)	-	77.04	0.22	0.07	21.9*** (2.283)	-	76.90	0.22	0.07
		Linear	5.97*** (0.575)	-	66.04	0.28	0.01	3.74*** (0.361)	-	66.04	0.28	0.01
		Quadratic	13.34*** (2.329)	-	161.51	0.18	0.11	8.32*** (1.46)	-	161.47	0.18	0.11
		Proposed	4.19*** (0.526)	0.36* (0.129)	57.68	0.32	0.03	2.62*** (0.331)	0.37* (0.129)	57.68	0.32	0.03
2	0.35	Fixed	35.6*** (4.168)	-	81.29	0.31	0.04	22.12*** (2.607)	-	81.13	0.32	0.04
		Linear	6.42*** (0.656)	-	59.47	0.27	0.08	4.02*** (0.411)	-	59.47	0.27	0.08
		Quadratic	12.95*** (2.196)	-	135.57	0.17	0.18	8.08*** (1.377)	-	135.51	0.17	0.18
		Proposed	4.91*** (0.677)	0.26* (0.123)	56.26	0.30	0.05	3.07*** (0.425)	0.26* (0.124)	56.26	0.30	0.05
3	0.34	Fixed	25.35*** (2.713)	-	70.90	0.49	0.16	15.81*** (1.701)	-	70.83	0.49	0.15
		Linear	6.28*** (0.628)	-	62.37	0.27	0.06	3.93*** (0.394)	-	62.37	0.27	0.06
		Quadratic	12.66*** (2.111)	-	142.20	0.17	0.17	7.89*** (1.322)	-	142.13	0.17	0.17
		Proposed	4.68*** (0.625)	0.29* (0.124)	57.81	0.31	0.03	2.93*** (0.392)	0.29* (0.125)	57.81	0.31	0.03
4	0.22	Fixed	33.8*** (3.34)	-	81.95	0.20	0.02	21.05*** (2.1)	-	81.76	0.20	0.02
		Linear	5.53*** (0.498)	-	62.05	0.29	0.07	3.46*** (0.313)	-	62.05	0.29	0.07
		Quadratic	12.62*** (2.151)	-	176.79	0.20	0.02	7.87*** (1.349)	-	176.73	0.20	0.02
		Proposed	4.17*** (0.448)	0.31* (0.106)	53.24	0.29	0.07	2.61*** (0.281)	0.31* (0.106)	53.24	0.29	0.07
5	0.29	Fixed	34.85*** (3.642)	-	80.48	0.24	0.04	21.7*** (2.288)	-	80.32	0.24	0.04
		Linear	5.94*** (0.569)	-	66.19	0.28	0.01	3.71*** (0.357)	-	66.19	0.28	0.01
		Quadratic	13.07*** (2.242)	-	161.64	0.18	0.11	8.16*** (1.405)	-	161.58	0.18	0.11
		Proposed	4.44*** (0.509)	0.33* (0.119)	58.46	0.29	0.00	2.78*** (0.32)	0.33* (0.119)	58.47	0.29	0.00
6	0.29	Fixed	33.1*** (3.493)	-	82.54	0.30	0.01	20.6*** (2.2)	-	82.32	0.30	0.01
		Linear	5.95*** (0.57)	-	66.17	0.28	0.01	3.72*** (0.358)	-	66.17	0.28	0.01
		Quadratic	12.8*** (2.154)	-	159.79	0.17	0.11	7.99*** (1.352)	-	159.73	0.17	0.11
		Proposed	4.45*** (0.511)	0.33* (0.119)	58.47	0.29	0.00	2.79*** (0.321)	0.33* (0.119)	58.47	0.29	0.00
7	0.28	Fixed	33.8*** (3.322)	-	67.80	0.17	0.10	21.02*** (2.081)	-	67.61	0.17	0.10
		Linear	5.88*** (0.557)	-	66.30	0.28	0.00	3.68*** (0.35)	-	66.30	0.28	0.00
		Quadratic	5.75*** (0.918)	-	160.25	0.53	0.25	3.59*** (0.575)	-	160.19	0.53	0.25
		Proposed	4.31*** (0.481)	0.45* (0.16)	55.81	0.22	0.06	2.69*** (0.302)	0.45* (0.161)	55.82	0.22	0.06
8	0.23	Fixed	33.8*** (3.323)	-	79.71	0.18	0.04	21.08*** (2.095)	-	79.52	0.18	0.04
		Linear	5.55*** (0.503)	-	62.76	0.29	0.06	3.47*** (0.316)	-	62.76	0.29	0.06
		Quadratic	12.1*** (2.121)	-	177.11	0.24	0.01	7.53*** (1.325)	-	177.03	0.24	0.01
		Proposed	4.47*** (0.504)	0.3* (0.134)	58.41	0.24	0.01	2.8*** (0.317)	0.3* (0.134)	58.41	0.24	0.01
9	0.24	Fixed	34*** (3.369)	-	80.05	0.19	0.04	21.18*** (2.117)	-	79.87	0.19	0.04
		Linear	5.6*** (0.512)	-	63.72	0.28	0.05	3.5*** (0.321)	-	63.72	0.28	0.05
		Quadratic	12.88*** (2.253)	-	176.09	0.21	0.03	8.03*** (1.414)	-	176.03	0.21	0.03
		Proposed	4.45*** (0.501)	0.32* (0.138)	58.55	0.24	0.00	2.78*** (0.314)	0.32* (0.138)	58.55	0.24	0.00

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Presented predicted probabilities, observed probabilities and absolute errors are rounded to two decimal places.

AIC $= 2b - 2\mathcal{L}(\hat{\boldsymbol{\beta}})$, where b is the number of estimated parameters.

† Values shown are the Maximum Likelihood Estimate with associated (standard error).

†In each row we withhold a focal experimental condition and estimate the relevant parameters on the remaining conditions. Based on such estimates, we compute the predicted probability $\hat{\mathbb{P}}(Y=1)$ for the focal condition and calculate the absolute error with respect to the actual probability $\mathbb{P}(Y=1)$.

Appendix C: Additional Experimental Investigation

For this investigation, we use the same experimental procedure, and criteria for the recruitment of participants and exclusions, as in Section §6, so we do not repeat these here. Based on the results in our main experimental investigation, in here we are interested in understanding the relative effect of α_H and α_L on the misreporting probability (8). Formally, we set the following null hypotheses:

H1.b. Changing the routing probability α_H does not have an effect on the proportion of participants that misreport.

H2.b. Changing the routing probability α_L does not have an effect on the proportion of participants that misreport.

Based on the above, in order to test these hypotheses, participants were randomly assigned to one of nine experimental conditions (see Table 10) which differ in both the routing probabilities, α_H and α_L, while keeping the waiting times in the queues constant.

Table 10 Experimental conditions.

Condition	α_H	α_L	W_1	W_2	Sample
1	1	0	2 min	15 min	141
2	1	0.2	2 min	15 min	140
3	1	0.4	2 min	15 min	141
4	0.8	0	2 min	15 min	138
5	0.8	0.2	2 min	15 min	141
6	0.8	0.4	2 min	15 min	133
7	0.6	0	2 min	15 min	138
8	0.6	0.2	2 min	15 min	140
9	0.6	0.4	2 min	15 min	130

We set the target sample size for the experiment and our analysis plans a priori. We pre-registered our experiment, and the corresponding As Predicted document can be found at: `https://aspredicted.org/2DV_J7D`. A total of 1,633 participants (41.58% female, mean age $M_{age} = 34.25$, standard deviation $SD_{age} = 11.70$) were recruited. In our experiment, we have a completion rate of 87%. From those who completed the experiment, 87% of participants took, on average, less than 30 seconds to click the advance in queue buttons, and the mean and median average click time was 17 seconds and 11 seconds, respectively. After exclusions, we are left with a sample of 1,242 participants (43.96% female, mean age $M_{age} = 34.78$, standard deviation $SD_{age} = 10.89$).

C.1. Experimental Results

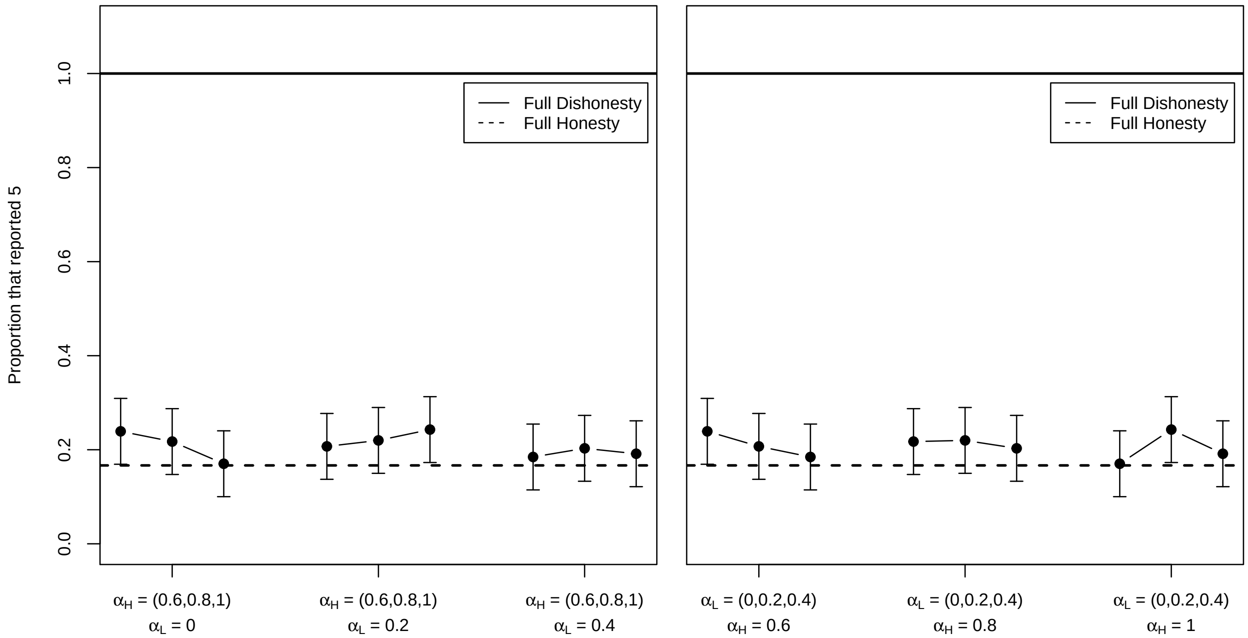
In Figure 2, we present the proportion of participants who reported the number 5 across experimental conditions. In Table 11, we present corresponding proportions. Participants have the incentive to report the number 5 to reduce their waiting time in the queue. We run exact binomial tests for the proportions of participants who reported the number 5 in each condition compared to the proportion that would have reported the number 5 under full honesty i.e., 1/6, (p-values for conditions 1 to 9 = (0.49, 0.01, 0.24, 0.07, 0.06, 0.15, 0.01, 0.12, 0.32)). We can see that, in some conditions, participants might have been fully honest. Importantly, we emphasize that the observed level of honesty in this additional experiment provides further support for the existence of lying costs, and replicates the result in the main experiment that not everyone misreports (i.e., provides support to H1), which underpins our model and derived scheduling policy results.

Table 11 Proportions and half widths of 95% confidence intervals of participants who reported the die roll 5 across experimental conditions.

Condition	$\mathbb{P}$(Claim 5)
1	0.17 ± 0.06
2	0.24 ± 0.07
3	0.19 ± 0.06
4	0.22 ± 0.07
5	0.22 ± 0.07
6	0.20 ± 0.07
7	0.24 ± 0.07
8	0.21 ± 0.07
9	0.18 ± 0.07

We run logistic regressions where we control for age and gender. We estimate the treatments effects on the probability to claim the number 5 (see Table 12). We observe that none of the treatment coefficients are significant. We can see that the coefficient for $\Delta\alpha$ is positive, which is consistent with the results in our

Figure 2 Proportions of participants that reported the number 5 across experimental conditions.



main experimental investigation, however, it is not significant. In light of the significant results in our main experimental investigation, we attribute this to the heterogeneity in the lying proportion between subject populations (see discussion about subject heterogeneity in the literature below). We argue that the lack of significance in this study arises from the fact that, overall, participants were very honest in this experiment, such that there is little room for any managerial intervention to further reduce dishonesty (leading to a not statistically significant effect). In the main experiment, dishonesty is sufficiently high for the scheduling policy to affect the misreporting behaviour, while in the additional experiment, almost everyone is already honest. Indeed, we note that the sample size in this additional experiment is large (1242 participants). Thus, we are quite confident that this subject population is indeed very honest. Importantly, we would like to highlight that our model is general enough to derive prescriptions contingent on how much a given population responds to changes in the routing probabilities. Indeed, Proposition 1 indicates that for a population such as the one observed in this experiment, it would be optimal to implement an honor policy.

Heterogeneity between subject populations in the literature. The observed heterogeneity in the lying proportions between the two experiments is an important point that is commonly recognized and discussed. Indeed, in the lying literature, it has been acknowledged that large differences in the percentages of liars

Table 12 Logistic Regressions

	$\mathbb{P}$(Claim 5)				
	(1a)	(2a)	(3a)	(4a)	(5a)
(Intercept)	-1.25 **	-1.31 ***	-1.20 **	-0.77	-1.39 ***
	(0.42)	(0.26)	(0.43)	(0.58)	(0.31)
Age	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
GenderM	0.00	0.00	0.00	0.01	0.00
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
α_H	-0.14	-	-0.14	-0.70	-
	(0.43)	-	(0.43)	(0.67)	-
α_L	-	-0.23	-0.23	-2.53	-
	-	(0.43)	(0.43)	(2.15)	-
$\alpha_H * \alpha_L$	-	-	-	2.86	-
	-	-	-	(2.63)	-
$\Delta\alpha$	-	-	-	-	0.04
	-	-	-	-	(0.30)
N	1242	1242	1242	1242	1242
AIC	1279.70	1279.52	1281.41	1282.23	1279.79
Pseudo R^2	0.00	0.00	0.00	0.00	0.00
Pseudo R^2 †	0.01	0.01	0.01	0.05	0.00

${}^{*}p < 0.05$, ${}^{**}p < 0.01$, ${}^{***}p < 0.001$.

† We compute McFadden's pseudo R^2 at the aggregate experimental condition level. Binary individual responses are grouped at the experimental condition $j \in \{0, \cdots, 9\}$ level with sample size n_j, such that the number of participants that claim the number 5 is captured by a binomial random variable k_j, and the log likelihood is given by $\sum_j log\left(\binom{n_j}{k_j} p_j^{k_j} (1-p_j)^{n_j-k_j}\right)$.

across studies are commonly observed (Janezic 2020). To illustrate this, Table 13 presents the lying prevalence observed in some of the studies that use the Fischbacher and Föllmi-Heusi (2013) experimental design with two different claim-dependent payoffs - this is the same as in our experimental design where participants are placed in the short queue if they claim to have obtained the number 5, and are placed in the long queue if they report any other number.

Table 13 Lying prevalence observed in some studies

Study	Country	Randomization method	Subjects	% Liars
Houser et al. (2012)	USA	Coin toss	502	45% - 53%
Hilbig and Hessler (2013)	Germany	Die roll	765	19.3%
Abeler et al. (2014)	Germany	Coin toss	658	$\sim$ 0%
Barfort et al. (2015)	Denmark	Die roll	862	42.2%
Djawadi and Fahr (2015)	Germany	Draw from urn	252	32.4%
Pascual-Ezama et al. (2015)	Multiple	Coin toss	1440	14%
Hilbig and Zettler (2015)	Germany	Die roll	88	35%
Zettler et al. (2015)	Germany	Coin toss	134	17.3%
Dieckmann et al. (2016)	Multiple	Coin toss	1015	32%
Kajackaite and Gneezy (2017)	USA	Die roll	1200	7.6% - 19.6%
Our main study	Multiple	Die roll	2021	6.4% - 22%
Our additional study	Mainly USA	Die roll	1242	$\sim$0% - 8.8%

Let b be the probability of obtaining the high payoff outcome. Let p be the observed proportion of participants that claim to have obtained the high payoff outcome. Let γ be the proportion of participants that obtained the low payoff outcome but lied and claimed to have obtained the high payoff outcome. We compute the % Liars $= \gamma$ by solving $p = b + \gamma(1-b)$. Note that this assumes no down reporting.

We note that most sample sizes in Table 13 are large, so we can confidently rule out the sampling variation of the randomized methods as an explanation for the marked differences in the percentage of liars. This heterogeneity in lying tendencies across papers has been a puzzle in the literature, and recently it has been discussed that such differences point to high heterogeneity in *lying preferences* between subject pools rather than heterogeneity of potential confounds, e.g., demographics and related macro-level indicators (Janezic 2020). Indeed, demographics such as age, gender, or country have been found to have only limited predictive power for lying behaviour (Fischbacher and Föllmi-Heusi 2013, Abeler et al. 2014, 2019, Janezic 2020). For example, while some studies have found that levels of honesty vary significantly across countries (Hugh-Jones

2016, Dieckmann et al. 2016), others show no significant difference and also show no meaningful relationship between dishonesty levels and related macro-level indicators including cultural values (Mann et al. 2016), social preferences (Janezic 2020), or common indices of corruption and transparency (Pascual-Ezama et al. 2015). Taking the literature in aggregate, Abeler et al. (2019)'s meta-analysis shows that indeed the country covariate has little predictive power for lying behaviour. In particular, the meta-analysis shows that the average lying report does not vary much between countries, but high variation within countries is observed.

