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Introduction

It is first necessary to clarify the term to discuss satisficing behaviour and mental accounting critically. Thaler (1999) states mental accounting 'is the set of cognitive operations used by individuals and households to organise, evaluate, and keep track of financial activities'. Hahnel et al (2020) add detail to this definition by exploring the link between mental budgets and specific acts of consumption and payments.

Simon (1955) introduces the concept of satisficing behaviour,' the adaptive behaviour of organisms in learning and choice situations, this adaptiveness falls far short of the ideal of maximising postulated in economic theory. Evidently, organisms adapt well enough to satisfice; they do not, in general, optimise'. Furthermore, satisficing behaviour is commonly practised in real-world situations such as consumer purchasing decisions, labour hours and general decision-making. Moreover, it is essential for behavioural economists to understand both concepts of mental accounting and satisficing behaviour to critically evaluate the effectiveness of the surge pricing model in reducing satisficing behaviour.

While perhaps breaking free from narrow framing which encourages short-satisficing behaviour is difficult, the surge algorithm is effective in intensifying drivers to work outside their narrow frame for an additional financial gain because positive supply elasticities and standard economic theory, anchoring on surge prices and reduced waiting times for customers. Therefore, I will holistically analyse behavioural economic theories to explain Camerer et al., (1997) study of the labour supply of New York City cab drivers short-satisficing behaviour and use Uber's surge price model to evidence how this behaviour can be reduced.

Understanding Satisficing Behaviour through Behavioural Economics

Simon's (1995) model of satisficing behaviour proposes that individuals and groups make decisions that are 'good enough' rather than optimal, with a minimum threshold of acceptability. Therefore, this model assumes that individuals have limited cognitive ability time and resources to make holistic rational choices, often settling for a satisfactory choice rather than optimal.

Camerer et al., (1997) provide a study of the labour supply of New York City cab drivers and exemplify how Simon's (1995) satisficing model can explain short-term satisficing behaviour. The study discovered that cab drivers usually set a daily income target and work until they achieve it rather than fixating on the number of hours worked. As a result of this, this behaviour is an example of short-term satisficing behaviour, denying the opportunity to earn additional money by working longer hours. Furthermore, cab drivers may display this behaviour due to seeking a minimum threshold of income rather than optimising their income longer term.

Prospect Theory

Satisficing behaviour demonstrated in Camerer et al., (1997) study may be influenced by behavioural economic theories such as prospect theory identifying multiple cognitive biases such as loss aversion and framing effects, influencing people to make suboptimal decisions.

Kahneman and Tversky (1979) in their journal "Prospect Theory: An Analysis of Decision Under Risk" demonstrated through compelling laboratory experiments that people systematically violate the predictions of expected utility theory through a new model of risk attitudes of prospect theory. Furthermore, Koszegi and Rabin (2006;2007;2009) express the influence of reference points to compute gains and losses in their expectations,' people derive utility from the difference between consumption and expected consumption, the utility function exhibits loss aversion from diminishing sensitivity.

Loss aversion

Satisficing behaviour may be influenced by cognitive biases such as loss aversion, a concept whereby the pain experienced from losses is stronger compared to the pleasures of gains of equal magnitude (Kahneman and Tversky, 1984; Kahneman 1991 et al.,). Consequently, both satisficing behaviour and loss aversion goes against standard economic rationality which assumes that decisions are based on maximising expected utility.

Novemsky and Kahneman (2005) demonstrate the effects of loss aversion through the experiment on used coffee mugs whereby participants were randomly assigned to be either sellers or buyers. Novemsky and Kanheman (2005) state 'sellers were asked about the minimum they would be willing to accept to give up the mug, and buyers were asked about the maximum they would be willing to pay to acquire the mug'. Furthermore, the study notes that on average buyers were not willing to pay more than $2.87 compared to sellers asking for $7.12. The difference between the figures is explained by loss aversion for the mug because sellers categorise the mug as a loss whereas buyers categorise it as a gain detriment of potential gains in the long term (Thaler, 1980).

