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Dedicated to family

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Chapter 1

Introduction

1.1. Overview

This thesis offers a comparison of the ideas of theorized bargaining with actual bargaining behavior in a laboratory (chapter 2), a field (chapter 3), and a market (chapter 4). Each chapter is motivated with real life examples. The second chapter, for instance, in a controlled laboratory environment, seeks to answer a broad range of questions like if consumers of a product could stand to gain out of a mere announcement of a maximum retail price (MRP), or if labor unions can gain from the mere existence of a minimum wage law, even when none is binding. Similarly, the third chapter is on a field experiment that focuses on considerations that may prevent dictators (agents with complete bargaining power) from settling on their most preferred allocation. The final chapter analyzes the role of an arbitrator in the settlement of bargaining outcomes and analyzes the requirements of the same to conclude that they are consistent with the fairness considerations in the spirit of Rabin (1993). The rest of this chapter provides a broad overview of each that follows.

1.2. A laboratory experiment: Set contraction and bargaining outcomes

The second chapter titled 'Set Contraction and Bargaining Outcomes: A Laboratory Experiment', is on an experiment designed to test for the axiom of the *Independence of Irrelevant Alternatives(IIA)* in the context of cooperative bargaining game theory, originally formalized by Nash (1950). The only previous experiment due to Nydegger and Owen (1975) that addresses the above question, does so in a restrictive setting involving *symmetric agents* (that is, with equal bargaining power), and establishes that the *IIA* axiom holds, that is, the introduction of contraction does not alter bargaining outcomes. Chapter 2 adds to the existing body of literature by reporting the results of a laboratory experiment that extends the test for the validity of the *IIA* axiom even in asymmetric settings – that is, when the bargaining power of one of the agents is different from (higher or lower than) that of the other. We look at an experiment where these two agents are involved in negotiating on how to split a given amount of money.

We look at an experiment with four treatments. In the first treatment, we ask two individuals (from a given homogenous population, and are therefore *symmetric*) to split Rs. 600 among themselves under the condition that they must agree on a split (since otherwise each would receive nothing, i.e. the disagreement payoff is zero for each). We find that each settles on 50% of the amount (i.e. Rs. 300 each). We call this the equal outcome. In a second treatment, we instruct the subjects to split Rs. 600 among themselves, subject to the requirement that one of the randomly chosen individuals should not get over Rs. 360 (i.e. 60% of the total amount, thereby introducing a contraction in the set of outcomes available to him/her, such that the original 50%-50% split is still an available choice). The disagreement payoff remains zero for each. We again find that both individuals agree on Rs. 300 each, leading us to conclude that merely contracting the feasible set of available alternatives will not generate an unequal outcome (where one individual gets more than the other). These two treatments together, replicate the Nydegger and Owen (1975) experiment mentioned earlier and confirm the validity of the IIA axiom. Since both the agents come from the same homogenous population, we count them as symmetric (specifically in terms of their bargaining power). In the next two treatments we introduce asymmetry in the bargaining powers of the two agents using what we call *'status effects'*.

Now we introduce a third treatment where one of the two individuals from the same population is made to believe that he/she has a higher status than the other (say, because he has scored higher in a test), and make sure that each individual is informed of his standing (higher or lower status) relative to the other. Thus, now our individuals are 'asymmetric'. We immediately find a significant departure from the 50%-50% split in favor of the superior individual. In order to generate even more asymmetry, in the fourth treatment, we impose the requirement that the 'low-status' individual (who has scored lower in the test) would not get to keep over Rs. 360 (thereby introducing exactly the same contraction in the second treatment), and find that the agreed split shifts even more (significantly) in favor of the superior individual. We now conclude that contraction of the feasible set matters, but only when both the individuals involved in bargaining are not symmetric. We go further and establish that the effect of contraction is stronger precisely when the degree of asymmetry between the individuals (captured in the absolute rank differences) is higher (and consequently, there is no contraction effect when there is no asymmetry, i.e. when the agents are symmetric), thereby unifying the results of the effects of contraction under both agent symmetry and asymmetry.

The results imply that a mere introduction of a minimum wage law or a maximum retail price (each of which makes for a contraction) may significantly alter bargaining outcomes, even if none is binding.

1.3. A field experiment: Dictator games in the field

In the third chapter titled 'Dictator Games in the Field: The Private Moral Calculus of Economic Agents, we address the recently growing concern over what we can conclusively learn from dictator games, given the multitude of (laboratory and field) outcomes associated with them. We argue that dictator games are useful, for they are good predictors of actual market behavior. Even more interestingly, we find that the offers that dictators choose to make to the recipients can be predicted by their real-life transaction behavior. Any participant in a dictator game frequently sees it as just a game, and not as a naturally occurring strategic interaction. We suitably modify a dictator game to draw parallels (from observations inside the lab) in the extra-lab world. Our subjects (three-wheeler taxi cab drivers in New Delhi) are put in a position of a proposer of a dictator game (by actors), without the knowledge that they are a part of an experiment. Our purpose is to focus on the private moral calculus of the auto drivers when they are faced with the dilemma of choosing between opportunism and compliance to existing social norms (anchored in a regulated fare), and we show that while a substantial proportion of drivers show a preference for the dictatorial outcome (signifying opportunism), social norms also play a strong role.

Specifically, we use actors (who pretend to be commuters) who 'hire' drivers of auto rickshaws (three-wheeler taxis) from a (pre-selected) point of origin, to a (again pre-selected) destination point. Instead of bargaining on the fare before travelling (which is how transaction prices are almost always determined in this market), our actors make an explicit revelation of their maximum willingness to pay (Rs. 150.00) which exceeds the legal fare (Rs. 50.00) for the given distance (5 kilometers), and then ask the auto driver for his quote (and accept the same without questioning or making any subsequent counter offer). Thus, the auto driver is in the position of a dictator, who must decide what fraction of the surplus(equivalent to the difference (Rs. 100.00) between the commuter's maximum willingness to pay, and the legal fare), each gets.

We continue to find a double-peaked distribution of offers (as is common with dictator games) with the first (and the higher) peak at the most selfish outcome (i.e. when the driver charges Rs. 150.00, corresponding to keeping the entire pie in a laboratory dictator game), with a frequency of close to 40% – just over Engel's meta-study of individuals who have ever played the dictator game (over 36%). We also find a second (and the lower) peak corresponding to an amount slightly over the legal fare suggesting that there is a significant proportion of auto drivers who stick to social norms (the legal fares are not adhered to by most auto drivers who typically choose to negotiate with commuters to settle on an amount over the legal fare).

What is interesting in our approach is that for all auto drivers, we also look at prices they charge their customers either immediately before (first treatment) or immediately after (second treatment) they play the dictator game. From these two treatments, we conclude that the driver's choice of outcome in a dictator game can predict, and in turn, be predicted by how he handles his daily market transactions. Thus, the tensions of opportunism versus compliance to social norms in the auto drivers' private moral calculus ubiquitously show up in both the dictator games and the regular transactions. Opportunists who settle for the dictatorial solution are often the ones who overcharge their customers significantly more than other auto drivers who stick to the social norms even when they play the dictator game. The predictive capacity of dictator games has so far been conclusively established from one setting (in the laboratory) to another (in the field), due to Stoop, 2014. We go beyond that to show that dictator game behavior also demonstrate predictive power for situations that intrinsically have nothing to do with dictator games.

Agent bargaining power is often a key determinant of the final outcome of any negotiation process. While both chapters 2 and 3 focus on how individuals themselves choose to play a game, for most of the literature on bargaining theory, the equilibrium outcomes can be interpreted as that outcome which would emerge were an impartial arbitrator were to step in to resolve the negotiating agents' problems. For instance, the axioms associated with any bargaining outcome, therefore, can be thought of as reflective of a social planner's preferences. This is the theme, to which we turn in Chapter 4.

1.4. A market study: Testing for fairness in regulation

The last chapter titled 'Testing for Fairness in Regulation: Application to the Delhi Transportation Market is in the field of empirical industrial organization. [1] The word 'impartial' in 'impartial arbitrator' hints on a social planner who displays a strong preference for fairness. The purpose of this paper is to examine if the legal fares imposed by the regulatory authorities can be counted as 'fair' (to both commuters and auto drivers). In the seminal paper titled 'Incorporating Fairness into Game Theory and Economics', Rabin (1993) presents the idea of 'Fairness Equilibria' based on the following three stylized facts:

1. People are willing to sacrifice their own material well-being to help those who are being kind.
2. People are willing to sacrifice their own material well-being to punish those who are being unkind.
3. Both motivations 1 and 2 above have a greater effect as the material cost of sacrificing becomes smaller.

In his formalization, Rabin therefore, models payoffs not just over players' actions, but also their beliefs. Thus, whether an action is preferred to an alternative action depends upon:

a. The direct material payoff

[1] This paper is now published in the Journal of Development Studies as: Banerjee, S. (2015). Testing for fairness in regulation: Application to the Delhi transportation market. Journal of Development Studies, 51(4): 464-483. doi: 10.1080/00220388.2014.963566.

b. The belief about whether rival players are being harmful or helpful

c. Whether chosen action helps or hurts rival players.

We use data collected by a non-governmental organization (NGO) called Prabodh for a study (called 'Third Wheel') not originally meant for the purposes of this paper. The data was collected in two waves (the first in March 2007 and the second in March 2008). The data on observed prices and costs of travel, and some transaction specific details (such as vehicle ownership, and proximity to a metro station) are used to back out commuters' maximum willingness to pay (for travel) using different allocation rules of cooperative bargaining. To explain this process in a simple Nash (1950) bargaining framework, if the cost of travel c for a given distance, is Rs. 10.00 and the observed price p for the travel is Rs. 50.00, then the maximum willingness to pay of the customer W should be Rs. 90.00, since this given value of p maximizes the product of the auto driver's material payoff ($p - c$), and the commuter's material payoff ($W - p$) from the transaction as per the requirement of the Nash solution.[2] W*e* then, as a second step, treat these values for maximum willingness to pay W, as data, and use the data on the costs of travel c, to work out Rabin's fair prices $p = f(W, c)$, i.e. the fairness prices are well-defined functions of W and c. The exact workings of the maximum and minimum chargeable prices (each being a function of W and c) consistent with Rabin's fairness requirements, are shown in the appendix to Chapter 4. We then compare these fairness prices with actual revised legal fares proposed by regulation, and observe that the fares proposed, interestingly lie in the range of prices consistent with Rabin's fairness considerations.

[2] The first order condition gives us $p = (W + c)/2$, so that we can solve for unobserved W in terms of observed p and c as $W = 2p - c$. We repeat this process to work out W for different bargaining solutions (Kalai-Smorodinsky, 1975, etc.) based on their axiomatic requirements.

It is interesting, that regulatory authorities, who have no a priori knowledge of Rabin's, (1993) fairness considerations (associated with a very specific utility function that internalizes the above considerations), have always proposed legal fares in the auto-rickshaw (three wheeler) market in New Delhi that satisfy them. Regulated fares are often ignored by auto rickshaw-drivers and customers. They bargain on prices among themselves. To ensure that the legal fares are adhered to by auto drivers, the regulatory authorities occasionally announce increases in legal fares. These newly announced fare hikes are effective enough to ensure the prevalence of legal uniform (non-negotiated) prices for a limited period of time, after which auto drivers again resort to bargaining over these new fares (i.e. at even higher prices), till the fares are revised again. I suggest that the two of the most recent hikes have satisfied Rabin's fairness considerations. We are aware of no previous study that evaluates a regulatory intervention on the grounds of fairness.

This brings up the possibility that social planners do have fairness considerations that mutually benefit all the concerned agents.

1.5. Summary

To sum up, this thesis looks at agent behaviour in the laboratory, in the field, and in the market. Firstly, we impose a requirement in the laboratory (Chapter 2) that mimics a regulatory environment (similar to the introduction of a maximum retail price, or a legal fare subject to which an economic transaction must take place), and study individual behaviour subject to our (imposed) requirements. We then study the effect of real-life regulation on the behaviour of economic agents in the field. While the effect of regulation is seen in the field (that is, we see that many auto drivers stick to social norms anchored in the legal fare in

Chapter 3), we explicitly study and evaluate the nature of regulation itself in the market against the backdrop of fairness considerations in Chapter 4.

In a nutshell, this thesis looks at bargaining from several dimensions which are listed below:

1. Cooperative (Chapters 2 and 4) versus non-cooperative (Chapter 3) game theory

2. In a laboratory (Chapter 2), a field (Chapter 3), and in market data (Chapter 4)

3. Individual decisions (Chapters 2 and 3) versus the social planner's preferences (Chapter 4).

4. With moderate and complete bargaining power possessed by agents.

From the above exercise, we learn that bargaining outcomes are empirically determined by bargaining power (at least in the form of statuses), both with and without contraction. Since, the regulated legal fare in the auto rickshaw market is an example of such contraction, we see our agents' behaviour influenced by it (and more so because of the implicit status differences). We also learn that regulation can be affected by considerations of fairness. Finally, further research can be devoted to more general forms of contraction of the feasible set (which has direct applications on regulatory pricing). We focus on only horizontal forms of contraction and find significant effects on bargaining outcomes. I also feel that dictator and ultimatum games need to be contextualised and taken to the field more often. Finally, regulatory practices could be evaluated, not only in terms of economic criteria such as performance, profits, and welfare etc., but also from psychological standpoints of fairness, trust, and reciprocity etc.

Chapter 2

Set Contraction and Bargaining Outcomes: A Laboratory Experiment

2.1. Introduction

Whether a mere introduction of a minimum wage law affects the bargaining position of laborers, is often a question of primary importance in developing countries. The introduction of a legal fare on three-wheeler (auto-rickshaw) services in India, has witnessed negotiations between individual customers and three-wheeler drivers who eventually settle on fares that are significantly higher than those prescribed by regulation. Another interesting question that relates to the above examples is, if consumers stand to gain out of a mere introduction of a maximum retail price (MRP) on a product ... even if the said MRPs significantly exceed the prices that would occur under bargaining. As it turns out, all the examples above can be understood as bargaining problems subject to contractions of the feasible set. It is also worth noting that the two parties involved in each example (e.g. consumers and sellers) need not be symmetric (say, because of 'status gaps' owing to different backgrounds and so on) in the sense that each negotiating party may possess a different bargaining power than the other. Indeed, real-life bargaining happens more often than not among agents with asymmetric bargaining power. These asymmetries may arise due to differences in agents’ backgrounds, possession of knowledge, and access to outside options etc. We introduce asymmetries in our setting in the form of status gaps.

In this paper we revisit the validity of Nash's (1950) axiom of *independence of irrelevant alternatives* (IIA hereafter) with the introduction of asymmetries in the context of his bargaining solution. This axiom can be explained as follows: the equilibrium outcome of the bargaining problem for a given feasible set (of outcomes) will also be the equilibrium outcome of the bargaining problem for any subset of that original feasible set, provided that such a subset has the initial outcome as one of its elements. The Nash solution was subsequently criticized (Raiffa (1953), Yu (1973), Kalai and Smorodinsky (1975), and Perles and Maschler (1981)) because of this axiom. The criticism, as Thomson (1994) puts it, was that, "the crucial axiom on which Nash had based his characterization requires that the solution outcome be unaffected by certain contractions of the feasible set, corresponding to the elimination of some of the options initially available ... but this independence is often not fully justified".[3]

This axiom, however, witnessed its first experimental validity when Nydegger and Owen (1975), found evidence against the Kalai-Smorodinsky (KS) solution (where contraction matters) in favor of the Nash solution in their controlled experimental set up. There was, however, one concern which related to the *random selection* of the individual in the advantageous position against his counterpart (due to the contraction). As Hoffman et al. (1994) point out, "randomization may not be neutral, since it can be interpreted by subjects as an attempt by the experimenter to treat them fairly ... thus experimenters may unwittingly induce 'fairness'. A subject may feel that, since the experimenter is being fair to them, they should be fair to each other." They could explain why first movers in *ultimatum games* offered significantly more to their counterparts than non-cooperative game theory would suggest. Hence, because of randomization, the axiom was only validated under *symmetric*

[3] For more detailed discussions on axiomatic approaches to bargaining theory, see Moulin (1988, 2003) and Roth (1979, 1985).

bargaining[4] in the Nydegger and Owen (1975) framework. The goal of this paper is to check if their results would survive in an asymmetric setting, so we borrow ideas from ultimatum games.[5]

In the ultimatum game experiment of Hoffman et al. (1994), the roles of sender and receiver were assigned randomly in the control group, and in the treatment group, the right to be the first mover was earned by scoring high on a general knowledge quiz (rights were reinforced by the instructions as being earned). To that effect, the role of the trivia test was to eradicate potential interpretation of fairness by the subjects that arises from randomization. The modal offer observed in the treatment group was significantly less than that made in the control group.[6] We borrow this idea to address the concern above by replacing randomization by a trivia test to generate self-regarding behavior and extend the research of Nydegger and Owen (1975) to test for contraction effects under asymmetric bargaining[7] - an open question so far. The central motivation of this experiment is thus, to test contraction effects under asymmetry, when the experiment does not oblige the subjects to be fair.[8]

2.2. The formulation

In the discussion that follows on the (theoretical) effects of contraction, the Kalai-Smorodinsky (KS hereafter) solution is used only as a representative example of allocation rules that violate the IIA axiom, many of which have been mentioned in the previous

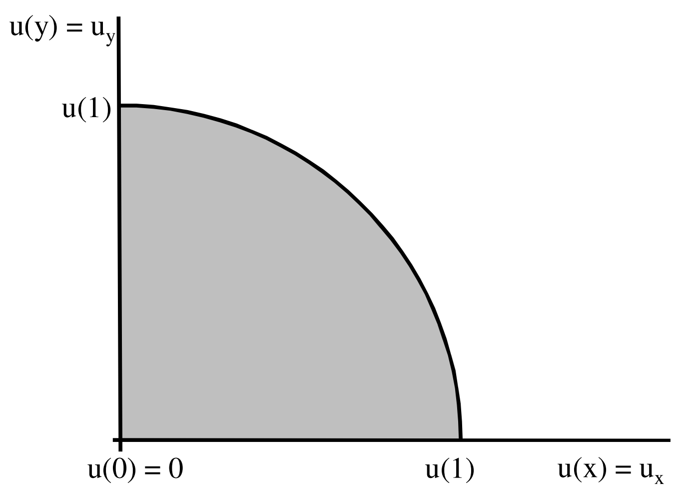
[4] This should not be confused with the *axiom of symmetry* in the context of cooperative bargaining. Here, by 'symmetry' we only mean that the individuals involved in bargaining are identical in every respect.
[5] For more examples see the discussions in Bardsley, et al. (2009); Chaudhuri (2009); Smith, (2008); Henrich and Henrich (2007); and Camerer (2003), Chakravarty et al. (2011) and the papers cited therein.
[6] Cardenas and Carpenter (2008), for example, also point out that the perception of how *deserving* recipients are, could be a strong predictor of altruism. Ball et al. (2001) interprets this (significant) effect of test performance as a 'status effect'.
[7] This means that one of the individuals has a 'status' advantage.
[8] For more literature on bargaining with fairness considerations, see Birkeland and Tungodden (2014), Bruyn and Bolton (2008), Burrows and Loomes (1994), and Buchan et al. (2004). The 50%-50% outcome may also be seen as a focal point (see Crawford et al. (2008)).

(introductory) section. While the KS solution itself is not central to the main theme (that is, the effects of contraction), of this paper, it will be useful for the understanding of how set contractions may alter bargaining outcomes (contrary to the Nash solution).[9] Throughout the discussion, we assume that the agents involved in bargaining gain nothing when there is a disagreement (that is, the disagreement payoff is zero for each agent). In general, disagreement payoffs may play an important role in the determination of bargaining outcomes (see Anbarci and Feltovich, 2013).

2.2.1. Symmetric bargaining in the absence of contraction

Two individuals X and Y (both from the same homogenous population[10]) get to share a pie of size z. Their respective shares are x and y (both non-negative), so that $x + y = z$.

Figure 2.1: The feasible set



We normalize z to be equal to unity so that x and y may be interpreted as the percentages (proportions/fractions) of the pie that X and Y (respectively) get, from which they derive

[9] Only the intuitions behind the Nash and the Kalai-Smorodinsky solutions have been employed in the subsections that follow. I thank Prof. Ariel Rubinstein for helping me finalize this entire section to appeal to a wider audience.

[10] Hence X and Y are symmetric by our definition.

utilities $v(x)$ and $v(y)$.[11] Figure 2.1 shows the feasible set (following a normalizing utility transformation u, explained in Appendix 2D). While, both the Nash and the KS solutions are formally presented in Appendix 2D, for now, for the non-specialist, it suffices to say that the (symmetric) KS solution requires that X and Y share the pie in proportion to the maximum each can get if the absence of the other.[12] Similarly, the (symmetric) Nash solution requires that X and Y share the pie such that the product of their utilities is maximized. The axioms of *symmetry* and *efficiency* together, in the Nash and the Kalai-Smorodinsky bargaining framework, are sufficient to guarantee that X and Y get 50% each (of the pie). This is verified in Appendix 2D.

2.2.2. Asymmetric bargaining in the absence of contraction

Coming to the case of *asymmetric* individuals, let X now, be the individual with a measurably higher bargaining power β (> 0) over individual Y.[13] Both the Nash and the KS solutions suggest that X will get a higher (than 50%) share.

To provide an intuition here, for the (asymmetric) Nash solution, we maximize the product of the utility of agent Y and that of agent X after raising the latter to the power of $(1 + \beta)$; and for the KS solution, we 'pretend' that agent X would be entitled to $(1 + \beta)$ times the utility that she would otherwise get in the absence of agent Y (before deciding on the final proportion in which both the agents finally share the pie). The asymmetric KS solution is explained in Figure 2.2. The derivations are trivial and have been deferred to Appendix 2D.

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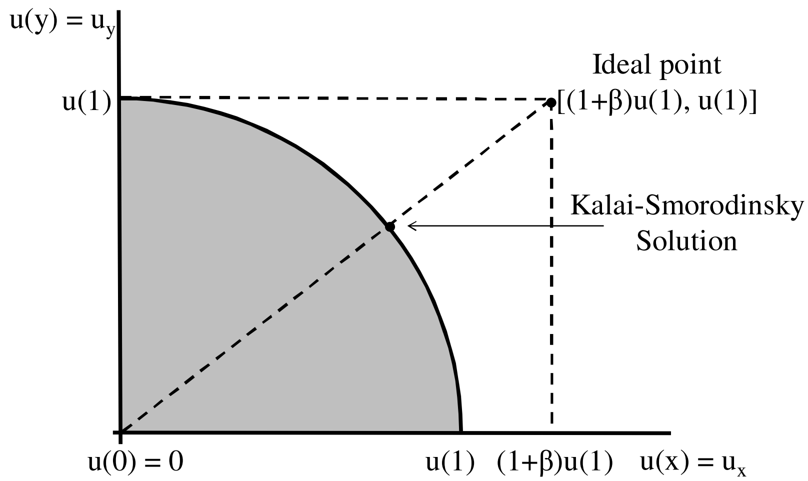
[11] That the functional form of v, of the utility of the individual X is identical to that of Y, is consistent with X and Y being from a homogeneous population (and therefore X and Y are 'symmetric').

[12] An alternate description for the KS solution would be: X and Y share the pie in proportion to what each can get if he/she were himself/herself a dictator (see the discussion on dictatorial solutions in Thomson 1994).

[13] While there is no immediate interpretation of β, it suffices, for now, to say that for any allocation rule, the bargaining power β is a determinant of the (positive) quantity by which x exceeds y.

Figure 2.2: The asymmetric Kalai-Smorodinsky solution

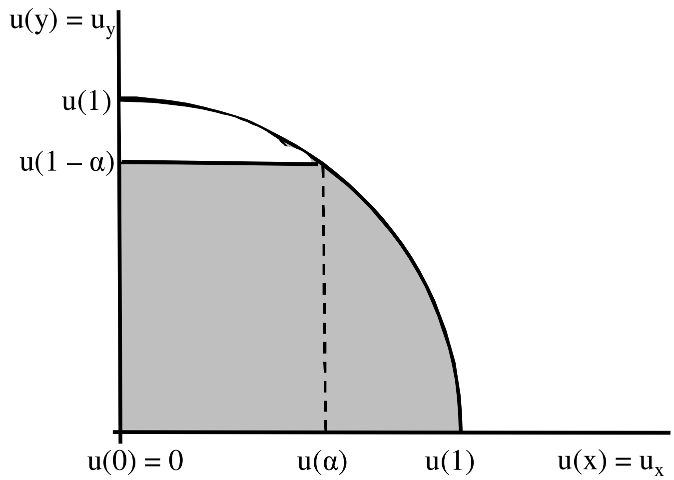


2.2.3. Symmetric bargaining in the presence of contraction

Now, we assume that X and Y share the pie subject to the requirement that *X* gets at least α (<1) fraction of the total pie size. This puts a cap on individual *Y*'s utility. We have a truncation of the feasible set which is shown in Figure 2.3. For $\alpha \leq 1/2$, the (symmetric) Nash bargaining solution remains the same as before (since contraction does not matter). The KS solution, however, suggests a higher share for individual *X* (contraction matters), and has been derived in Appendix 2D.

For example, if we want individuals *X* and *Y* to split \$1 amongst themselves (with $v(x) = x$), subject to the constraint that *Y* gets to keep no more than 50 cents (so that $\alpha = 0.5$), then the Nash solution will still predict a split where each individual gets 50 cents, but the KS solution will predict a split where *X* gets to keep two-thirds and *Y* one-third of the pie (the axiom of *independence of irrelevant alternatives* has been violated since the truncated set now still has the point (0.5, 0.5) as its element, but the final outcome is different).

Figure 2.3: The feasible set with contraction



2.2.4. Asymmetric bargaining in the presence of contraction

Theoretically, asymmetry in the Nash bargaining model accompanied by a contraction of the feasible set leads to the same solution in the asymmetric Nash framework without contraction (since contraction does not matter in the Nash setting). The KS solution, however shifts further in favor of individual *X* (details in Appendix 2D). Now we will summarize the results of a previous study.

Nydegger and Owen (1975) had a control group of pairs of individuals that were required to split $1 amongst themselves over face-to-face negotiations. In the treatment group, one of the randomly assigned individuals was to get at least 40 cents (i.e. $\alpha = 0.4$) subject to which both the individuals negotiated. On observing that all the pairs of individuals in both the treatment and the control groups, had chosen on an equal split of 50 cents each, the study did not reject Nash's axiom of *independence of irrelevant alternatives* (in the symmetric case). The very process of *randomly* selecting the individual in the treatment group, who gets to keep at least 40% of the split, however, may have induced both the individuals to be fair to each other (since at the first place, each individual has an equal chance of capitalizing on the constraint), which may have led to the observed equal splits. The aim of our experiment is to eradicate the effects of randomization that induce fairness by replacing randomization by a test and thereby introducing asymmetry in the setting.

2.3. Key features of the experimental design

The subject pool consisted of undergraduate and MBA students at institutions in New Delhi. Each individual was randomly assigned to either the control group, or one of three treatment groups. Subjects were grouped into pairs in each treatment. Each individual received a show-up fee of Rs. 125. In addition, they retained the part of Rs. 600 that was negotiated with their respective partners under relevant treatment conditions. In each treatment, if a pair did not agree on any split of Rs. 600, each individual got nothing (i.e. the disagreement payoff was zero), otherwise they took away the amounts as negotiated. The key features of the experiment are *anonymity* (to generate asymmetry) and *dialogue* (a key element of any negotiation process).

The control group in this experiment receives the symmetric bargaining treatment of Nydegger and Owen (1975). In one of the treatments, the feasible set of bargaining outcomes, is restricted or contracted by stipulating that a randomly chosen individual of a bargaining pair must at least receive a payoff greater than a minimum. The minimum is so chosen that the contracted set includes all the bargaining outcomes observed in the control group (without the contraction of the feasible set). This treatment is called *random contraction*. Nydegger and Owen showed that such a random contraction did not alter the bargaining outcome thus validating the axiom of independence of irrelevant alternatives.