In line with this, we note that in our main experiment, we do not find a significant relation between country and the propensity to lie (see Table 14). Moreover, consistent with the aforementioned variability within countries, for USA participants, we see in the main experiment an overall lying prevalence (i.e., across conditions) of 15% while in the additional experiment, we see an overall lying prevalence of 5.2%. Moreover, for the case of condition 3 in the main experiment and condition 1 in the additional experiment (these conditions have the same parameter settings) we see a lying prevalence of USA participants of 18.4% and 1%, respectively. We note that both USA samples are of similar size: In the main experiment, 69% of participants (i.e., 1386 subjects) come from the USA, while in the additional experiment, 98% of participants (i.e., 1218 subjects) come from the USA. These results strongly point to heterogeneity in lying tendencies across subject populations.

Table 14 Logistic Regressions with Country Covariate

	$\mathbb{P}$(Claim 5)			
	(1a)	(2a)	(3a)	(4a)
(Intercept)	-0.93***	-1.07***	-1.17***	-1.00***
	(0.22)	(0.21)	(0.24)	(0.28)
Age	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
GenderM	0.15	0.14	0.14	0.15
	(0.10)	(0.10)	(0.10)	(0.10)
Country:India	-0.01	0.02	0.02	0.02
	(0.14)	(0.14)	(0.14)	(0.14)
Country:Brazil	-0.31	-0.30	-0.31	-0.32
	(0.26)	(0.26)	(0.26)	(0.26)
Country:United Kingdom	-0.26	-0.23	-0.23	-0.23
	(0.33)	(0.33)	(0.33)	(0.33)
Country:Italy	-0.05	-0.06	-0.07	-0.08
	(0.33)	(0.33)	(0.33)	(0.33)
Country:Canada	-0.68	-0.62	-0.65	-0.64
	(0.46)	(0.46)	(0.46)	(0.46)
…				
ΔW	0.01	-	0.01	-0.01
	(0.01)	-	(0.01)	(0.02)
$\Delta\alpha$	-	0.40**	0.41**	0.09
	-	(0.14)	(0.14)	(0.30)
$\Delta\alpha * \Delta W$	-	-	-	0.04
	-	-	-	(0.03)
N	2021	2021	2021	2021
AIC	2441.36	2433.59	2434.56	2435.15
Pseudo R^2	0.00	0.01	0.01	0.01

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Note: United States serves as a reference factor in the regression. Due to space constraints, we do not present all the countries in the table. The presented countries correspond to more than 95% of the subjects in the experiment. Other countries include Germany, Spain, France, among others.

Appendix D: General Conditions for the Optimal Scheduling Policy

We consider the case in which $\alpha_H > \alpha_L$, such that L type customers are those that have the incentive to misreport. Based on this, to derive general conditions for the identified optimal scheduling policy, we assume that H type customers never down-report, which is intuitive, and that L type customers best respond by misreporting with some probability that does not depend on waiting times. This is consistent with our experimental results and with the extant literature that finds that misreporting behaviour is insensitive to material incentives (Abeler et al. 2019). The insensitivity to waiting times implies that customers' misreporting equilibrium is a function that depends only on the routing probabilities, $\eta(\alpha_H, \alpha_L)$. To see this, note that, generally speaking, the misreporting equilibrium probability (call it ν) is given by the solution of the fixed-point problem $\nu = \eta(\alpha_H, \alpha_L, W_1(\nu), W_2(\nu))$ (where waiting times and misreporting are consistent and endogenously determined and η denotes the best-response function). However, since we have that $\eta(\alpha_H, \alpha_L)$, it simply follows that $\nu = \eta(\alpha_H, \alpha_L)$. This is intuitive since customers individual best responses do not care for the waiting times. Since customers affect each other only through the resulting waiting times, all individual best responses represent a best response correspondence, forming a customer equilibrium where a proportion equal to $\eta(\alpha_H, \alpha_L)$ misreports. Based on this, the task at hand is to determine under which assumptions regarding $\eta(\alpha_H, \alpha_L)$, an honor policy or an upgrading policy will be optimal. Here, we present a general set of sufficient conditions.

Proposition 2. *Assume that $\alpha_H > \alpha_L$, that H type customers never down-report, that L type customers misreport with probability $\eta(\alpha_H, \alpha_L)$, and that $\eta(\alpha_H, \alpha_L)$ is differentiable at all $\alpha_H > \alpha_L$. If $-\frac{\partial}{\partial \alpha_L}\eta(\alpha_H, \alpha_L) \geq \frac{\partial}{\partial \alpha_H}\eta(\alpha_H, \alpha_L)$ for all $\alpha_H \geq \alpha_L$, then it follows that the optimal scheduling policy will be either $(\alpha_H^* = 1, \alpha_L^* = 0)$ or $(\alpha_H^* = 1, \alpha_L^* \in (0,1))$. That is an honor policy or an upgrading policy.*

Proposition 2, shows that if the marginal effect of upgrading to mitigate misreporting is greater than or equal to the marginal effect of downgrading (for all $\alpha_H > \alpha_L$), then the same optimal scheduling policy (i.e., honor policy or upgrading policy) holds. For example, consider the customer problem (2). In this case, since $\alpha_H > \alpha_L$, we know that H type customers do not down-report. Now, assume that L type customers experience a lying cost captured by $c_L(W_2 - W_1)$, that is by the difference between expected waiting times in *priority queues* (rather than in *priority classes* as in the main paper). In this case, we have that $\eta = \Phi(\alpha_H - \alpha_L)$. We can see that the conditions of the above proposition are satisfied: $-\frac{\partial}{\partial \alpha_L}\eta(\alpha_H, \alpha_L) = \phi(\alpha_H - \alpha_L) \geq$

$\phi(\alpha_H - \alpha_L) = \frac{\partial}{\partial \alpha_H}\eta(\alpha_H, \alpha_L)$. For another example, assume that L type customers experience a lying cost captured by $c_L(W_2 - W_H)$, that is by the difference between the *deserved* waiting cost and the expected one from misreporting. In this case we have that $\eta = \Phi(\frac{\alpha_H - \alpha_L}{\alpha_H})$. We can see that the conditions of the above proposition are satisfied: $-\frac{\partial}{\partial \alpha_L}\eta(\alpha_H, \alpha_L) = \phi(\frac{\alpha_H - \alpha_L}{\alpha_H})\frac{1}{\alpha_H} \geq \phi(\frac{\alpha_H - \alpha_L}{\alpha_H})\frac{\alpha_L}{\alpha_H^2} = \frac{\partial}{\partial \alpha_H}\eta(\alpha_H, \alpha_L)$. Finally, consider a different formalization of the customer problem, based on a discrete choice framework. In this case, the misreporting choice probability can be modelled by $\mathbb{P}(\varepsilon < \beta_0 + \beta_1 \Delta\alpha + \beta_2 \Delta W)$, where ε is a random term, and $\beta_0 + \beta_1 \Delta\alpha + \beta_2 \Delta W$ is a linear predictor that captures differences across choice alternatives (Train 2009). If we let ε be logistically distributed, we obtain a logit choice model. Notice that our logistic regressions in Table 3 suggest that the misreporting choice probability can be well captured by $\mathbb{P}(\varepsilon < \beta_0 + \beta_1 \Delta\alpha)$, such that the misreporting probability is equal to $\Psi(\beta_0 + \beta_1 \Delta\alpha)$, where Ψ is the CDF of the logistic distribution. Based on this, we can see that the conditions of the above proposition are satisfied: $-\frac{\partial}{\partial \alpha_L}\eta(\alpha_H, \alpha_L) = \psi(\beta_0 + \beta_1 \Delta\alpha)\beta_1 \geq \psi(\beta_0 + \beta_1 \Delta\alpha)\beta_1 = \frac{\partial}{\partial \alpha_H}\eta(\alpha_H, \alpha_L)$, where ψ is the logistic density function. Based on this, and assuming that H types never down-report. In all of the above examples, from the above Proposition 2 and Lemma 1, it is straightforward to see which of the two policies is the optimal one: an honor policy is optimal if $\delta_L(1, 0) \leq \delta_L(1, \alpha_L^*)$ for $\alpha_L^* \in (0, 1)$, otherwise an upgrading policy is optimal. This can be easily solved by numerically identifying the $\alpha_L^* \in \arg\min\ \delta_L(1, \alpha_L) = \eta(1, \alpha_L) + \alpha_L(1 - \eta(1, \alpha_L))$. We could impose further assumptions on the structure of η to derive further conditions under which each policy is optimal. However, this preserves the generality of our results (and obtaining the optimal policy requires simply to numerically compute δ_L as a function of α_L). We now present the proof of the above Proposition 2.

Proof. In this proof, for any function $q(\cdot)$, we use $q'_z(\cdot)$ to denote the first partial derivative of $q(\cdot)$ with respect to z. Consider the case in which customers misreport with probability $\eta(\alpha_H, \alpha_L)$, where $\alpha_H \geq \alpha_L$. Based on the above, the Manager anticipates the following prioritization error probabilities:

$$\delta_H(\alpha_H, \alpha_L) = 1 - \alpha_H,$$

$$\delta_L(\alpha_H, \alpha_L) = \alpha_L + (\alpha_H - \alpha_L)\eta(\alpha_H, \alpha_L).$$

The Manager defines the routing probabilities $\alpha_H, \alpha_L \in [0, 1]$ in order to minimize the expected waiting cost $\mathcal{C}$ in the system which can be written as:

$$\mathcal{C} = c \cdot f(\alpha_H, \alpha_L),$$

where

$$c = \left(\frac{\rho^2}{1-\rho}\right) > 0,$$

$$f(\alpha_H,\alpha_L) = \frac{p_H c_H(1-\rho(1-\delta_H(\alpha_H,\alpha_L))) + p_L c_L(1-\rho\delta_L(\alpha_H,\alpha_L))}{p_H(1-\rho(1-\delta_H(\alpha_H,\alpha_L))) + p_L(1-\rho\delta_L(\alpha_H,\alpha_L))},$$

$$f'_{\alpha_H} = \frac{d(\alpha_H,\alpha_L)\gamma(\alpha_H,\alpha_L)}{g(\alpha_H,\alpha_L)},$$

$$f'_{\alpha_L} = \frac{d(\alpha_H,\alpha_L)(1-\rho\alpha_H)\kappa(\alpha_H,\alpha_L)}{g(\alpha_H,\alpha_L)},$$

$$d(\alpha_H,\alpha_L) = p_H p_L \rho(c_H - c_L) > 0,$$

$$g(\alpha_H,\alpha_L) = (p_H(1-\rho(1-\delta_H(\alpha_H,\alpha_L))) + p_L(1-\rho\delta_L(\alpha_H,\alpha_L)))^2 > 0,$$

$$\gamma(\alpha_H,\alpha_L) = -(1-\rho\alpha_L)(1-\eta(\alpha_H,\alpha_L)) + (1-\rho\alpha_H)(\alpha_H-\alpha_L)\eta'_{\alpha_H}(\alpha_H,\alpha_L),$$

$$\kappa(\alpha_H,\alpha_L) = (1-\eta(\alpha_H,\alpha_L)) + (\alpha_H-\alpha_L)\eta'_{\alpha_L}(\alpha_H,\alpha_L),$$

We want to solve the problem: $Min\ \ c\cdot f(\alpha_H,\alpha_L)$, subject to the constraints: $\alpha_L \ge 0 \iff -\alpha_L \le 0; \alpha_L \le \alpha_H \iff \alpha_L - \alpha_H \le 0$; and $\alpha_H \le 1 \iff \alpha_H - 1 \le 0$. For this, we construct the lagrangian: $\mathcal{L} = cf(\alpha_H,\alpha_L) - \mu_1(\alpha_L) + \mu_2(\alpha_L-\alpha_H) + \mu_3(\alpha_H - 1)$, and derive the KKT conditions:

Stationarity: $\mathcal{L}'_{\alpha_H} = cf'_{\alpha_H^*} - \mu_2 + \mu_3 = 0$; $\mathcal{L}'_{\alpha_L} = cf'_{\alpha_L^*} - \mu_1 + \mu_2 = 0$.

Complementary Slackness: $\mu_1(-\alpha_L^*) = 0$; $\mu_2(\alpha_L^* - \alpha_H^*) = 0$; $\mu_3(\alpha_H^* - 1) = 0$.

Dual Feasibility: $\mu_1,\mu_2,\mu_3 \ge 0$.

Primal Feasibility: $\alpha_L^* \ge 0$; $\alpha_L^* \le \alpha_H^*$; $\alpha_H^* \le 1$.

Potential Candidate 1: $(\alpha_H^* = 1, \alpha_L^* = 0)$.

Complementary Slackness: $\mu_1 \ne 0 \Rightarrow \alpha_L^* = 0$; $\mu_2 = 0$; $\mu_3 \ne 0 \Rightarrow \alpha_H^* = 1$.

Stationarity: $\mu_3 = -cf'_{\alpha_H^*} = -\frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = -\frac{cd(1,0)\gamma(1,0)}{g(1,0)}$; $\mu_1 = cf'_{\alpha_L^*} = \frac{cd(\alpha_H^*,\alpha_L^*)(1-\rho\alpha_H^*)\kappa(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = \frac{cd(1,0)(1-\rho)\kappa(1,0)}{g(1,0)}$.

Dual Feasibility: $\mu_3 \ge 0 \iff \frac{cd(1,0)\gamma(1,0)}{g(1,0)} \le 0 \iff \gamma(1,0) \le 0 \iff \eta'_{\alpha_H}(1,0) \le (1-\eta(1,0))/(1-\rho)$; $\mu_1 \ge 0 \iff \frac{cd(1,0)(1-\rho)\kappa(1,0)}{g(1,0)} \ge 0 \iff \kappa(1,0) \ge 0 \iff -\eta'_{\alpha_L}(1,0) \le (1-\eta(1,0))$.

Primal Feasibility: $\alpha_L^* \ge 0$; $\alpha_L^* \le \alpha_H^*$; $\alpha_H^* \le 1$.

Notice that as long as $-\eta'_{\alpha_L}(1,0) \ge (1-\rho)\eta'_{\alpha_H}(1,0)$, this solution is a possible candidate whenever $-\eta'_{\alpha_L}(1,0) \le (1-\eta(1,0))$.

Potential Candidate 2: $(\alpha_H^* = 1, \alpha_L^* \in (0,1))$.

Complementary Slackness: $\mu_1 = 0$; $\mu_2 = 0$; $\mu_3 \neq 0 \Rightarrow \alpha_H^* = 1$.

Stationarity: $cf'_{\alpha_L^*} = 0 \iff \frac{cd(\alpha_H^*,\alpha_L^*)(1-\rho\alpha_H^*)\kappa(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = \frac{cd(1,\alpha_L^*)(1-\rho)\kappa(1,\alpha_L^*)}{g(1,\alpha_L^*)} = 0 \iff \kappa(1,\alpha_L^*) = 0 \iff -\eta'_{\alpha_L}(1,\alpha_L^*)) = \frac{(1-\eta(1,\alpha_L^*))}{1-\alpha_L^*}$; $\mu_3 = -cf'_{\alpha_H^*} = -\frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = -\frac{cd(1,\alpha_L^*)\gamma(1,\alpha_L^*)}{g(1,\alpha_L^*)}$.

Dual Feasibility: $\mu_3 \geq 0 \iff \frac{cd(1,\alpha_L^*)\gamma(1,\alpha_L^*)}{g(1,\alpha_L^*)} \leq 0 \iff \gamma(1,\alpha_L^*) \leq 0 \iff -\eta'_{\alpha_L}(1,\alpha_L^*) \geq \frac{(1-\rho)\eta'_{\alpha_H}(1,\alpha_L^*)}{1-\rho\alpha_L^*}$.

Notice that $\frac{1-\rho}{1-\rho\alpha_L^*} < 1$.

Primal Feasibility: $\alpha_L^* \geq 0 \iff -\eta'_{\alpha_L}(1,0) > 1-\eta(1,0)$; $\alpha_L^* \leq \alpha_H^*$; $\alpha_H^* \leq 1$. We define the function $v(\alpha_L) = -\eta'_{\alpha_L}(1,\alpha_L)(1-\alpha_L) - (1-\eta(1,\alpha_L))$. We can see that $v(0) > 0$ whenever $-\eta'_{\alpha_L}(1,0) > 1-\eta(1,0)$, and that $v(1) < 0$. Since $v(\alpha_L)$ is continuous in $\alpha_L \in (0,1)$ it follows that there is at least one $\alpha_L^* \in (0,1)$ such that $v(\alpha_L^*) = 0$. It follows that whenever $-\eta'_{\alpha_L}(1,0) > 1-\eta(1,0)$, upgrading is a candidate. We note that depending on the structure of η, it is still *possible* that upgrading is a candidate whenever $-\eta'_{\alpha_L}(1,0) \leq 1-\eta(1,0)$. We could easily impose further assumptions to avoid this case and to *guarantee* the uniqueness of α_L^*, however, to preserve generality in our results we decide not to do so.

Potential Candidate 3: $(\alpha_H^* \in (\alpha_L^*, 1), \alpha_L^* = 0)$.

Complementary Slackness: $\mu_1 \neq 0 \Rightarrow \alpha_L^* = 0$; $\mu_2 = 0$; $\mu_3 = 0$.

Stationarity: $cf'_{\alpha_H^*} = 0 \iff \frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = 0 \iff \frac{cd(\alpha_H^*,0)\gamma(\alpha_H^*,0)}{g(\alpha_H^*,0)} = 0 \iff \gamma(\alpha_H^*,0) = 0 \iff \eta'_{\alpha_H}(\alpha_H^*,0) = \frac{1-\eta(\alpha_H^*,0)}{(1-\rho\alpha_H^*)\alpha_H^*}$; $\mu_1 = cf'_{\alpha_L^*} = \frac{cd(\alpha_H^*,\alpha_L^*)(1-\rho\alpha_H^*)\kappa(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = \frac{cd(\alpha_H^*,0)(1-\rho\alpha_H^*)\kappa(\alpha_H^*,0)}{g(\alpha_H^*,0)}$.