Therefore, loss aversion can help explain why people engage in short-satisficing behaviour, focusing more on avoiding potential losses than acquiring gains and choosing a safer option that guarantees a minimum level of outcomes. Furthermore, prospect theory exemplifies cab drivers denying the opportunity to work longer hours after reaching the reference point of their daily income demonstrating short-satisficing behaviour (Helson, 1964).

Benartzi and Thaler (1999) note short-term satisfaction as myopic loss aversion to explain that individuals prioritise immediate gains over more beneficial longer-term strategies through the example of university employees choosing bonds with lower returns over stocks when viewed as one-year rates of return compared to thirty-year rates of return. Moreover, this short-term satisfaction is exemplified by the volatility of short-term trends influences individuals to be more risk-averse (Hassan et al.,2006).

Narrow Bracketing

Narrow bracketing refers to the tendency to make decisions in isolation, separate from either temporal or across different activities (Read et al., 2000). Hassan et al., (2006) adds detail to this definition by noting that narrow bracketing manifests itself in the order of events ‘one at a time’, each gain being bracketed as a separate event.

Narrow bracketing is exemplified in Thaler’s (1985) “Mental Accounting and Consumer Choice” paper, Thaler uses horse racing as an example to demonstrate narrow bracketing and satisficing behaviour. In this study, Thaler notes that betters tend to allocate money according to particular and individual races and once that money is gone they stop betting on that particular race. Furthermore, focusing each race in isolated ‘mental accounts’ rather than the overall betting strategy in a larger context, engaging in satisficing behaviour through potential suboptimal choices. Furthermore, evidence for reducing inputs after reaching income targets has been observed among physicians, sole proprietors, and farmers (Wales, 1973; Berg 1961).

Camerer et al., (1997) observed narrow bracketing in the study of the labour supply of New York City cab drivers through their short-term planning by establishing daily income targets. The drivers were noted to stop work sooner on lucrative days than on slower days such as when there is bad weather. This pattern can be explained by their daily income target as a reference point on the value function, and then the marginal value of additional income falls sharply (Rizzo and Zeckhauser, 2003).

According to Thaler (1999), cab drivers reset their reference points too often which leads to stopping work early on good days if they achieve their income targets, reducing additional income, therefore, drivers demonstrate short-satisficing behaviour.

Surge Pricing Model

Chen and Sheldon (2015) state ‘in many markets, new technologies allow traditional jobs to be divided into discrete tasks that are widely distributed across workers and dynamically priced given prevailing supply and demand conditions’ forming the ‘gig’ economy. Furthermore, this ‘gig’ economy transcends traditional fixed employment contracts to more flexible agreements mostly in two-sided markets to provide services for consumers. A major notable player in the ‘gig’ economy is Uber, a technology firm managing a ride-sharing platform on a mobile application, creating a two-sided market for on-demand transportation mainly in cities. For a driver, the ride order appears on the nearest driver’s smartphone, and they can accept or reject the ride (Slavuji et al., 2016). Moreover, riders pay a price calculated by the distance and time taken on their trip which drivers receive after deducting a service fee paid to Uber. Uber and other ‘gig’ economy players such as Lyft interrupt traditional taxicab business models and public transit systems (Cohen and Kietzmann, 2014).

The ride-sharing company, Uber, connects drivers to riders using dynamic pricing systems known as surge pricing. The surge pricing model adjusts ‘true’ market prices in real-time using an algorithm in response to the supply and demand in the location, incentivising more drivers to meet and balance the demand. Chen and Sheldon (2015) note ‘trip prices are adjusted by multiplying the prices of the underlying components which make up fare –the base fare, the price per mile, and the price per minute–10 by a multiplier output by the surge algorithm’. As a result of this, the higher surge prices involve paying drovers a higher rate during periods of high demand. Consequently, according to standard economic theory, this should motivate employees to work additional hours for the additional financial gain.

Behavioural economics is crucial to determine the effectiveness of surge pricing models, addressing the interface between psychology and economics (Rabin 1998).

Therefore, to critically evaluate the effectiveness of the surge pricing model in reducing short satisficing behaviour, I will holistically analyse behavioural economics theories.