As mentioned before, the goal of the experiment is to test for the axiom of independence of irrelevant alternatives in asymmetric bargaining. The challenge was to generate asymmetry among otherwise similar individuals. To achieve that, subjects were given a test. While the test was administered to all the treatment groups to ensure uniformity, it was immaterial to the control group and to the random contraction treatment. In the `rank bargaining' treatment, individuals were informed about their ranks in the test. Although the ranks were randomly assigned, subjects were told that they were assigned on the basis of their performances in the test.[14] Higher ranked subjects were matched with lower ranked subjects for the bargaining experiment. Subjects had full knowledge of their own ranks and the ranks of the subjects they were paired with. In a variant of this treatment, called the `rank contraction', the feasible set was contracted. The stipulation that governed the contraction was that the higher ranked individual of a bargaining pair must at least receive a payoff greater than a minimum. Once again, the minimum payoff guaranteed to the higher ranked subject (in the event of agreement) was so chosen that the contracted set included all the bargaining outcomes of the rank bargaining treatment. The details of all the treatments are summarized in Table 2.1.

Overall, 130 subjects (69 males and 61 females) participated in the experiment. 58 subjects were from the FORE School of Management, and the remaining 72 were from the University of Delhi (44 from St. Stephen's college and 28 from Hansraj College).

[14] This (fortunately mild) form of deception is very important for our experiment. Although the results from pilot studies (available on request), that in fact, do assign ranks based on the subjects' actual test performances, are qualitatively very similar to those that we report in this paper, one would raise immediate concerns with such pilot analyses. This is because, although the assignment to this treatment group would still remain exogenous, the experimental effect itself will be correlated with unobserved subject ability – that is, we will not be sure of the smarter subjects get higher shares simply because they are smarter, or because of the treatment effect (in this case, status effect), or both. In order to make our form of (the already mild) deception even milder, nowhere do we explicitly suggest (or impose) that the higher ranked subjects, should in fact, receive more than their lower-ranked counterparts (see DeMartino and McCloskey, 2016). I thank my adviser for this idea. Ball at al. (2001) employ a similar strategy.

Table 2.1: Summary of the treatments

	Control Group	Rank Bargaining	Random Contraction	Rank Contraction
Test	Yes	Yes	Yes	Yes
Asymmetry/Rank	No	Yes	No	Yes
Contraction	No	No	Yes	Yes
Feasible Set	Figure 1	Figure 1	Figure 3	Figure 3
Zero Disagreement	Yes	Yes	Yes	Yes

2.4. The experiment

The Baseline Treatment (Control Group, T0): This baseline treatment replicates the standard Nash-bargaining protocol. Subjects were randomly paired. In each pair, the subjects were given a set of instructions (shown in the appendix) to split Rs. 600 among themselves. Negotiation happened over Skype, and a maximum of ten minutes were allotted to both the candidates in each pair to arrive at an agreement.[15] The negotiated outcomes in this treatment were then observed before introducing others to make sure that each outcome in this treatment was also an element in the feasible sets of all the other treatments that followed. Based on the Nydegger and Owen (1975) experiment and the existing theory on symmetric bargaining, one might expect the highest frequency of equal splits (i.e. Rs. 300 each) in this treatment. The control group was assigned a sample size of ten pairs. In the Appendix, it is

[15] Candidates were not allowed to disclose their names/identity in the chat conversations (which were saved) violating which, entailed a penalty of the full amount earned (including the show-up fees) for both the individuals in the pair. This ensured anonymity. The login names used for this treatment were Candidate.001, Candidate.002 and so on. The sufficiency of ten minutes was observed from the pilot studies.

shown that such a sample size has reasonable power for testing the null hypothesis of equal split. In this treatment, we observe that nine out of ten pairs settle on the 50%-50% split.

Rank-Based Bargaining Treatment (T1): Subjects were told that they were ranked according to their test performances. In reality, the ranks were *randomly* assigned and the subjects did not know this.[16] Each member ranked in the top half was randomly paired with a member in the bottom half. Subjects in each pair knew their own and each others' ranks prior to negotiation (this is how we exogenously imposed asymmetry) which happened over Skype with a time limit of ten minutes.[17] The feasible set remained just as that of the control group (as in Figure 2.1). 19 pairs of subjects were randomly put into this treatment. One could expect a departure from the 50% solution predicted in symmetric bargaining if the test (as discussed above) has the effect of preventing individuals from behaving in a fair manner (i.e. $\beta > 0$ in (2D.2) of Appendix 2D, so the higher ranked individual gets a share greater than 50%).[18] In this treatment, we observe that the high-ranked individuals, on an average, got close to 59% of the total negotiable amount of Rs. 600.

Random Contraction Treatment (T2): Subjects were randomly paired. Individuals in each pair divided Rs. 600 in any way they wished, but with the additional constraint that one of the *randomly assigned* individuals in each pair received no more than 60% (i.e. Rs. 360, or α = 0.4) of the total pie size (subject to negotiation agreement). α was chosen so as to ensure that each outcome in the control group remained in the (contracted) feasible set of this treatment group (as in Figure 2.3). Negotiation happened over Skype with a maximum permissible limit

[16] Ball et al. (2001) employ a similar approach in their paper titled "Status in Markets".

[17] As before, the negotiation happened over Skype, but this time with rank-defining usernames such as Rank.001, Rank.002 etc.

[18] See Dahl (1957), Frank (1985), Babcock et al. (1996) and Harsanyi (1962a, 1962b, 1966) for discussions on how status effects matter in bargaining, resulting in asymmetric outcomes. Bohnet and Zeckhauser (2004) also provide evidence for social comparisons. For more recent literature on the role of entitlements, see Bruce and Clark (2012), Croson and Johnston (2000), Gächter and Riedl (2005), Gächter and Riedl (2006); and Karagözoğlu (2014). Additionally see Erkal et al. (2011), for evidence that high-ranked individuals want to give away less.

of ten minutes to reach an agreement.[19] All the remaining instructions remained the same as in the baseline treatment above. 17 pairs of subjects were randomly put into this treatment. This treatment, together with the baseline treatment replicate the Nydegger and Owen experiment covering symmetric bargaining. In this treatment one might again expect a high frequency of equal splits for issues pointed out by Hoffman et al. (1994) – the very process of randomization may induce them to act in a fair manner (as witnessed in the Nydegger and Owen experiment). In this treatment, those who were favored by the contraction got, on an average, close to 52% of the negotiable amount of Rs. 600.

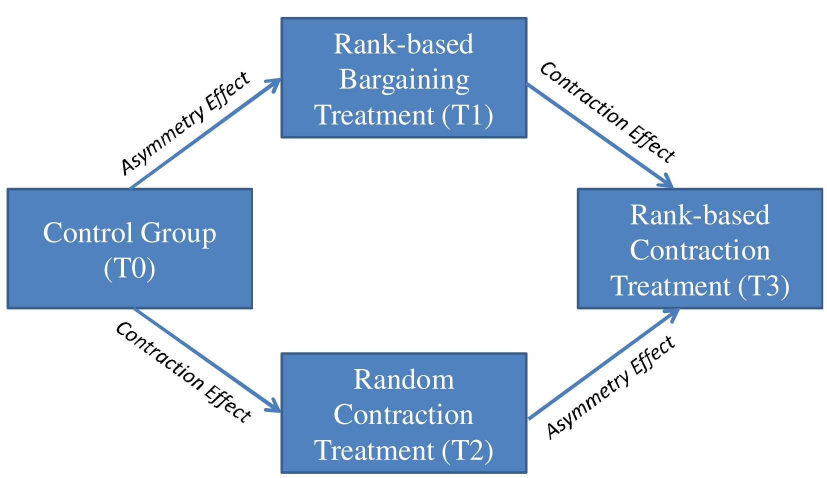
Rank-Based Contraction Treatment (T3): This treatment looks at the combined effects of contraction and asymmetry. It followed all the other treatments to ensure that the observed average outcomes of all the above treatments remained within the feasible set of this treatment (as in Figure 2.3). Each member among the top half rankers was randomly paired with a member in the bottom half (again, these ranks were assigned randomly). Subjects in each pair knew their own and each others' ranks prior to negotiation which happened over Skype with a time limit of ten minutes.[20] The lower-ranked subjects in each pair could not receive more than 60% (i.e. Rs. 360, just like the randomly selected individuals in T2 above) of the total Rs. 600 (subject to negotiation agreement). 19 pairs of subjects were randomly put into this treatment. The treatment groups 1 and 3 above, extend Nydegger and Owen's framework to the asymmetric case. One might expect self-regarding behavior on the part of individuals ranked in the top half in this treatment as well ($\beta > 0$ in both (2D.2) and (2D.6) of Appendix 2D).

[19] The usernames were the same as in the baseline treatment.
[20] As in the Rank-Based Bargaining Treatment above, the Skype usernames were rank-defining (Rank.001, Rank.002etc.).

2.5. A discussion

While the Nydegger and Owen framework depended on face-to-face negotiations (see Chakravarty et al, 2013 that implement a similar approach), the experimental approach of Hoffman et al. (1994) followed a double-blind protocol. Since students come from similar backgrounds, it is highly probable that those involved in a given pair would know each other or even be friends. This will tend to mitigate the intended effect of the test: to generate *self-regarding behavior* and *asymmetry*. Thus, like the Hoffman et al. (1994) experiment, we would like to preserve anonymity in our protocol. However, we also need to maintain the crucial feature of any negotiation - *dialogue between the individuals*, as was the case with the Nydegger and Owen experiment. The very idea of making individuals of a given pair chat over Skype has the dual effect of preserving anonymity (since those chatting only knew the user IDs and were not supposed to disclose their identities) and dialogue (saved in the chat history) thereby making our results comparable with those of Nydegger and Owen.

Figure 2.4: A summary of treatments



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In treatment 3 we observe the combined effects of treatments 1 and 2 (Figure 2.4 explains how). We account for the possibility that the effect of contraction need not be independent of that of asymmetry. We allow for contraction to have different effects under the symmetric and asymmetric bargaining conditions. One can think of 'asymmetry-effect' as the movement from the control group to T1 (or T2 to T3), and 'contraction-effect' as the movement from the control group to T2 (or T1 to T3).

2.6. Empirical strategy

For the treatments involving contraction of the feasible set, we say that individual j (in pair i) has a contraction advantage, if the contraction specifies this individual j must receive a minimum share (α). Then the following dummy is defined.

$$ContrAdv_j = \begin{cases} 1, & if\ j\ has\ a\ contraction\ advantage \\ -1, & if\ j\ is\ paired\ with\ a\ subject\ who\ has\ a\ contraction\ advantage \end{cases}$$

Similarly, for treatments involving rank, we define another dummy as follows.

$$HighRank_j = \begin{cases} 1, & if\ j\ has\ a\ higher\ rank\ than\ the\ subject\ he\ is\ paired\ with \\ -1, & if\ j\ has\ a\ lower\ rank\ relative\ to\ the\ subject\ he\ is\ paired\ with \end{cases}$$

We finally define a variable (*RelPos*) which summarizes the *relative position* of any subject with his/her pair in terms of rank and contraction.

$$RelPos_j = \begin{cases} ContrAdv_j, & if\ j\ belongs\ to\ a\ pair\ in\ a\ treatment\ involving\ contraction \\ HighRank_j, & if\ j\ belongs\ to\ a\ pair\ in\ a\ treatment\ involving\ asymmetry \\ 0, & if\ j\ belongs\ to\ a\ pair\ in\ the\ control\ group \end{cases}$$

In other words, $RelPos_j$ is a ternary dummy that takes the value 1 for subjects who are either high ranked or with a contraction advantage (or both); –1 for subjects who are either low-ranked or are paired with individuals with contraction advantage (or both); and 0 for subjects in the control group. The regression equation we are interested in is

$$
\begin{aligned}
Share_{ij} = \quad & \alpha_0 + \alpha_1 RankBarg_i \bullet RelPos_j + \alpha_2 RandmContr_i \bullet RelPos_j \\
& + \alpha_3 RankContr_i \bullet RelPos_j + \boldsymbol{X_{ij}\beta} + \varepsilon_{ij} \qquad (2.1)
\end{aligned}
$$

where, $Share_{ij}$ represents the share of the jth individual in the ith pair. $RelPos_j$ is defined as above. α_0 is the constant of regression. *RankBarg*, *RandmContr* and *RankContr*, are the treatment dummies that respectively represent if the ith pair belongs to treatment groups 1, 2 or 3. $\boldsymbol{X_{ij}}$ is a vector of other observed covariates (gender of involved individuals, background, institution, income etc.) with the coefficient vector $\boldsymbol{\beta}$. ε_{ij} is the random error term.[21] Thus, the (average) outcome in the control group can be represented by α_0; the share of the higher-ranked individual (on an average) in the rank-based bargaining treatment (T1) is represented by $\alpha_0 + \alpha_1$; the (average) share of the individual with contraction advantage in the random contraction treatment (T2) is represented by $\alpha_0 + \alpha_2$; and that of the high-ranked individual (also with the contraction advantage) in the rank-based contraction treatment (T3) is represented by $\alpha_0 + \alpha_3$.[22]

2.6.1. Testable hypotheses

Testing for asymmetry: We start with the following hypothesis

[21] Note that for α_0, to represent the average share of the control group, each variable included in $\boldsymbol{X_{ij}}$ needs to be appropriately normalized to have mean zero.

[22] Note that the regression specification in (1) is different from the following specification
$Share_{ij} = \alpha_0 + \alpha_1 RankTreatment_i \bullet RelPos_j + \alpha_2 ContrTreatment_i \bullet RelPos_j + \boldsymbol{X_{ij}\beta} + \varepsilon_{ij};$
where $RankTreatment_i$ is a dummy for a treatment involving rank-based bargaining and $ContrTreatment_i$ is a dummy for a treatment involving a contraction. In such a specification, the (expected) share of the high-ranked individual in the rank-based contraction treatment will be represented by $\alpha_0 + \alpha_1 + \alpha_2$. This specification therefore, clearly imposes a restriction that rank effects and contraction effects are additive (which may not be true). The specification in (1), clearly does not impose this additivity, and is thus, less restrictive.

Hypothesis 1: $\alpha_1 = 0$

against the alternative that α_1 is significantly greater than zero ($\alpha_1 > 0$). The rejection of the above hypothesis, means that the average observed outcome in the Rank-bargaining treatment deviates from the symmetric (1/2, 1/2) solution in favor of the higher-ranked individuals. If the *Hypothesis 1* is not rejected, then the rank bargaining treatment does not lead to significantly asymmetric outcomes.

The effect of contraction in the symmetric case: We test the following hypothesis that contraction does not matter in the symmetric bargaining setting.

Hypothesis 2: $\alpha_2 = 0$

against the alternative that $\alpha_2 > 0$. If *Hypothesis* 2 above, is not rejected, then we infer that the introduction of contraction in the baseline treatment does not significantly matter. Recall that in the baseline treatment, the individuals were not subject to any contraction or the assignment of ranks. Rejecting *Hypothesis* 2 above, leads to the inference that the axiom of independence of irrelevant alternatives is violated significantly. Such a result would be inconsistent with the symmetric Nash bargaining solution.

The effect of contraction in the asymmetric case: If *Hypothesis* 1 is rejected in favor of $\alpha_1 > 0$, then the following hypothesis comes to be of interest.

Hypothesis 3: $\alpha_1 = \alpha_3$

against the alternative that $\alpha_1 < \alpha_3$. *Hypothesis 3* means that the observed outcomes in treatment groups T1 and T3 are statistically identical. Since both the treatments involve assignment of ranks (leading to asymmetric bargaining outcomes), the observed differences (if any) between their average behaviors can only be attributed to contraction. Thus, if we do not reject the above hypothesis, then we conclude that contraction does not significantly matter in the asymmetric case. But if we reject *Hypothesis 3,* then we conclude that contraction matters significantly in the asymmetric case.

2.6.2. Are contraction effects sensitive to the presence (or absence) of bargaining asymmetry?

If both the hypotheses 2 and 3 above are not rejected, then we can infer that the Nash axiom of independence of irrelevant alternatives is universally true, thereby extending Nydegger and Owen's research to the asymmetric case. If both are rejected, then we can infer that the axiom of *independence of irrelevant alternatives* does not go through at all – this result will be contrary to the findings of Nydegger and Owen (and therefore the Nash solution). Not rejecting hypothesis 2 and rejecting hypothesis 3 lead us to infer that contraction matters only in the asymmetric case.

2.7. Results

2.7.1. Descriptive statistics

From the rows in Table 2.2a, that report the minimum and the maximum shares of all the treatment groups, we learn that all the outcomes observed in the control group belong to the feasible sets of the remaining treatments. We also learn that the feasible set of the Rank Contraction treatment allows for all the outcomes observed in all the other treatments. Thus, we are in a position to test the validity of the IIA axiom for both symmetric and asymmetric bargaining. For the purposes of this paper, we are more importantly interested in the figures reported in the rows named 'Mean Share (RelPos = 1)' and 'Mean Share (RelPos = -1)' in Table 2.2a.

Table 2.2a: Descriptive statistics by treatment

	Control Group	Rank Bargaining	Random Contraction	Rank Contraction
Observations	20	38	34	38
Mean Share	0.500	0.500	0.500	0.500
Standard Deviation	0.027	0.117	0.053	0.176
Minimum Share	0.417	0.250	0.300	0.125
Maximum Share	0.583	0.750	0.700	0.875
Mean Share (RelPos = 1)	n.a.	0.587	0.516	0.636
Mean Share (RelPos = – 1)	n.a.	0.413	0.484	0.364
No. of Males	13	21	19	16

Since the variable RelPos is defined to be zero for observations in the control group, no figure is reported under the same. In the Rank-based bargaining treatment (T1), 'Mean Share (RelPos = 1)' represents the average share of the high-ranked subject in a given pair. We learn that the high-ranked subjects in this treatment received, on an average, about 59% of the pie, leaving the remaining 41% (the corresponding figure listed in 'Mean Share (RelPos = -1)' under the same treatment) on an average, for their lower-ranked counterparts. Similarly, it is seen that subjects with a contraction advantage in the Random contraction treatment (T2), received, on an average, 52% of the pie, leaving about 48% for their counterparts without the advantage. In the Rank-based contraction treatment (T3), those with high-ranks (and hence with the contraction advantage) received, on an average, close to 64% of the pie-size, leaving only about 36% for their lower-ranked counterparts. These figures, suggest that while the effect of contraction of the feasible set is insignificant in symmetric bargaining settings, it is not insignificant in asymmetric settings.[23]

Table 2.2b: Share distribution by personal characteristics

	No. of Observations	Mean Share	Standard Deviation	Minimum Share	Minimum Share
Female	61	0.504	0.120	0.233	0.767
Male	69	0.496	0.115	0.125	0.875
Business Background	51	0.502	0.095	0.125	0.767
Other Background	79	0.498	0.145	0.167	0.875
Low Income (< Rs. 2.5 Lakhs)	19	0.500	0.108	0.250	0.700
High Income (> Rs. 10.0 Lakhs)	39	0.507	0.085	0.233	0.767
Post Graduate Father	53	0.517	0.109	0.250	0.875
Post Graduate Mother	46	0.501	0.121	0.167	0.875
Hostel Experience	67	0.513	0.087	0.300	0.833

Table 2.2b displays the average shares received by subjects, based on their personal characteristics. Both female and male subjects receive, on an average, very close to 50% of the pie-size, suggesting that gender is not a significant determinant of the bargaining outcomes. This is contrary to the findings of Sutter et al. (2009); and Castillo et al. (2013),

[23] T-test results for a simple test of means for individuals with RelPos = 1, in the Rank-bargaining treatment against those in the Rank-contraction treatment, yield a t-statistic (d.f. = 36) with a value of 1.59 and an associated p-value of 0.06, suggesting some evidence of significance. A similar comparison between all the observations in the control group, and those with RelPos = 1, in the Random-contraction treatment, shows no significant difference (p-value of 0.23, for a t-statistic (d.f. = 35), with a value of 1.22).

among still others. Similarly it did not (significantly) matter if a subject came from a family with a background in business (or shop-ownership), although such families are more accustomed to negotiation on a daily basis, and could therefore, be thought to possess certain negotiation-specific skills to settle on more favorable outcomes. Students who experienced hostel lives did not get significantly higher shares than those who did not. Parents' education are not significant determinants of bargaining outcomes either. A regression of observed share on family income level suggests that the latter is not a significant determinant of the former (p-value is 0.31). The fact that none of the personal or intrinsic characteristics discussed above (possibly known by the subjects about each other owing to daily interaction) were strong determinants of observed shares, potentially explains the strength of anonymity in our experimental setting.

2.7.2. Key findings

Table 2.3a shows the results of regression equation (2.1). As we will immediately see, these results are consistent with the observations made in Table 2.2a. In Column 1, we see that the effect of rank-bargaining leads to asymmetric outcome, i.e. we observe a significant departure from the 50-50 solution (therefore we reject *Hypothesis* 1, that rank bargaining does not lead to asymmetry).

The regression estimate suggests that on an average, the high-ranked subject in any pair, managed to get a share of close to 59% (over Rs. 350 out of Rs. 600), leaving close to 41% for his/her low-ranked counterpart. The second result is that the effect of contraction in symmetric bargaining is only marginally significant. The effect of contraction in asymmetric bargaining can be understood by testing for the equality of the coefficients of RankBargaining*RelPos and RankContraction*RelPos (*Hypothesis 3*). The regression result suggests that the high-ranked subject in a pair gets, on an average, close to 64% of the total pie size (leaving the remaining 36% for his/her low-ranked counterpart) in the Rank-contraction treatment. This treatment differs from the Rank-bargaining treatment only in the allotment of contraction-advantage to the high-ranked individual. Now we formally test *Hypothesis* 3. The F-Statistic for this test is 5.16 (with a p-value of 0.02). We therefore, reject *Hypothesis* 3 and conclude that contraction matters in asymmetric bargaining.

Table 2.3a: The effect of contraction on bargaining outcomes

Dependent Variable: Share	(1) Least Squares	(2) Least Squares	(3) Least Squares
RankBargaining*RelPos	0.0868***	0.0652***	0.0651***
	(0.0126)	(0.0163)	(0.0164)
RandomContraction*RelPos	0.0162*	-0.0108	-0.0109
	(0.0087)	(0.0131)	(0.0132)
RankContraction*RelPos	0.1364***	0.1098***	0.1101***
	(0.0178)	(0.0175)	(0.0177)
FORE*RelPos		0.0235	0.0232
		(0.0160)	(0.0162)
HansRaj*RelPos		0.0676***	0.0682***
		(0.0204)	(0.0208)
Gender (Male = 1)			0.0022
			(0.0133)
GenderOfOpponent (Male = 1)			-0.0022
			(0.0133)
Constant	0.500***	0.500***	0.500***
	(0.0068)	(0.0066)	(0.0118)
F ($\alpha_1 = \alpha_3$)	F(1, 126) = 5.16	F(1, 124) = 5.10	F(1, 122) = 5.01
(P-Value for F-Statistic)	(0.0248)	(0.0257)	(0.0270)
Observations	130	130	130
R-Squared	0.567	0.605	0.605

Notes: [a] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively.
[b] Robust standard errors reported in parentheses

In Column 2, we run the same regression with the introduction of institution dummies,[24] and in Column 3, we introduce controls for gender.[25] In both these specifications, the effects of asymmetry remains (we reject *Hypothesis* 1, since the high-ranked subject of any pair, gets on an average, over 56% of the total pie-size, which is significantly higher than what his/her low-ranked counterpart gets). The effect of contraction, however, in symmetric bargaining is no longer significant (we therefore do not reject *Hypothesis* 2). The F-Statistics for the test of *Hypothesis* 3 in both the specifications of Columns 2 and 3 (5.10 and 5.01 respectively) suggest that the effect of contraction in asymmetric bargaining is significant.[26] These results verify Nydegger and Owen's conclusion that contraction does not matter in the symmetric setting, and demonstrate the invalidity of the IIA axiom in asymmetric bargaining settings. We reject *Hypotheses* 1 and 3 and do not reject *Hypotheses* 2.

It should be noted that regression equation (1) above has been estimated, using least squares, and includes both sides of the bargaining table in the data-set.[27] This violates the assumption that the errors are uncorrelated, and therefore the reported standard errors become questionable. Thus, the inferences drawn so far, are at best naïve. In order to correctly identify the effects, we do fixed-effects regression by differencing the data at the pair level. The beauty of the fixed-effects regression is that the treatment dummies do not vanish even though any two individuals of a pair, by definition, belong to the same treatment. This is

---

[24] Note that there is no institution dummy for St. Stephen's College in our specification. This is because, the following linear relation always holds:

RankBargaining•RelPos + RandomContraction•RelPos + RankContraction•RelPos = FORE•RelPos + HansRaj•RelPos + Stephens•RelPos.

[25] Female subjects may behave differently from male subjects. See Dasgupta and Mani (2015), Andreoni and Vesterlund (2001), Chaudhuri and Gangadharan (2007) for examples.

[26] These results persist when we introduce further controls for: education levels attained by the subjects' parents'; subjects' home income levels; whether subjects belong to business families; subjects' age; whether subjects lived in hostel etc. The introduction of institution dummies only confirms that subjects from different institutions reacted to treatments with some variation. Students from Hans Raj College, for instance were perhaps more serious about the tests than those from the other institutions. We cannot conclusively say why students from Hans Raj College were more sensitive to our interventions. In any given pair, the two subjects belonged to the same institution.

[27] That is, if subjects agree on a 62% and 38% split, we include both 0.62 and 0.38 in the regression. Thus, the errors associated with both the subjects in any given pair will be correlated with each other.

because of the *RelPos* variable that assumes different values for the two individuals of any given pair. Specifically, for each pair i, if we subtract the share (s_{il}) of the individual without the contraction or a rank advantage from that of the individual (s_{ih}) with either (or both) of those advantages, then the left hand side of the regression equation (1) equals: $\Delta^j Share_{ij} = s_{ih} - s_{il} = s_{ih} - (1 - s_{ih}) = 2s_{ih} - 1$.[28] The right hand side equals: $\alpha_1 RankBarg_i \bullet \Delta^j RelPos_j + \alpha_2 RandmContr_i \bullet \Delta^j RelPos_j + \alpha_3 RankContr_i \bullet \Delta^j RelPos_j + (\Delta^j \mathbf{X_{ij}})\boldsymbol{\beta} + \Delta^j \varepsilon_{ij}$. Now we know that $\Delta^j RelPos_j \equiv 2$, for every pair in each treatment except in the control group.[29] The differenced equation (after some algebraic steps) therefore becomes[30]

$$s_{ih} = 0.5 + \alpha_1 RankBarg_i + \alpha_2 RandmContr_i + \alpha_3 RankContr_i + (\Delta^j \mathbf{X_{ij}})\boldsymbol{\gamma} + u_i \tag{2.2}$$

where, $u_i = (\Delta^j \varepsilon_{ij}/2)$, and $\boldsymbol{\gamma} = (1/2)\boldsymbol{\beta}$. Note that there is no α_0 in the above regression equation and that the constant of the regression equation equals 0.5. The fixed-effects regression equation above, therefore expresses the share of the individual (in excess of 0.5) with a rank or a contraction advantage (or both) in terms of which treatment group he/she is a part of. The hypotheses of interest remain the same and Table 2.3b presents the results.[31]

The results are similar, and for all the specifications, we can conclusively reject *Hypotheses 1* and *3*. We do not reject *Hypothesis 2*. We now have more conclusive evidence that

[28] Putting Δ^j before a variable, indicates differencing that variable over the index j for any given pair (that is, by holding that pair i fixed).

[29] This is true since *RelPos* = 1 for the subject with a higher rank or a contraction advantage, and *RelPos* = - 1, for his/her partner, and we are looking at the difference between the two.

[30] Direct differencing gives us: $2s_{ih} - 1 = 2\alpha_1 RankBarg_i + 2\alpha_2 RandmContr_i + 2\alpha_3 RankContr_i + (\Delta^j \mathbf{X_{ij}})\boldsymbol{\beta} + \Delta^j \varepsilon_{ij}$. On rearranging the terms and dividing this equation throughout by 2, gives us the expression shown.

[31] I am extremely grateful to Prof. Martin Cripps for this entire discussion on looking beyond least-squares regressions. On a closer look, this is one of the rare instances, where using fixed-effects regressions actually eradicates problems related to autocorrelation (rather than contributing to them). Random effects regressions (that account for autocorrelation) and tobit regressions also produce almost identical results, to those reported in this paper (with similar test results, and almost identical coefficient values for the significant variables of this paper) and can be made available on request (although neither adds significantly more to the discussion on our already established conclusions – we continue to reject Hypotheses 1 and 3, and as before do not reject Hypothesis 2).

contraction matters only when there is bargaining asymmetry, and not otherwise – but this is not the end of the story.