Dual Feasibility: $\mu_1 \geq 0 \iff \frac{cd(\alpha_H^*,0)(1-\rho\alpha_H^*)\kappa(\alpha_H^*,0)}{g(\alpha_H^*,0)} \geq 0 \iff \kappa(\alpha_H^*,0) \geq 0 \iff -\eta'_{\alpha_L}(\alpha_H^*,0) \leq (1-\rho\alpha_H^*)\eta'_{\alpha_H}(\alpha_H^*,0)$.

Notice that as long as $-\eta'_{\alpha_L}(\alpha_H^*,0) \geq \eta'_{\alpha_H}(\alpha_H^*,0)$, this does not hold.

Potential Candidate 4: $(\alpha_H^* \in (\alpha_L^*, 1), \alpha_L^* \in (0, \alpha_H^*))$.

Complementary Slackness: $\mu_1 = 0$; $\mu_2 = 0$; $\mu_3 = 0$.

Stationarity: $cf'_{\alpha_L^*} = 0 \iff \frac{cd(\alpha_H^*,\alpha_L^*)(1-\rho\alpha_H^*)\kappa(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = 0 \iff \kappa(\alpha_H^*,\alpha_L^*) = 0 \iff 1-\eta(\alpha_H^*,\alpha_L^*) = -\eta'_{\alpha_L}(\alpha_H^*,\alpha_L^*)(\alpha_H^*-\alpha_L^*)$; $cf'_{\alpha_H^*} = 0 \iff \frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = 0 \iff \frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = 0 \iff \gamma(\alpha_H^*,\alpha_L^*) = 0 \iff 1-\eta(\alpha_H^*,\alpha_L^*) = \eta'_{\alpha_H}(\alpha_H^*,\alpha_L^*)(\alpha_H^*-\alpha_L^*)\frac{(1-\rho\alpha_L^*)}{(1-\rho\alpha_H^*)}$.

Since we have that $\alpha_H^* > \alpha_L^*$, we can see that this can never happen if $-\eta'_{\alpha_L}(\alpha_H^*,\alpha_L^*) \geq \eta'_{\alpha_H}(\alpha_H^*,\alpha_L^*)$.

Potential Candidate 5: $(\alpha_H^* = \alpha_L^* \in (0,1))$.

Complementary Slackness: $\mu_1 = 0$; $\mu_2 \neq 0 \Rightarrow \alpha_H^* = \alpha_L^*$; $\mu_3 = 0$.

Stationarity: $\mu_2 = cf'_{\alpha_H^*} = \frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = -\frac{cd(\alpha_H^*,\alpha_L^*)(1-\rho\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)}$.

Dual Feasibility: $\mu_2 \geq 0 \iff -\frac{cd(\alpha_H^*,\alpha_L^*)(1-\rho\alpha_H^*)}{g(\alpha_H^*,\alpha_L^*)} \geq 0 \iff -(1-\rho\alpha_L^*) \geq 0$ which is never the case.

Potential Candidate 6: $(\alpha_H^* = \alpha_L^* = 0)$.

Complementary Slackness: $\mu_1 \neq 0 \Rightarrow \alpha_L^* = 0$; $\mu_2 \neq 0 \Rightarrow \alpha_H^* = \alpha_L^*$; $\mu_3 = 0$.

Stationarity: $\mu_2 = cf'_{\alpha_H^*} = \frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = -\frac{cd(0,0)}{g(0,0)}$.

Dual Feasibility: $\mu_2 \geq 0 \iff -\frac{cd(0,0)}{g(0,0)} \geq 0$ which is never the case.

Potential Candidate 7: $(\alpha_H^* = \alpha_L^* = 1)$.

Complementary Slackness: $\mu_1 = 0$; $\mu_2 \neq 0 \Rightarrow \alpha_H^* = \alpha_L^*$; $\mu_3 \neq 0 \Rightarrow \alpha_H^* = 1$.

Stationarity: $\mu_2 = -cf'_{\alpha_L^*} = -\frac{cd(\alpha_H^*,\alpha_L^*)\gamma(\alpha_H^*,\alpha_L^*)}{g(\alpha_H^*,\alpha_L^*)} = -\frac{cd(1,1)(1-\rho)}{g(1,1)}$.

Dual Feasibility: $\mu_2 \geq 0 \iff -\frac{cd(1,1)(1-\rho)}{g(1,1)} = -(1-\rho) \geq 0$ which is never the case.

We can see that if $-\eta'_{\alpha_L}(\alpha_H,\alpha_L) \geq \eta'_{\alpha_H}(\alpha_H,\alpha_L)$, only candidates 1 and 2 comply with the KKT conditions. This means that if $-\eta'_{\alpha_L}(\alpha_H,\alpha_L) \geq \eta'_{\alpha_H}(\alpha_H,\alpha_L)$, then only an honor policy or an upgrading policy can be optimal. Importantly, since we have that $\alpha_H^* = 1$ in both candidates, from Lemma 1, the $\alpha_L^* \in [0,1)$ that minimizes the over-prioritization probability $\delta_L(1,\alpha_L) = \eta(1,\alpha_L) + \alpha_L(1-\eta(1,\alpha_L))$, minimizes the expected delay cost in the system. ■

Appendix E: A Numerical Analysis on the Performance of the Optimal Scheduling Policy

In this section, we conduct a numerical analysis on the performance of the optimal α-policy (i.e., honor policy or upgrading policy). For this, we first present a general expression for the expected delay cost in the system under a given α-policy, π_α, and under the First-Best (FB) policy i.e., the $c\mu$ policy assuming fully observable customer types, which amounts to prioritizing the H class:

$$\mathcal{C}^{\pi_\alpha}(\delta_H^{\pi_\alpha}, \delta_L^{\pi_\alpha}) = \left(\frac{\rho^2}{1-\rho}\right) \frac{p_H c_H(1-\rho(1-\delta_H^{\pi_\alpha})) + p_L c_L(1-\rho\delta_L^{\pi_\alpha})}{p_H(1-\rho(1-\delta_H^{\pi_\alpha})) + p_L(1-\rho\delta_L^{\pi_\alpha})}, \tag{15}$$

$$\mathcal{C}^{FB} = \left(\frac{\rho^2}{1-\rho}\right) \frac{p_H c_H(1-\rho) + p_L c_L}{p_H(1-\rho) + p_L}. \tag{16}$$

Recall that $\delta_H^{\pi_\alpha}$ and $\delta_L^{\pi_\alpha}$, as in expressions (10) and (11), represent the under and over-prioritization probabilities that a given α-policy, π_α, achieves. For example, expression (15) can capture the cost under the identified optimal α-policy, π_α^*, by setting $\delta_H^{\pi_\alpha^*} = 1 - \alpha_H^*$ and $\delta_L^{\pi_\alpha^*} = \Phi(\tau(\Delta\alpha^*)) + \alpha_L^*(1 - \Phi(\tau(\Delta\alpha^*)))$, where $\Delta\alpha^* = \alpha_H^* - \alpha_L^*$ with α_H^* and α_L^* as described in Proposition 1. Recall that $(\alpha_H^* = 1, \alpha_L^* = 0)$ represents an honor policy, and $(\alpha_H^* = 1, \alpha_L^* \in (0,1))$ represents an upgrading policy. Also, expression (15) can capture the cost under a FCFS policy by setting $\delta_H^{\pi_\alpha} = 0$ and $\delta_L^{\pi_\alpha} = 1$ (or vice versa).

Percentage cost increase. To study the performance of a given α-policy, π_α, we measure the *percentage cost increase* that it yields in comparison to the FB policy:

$$r^{\pi_\alpha} = \frac{\mathcal{C}^{\pi_\alpha}(\delta_H^{\pi_\alpha}, \delta_L^{\pi_\alpha}) - \mathcal{C}^{FB}}{\mathcal{C}^{FB}} * 100. \tag{17}$$

We note that under the optimal α-policy, π_α^*, the under-prioritization probability is eliminated, $\delta_H^{\pi_\alpha^*} = 0$, and the over-prioritization probability is $\delta_L^{\pi_\alpha^*} \in (0,1)$. Based on this, we begin by studying some comparative statics of r^{π_α} for α-policies, π_α, that achieve $\delta_H^{\pi_\alpha} = 0$ and $\delta_L^{\pi_\alpha} \in (0,1)$. Note that this includes π_α^*.

PROPOSITION 3. *Let π_α be an α-policy that for fixed (α_H, α_L) achieves $\delta_H^{\pi_\alpha} = 0$ and $\delta_L^{\pi_\alpha} \in (0,1)$, and let r^{π_α} be the percentage cost increase that it yields in comparison to the First-Best policy in expression (17). For $\rho \in (0,1)$, $p_H \in (0,1)$, and $c_H > c_L > 0$, we have the following properties:*

- *r^{π_α} increases in c_H and decreases in c_L.*
- *r^{π_α} is a unimodal function of p_H, with a unique maximum at $\bar{p_H} \in (0,1)$. Moreover, we have that $\lim_{p_H \to 0} r^{\pi_\alpha} = 0$ and $\lim_{p_H \to 1} r^{\pi_\alpha} = 0$.*

- r^{π_α} *is a unimodal function of* ρ*, with a unique maximum at* $\bar{\rho} \in (0,1)$*. Moreover, we have that* $\lim_{\rho \to 0} r^{\pi_\alpha} = 0$ *and* $\lim_{\rho \to 1} r^{\pi_\alpha} = 0$.

Proof. The expression for the percentage cost increase is given by:

$$\begin{aligned} r^{\pi_\alpha} &= \frac{\mathcal{C}^{\pi_\alpha}(\delta_H^{\pi_\alpha}, \delta_L^{\pi_\alpha}) - \mathcal{C}^{FB}}{\mathcal{C}^{FB}} * 100 \\ &= \frac{(c_H - c_L) p_H p_L \rho (\delta_H^{\pi_\alpha} + \delta_L^{\pi_\alpha}(1-\rho))}{(p_H c_H (1-\rho) + p_L c_L)(p_H(1 - \rho(1-\delta_H^{\pi_\alpha})) + p_L(1-\rho\delta_L^{\pi_\alpha}))} * 100. \end{aligned} \tag{18}$$

From (18) we can easily see that $\lim_{\rho \to 0} r^{\pi_\alpha} = 0$, $\lim_{p_H \to 0} r^{\pi_\alpha} = 0$, and $\lim_{p_H \to 1} r^{\pi_\alpha} = 0$. For policies that perform better than FCFS (i.e., $\delta_H^{\pi_\alpha} + \delta_L^{\pi_\alpha} < 1$), from (18) we can observe that $\lim_{\rho \to 1} r^{\pi_\alpha} = \frac{(c_H - c_L) p_H \delta_H^{\pi_\alpha}}{p_H c_L \delta_H^{\pi_\alpha} + p_L c_L (1 - \delta_L^{\pi_\alpha})} * 100$. Upon further inspection, we can see that for any policy π_α that achieves $\delta_H^{\pi_\alpha} = 0$ and $\delta_L^{\pi_\alpha} < 1$, we have that $r^{\pi_\alpha} = \frac{(c_H - c_L) p_H p_L \rho \delta_L^{\pi_\alpha}(1-\rho)}{(p_H c_H (1-\rho) + p_L c_L)(p_H(1-\rho) + p_L(1-\rho\delta_L^{\pi_\alpha}))} * 100$, and thus $\lim_{\rho \to 1} r^{\pi_\alpha} = 0$. We note that this is always the case for both an honor policy and an upgrading policy. In contrast, consider a FCFS policy (i.e., $\delta_H = 0$ and $\delta_L = 1$) from (18) we can see that $\lim_{\rho \to 1} r^{FCFS} = \frac{(c_H - c_L) p_H}{c_L} * 100$.

Based on expressions (15)- (18), for policies that achieve $\delta_H^{\pi_\alpha} = 0$ and $\delta_L^{\pi_\alpha} \in (0,1)$, after some algebraic manipulations we can see that for $\rho \in (0,1)$ and $p_H \in (0,1)$:

$$\frac{\partial r^{\pi_\alpha}}{\partial c_H} = \frac{c_L \delta_L^{\pi_\alpha} p_H p_L \rho (1-\rho)(1-\rho p_H)}{(p_H c_H(1-\rho) + p_L c_L)^2 (p_H(1-\rho) + p_L(1-\rho\delta_L^{\pi_\alpha}))} * 100 > 0, \tag{19}$$

$$\frac{\partial r^{\pi_\alpha}}{\partial c_L} = -\frac{c_H \delta_L^{\pi_\alpha} p_H p_L \rho (1-\rho)(1-\rho p_H)}{(p_H c_H(1-\rho) + p_L c_L)^2 (p_H(1-\rho) + p_L(1-\rho\delta_L^{\pi_\alpha}))} * 100 < 0, \tag{20}$$

$$\frac{\partial r^{\pi_\alpha}}{\partial \rho} = \frac{(c_H - c_L) p_H p_L \delta_L^{\pi_\alpha} \kappa(\rho)}{(p_H c_H(1-\rho) + p_L c_L)^2 (p_H(1-\rho) + p_L(1-\rho\delta_L^{\pi_\alpha}))^2} * 100, \tag{21}$$

$$\kappa(\rho) = p_H c_H (1-\rho)^2 + p_L c_L (1 - \rho(2 - \rho(p_H + p_L \delta_L^{\pi_\alpha}))), \tag{22}$$

$$\frac{\partial \kappa(\rho)}{\partial \rho} = -2(p_H c_H (1-\rho) + p_L c_L (1 - \rho(p_L \delta_L^{\pi_\alpha} + p_H))) < 0. \tag{23}$$

$$\frac{\partial r^{\pi_\alpha}}{\partial p_H} = \frac{(c_H - c_L) \rho (1-\rho) \delta_L^{\pi_\alpha} \nu(p_H)}{(p_H c_H(1-\rho) + p_L c_L)^2 (p_H(1-\rho) + p_L(1-\rho\delta_L^{\pi_\alpha}))^2} * 100, \tag{24}$$

$$\nu(p_H) = c_L (1-p_H)^2 (1 - \rho \delta_L^{\pi_\alpha}) - c_H p_H^2 (1-\rho)^2, \tag{25}$$

$$\frac{\partial \nu(p_H)}{\partial p_H} = -2(p_H c_H (1-\rho)^2 + p_L c_L (1 - \rho \delta_L^{\pi_\alpha})) < 0. \tag{26}$$

Note that $\kappa(0) = p_H c_H + p_L c_L > 0$, $\kappa(1) = -c_L p_L^2 (1 - \delta_L^{\pi_\alpha^*}) < 0$, and that $\frac{\partial \kappa(\rho)}{\partial \rho} < 0$. Then, since $\kappa(\rho)$ is a continuous function of ρ, we conclude that there exists a unique $\bar{\rho} \in (0,1)$ such that $\kappa(\bar{\rho}) = 0$ and consequently a unique $\bar{\rho} \in (0,1)$ such that $\frac{\partial r^{\pi_\alpha}}{\partial \rho} = 0$. Since $\frac{\partial r^{\pi_\alpha}}{\partial \rho}$ is positive below $\bar{\rho} \in (0,1)$ and negative above it, we conclude that $\bar{\rho} \in (0,1)$ maximizes r^{π_α}. Similarly, note that $\nu(0) = c_L(1 - \rho\delta_L^{\pi_\alpha}) > 0$, $\nu(1) = -c_H(1-\rho)^2 < 0$, and that $\frac{\partial \nu(p_H)}{\partial p_H} < 0$. Then, since $\nu(p_H)$ is a continuous function of p_H, we conclude that there exists a unique $\bar{p_H} \in (0,1)$ such that $\nu(\bar{p_H}) = 0$ and consequently a unique $\bar{p_H} \in (0,1)$. Since $\frac{\partial r^{\pi_\alpha}}{\partial p_H}$ is positive below $\bar{p_H} \in (0,1)$ and negative above it, we conclude that $\bar{p_H} \in (0,1)$ maximizes r^{π_α}. ■

Interestingly, Proposition 3 shows that the percentage cost increase metric is unimodal in system congestion and that for sufficiently high levels of congestion, $\rho \geq \bar{\rho}$, the performance of the considered α-policies gets increasingly closer (as ρ increases) to that of the FB policy. The intuition comes from Lemma 1, which states that as congestion increases, the delay cost in the system is increasingly dominated by the under-prioritizing probability $\delta_H^{\pi_\alpha}$ (rather than the over-prioritization $\delta_L^{\pi_\alpha}$). When system congestion is sufficiently large, $\rho \geq \bar{\rho}$, the percentage cost increase metric r^{π_α} decreases since we have that $\delta_H^{\pi_\alpha} = 0$ and that the over-prioritization errors $\delta_L^{\pi_\alpha}$ becomes increasingly (as congestion increases) negligible compared to the total waiting cost in the system. Also, Proposition 3 shows that the percentage cost increase metric is unimodal in the proportion of H type customers and that for very low or very high p_H levels, the performance of the considered α-policies approaches that of the FB policy. Intuitively, if there is only one type of customer, the delay cost in the system cannot be modified through scheduling.