Evidence for the effectiveness of Uber's surge pricing model

Hall et al., (2015) illustrates 'the underlying economics by taking a typical example of surge in action' such as popstar Ariana Grande's Madison Square Garden show on March 21st, 2015, reflected in Appendix A. Furthermore, it is apparent that after the concert finished the number of customers opening the app had quadrupled normal app opening figures. As a result of this, the number of drivers in the area increased by up to two times the pre-surge baseline (Hall et al., 2015). This is because a key finding in empirical literature regarding labour supply elasticities has concluded evidence of positive supply elasticities in line with the standard economic theory of temporal substitution of labour; individuals work based on their expectations of future earnings or consumption opportunities. For example, positive labour supply elasticities have been demonstrated in the construction work on the Trans-Alaskan pipeline, stadium vendors and lobster drives (Carrington, 1996; Ottenginer, 1999; Stafford, 2015). Therefore, following standard economic theory, surge pricing models should be effective in encouraging drivers to work additional hours in high demand times because of the additional financial gains, demonstrated in Appendix B. The estimated increase in earnings the drivers earnt because of the surge algorithm was 13% on that day of the concert (Hall et al., 2015).

This reduces short-satisficing behaviour because positive supply elasticities suggest that drivers are elastic to dynamic changes such as surge peak times by adapting more flexibly to work in times of better financial gains, a more efficient allocation of resources in the market.

Moreover, expected utility theory, part of standard economic theory assumes that decisions are made with considerable knowledge, information and preferences and that consumers will choose the decision which maximises utility (Broome, 1991).

During surge periods of high demand, drivers are faced with aversions such as higher costs, a longer commute to pick up passengers in higher demand areas or missing out on valuable leisure time such as New Year's Eve. Consequently, drivers need to evaluate the potential benefits of additional journeys against the potential costs in doing so. This analysis of a higher opportunity cost is also reflected by Cramerer et al., (1997) in Appendix C which demonstrates variables such as warmer days reducing labour supplies.

As a result of this, Hall et al., 2015 evidences the effectiveness of surge prices, demonstrating that when, due to a technical glitch, the surge pricing algorithm was not in effect the percentage of requests completed plummeted from 100% to only a mere 15%, reflected in Appendix D. Therefore, aligning with loss aversion, which Morrison and Clark (2016) define as ‘the value people impute to their possessions’ that ‘people endow what they possess with a use value which they are reluctant to give up’. In the 30 minutes surge outage, drivers would deem the decrease in wages compared to when surge prices were in effect (the reference point) a loss and return to short-satisficing behaviour; proving its effectiveness.

Evidence for it not being effective.

However, Camerer et al (1997) study of New York City cab drivers discovered radical evidence of negative earning elasticities justified by the concept of ‘income targeting’, the idea that the driver has a daily income target and after achieving this they are far more likely to stop providing rides (Mankiw et al., 1985). Camerer et al., (1997) states ‘Imagine, for example, that cabdrivers havd an earnings target beyond which they derived zero marginal utility of income’ if applied daily, such a target would produce wage elasticities of -1’ because drivers would cut back their hours proportionality at the same rate as their increased earnings because exceeding it adds no utility.

Furthermore, it is evident that the direction of labour supply elasticities is very influential in the effectiveness of dynamic labour-pricing strategies such as Uber surge prices. Therefore, the effectiveness of the surge pricing model may be limited if the labour supply of drivers is inelastic to changes in demand and price (Chen and Sheldon 2015).

Analysing Appendix F, despite the number of app openings during surge pricing times increased considerably when implementing the surge algorithm, the actual number of requests did not increase to the same degree (Hall et al., 2015). This derived from riders seeing an increase in price and decided to take an alternate form of transportation or waiting until the prices had decreased. Furthermore, this change consumer behaviour aligns with Tversky and Kahneman (1974) conceptualisation of the anchoring effect, the disproportionate influence on consumers when making decisions to judge biased toward an initially presented value.

Tversky and Kahneman (1974) demonstrated this cognitive bias through their classical study of estimations of African countries in the United Nations with reference to a range which was generated by a wheel of fortune between nominal figures of 0-100.