Table 2.3b: The effect of contraction on bargaining outcomes

Dependent Variable: Share	(1) Fixed Effects	(2) Fixed Effects	(3) Fixed Effects
RankBargaining*RelPos	0.0868***	0.0652***	0.0651***
	(0.0126)	(0.0146)	(0.0147)
RandomContraction*RelPos	0.0162	-0.0108	-0.0109
	(0.0134)	(0.0168)	(0.0132)
RankContraction*RelPos	0.1364***	0.1098***	0.1101***
	(0.0126	(0.0166)	(0.0168)
FORE*RelPos		0.0235	0.0232
		(0.0167)	(0.0169)
HansRaj*RelPos		0.0676***	0.0682***
		(0.0197)	(0.0200)
Gender (Male = 1)			0.0022
			(0.0135)
Constant	0.500***	0.500***	0.500***
	(0.0068)	(0.0066)	(0.0118)
Chi-Squared test for ($\alpha_1 = \alpha_3$)	$\chi^2(1) = 7.68$	$\chi^2(1) = 6.45$	$\chi^2(1) = 6.39$
(P-Value for χ^2-Statistic)	(0.0056)	(0.0111)	(0.0114)
Observations	65	65	65
R-Squared	0.567	0.605	0.605

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively.
[b.] Robust standard errors reported in parentheses

2.7.3. The central story

The regressions reported in Tables 2.3a and 2.3b only suggest that the IIA axiom holds in symmetric bargaining settings and not in asymmetric settings. However, so far, no underlying mechanism that explains these results has been put forward. Now we turn to this main theme. The regressions ignore a crucial aspect of our experimental bargaining framework that relates to the differences in rankings. To check if the absolute ranks or the rank differences matter, we define a variable RD_i as the (absolute) rank difference between the two subjects in the ith pair. The difference in ranks could be thought of as a measure of the degree of asymmetry between two individuals in a pair. We therefore, define $RD_i = 0$ for pairs belonging to the control group and the Random Contraction treatment group. One would expect close to equal splits in pairs with subjects who are very close in rank, and more unequal splits in pairs with subjects who are far apart in rank.[32]

Table 2.4 tests this intuition. Column 1 reports the regression of subjects' observed shares on their individual ranks and Column 2 reports the regression of observed shares on the rank differences between the subjects and the individuals they are paired with. While individually they are significant determinants of observed shares, the effect of individual ranks goes away when we regress observed shares on both (Column 3).

For the *Rank Bargaining* treatment, the average rank difference was 6 (with a minimum observed rank difference of 1, a maximum of 13, and a standard deviation of 3.5); and for the *Rank Contraction* treatment, the average observed rank difference was 5 (with a minimum observed rank difference of 2, a maximum of 13, and a standard deviation of 2.8).

We learn that the individual ranks do not matter as much as the differences in ranks (between the two individuals in any given pair) do in the determination of final shares received by individuals. We need to account for the effect of rank differences in our specification.[33]

[32] See for example Dubey and Geanakoplos (2005). Bohnet and Zeckhauser (2004) also provide evidence for social comparisons. Chakravarty and Somanathan (2008) demonstrate that high ranks are linked to high pay.

[33] Note that in Panels 1 and 3, there are only 76 observations, whereas in Panel 2, there are 130 observations. This is because only 76 individuals belonged to the treatments that involved ranks and therefore had individual ranks (for the remaining 54, it was missing data). However, rank difference is defined to be zero for those in treatments that did not involve ranks (consistent with our definition of symmetry).

Table 2.4: The effect of individual ranks and rank differences

Dependent Variable: Share	(1) Least Squares	(2) Least Squares	(3) Least Squares
IndividualRank	-0.0224***		2.42e-11
	(0.0038)		(0.0042)
RD*RelPos		0.0187***	0.0187***
		(0.0019)	(0.0028)
Constant	0..640***	0.500***	0.500***
	(0.0251)	(0.0063)	(0.0245)
Observations	76	130	76
R-Squared	0.402	0.630	0.671

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively. [b.] Robust standard errors reported in parentheses.

In order to account for rank differences in our specification, we modify (2.1) as under

$$
\begin{aligned}
Share_{ij} = \quad & \alpha_0 \\
& + \alpha_1 RankBarg_i \bullet RelPos_j \bullet RD_i + \alpha_2 RandmContr_i \bullet RelPos_j \\
& + \alpha_3 RankContr_i \bullet RelPos_j \bullet RD_i + \boldsymbol{X}_{ij}\boldsymbol{\beta} + \varepsilon_{ij}. \qquad (2.3)
\end{aligned}
$$

Table 2.5a reports the naïve (least squares) results, and Table 2.5b reports the fixed-effects regression results for the above equation (for reasons pointed out in the previous section).[34] Column 1 in each reports the basic results, Column 2 controls for institution dummies and Column 3 controls for some personal characteristics. We are interested in the same set of hypotheses (1, 2 and 3). After accounting for rank differences, we see that rank-bargaining still generates asymmetry (as before, we reject *Hypothesis 1* in the specifications of Columns 1, 2 and 3). We also conclude that contraction does not significantly matter in symmetric bargaining. As before, we do not reject *Hypothesis 2* for any of the specifications. Further, we continue to reject *Hypothesis 3*, suggesting that contraction does matter when there is bargaining asymmetry (with F-Statistics equal to 19.80, 28.39, and 14.98 respectively in

[34] The share of the higher-ranked individual (on an average) in the rank-based bargaining treatment (T1) will be represented by $\alpha_0 + \alpha_1$ if he is only one position ahead of the subject he is paired with. It is $\alpha_0 + 2\alpha_1$ if he is two positions ahead and so on. The idea is exactly the same for the rank-based contraction treatment. The maximum observed rank difference for both the treatments (involving ranks) was 13 (the average being 5.63).

columns 1, 2 and 3 of Table 2.5b, and negligible p-values for each just like in the reported chi-squared tests that follow).

Table 2.5a: The effect of contraction accounting for rank differences

Dependent Variable: Share	(1) Least Squares	(2) Least Squares	(3) Least Squares
RankBargaining*RelPos*RD	0.0128***	0.0171***	0.0166***
	(0.0018)	(0.0024)	(0.0024)
RandomContraction*RelPos	0.0162*	0.0196	0.0164
	(0.0087)	(0.0136)	(0.0138)
RankContraction*RelPos*RD	0.0270***	0.0363***	0.0340***
	(0.0018)	(0.0018)	(0.0033)
SessionTiming*RelPos		-0.0179***	-0.0175***
		(0.0039)	(0.0039)
FORE*RelPos		0.0427***	0.0433***
		(0.0151)	(0.0159)
HansRaj*RelPos		0.1206***	0.1219***
		(0.0193)	(0.0191)
Stephens*RelPos		0.0204	0.0242
		(0.0230)	(0.0231)
Gender (Male = 1)			0.0019
			(0.0087)
GenderOfOpponent (Male = 1)			-0.0019
			(0.0087)
RankBargaining*RelPos*ARD			0.0008
			(0.0013)
RankContraction*RelPos*ARD			-0.0024
			(0.0028)
Constant	0.500***	0.500***	0.500***
	(0.0055)	(0.0041)	(0.0088)
F ($\alpha_1 = \alpha_3$)	F(1, 126) = 31.22	F(1, 124) = 68.22	F(1, 122) = 28.59
(P-Value for F-Statistic)	(0.0000)	(0.0000)	(0.0000)
Observations	130	130	130
R-Squared	0.723	0.846	0.848

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively. [b.] Robust standard errors reported in parentheses.

In fact, the effect of contraction seems to interact with the degree of asymmetry (which we capture in our rank-differences – putting RD_i equal to zero, takes us back to the zero asymmetry condition, where contraction does not matter). We conclude that Nydegger and Owen (1975) established the validity of the axiom of *independence of irrelevant alternatives* in a restricted setup involving no asymmetry. The axiom fails to hold when there are bargaining asymmetries, in the sense that contraction begins to matter. Clearly, from the results of Column 3, we see that when there is no contraction advantage, then the high-ranked individual is expected to get 51.7% of the total pie if he is only one position ahead of his low-ranked partner; he is expected to get 53.3% of the total pie if he is two positions ahead of his low-ranked partner; he is expected to get 55.0% when he is three ranks ahead and so on. The corresponding figures for the high-ranked subject when there is contraction advantage are 53.4%, 56.8% and 60.2% and so on. These simulations for a complete set of observed rank differences are presented in Figure 2.5a (and in Figure 2.5b, along with 95% confidence intervals). For any given rank difference, the vertical distance between the two lines represents the effect of contraction. We see that the effect of contraction grows with greater degrees of asymmetry (i.e. higher rank differences).

An interesting observation is that, subjects who had to wait for their bargaining session towards the end (since the order in which we ran the treatments was important), tended to gravitate toward more equal splits. This effect has been captured by the significantly negative coefficient of the variable SessionTiming*RelPos in columns 2 and 3. The experimental lab could only accommodate a limited number of students at one go. The variable *SessionTiming* takes the value 1 for all the subject-pairs who were the first to be made to bargain in the experimental lab; it takes the value 2 for all subject-pairs who bargained after the previous set of subject-pairs and so on. There is a concern that, due to the not-so-large sample size, observed ranks could be possibly correlated with unobserved ability. This may cause our results to be biased. To account for the possibility of a bias, the math-tests were graded to assign *actual ranks* to subjects who took the test based on their *actual* performance. Figure 2.6 shows that there is no significant correlation between the assigned and the actual ranks.

Figure 2.5a: A simulation

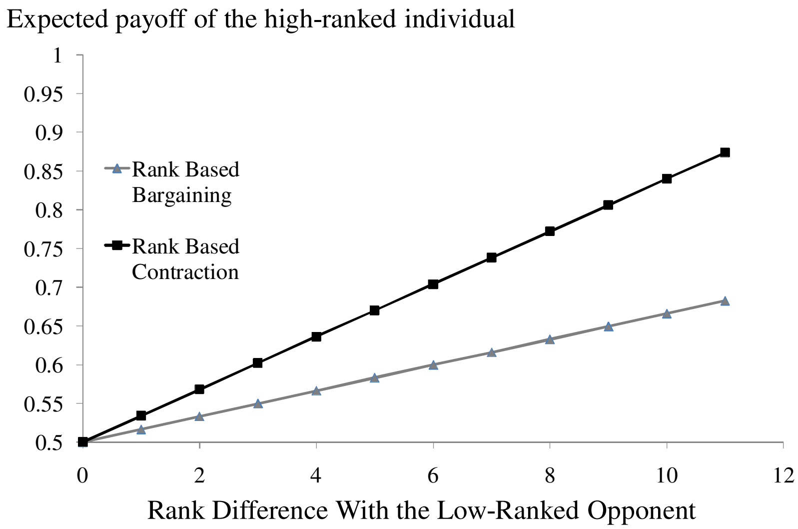
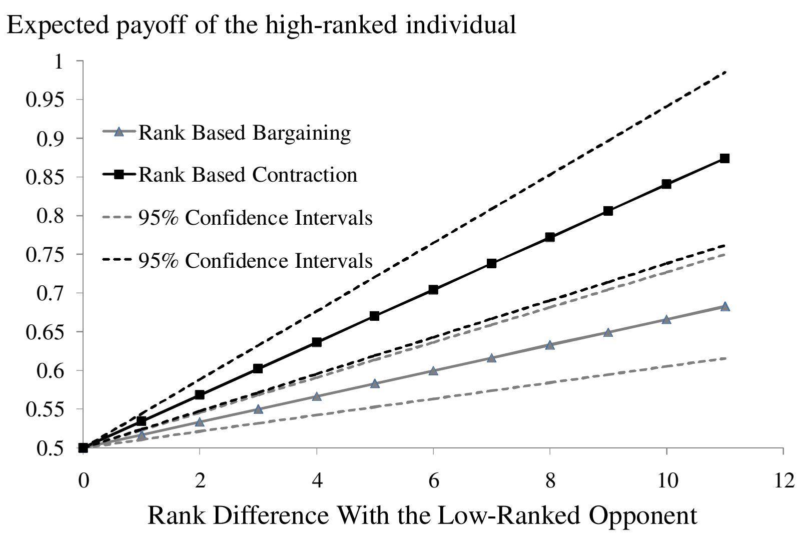
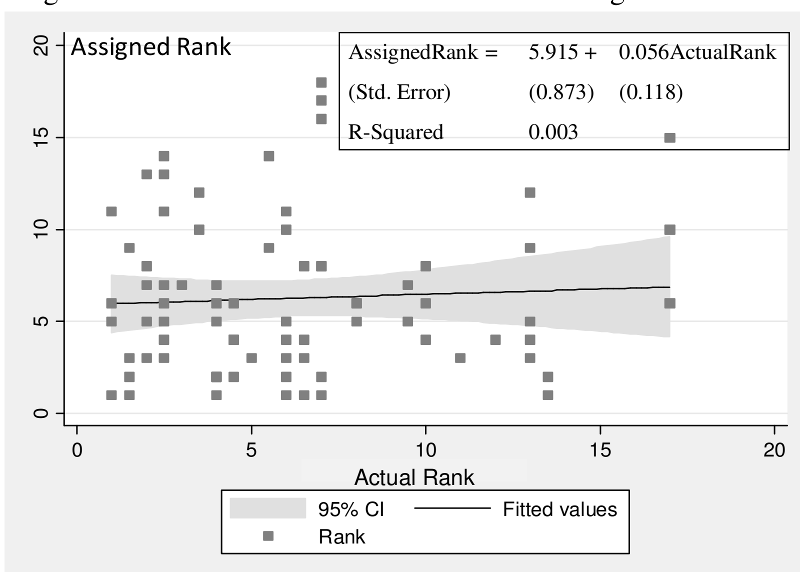


Figure 2.5b: A simulation



The variable ARD_i (Column 3) stands for the *actual rank difference* between the subjects in the *i*th pair. This variable can be thought of as a measure of smartness (and therefore an individual characteristic). One may reason that the generally smarter individuals would tend to get better deals out of their bargaining (simply because they are smarter). The fact that the interaction of the treatment dummies with ARD_i has no significant impact on the final shares leads us to infer that the status effects that generate the asymmetries are in fact, *pure status effects* (actual ranks were not determining final shares).[35] The fact that observed shares are not being determined by actual ranks supports our valid randomization, thereby making our results robust.

Figure 2.6: Relation between actual rank and assigned rank



Overall, the reported test results display remarkable levels of significance, and all regression models presented in Tables 2.5a and 2.5b (accounting for rank differences), perform significantly better than those reported in Tables 2.3a and 2.3b (with much higher values of R-squared). The high values of R-squared are reflective of the level control in the

[35] Making individuals bargain, based on the disclosure of actual ranks could have given us biased results since actual ranks are correlated with unobserved factors such as ability etc.

experimental setting.[36] Both the models in Tables 3 (a and b) and 5 (a and b) convey the same message about the effects of contraction in symmetric and asymmetric settings.

Table 2.5b: The effect of contraction accounting for rank differences

Dependent Variable: Share	(1) Fixed Effects	(2) Fixed Effects	(3) Fixed Effects
RankBargaining*RelPos*RD	0.0128***	0.0171***	0.0166***
	(0.0021)	(0.0029)	(0.0031)
RandomContraction*RelPos	0.0162	0.0196	0.0164
	(0.0152)	(0.0208)	(0.0216)
RankContraction*RelPos*RD	0.0270***	0.0363***	0.0340***
	(0.0024)	(0.0038)	(0.0051)
SessionTiming*RelPos		-0.0179***	-0.0175***
		(0.0056)	(0.0058)
FORE*RelPos		0.0427*	0.0433***
		(0.0248)	(0.0254)
HansRaj*RelPos		0.1206***	0.1219***
		(0.0295)	(0.0302)
Stephens*RelPos		0.0204	0.0242
		(0.0352)	(0.0362)
Gender (Male = 1)			0.0037
			(0.0184)
RankBargaining*RelPos*ARD			0.0008
			(0.0016)
RankContraction*RelPos*ARD			-0.0024
			(0.0035)
Constant	0.500***	0.500***	0.498***
	(0.0078)	(0.0060)	(0.0115)
F ($\alpha_1 = \alpha_3$)	F(1, 62) = 19.80	F(1, 58) = 28.39	F(1, 55) = 14.98
(P-Value for F-Statistic)	(0.0000)	(0.0000)	(0.0003)
Chi-Squared test for ($\alpha_1 = \alpha_3$)	$\chi^2(1) = 40.24$	$\chi^2(1) = 59.72$	$\chi^2(1) = 32.15$
(P-Value for χ^2-Statistic)	(0.0000)	(0.0000)	(0.0000)
Observations	65	65	65
R-Squared	0.723	0.846	0.848

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively.
[b.] Robust standard errors reported in parentheses

[36] As before, random effects and tobit regressions that report almost identical results for these specifications (similar coefficient values for the significant variables and final test results) can be made available on request.

2.8. Conclusion

We have established that contraction, on its own, has no effect on the bargaining outcome. The effect of contraction, however, emerges with the introduction of asymmetry, and increases with rising degrees of asymmetry. The results established may be relevant to the ideas behind MRPs since they can be thought of as contraction in some cases ... and should therefore matter because consumers and sellers are not necessarily symmetric. The legal fare in the auto-rickshaw market in India could also be thought of as such a contraction. In general, such contractions matter because buyers and sellers are not regarded similar in status (i.e. asymmetries remain). Therefore, from our conclusions, it can be argued that laborers could stand to gain in negotiating wages with firms when they are backed with a minimum wage law (see Comay et al. (1974) for other examples). It must be noted that this paper looks at the effects of only horizontal contractions under asymmetric conditions. There could, in general, be other types of contraction, the effects of which have not been analyzed in this paper. Such contractions may respond differently to different degrees of asymmetry. Alongside this thought for future research, one could even think of taking this experiment to the field with appropriate contextualization (a well-defined MRP, a ceiling or a floor etc.).

Finally, one may speculate that the choice of such subjects may affect behavioral results (we address this issue by studying bargaining in the market in Chapters 3 and 4). The possibility that Indian students could be inherently more rank sensitive compared to their western counterparts (because of the caste system), may well lead us to the inference that any bargaining process involving status effects may lead to asymmetric outcomes only in India. This speculation however, can be easily subject to questioning from the findings of Ball et al (2001) where status differences led to significantly asymmetric bargaining outcomes in favor of the high-status individuals, although the subjects were students of western universities.

Nevertheless, the possibility that Indians take ranks seriously makes our experimental setting ideal to study bargaining outcomes in the backdrop of status effects.

To sum up, no asymmetry implies no contraction effect, and the higher the degree of asymmetry, the higher would be the contraction effect. The results of the Nydegger and Owen (1975) experiment are subsumed in the results that we report, although with the exact opposite conclusion on the effect of contraction. So far, no theoretical bargaining solution predicts the results we report. An immediate area of theoretical research, therefore, could be towards finding a set of axioms to construct an allocation rule that could possibly explain the observations made in the lab. While, a complete axiomatization accounting for all possible types of contraction may, at the moment, be very difficult, any theoretical construct allowing for the interaction of some forms of contraction with asymmetry effects could be seen as a potential value addition to the existing literature.

Appendices to Chapter 2

Appendix 2A: A Thought Experiment

Name:

Group:

Gender:

Please read carefully and answer the questions that follow (you have TEN minutes)

Suppose you were a judge required to split a prize money totalling Rs. 600 among two individuals A and B who took the test you have just taken. You are given information about the performances of A and B in the test. How would you split Rs. 600 if

A's rank in the test is 4 and B's rank in the test is 16?

A gets Rs. __________/- B gets Rs. __________/-

A's rank in the test is 7 and B's rank in the test is 9?

A gets Rs. __________/- B gets Rs. __________/-

Appendix 2B: Test Details

A Test of Puzzles

Instructions: You have 25 minutes to complete this test. **There are 10 questions.**

Each question (marked 1, 2, 3, etc.) is immediately followed by four options (marked a, b, c, and d). Only one of the options correctly answers the associated question. Your task is **to mark a tick on what you believe to be the correct answer and maximize your score**. Each correct entry carries one point. There is no negative marking. You may begin. All the best.

Name:

Gender (M/F):

Course:

Please leave the following spaces blank.

Time:

Score:

Experimental Reference ID:

1. A three-man jury has two members, each of whom independently has a 60% chance of making the correct decision and a third juror who flips a coin for each decision (majority rules). A one man jury has a 60% chance of making the correct decision. Which of the following is true?

a. The three-man jury is better than the one-man jury

b. The one-man jury is better than the three-man jury

c. Both of them are equally good

d. There is no conclusive answer

Answer the following two questions (2 and 3) based on the following information.

Jack is captured by a tribe. Whether or not he gets to live is decided by the tribe members based on the outcome of the following exercise. There are 50 black and 50 white balls, which Jack must distribute between two identical and opaque boxes (that the tribe provides to him) in any way he wishes, but with the requirement that each ball must be put into one of the two boxes. The tribe then secretly allocates the balls among the two boxes as instructed by Jack and closes them before putting them in front of him. Jack gets to randomly pick a box before they blindfold him and make him draw a ball from it. If the ball is white, he survives, otherwise they execute him. Answer the following two questions.

2. Jack's maximum probability of survival is

a. 1/2

b. 74/99

c. 3/4

d. 71/100

3. If Jack were offered five boxes instead of just two above, then his maximum probability of survival will

a. definitely increase

b. definitely decrease

c. remain the same

d. well ... cannot say

4. In how many ways can four guards Mr. A, Mr. B, Mr. C and Mr. D be placed at the four gates (North, South, East and West gates) of a circular adventure park?

a. 24

b. 6

c. 2

d. 1

5. A truel is similar to a duel, except that there are three participants rather than two. One morning Mr. Black, Mr. Grey, and Mr. White decide to resolve a conflict by truelling with pistols until only one of them survives. Mr. Black is the worst shot, hitting his target on average only one time in three. Mr. Grey is a better shot hitting his target two times out of three. Mr. White is the best shot hitting his target every time. To make the truel fairer, Mr. Black is allowed to shoot first, followed by Mr. Grey (if he is still alive), followed by Mr. White (if he is still alive) and round again (and again) until only one of them survives. Where should Mr. Black aim his first shot?

a. He should aim at Mr. White

b. He should aim at Mr. Grey

c. He should shoot himself

d. He should shoot in the air

6. To encourage Bob's promising tennis career, his father offers him a prize if he wins (at least) two tennis sets in a row in a three-set series to be played with his father and a club champion alternately: father-champion-father or champion-father-champion, according to

Bob's choice. The champion is a better player than Bob's father. Which series should Bob choose (assume that the outcome of each game in a given series in independent of another)?

a. father-champion-father

b. champion-father-champion

c. He will be indifferent between the two

d. There is no definite answer

7. If p is a prime number (other than 2 and 5) less than 10, then 1/p recurs after ________

a. p – 1 decimal places

b. p + 1 decimal places

c. a factor of p – 1 decimal places

d. a multiple of p – 1 decimal places

8. The sum of two numbers is 15. The sum of their reciprocals is 3/10. The numbers are

a. 50 and -35

b. 5 and 10

c. 6 and 9

d. 3 and 12

9. Which of the following numbers lies between a perfect square and a perfect cube?

a. 5

b. 17

c. 26

d. 65

10. There are three women on the platform of a train station. The train that they are waiting for has five coaches. In how many ways can they board the train such that no two women are together in the same coach?

a. 30 ways

b. 5^3 ways

c. 60 ways

d. 3^5 ways

Appendix 2C: Working of Sample Size for the Control Group

Let the ith pair of shares be (x_1^i, x_2^i), where $x_1^i + x_2^i = 1$. Since $|x_1^i - 0.5| = |x_2^i - 0.5|$, we can define, without loss of generality $Z_i = |x_1^i - 0.5|$. Then let $\bar{Z} = \frac{Z_1 + \ldots + Z_n}{n}$ (where n is the number of observed pairs). $\bar{Z}$ measures the average deviation of the negotiated shares from the equal division solution (0.5, 0.5). Suppose that the population mean of this variable is μ_0. Now, consider the test of the null hypothesis that $\mu_0 = 0$ (i.e. the equal division solution is the population mean). The question is: what would be the minimum sample that is required for such a test to have reasonable power against an alternative hypothesis that the population mean is $\mu_1 > 0$? We consider the alternative hypothesis to be $\mu_1 = 0.02$. It is clear that the sample size that has reasonable power for this alternative hypothesis would also have at least that much power for any $\mu_1 > 0.02$. We do not make any assumption(s) on the distribution of Z_i (and therefore $\bar{Z}$) under the null or the alternate hypothesis.

Let α be the size of the type-I error. Let c be a non-negative constant such that $P(\bar{Z} - \mu_0 > c | \mu = \mu_0) \leq \alpha$. In other words, the null is rejected whenever $\bar{Z} > \mu_0 + c$. To determine c as a function of α and n, we note the following inequalities (the first one of which is $P(\bar{Z} \leq \mu_0 + c) \geq P(\mu_0 - c \leq \bar{Z} \leq \mu_0 + c) \geq P(\mu_0 - c < \bar{Z} < \mu_0 + c)$).

$P(\bar{Z} \leq \mu_0 + c) \geq P(\mu_0 - c < \bar{Z} < \mu_0 + c)$; {∵ LHS spans more values}

$P(\mu_0 - c < \bar{Z} < \mu_0 + c) = P(|\bar{Z} - \mu_0| < c) \geq 1 - \frac{\sigma_Z^2}{nc^2}$; {∵ Chebyshev's inequality}

We combine the two inequalities above as follows

$$P(\bar{Z} \leq \mu_0 + c) \geq 1 - \frac{\sigma_Z^2}{nc^2}$$

$$\Rightarrow \quad P(\bar{Z} - \mu_0 > c | \mu = \mu_0) \leq \frac{\sigma_Z^2}{nc^2}$$

$\Rightarrow \qquad$ P(Type I error) $\leq \frac{\sigma_Z^2}{nc^2} = \alpha$

$\Rightarrow \qquad c = \frac{\sigma_Z}{\sqrt{\alpha n}}$ (2C.1)

Thus, the probability of a Type-I error does not exceed α when $c = \frac{\sigma_Z}{\sqrt{\alpha n}}$. Now we turn to Type II error (which should not exceed β).

$P($Type II error$) = P(\overline{Z} < \mu_0 + c|\mu = \mu_1)$

Now $\mu_0 = 0$, and we substitute for c from (A3.1), we get

$P($Type II error$) = P(\overline{Z} < \frac{\sigma_Z}{\sqrt{\alpha n}}|\mu=\mu_1)$

Note that for any k, we know from Chebyshev's inequality that

$P(\mu_1 - k < \overline{Z} < \mu_1 + k|\mu = \mu_1) \geq 1 - \frac{\sigma_Z^2}{nk^2}$

We now take $k = \mu_1 - \frac{\sigma_Z}{\sqrt{\alpha n}}$ in the above inequality to get

$P(\frac{\sigma_Z}{\sqrt{\alpha n}} < \overline{Z} < 2\mu_1 - \frac{\sigma_Z}{\sqrt{\alpha n}}|\mu = \mu_1) \geq 1 - \frac{\sigma_Z^2}{nk^2}$ (2C.2)

But

$P(\overline{Z} \geq \frac{\sigma_Z}{\sqrt{\alpha n}}|\mu = \mu_1) \geq P(\frac{\sigma_Z}{\sqrt{\alpha n}} < \overline{Z} < 2\mu_1 - \frac{\sigma_Z}{\sqrt{\alpha n}}|\mu = \mu_1)$; {$\because$ LHS spans more values}

(2C.3)

The LHS above spans more values since:

$P(\overline{Z} \geq \frac{\sigma_Z}{\sqrt{\alpha n}}|\mu = \mu_1) \geq P(\overline{Z} > \frac{\sigma_Z}{\sqrt{\alpha n}}|\mu = \mu_1) \geq P(\frac{\sigma_Z}{\sqrt{\alpha n}} < \overline{Z} < 2\mu_1 - \frac{\sigma_Z}{\sqrt{\alpha n}}|\mu = \mu_1)$

On combining the inequalities (2C.2) and (2C.3), we get

$P(\overline{Z} \geq \frac{\sigma_Z}{\sqrt{\alpha n}}|\mu = \mu_1) \geq 1 - \frac{\sigma_Z^2}{nk^2}$

$\Rightarrow \qquad 1 - P(\overline{Z} \geq \frac{\sigma_Z}{\sqrt{\alpha n}}|\mu = \mu_1) \leq 1 - (1 - \frac{\sigma_Z^2}{nk^2}) = \frac{\sigma_Z^2}{nk^2}$

$\Rightarrow \qquad P(\overline{Z} < \frac{\sigma_Z}{\sqrt{\alpha n}}|\mu = \mu_1) \leq \frac{\sigma_Z^2}{nk^2}$

$\Rightarrow \qquad P($Type II error$) \leq \frac{\sigma_Z^2}{nk^2} = \beta$ (2C.4)

Thus, the probability of a Type II error does not exceed β when $\frac{\sigma_Z^2}{nk^2} = \beta$. Substituting for $k = \mu_1 - \frac{\sigma_Z}{\sqrt{\alpha n}}$, we get

$$\beta = \frac{\sigma_Z^2}{n(\mu_1 - \frac{\sigma_Z}{\sqrt{\alpha n}})^2} \tag{2C.5}$$

$$\Rightarrow \qquad n = \frac{\sigma_Z^2}{(\mu_1 - \mu_0)^2}\left(\frac{1}{\sqrt{\alpha}} + \frac{1}{\sqrt{\beta}}\right)^2 \tag{2C.6}$$

In this expression, we fix the probabilities of Type - I error (α) and Type - II error (β) to be 0.05 and 0.10 respectively. We take $\mu_1 = 0.02$. The only limitation is that we do not know the value of σ_Z. To estimate σ_Z, we use a pilot study that had 14 subjects (7 pairs) in the control group. In this sample, $\widehat{\sigma_Z} = 0.0075592$. Using this value gives us $n^* = 8.33 \approx 9$ pairs (18 subjects). Note that c equals 0.01 for this value of n. In other words, with just 18 subjects, we can be 95% confident that the average outcome is the 50%-50% split (and not a 51%-49% split).