E.1. Numerical Analysis

Given the properties of the r^{π_α} metric, we conduct a numerical analysis to gain further insight into the performance of the optimal α-policy and its dependence on customer misreporting behaviour. For this, we assume that customers misreport with probability $\Phi((\Delta\alpha)^\varphi)$, where $\theta \sim Exp(\gamma)$ so that $\Phi((\Delta\alpha)^\varphi) = 1 - e^{-\gamma(\Delta\alpha)^\varphi}$. We consider such a functional form for different reasons. First, such a proposed specification is flexible as it allows the function Φ to depend on its argument in a linear, strictly concave, or strictly convex fashion through the parameter φ. Second, in Appendix B.4, we show that such specification achieves a good fit to our experimental data and good out-of-sample predictive ability. Third, based on Proposition 1, such a specification allows to compute the optimal policy easily: Honor policy is optimal whenever $\varphi\gamma \leq 1$, and upgrading is optimal otherwise. In particular, the optimal upgrading probability is the unique α_L^* that solves $1 - \varphi\gamma(1-\alpha_L^*)^\varphi = 0$, which can be easily computed numerically. Finally, such a specification presents a natural interpretation for its parameters in terms of lying behaviour: Populations with higher φ are more responsive to upgrading, in the sense that, for $\varphi = 0$, misreporting is not affected by upgrading at all, and for any level of upgrading, higher values of $\varphi > 0$ correspond to lower levels of misreporting. Also, higher γ

values represent more dishonest populations since for the exponential distribution we have that the expected lying aversion is $\mathbb{E}[\theta] = 1/\gamma$. This provides intuitive and parsimonious insights in the discussion of the results.

In our numerical analysis, we consider different values for system parameters c_H, c_L, p_H, p_L, ρ and misreporting behaviour parameters γ and φ. In Figures 3 - 5, we report the results of representative examples where $\varphi \in \{1,3,5\}$ and $\gamma \in \{0.2,1,2\}$. For these γ values, the misreporting prevalence in the absence of upgrading, i.e., $\Phi(1)$, is equal to $0.18, 0.63$, and 0.86, respectively. In particular in Figure 3, we keep $c_H = 5, c_L = 1, p_H = 0.5$ fixed and vary $\rho \in (0,1)$. In Figure 4, we keep $c_H = 5, c_L = 1, \rho = 0.85$ fixed and vary $p_H \in (0,1)$. And finally, in Figure 5, we keep $c_L = 1, p_h = 0.5, \rho = 0.85$ fixed and vary $c_H \in [2,500]$. Figures 3 - 5 show the percentage cost increase over the FB policy achieved under the optimal α-policy, and under a FCFS policy for comparison - this comparison allows us to understand the value of using customer claims for their scheduling. Recall that the optimal α-policy can be either an honor policy (i.e., $\alpha_H^* = 1, \alpha_L^* = 0$) or an upgrading policy (i.e., $\alpha_H^* = 1, \alpha_L^* \in (0,1)$). Thus, to illustrate the difference between these two, in Figures 3 - 5 we also present the percentage cost increase of the honor policy even when this policy is not optimal.

Results and Discussion. Recall that the parameters φ and γ capture, respectively, the two factors that determine the optimal α-policy: (1) the responsiveness to upgrading, and (2) the level of dishonesty in a given customer population. From Proposition 1, we know that upgrading is optimal whenever the *semi-elasticity* $-\mathcal{S}(1) > 1$ if, and only if $\varphi\gamma > 1$, and an honor policy is optimal otherwise.

First, for a fixed γ and sufficiently high φ (i.e., $\varphi\gamma > 1$), the optimal α-policy is an upgrading policy. In particular, we can see in all Figures 3 - 5, that as the parameter φ increases, the performance of the optimal upgrading policy gets closer to the FB policy. This happens since populations with higher φ are more responsive to upgrading. The optimal α-policy is an upgrading policy also for fixed φ and sufficiently high γ (i.e., $\varphi\gamma > 1$). In this case, we can see that as γ increases, the performance of upgrading in comparison to an honor policy improves. Since higher γ values represent more dishonest populations, i.e., $\mathbb{E}[\theta] = 1/\gamma$, this suggests that upgrading policies are well warranted for more dishonest populations.

For a fixed φ and sufficiently low γ (i.e., $\varphi\gamma \leq 1$), the optimal α-policy is an honor policy. In particular, we can see in all Figures 3 - 5, that in this case such policy captures most of the potential improvements (i.e., it is very close to the FB policy). This happens since an honor policy provides full priority to those that make *H claims*, and when customers are very honest this is similar to the FB policy where *H types* are provided full priority. More generally, as γ decreases, we can see in all Figures 3 - 5, that the performance of the optimal α-policy (either honor policy or upgrading) improves since lower γ values represent more honest customer populations.

Overall, we see that the optimal α-policy performs well under the considered parameters. From Figures 3 - 5, we see that the optimal α-policy yields well below the 50% cost increase and does not change much as ρ, p_H, and c_H change. Moreover, based on the considered parameters, we see (in Figure 5 for parameters $c_H = 500, c_L = 1, p_H = 0.5, \rho = 0.85, \gamma = 2$ and $\varphi = 1$) that the highest difference between the optimal α-policy and the FB policy is given by 150% cost increase (i.e., a cost that is 2.5 times higher than the FB policy). Following this, to get a better sense of a worst-case type of performance for the optimal α-policy, we numerically compute the values for p_H and ρ that maximize the percentage cost increase given the parameters $c_H = 500$ and $c_L = 1$ for each of the $\varphi \in \{1, 3, 5\}$ and $\gamma \in \{0.2, 1, 2\}$ pairs. In Table 15 (a), we show such a maximum percentage cost increase. Moreover, as a comparison, in (b) we present the percentage cost increase that the FCFS policy yields at the same identified parameters p_H and ρ.

We can observe from Table 15 that, due to customers' lying aversion, Managers can considerably improve the performance in the system by using customers' own claims. For example, in (a) we see that the optimal α-policy can yield up to a 363.08% cost increase over the FB policy (i.e., a cost that is 4.63 times higher than the FB policy), while for the same system parameters, a FCFS policy yields a 4711.02% increase (i.e., a cost that is 48.11 times higher than the FB policy). We note that these worst-case performances are calculated under "extreme" conditions (e.g., $\gamma = 2$ represents a customer population where 86% of L types misreport). Of course, it remains that the performance of the optimal α-policy depends entirely on customers lying costs, such that in the unrealistic case where everyone misreports, its performance will be the same as under FCFS.

Table 15 Maximum percentage cost increase over the FB policy for $c_H = 500, c_L = 1, \gamma = 2$ and $\varphi = 1$

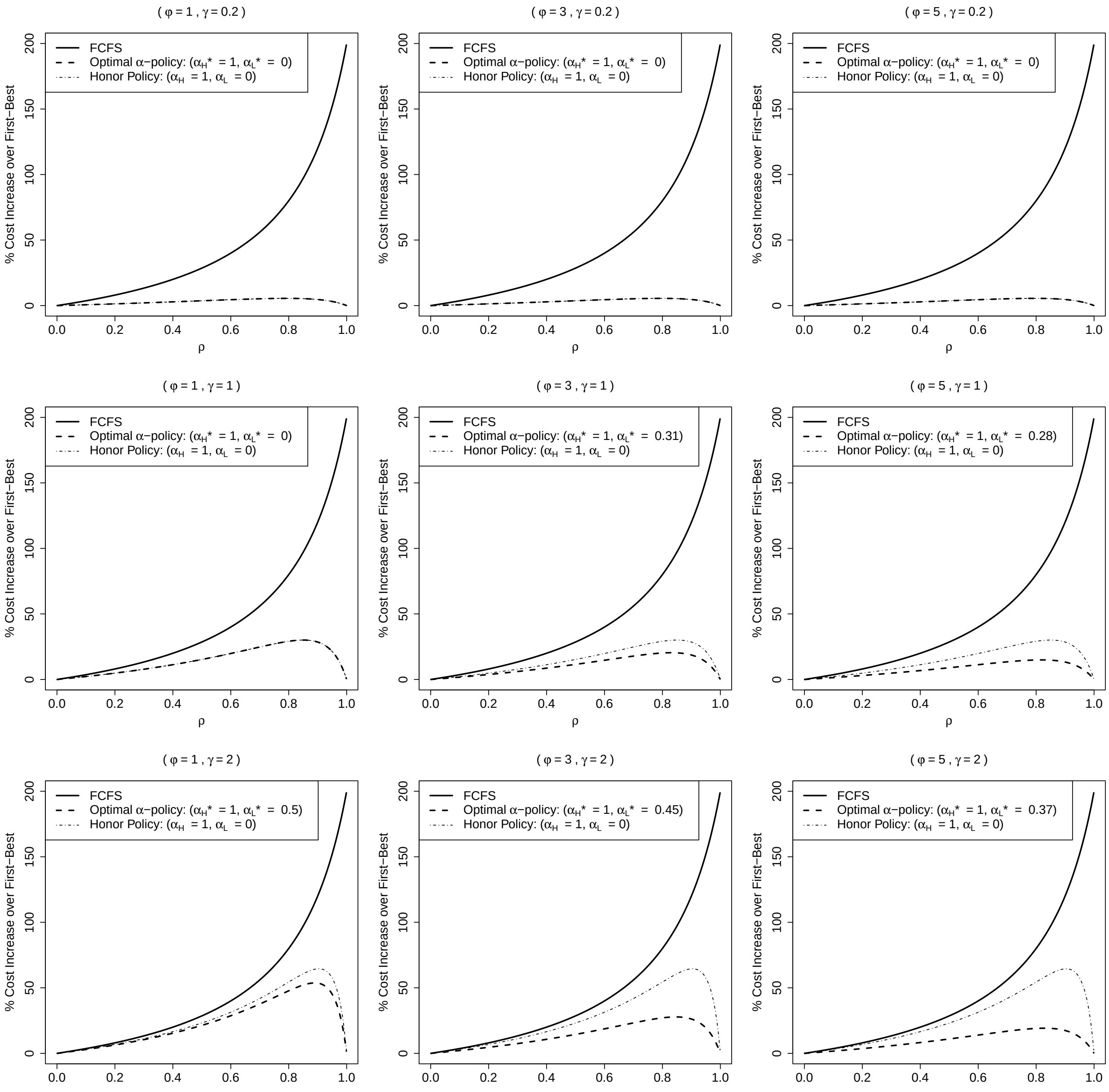
(a) Optimal α-policy

	$\varphi = 5$	$\varphi = 3$	$\varphi = 1$
$\gamma = 0.2$	20.06%	20.06%	20.06%
$\gamma = 1$	61.08%	89.37%	148.74%
$\gamma = 2$	82.77%	133.58%	363.08%

(b) FCFS

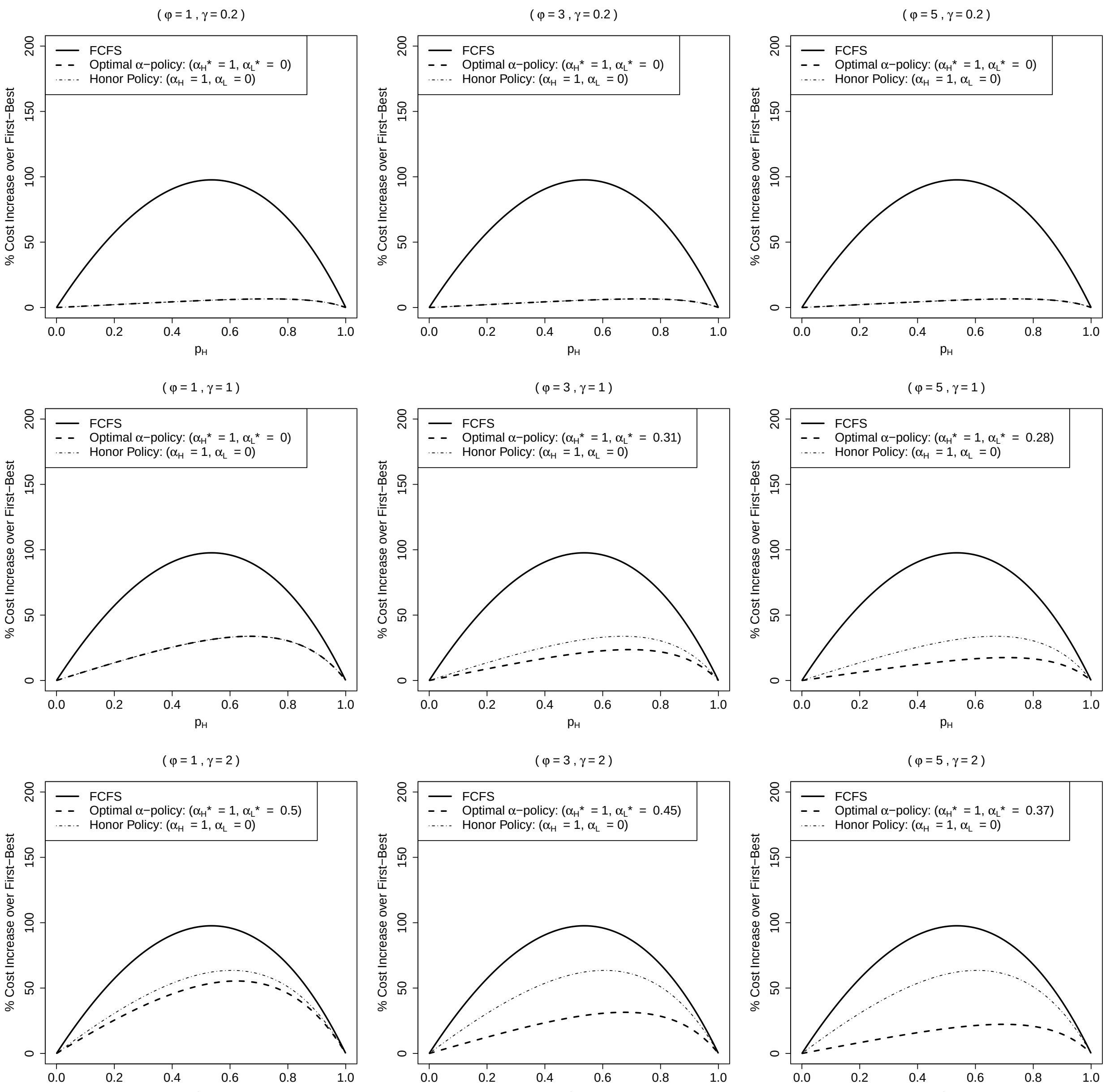
	$\varphi = 5$	$\varphi = 3$	$\varphi = 1$
$\gamma = 0.2$	2347.12%	2347.12%	2347.12%
$\gamma = 1$	2735.11%	2975.03%	3425.23%
$\gamma = 2$	2921.61%	3313.43%	4711.02%

Figure 3 **Percentage cost increase over the FB policy under optimal α-policy, honor policy, and FCFS policy for different levels of system congestion ρ.**



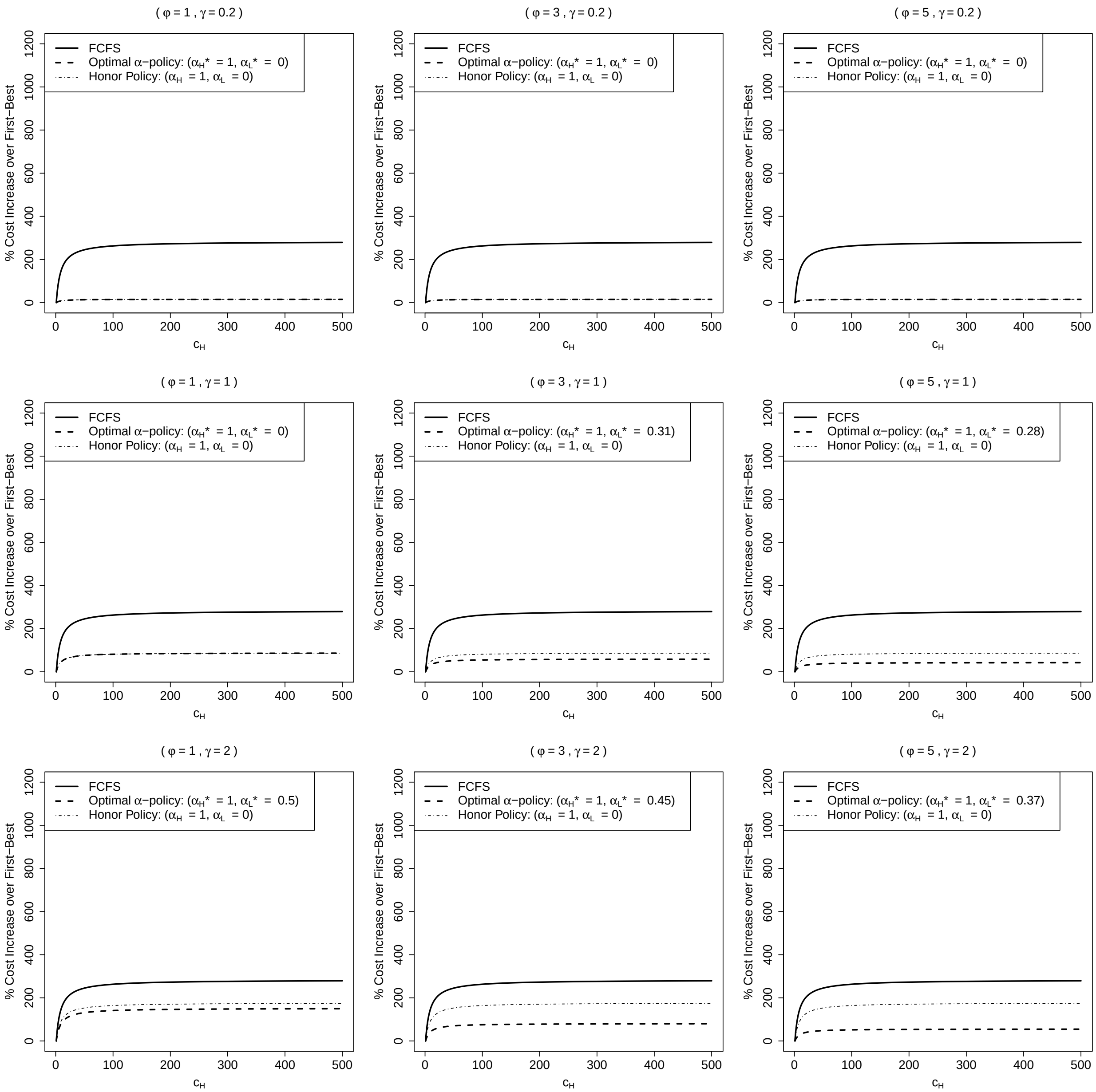
Notes: $c_H = 5, c_L = 1, p_H = 0.5, \varphi \in \{1,3,5\}, \gamma \in \{0.2, 1, 2\}$, and $\rho \in (0,1)$.