Participants had to conclude whether the real answer was above or below the reference figure of comparative judgement whereby participants fixate on the first piece of information they receive; the anchor (Furnham and Boo, 2011). Therefore, aligning with Uber surge prices, arguably, the riders rely too heavily and anchor on the initial fare for the ride and may compare subsequent surge time fares to that initial price when deciding whether to pay the price.

Tversky and Kahneman (1981) conceptualisation of decision framing suggest that the drivers will simplify complicated phenomena into more manageable, understandable outlines. Furthermore, Thaler (1985) suggests that the drivers will frame problems into subproblems and allocate investment problems into mental accountings. Huang (2004) adds detail to the influence of framing on decision making, an important consideration under risk. Therefore, if despite surge pricing models drivers will continue demonstrating their short satisficing behaviour by evaluating their income daily, in a narrow frame. This aligns with Barberis et al., (2006) Equity Premium Puzzle.

Barberis et al., (2006) state ‘the equity premium puzzle…asks why stocks historically earned a higher average return, relative to T-bills, than seems justified by standard measures of risk’ (Mehra, 2007). Furthermore, narrow framing describes how when people are offered a new gamble, it is often evaluated in isolation from other risks, disagreeing with traditional utility functions, demonstrated in the example in Appendix E. Therefore, this suggests that Uber Surge Prices will not change short-satisficing behaviour because it is deep-rooted in how drivers organise their mental accounts.

However, Cramerer et al., (1997) suggests that ‘drivers may learn over time that driving more on high wage days and less on low wage days provides more income and more leisure’ therefore ‘the labour supply curve of experienced drivers would have a more positive wage elasticity than that of inexperienced drivers’.

Conclusion

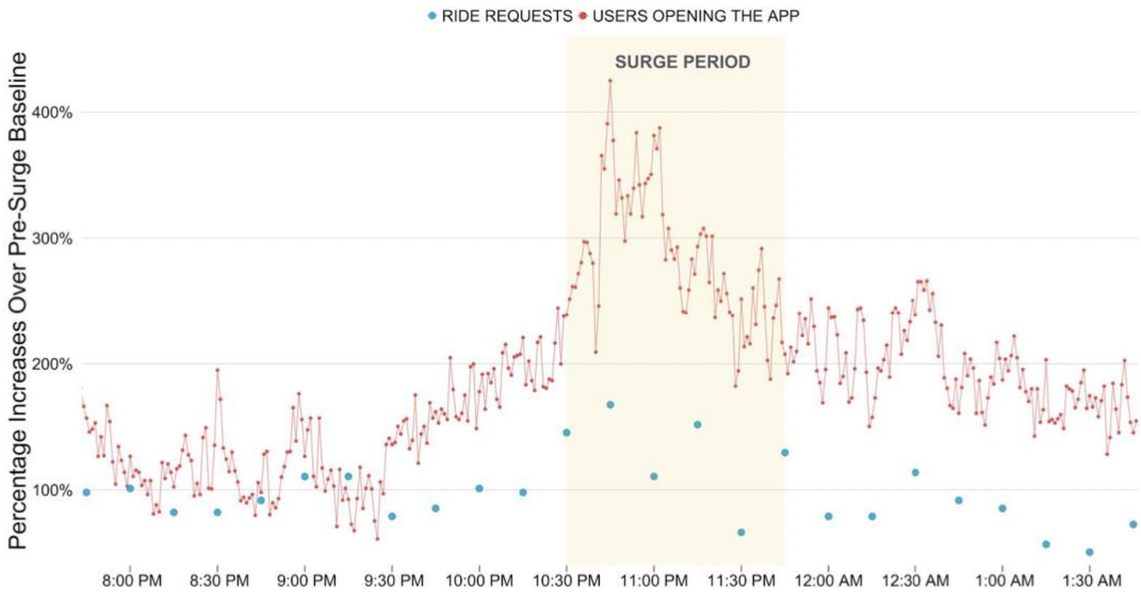
To summarise, it is agreed that there are both evidence for and against the effectiveness of Uber’s surge pricing algorithm in reducing short-satisficing behaviour. Both, Thaler (1999) and Hahnel et al (2020) conceptualise mental accounting and its importance and influence on decision-making. Furthermore, Camerer et al., (1977) study of the labour supply of New York City cab drivers demonstrated clear short-satisficing behaviour common in taxi drivers. Collectively, Kahneman and Tversky (1979), Novemsky and Kahneman

(2005) and Read et al., (2000) demonstrate the three behavioural economic theories which I deem most relevant: prospect theory, loss aversion and framing effects to explore short-satisficing behaviour.