Appendix 2D: Derivations of the Bargaining Solutions

The axioms of *symmetry* and *efficiency* together, in the Nash and the Kalai-Smorodinsky bargaining framework, are sufficient to guarantee that X and Y get 50% each (of the pie). To verify this with a specific example, in what follows, we assume that X and Y have utilities $v(x)$ and $v(y)$, with $v \geqq 0$, $v' > 0$ and, $v'' < 0$.[37] Finally, I make a transformation $u = v - v(0)$, so that $u(0) = 0$. I assume a zero disagreement-payoff vector. The feasible set of interest is shown in the shaded region of Figure 1.

The symmetric Nash solution: This solution can be formulated as follows (ignoring the non-negativity constraint)

$$\textit{Maximize:} \quad u(x)u(y)$$

$$\textit{Subject to:} \quad x + y = 1$$

which is the same as the following problem

$$\textit{Maximize:}\ \ln[u(x)u(y)] = \ln u(x) + \ln u(1 - x)$$

which involves taking a monotonic transformation of the objective function and feeding the constraint into the same. The first order condition of the above problem is

$$\frac{u'(x)}{u(x)} = \frac{u'(1-x)}{u(1-x)} \tag{2D.1}$$

Now, if we define $w(x) = \ln\left(\frac{u'(x)}{u(x)}\right) = \ln u'(x) - \ln u(x)$. Then

$$w'(x) = \frac{u''(x)}{u'(x)} - \frac{u'(x)}{u(x)} < 0$$

Thus, w (and hence e^w) is monotonic for $x > 0$. Now (2D.1) can be written as $e^{w(x)} = e^{w(1-x)}$, and from the monotonicity of e^w, we get $x = 1 - x$. This gives us $x = y = 1/2$ as our unique (symmetric) Nash Bargaining solution.

[37] The functional form of X's utility is identical to that of Y's. This captures the feature that X and Y come from a homogenous population.

The symmetric Kalai-Smorodinsky solution: For ease of notation, we write $u(x) = a$, and $u(y) = b$, to transform the (x,y)-plane to the (a,b)-plane. The boundary $x + y = 1$ is therefore, transformed to $u^{-1}(a) + u^{-1}(b) = 1$. The coordinates of the *maximal point* on this plane are given by $(u(1), u(1))$. The equation of the line joining the disagreement payoff $(u(0),u(0)) = (0,0)$ and the *maximal point* is given by

$$\frac{a-0}{u(1)-0} = \frac{b-0}{u(1)-0} \Rightarrow u(x) = u(y)$$

feeding the constraint $(y = 1 - x)$ into which gives us $u(x) = u(1 - x)$, or $x = y = 1/2$ (from the monotonicity of u) as our Kalai-Smorodinsky solution.

To summarize, for a *symmetric game (i.e. with homogenous individuals)* involving the division of a given pie size (say \$1) in the absence of any (favourable) contraction, theory (Nash, Kalai-Smorodinsky and others) predicts an equal split i.e. both the individuals X and Y, get to keep 50 cents each.

The asymmetric Nash solution: For individual X with a higher bargaining power β, this allocation rule (that puts more weight on agent X's utility), is formulated as follows (ignoring the non-negativity constraint)

$$\textit{Maximize:} \quad u(x)^{(1+\beta)}u(y)$$

$$\textit{Subject to:} \quad x + y = 1$$

The first order condition of the above problem is

$$(1+\beta)\frac{u'(x)}{u(x)} = \frac{u'(1-x)}{u(1-x)}$$

Now, defining $w(x)$ as before, the above condition can be written as $(1+\beta)e^{w(x)} = e^{w(1-x)}$. Since $(1+\beta) > 1$, it follows that $e^{w(x)} < e^{w(1-x)}$, or $w(x) < w(1 - x)$. Finally with $w' < 0$, we conclude that $x > 1 - x$, or $x > 1/2$. In other words, the person with a higher bargaining power gets the higher share.

The asymmetric Kalai-Smorodinsky solution: Here, agent X's higher bargaining power (β) is captured in a different way. This solution concept is explained in Figure 2. Transforming the *(x,y)*-plane to the *(a,b)*-plane and using the equation of the line joining the disagreement payoff and the *maximal/ideal point* given by

$$\frac{a-0}{(1+\beta)u(1)-0} = \frac{b-0}{u(1)-0} \Rightarrow u(x) = (1+\beta)u(y)$$

leads us to conclude that $u(x) > u(y)$, or $x > y$ (from the monotonicity of u). Feeding the constraint ($y = 1 - x$) into which gives us $x > 1 - x$, or $x > 1/2$. Again, the person with a higher bargaining power gets the higher share.

In the specific case where $u(x) = x$, it is well known that both the Nash and the Kalai-Smorodinsky solutions will be given by[38]

$$\text{argmax}_x x^{1+\beta}(1 - x) = \frac{1+\beta}{2+\beta} \tag{2D.2}$$

Both the solutions predict the same asymmetric outcome in the presence of asymmetric bargaining power. This is a more general solution to the bargaining problem, since if $\beta = 0$ (in (2D.2)), then we get back the symmetric solution.

The symmetric Kalai-Smorodinsky solution with contraction: There is a cap on individual *Y*'s utility equivalent to $u(1 - \alpha)$. The coordinates of the *maximal point* on the *(a,b)*-plane (see Figure 2.3) are given by $(u(1),u(1 - \alpha))$. The equation of the line that intersects this point with the disagreement payoff is given by

$$\frac{a-0}{u(1)-0} = \frac{b-0}{u(1-\alpha)-0} \Rightarrow \frac{u(x)}{u(y)} = \frac{u(1)}{u(1-\alpha)} > 1; \ \{\because 1 > 1-\alpha \text{ and } u' > 0\}$$

which gives us $u(x) > u(y)$ or $x > y$. Finally, using the constraint $y = 1 - x$ gives us $x > 1/2$. That the solution is unique is verified from the expression above (using the constraint) which translates to

$$\frac{u(x)}{u(y)} = \frac{u(x)}{u(1-x)} = \frac{u(1)}{u(1-\alpha)} \tag{2D.3}$$

Now, we define $w(x) = \ln[u(x)/u(1 - x)] = \ln u(x) - \ln u(1 - x)$.

---

[38] Note that $\beta > 0 \Rightarrow \beta > (\beta/2) \Rightarrow 1+\beta > 1+(\beta/2) \Rightarrow \frac{1+\beta}{1+(\beta/2)} > 1 \Rightarrow \frac{1}{2}\left(\frac{1+\beta}{1+(\beta/2)}\right) > 1/2 \Rightarrow \frac{1+\beta}{2+\beta} > 1/2$.

$$w'(x) = \frac{u'(x)}{u(x)} + \frac{u'(1-x)}{u(1-x)} > 0$$

so that w is monotonic for $x > 0$ and (2D.3) can be written as $e^{w(x)} = u(1)/u(1\text{-}\alpha)$. The uniqueness of x is immediately verified from the monotonicity of w. It is interesting that the Kalai-Smorodinsky solution is insensitive to power transformations under contraction. To explain this point, let α be a fixed parameter and u be such that $u(x) = x^{\gamma}$ so that the basic assumptions i.e. $u \geqq 0$, $u' > 0$, $u'' < 0$, and, $u(0) = 0$ hold.[39]

A well-known property that $\frac{u(x)}{u(y)} = u(x/y)$ is satisfied. Thus, (2D.3) can be written as

$$\frac{u(x)}{u(1-x)} = u\left(\frac{1}{1-\alpha}\right)$$

which leads us to the unique solution $x = 1/(2 - \alpha)$ given the monotonicity of u, for this general class of utility functions including $u(x) = x$, in which case, the Nash solution is given as

$$\text{Nash: } x_N = \begin{cases} 0.5; & for\ 0 \le \alpha < 0.5 \\ \alpha; & for\ 0.5 \le \alpha \le 1 \end{cases} \tag{2D.4}$$

The Kalai-Smorodinsky solution (written below) is, therefore, different from Nash when there is feasible set contraction

$$\text{Kalai-Smorodinsky: } x_{KS} = \frac{1}{(2-\alpha)};\ \forall\ \alpha \in [0,1] \tag{2D.5}$$

Asymmetric Bargaining in the Presence of Contraction: The Nash solution, with $u(x) = x$ remains as in (2D.2) but the Kalai-Smorodinsky solution changes. Specifically, with $u(x) = x$, it changes to

$$x_{KS} = \frac{1+\beta}{(2+\beta-\alpha)}. \tag{2D.6}$$

[39] Of course, this will require the additional assumption that $0 < \gamma < 1$.

Note again that in the absence of asymmetry *($\beta = 0$)*, the Kalai-Smorodinsky solution above is identical to the one involving only contraction. While we show the effects of asymmetric *entitlements* in this section and demonstrate the experimental ability of the same to affect final allocations, it is interesting to note that even asymmetric *liabilities* have been experimentally shown to affect allocations (see Abbink et al, 2014).

Appendix 2E: Experimental Instructions

GENERAL INSTRUCTIONS

Hello and welcome to this experiment. **You will receive a sum total of Rs. 125 as a show-up fee of this experiment. This is the minimum amount you will get (provided you stick to the rules of this experiment).** In today's session you have to bargain over a sum of Rs. 600 with individuals you will be paired with. Any amount you earn here will be additional earnings. For purposes of confidentiality you will be identified only by your ID (identity) numbers which will be provided to you.

You will be given a form that requests your consent for participating in the experiment. You will have to sign it and return it to us. The amount that is due to you will be filled in after the experiment when we can determine your winnings.

Please raise your hands if you have any questions, otherwise we are ready to move on to the main part of the experiment.

You will now be divided into different groups.

Please come one by one to the computer screen and hit enter; and give your names.

(We run the command on R for each student to hit enter and record their names in the reference sheet)

Stay in this room (i.e. if the output is 0 or 2)

Go to the next room (if the output is 1 or 3; the research assistants guide them to the room(s))

INSTRUCTIONS TO THE BASELINE TREATMENT GROUP

Instructions in the waiting room **before** the test:

1. Please read the instructions carefully and fill in your details
2. Your goal is to **direct all your efforts** towards scoring as high as possible
3. Do you have any questions?
4. You may begin now.

(Test begins)

(Test is over and answer scripts are collected)

Instructions in the waiting room **after** the test:

1. Each candidate in this group will now be randomly paired with another candidate in this room.
2. You will move to the experimental lab in groups of six (three pairs per session)
3. Once just outside the experimental lab, you will be called in one by one by your **names** and seated on your allotted workstations
4. On your workstations, you will get to know your Candidate ID number and the related Skype Username.
5. You will have to (text) **chat** in **English** on Skype with the individual you have been paired with to decide on how to split Rs. 600 between yourselves.
6. You will have only **ten minutes** to complete this conversation.

7. Should you disagree or not reach an agreement in ten minutes, you will be given nothing but the show-up fee; otherwise, you will be given your share in Rs. 600, as negotiated, plus, the show-up fee.
8. You will be asked to report your negotiated amounts and some other details about yourself in the pages that appear after your chat conversation.
9. Do you have any questions?
10. More instructions will be given to you once in the lab.

Instructions in the lab:

Candidates are taken through the presentation and the following instructions are given:

1. **Do not disclose** your identities. Any implicit or explicit attempt to do so will lead to the immediate cancellation of both the show-up fee and the negotiated amount. Remember your chat histories are saved by us.
2. **Do not misreport** your negotiated amounts in the pages that appear after the chat conversation. Any attempt to do so will lead to the immediate cancellation of both the show-up fee and the negotiated amount.
3. Please remember that your responses are confidential and the raw data collected from this experiment will not be given to anyone outside this project.
4. Do you have any questions?
5. You may begin now.

Once the total amount is displayed on the **candidates'** screens, we make them fill up, and sign the receipts, and pay them accordingly.

INSTRUCTIONS TO THE RANK BARGAINING TREATMENT GROUP (T1)

Instructions in the waiting room **before** the test:

1. Please read the instructions carefully and fill in your details
2. Your goal is to **direct all your efforts** towards scoring as high as possible
3. Do you have any questions?
4. You may begin now.

(Test begins)

Instructions in the waiting room **after** the test and **before** the thought experiment:

(Test is over and answer scripts are collected)

1. Your tests will now be evaluated.
2. You will all now do a thought experiment which you have **ten** minutes to complete.

Instructions in the waiting room **after** the thought experiment:

1. Your tests have now been evaluated.
2. Based on your test performances, you have all been ranked.
3. Each individual in the top half will be randomly paired with an individual in the bottom half.

   (instructions 4-12 below are the same as 2-10 in the baseline treatment above)
4. You will move to the experimental lab in groups of six (three pairs per session)
5. Once just outside the experimental lab, you will be called in one by one by your **names** and seated on your allotted workstations

6. On your workstations, you will get to know your Rank ID number and the related Skype Username.
7. You will have to **chat** in **English** on Skype with the individual you have been paired with to decide on how to split Rs. 600 between yourselves.
8. You will have only **ten minutes** to complete this conversation.
9. Should you disagree or not reach an agreement in ten minutes, you will be given nothing but the show-up fee; otherwise, you will be given your share in Rs. 600, as negotiated, plus, the show-up fee.
10. You will be asked to report your negotiated amounts and some other details about yourself in the pages that appear after your chat conversation.
11. Do you have any questions?
12. More details will be given to you once in the lab.

Instructions in the lab:

Candidates are taken through the presentation and the following instructions are given:

1. **Do not disclose** your identities. Any implicit or explicit attempt to do so will lead to the immediate cancellation of both the show-up fee and the negotiated amount. Remember your chat histories are saved by us.
2. **Do not misreport** your negotiated amounts in the pages that appear after the chat conversation. Any attempt to do so will lead to the immediate cancellation of both the show-up fee and the negotiated amount.
3. Please remember that your responses are confidential and the raw data collected from this experiment will not be given to anyone outside this project.
4. Do you have any questions?

5. You may begin now.

Once the total amount is displayed on the **candidates'** screens, we make them fill up, and sign the receipts, and pay them accordingly.

INSTRUCTIONS TO THE RANDOM CONTRACTION TREATMENT GROUP (T2, Room: 22)

Instructions in the waiting room **before** the test:

(these are same as the instructions in the baseline treatment)

Instructions in the waiting room **after** the test:

(these are same as the instructions in the baseline treatment)

Instructions in the lab:

Candidates are taken through the presentation and the following instructions are given:

1. In each pair, one of the **randomly selected** individuals will be **awarded a star**. The subject he/she (i.e. the starred individual) is paired with cannot get more than 60% (i.e. Rs. 360) of the total Rs. 600. The starred individual can get any amount provided there is agreement (we remind Point No. 7 in the instructions **after** the test - this is the same for the control group).

   (We then discuss two examples)[40]
2. If you have a star on your workstation, then you are the starred subject in your pair. Otherwise, your partner is the starred subject in your pair.
3. **Do not disclose** your identities. Any implicit or explicit attempt to do so will lead to the immediate cancellation of both the show-up fee and the negotiated amount. Remember your chat histories are saved by us.

[40] Let us discuss a few examples to make this clear. Are the following splits acceptable?

Rs. 200 for the starred individual and Rs. 400 for his/her partner?

Rs. 400 for the starred individual and Rs. 200 for his/her partner?

4. **Do not misreport** your negotiated amounts in the pages that appear after the chat conversation. Any attempt to do so will lead to the immediate cancellation of both the show-up fee and the negotiated amount.
5. Please remember that your responses are confidential and the raw data collected from this experiment will not be given to anyone outside this project.
6. Do you have any questions?
7. You may begin now.

Once the total amount is displayed on the **candidates'** screens, we make them fill up, and sign the receipts, and pay them accordingly.

INSTRUCTIONS TO THE RANK CONTRACTION TREATMENT GROUP (T3, Room: 23)

Instructions in the waiting room **before** the test:

(these are same as the instructions in the rank bargaining treatment above)

Instructions in the waiting room **after** the test:

(these are same as the instructions in the rank bargaining treatment above)

Instructions in the lab:

Candidates are taken through the presentation and the following instructions are given:

1. In each pair, the **higher-ranked** individual will be **awarded a star**. The subject he/she (i.e. the starred individual) is paired with cannot get more than 60% (i.e. Rs. 360) of the total Rs. 600. The starred individual can get any amount provided there is agreement (we remind Point No. 7 in the instructions **after** the test - this is the same for the control group).
   (We then discuss two examples)[41]
2. If you have a star on your workstation, then you are the starred subject in your pair. Otherwise, your partner is the starred subject in your pair.
3. **Do not disclose** your identities. Any implicit or explicit attempt to do so will lead to the immediate cancellation of both the show-up fee and the negotiated amount. Remember your chat histories are saved by us.

[41] Let us discuss a few examples to make this clear. Are the following splits acceptable?
Rs. 200 for the starred individual and Rs. 400 for his/her partner?
Rs. 400 for the starred individual and Rs. 200 for his/her partner?

4. **Do not misreport** your negotiated amounts in the pages that appear after the chat conversation. Any attempt to do so will lead to the immediate cancellation of both the show-up fee and the negotiated amount.
5. Please remember that your responses are confidential and the raw data collected from this experiment will not be given to anyone outside this project.
6. Do you have any questions?
7. You may begin now.

Once the total amount is displayed on the **candidates'** screens, we make them fill up, and sign the receipts, and pay them accordingly.

Appendix 2F: Personal Characteristics by Treatment

Table: 2F.1. Distribution of personal characteristics by treatment

	Control Group	Rank Bargaining	Random Contraction	Rank Contraction
Observations	20	38	34	38
No. of Males	13	21	19	16
Average Age	21.3	20.2	20.9	21.1
Business Family	9	11	11	20
Hostlers	11	13	24	19
Postgraduate Father	9	14	16	14
Postgraduate Mother	6	11	11	18
Low Income Family < INR 2,50,000	2	5	7	5
High Income Family > INR 10,00,000	7	10	10	12

Chapter 3

Dictator Games in the Field: The Private Moral Calculus of Economic Agents*

3.1. Introduction

Three-wheeler taxis are common in many parts of the developing world. In India, they are popularly known as `auto-rickshaws' or simply `autos'. This paper reports on the outcome of a dictator game with the drivers of these autos in the city of New Delhi. Four key features characterize our experiment.

First, the game qualifies as a natural field experiment in the taxonomy of experiments proposed by Harrison and List (2004). The auto drivers were unaware that they were participating in an experiment.[1] Second, unlike previous dictator game field experiments, the dictator game in our experiment was embedded in routine economic transactions. Subjects were presented with an opportunity to appropriate a large surplus from a regular commercial transaction. Third, as auto drivers confront the choice between opportunism and pro-social behavior in their daily normal course of work, the experiment offers the prospect of capturing well-considered decisions of experienced subjects. Fourth, the experiment affords the opportunity of asking whether dictator game choices are correlated with fares charged in regular transactions. In other words, the experiment asks whether the proclivity for opportunism demonstrated in dictator games predicts similar proclivity in real-world

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* This research is joint work with my thesis supervisor Prof. Bharat Ramaswami.

[1] We collected data using undergraduate students of the University of Delhi who 'acted' as commuters.

transactions (and vice-versa). We are not aware of any other study whose design allows such a question to be posed.

Although auto fares are regulated in the major cities of India, autos have a reputation for charging above metered fares. On the Internet and in social media, many articles bemoan `greedy' auto drivers.[2] In May 2013, after increasing the metered fares, the state transport minister in Delhi issued a warning that they "will take action against those auto-drivers who refuse to ply by the metre".[3] Just a few months later, a different strategy was employed. In February 2014, the Chief Minister of Delhi administered an oath to 10,000 taxi drivers that they would not overcharge passengers.[4] In April 2015, the state transport minister in Mumbai went on record to say "Based on the number of complaints I get from people, auto drivers are the ones who loot the people most…" (Rao, 2015). There are also articles that record a counter-narrative about how difficult economic circumstances, corrupt police and insensitive regulation make it very difficult for auto drivers to comply with metered fares.[5] Implicit in all these reports is the shared consensus that enforcement of metered fares is spotty and uneven.

The experiment was conducted with the help of over a dozen actors who posed as passengers. In the dictator game, the actor told the subject that s/he wished to travel from point A to point B and was willing to pay up to Rupees 150.00 which was, on average, about three times the metered fare. The subject was then asked to state the fare that he would charge. Although the interactions were face to face, the taxis were hired off the street and so the dealings were impersonal just as in any typical taxi transaction.

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[2] See Phys.Org (2011); and Singh (2013). Alongside these, the following link provides more insights: http://www.indiamike.com/india/polls-f79/which-city-has-the-worst-autorickshaw-drivers-t21965/.

[3] See NDTV (2013), the link to which is: http://www.ndtv.com/delhi-news/delhi-auto-drivers-to-face-action-for-overcharging-warns-government-521366.

[4] See Hindustan Times (2014). The link is: http://www.hindustantimes.com/delhi/swear-on-your-kids-you-won-t-overcharge-kejriwal/story-ANCdo2YcyMSoZqwaNYNsXO.html.

[5] See Mohan and Roy (2003); Robinson (2007); Harding (2013); and Vij (2010). Alatas et al. (2009), similarly report that Indonesian public servants blame low government salaries for unjust practices (corruption). Thus, underdevelopment can create 'occasions for corruption' (Bose, 2012).

Previous work has highlighted that the willingness of dictators to share with recipients need not be due to altruism alone but could also be because of social norms that dictate fairness (Bardsley, 2008; Camerer and Thaler, 1995; Dana et al, 2006; Bose et al, 2014). The devotion to fairness is, however, contextual and therefore malleable (Franzen and Pointner, 2012; Hoffman et al 1994; Hoffman et al 1996; Levitt and List, 2007). Games in which the dictator perceived a greater right over the windfall gain saw smaller payouts to recipients. The payouts are also sensitive to social framing and whether the experimenter and the recipient know the choices of the subjects.[6] Hoffman et al, 1994 conclude that dictator game sharing "may be due not to a taste for "fairness" (other-regarding preferences), but rather to a social concern for what others may think, and for being held in high regard by others." More recent work including Andreoni and Bernheim (2009), and Krupka and Weber (2013) model dictator game outcomes as a trade-off between self-interest and compliance with social norms. Eckel and Grossman (1996) point out that while altruism cannot be expected from games with anonymous agents, charitable behavior can be induced if subjects know that the recipient is a worthy organization.[7]

In our experiment setting, however, it would be hard to argue that altruism or the concern to appear fair (i.e., `social image' in the words of Andreoni and Bernheim, 2009) are primary factors in determining any departures from opportunism. Altruism cannot be expected

[6]Dreber et al, 2012 report that there are no social framing effects in dictator game experiments.

[7]Field experiments on charitable giving include studies by DellaVigna et al, 2012 who demonstrate the roles of altruism and social pressures in the decisions involving donations. Similar studies by Andreoni and Bernheim, 2009; Dana et al, 2006; and Dana et al, 2007 suggest that subjects only want to *seem* fair rather than *be* fair. Reinstein and Riener (2012) find mixed evidence of "reputation-seeking" and Croson and Shang (2008), report that individual donations are determined by the information on donations by other members of a society or a group. Charness and Cheung (2013) establish that 'charity amounts suggested' influence donations made in a restaurant. Tipping decisions can be understood from the research of Ruffle (1998), where it is concluded (in a dictator game setting) that allocators (dictators), reward skillful recipients and marginally punish those who are unskillful. Parrett (2006) reports that tipping behavior is observed primarily due to reciprocity and guilt aversion, and that the size of the tip increases in table size. Among other field studies that look at recipient attributes, Jacob et al. (2010) and Solnick and Schweitzer (1999), provide useful insights. Ironically though, tipping in principle is considered as only a reward for the perceived quality of the service provided (Azar, 2004). Additionally see Azar et al (2013) and Conlin et al (2003).

because the transactions are impersonal and nothing marks out the actors as specially deserving.[8] Furthermore, when this seemingly clueless customer offers to pay three times the metered fare, the auto drivers are unlikely to perceive a social cost (in terms of disapproval from the passenger) of deviating from the metered fare. Therefore, social image concerns are also likely to be weak as well.

The metered fare and the governmental attempts to enforce it either by threatening punishment or by moral suasion may have anchored social norms for at least some of the auto drivers. It is, therefore, possible that such subjects experience a private cost in terms of their own self-image by departing from the metered fare. If this is so, subjects that are reluctant to be opportunists in the dictator game may well exhibit similar reluctance in regular transactions. The experiment design allows this to be probed by a second transaction with the same subject auto driver. In one treatment, a second actor hires the same auto in the reverse direction (for the same route). This actor informs that subject that s/he would like to travel from point B to point A and asks the auto driver to state his fare. The difference from the dictator game is that the actor does not state his or her maximum willingness to pay. In another treatment, this regular transaction precedes the dictator game.

Stoop (2014) and Winking and Mizer (2013) are two studies that have employed the dictator game as a natural field experiment. The interest in these studies was to examine whether the lab findings extrapolate to field settings. While Stoop's (2014) experiment confirms lab studies in terms of demonstrating considerable pro-social behavior, Winking and Mizer (2013) do not find this. Unlike these studies, our field experiment is embedded in the normal work transactions of subjects. Second, as mentioned earlier, while the context of our experiment does not allow us to examine altruism, social image and other signaling motives

[8] If anything, the actors visibly belong to a class with higher economic status (as do most other passengers as well) than the auto drivers.

for pro-social behavior, it does uncover the tension between opportunism and compliance to a social norm that is in place because of regulation (metered fares). This trade-off will have larger relevance if dictator game behavior predicts and is predicted by real world transactions. The ability to demonstrate this correlation is a key feature of our experiment design. Our study of sharing motives can be related to the research of Ligon and Schechter (2012).

3.2. The auto-rickshaw market

Autos are three-wheeler taxicabs intrinsic to the public transport mechanism in India, alongside public buses, four-wheeler taxi cabs, and local metro railways. Public buses and metro railways are cheaper modes of travel than autos. Autos however, offer the conveniences of personal comfort in terms of space, speed, and carrying luggage. Further, autos are compact and can therefore, easily be driven on narrow lanes not accessible to cars and buses.

Auto drivers in Delhi largely come from low income family groups and maintain families of, on an average, five to eight members (Mohan and Roy, 2003). Not many can afford to buy auto rickshaws and thus (80% of them) take them on rent (of over Rs. 250.00 per day, amounting to over 40% of their daily earnings) on a daily basis from their actual owners (see Harding, 2010; additionally see Kurosaki et al (2012) that reports that these daily rents are common for even cycle rickshaw pullers). There are over 74,000 licensed autos on Delhi roads.[9] Acquiring a license is a painstaking enough process that auto drivers are forced to engage the services of middlemen that effectively increases the cost of obtaining a license (Mohan and Roy, 2003). Consumers are supposed to pay a regulated fare, which depends on

[9] The official link to the directory of all the auto rickshaw license holders in New Delhi is: http://www.delhi.gov.in/wps/wcm/connect/288f5b8047095074932eff7d994b04ce/Passenger%2BPermit%2BReport.pdf?MOD=AJPERES&lmod=1808150906.

the distance travelled, luggage and time of the day (night fares are higher). The current fare structure is Rs. 25.00, as a down payment applicable for the first two kilometers and Rs. 8.00 for every subsequent kilometer travelled.[10] Compared with four wheeled sedan taxis, autos are cheaper. For instance, for a distance of 20 kilometers, the regulated auto fare amounts to Rs. 169.00, but for four-wheeler taxis, the fare for the same distance amounts to at least Rs. 250.00 (and can go up to at least Rs. 450.00 depending on the service provider chosen). The regulated legal fare is displayed on a taximeter (meter, hereafter) attached to the autos. The meter also shows the distance travelled and is supposed to be reset individually for every customer.