Figure 4 **Percentage cost increase over FB under optimal α-policy, honor policy, and FCFS policy for different levels of H type proportion p_H.**



Notes: $c_H = 5, c_L = 1, \rho = 0.85, \varphi \in \{1,3,5\}, \gamma \in \{0.2,1,2\}$, and $p_H \in (0,1)$.

Figure 5 **Percentage cost increase over FB under optimal α-policy, honor policy, and FCFS policy for different levels of H type delay sensitivity c_H.**



Notes: $c_L = 1, p_H = 0.5, \rho = 0.85, \varphi \in \{1,3,5\}, \gamma \in \{0.2,1,2\}$, and $c_H \in [2,500]$.

Appendix F: A Numerical Analysis of the Optimal Policy when Misreporting Depends on Waiting Times

In this work, we have experimentally shown that misreporting behaviour depends on the routing probabilities and does not vary as the difference in waiting times between queues, ΔW, changes. In consequence, we have modelled the misreporting probability in line with such empirical observations and derived the optimal scheduling policy in Proposition 1. To better understand the impact of capturing such empirical observations in our model, in this section, we study how the identified policy in Proposition 1 performs if the difference in waiting times did actually influence misreporting behaviour. To do so, we consider two of the common models in the literature described in §5.2. We consider that the underlying true misreporting behaviour is consistent with a *fixed lying cost* and a *quadratic lying cost* model, respectively. Based on such models, we have seen in §5.2 that customers best respond by misreporting with probabilities:

$$\text{[fixed]} \quad \mathbb{P}(Y=y|X=x)=\Phi\left(c_x\Delta\alpha\Delta W\right) \quad \text{for} \quad y\neq x, \tag{27}$$

$$\text{[quadratic]} \quad \mathbb{P}(Y=y|X=x)=\Phi\left(\frac{1}{c_x\Delta\alpha\Delta W}\right) \quad \text{for} \quad y\neq x, \tag{28}$$

where $\Delta\alpha=\alpha_y-\alpha_x$ and $\Delta W=W_2-W_1$. These models allow to study the impact of ΔW in two directions: In a fixed cost model, misreporting increases in ΔW, while in a quadratic model, it decreases in ΔW. For our numerical analysis, we consider the case in which $\theta\sim Exp(\gamma)$, such that the best response misreporting probability under a fixed cost model is given by $\Phi(c_x\Delta\alpha\Delta W)=1-e^{-\gamma c_x\Delta\alpha\Delta W}$, and under a quadratic cost model by $\Phi(1/c_x\Delta\alpha\Delta W)=1-e^{-\frac{\gamma}{c_x\Delta\alpha\Delta W}}$.

For those considered lying cost functions, the misreporting probability in equilibrium (denoted by η), arises from the solution of a fixed point problem. For the fixed lying cost case, we have that $\eta=\Phi(c_x\Delta\alpha\Delta W)$. For the quadratic lying cost case, we have that $\eta=\Phi(1/c_x\Delta\alpha\Delta W)$. These represent fixed point problems since the difference between waiting times in our M/M/1 system (see §3), $\Delta W=\frac{\rho^2}{\mu(1-\rho)(1-\rho_1)}$, with $\rho_1=\rho(p_H(1-\delta_H)+p_L\delta_L(\eta))$, is itself a function of the equilibrium misreporting probability. In particular, focusing on the case in which L type customers are those that have the incentive to misreport (i.e., $\alpha_H>\alpha_L$), we have that $\rho_1=\rho(p_H\alpha_H+p_L(\alpha_L+\eta\Delta\alpha))$. Recall that for any $\alpha_H<\alpha_L$, L type customers are given priority over H type customers, and since $c_H>c_L$ the waiting cost in the system is higher than in a FCFS policy. Also, for $\alpha_H=\alpha_L$, irrespective of customers' claiming behaviour, the waiting cost in the system is equal to a FCFS policy.

For both lying-cost functions, we solve for the customer equilibrium numerically. We also identify the optimal α-policy numerically with the use of *nloptr* package in R. That is, we identify the routing probabilities α_H^* and α_L^* that minimize the waiting cost in the system, when customer misreporting behaviour is in line with the fixed and quadratic lying cost models.

As mentioned above, our main objective is to understand how the identified policy in Proposition 1 performs under the case in which the difference in waiting times, ΔW, does influence misreporting behaviour. Moreover, we are interested in studying *how bad* is the performance of the identified policy in Proposition 1 in comparison to the optimal α-policy. For this, we derive policies that assume (incorrectly) that customers misreport with probability $\Phi((\Delta\alpha)^{\varphi})$, where $\theta \sim Exp(\gamma)$ so that $\Phi((\Delta\alpha)^{\varphi}) = 1 - e^{-\gamma(\Delta\alpha)^{\varphi}}$. As described in Appendix E, among other benefits, this functional specification presents a natural interpretation for its parameters in terms of lying behaviour: Populations with higher φ are more responsive to upgrading, and higher γ values represent more dishonest populations.. Since the true misreporting behaviour, in this analysis, is indeed affected by the difference in waiting times, we call such policies *naive policies*. Based on Proposition 1, under the incorrect assumption that misreporting is given by $1 - e^{-\gamma(\Delta\alpha)^{\varphi}}$, such naive policies are given by: honor policy whenever $\varphi\gamma \leq 1$, and upgrading otherwise, with upgrading probability as the unique α_L^* that solves $1 - \varphi\gamma(1 - \alpha_L^*)^{\varphi} = 0$.

In line with the numerical analysis in Appendix E, we study the performance of a policy in terms of the *percentage cost increase* that it brings in comparison to the First-Best (FB) policy (see Appendix E for details). Also, to study the performance of the naive policies in comparison to the optimal α-policy, we compute the *percentage cost increase* that a naive policy brings in comparison to the optimal α-policy. In our numerical analysis, we consider different values for system parameters c_H, p_H, ρ and misreporting behaviour parameters γ and φ. In Figures 6 - 11, we report the results of representative examples. In particular, for the fixed and quadratic models respectively, in Figures 6 and 9, we keep $c_H = 5, c_L = 1, p_H = 0.5$ fixed and vary $\rho \in (0,1)$. For the fixed and quadratic models respectively, in Figures 7 and 10, we keep $c_H = 5, c_L = 1, \rho = 0.5$ fixed and vary $p_H \in (0,1)$. Finally, for the fixed and quadratic models respectively, in Figures 8 and 11, we keep $c_L = 1, p_H = 0.5, \rho = 0.5$ fixed and vary $c_H \in [2, 500]$.

F.1. Results and Discussion

Figures 6 - 11 show the results of the analysis for different $\gamma \in \{0.2, 1, 2\}$ values for the optimal α-policy, and for different $\gamma \in \{0.2, 1, 2\}$ and $\varphi \in \{1, 3, 5\}$ values for the naive policies. In particular, Figures 6 - 11 show, in the first row, the identified optimal α-policy and the naive policies. In the second row, they show the misreporting probability that arises in equilibrium under those policies. In the third row, they show the *percentage cost increase* that those policies yield over the FB policy. We also include the percentage cost increase that a FCFS policy achieves over the FB policy for comparison - this comparison allows us to understand the value of using customer claims for their scheduling. Finally, in the last row, Figures 6 - 11, show the *percentage cost increase* that the naive policies and a FCFS policy yield over the optimal α-policy.

Fixed lying cost model. We find that the optimal α-policy is either an honor policy (i.e., $\alpha_H^* = 1$ and $\alpha_L^* = 0$) or an upgrading policy (i.e., $\alpha_H^* = 1$ and $\alpha_L^* \in (0,1)$). The difference between this optimal policy and the one derived in Proposition 1, is that we that the conditions under which upgrading is optimal, and the actual upgrading level, all depend on system parameters. This happens since under the fixed lying cost model, misreporting depends on waiting times. We have numerically observed that other types of partial priority policies (e.g., $1 < \alpha_H < \alpha_L < 0$) can achieve optimality as well, i.e., the optimal policy is not necessarily unique in this case. To illustrate the parallel between an optimal α-policy and the one derived in Proposition 1, we report here the upgrading policy that indeed achieves optimality. In particular, from Figure 6, we see that in the optimal α-policy, an honor policy is optimal for sufficiently low levels of congestion, and an upgrading policy (whose upgrading level increases in system congestion) is optimal for sufficiently high levels of congestion. This follows since we observe that customer misreporting probability in equilibrium increases in ρ, and higher levels of the upgrading probability, α_L, induce more honesty. Also, from Figure 7, we see that when an upgrading policy is used, the upgrading level increases in the proportion of H types. This follows since we observe that customer misreporting probability in equilibrium increases in p_H and higher levels of the upgrading α_L probability induce more honesty.

In terms of performance, we can see from Figures 6 - 8, that the optimal α-policy always performs better than FCFS, and that naive policies perform better than FCFS for most considered system parameters. We note that under a fixed cost model, for a sufficiently high congestion level, it is possible for all customers to misreport in equilibrium. If all customers misreport, then the delay cost in the system is equivalent to the one under a FCFS policy. The optimal α-policy allows to perform better than a FCFS scheme, since it upgrades more customers as congestion increases. Having said this, we note that the naive policies and the optimal α-policy provide a similar percentage cost increase over the FB policy across the considered system parameters. Indeed, we further note that the percentage cost increase that the naive policies yield over the optimal α-policy is close to 0. Finally, we see that changes in the parameter φ have little effect on the performance of the naive policies.

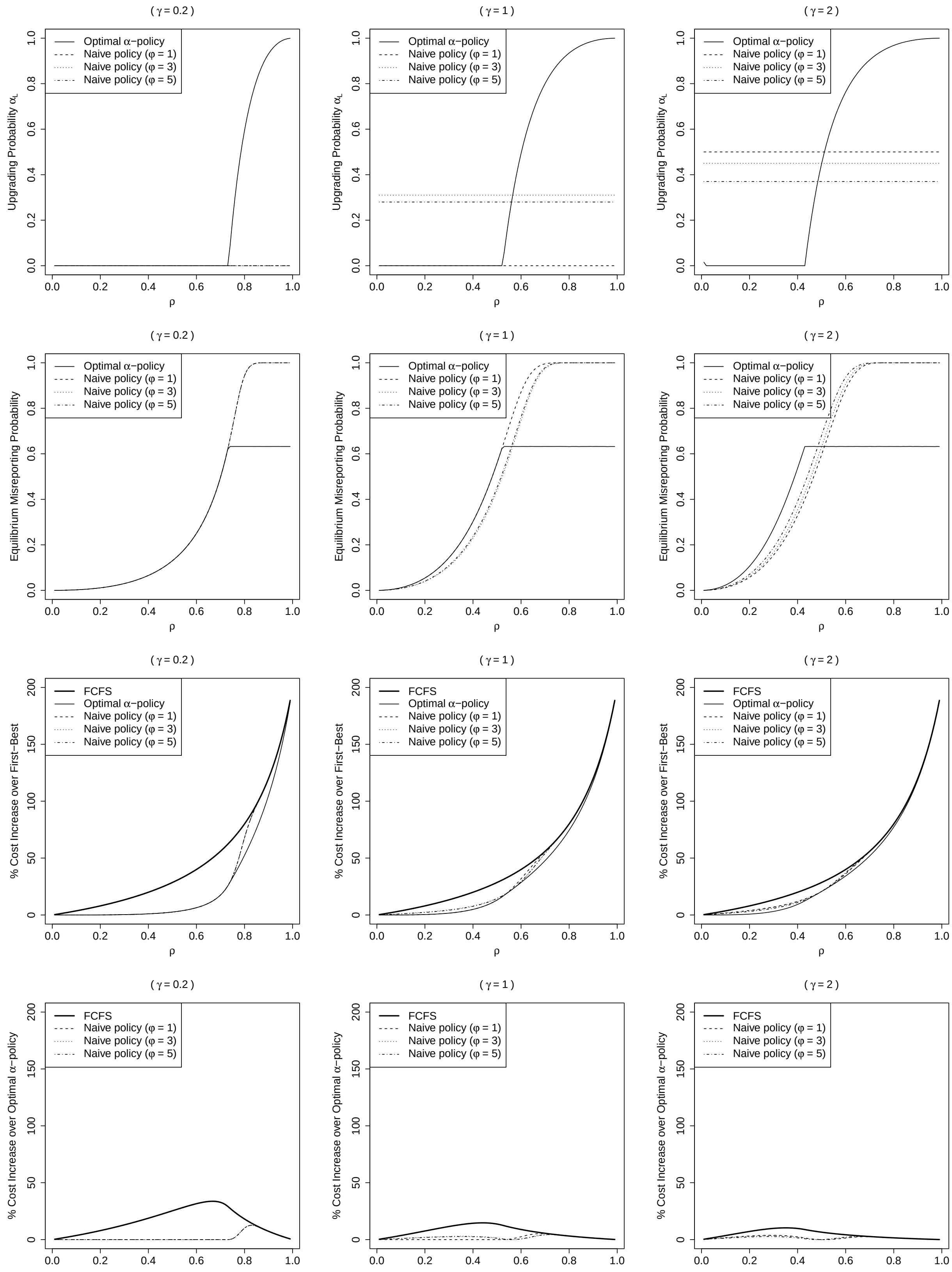
In Appendix E, we had seen that the benefits of using customer claims for the performance of the system were particularly relevant under high levels of system congestion. In the case of a fixed lying cost model, since misreporting increases in system congestion, such benefits become less relevant. Indeed, we can see that for high system congestion, the performance of all considered policies (including FCFS) are very similar. This result highlights the managerial value of the experimental finding that misreporting behaviour does not increase in ΔW (see §6.3). Under this identified misreporting behaviour property, and in light of the results under a fixed cost model, the relevance of using customer claims for their scheduling is accentuated.

Quadratic lying-cost model. In the case of a quadratic lying cost, we can observe in Figures 9 - 11, that for all the considered system parameters, the optimal α-policy is an honor policy (i.e., $\alpha_H^* = 1, \alpha_L^* = 0$). This happens because we observe that the customer misreporting probability in equilibrium decreases in α_H and increases in the α_L probability.

In terms of performance, we can see from Figures 9 - 11, that the optimal α-policy and the naive policies perform better than FCFS for most considered system parameters. We note that under a quadratic cost model, for a sufficiently low congestion level, it is possible for all customers to misreport in equilibrium. If all customers misreport, then the delay cost in the system is equivalent to one under a FCFS policy. Importantly, we see that for sufficiently high levels of system congestion, the optimal α-policy and the naive policies provide good system performances. This happens because we can observe that misreporting behaviour in equilibrium decreases in system congestion. We also note that the naive policies and the optimal α-policy provide a similar percentage cost increase over the FB policy across the considered system parameters. Indeed, we further note that the percentage cost increase that the naive policies yield over the optimal α-policy is close to 0. The performance loss from naive policies arises when customers are upgraded. Since in this case, upgrading does not incentivize more honesty, this control only increases the over-prioritization probability. Finally, we see that changes in φ have little effect on the performance of the naive policies.

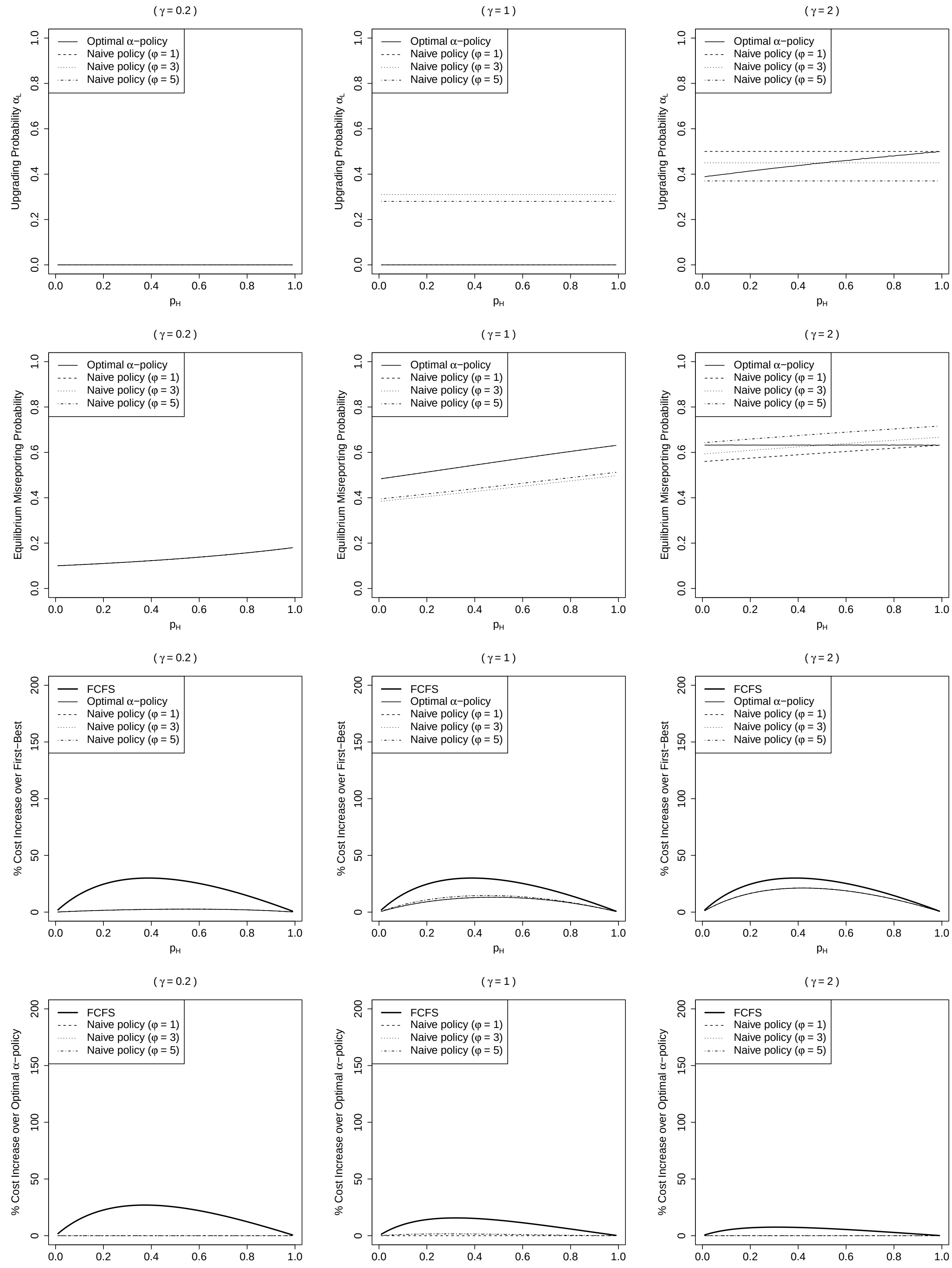
Overall, we observe that the identified optimal α-policy in our numerical analysis is very similar to the one derived in Proposition 1. For a quadratic lying cost model, it is an honor policy (i.e., $\alpha_H^* = 1, \alpha_L^* = 0$), and for a fixed lying cost model, it is either an honor policy or an upgrading policy (i.e., $\alpha_H^* = 1$ and $\alpha_L^* \in (0,1)$) where the actual upgrading level depends on system and lying behaviour parameters. We recall that because waiting times do not affect misreporting behaviour in Proposition 1, system parameters do not play a role there. Finally, for the optimal α-policy and naive policies, in the fixed (quadratic) lying cost case, an increase in ΔW affects their performance negatively (positively) since misreporting increases (decreases) in system congestion. Ultimately, the performances of all of these policies depend strongly on the level of honesty in the customer population. Importantly, in both of the fixed and quadratic lying cost cases, even though naive policies ignore the effect of waiting time on misreporting behaviour, we see that they allow to bring most of the benefits from the optimal α-policy.