Additionally, when analysing the effectiveness of Uber's surge pricing algorithm, Hall et al., 2015, analysis provides evidence and reasons for why the algorithm would be effective in reducing short-satisficing behaviour through drivers using new surge prices as reference points, therefore working outside of these times would feel like a loss, aligning with loss aversion. Conversely, Furnham and Boo (2011) argue that riders would fixate on the original non-surge prices and not conform with these new surge prices, aligning with the anchoring effect and therefore reducing the demand for Uber rides, reducing the success of the dynamic pricing strategy. As a result of this, this suggests that if there is a decrease in the demand for Ubers, drivers may experience an increase in waiting times, reducing their likelihood to work additional hours, ineffective when reducing short-satisficing behaviour.

To conclude, there is sufficient evidence to argue that while breaking free from narrow framing which encourages short-satisficing behaviour is difficult, the surge algorithm is effective in intensifying drivers to work outside their narrow frame for an additional financial gain because positive supply elasticates and standard economic theory, anchoring on surge prices and reduced waiting times for customers. Overall, perhaps, the effectiveness of Uber's surge pricing model in reducing short-satisficing behaviour depends on the experience of the drivers, the more experienced the more positive the wage elasticity (Cramerer et al., 1997).

Appendix A – Demand for Uber Spikes Following Sold-Out Concert on March 21, 2015



Source: Hall, J., Kendrick, C. and Nosko, C., 2015. The effects of Uber's surge pricing: A case study. *The University of Chicago Booth School of Business*. https://leeds-faculty.colorado.edu/leachj/BCOR1015/Readings%20not%20linked%20to%20Library%20Page/Effects_of_uber's_surge_pricing%20CASE.pdf

Appendix B – Uber Drive-Partner Supply Increases to Match Spike in Demand

Source: Hall, J., Kendrick, C. and Nosko, C., 2015. The effects of Uber's surge pricing: A case study. *The University of Chicago Booth School of Business*. https://leeds-faculty.colorado.edu/leachj/BCOR1015/Readings%20not%20linked%20to%20Library%20Page/Effects_of_uber's_surge_pricing%20CASE.pdf

Appendix C – Table Showing Labour Supply of NYC Cabdrivers

TABLE II
OLS LOG HOURS WORKED EQUATIONS

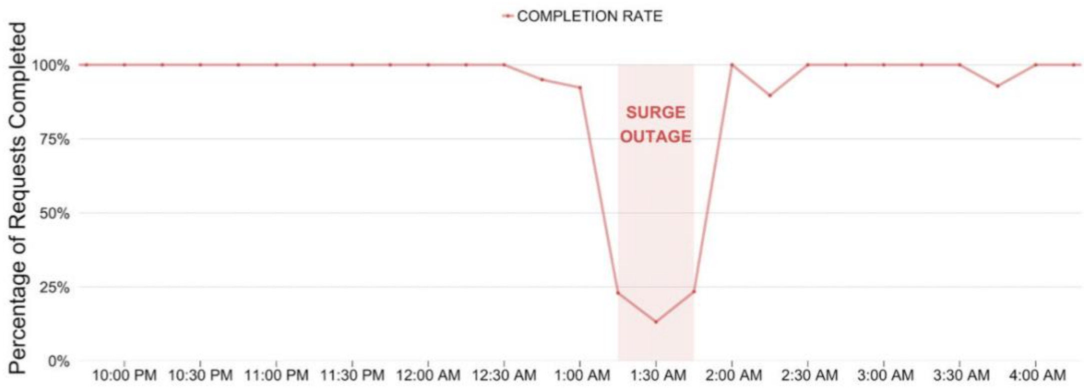
Sample	TRIP		TLC1		TLC2
Log hourly wage	−.411	−.186	−.501	−.618	−.355
	(.169)	(.129)	(.063)	(.051)	(.051)
High temperature	.000	−.000	.001	.002	−.021
	(.002)	(.002)	(.002)	(.002)	(.007)
Shift during week	−.057	−.047	−.004	.030	—
	(.019)	(.033)	(.035)	(.042)	
Rain	.002	.015	—	—	−.150
	(.035)	(.035)			(.062)
Night shift dummy	.048	−.049	−.127	−.294	−.253
	(.053)	(.049)	(.034)	(.047)	(.038)
Day shift dummy	—	—	.000	.053	—
			(.028)	(.045)	
Fixed effects	No	Yes	No	Yes	No
Adjusted R^2	.243	.484	.175	.318	.146
Sample size	70	65	1044	794	712
Number of drivers	13	8	484	234	712