The Delhi police maintains websites and hotlines for commuters to register complaints about overcharging, refusal to take fares and misbehavior.[11] The primary power of the police is that it can issue traffic fines (Rs. 90 for the first offence and Rs. 290 subsequently). At the time of the experiment, the police also had the power of impounding vehicles till the fines are paid. However, subsequently, these actions were reserved for `major' offences.[12] The difficulties of prosecution have led governments to consider other means of protecting consumers.[13] Many cities, including Delhi, offer the facility of pre-paid fares at railway and bus stations and at airports where passengers are particularly vulnerable.[14]

3.3. The experiment

Twenty-three pairs of origin and destination spots (interchangeably called A and B for our purposes) were used for this research. Points A and B are chosen such that they are similar

[10]An additional Rs. 10.00 applies for every unit of luggage carried by the commuter(s).
[11] The official websites to register such complaints are: https://delhitrafficpolice.nic.in/complaint-against-tsr/, and http://www.complaintboard.in/complaints-reviews/autorickshaw-l190475.html.
[12] These include the lack of proper documents such as driver's license, auto permits and fitness certificate.
[13] The difficulties include the possibility that stringent powers could lead to harassment and demand from bribes by the police (see Bose, 2004 for a related discussion on the fact that bribes are often elicited in LDCs). This was the reason why the power to seize auto vehicles for `minor' offences was taken away from the police.
[14] The police staffs these pre-paid booths and passengers pay in advance for travel to specified destinations.

and comparably busy (such as both metro-rail stations, both colleges, both shopping malls) and approximately five kilometers apart. For this distance, the legal fare is approximately Rupees 50. Table 3.1 lists all the routes, the distances and the legal fares. The locations of these routes are mapped in Figure 3.1. The two treatments of our experiment are described below.

Dictator-First Treatment: The dictator game is played before a regular transaction is observed.

Regular-First Treatment: A regular transaction is observed before the dictator game is played.

In both the treatments, one of the actors 'hires' an auto from A to B, and another actor of the same gender stationed at B, 'hires' the same auto back to A. Thus, each auto driver belongs to exactly one of the treatments above and provides us with two prices – one under the dictator game, and the other as a regular transaction. In relation to our experiment, these treatments (as we will learn later) will help us understand the role of intrinsic characteristics (inherently opportunistic or legally compliant) of our agents in the choices that they make.

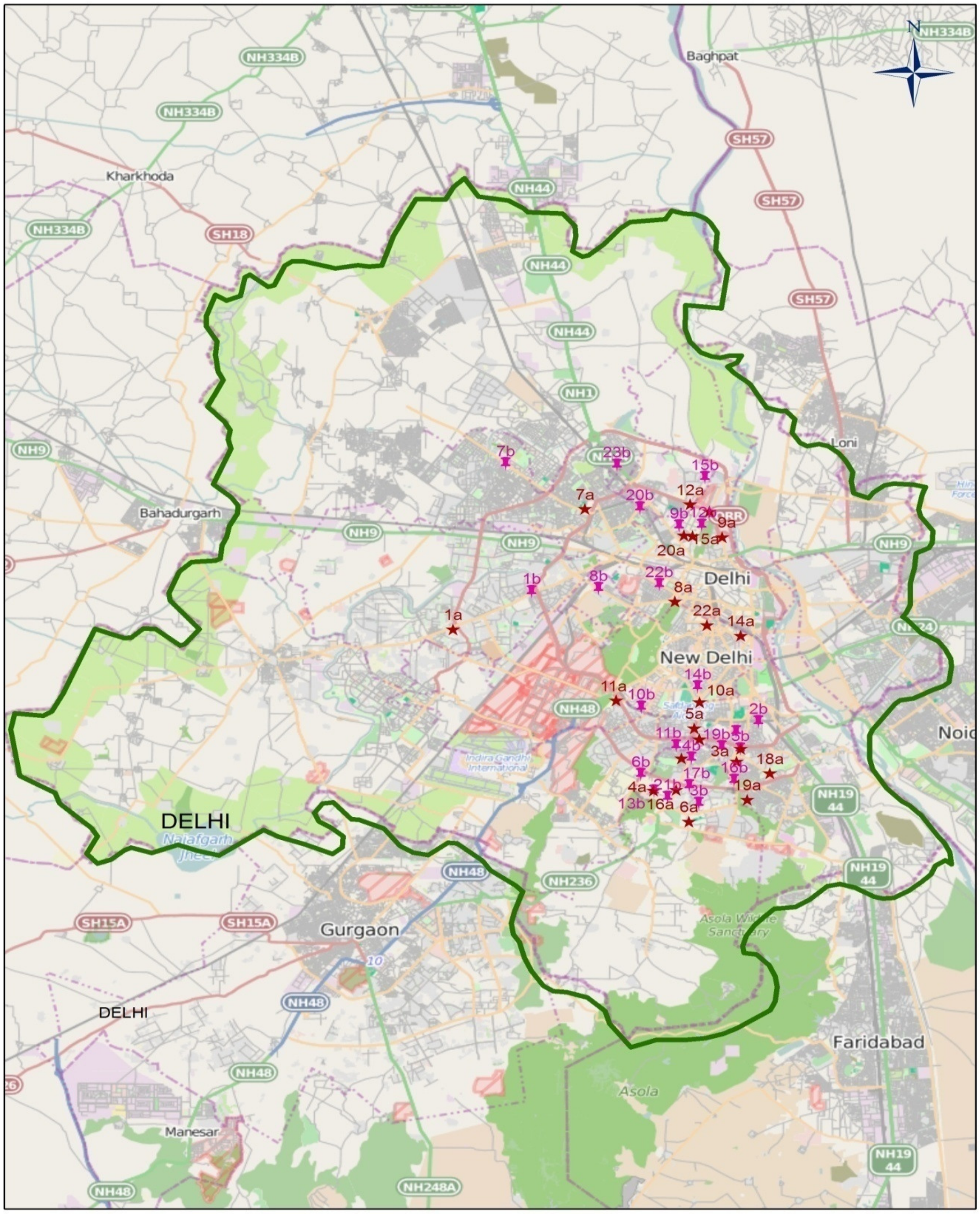
Male and female undergraduate students (our 'actors') from the University of Delhi acted as 'customers' for auto drivers, trained with two dialogues in Hindi – one for the dictator game and the other for the regular transaction. In a dictator-first treatment, an auto is hired at point A and the dialogue for the dictator game translates to "I want to go to place B. I can pay up to Rs. 150. How much will you take?" Thus, the total surplus (over the legal fare) to be distributed between the auto driver and the customer is (approximately) Rs. 100. The auto driver's response (quote) to this question is discreetly (audio) recorded (along with the dialogue) by our actor, alongside other details (in a notebook, without the driver noticing) pertaining to that transaction, such as the time of the day, the day of the week, origin and destination points among still others, as the actor boards the auto. The driver's quote is always accepted and the travel commences. The auto driver's decision corresponds to a dictator game with taking options (Bardsley 2008; List, 2007).

Table 3.1: List of places of origin and destination

Sl. No.	Origin (a)	Destination (b)	Legal Fare (Rs.)	Distance (Kilometers)
1.	INA Metro Station	Moolchand Metro Station	48.20	4.9
2.	Janak Puri Metro Station	Rajori Garden Metro Station	46.60	4.7
3.	Lajpat Nagar Bus Stop	AIIMS Bus Stop	51.40	5.3
4.	N Block Market (GK I)	Malviya Nagar Market	49.80	5.1
5.	Katwaria Sarai	Yusuf Sarai	49.80	5.1
6.	BerSarai	PVR Anupam	51.40	5.3
7.	NSP	Rithala	61.00	6.5
8.	Jhandewalan Metro Station	Shadipur Metro Station	47.40	4.8
9.	IP	Roop Nagar	45.80	4.6
10.	Venkateshwara	Safdarjung Enclave	61.80	6.6
11.	Safdarjung Tomb (Tourist Spot)	Railway Museum (Tourist Spot)	52.20	5.4
12.	GTB Nagar	St. Stephen's	49.00	5.0
13.	Green Park	KatwariaSarai	44.20	4.4
14.	Race Course	Mandi House	49.00	5.0
15.	Kamla Nagar	Batra Cinema	47.40	4.8
16.	Mother's International School	GK II (Apeejay Education Society)	51.40	5.3
17.	Moolchand Metro Station	Hauz Khas Metro Station	43.40	4.3
18.	Nehru Place	Defence Colony Market	52.20	5.4
19.	Kohinoor (GK II)	Ansal Plaza	54.60	5.7
20.	Hans Raj College	Satyawati College	45.00	4.5
21.	Adhchini Crossing	AIIMS Crossing	44.20	4.4
22.	Connaught Place	Karol Bagh	43.40	4.3
23.	Vishwavidalaya Metro Station	Adarsh Nagar Metro Station	57.00	6.0

Notes: [a.]These locations were shortlisted using Google Maps. The exact spots at these locations were chosen so that the coordination between the actors at A and B was convenient enough to ensure that the auto drivers were not 'lost' to another customer. To avoid suspicion (by coordinating over the phone while driven by, and in the presence of an auto driver), these exact spots were surveyed and chosen beforehand to ease coordination. For instance, A would ensure that he (she) stopped the auto close enough to where B was standing, and yet sufficiently far enough from any other customer to maximize the chances that B (and not any other customer) would hire the auto next. The distances reported above, therefore, are slightly different from those that Google Maps would produce (specifically within a deviation/difference of half a kilometer).

Figure 3.1: The choice of locations



When this auto reaches place B, it is hired by another actor (of the same gender) for another transaction that we call the regular transaction. This time the dialogue translates to "I want to go to place A. How much will you take?" The auto driver's response (quote) to this question is again discreetly (audio) recorded (along with the dialogue) by our actor, alongside other details (again in a small notebook, without the driver noticing) pertaining to that transaction such as the time of the day, the day of the week, origin and destination points among still others, as the actor boards the auto.[15] The auto driver's quote is always accepted and the trip completed. However, as the auto driver may have anticipated a counter-offer by our actor, the fare in this regular transaction may be properly regarded as the driver's initial offer in a bargaining game.

The dialogues for the *Regular-First* treatment are the same. The only difference is that the regular transaction precedes the dictator game.

These locations A and B were shortlisted using Google Maps. The exact spots at these locations were chosen so that the coordination between the actors at A and B was convenient enough to ensure that the auto drivers were not 'lost' to another customer. To avoid suspicion (by coordinating over the phone while driven by, and in the presence of an auto driver), these exact spots were surveyed and chosen beforehand to ease coordination. For instance, the actor travelling from A would ensure that he (she) stopped the auto close enough to where the other actor at B waited, and yet sufficiently far enough from any other customer to maximize the chances that the actor at B (and not any other customer) would hire the auto next.[16] Further, for the purposes of effective coordination, each actor in the first transaction of each treatment, sent a text message (while travelling) to the actor waiting at the destination, with the vehicle number of the auto he/she hired in order to ease the task (for the actor at the destination) of looking for the right auto to hire (back to the place of origin). Tracking vehicle

[15]The actors put on earphones connected to their mobile devices, pretending to listen to music.
[16]It will become evident in the next section (from a few differences in the sample sizes across different quotes under each treatment) that we have, in fact, lost some data due to this reason. The most stated reason (on the part of the auto driver) for disagreeing to take the customer (second actor), back to the place of origin, was that the drivers intended to head elsewhere (and not the actor's chosen destination).

numbers also ensured that no auto rickshaw/driver was hired more than once in our experiment.

3.4. Opportunism and compliance

Following the literature on individual interest and social norms (Andreoni and Bernheim, 2009; Dreber et al, 2013; Krupka and Weber, 2013), we suppose that auto drivers have a utility function that includes within it a concern for compliance with metered fares. The utility from a particular transaction takes the following form:

$$U_i = V_i(f) - \gamma_i(s) Max\{0, (f - m)\} \quad (3.1)$$

where, f is the fare received, m is the metered fare, γ is a parameter that indicates how strongly the auto driver is concerned with complying with the metered fare, s is a state of the world that includes the previous history of all transactions and i indexes the auto driver. As argued earlier, transactions are impersonal and so auto drivers are unlikely to be concerned with their social image. The $\gamma(> 0)$ parameter is best interpreted as the costs of non-compliance from the private moral calculus of the auto driver.

From (3.1) it is immediate that auto drivers with a higher γ will be constrained in their choice of fares in the dictator game. They are less opportunistic and will therefore charge lower fares in the dictator transaction.

As for the effect of γ on regular transactions, recall that the fare in these transactions is the initial offer by the auto driver in a bargaining game. Suppose the auto driver believes that there are two types of passengers: informed and uninformed. The informed passenger's maximum willingness to pay (WTP) is less than the WTP of the uninformed passenger. Also assume that while the driver knows the maximum willingness to pay of either passenger type he does not know the type of passenger who is hiring him.

Now suppose the bargaining game is as follows. If the passenger is uninformed, the driver's initial offer is accepted or rejected (depending on the passenger's WTP) and the game ends. If the passenger is informed, the offer is accepted (if the initial offer < WTP) or the customer makes a counter-offer (if the initial offer > WTP). The driver accepts or rejects this offer, depending on his reservation value, and the game ends. The driver knows the structure of this game. It can be seen that in this simple game, that if non-compliance costs are absent, it will always be optimal for the driver to pitch the initial offer to be the WTP of the uninformed customer. The presence of non-compliance costs will drag down the initial offer. Furthermore, the higher is γ, lower will be the initial offer.

This model will, therefore, predict that fares in dictator transactions and fares in regular transactions will be correlated with each other because of their correlation with a common factor: γ. If dictator game quotes and regular fares are uncorrelated, then that may not necessarily invalidate (3.1). This could be the outcome if auto drivers perceive the probability of uninformed passenger types to be negligible and therefore pitch their initial offers to be close to the willingness to pay of informed customers. Unlike in the literature, (3.1) allows the non-compliance costs to be dependent on the state of the world including the history of their own transactions. This is because the dictator transaction in the regular-first treatment follows, within a short interval, a regular transaction on the same route while a dictator transaction in the dictator-first treatment has no prior treatment from us. Similarly, the regular transaction in the dictator-first treatment follows, within a short interval, a dictator transaction on the same route while a regular transaction in the regular-first treatment has no prior treatment from us. If history does not matter, neither the dictator fares nor the regular fares would vary across treatments.

3.5. Descriptive statistics

The experiment was conducted over two waves, the first of which happened in July 2014, and the second, in March 2015. Data was collected between 8:00AM and 11:30AM on all days of the week. In the first wave, only the *Dictator-First* treatment was done. As mentioned earlier, actor X travelled from point A to point B with a dictator game transaction. Actor Y hired the same auto from point B to point A for a regular transaction. For a particular auto, actors X and Y were chosen to be of the same gender to avoid biases stemming from gender specific responses. Actor X returned to point A by randomly selecting another auto using the dialogues for a regular transaction. We call this the control transaction. Notice that it is initiated at about the same time and for the same route as the regular transaction. We did the control to see if the dictator treatment contaminated the responses in the regular transaction. Table 3.2a displays the descriptive statistics from this wave. In this wave, 150 auto drivers received the dictator-first treatment and we have information on their dictator and regular transactions (one less for the latter as we 'lost' this driver to another customer). Another 150 auto drivers served as control transactions.

Table 3.2a: Details of the first wave

Dictator-First Treatment			
Transaction	Observations	Mean Offer	Standard Deviation
Dictator Game	150	95.1200	45.7281
Regular	149	63.9463	17.2379
Control	150	59.1933	11.8767

In the second wave, both treatments were done. The *dictator-first* treatment proceeded as above. The control transaction from point B to A became the first transaction of the *regular-first* treatment. At point A, the auto of the control transaction was hired to go back to point B with a dictator game transaction. Notice that while the regular transactions of the *regular-first* treatment are the control transactions of the *dictator-first* treatment, there are no controls for the regular-first treatment. In particular, regular transactions of the *dictator-first* treatment cannot serve as controls even if they are at the same time and on the same route because the behavior of auto drivers could have been affected by the dictator transactions. The only way to have controls for the regular transactions of regular-first treatment would have been to have stand-alone controls just as it was done in the first wave. However, controls are unnecessary in this case because the regular transactions of the regular-first treatment are uncontaminated by any prior treatment.

Table 3.2b: Details of the second wave

Transaction	Observations	Mean Offer	Standard Deviation
Dictator First treatment			
Dictator Game	287	112.3303	45.3848
Regular	285	71.2386	22.2587
Control	287	64.4007	15.5872
Regular First treatment			
Dictator Game	283	101.2085	45.5082
Regular	287	64.4007	15.5872
Control	N/A	N/A	N/A

Table 3.2b contains the descriptive statistics from the second wave. In this wave, 287 auto drives received the dictator first treatment and we therefore have information on their dictator and regular transactions (minus two for the regular transactions because of reasons mentioned before). Another 287 auto drivers served as controls. However, since these auto drivers were

subsequently hired for a dictator transactions, the controls are the regular transactions in the regular-first transaction. In a very small number of cases, auto drivers declined to be hired for a second time presumably because they did not wish to return to the point of origin. However, it can be seen from Tables 3.2a and 3.2b, that such attrition is negligible.

Waves 1 and 2 are merged in Table 3.3. Overall, we have 720 observations on dictator transactions of which 437 are from *dictator-first* treatment and the remainder from *regular-first* treatment. The number of observations on regular transactions is almost identical; the difference is because of attrition in the second transaction of the treatment. The average distance travelled per trip was 5.04 kilometers, and the metered legal fare for these observations averaged Rs. 49.29.

Table 3.3: Dictator game and regular offers by experiment type

Experiment Type	*Dictator-First (DF) Treatment*	*Regular-First (RF)Treatment*	Combined
N (Dictator)	437	283	720
Mean Offer in Dictator Game	106.4229	101.2085	104.3733
N (Regular)	434	287	721
Mean Regular Offer	68.7350	64.4007	67.0097

3.6. Experiment findings

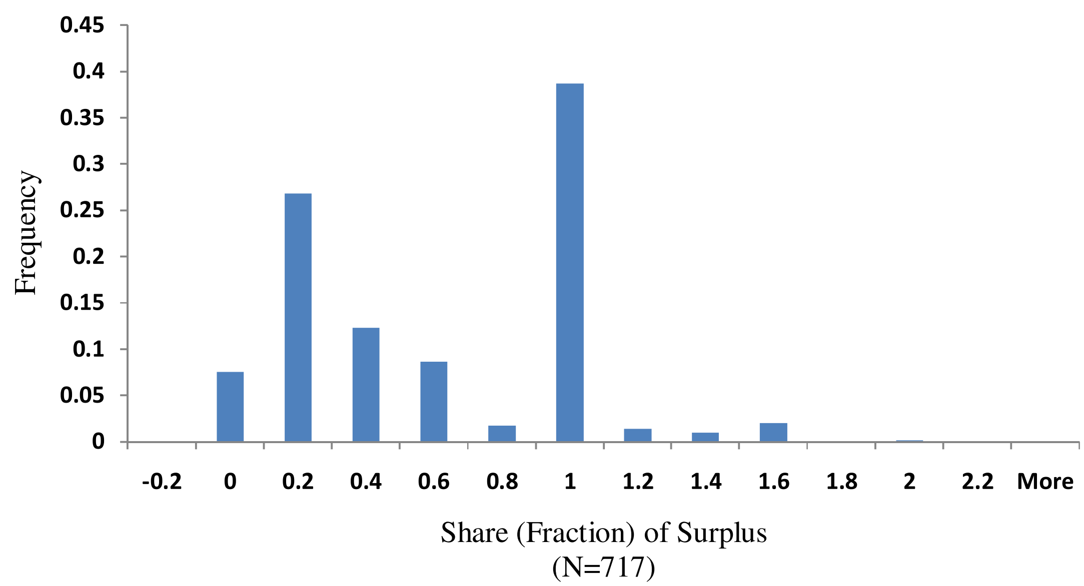
3.6.1. Dictator game transactions

Our variant of a dictator game is different from the rest in the literature, where dictators are known to receive their endowment exogenously from the *experimenters* (even if they have to earn the same), and are instructed to make an offer to their *partners*. In our variant, it is the *partners* who make the dictators' endowment available for the latter to choose how much they would want to keep. Thus, our dictator game is akin to a taking game in the laboratory, where the endowment is earned by the subject who is not the dictator (see Cardenas and Carpenter, 2008).

The literature on dictator games has observed two peaks in the distribution of transfers: Engel's (2011) meta-study of over 100 dictator games shows that, on average, 36.11% of subjects give nothing while about 16.74% of subjects share about 50% of the surplus. In order to make our analysis comparable with the existing literature, we look at the distribution of the 'fraction of surplus' over the legal fare that is retained by the auto driver. This is calculated as shown below (Figure 3.2 shows this distribution).

$$\text{Subject's share of surplus} = \frac{\text{Driver's Quote} - \text{Legal Fare}}{\text{Total Surplus}} = \frac{\text{Driver's Quote} - \text{Legal Fare}}{150 - \text{Legal Fare}} \qquad (3.2)$$

Figure 3.2: Distribution of surplus retained by dictators



Note: While there are 720 dictator game quotes, we do not have the exact legal fares for three transactions because of slightly different routes taken by the auto drivers.

We immediately notice that there is a positive frequency for some values greater than one, which corresponds to quotes above Rs. 150.00. Our actors accepted these fares as well and completed the trips.

Like the literature, Figure 3.2 also exhibits a double-peaked distribution with the higher mode (with a frequency of 38.63%) at the value one, which corresponds to 'consuming the entire pie' (i.e. charging exactly Rs. 150.00), or giving nothing in the lab dictator game. Including those subjects who charged more than Rs. 150, we find that close to 43% settled for amounts that corresponded to consuming the entire pie or more, if possible. Compared to the finding in Engel's meta-analysis (that about 36% of lab subjects give nothing to the recipient), it appears that our subject pool of auto drivers is more opportunistic. However, we also observe a second peak (with a frequency of 26.78%) at the value 0.20, which corresponds to auto drivers keeping only 20% of the pie, and giving away the remaining 80% to the recipient. Since dictators in the lab rarely give away over 50% of the pie size, this finding suggests that our subject pool is *less* opportunistic which is possibly due to the strength of social norms anchored in the legal fare. Thus, charging the legal fare acts as a reference point akin to giving everything away (taking nothing from the recipient) in a laboratory dictator (taking) game. This finding is similar to List (2007) and Bardsley (2008) that observe higher shares resting with the dictators of the dictator game(s) compared with those of the taking game(s). The sense of an implicit entitlement of the endowment resting with the subject who is not the dictator prevents the dictators from keeping too much of the pie. Cardenas and Carpenter (2008) also conclude that giving is positively determined by a perception of how deserving the recipient is. Our design observes this psychological effect of the perception of entitlements. The fact that the dictators may mentally overcome such psychological considerations because they are *earning* at least, a part of the endowment by offering a well-defined service, makes our setting all the more interesting. As many as 7.5% stick to the legal fare (corresponding to giving everything away to the recipient in the dictator game) compared to the average of 5.4% for a similar response in Engel's meta-study. These results broadly point to the heterogeneity in subject responses. In terms of equation (3.1), it would seem that the trade-off between opportunism and bearing the costs of non-compliance (summarized by the parameter γ) is felt differently by different auto drivers. The average percentage of surplus retained by subjects in the sample is 55% (with standard error of 1.7). The giving rate of 45% is substantially higher than the average offer of 28.35% reported in Engel's meta-analysis. While the average is comparable to the 50-50 split commonly observed in games with audience effects (Andreoni and Bernheim, 2009), it is not the modal value and is simply the outcome of behavior extremes of opportunism and pro-social behavior.

We now come to the predictors of dictator game offers. Table 3.4 compares the dictator game fares between the *dictator-first* and *regular-first treatments.* The fare in the *Dictator-First* treatment is, on average, higher than in the *Regular-First* by about five Rupees. The difference is significant at the 1% level. The dictator fare in the *Regular-First* treatment is influenced by the prior regular transaction. The *Regular-First* dictator has just travelled the exact same route (albeit in the opposite direction) and he knows for sure the distance and the legal fare. The *Dictator-First* treatment does not receive this mental cue.

The table also shows a significant difference (by about eight Rupees) between the fares charged to male actors and the fares charged to female actors. This cannot be explained by an assessment that women have lower willingness to pay or by a preference for carrying female passengers (all auto drivers are males) because the maximum willingness to pay is the same for male and female actors and auto drivers know that the passenger would not decline the ride as long as the fare is less than Rs. 150.

Table 3.4: T-test of dictator game prices by experiment type and gender

Experiment Type	Dictator Game N (1)	Dictator Game Mean (2)	Gender Type	Dictator Game N (3)	Dictator Game Mean (4)
Dictator-First (DF) Treatment	437	106.4229 (2.2091)	*Male*	233	109.8927 (2.8689)
Regular-First (RF)Treatment	283	101.2085 (2.7052)	*Female*	487	101.7326 (2.1194)
Combined	720	104.3733 (1.7127)		720	104.3733 (1.7127)
Difference		5.2144 (3.5035)			8.1601 (3.6506)
P Value against *DF > RF*; *M>F*		0.0686			0.0129
T Statistic (d.f.)		1.4883 (718)			2.2352 (718)

The effect of treatment and gender on dictator fares suggests that non-compliance costs are contextual and depend on the state of the world. Our findings relate with that of Castillo et al (2013), that concludes that women commuters get better deals due to statistical discrimination. This is explored further in Tables 3.5a and 3.5b where dictator game offers are regressed on the experiment type, gender, distance, month of experiment, and week day dummies. The difference between the tables is that in Table 3.5a, the dependent variable is dictator fares while in Table 3.5b the dependent variable is the share of surplus retained by the auto driver.

The results are similar in both tables. The regressions confirm that dictator fares and the proportion of surplus retained by the subject are higher if the passenger is male and if the treatment is *Dictator-First*. The regressions also show that dictator fares are higher for longer distances and for the experiment conducted in the second wave. The latter result suggests that opportunism, in the calculations of auto drivers, has greater justification for greater effort and for uncompensated inflation.[17]

Table 3.5a: Predictors of dictator game offers

Dependent Variable: Dictator Prices	Full Sample Least Squares (1)	Full Sample Least Squares (2)	Full Sample Least Squares (3)
Gender	7.9291**	9.5339***	9.6265***
(Male = 1)	(3.5852)	(3.5904)	(3.6164)
Regular-First	-6.3785*	-11.1331***	-11.1759***
	(3.5045)	(3.7784)	(3.7638)
Distance	11.8592***	9.2266***	11.3397***
	(3.2605)	(3.3571)	(3.4297)
Second Wave		15.2858***	14.7815***
		(4.7259)	(4.7625)
Sunday			-1.6870
			(5.6980)
Monday			4.5710
			(6.4667)
Tuesday			-11.5336
			(5.9677)
Thursday			-8.3324
			(6.6130)
Friday			-8.7683
			(6.4897)
Saturday			-6.2015
			(5.9411)
Constant	44.6682***	47.1292***	41.4161**
	(16.3557)	(16.4095)	(16.6590)
R-Squared	0.0287	0.0425	0.0540
P Value for Joint Significance	0.0002	0.0000	0.0000
N	717	717	717

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively. The regression results remain unchanged with the inclusion of location dummies.
[b.] Robust standard errors reported in parentheses

[17]The average year on year inflation, for the period between the two waves (July 2014 to March 2015) was 6.12% (Source: *Economic Political Weekly* Database for Consumer Price Index of Industrial Workers for All India, 2015).