Figure 6 Numerical results under fixed lying cost model for different levels of system congestion ρ.



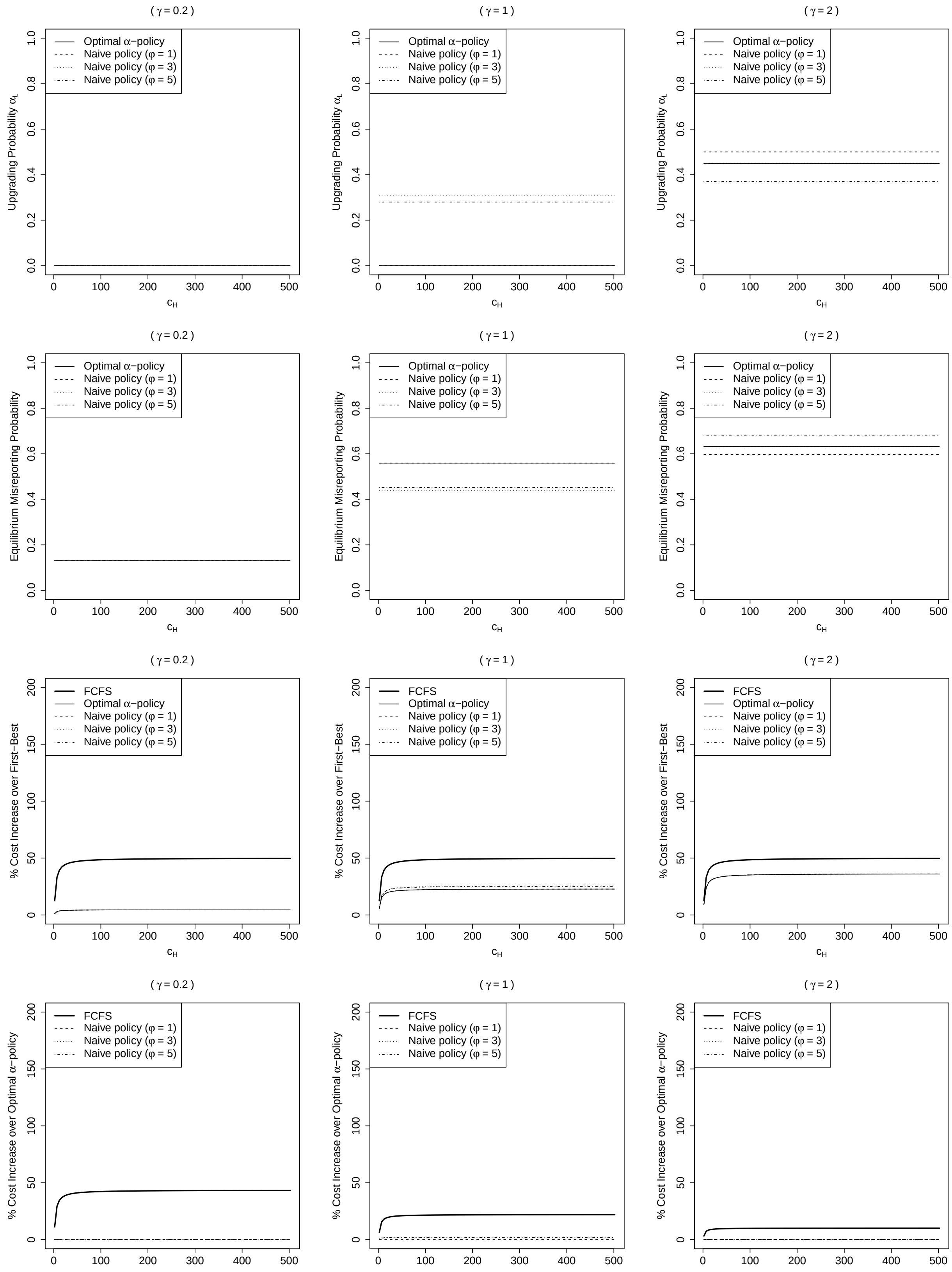
Notes: $c_H = 5, c_L = 1, p_H = 0.5, \varphi \in \{1, 3, 5\}, \gamma \in \{0.2, 1, 2\}$, and $\rho \in (0, 1)$. Also, we have $\alpha_H = 1$ under the optimal α-policy and naive policies.

Figure 7 Numerical results under fixed lying cost model for different levels of H type proportion p_H.



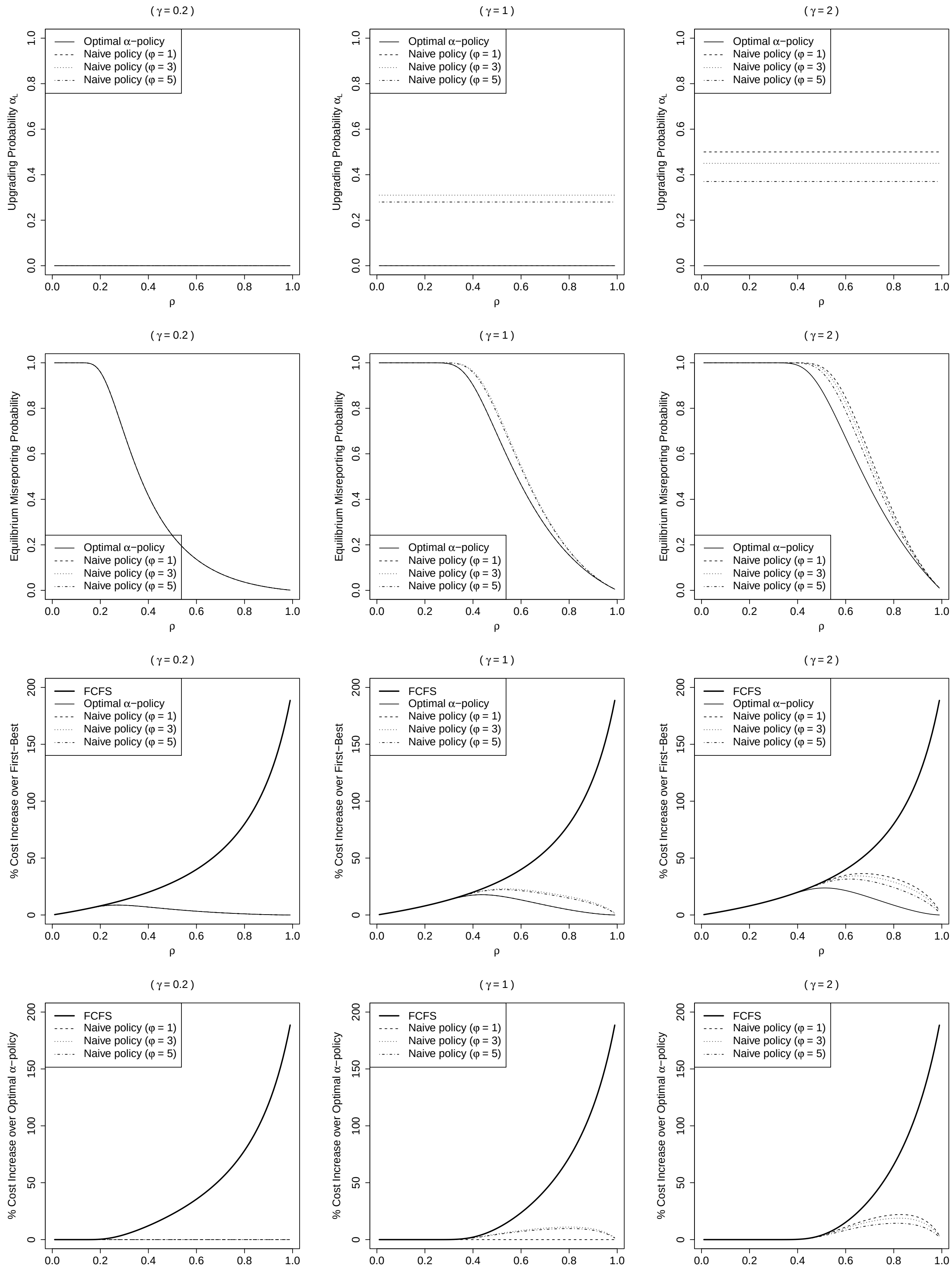
Notes: $c_H = 5, c_L = 1, \rho = 0.5, \varphi \in \{1, 3, 5\}, \gamma \in \{0.2, 1, 2\}$, and $p_H \in (0, 1)$. Also, we have $\alpha_H = 1$ under the optimal α-policy and naive policies.

Figure 8 Numerical results under fixed lying cost model for different levels of H type delay sensitivity c_H.



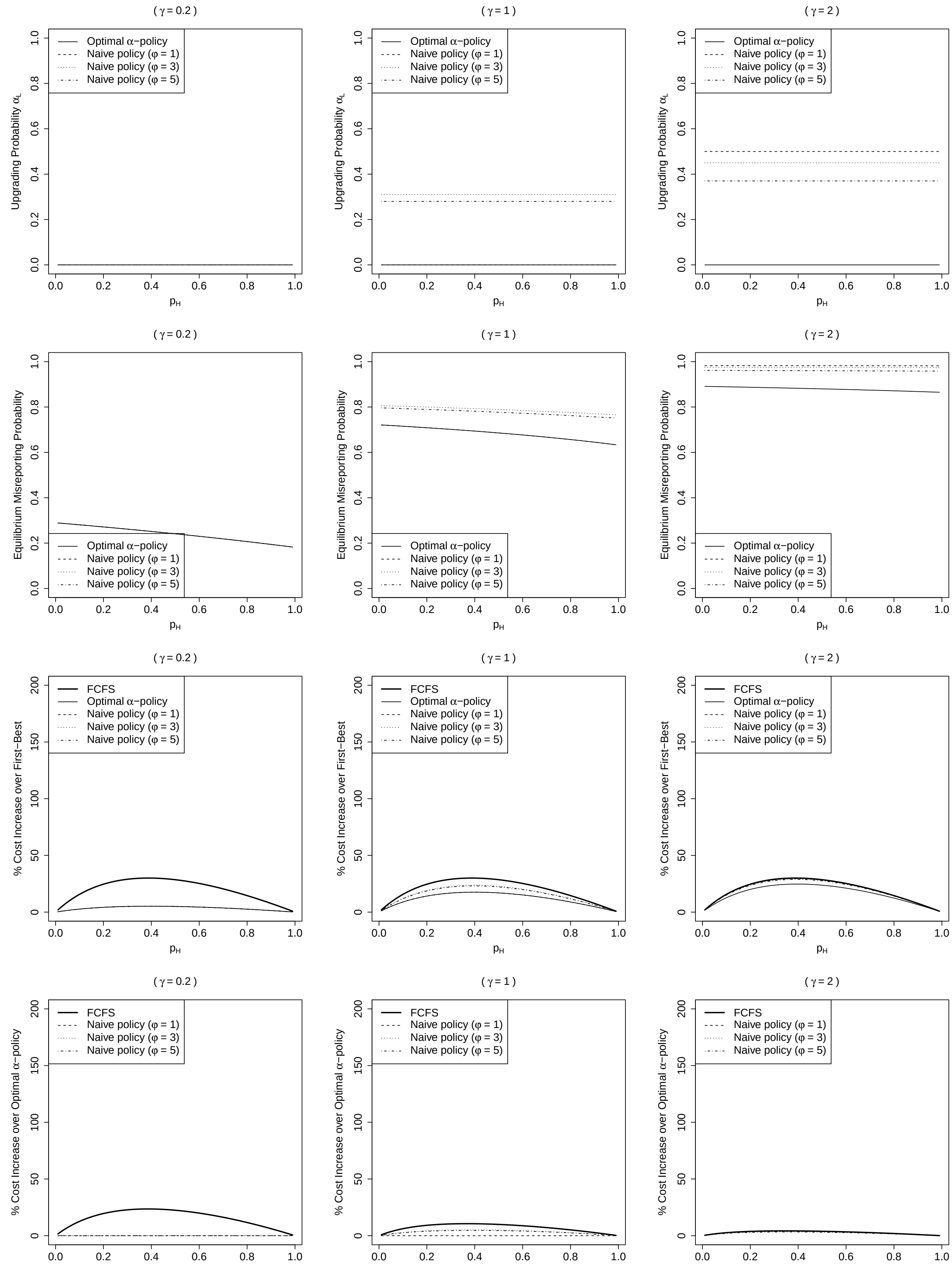
Notes: $c_L = 1, p_H = 0.5, \rho = 0.5, \varphi \in \{1, 3, 5\}, \gamma \in \{0.2, 1, 2\}$, and $c_H \in [2, 500]$. Also, we have $\alpha_H = 1$ under the optimal α-policy and naive policies.

Figure 9 **Numerical results under quadratic lying cost model for different levels of system congestion ρ.**



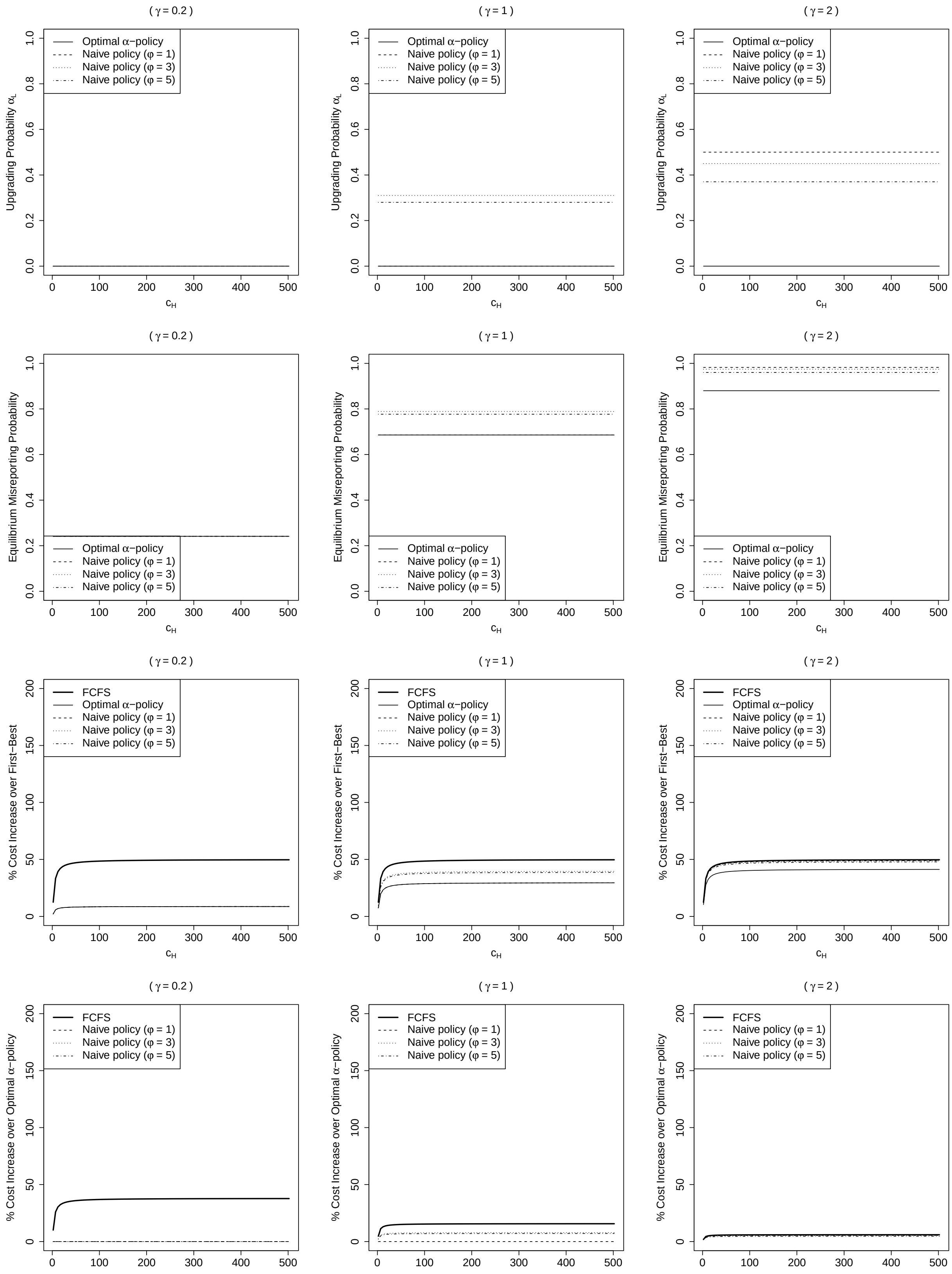
Notes: $c_H = 5, c_L = 1, p_H = 0.5, \varphi \in \{1,3,5\}, \gamma \in \{0.2,1,2\}$, and $\rho \in (0,1)$. Also, we have $\alpha_H = 1$ under the optimal α-policy and naive policies.