Dependent variable is the log of hours worked. Standard errors are in parentheses and are corrected for the nonfixed effects estimates in coulmns 1 and 3 to account for the panel structure of the data. Explanatory variables are described in Appendix 1.

Source: Camerer, C., Babcock, L., Loewenstein, G., & Thaler, R. (1997). Labor Supply of New York City Cabdrivers: One Day at a Time. *The Quarterly Journal of Economics*, *112*(2), 407– 441. https://doi.org/10.1162/003355397555244

Appendix D- Impact of a Surge Pricing Disruption on Completed Ride Requests on New Year's Eve

Figure 6: Impact of a Surge Pricing Disruption on Completed Ride Requests on New Year's Eve



Note: Figure reports the "completion rate" for a given 15 minute interval over the course of New Year's Eve, December 31, 2014 to January 1, 2015, for uberX vehicles within the geospatial bounding box noted earlier (red line). "Completion rate" is defined as the percentage of requests that are fulfilled (calculated as the number of completed trips within the 15 minute interval, divided by the sum of completed trips and unfulfilled trips). "Surge outage" (red box) is the time period during which Uber's surge pricing algorithm broke down due to a technical glitch.

Source: Hall, J., Kendrick, C. and Nosko, C., 2015. The effects of Uber's surge pricing: A case study. *The University of Chicago Booth School of Business*. https://leeds-faculty.colorado.edu/leachj/BCOR1015/Readings%20not%20linked%20to%20Library%20Page/Effects_of_uber's_surge_pricing%20CASE.pdf

Appendix E – Demonstration of Narrow Framing by Tversky and Kahneman (1981)

The classic demonstration of narrow framing is due to Tversky and Kahneman (1981), who ask 150 subjects the following question:

Imagine that you face the following pair of concurrent decisions. First examine both decisions, and then indicate the options you prefer.

Choice I. Choose between

A. a sure gain of $240,

B. a 25 percent chance to gain $1,000 and a 75 percent chance to gain nothing.

Choice II. Choose between

C. a sure loss of $750,

D. a 75 percent chance to lose $1,000 and a 25 percent chance to lose nothing.

Tversky and Kahneman (1981) report that 84 percent of subjects chose A, with only 16 percent choosing B, and that 87 percent chose D, with only 13 percent choosing C. In particular, 73 percent of subjects chose the combination A&D, namely

a 25% chance to win \$240, a 75% chance to lose \$760, (2)

which is surprising, given that this choice is dominated by the combination B&C, namely

a 25% chance to win \$250, a 75% chance to lose \$750. (3)

Source: Kahneman, D. and Tversky, A., 1981. *The simulation heuristic*. Stanford Univ CA Dept of Psychology.

<u>Appendix F- Supply Rises to Meet Demand Following a Sold-Out Concert on March 21, 2015</u>

Source: Hall, J., Kendrick, C. and Nosko, C., 2015. The effects of Uber's surge pricing: A case study. *The University of Chicago Booth School of Business*. https://leeds-faculty.colorado.edu/leachj/BCOR1015/Readings%20not%20linked%20to%20Library%20Page/Effects_of_uber's_surge_pricing%20CASE.pdf

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