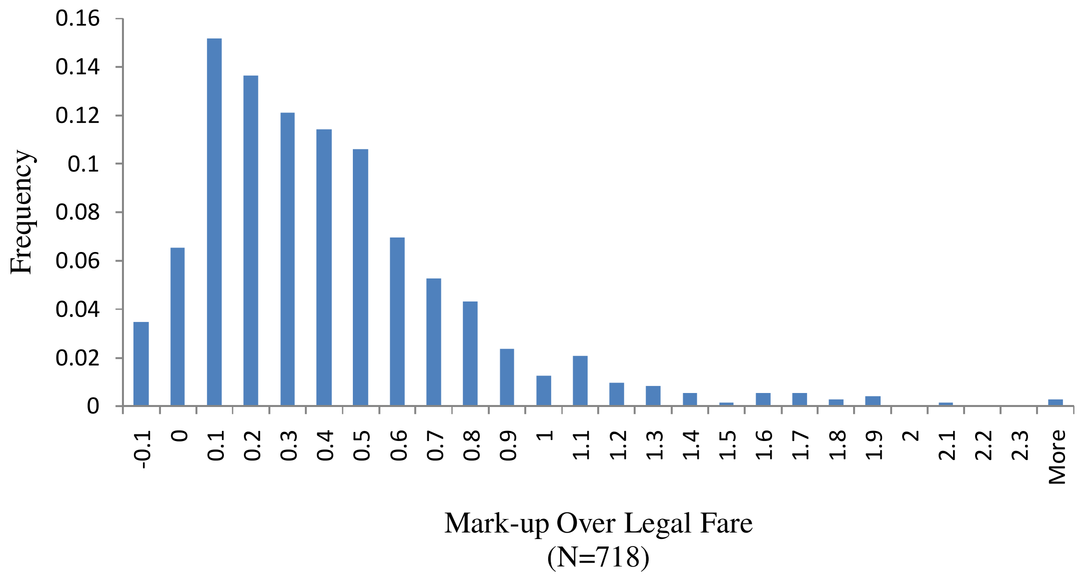
Table 3.5b: Predictors of surpluses retained by dictators

Dependent Variable: Surplus	Full Sample Least Squares (1)	Full Sample Least Squares (2)	Full Sample Least Squares (3)
Gender	0.0762**	0.0917***	0.0926***
(Male = 1)	(0.0357)	(0.0357)	(0.0361)
Regular-First	-0.0620*	-0.1080***	-0.1084***
	(0.0350)	(0.0379)	(0.0377)
Distance	0.0851**	0.0596*	0.0807**
	(0.0339)	(0.0349)	(0.0357)
Second Wave		0.1481***	0.1432***
		(0.0464)	(0.0468)
Sunday			-0.0130
			(0.0564)
Monday			0.0456
			(0.0632)
Tuesday			-0.1150
			(0.0592)
Thursday			-0.0841
			(0.0664)
Friday			-0.0812
			(0.0642)
Saturday			-0.0576
			(0.0587)
Constant	0.1206	0.1445	0.0854
	(0.1688)	(0.1696)	(0.1721)
R-Squared	0.0196	0.0327	0.0444
P Value for Joint Significance	0.0053	0.0001	0.0000
N	717	717	717

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively. The regression results remain unchanged with the inclusion of location dummies.
[b.] Robust standard errors reported in parentheses

The last result provides support for the view that overcharging is, in part, due to difficult economic circumstances (Harding, 2010; Mohan and Roy, 2003).

Figure 3.3: Distribution of regular fares as a mark-up over the legal fare



3.6.2. Regular transactions

Figure 3.3 shows the distribution of regular offers as a percentage markup over legal fares for both the treatments combined. We see that only 10.02% of the drivers choose to stick to the legal fare or even less (the latter is usually the cause of the auto drivers' willingness to give up some amount in the absence of change), and 89.98% of the drivers quote an amount that is the legal fare plus a positive mark-up, thereby confirming that overcharging is a fact of life. About 28.83% of the drivers tend to make an initial quote that equals a mark-up of 10% to 20% over the legal fare.

The regular transaction fares in the *Dictator-First* treatment can be compared with their control transaction fares (which in wave 2 are nothing but the regular transaction fares of the *Regular-First* treatment). A pair-wise t-test for the equality of the means of regular fares and the control prices for all the 434 observations in the *Dictator-First* treatment yields a t statistic value of 5.3 associated with a negligible p-value. It would, therefore, seem that the experience of a dictator game transaction immediately before a regular transaction tends to significantly increase (by Rs. 6.15) the average offer of the latter (Rs. 68.74) compared with that of the control prices (Rs. 62.59).

To confirm this, we ran a regression of regular transaction quotes on the same set of controls. The results are reported in Tables 3.6a (where the dependent variable is regular transaction quotes) and 3.6b (where dependent variable is the percentage markup of the regular fare over the legal fare). Regular transaction fares and its markup over the regular fare are lower in *Regular-First* transactions. Gender and the second wave dummy have qualitatively the same impacts as in dictator transactions; however, their significance is weaker. Distance has a positive and strongly significant impact on regular transaction fares but the effect is negative on the percentage markup over the legal fare.

Compared to the dictator transaction results, the interpretation of these findings is not straightforward. In dictator game transactions, the maximum willingness to pay is known and held constant at Rupees 150. Hence the correlation of the independent variables with dictator transaction fares could be attributed to the effect of these variables on the parameter γ.

In regular fare transactions, on the other hand, the independent variables could vary both with the γ parameter as well as auto driver's perception of the passenger's willingness to pay as well and it is not possible to disentangle these effects. Thus, the higher regular transaction fares in the *Dictator-First* treatment could be because the prior dictator transaction stokes opportunism but it is just as likely that it leads the subjects to revise the willingness to pay of the passengers. A similar story could be told for the other controls as well.

Table 3.6a: Predictors of regular offers

Dependent Variable: Regular Prices	Full Sample Least Squares (1)	Full Sample Least Squares (2)	Full Sample Least Squares (3)
Gender	1.8752	2.3954	2.4839
(Male = 1)	(1.5223)	(1.5119)	(1.5502)
Regular-First	-5.3069***	-6.8482***	-6.8310***
	(1.3677)	(1.5798)	(1.5601)
Distance	7.8061***	6.9669***	7.4638***
	(1.4071)	(1.4666)	(1.5141)
Second Wave		4.9540**	4.8918**
		(1.9953)	(2.0290)
Sunday			-3.4421
			(2.3255)
Monday			2.3254
			(2.8176)
Tuesday			-8.5878
			(2.3479)
Thursday			-0.1560
			(2.9005)
Friday			-5.5372
			(2.4663)
Saturday			-3.3394
			(2.6497)
Constant	29.2703***	29.9962***	30.8671***
	(6.9381)	(6.9802)	(7.2298)
R-Squared	0.0627	0.0710	0.0930
P Value for Joint Significance	0.0000	0.0000	0.0000
N	718	718	718

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively. The regression results remain unchanged with the inclusion of location dummies.
[b.] Robust standard errors reported in parentheses

Table 3.6b: Predictors of mark-up over the legal fare

Dependent Variable: Regular Mark-ups	Full Sample Least Squares (1)	Full Sample Least Squares (2)	Full Sample Least Squares (3)
Gender	0.0463	0.0568*	0.0584*
(Male = 1)	(0.0306)	(0.0304)	(0.0311)
Regular-First	-0.1089***	-0.1400***	-0.1397***
	(0.0273)	(0.0316)	(0.0313)
Distance	-0.0516**	-0.0686**	-0.0582**
	(0.0262)	(0.0276)	(0.0284)
Second Wave		0.1000**	0.0988**
		(0.0411)	(0.0417)
Sunday			-0.0785
			(0.0478)
Monday			-0.0595
			(0.0577)
Tuesday			-0.1745
			(0.0482)
Thursday			-0.0143
			(0.0578)
Friday			-0.1193
			(0.0512)
Saturday			-0.0744
			(0.0544)
Constant	0.6522***	0.6668***	0.6895***
	(0.1314)	(0.1323)	(0.1378)
R-Squared	0.0320	0.0407	0.0628
P Value for Joint Significance	0.0000	0.0000	0.0000
N	718	718	718

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively. The regression results remain unchanged with the inclusion of location dummies.
[b.] Robust standard errors reported in parentheses

3.6.3. Correlation between dictator and regular transaction fares

Consider the *Regular-First* treatment. Could the regular transaction fares predict the dictator fares in the subsequent transaction? Figure 3.4a shows the scatter of regular and associated dictator transactions and a linear plot between the two. The suggestive relation in the figure is probed further by a regression of the dictator fare (the second transaction) on the regular transaction fare (the prior transaction) as well as other controls. The results are in Tables 3.7a. Table 3.7b has the regressions for the case when dictator and regular transactions are in logs.

We see that regular prices are significant predictors of dictator game quotes. A 10% increase in dictator game fares is associated with a 4% increase in regular transaction fares. Figure 3.4b is the prediction from a semi-parametric regression of dictator transaction fares on regular fares (controls other than regular fares enter the function linearly). This demonstrates the positive association between these fares and, therefore, how an auto driver behaves in a dictator game can be predicted by how he behaves in a regular transaction.

Table 3.7a: Predicting dictator game offers in the *Regular-First Treatment*

Dependent Variable: Dictator Prices	Sample: *Regular-First* Least Squares (1)	Sample: *Regular-First* Least Squares (2)	Sample: *Regular-First* Least Squares (3)
Regular Offer	0.4593***	0.4415**	0.4378**
	(0.1766)	(0.1834)	(0.1808)
Distance	12.5058***	12.5590***	15.5052***
	(4.8503)	(4.8671)	(5.0363)
Gender		15.1060***	16.0334***
(Male = 1)		(5.8149)	(5.7530)
Sunday			6.4293
			(8.5941)
Monday			21.7770
			(9.9382)
Tuesday			-6.9274
			(9.2804)
Thursday			-2.5750
			(10.1478)
Friday			7.9551
			(10.6340)
Saturday			-0.1286
			(9.2821)
Constant	7.6691	4.1687	-13.7620
	(25.3652)	(25.5457)	(25.7652)
R-Squared	0.0607	0.0834	0.1135
P Value for Joint Significance	0.0002	0.0001	0.0002
N	283	283	283

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively. The regression results remain unchanged with the inclusion of location dummies.
[b.] Robust standard errors reported in parentheses.

Table 3.7b: Predicting dictator game offers in the *Regular-First Treatment*

Dependent Variable: Log(Dictator Prices)	Sample: *Regular-First* Least Squares (1)	Sample: *Regular-First* Least Squares (2)	Sample: *Regular-First* Least Squares (3)
Log(Regular Offer)	0.4174***	0.4050***	0.3958***
	(0 .1290)	(0.1307)	(0.1292)
Distance	0.1316***	0.1322***	0.1643***
	(0.0502)	(0.0503)	(0.0522)
Gender		0.1557**	0.1639***
(Male = 1)		(0.0613)	(0.0606)
Sunday			0.0758
			(0.0904)
Monday			0.2318
			(0.1058)
Tuesday			-0.0767
			(0.1005)
Thursday			-0.0292
			(0.1039)
Friday			0.0838
			(0.1140)
Saturday			-0.0154
			(0.0947)
Constant	2.1066***	2.1101***	1.9533***
	(0.5432)	(0.5527)	(0.5469)
R-Squared	0.0793	0.1012	0.1338
P Value for Joint Significance	0.0000	0.0000	0.0002
N	283	283	283

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively. The regression results remain unchanged with the inclusion of location dummies.
[b.] Robust standard errors reported in parentheses.

Figure 3.4a: Dictator game offers can be predicted by regular transactions

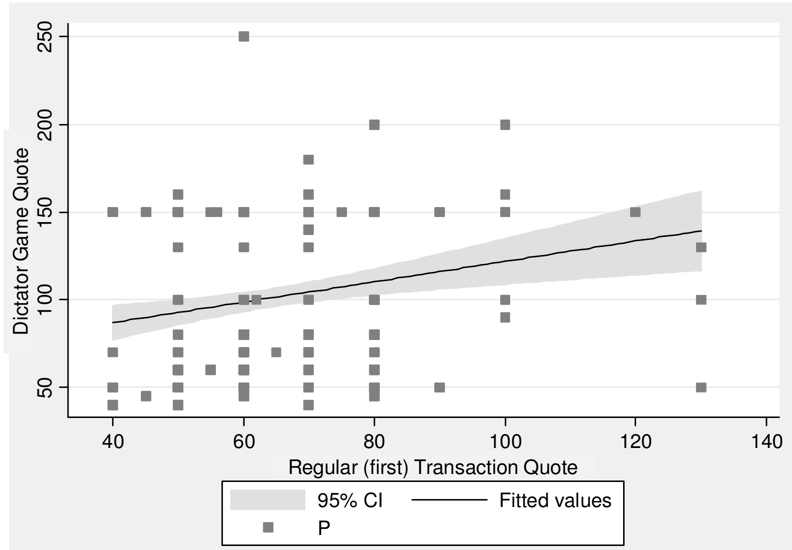


Figure 3.4b: Dictator game offers can be predicted by regular transactions (semi-parametric plot)

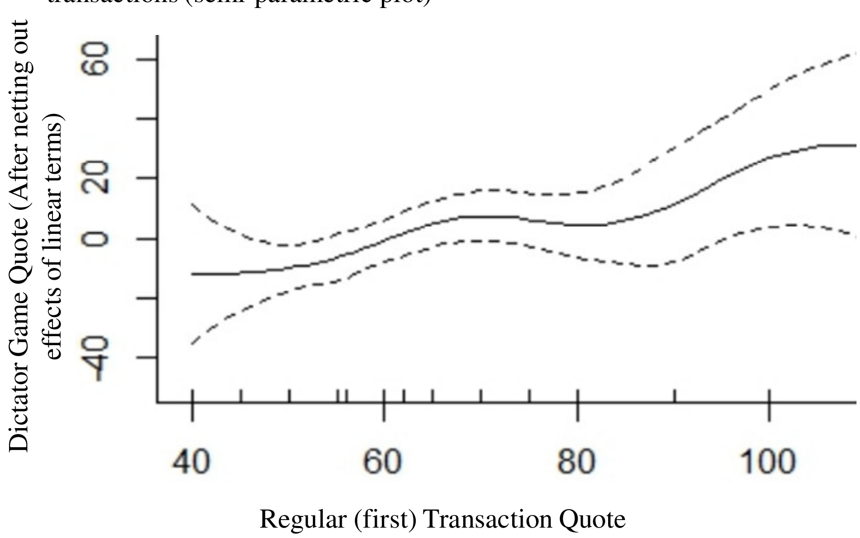


Figure 3.5a: Regular transactions can be predicted by dictator game offers

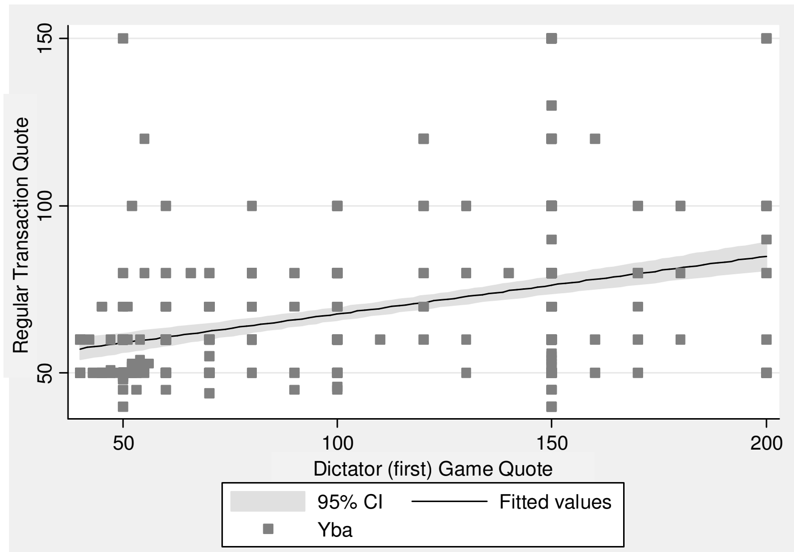
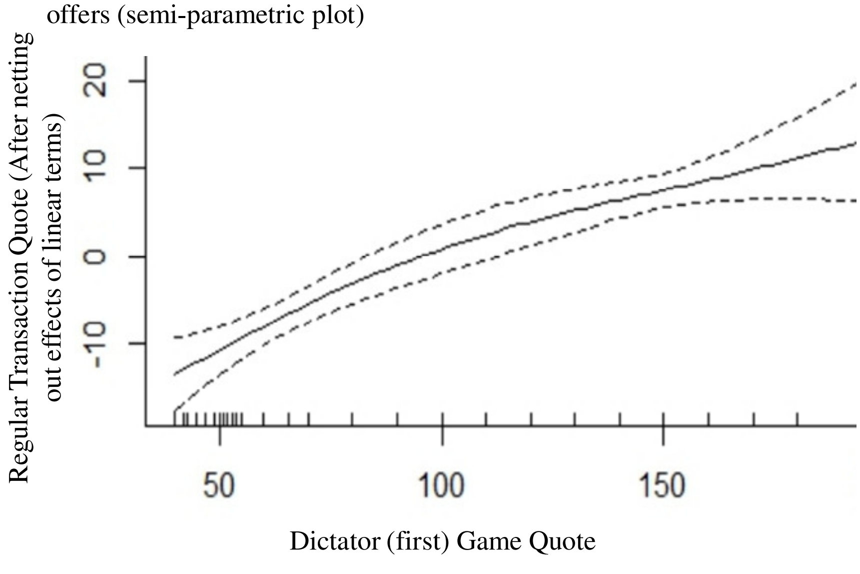


Figure 3.5b: Regular transactions can be predicted by dictator game offers (semi-parametric plot)



Is this true of the reverse as well? Can the dictator game behavior in the *Dictator-First* treatment predict behavior in regular transactions? The scatter plot in Figure 3.5a suggests that this could well be the case.

Table 3.8a: Predicting regular price offers in the *Dictator-First Treatment*

Dependent Variable: 'Regular' Prices	Sample: *Dictator-First* Least Squares (1)	Sample: *Dictator-First* Least Squares (2)	Sample: *Dictator-First* Least Squares (3)
Dictator Game Offer	0.1648***	0.1607***	0.1577***
	(0.0213)	(0.0218)	(0.0218)
Distance	6.2466***	5.5130**	5.5861**
	(1.9972)	(2.1969)	(2.2032)
Gender	1.7276	2.1842	2.2702
(Male = 1)	(1.9158)	(1.9204)	(1.9386)
Second Wave		2.6922	2.7491
		(2.0275)	(2.0686)
Sunday			-0.9176
			(3.2343)
Monday			0.4508
			(3.8477)
Tuesday			-6.2633
			(3.1488)
Thursday			3.4662
			(3.7869)
Friday			-2.7991
			(3.3556)
Saturday			-1.0388
			(3.4707)
Constant	19.5792*	21.7425**	22.7689**
	(10.3329)	(10.8757)	(11.2802)
R-Squared	0.1703	0.1734	0.1900
P Value for Joint Significance	0.0000	0.0000	0.0000
N	431	431	431

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively. The regression results remain unchanged with the inclusion of location dummies.
[b.] Robust standard errors reported in parentheses.

Table 3.8b: Predicting regular price offers in the *Dictator-First Treatment*

Dependent Variable: Log('Regular' Prices)	Sample: *Dictator-First* Least Squares (1)	Sample: *Dictator-First* Least Squares (2)	Sample: *Dictator-First* Least Squares (3)
Log(Dictator Game Offer)	0.2162***	0.2107***	0.2073***
	(0.0243)	(0.0250)	(0.0251)
Distance	0.0829***	0.0740***	0.0746***
	(0.0252)	(0.0275)	(0.0275)
Gender (Male = 1)	0.0273	0.0329	0.0336
	(0.0240)	(0.0243)	(0.0244)
Second Wave		0.0328	0.0336
		(0.0264)	(0.0269)
Sunday			-0.0133
			(0.0405)
Monday			-0.0050
			(0.0472)
Tuesday			-0.0808
			(0.0407)
Thursday			0.0404
			(0.0458)
Friday			-0.0392
			(0.0416)
Saturday			-0.0212
			(0.0432)
Constant	2.7847***	2.8301***	2.8601***
	(0.1647)	(0.1754)	(0.1805)
R-Squared	0.1896	0.1924	0.2081
P Value for Joint Significance	0.0000	0.0000	0.0000
N	431	431	431

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively. The regression results remain unchanged with the inclusion of location dummies.
[b.] Robust standard errors reported in parentheses.

To confirm this, we regress the regular transaction fares of the *Dictator-First* on the associated dictator fares and controls. The results are in Tables 3.8a and 3.8b (where fare variables are in logs). We see that the dictator transactions predict regular fares as well. In other words, an auto driver's regular transactional habits can be predicted remarkably well by his responses in the dictator games. This is also shown by the graph (Figure 3.5b) of the predicted regular transaction fare from a semi-parametric regression where all controls other than the dictator fare of the preceding transaction enter linearly.

The correlation between dictator and regular transactions (controlling for gender, distance, and wave) is consistent with the model in equation (3.1): that individuals trade-off between opportunism and compliance to metered fares. Thus those with higher values of the parameter γ choose lower dictator and lower regular transaction fares. It is possible that, in the *Dictator-First* treatment, the higher regular fares follow higher dictator fares because the more opportunistic individuals are also more likely to revise upwards the passenger's willingness to pay. Such an effect, however, cannot explain why higher dictator fares (where willingness to pay is known and fixed) follow higher regular fares in the *Regular-First* treatment.

3.7. Conclusion

This paper has reported on a field dictator game experiment with auto taxi drivers of New Delhi. The paper uses the dictator game setting to uncover the tension between opportunism and compliance to metered fares. This follows recent literature that posits utility functions as a sum of sub-utilities deriving from self-interest and from compliance to a social norm (the understanding of the latter being a particularly important issue (Guala and Mittone, 2010). It may be noted that while a disclosure of the maximum willingness to pay is a relatively rare event, auto drivers do, on a regular basis, meet customers who are clueless about the details of a transaction. Field experiments sometimes do have a cost of contextualization equivalent to making the experiment itself a rare event. For example, how likely is someone to receive a sealed cash envelope when the intended recipient is in fact, someone else (see Stoop, 2014)?

A testable implication of this model is that opportunism (or pro-social behavior) in dictator games would be correlated with opportunism (or pro-social behavior) in real-world transactions. The paper demonstrates this correlation in a natural experiment. Although the law requires fares to be metered, there is widespread acknowledgement that this is not always observed. Nonetheless, our findings show, that a desire to be compliant constrains opportunism. Indeed, the opportunism of taxi drivers in the dictator game is less than the average opportunism in lab dictator games as summarized by Engel (2011). To be sure, the law is not fully effective. However, neither is it completely ineffective.

The second significant finding of our experiment is that the costs of opportunism are contingent. The literature has emphasized some factors such as social framing and social control. Our experiment is in a field setting and therefore there is no variation in social framing. Social control is unimportant because transactions are impersonal as one would expect in taxi hiring in a large city. The costs of opportunism, if at all, stem from the subject's own private costs of non-compliance and possibly the subject's perceptions of the risks from overcharging (in terms of trouble with police). In this experiment, the willingness to depart from metered fares varies systematically with gender of passenger, distance travelled, uncompensated inflation and the type of experiment. Depending on the values of these variables, subjects are willing to persuade themselves to be opportunistic.

This research can also be seen as an addition to the literature on experiments in developing countries (see Ado and Kurosaki, 2014; Henrich et al, 2006; Henrich et al, 2001), and, by extension, the literature that draws a comparison of subject behavior between developing and developed countries. For instance, Cardenas and Carpenter (2008), and Henrich and Henrich (2007) do a comparison of results in Carpenter et al. (2005); Ashraf et al. (2006); Holm and Danielson (2005); Ensminger (2000); Gowdy et al. (2003); and Henrich et al. (2006) among others. An interesting extension of this study would be that of gender effects in a location where there are female cab drivers as well (see Eckel and Grossman, 1998 for gender effects in dictator games; see Friesen and Gangadharan, 2012 for gender differences in dishonesty; and see Dasgupta, 2011, that interestingly establishes that female dictators are more sensitive to variations in entitlement processes). Finally, we connect our research to literature that connects behavior in a game to that in the real world (see Charness and Fehr, 2015; Fehr and Leibbrandt, 2011; Liu, 2013; and Karlan, 2005).

Lastly, we would like to point out that Auto-drivers could be opportunistic even in the Regular transactions. In the Dictator transactions though, the maximum willingness to pay is a reference point for opportunism which is therefore, more socially acceptable in this scenario. The costs of deviating from the legal fare on moral grounds in the Regular transaction should exceed that in the Dictator transaction. It should be noted that the legal implications of over-charging are the same in both transactions. Thus, the moral costs of non-compliance may vary across transactions. This may be worth exploring in future research since the transactions allow for a difference in morality or fairness cost, keeping legal compliance costs the same.

Chapter 4

Testing for Fairness in Regulation: Application to the Delhi Transportation Market*

4.1. Introduction

When a regulatory authority steps in to take a decision on any issue raised by two or more conflicting groups of individuals, fairness considerations often crop up. For instance, if the government decides that construction workers in New Delhi deserve a minimum of just over Rupees (Rs.) 200 per day, for all the labour they supply, such a decision is often a result of recommendations of task forces or working groups who address several questions which revolve around fairness considerations. Questions like – "will it be *fair* to offer just Rs. 200 to an average labourer who runs a family of six under the present inflationary conditions?" are often addressed. Assessing the existence of (implicit) fairness considerations in (observed) regulatory decisions involve value judgments and renders their econometric testing an open question.[1]

This paper evaluates real-life transactions in the auto rickshaw (auto hereafter) market characterised by regulated prices that are hardly taken seriously. Auto drivers and customers choose instead to bargain on the prices among themselves. This is possibly because auto drivers do not perceive regulated prices as 'fair' and costumers, on recognizing this, are

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[1] We are aware of no previous study that examines regulatory interventions on the grounds of fairness.

willing to pay higher than legally prescribed rates without complaining, thus adding to enforcement related problems. The idea of 'fairness' itself, is open to subjective interpretation. I formalise the same using Rabin's, 1993 approach. I examine the historically observed regulatory fare hikes in this market and conclude that they are consistent with (theoretical) fairness prices that would prevail if each auto driver had some market power but valued fairness considerations held by customers. Since the nature of bargaining remains unobserved (I do not know what axioms actually characterise the real life negotiations and thus make no assumption on the same), I do a robustness check with different models of cooperative bargaining to conclusively establish the results. The interested reader could look into (experimental) evidence on the validity of such axioms (Nydegger and Owen, 1975).[2] Finally, I make a case for metro rail (metro hereafter) network extension as a direct substitute for autos (among other forms of transportation) for increased compliance with legally announced fares. While I am not aware of any previous study aimed at empirically evaluating regulatory decisions on the grounds of fairness, this work adds to the contributions of Chaudhuri and Gangadharan, 2007; and Kahneman et al, 1986, among others that largely study the nature of fairness considerations in games of trust and those in varied market situations.[3] This work also relates to the works of Uchida, 2006; Andreoni and Vesterlund, 2001; and Comay et al, 1974 among others that focus on the significant determinants of bargaining. The point that focuses on the effects of (metro) railway construction can be closely related to the works of Banister and Berechman, 2001; and Blum et al, 1997.

To offer an introductory note to the organisation of our paper, let us think of two periods 1 and 2, each divided into sub-periods (a) and (b). Then the auto-market story can be summarised as follows.

[2] See Moulin, 1988; Roth, 1979; and Thomson, 1994 for more detailed discussions.
[3] More work on fairness is cited in Chaudhuri, 2009, and Moulin, 2003.

Period 1(a): Drivers charge price $P(1a) > L(1a)$, the prevailing legal fare.

Regulation hikes (to prevent bargaining) the legal fare to $L(1b) > L(1a)$.

Period 1(b): Drivers go by the legal fare $L(1b)$ throughout this sub-period.

Period 2(a): Drivers charge price $P(2a) > L(2a) = L(1b)$, the prevailing legal fare.

Regulation hikes (again, to prevent bargaining) the legal fare to $L(2b) > L(2a)$.

Period 2(b): Drivers go by the legal fare $L(2b)$ throughout this sub-period.

Using prices $P(1a)$, which are related to $L(1a)$ above, I use different bargaining rules to infer valuations $W(1a)$. Using information on $W(1a)$, I work out Rabin's 'fair prices' $Z_U(1a)$ and $Z_L(1a)$, which are respectively the upper and lower bounds for all prices comprising fairness equilibria. I argue that the *next* regulatory hike $L(1b)$, which is not considered in calculating $W(1a)$, (and hence the fair prices) above, remarkably lies in the Rabin's range of fair prices – or more specifically, that $Z_U(1a) > L(1b) > Z_L(1a)$. Similarly, I do the same exercise for Period 2 and argue that $Z_U(2a) > L(2b) > Z_L(2a)$. In other words, the regulatory authority does raise fares, but only (and always) subject to fairness considerations held by the customers (in the immediate or a recent past).