Figure 10 **Numerical results under quadratic lying cost model for different levels of H type proportion p_H.**



Notes: $c_H = 5, c_L = 1, \rho = 0.5, \varphi \in \{1,3,5\}, \gamma \in \{0.2,1,2\}$, and $p_H \in (0,1)$. Also, we have $\alpha_H = 1$ under the optimal α-policy and naive policies.

Figure 11 **Numerical results under quadratic lying cost model for different levels of H type delay sensitivity c_H.**



Notes: $c_L = 1, p_H = 0.5, \rho = 0.5, \varphi \in \{1,3,5\}, \gamma \in \{0.2,1,2\}$, and $c_H \in [2,500]$. Also, we have $\alpha_H = 1$ under the optimal α-policy and naive policies.

Appendix G: A Simulation Analysis on Data-driven Heuristics for the Identification of the Optimal Upgrading Policy

We have seen in Proposition 1 that the optimal upgrading policy ($\alpha_H = 1, \alpha_L \in [0,1)$) depends on the functional form of L type customers' misreporting probability $\mathbb{P}(Y = H|X = L)$, which for simplicity we will denote as $\eta(\alpha_L)$. However, in practice, such functional form may be *unknown* to the Manager, and the only available information is customers' *claim data*: sets of binary claims (i.e., L and H claims) in response to different α_L values. We envision that the Manager would use different α_L values, leading to different lying proportions, in order to be able to estimate the underlying (unknown) customer lying behavior. Then, using such estimates, the Manager can determine the optimal α_L that should be used. In light of this, we study *how the Manager can set the optimal upgrading policy based on claim data alone.*

Claim data: We assume that in the claim data, there are K different α_L values (indexed as α_L^k for $k = 1, \cdots, K$), and for each of them there are n independent binary claims (indexed as n^k for $k = 1, \cdots, K$). Moreover, we assume that the Manager knows the proportion of H types p_H in the population, that H types always claim their type, and that L types misreport with a probability according to the unknown $\eta(\alpha_L)$ function. Based on this, we have that for each k, the total number of H claims, $N_H^k \sim \mathcal{B}(n^k, p_H + (1 - p_H)\eta(\alpha_L^k))$, is a binomial random variable.

G.1. Proposed data-driven heuristics

We propose different data-driven heuristics to determine the optimal upgrading policy and conduct a simulation analysis to asses their performances.

Structural estimation heuristic. We propose to use $\Phi((\Delta\alpha^k)^\varphi) = \Phi((1 - \alpha_L^k)^\varphi)$ (recall that we assume that $\alpha_H = 1$) with $\theta \sim Exp(\gamma)$ as a model for the unknown misreporting probability of customers, where the parameters φ and γ are estimated from the claim data. We propose such functional form as it is flexible and allows to easily identify the optimal policy. Let n^k be the total number of claims and n_H^k the realized number of H claims, for a given α_L^k. Given some claim data, it follows that the log-likelihood is:

$$\mathcal{L}(\varphi, \gamma) = \sum_k log\big(\binom{n^k}{n_H^k} p_k^{n_H^k} (1 - p_k)^{n^k - n_H^k}\big),$$

where $p_k(\varphi, \gamma) = p_H + (1 - p_H)\Phi((1 - \alpha_L^k)^\varphi)$. We estimate the parameters $\hat{\varphi}$ and $\hat{\gamma}$ that maximize $\mathcal{L}$. Once we compute such parameters, we can define the estimated upgrading policy $\hat{\alpha_L}$ based on Proposition 1: $\hat{\alpha_L} = 0$

if $-\mathcal{S}(1) \leq 1 \iff \hat{\varphi}\hat{\gamma} \leq 1$, otherwise if $\hat{\varphi}\hat{\gamma} > 1$, the optimal upgrading probability is the unique $\hat{\alpha_L}$ that solves $1 + (1 - \hat{\alpha_L})\mathcal{S}(1 - \hat{\alpha_L}) = 0 \iff 1 - \hat{\varphi}\hat{\gamma}(1 - \hat{\alpha_L})^{\hat{\varphi}} = 0$. We can easily solve for such $\hat{\alpha_L}$ numerically.

Stochastic approximation heuristics. We construct two simple heuristics based on algorithms used to approximate extreme values of a function $e(x) = \mathbb{E}[F(x)]$ that cannot be computed directly, but only estimated via noisy observations from a random variable $F(x)$, depending on a parameter x. In our analysis, since we assume that we do not have downgrading nor down-reporting, we have that there is no under-prioritization error, i.e., $\delta_H = 0$. Based on this and based on Lemma 1, it follows that the waiting cost in the system is minimized at the α_L that minimizes the over-prioritization error $\delta_L = \alpha_L + \eta(\alpha_L)(1 - \alpha_L)$. Notice that since $\eta(\alpha_L)$ cannot be directly measured (because for a given number of H claims, the Manager does not know which particular customers are honest and which ones are dishonest) we have that δ_L cannot be directly measured. We can see that stochastic approximation is well suited for our setting since we want to identify the α_L that minimizes the function δ_L, and such function δ_L cannot be directly measured. As a first step, we construct $F(N_H^k, \alpha_L^k)$ such that $\mathbb{E}[F(N_H^k, \alpha_L^k)] = \delta_L(\alpha_L^k)$:

$$\begin{aligned}
F(N_H^k, \alpha_L^k) &= \alpha_L^k + (1 - \frac{n^k - N_H^k}{n^k(1 - p_H)})(1 - \alpha_L^k), \\
\mathbb{E}[F(N_H^k, \alpha_L^k)] &= \alpha_L^k + (1 - \frac{n^k - \mathbb{E}[N_H^k]}{n^k(1 - p_H)})(1 - \alpha_L^k) \\
&= \alpha_L^k + (1 - \frac{n^k - n^k(p_H + (1 - p_H)\eta(\alpha_L^k))}{n^k(1 - p_H)})(1 - \alpha_L^k) \\
&= \alpha_L^k + \eta(\alpha_L^k)(1 - \alpha_L^k) = \delta_L(\alpha_L^k).
\end{aligned}$$

In particular, we study the performance of two heuristics based on a simple *Random Search algorithm* and the *Kiefer–Wolfowitz (KW) algorithm.* The objective is to calculate an estimate, $\hat{\alpha_L}$, of the optimal upgrading probability, α_L^*, which minimizes δ_L. In our random search heuristic, we draw independently an α_L^k from $U[0,1]$ for each $k = 1, 2, \cdots, K$. Then, for each α_L^k, we collect n^k claims, observe the realized number of H claims n_H^k, and based on these compute $F(n_H^k, \alpha_L^k)$, which represent the realized values for $F(N_H^k, \alpha_L^k)$ in the data. We define the estimated upgrading policy $\hat{\alpha_L}$ as the α_L^k that yields the lowest $F(n_H^k, \alpha_L^k)$. The KW algorithm is a gradient-like method that uses finite differences to select α_L^k iteratively: $\alpha_L^{k+1} = \alpha_L^k - z_k(\frac{F(m_H^k, \alpha_L^k + v_k) - F(l_H^k, \alpha_L^k - v_k)}{2v_k})$, where $v_k = \frac{1}{5}k^{-1/3}$ represents a sequence of finite difference widths for the gradient approximation, $z_k = k^{-1}$ represents a sequence of step sizes taken along the direction of the gradient, m_H^k is the realized number of H claims for $\alpha_L^k + v_k$, and l_H^k is the realized number of H claims for

$\alpha_L^k - v_k$; see Kiefer and Wolfowitz (1952) for further details. If $\alpha_L^k + v_k > 1$, we use $(1 - v_k)$ and evaluate observe realization of $F(N_H^k, 1 - v_k)$ in the data. Similarly, if $\alpha_L^k - v_k < 0$, we evaluate we use v_k and evaluate observe realization of $F(N_H^k, v_k)$ in the data. Based on the iterative rule, this process continues for $K/2$ iterations. We define the estimated upgrading policy $\hat{\alpha_L}$ as the last computed α_L^k.

We focus on the heuristics above as they are simple and represent different ways to use claim data to identify the optimal upgrading policy. One benefit of the structural estimation heuristic is that it allows the Manager to freely select any set of upgrading policies to investigate α_L^k. In contrast, the proposed stochastic approximation heuristics restrict the way in which data is collected. Indeed, the random search heuristic requires random selections of α_L^k, and the KW heuristic as a gradient-like method iteratively defines the α_L^k. Based on this, another benefit of the structural estimation heuristic is that it can be used for already existing data sets. On the other hand, one benefit of stochastic approximation heuristics is that they do not require the Manager to assume a particular functional form to fit the unknown misreporting probability. Finally, we note that one advantage of both structural estimation and random search heuristics is that they can experiment with all defined α_L^k at once, while the KW requires a sequential one-by-one process. Overall, while the above represent important considerations for Managers, ultimately, we are interested in assessing their performance to identify the optimal upgrading policy.

Random Guess Benchmark. As a baseline for the performance of the mentioned heuristics, we evaluate the performance of a random guess: The estimated upgrading policy $\hat{\alpha_L}$ is randomly drawn from $U[0,1]$.

G.2. Simulation Analysis

To assess the performance of the proposed heuristics, we conduct a simulation analysis where we consider different functional forms and parametrizations for customers' misreporting probability $\eta(\alpha_L)$. In particular, we consider the following 4 functional forms with their respective parametrizations: (1) $\frac{1}{c}\Phi(1-\alpha_L)$ where Φ is a beta CDF with parameters $a \in \{1,5\}$, $b \in \{1,3\}$ and $c \in \{1.25, 2, 5\}$; (2) $\frac{(1-\alpha_L)^g}{c((1-\alpha_L)^g + \alpha_L^g)^{\frac{1}{g}}}$ a functional form based on Tversky and Kahneman (1992) probability weighting function, with $g \in \{0.5, 0.75, 1, 2\}$ and $c \in \{1.25, 2, 5\}$; (3) $\frac{1}{c}e^{-(-\log(1-\alpha_L))^d}$ a functional form based on Prelec (1998) probability weighting function, with $d \in \{0.2, 0.5, 1, 1.5\}$ and $c \in \{1.25, 2, 5\}$; and (4) $\Phi((1-\alpha_L)^{\varphi})$ where Φ is an exponential CDF with parameters $\varphi \in \{0.5, 1, 3, 5\}$ and $\gamma \in \{0.223, 0.693, 1.609\}$. Table 16 summarizes all considered functional forms and parametrizations with their respective true optimal policy α_L^* and true achieved over-prioritization probability δ_L^* based on such optimal policy. We select such functional forms and parametrizations to capture customer populations that differ in their misreporting levels at $\alpha_L = 0$, and in the convexity/concavity of their misreporting probability as a function of upgrading. In particular, we note that functional specification (4) is the same as the one considered in the structural estimation heuristic. This serves as a baseline to study the relative performance of the structural estimation heuristic in the remaining cases.

Table 16 Considered functional forms and parametrizations

Form	a	b	c	g	d	γ	φ	True α_L^*	True δ_L^*	Form	a	b	c	g	d	γ	φ	True α_L^*	True δ_L^*
(1)	1	1	5	-	-	-	-	0.000	0.200	(3)	-	-	5	-	0.2	-	-	0.013	0.143
(1)	1	3	5	-	-	-	-	0.000	0.200	(3)	-	-	5	-	0.5	-	-	0.012	0.189
(1)	5	1	5	-	-	-	-	0.036	0.197	(3)	-	-	5	-	1	-	-	0.000	0.200
(1)	5	3	5	-	-	-	-	0.000	0.200	(3)	-	-	5	-	1.5	-	-	0.000	0.200
(1)	1	1	2	-	-	-	-	0.000	0.500	(3)	-	-	2	-	0.2	-	-	0.043	0.323
(1)	1	3	2	-	-	-	-	0.000	0.500	(3)	-	-	2	-	0.5	-	-	0.084	0.425
(1)	5	1	2	-	-	-	-	0.197	0.331	(3)	-	-	2	-	1	-	-	0.000	0.500
(1)	5	3	2	-	-	-	-	0.000	0.500	(3)	-	-	2	-	1.5	-	-	0.000	0.500
(1)	1	1	1.25	-	-	-	-	0.375	0.688	(3)	-	-	1.25	-	0.2	-	-	0.089	0.480
(1)	1	3	1.25	-	-	-	-	0.000	0.800	(3)	-	-	1.25	-	0.5	-	-	0.210	0.599
(1)	5	1	1.25	-	-	-	-	0.269	0.391	(3)	-	-	1.25	-	1	-	-	0.375	0.688
(1)	5	3	1.25	-	-	-	-	0.470	0.588	(3)	-	-	1.25	-	1.5	-	-	0.506	0.725
(2)	-	-	5	0.5	-	-	-	0.021	0.172	(4)	-	-	-	-	-	0.223	0.5	0.000	0.200
(2)	-	-	5	0.75	-	-	-	0.003	0.199	(4)	-	-	-	-	-	0.223	1	0.000	0.200
(2)	-	-	5	1	-	-	-	0.000	0.200	(4)	-	-	-	-	-	0.223	3	0.000	0.200
(2)	-	-	5	2	-	-	-	0.000	0.200	(4)	-	-	-	-	-	0.223	5	0.022	0.199
(2)	-	-	2	0.5	-	-	-	0.085	0.366	(4)	-	-	-	-	-	0.693	0.5	0.000	0.500
(2)	-	-	2	0.75	-	-	-	0.089	0.465	(4)	-	-	-	-	-	0.693	1	0.000	0.500
(2)	-	-	2	1	-	-	-	0.000	0.500	(4)	-	-	-	-	-	0.693	3	0.216	0.439
(2)	-	-	2	2	-	-	-	0.000	0.500	(4)	-	-	-	-	-	0.693	5	0.220	0.361
(2)	-	-	1.25	0.5	-	-	-	0.163	0.515	(4)	-	-	-	-	-	1.609	0.5	0.000	0.800
(2)	-	-	1.25	0.75	-	-	-	0.271	0.647	(4)	-	-	-	-	-	1.609	1	0.379	0.771
(2)	-	-	1.25	1	-	-	-	0.375	0.688	(4)	-	-	-	-	-	1.609	3	0.408	0.576
(2)	-	-	1.25	2	-	-	-	0.444	0.637	(4)	-	-	-	-	-	1.609	5	0.341	0.460

Note: α_L^* values are identified numerically with a simple exhaustive search and presented values for α_L^* and δ_L^* are rounded to 3 decimal places.

For a given functional form and parametrization, we fix some values of n^k and K. For simplicity, we study the case in which $n^k = n$, that is, the case in which all n^k are the same for all k. Depending on the heuristic used (each heuristic uses different α_L^k as described above), we randomly generate a synthetic data set based on $N_H^k \sim \mathcal{B}(n^k, p_H + (1-p_H)\eta(\alpha_L^k))$ for each k. For the purposes of this analysis, in the structural estimation heuristic, for a given K the α_L^k are selected such that $\alpha_L^1 = 0$ and $\alpha_L^k = \alpha_L^{k-1} + \frac{1}{K}$. Based on the K generated data sets, a particular heuristic under consideration provides an estimated optimal policy $\hat{\alpha_L}$. We call this a run of the *estimation procedure* (i.e., the generation of an estimated optimal policy $\hat{\alpha_L}$ based on K data sets). Since we know the true $\eta(\alpha_L)$, we compute the *absolute error* of the estimated policy $\hat{\alpha_L}$ and the *true* optimal policy α_L^* in each run of the *estimation procedure*. We also compute the *absolute error* of the achieved over-prioritization probability $\hat{\delta_L} = \hat{\alpha_L} + \eta(\hat{\alpha_L})(1-\hat{\alpha_L})$ based on the estimated policy and the *true* optimal $\delta_L^* = \alpha_L^* + \eta(\alpha_L^*)(1-\alpha_L^*)$. We do this since the waiting cost in our model, as described in Lemma 1, is directly driven by the over-prioritization probability δ_L, and since policies closer to α_L^* do not necessarily yield over-prioritization probabilities closer to δ_L^*. We note that we do not asses the performance of the heuristics based on deviations between the achieved and the optimal waiting cost directly. This is because such deviations also depend on system parameters (e.g., for the same absolute error in over-prioritization, waiting cost deviations increase in ρ).