4.2. The auto-rickshaw market

The market for autos (three wheelers) services in Delhi, India, presents itself as a prominent case of regulation failure. Auto drivers are supposed to charge consumers based on regulated fare, which depends on the distance travelled, luggage and time of the day (night rates are higher than day rates). This fare is displayed on a taximeter (meter, hereafter) attached to the autos. The meter also shows the distance travelled and is supposed to be reset individually for every customer, since different customers have different starting points and destinations and accordingly travel different lengths of distance, they therefore, must pay different fares. These meters, however, are hardly used by auto drivers and instead, the resultant fares paid by customers are pre-negotiated or bargained with these auto drivers before any journey. While customers prefer travelling by the meter, they generally give in to the auto drivers' desire for a mark-up over the publicly known legal fare. It is this mark-up (and hence, effectively the total price) that the customers and drivers bargain over.

In a nutshell, although there exists a regulated legal fare, we observe bargaining in this market. The customers' preference to travel on a pre-negotiated basis, over filing complaints signals their belief that legal fare rates are perhaps not 'fair' to auto drivers (in fact, whatever little evidence there is of such complaints, only confirms the fact of poor enforcement). It is interesting that although there are over 55,000 autos[4] on Delhi roads everyday auto drivers hardly compete for customers. They are in fact, known to charge two customers differently for exactly the same journey[5] – a given customer may also end up paying different amounts for the same journey on two different days because (say) on one of the days he may have to reach the given destination urgently.[6,7] The evidence given by Kahneman et al., 1986 that highlights a strong preference for equity, even if it is costly in terms of personal material utility, suggests that customers may be willing to pay higher, but uniform amounts rather than different amounts even if they could be possibly lower.[8]

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[4] This is a number good enough to qualify for perfect competition. However, the negotiated prices are often a mark-up on the legal fare, highlighting that Indians are relatively tolerant to corrupt and unjust practises (Cameron et al, 2009).

[5] Same journey refers to the same starting point and the same destination (hence the same distance) and during the same time interval of the day.

[6] Comay et al, 1974 argues that one's bargaining ability can be affected by his or her level of impatience.

[7] Babcock, Wang and Lowenstein, 1996, and Frank, 1985, provide similar examples that highlight this issue of comparison broadly. In the words of Bohnet and Zeckhauser, 2004, "prospective employees typically do not compare their wage (or wage less reservation price) with the surplus the employer reaps from their employ, but rather with the wages of similarly suited employees." We expect customers to do the same.

[8] Bohnet and Zeckhauser, 2004 show that both social comparison and pie-size information substantially increase subsequent offers made by proposers in an ultimatum game – the implicit revelation of willingness to pay by a

The caps on the maximum number of operational auto licenses during the last ten years, have acted as entry barriers. They have been justified on the grounds of *increased road congestion* owing to the rapidly growing population (and hence private vehicles) in Delhi and the work-in-progress metro constructions (that prohibited driving on certain areas in Delhi) that added to the same for the period of focus in this paper.[9,10] We expect peoples' impatience to be strictly increasing and convex in elapsed time (Comay et al, 1974) since congestion is an economic bad (additionally see Bose, 1996).

My (elementary) findings suggest that customers, on an average, paid amounts, as high as, close to 20% more than the legally accepted fare. In fact, between August 2007 and August 2008, auto drivers managed to earn well over Rs. 180.00 crores (approx. $46.31 million) more than what they could have legally earned (that is, if they had only travelled by the meter). Auto drivers largely come from low income family groups primarily based in Uttar Pradesh and Bihar. Not many can afford to buy auto rickshaws and thus take them on rent on a daily basis from their actual owners. Before March 2001, however, most of the autos were owner driven. A regulation favouring a cleaner fuel (from motor spirit/petrol to Compressed Natural Gas (CNG hereafter) during that time required these owners to spend Rs.30,000 for retrofitting of their vehicles with CNG kits.[11] The auto owners could not afford these expenses on such short notice. Formal credit markets traditionally did not advance loans to the auto drivers. Drivers therefore resorted to private financiers who charged high interest

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customer by agreeing to pay higher than the legal fare generates a subsequent 'norm' of higher prices. Rejection rates of settling on a transaction, however, also get higher since a higher proportion of offers are now perceived to be low (by the drivers), even if they are actually higher than prescribed by existing regulation.

[9] "Despite increase in road length, the average speed of vehicles is expected to drop from the existing 15 kilometre per hour to 10 kilometres per hour in the national Capital by the end of 2011." – Rajesh Kumar, *"Average speed of vehicles to drop to 10 km/hr: Report"*, June 7, 2010, *The Pinoeer.*
(link: http://www.dailypioneer.com/260874/Average-speed-of-vehicles-to-drop-to-10-km/hr-Report.html)

[10] Having more auto rickshaws operating on Delhi roads could only worsen the problem and possibly even increase the time an auto driver spends travelling with a particular customer, which means that more time would be lost at earning the same amount from the given customer. More time per customer directly translates to lesser number of customers per day, and hence lesser daily earnings.

[11] After vacillating for almost two years, the government went about implementing this decision in a haphazard and hasty manner.

rates. On the non-payment of debt, the drivers were forced to sell their vehicles to private financiers who retrofitted the vehicles with CNG kits. These vehicles were then rented back to the original owners at exorbitant daily rents in the range of Rs.200.00-250.00, amounting to roughly Rs.7, 000 per month.[12] Finally, even as late as in March 2007, although the marginal fuel cost of every kilometre travelled (CNG expenses not even exceeding Re. 0.70 per kilometre travelled even after accounting for waiting time, or travel undertaken in search for customers)[13] was significantly less than the legally prescribed marginal earnings (Rs. 3.50), the daily rents they paid to auto owners amounted to over 40% of their total daily earnings.[14] Regulated fares could not match up with rising costs for long. An upward revision of *regulated* auto-fares was put into effect from June 6, 2007 (details in Section 4.5). This led drivers and customers to go by the legal fare for just over six months. Auto drivers again largely resorted to bargaining by 2009, and thus on July 1, 2010, legal fares were raised yet again (details in Section 4.5).

I now classify the possible substitutes to the auto (such as public buses, metro, taxis and cycle rickshaws) in terms of distance travelled.

- *Short distances (less than five kilometres):* The closest substitutes would be buses and cycle rickshaws. Both are cheaper than autos. Autos however, offer more comfort in terms of space (not crowded, compared with a bus), speed (faster than cycle rickshaws and do not have stoppages as buses do), luggage carrying, and even customer image.[15]

[12] These rates persisted till mid 2009. Today drivers pay over Rs. 300.00 daily.
[13] "Project Third Wheel: Deregulation of Intermediate Public Transport of Delhi (2009)"; Prabodh, Delhi based Liberal youth group working on Governance and livelihood related Public policy reforms.
[14] This excludes the initial costs that were already covered (both legal and illegal) in order to obtain licenses.
[15] A person travelling by an auto may be considered superior to someone else travelling in a bus. Image really matters in North India.

- *Medium to long distances (five to twenty kilometres):* The closest substitutes would be public buses and taxis. Even though buses are less costly, the questions of image, space and speed remain. Further, there may even not be a direct bus route from one destination to another, in which case a customer may need to switch busses. This is quite uncomfortable, and more so when one carries luggage. An auto, on the other hand, is flexible with routes. Finally, compared with taxis, autos are way cheaper.

Although metro rails are cheaper, faster, maintain customer image and are comfortable enough, and thus can be called close substitutes, as of 2009, metros were not developed enough to cover even half of Delhi.

4.3. Fairness pricing and bounded rationality

We adopt Rabin's, 1993, approach to formalizing ideas of 'fairness' in player utilities which depends on the "following three stylised facts:

1. People are willing to sacrifice their own material well-being to help those who are being kind.
2. People are willing to sacrifice their own material well-being to punish those who are being unkind.
3. Both motivations 1 and 2 above have a greater effect as the material cost of sacrificing becomes smaller."

Payoffs are therefore, defined not just over players' actions, but also their beliefs. Whether an action is preferred to an alternative action depends upon

a. The direct material payoff

b. The belief about whether rival players are being harmful or helpful

c. Whether chosen action helps or hurts rival players.

For example, let us suppose that a customer finds an auto driver who is more than willing to travel to a destination where there are narrow lanes making it inconvenient and time consuming for an auto to get in and out. The customer being aware of the auto driver's option to wait (for not so long) for another customer wanting to travel to a more convenient destination (and possibly offering a higher payment) forms a belief that the auto driver is being kind to him and accordingly finds satisfaction in paying him higher than the legal fare. On the other hand, if an auto driver asks for a very high amount for an extremely convenient location, then even if it hurts the customer to say no to him, he would (revenge is sweet). Rabin's utility function has two additively separable components – the direct material payoff and a fairness function. I defer the introduction to Rabin's utility specifications to Appendix 4A and provide an intuition here.

We recognise that auto drivers would want to act as dictators (monopolists) in this market. Customers would also not want to trade on prices perceived as unfair. Thus, I look at two pricing rules that treat the auto driver as a dictator, but also require that he values fairness considerations held by even the most difficult customer (whom we will later designate as our 'critical customer').

4.3.1. Determination of fairness prices

Let L denote the legal fare for the journey and θ be the mark-up on the same. Let W denote the valuation of the customer, and F denote the total fuel cost of the travel. I define 'desired price' p as a strategy of the auto-driver and 'reservation price' r of the customer as follows

$$p = (1 + \theta)L \; ; \;\; p \in [L, W]; \qquad r \in [L, W]$$

The game involves the simultaneous determination of p and r. I defer the derivations to Appendix 4A and simply state the pricing rules here. The first rule is in the customer's interest that maximises the utility gained by him from deviating from a 'no travel' strategy to a 'travel' strategy. This is given by

$$Z_L = L + \sqrt{\frac{2(W-L)(L-F)}{[2(W-L)+1]}} \tag{4.1}$$

Apart from this, Rabin himself proposed a solution given by

$$Z_U = \left[\frac{2W^2 - 2WF + F}{2(W-F)+1}\right] \qquad = W - \frac{1}{2} + \frac{1}{2}\left[\frac{1}{2(W-F)+1}\right] \tag{4.2}$$

which is the maximum price chargeable to the customer that is consistent with the notion of fairness. We call the former in (4.1), the *optimal fairness fare*, and the latter in (4.2), the *maximal fairness fare*. Note that both L and F (and even W) above are functions of the distance travelled. Therefore, both Z_L and Z_U, above are functions of distance travelled too.

Intuitively speaking, we model a customer, who decides between taking and not taking the trip for each possible price. Thus, one can define a 'net benefit curve' or a 'differential utility curve' (shown in Appendix 4A) that plots the customer's utility gain from taking the trip (over not taking the trip) for each price. At prices just above the legal fare, the customer gains more (Rabin's) utility by offering higher prices. This is because as per Rabin's framework, he is willing to give up some material utility (cash lost) to the auto driver who is being kind to the customer (by agreeing to take the customer for only a limited mark-up over the legal fare – this is Rabin's stylized fact 1). But this kindness has a limit (Rabin's stylized fact 3), since the material cost of rewarding the driver's kindness eventually increases. Thus, the customer prefers to pay an amount that balances the material and the kindness considerations. This is the optimal fairness fare – the minimum amount the customer is willing to pay to the driver (at lower prices, the customer's utility will actually fall in Rabin's framework, due to stylized fact 1, because the kindness considerations dominate the monetary considerations). At prices higher than the optimal fairness fare, material considerations dominate kindness considerations, thus the customer's utility (from agreeing to travel) diminishes. At the maximal fairness fare, the customer is indifferent between travelling and not travelling (net benefit is zero). A customer with fairness considerations does not pay anything over this price if he travels (so this is the upper bound on the fairness prices).

We expect the *maximal fairness fare* to exceed the *optimal fairness fare,* and hence reject the solutions that imply otherwise (we will see later that defining fairness utilities in a dictatorial regime that is by definition, not fair, leads to such problems).[16]

Now, although we have data on *L* and *F*, we do not have information on *W*. To calculate the fair prices in (4.1) and (4.2), one must have information on all the three. In the two sections that follow, I first describe the data, and then discuss the process of estimating *W*.

4.4. Data

4.4.1. NGO data

Customers have heterogeneous payoffs (and hence, reservation prices) based on several characteristics. Since rental and fuel costs are identical for all drivers, I assume homogeneity in their payoff specifications. A study was done by Prabodh (an NGO based in Delhi), for purposes not central to this paper. The output was a documentary video of about an hour's

[16] Algebraically there is no reason why maximal fairness fare should always exceed the optimal fairness fare (on directly comparing equations (1) and (2) – just by looking at the equations one can possibly say that it may well be the other way round for solutions that predict a maximum willingness to pay extremely close to the legal fare.

length titled ‘Third Wheel’.[17] Data was collected on people who had (active and non-active) membership with Prabodh, living in Delhi and have been travelling (frequently or infrequently) by autos. These members were not involved with this project in particular. The information was collected in two waves, the first of which happened in March 2007 and the second happened in March 2008. There was an upward revision in auto fares in between (June 2007).

A total of 126 respondents – 60 men and 66 women in the age group of 21 to 36 years, were personally interviewed in each wave. Out of these 126 people from different backgrounds and varied personal characteristics, 94 participated in both the waves.[18] There were no foreigners.

4.4.2. Information details

During the interviews, while information on gender, availability of personal vehicle, and location of metro stations in the vicinity of residence were easily obtainable, information on the frequency of meter travel, and excess paid when not travelling by the meter were difficult to get. All respondents were thus asked to take notes for their next ten auto travels from close to their places of residence. They were asked to note the number of meter travels (in which case they knew the exact legal fare) and the amounts charged when they were not travelling by the meter in these ten travels. The excess over the legal fare in the latter case, a priori seems very difficult to obtain since, at the first place, if a person does not travel by the meter, he will not know what the legal fare should be (let alone the magnitude of the ‘excess’ over

[17] A shorter version of this documentary can be accessed through the link http://www.youtube.com/watch?v=TVWjuH8p1_Q: the documentary firstly focuses on the troubles faced by the general public due to non-compliance with legal fares on the part of the auto drivers – and then suggests that auto drivers have to resort to surplus extraction under the existing situation. For the former part, I had informally suggested to them that looking into the fraction of times customers manage to travel by the meter would help. For this study overall, my contribution was insignificant.

[18] People were asked to report figures for their next ten travels, and did so, on the basis of their auto-travels starting from their residence. The metro availability variable (Explained in Table 4.1) therefore remained constant for these individuals (0, 1 or 2 throughout the ten observations) for any given wave.

the same). Here, three factors had been exploited that led to the accurate collection of data on this variable.[19]

- First, and most often, when prices are negotiated before any journey, the meter is not used, and auto drivers do not care to reset the meter and leave it running. The customer can, therefore, read the 'distance travelled' displayed on the meter, at the start of the journey and compare it with the reading at the end of the journey. The exact legal fare is always based on the difference between the two.[20]

- This concerns people who take the same route several times (same starting and destination points) – travelling even once by the meter lets them know the legal fare and draw comparisons with the amounts they end up paying when not travelling by the meter.

- Third (and probably not needed, given the two above), the official website for fare calculation gives a fairly accurate idea of the legal fare before one decides to travel.[21]

The successful generation of data on amounts 'illegally' paid by the customers over what is required by regulation is the key merit of this dataset that makes it most suited to our purpose. It is noteworthy that it would be practically impossible to generate data on 'illegal' amounts paid over the legal fares were it not for this study undertaken by Prabodh. Table 4.1 summarizes the information on available variables.

[19] This was suggested to all the respondents before they participated.

[20] For instance, if the meter is not reset to zero distance and is left running, any new customer can see the distance reading at the start of the journey – suppose this is 11.5 kilometres. Now, if the customer's destination is 5.1 kilometres apart (this is not a priori known to him), the final reading on the meter (after he travels) will be 16.6 kilometres. The customer can calculate his legal fare based on the difference in these two readings. For example, with Rs. 10.00 for the first kilometre and Rs. 4.50 for every subsequent kilometre travelled, the legal fare works out to be Rs. 28.45.

[21] The official link when the data was collected was: http://delhigovt.nic.in/autofares/Transport.asp. Now it is http://www.taxiautofare.com/.

Table 4.1: Description of variables

Outcome variables	
1. Proportion of Meter Travel *(ρ)*	Represented as the fraction of times an individual would travel by the meter in an auto[22]
2. Excess over Legal Fare when Not Travelling by Meter *(θ)*	Represented as the amount (proportion) an individual will end up paying in excess of the legal fare when not travelling by the meter
3. Overall Bargaining Power *(θ_{ac})*	The amount that a customer pays on an average when he is legally supposed to pay Re. 1.00
Explanatory variables (Components of $[\boldsymbol{X_c} \vdots \boldsymbol{D_c}]$)	
4. $Unemp_c$	A dummy taking value 1 if the individual is unemployed and 0 otherwise
5. $Metro_c$	The presence of a metro station, coded as 2 if the nearest metro station falls within 1 kilometre of residence; 1 if the nearest metro station falls within 2 kilometres of residence; and 0 otherwise
6. $VecOwn_c$	A dummy taking value 1 if the individual has a vehicle at his/her disposal and 0 otherwise
7. $Gender_c$	A dummy taking value 1 if the individual is male and 0 if female

Table 4.2: Descriptive statistics

Variable	2007 (1)	2008 (2)
1. Total number of respondents	126	126
2. Number of male respondents (% of total)	60 (47.6%)	60 (47.6%)
3. Number of unemployed people (% of total)	62 (49.2%)	41 (32.5%)
4. People living in residences with metro stations < 1 km away (% of total)	10 (0.08%)	15 (11.9%)
5. People living in residences with metro stations < 2 km away (% of total)	46 (36.5%)	55 (43.6%)
6. People with vehicle at disposal	32 (25.4%)	53 (42.1%)
7. Average proportion of meter travel	32.55%	32.47%
8. Average excess over legal fare when not travelling by the meter	24.09%	23.96%
9. Average overall excess paid by customers *($\bar{\theta}_{ac}$)*	18.78%	18.39%
10. Number of women with vehicle at disposal (% of total)	20 (15.9%)	27 (21.42%)

[22] For example, if a person reported that he managed to travel by the meter six times out of ten, then $\rho = 0.6$ for him.

4.4.3. Descriptive statistics

These have been summarised in Tables 4.2, 4.3 and 4.4. The average proportion of meter travel, and the average excess paid over the legal fare largely remained constant during the two periods. We immediately see that the meter is not used in about two-thirds of the transactions and in such cases, the auto drivers manage to charge a mark-up of about one-fourth of the legal fare. In tables 4.3 and 4.4, we look at the determinants of both meter travel and the mark-up over the legal fare.

Table 4.3: Determinants of meter travel and negotiated fare in 2007

2007	Dependent Variable: Proportion of Meter Travel = ρ (Least Squares) (1)	Dependent Variable: Proportion of Meter Travel = ρ (Probit) (2)	Dependent Variable: Excess over Legal Fare when Not Travelling by Meter = θ (Least Squares) (3)
Unemp	0.1150**	1.2003***	-0.0346*
	(0.0470)	(0.3335)	(0.0188)
Gender	-0.0480	-0.1495	0.0184
	(0.0432)	(0.2946)	(0.0166)
VecOwn	0.02391	0.2655	-0.0016
	(0.0514)	(0.3162)	(0.0213)
Metro	0.2149***	0.5809**	-0.0741***
	(0.0385)	(0.2483)	(0.0152)
Constant	0.1901***	0.3314	0.2826***
	(0.0474)	(0.2663)	(0.0210)
R-Squared	0.3300	-	0.2737
Pseudo-R Squared	-	0.1686	-
P Value for Joint Significance	0.0000	0.0001	0.0000
N	126	126	126

Source: Prabodh (2009a)

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively
[b.] Robust standard errors reported in parentheses

Table 4.4: Determinants of meter travel and negotiated fare in 2008

2008	Dependent Variable: Proportion of Meter Travel = ρ (Least Squares) (1)	Dependent Variable: Proportion of Meter Travel = ρ (Probit) (2)	Dependent Variable: Excess over Legal Fare when Not Travelling by Meter = θ (Least Squares) (3)
Unemp	0.0793*	0.5406*	0.0002
	(0.0454)	(0.3277)	(0.0187)
Gender	-0.0701*	-0.2193	0.0178
	(0.0423)	(0.2820)	(0.0172)
VecOwn	0.0043	-0.0729	-0.0002
	(0.0459)	(0.2742)	(0.0186)
Metro	0.1439***	0.1875	-0.0585***
	(0.0309)	(0.1837)	(0.0132)
Constant	0.2504***	0.9725***	0.2636***
	(0.0477)	(0.2979)	(0.0198)
R-Squared	0.1844	-	0.1654
Pseudo-R Squared	-	0.0402	-
P Value for Joint Significance	0.0000	0.2817	0.0005
N	126	126	126

Source: Prabodh (2009a)

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively
[b.] Robust standard errors reported in parentheses

Employment status and metro availability strongly influenced both, excess paid over the legal fare when not travelling by the meter and probability of meter travel for both the years. While gender does not seem to be an important factor in 2007, women did end up travelling by the meter 7% more than men in 2008. Whether or not a vehicle is owned by an individual hardly matters in any negotiation.[23] Kurosaki (2012) studies metro-effects on cycle rickshaw rents.

[23] This will be explained in the notation of what follows. Although our theoretical specification allows for just one substitute, I have included both availability of metros nearby and vehicle ownership to ensure robustness in

4.5. Empirical strategy

4.5.1. The framework

In what follows, I index auto-drivers with the letter *a,* and customers with the letter *c.* The market is characterised by one time transactions – a given customer will, with high probability not meet the same auto driver again. An auto driver *a* is supposed to charge a customer *c* based on regulated (legal) fare depending on the total distance travelled *k* (in kilometres), displayed on the meter as follows

$$L(k) = sq + t(k - q)$$

where, *s* is the down-payment for the first *q* kilometres, and *t* is the amount paid for every subsequent kilometre travelled by the customer. Table 4.5 below displays the fare structure during the period 2007 to 2010.

Table 4.5: Past revisions in regulated fare

Period	**Down-payment applicability 'q' (kms)**	**Down-payment 's' (Rs.)**	**Rate-per-kilometre subsequently travelled 't' (Rs.)**
Before June 2007	First kilometre	8.00	3.50
June 2007 to July 2010	First kilometre	10.00	4.50
After July 2010	First two kilometres	19.00	6.50

the regressions. The insignificance of vehicle ownership ($VecOwn_c$) means that its coefficient $\gamma_v = 0$ and hence $\gamma_v VecOwn_c = 0$, and disagreement, $D_c = \max\{0, \gamma_m Metro_c\}$ where $Metro_c$ represents the existence of a metro station nearby. Thus the closest substitute $S_c = Metro_c$ and $\gamma_s S_c = \gamma_m Metro_c$ (meaning that metro is the stronger substitute).

We are interested in the period before July 2010. Although fuel costs f per kilometre ($f = F/k$) were very low, even after accounting for waiting/search time (about Rs. 0.60 according to the in-house research by Prabodh, 2009a), the daily rents (for a 12 hour period) auto-drivers paid to auto owners were very high. Suppose that customer c manages to travel by the meter only a fraction ρ times, and pays a mark-up θ over the legal fare in the remaining $(1 - \rho)$ fraction of total auto travels. An auto driver's expected earnings on any given travel with this customer is

$$\Pi_a = \rho[L(k) - fk] + (1 - \rho)[(1 + \theta)L(k) - fk] = [1 + (1 - \rho)\theta]L(k) - fk$$

Let $\theta_{ac} = (1 - \rho)\theta$ be the expected mark-up, so that

$$\Pi_a = (1 + \theta_{ac})L(k) - fk \tag{4.3}$$

where θ_{ac}[24] is the bargaining solution we observe (on an average) that is the mutually agreed upon (average) mark-up over the legal fare $L(k)$. Clearly, auto drivers do not want to travel by the meter, since otherwise, θ_{ac} equals zero. The earnings, by an auto driver from any given customer monotonically increases in θ_{ac}, but only up to a point where the product $(1+\theta_{ac})L(k)$ equals W_c, the customer's valuation. I now state a few assumptions.

Assumption 1: I assume that θ (and hence θ_{ac}) is independent of k for two reasons. First, the decision on the final amount a customer pays, (which ultimately comes down to deciding θ_{ac}) is only taken after the distance to be travelled is exogenously given, so it is fixed. Thus θ_{ac} can vary although k is fixed (the customer obviously knows where he wants to go and the driver takes that as given). Second, it maintains the possibility that a customer who travels a lesser distance than another customer with a given auto driver can actually end up paying substantially higher. The only restriction on θ_{ac} is that it be non-negative.

[24] This term is subscripted by '*ac*' to denote that it is a result of (average) bargaining between both the auto-driver and the customer.

In order to determine fairness prices (4.1) and (4.2), we need information on the legal fare, costs and valuation. While there is data available on costs, valuation remains unobserved. I make the following assumption based on the works cited in the introduction to add to the existing body of research.

Assumption 2: I take W_c to depend on factors such as one's gender (from experimental evidence, women tend to trust less and hence bargain more than men);[25] employment status (those unemployed, have a greater incentive to bargain) and so forth. This is summarized in $\boldsymbol{X_c}$. W_c increases in the distance travelled (Table 4.1 presents a summary of the explanatory variables). I further assume that the determinants of valuation assume the following form[26]

$$W_c = \alpha_k + \boldsymbol{X_c \alpha} + v_c \tag{4.4}$$

where α_k is a representative constant for a given distance k for *every* customer. The valuations of different customers hover around this representative constant, depending on their characteristics summarised by the components of the vector $\boldsymbol{X_c}$ (which does not include the constant of regression). $\boldsymbol{\alpha}$ is the vector of parameters and v_c is a customer (or a transaction) specific error term.

In order to know the important determinants of valuation in (4.4), we must know which components of $\boldsymbol{\alpha}$ are significant. We cannot, however, directly estimate $\boldsymbol{\alpha}$ since the left hand side of (4.4) is unobserved. I use theoretical bargaining solutions as in Thomson, 1994 that lead to structural equations from which $\boldsymbol{\alpha}$ can be recovered. In what follows, I specifically use the Nash, 1950 solution to explain the process of calculating costumer valuation.

[25] See Chaudhuri and Gangadharan, 2007, and Andreoni and Vesterlund, 2001. Additionally, this equation may capture the fact that there could be gender differences in reactions to corrupt and unjust behaviour (see Alatas et al. 2009. Women for instance, may be willing to pay less to auto drivers who often loot people. Dasgupta and Menon (2011) report that economics majors (male or female) tend to deviate from trustworthiness while sticking to trusting actions like others.

[26] This is different from the idea of Karni and Safra, 2002 who look into a 'hexagon condition' implying the additive seperability of components of utility. We have already used this condition at the stage in the construction of Rabin utilities where the material and the moral value components are additively separable.