For a given parametrization, we run the estimation procedure a 1000 times and, to get an average measure of the heuristics performance in a given functional form, we compute the *mean absolute error* (MAE) of the aforementioned metrics across parametrizations (for each functional form). To clarify, since a given functional form consists of 12 different parametrizations, and for each parametrization we run the estimation procedure a 1000 times, this means that the MAE represents the average of 12,000 absolute errors. We repeat this process for all considered functional forms and for different values of $p_H \in \{0.2, 0.5, 0.8\}$, $K \in \{6, 50, 100\}$ and $n \in \{50, 250, 1000\}$ (recall that for simplicity we study the case in which $n^k = n$). We present the results of the simulation analysis in the following Tables 17-19.

G.3. Results and Discussion

First, we can see that for all considered functional forms, the random guess benchmark yields a policy that deviates approximately 41 percentage points (on average) from the true optimal policy. This, in turn, translates into an over-prioritization that deviates approximately 22 percentage points (on average) from the true minimum achievable over-prioritization probability. We can see that, for all functional forms, parametrizations, and values for p_H, K, and n, all considered heuristics perform better than such a random guess benchmark. This shows that the proposed heuristics indeed manage to leverage customers' claim-data to define a better scheduling policy.

We note that, for a fixed K, the performance of the structural estimation heuristic, both in terms of the provided policy and the achieved over-prioritization probability, improves as n increases, in all functional forms. In contrast, only for functional form (4), for a fixed n, the performance of the heuristic improves as K grows larger. For functional forms (1)-(3), for a fixed n, the performance of the heuristic does not always improve as K grows larger. Moreover, we see that the performance of the heuristic in functional form (4) is overall better than in the rest of the forms, (1)-(3). This is intuitive since as mentioned previously this heuristic calibrates the same model as the one used in functional form (4). Importantly, we can see that for functional forms (1),(2),(3), and (4) respectively, this heuristic provides *in the worst case* an over-prioritization probability that deviates on average no more than 3.1, 4.4, 7.2, and 2.5 percentage points from the true optimal δ_L^*. This shows that the proposed functional form in the heuristic is flexible enough to provide good performance even when the used model is not the same as the underlying true misreporting probability.

We observe that the performance of the stochastic approximation heuristics, both in terms of the provided policy and the achieved over-prioritization probability, improves as more data is available in all functional forms. In particular, we see that for a fixed n, the performance improves as K increases. Similarly, for a fixed K, the performance increases as n grows larger. We observe that for lower values of n and K, the random search heuristic performs better than the KW heuristic, and for sufficiently large values of n and K, the KW heuristic performs better than the random search heuristic, although this improvement is relatively small.

When comparing the heuristics, we can see that for low to medium n and K values, the structural estimation heuristic performs better (both in terms of the provided policy and the achieved over-prioritization probability) than the stochastic approximation heuristics, and for high n and K values the performance of all heuristics is roughly similar. Finally, we can observe that in general, the performance of all heuristics improves as p_H decreases, that is, as the pool of true L type customers (which are those that may misreport) increases.

Based on our simulation results, as a general guideline we suggest using the proposed structural estimation heuristic to identify the optimal policy, especially when the Manager does not have the possibility to collect large amounts of data. Only if the Manager can collect large amounts of data we suggest using the stochastic approximation heuristics. Indeed, we note that for all functional forms, and for $n = 1000$ and $K = 100$ the stochastic approximation heuristics are able to identify policies that provide *in the worst case* an over-prioritization probability that deviates on average no more than 1.6 percentage points from the true optimal δ_L^*. Finally, while the KW heuristic performs better than the random search heuristic for large amounts of data, we propose to use the random search heuristic as such improvement is relatively small and because the random search heuristic is easier to implement and does not require sequential data collection as in the case of KW.

Overall we have shown that Managers can use claim data to set the optimal upgrading policy when the underlying functional form of the misreporting probability is unknown. However, we want to emphasise that we have focused on simple heuristics for the purpose of *illustrating* different data-driven approaches. With this in mind, we highlight that the derived results and suggestions in this analysis should be taken as initial/general guidelines for Managers, where further steps are well warranted to improve the observed performance. In the case of the structural estimation heuristic, the investigated functional form was selected as it is parsimonious, allows to retrieve the optimal policy in a tractable manner, and presents a natural interpretation for its parameters in terms of lying behaviour.

To improve performance, Managers can further explore more general forms in the structural estimation heuristic (e.g., forms that capture that misreporting is neither strictly convex nor concave for all upgrading levels). In the case of the stochastic approximation heuristics, we selected simple heuristics to better communicate and illustrate how the data-driven identification of our policy can be formulated and solved in terms of stochastic approximation. To improve the performance, Managers can further explore more sophisticated algorithms (e.g., Broadie et al. (2011) proposes an adaptive version of KW with the aim of improving its finite-time behaviour).

Table 17 Simulation Results: Heuristics' Performance for $p_H = 0.2$

Form	n	K	Structural Estimation Heuristic MAE $\lvert\alpha_L^* - \hat{\alpha_L}\rvert$	Structural Estimation Heuristic MAE $\lvert\delta_L^* - \hat{\delta_L}\rvert$	Random Search Heuristic MAE $\lvert\alpha_L^* - \hat{\alpha_L}\rvert$	Random Search Heuristic MAE $\lvert\delta_L^* - \hat{\delta_L}\rvert$	KW Heuristic MAE $\lvert\alpha_L^* - \hat{\alpha_L}\rvert$	KW Heuristic MAE $\lvert\delta_L^* - \hat{\delta_L}\rvert$	Random Guess MAE $\lvert\alpha_L^* - \hat{\alpha_L}\rvert$	Random Guess MAE $\lvert\delta_L^* - \hat{\delta_L}\rvert$
(1)	50	6	0.066	0.010	0.163	0.060	0.183	0.074	0.418	0.222
(1)	50	50	0.067	0.008	0.083	0.025	0.105	0.026	0.418	0.222
(1)	50	100	0.066	0.007	0.071	0.021	0.094	0.021	0.418	0.222
(1)	250	6	0.058	0.008	0.139	0.051	0.168	0.070	0.418	0.222
(1)	250	50	0.065	0.007	0.060	0.015	0.073	0.015	0.418	0.222
(1)	250	100	0.064	0.007	0.051	0.013	0.063	0.012	0.418	0.222
(1)	1000	6	0.057	0.008	0.130	0.048	0.175	0.078	0.418	0.222
(1)	1000	50	0.064	0.007	0.044	0.011	0.055	0.011	0.418	0.222
(1)	1000	100	0.064	0.007	0.035	0.008	0.048	0.009	0.418	0.222
(2)	50	6	0.066	0.026	0.149	0.052	0.146	0.049	0.408	0.217
(2)	50	50	0.056	0.044	0.079	0.018	0.082	0.019	0.408	0.217
(2)	50	100	0.056	0.043	0.071	0.016	0.070	0.015	0.408	0.217
(2)	250	6	0.047	0.020	0.125	0.042	0.107	0.035	0.408	0.217
(2)	250	50	0.054	0.042	0.057	0.011	0.044	0.008	0.408	0.217
(2)	250	100	0.055	0.042	0.051	0.009	0.036	0.006	0.408	0.217
(2)	1000	6	0.043	0.018	0.116	0.040	0.091	0.033	0.408	0.217
(2)	1000	50	0.053	0.042	0.044	0.007	0.028	0.005	0.408	0.217
(2)	1000	100	0.054	0.042	0.038	0.005	0.022	0.004	0.408	0.217
(3)	50	6	0.058	0.050	0.152	0.061	0.141	0.052	0.418	0.230
(3)	50	50	0.048	0.071	0.078	0.022	0.077	0.023	0.418	0.230
(3)	50	100	0.046	0.072	0.070	0.018	0.065	0.018	0.418	0.230
(3)	250	6	0.037	0.049	0.126	0.050	0.101	0.040	0.418	0.230
(3)	250	50	0.045	0.072	0.053	0.013	0.040	0.011	0.418	0.230
(3)	250	100	0.044	0.072	0.046	0.010	0.032	0.008	0.418	0.230
(3)	1000	6	0.031	0.051	0.118	0.047	0.087	0.037	0.418	0.230
(3)	1000	50	0.044	0.072	0.038	0.009	0.026	0.007	0.418	0.230
(3)	1000	100	0.044	0.072	0.032	0.006	0.020	0.005	0.418	0.230
(4)	50	6	0.037	0.005	0.155	0.053	0.168	0.063	0.403	0.214
(4)	50	50	0.013	0.001	0.086	0.020	0.086	0.020	0.403	0.214
(4)	50	100	0.009	0.001	0.079	0.018	0.074	0.016	0.403	0.214
(4)	250	6	0.014	0.001	0.131	0.043	0.141	0.054	0.403	0.214
(4)	250	50	0.006	0.000	0.063	0.013	0.044	0.010	0.403	0.214
(4)	250	100	0.004	0.000	0.057	0.011	0.036	0.007	0.403	0.214
(4)	1000	6	0.007	0.000	0.122	0.041	0.129	0.051	0.403	0.214
(4)	1000	50	0.003	0.000	0.046	0.008	0.027	0.006	0.403	0.214
(4)	1000	100	0.002	0.000	0.04	0.006	0.022	0.005	0.403	0.214

Note: All results are rounded to 3 decimal places.

Table 18 Simulation Results: Heuristics' Performance for $p_H = 0.5$

Form	n	K	Structural Estimation Heuristic		Random Search Heuristic		KW Heuristic		Random Guess	
			MAE		MAE		MAE		MAE	
			$\lvert\alpha_L^* - \hat{\alpha_L}\rvert$	$\lvert\delta_L^* - \hat{\delta_L}\rvert$	$\lvert\alpha_L^* - \hat{\alpha_L}\rvert$	$\lvert\delta_L^* - \hat{\delta_L}\rvert$	$\lvert\alpha_L^* - \hat{\alpha_L}\rvert$	$\lvert\delta_L^* - \hat{\delta_L}\rvert$	$\lvert\alpha_L^* - \hat{\alpha_L}\rvert$	$\lvert\delta_L^* - \hat{\delta_L}\rvert$
(1)	50	6	0.078	0.016	0.178	0.067	0.212	0.091	0.418	0.222
(1)	50	50	0.068	0.009	0.100	0.032	0.140	0.042	0.418	0.222
(1)	50	100	0.067	0.008	0.087	0.027	0.126	0.035	0.418	0.222
(1)	250	6	0.059	0.008	0.149	0.054	0.170	0.069	0.418	0.222
(1)	250	50	0.064	0.007	0.073	0.020	0.085	0.020	0.418	0.222
(1)	250	100	0.063	0.007	0.064	0.017	0.074	0.016	0.418	0.222
(1)	1000	6	0.056	0.008	0.136	0.050	0.171	0.074	0.418	0.222
(1)	1000	50	0.062	0.007	0.054	0.013	0.063	0.014	0.418	0.222
(1)	1000	100	0.063	0.007	0.045	0.011	0.057	0.011	0.418	0.222
(2)	50	6	0.085	0.031	0.163	0.059	0.184	0.069	0.408	0.217
(2)	50	50	0.058	0.043	0.094	0.025	0.119	0.035	0.408	0.217
(2)	50	100	0.055	0.043	0.085	0.022	0.105	0.028	0.408	0.217
(2)	250	6	0.058	0.019	0.134	0.046	0.121	0.038	0.408	0.217
(2)	250	50	0.051	0.042	0.069	0.015	0.061	0.013	0.408	0.217
(2)	250	100	0.051	0.041	0.063	0.013	0.051	0.010	0.408	0.217
(2)	1000	6	0.052	0.018	0.122	0.042	0.098	0.034	0.408	0.217
(2)	1000	50	0.050	0.041	0.052	0.010	0.036	0.007	0.408	0.217
(2)	1000	100	0.051	0.041	0.045	0.007	0.030	0.005	0.408	0.217
(3)	50	6	0.082	0.050	0.166	0.067	0.178	0.072	0.418	0.230
(3)	50	50	0.049	0.069	0.094	0.029	0.116	0.040	0.418	0.230
(3)	50	100	0.047	0.070	0.085	0.025	0.101	0.033	0.418	0.230
(3)	250	6	0.049	0.040	0.135	0.053	0.115	0.043	0.418	0.230
(3)	250	50	0.045	0.071	0.064	0.018	0.055	0.016	0.418	0.230
(3)	250	100	0.044	0.071	0.058	0.015	0.044	0.012	0.418	0.230
(3)	1000	6	0.036	0.037	0.122	0.049	0.092	0.038	0.418	0.230
(3)	1000	50	0.044	0.071	0.046	0.011	0.033	0.010	0.418	0.230
(3)	1000	100	0.043	0.071	0.039	0.009	0.026	0.007	0.418	0.230
(4)	50	6	0.057	0.011	0.168	0.059	0.198	0.080	0.403	0.214
(4)	50	50	0.020	0.002	0.101	0.027	0.123	0.036	0.403	0.214
(4)	50	100	0.014	0.001	0.092	0.023	0.109	0.030	0.403	0.214
(4)	250	6	0.023	0.002	0.140	0.047	0.147	0.056	0.403	0.214
(4)	250	50	0.009	0.001	0.075	0.017	0.062	0.014	0.403	0.214
(4)	250	100	0.007	0.000	0.068	0.014	0.051	0.011	0.403	0.214
(4)	1000	6	0.010	0.001	0.127	0.043	0.132	0.051	0.403	0.214
(4)	1000	50	0.005	0.000	0.055	0.011	0.036	0.008	0.403	0.214
(4)	1000	100	0.004	0.000	0.049	0.009	0.029	0.006	0.403	0.214

Note: All results are rounded to 3 decimal places.

Table 19 Simulation Results: Heuristics' Performance for $p_H = 0.8$

Form	n	K	Structural Estimation Heuristic		Random Search Heuristic		KW Heuristic		Random Guess	
			MAE		MAE		MAE		MAE	
			$\lvert\alpha_L^* - \hat{\alpha_L}\rvert$	$\lvert\delta_L^* - \hat{\delta_L}\rvert$	$\lvert\alpha_L^* - \hat{\alpha_L}\rvert$	$\lvert\delta_L^* - \hat{\delta_L}\rvert$	$\lvert\alpha_L^* - \hat{\alpha_L}\rvert$	$\lvert\delta_L^* - \hat{\delta_L}\rvert$	$\lvert\alpha_L^* - \hat{\alpha_L}\rvert$	$\lvert\delta_L^* - \hat{\delta_L}\rvert$
(1)	50	6	0.104	0.031	0.206	0.082	0.282	0.135	0.418	0.222
(1)	50	50	0.078	0.014	0.128	0.045	0.231	0.092	0.418	0.222
(1)	50	100	0.072	0.011	0.112	0.039	0.211	0.079	0.418	0.222
(1)	250	6	0.067	0.012	0.170	0.063	0.194	0.081	0.418	0.222
(1)	250	50	0.066	0.008	0.094	0.029	0.120	0.035	0.418	0.222
(1)	250	100	0.064	0.008	0.084	0.025	0.105	0.028	0.418	0.222
(1)	1000	6	0.056	0.008	0.147	0.053	0.166	0.068	0.418	0.222
(1)	1000	50	0.062	0.007	0.071	0.019	0.081	0.019	0.418	0.222
(1)	1000	100	0.062	0.007	0.060	0.016	0.071	0.015	0.418	0.222
(2)	50	6	0.105	0.039	0.189	0.073	0.269	0.123	0.408	0.217
(2)	50	50	0.073	0.042	0.120	0.037	0.212	0.084	0.408	0.217
(2)	50	100	0.063	0.042	0.107	0.031	0.190	0.072	0.408	0.217
(2)	250	6	0.074	0.025	0.154	0.055	0.165	0.059	0.408	0.217
(2)	250	50	0.054	0.041	0.089	0.023	0.100	0.028	0.408	0.217
(2)	250	100	0.052	0.042	0.080	0.019	0.084	0.021	0.408	0.217
(2)	1000	6	0.059	0.019	0.132	0.045	0.111	0.036	0.408	0.217
(2)	1000	50	0.049	0.041	0.068	0.015	0.055	0.012	0.408	0.217
(2)	1000	100	0.050	0.041	0.060	0.012	0.045	0.009	0.408	0.217
(3)	50	6	0.105	0.054	0.193	0.082	0.267	0.127	0.418	0.230
(3)	50	50	0.062	0.068	0.121	0.042	0.213	0.093	0.418	0.230
(3)	50	100	0.054	0.069	0.109	0.036	0.190	0.080	0.418	0.230
(3)	250	6	0.071	0.044	0.156	0.063	0.156	0.060	0.418	0.230
(3)	250	50	0.047	0.068	0.087	0.027	0.096	0.032	0.418	0.230
(3)	250	100	0.045	0.070	0.077	0.022	0.078	0.025	0.418	0.230
(3)	1000	6	0.051	0.036	0.133	0.053	0.105	0.040	0.418	0.230
(3)	1000	50	0.044	0.070	0.061	0.017	0.050	0.015	0.418	0.230
(3)	1000	100	0.044	0.071	0.054	0.014	0.039	0.011	0.418	0.230
(4)	50	6	0.094	0.025	0.194	0.073	0.272	0.127	0.403	0.214
(4)	50	50	0.040	0.008	0.126	0.039	0.215	0.084	0.403	0.214
(4)	50	100	0.028	0.005	0.114	0.033	0.193	0.071	0.403	0.214
(4)	250	6	0.042	0.007	0.159	0.055	0.180	0.071	0.403	0.214
(4)	250	50	0.016	0.002	0.097	0.025	0.103	0.029	0.403	0.214
(4)	250	100	0.011	0.001	0.087	0.021	0.088	0.023	0.403	0.214
(4)	1000	6	0.019	0.002	0.138	0.046	0.143	0.055	0.403	0.214
(4)	1000	50	0.008	0.001	0.072	0.016	0.056	0.013	0.403	0.214
(4)	1000	100	0.006	0.000	0.065	0.014	0.046	0.010	0.403	0.214

Note: All results are rounded to 3 decimal places.