Firstly, we discuss the role of outside options. To ease our formulation, I normalise any given auto driver's disagreement payoff to zero. The customer's disagreement payoff equation can be defined as follows (see footnote 22)

$$D_c = \gamma_s S_c = max[\gamma_v VecOwn_c; \gamma_m Metro_c]$$

Where $Metro_c$ denotes the presence of a metro station in a nearby area and $VecOwn_c$ denotes ownership of a vehicle (as in Table 4.1).[27] To offer an explanation, if a person has no substitutes available nearby, then both $VecOwn_c$ and $Metro_c$ are equal to zero – hence his disagreement payoff will also be zero. On the other hand, if a customer has both the options, then he would settle for that which gives him the higher payoff (on choosing not to transact with the auto driver in question). The (material) payoff to the customer is given by the difference between his valuation and what he actually ends up paying

$$\Pi_c = W_c - (1 + \theta_{ac})L(k) \tag{4.5}$$

The payoff specifications in (4.3) and (4.5) justify the idea of treating auto drivers as homogenous and customers as heterogeneous.[28]

4.5.2. Estimation of valuation using the Nash solution

Figure 4.1 illustrates the payoff frontier assuming (at the moment just to keep the discussion simple), zero disagreement payoffs for both the customer and the auto driver. The vertical axis measures the (material) payoff to the customer (Π_c) and the horizontal axis measures that of the auto driver (Π_a). The total surplus (the difference between the valuation of the customer and the fuel costs incurred by the auto driver) is to be distributed among them with

[27] $S_c = VecOwn_c$ if s = v (so that $\gamma_s S_c = \gamma_v VecOwn_c$) and $S_c = Metro_c$ if s = m (so that $\gamma_s S_c = \gamma_m Metro_c$); *the letter S denotes substitute.*

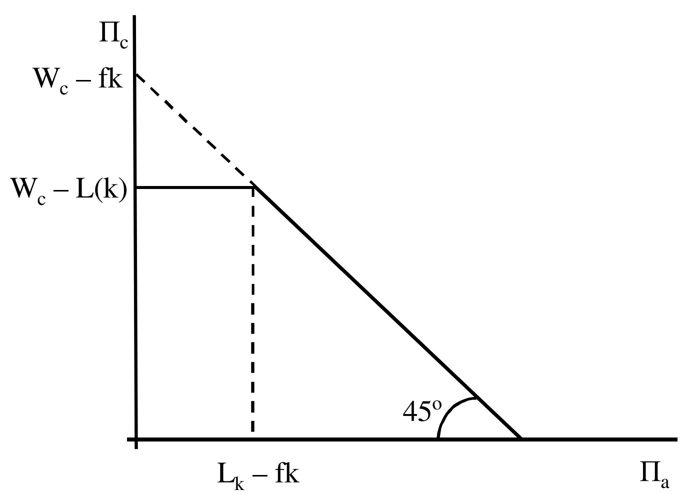
[28] This is a fairly reasonable assumption, even if one takes into account that there are auto-drivers (very few of them) who own their autos and do not take them on a daily rent basis. It is, in fact in their interest to overcharge their customers at rates charged by those who do not own autos. Overcharged rates act as 'focal points' (Knittel and Stango, 2003) for those who drive self-owned autos.

the constraint that the auto driver earns a minimum of $L(k)$ from the transaction. Formally, the boundary of the utility frontier has the following equation.

$$\Pi_a + \Pi_c = W_c - fk \qquad ; \Pi_a \geq L(k) - fk \tag{4.6}$$

For a given distance, the customer and the auto driver distribute a surplus equivalent to the difference between the customer's maximum willingness to pay and the driver's fuel costs of travel. The driver is guaranteed a minimum legal payoff defined by regulation which also puts a cap on the customer's payoff.

Figure 4.1: The feasible set.



The Nash bargaining solution can be characterised by the following formulation.

$$\text{Maximize: } \Pi_a(\Pi_c - D_c) \qquad \text{with respect to } \theta_{ac} \tag{4.7}$$

Using (4.3) and (4.5) we work out the first order condition of (4.7) above as follows

$$(1 + \theta_{ac}) = \frac{W_c - D_c + fk}{2L(k)}$$

Using (4.4) to replace W_c above by $\alpha_k + \boldsymbol{X_c\alpha} + v_c$ along with the disagreement equation in the above expression and rearranging the terms, gives us

$$(1 + \theta_{ac}) = \underbrace{(\frac{\alpha_k + fk}{2L(k)})}_{\beta_0} + \boldsymbol{X_c}\underbrace{(\frac{\boldsymbol{\alpha}}{2L(k)})}_{\boldsymbol{\beta}} - \underbrace{(\frac{\gamma_s}{2L(k)})}_{\mu_S}S_c + \underbrace{\frac{v_c}{2L(k)}}_{\eta_c} \qquad (4.8)^{29}$$

This leads us to the following structural equation depicting the average mark-up as a function of determinants of valuation and the availability of substitutes.

$$(1 + \theta_{ac}) = \beta_0 + \boldsymbol{X_c\beta} + \mu_s S_c + \eta_c \qquad (4.9)$$

Note that (4.9) above is estimable, since both the left and the right hand sides are observable. After observing $\widehat{\beta}_0$, $\widehat{\boldsymbol{\beta}}$ and $\widehat{\mu}_s$, we invert the explicitly stated relations in (4.8) above to arrive at $\widehat{\alpha}_k$, $\widehat{\gamma}_s$, and the $\widehat{\boldsymbol{\alpha}}$ vector as follows.

$$\widehat{\alpha}_k = 2\widehat{\beta}_0 L(k) - fk\,; \quad \widehat{\gamma}_s = -2\widehat{\mu}_s L(k)\,; \qquad \text{and} \qquad \widehat{\boldsymbol{\alpha}} = (2L(k))\widehat{\boldsymbol{\beta}} \qquad (4.10)$$

We finally write customer valuation (using (4.4)) explicitly as a function of distance k.

$$\widehat{W}_c = \widehat{\alpha}_k + \boldsymbol{X_c}\widehat{\boldsymbol{\alpha}} \qquad (4.11)$$

We repeat the above process for the Kalai-Smorodinski, 1975 (KS hereafter); Egalitarian; Dictatorial (either player could become a dictator); Raiffa, 1953; Equal Area (EA hereafter); and the Yu (1973) solutions. Each gives us a specific functional form of W_c. Clearly, focusing only on the Nash solution is not enough for the purposes of this paper since we do not know the axioms that actually govern negotiation in this market. In the words of Thomson, 1994, for example, "the crucial axiom on which Nash had based his characterization requires that the solution outcome be unaffected by certain contractions of the feasible set, corresponding to the elimination of some of the options initially available ... but this independence is often

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[29] Note that $\boldsymbol{\alpha}$ is a vector. The expression $(\frac{\boldsymbol{\alpha}}{L(k)})$ only means that each component of the $\boldsymbol{\alpha}$ vector is getting divided by $L(k)$

not fully justified." The non-binding legal constraint ($\Pi_a \geq L(k) - fk$) acts as such a contraction, the very existence of which may influence bargaining solutions. So we look at theoretical models that explicitly take this into account for robustness in our results.[30,31]

Table 4.6: Estimation of structural equations (2007)

2007	Type 1: Nash-Egalitarian, Dictatorial, Raiffa and Yu Solutions (1)	Type 2: Kalai-Smorodinski Solution (2)	Type 3: Equal Area Solution (3)
Unemp	-0.0557*	-0.1268	-0.1421
	(0.0306)	(0.0767)	(0.0894)
Gender	0.0164	0.0494	0.0606
	(0.0302)	(0.0764)	(0.0892)
VecOwn	0.0369	0.1009	0.1212
	(0.0352)	(0.0866)	(0.1002)
Metro	-0.0779**	-0.2108**	-0.2500**
	(0.0393)	(0.1023)	(0.1203)
Constant	1.2396***	1.7307***	1.8893***
	(0.0325)	(0.0805)	(0.0933)
R-Squared	0.3334	0.3418	0.3438
Implied RMSE in Appendix 4C	0.2622 (against Type 2) 0.3085 (against Type 3)	0.2597	0.3045
Implied RMSE in Appendix 4D	0.1019	0.1017 (implied)	0.0991 (implied)
P-value for joint Significance	0.0000	0.0000	0.0000
N	126	126	126

Source: Prabodh (2009a)

Notes:
[a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively
[b.] Robust standard errors reported in parentheses
[c.] Unemp*Gender has been dropped because of high multicollinearity with both U and G
[d.] Constant (*fk/L(k)*) is taken at the limiting value of 0.143. Regression coefficients are largely insensitive to changes in this constant (for Kalai-Smorodinski and Equal Area solutions)
[e.] To ensure robustness in regression results, the regressions shown above account for all possible interaction terms among the variables represented by the ***X*** vector in Appendices 4C and 4D.

[30] The KS solution for instance points out that the existence of a legal constraint, although non-binding may lead to a change in the optimal solution. People may not go by the legal fare but acknowledge its presence and hence form their expectations accordingly.
[31] The derivations for other solutions can be made available upon request.

Table 4.7: Estimation of structural equations (2008)

2008	Type 1: Nash-Egalitarian, Dictatorial, Raiffa and Yu Solutions (1)	Type 2: Kalai-Smorodinski Solution (2)	Type 3: Equal Area Solution (3)
Unemp	0.0135	0.0434	0.0546
	(0.0352)	(0.0893)	(0.1044)
Gender	0.0168	0.0602	0.0769
	(0.0372)	(0.0935)	(0.1090)
VecOwn	0.0171	0.0614	0.0785
	(0.0349)	(0.0870)	(0.1012)
Metro	-0.0762***	-0.2052***	-0. 2434***
	(0.0284)	(0.0747)	(0.0882)
GenderMetro	0.0514*	0.1420**	0.1699**
	(0.0276)	(0.0711)	(0.0836)
Constant	1.2131***	1.6676***	1.8175***
	(0.0318)	(0.0800)	(0.09323)
R-Squared	0.2072	0.2243	0.2290
Implied RMSE in Appendix 4C	0.2743 (against Type 2) 0.3227 (against Type 3)	0.2724	0.3193
Implied RMSE in Appendix 4D	0.1066	0.1067 (implied)	0.1069 (implied)
P-value for joint Significance	0.0000	0.0000	0.0000
N	126	126	126

Source: Prabodh (2009a)

Notes: [a.] ***, **, * mark out coefficients that are significant at 1, 5 and 10 percent levels of significance respectively
[b.] Robust standard errors reported in parentheses
[c.] Constant *(fk/L(k))* is taken at the limiting value of 0.133. Regression coefficients are largely insensitive to changes in this constant (for Kalai-Smorodinski and Equal Area solutions)
[d.] To ensure robustness in regression results, the regressions shown above account for all possible interaction terms among the variables represented by the ***X*** vector in Appendices 4C and 4D.

In general, I arrive at three classes (types) of reduced-form equations (based on the transformations of the mark-up - our left-hand-side) that encompass all the above mentioned solutions. Specifically, apart from the KS (Type 2, shown in Appendix 4B) and the EA (Type 3) solutions, all the remaining solutions are structurally indistinguishable from that implied by the Nash solution (Type 1) above (shown in (4.9)). The results of these regressions are presented in Tables 4.6 (for 2007) and 4.7 (for 2008).

We get a distribution of $\widehat{W}_c$ functions (of distance travelled) for different individuals based on observed characteristics. I thus, formally define the *critical customer*, as the person whose willingness to pay is the least when compared with that of individuals with characteristics different from his (or her). Thus the critical customer is the most difficult customer with the maximum incentive to bargain. I denote his valuation by W_c^* (= $W(\boldsymbol{X}_c^*)$). The prices considered as 'fair' by the critical customer will suit all the other individuals who (by definition) have higher valuations. This is in line with the objective that any new fairness pricing rule will not exclude any of the existing customers from the market – or on a less ambitious note, the number of customers who exit the market (because their valuation will be lower than the newly announced fare) will be a bare minimum.

4.6. Results and discussion

I now use the regression results (the coefficient signs) to identify the critical customer and instead of calculating valuation, I work out his maximum willingness to pay (as a function of distance) for each year.[32] I then discuss the idea of fair prices based on them. Before we step further, it is important to note that the hypothesis of a dictatorship regime where the customer is the dictator (say Type 4) can simply be ignored by rejecting the null $\theta_{ac} = 0$, for both the years ($\bar{\theta}_{ac} = 0.188$ for 2007, and $\bar{\theta}_{ac} = 0.184$ for 2008).

[32] Although the existence of metro stations nearby should not affect valuation, it does affect maximum willingness to pay. The process of arriving at the willingness to pay function is discussed in footnote 33. I define our critical customer accordingly.

4.6.1. Maximum willingness to pay and fair prices in 2007

Based on the regression results in Table 4.6, it is easy to identify that our critical customer is an unemployed female citizen (*Unemp** = *1;* and *Gender** = *0*) with a metro station nearby (*Metro** = *2*). I use a conservative (10%) significance rule to specify the $\hat{\boldsymbol{\alpha}}$ vector and using (4.11) I estimate maximum willingness to pay for the critical customer for different solutions and plot the same in Figures 4.2 and 4.3 (for type 1 and types 2 and 3 respectively).[33] Legal Fare (2007) in the figures refers to the regulatory fares prevalent during March 2007 (the first wave), that is before the hike of June 2007.

Unemployment seems to be a significant variable as far as type 1 solutions are concerned, while it is not significant as far as the KS and the EA solutions go (Table 4.6). With the evidence we have, those employed paid, on an average, 5.5% more than those unemployed. Gender did not seem to be an important determinant of bargaining power. Vehicle ownership is not important either. This makes sense, for, while a person is negotiating with an auto driver, he does not really think much about the vehicle he has left home. Finally, metro seems to play an important role in determining negotiated fares (hence *M*etro (and not Vec*Own*) in Table 4.1 represents our disagreement point). Those with metros in the vicinity of a kilometre paid on an average, over 15% less than those who did not have metro nearby. While Figures 4.2 and 4.3 represent the maximum willingness to pay of the critical customer, I have intentionally presented the overall average observed negotiation for different distances ($\bar{\theta}_{ac}$ = 0.188 for 2007, but $\bar{\theta}^*$ = 0.027 for the critical customer in 2007). This is because if the critical customer's maximum willingness to pay is exceeded by the (average) observed transactions (in March 2007) then any upward revision in auto fares based on the latter would necessarily leave the critical customer out of the market after the hike (in June 2007).

[33] Here, keeping in mind that our critical customer is the person who has the maximum incentive to bargain, we also put *Metro** = *2*, and augment it in our valuation function (i.e we use $[\boldsymbol{X_c} \vdots D_c]$ instead of $\boldsymbol{X_c}$) and call it the willingness to pay function. This willingness to pay function is the one plotted in the diagrams.

Figure.4.2: Type 1 Solutions: (a) Nash; (b) Dictatorial; (c) Raiffa (discrete); and (d) Yu Solutions – horizontal axis is measured in kilometres and vertical axis in Rs.

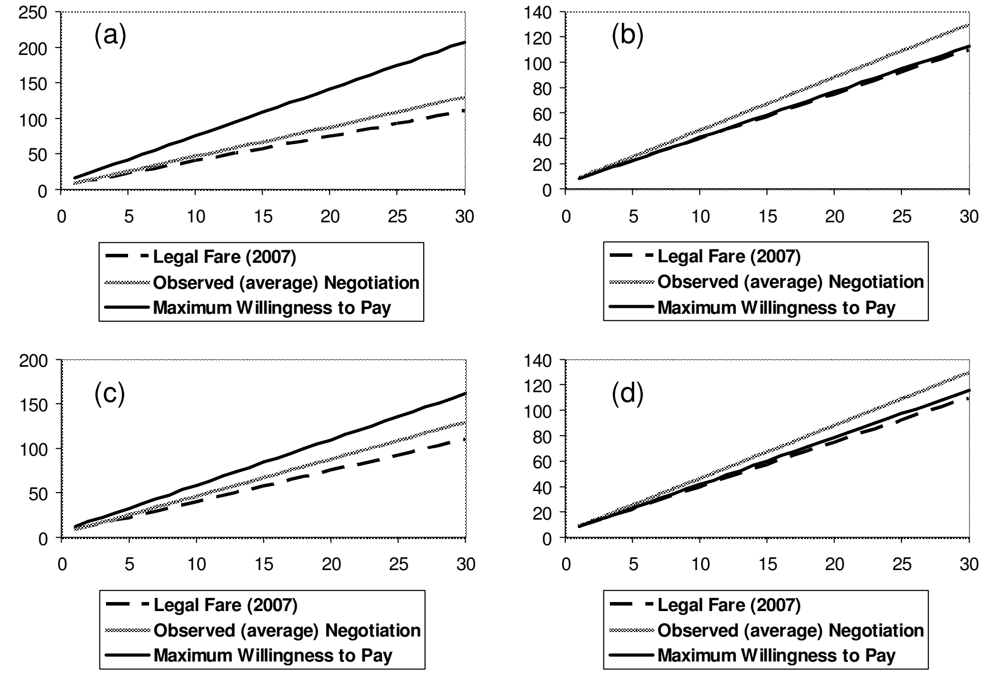


Figure 4.3: Type 2 and 3 Solutions: (a) Kalai-Smorodinski (Type 2); and (b) Equal Area (Type 3) Solutions – horizontal axis is measured in kilometres and vertical axis in Rs.

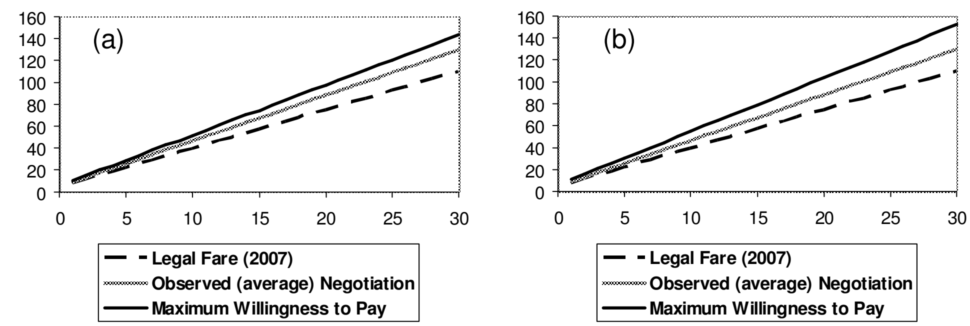


Figure 4.4: Type 1 Pricing Rules: (a) Nash; (b) Dictatorial; (c) Raiffa (discrete); and (d) Yu Solutions – horizontal axis is measured in kilometres and vertical axis in Rs.

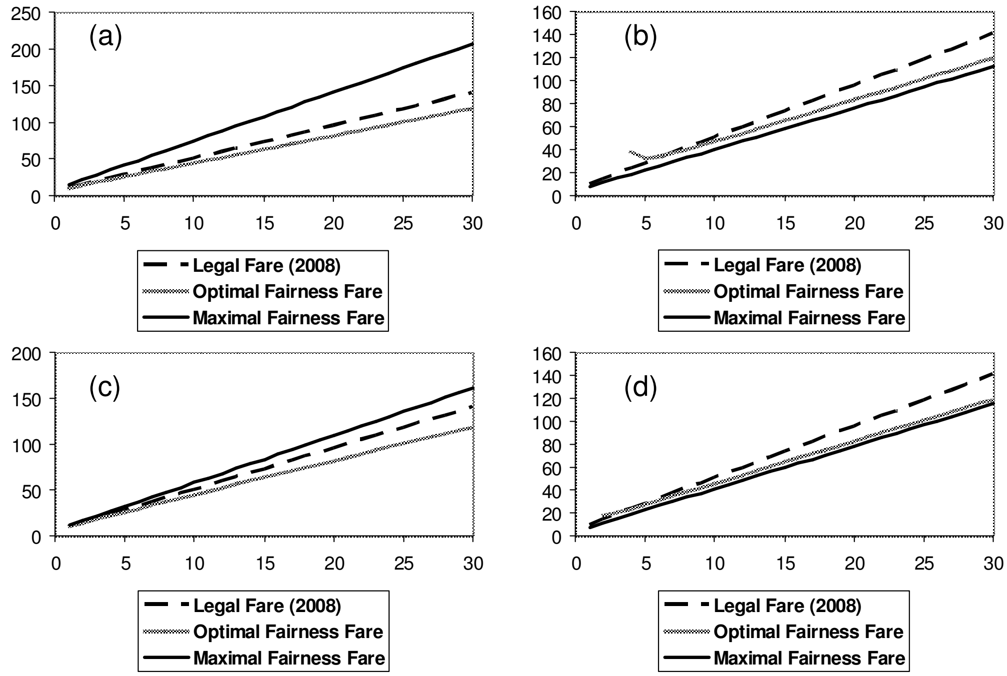
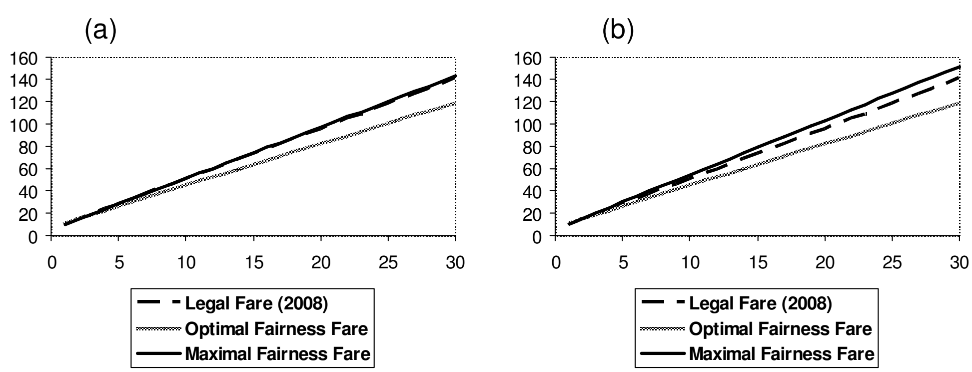


Figure 4.5: Type 2 and 3 Pricing Rules: (a) Kalai-Smorodinski (Type 2); and (b) Equal Area (Type 3) Solutions – horizontal axis is measured in kilometres and vertical axis in Rs.



Models that predict a maximum willingness to pay very close to (albeit higher than) the legal fare, run the risk of a contradiction – that the (current) legal fare might exceed the *maximal fairness fare*, in which case, the very critical customer we have identified from existing data should not have been observed in the market at the first place.[34] Even if a solution escapes this contradiction (when the maximal fairness fare marginally exceeds the legal fare), it may fall into yet another trap – the *optimal fairness fare* in (4.1) is notably higher than the legal fare, and may thus exceed the *maximal fairness fare*. We reject such solutions (the likely candidates are the dictatorial and the Yu solutions).

We now look into the optimal fairness and the maximal fairness pricing rules and compare them with the related revised regulatory fare (the hike in June 2007) which we call as Legal Fare (2008) since these fares lasted throughout 2008 (and even 2009 – the next revision was in 2010) for each bargaining solution (Figure 4.4 for Type 1 solutions and Figure 4.5 for Type 2 and 3 solutions). We see in Figure 4.4 that optimal fairness fares do exceed the maximal fairness fares implied by the dictatorial and the Yu solutions. I therefore reject those solutions and focus on the Nash, Raiffa, KS and the EA solutions. We arrive at the interesting result that although these solutions differ substantially in their prediction of maximum willingness to pay, all of them individually generate fairness zones bounded by (4.1) and (4.2) such that the newly announced fare hike lies within these zones.

Testing for fairness: I test the null hypothesis, that the regulatory hike was fair, against the alternative that it was not, using the following rule.

Accept Null if: Optimal Fairness Fare ≤ Legal Fare (2008) ≤ Maximal Fairness Fare

Do Not Accept Otherwise.

[34] Remember that the maximal fairness fare here, is that of the critical customer. So if the legal fare exceeds the maximum fare that our critical customer feels is fair, then our critical customer would not avail auto services in the first place.

I infer that the actual legal fare raised by regulation can be deemed 'fair' since it lies in the region bounded by the optimal and the maximal fairness prices (the fairness zone). The raise in the legal fare is closer to the maximal fair pricing rule suggesting a greater weight (68%) is put on the needs of the auto drivers (customers would prefer optimal fairness pricing).

We cannot directly employ the RMSE[35] rule for robustness here since the dependent variables are different for all the types (1, 2 and 3) of structural equations. In Appendices 4C and 4D, I explain the methods involving appropriate inversions to arrive at comparable residuals for the three types. The EA solution that (although very marginally) seems to best explain the customer-driver bargaining story gives us some insight on certain aspects of negotiation. The customer perhaps thinks in terms of the surplus he would be willing to give up rather than his maximum gain from a negotiation. Based on this, the maximal fairness fare rule suggests Rs. 10.50 as a down-payment for the first kilometre and Rs. 4.80 for every subsequent kilometre travelled. The actual legal fare was raised to Rs. 10.00 for the first kilometre and Rs. 4.50 for every subsequent kilometre travelled (Legal Fare 2008). The maximal fairness pricing rule implied by the KS solution (Rs. 10.00 for the first kilometre and Rs. 4.60 for every successive kilometre) seems to best fit the actual (next) legal fare raise.[36]

4.6.2. Maximum willingness to pay and fair prices in 2008

Again, the critical customer is a female with a metro nearby (Table 4.7). The maximum willingness to pay is plotted using (4.11) in Figures 4.6 and 4.7 (for type 1, and types 2 and 3 respectively). Unemployment is no longer significant. Gender and vehicle ownership, continue to remain unimportant determinants of negotiated prices, although, females seem to

[35] Kadiyali, 1996 for example, in her paper looking into market characteristics as determinants of entry and exit in the photographic film industry uses the criterion of the lowest minimised sum of squared errors to identify the market regime (among various market structures) in the post entry period.
[36] It suggests an almost 90% weight on the auto-driver's preferences and only 10% weight on customers' preferences.

capitalise on the presence of metros more than males (the interaction term is significant). Those with metros in the vicinity of a kilometre paid yet again on an average, over 15% less than those who did not have a metro station nearby. The dictatorial and the Yu solutions remain problematic for the reasons mentioned before. Figures 4.8 and 4.9 represent the maximal and the optimal pricing rules implied by each bargaining regime. None of the types significantly explains the customer-driver bargaining story better than the others (Table 4.7 reports mixed results based on the methods in Appendices 4C and 4D). Using the same testing rule as in the previous subsection, one would infer that the fare hike cannot be considered fair since it even exceeds the maximal pricing rule for most bargaining solutions (Nash and Raiffa are exceptions) suggesting a more than 100% weight (about 142%) put on the needs of the auto drivers. There is, however, a caveat that comes with such an inference.

We need to recognise that while the survey period March 2007 was closer to the next hike (three months from then), March 2008 (our next wave) is distant from the next hike (in 2010, over two years from then). Rents have risen and so have fuel costs before and during 2010. The maximum willingness to pay curve (and hence the fairness pricing curves) may have shifted upwards during the two years before the next hike was announced. Thus we may actually consider the newly revised prices to be 'fair'. Current Legal Fare refers to the hike announced in July 2010. The EA solution suggests Rs. 19.00 as a down-payment for the first two kilometres and Rs. 6.00 for every subsequent kilometre travelled. The actual legal fare has been raised to Rs. 19.00 for the first two kilometres and Rs. 6.50 for every subsequent kilometre travelled. The additional Rs. 0.50 may very well be attributable to the additional changes in rent and fuel costs mentioned previously.

Figure 4.6: Type 1 Solutions: (a) Nash; (b) Dictatorial; (c) Raiffa (discrete); and (d) Yu Solutions – horizontal axis is measured in kilometres and vertical axis in Rs.

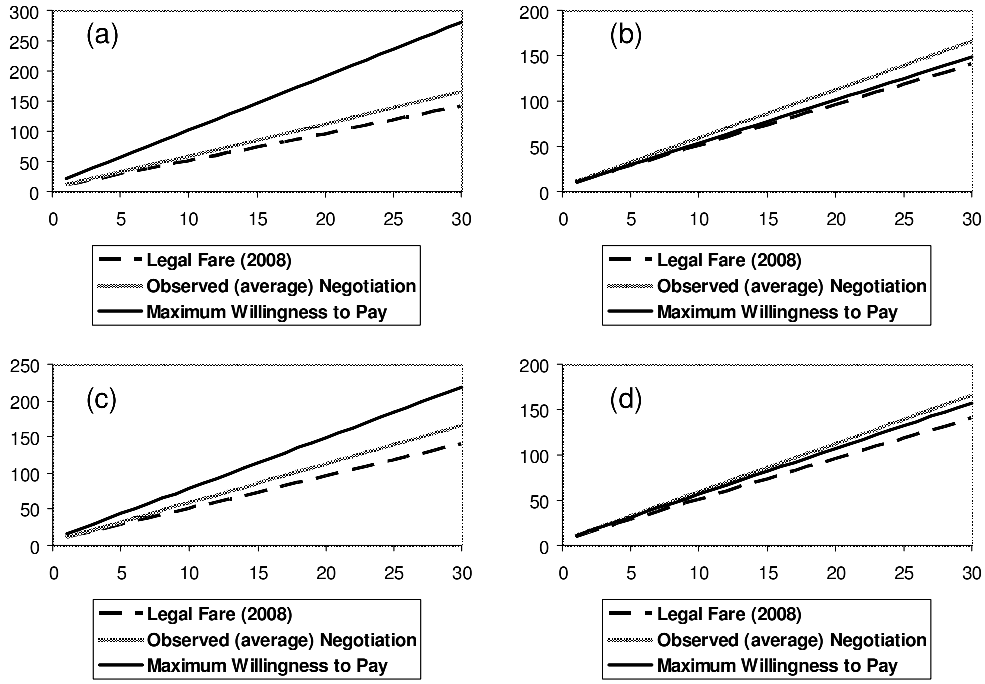


Figure 4.7: Type 2 and 3 Solutions: (a) Kalai-Smorodinski (Type 2); and (b) Equal Area (Type 3) Solutions – horizontal axis is measured in kilometres and vertical axis in Rs.

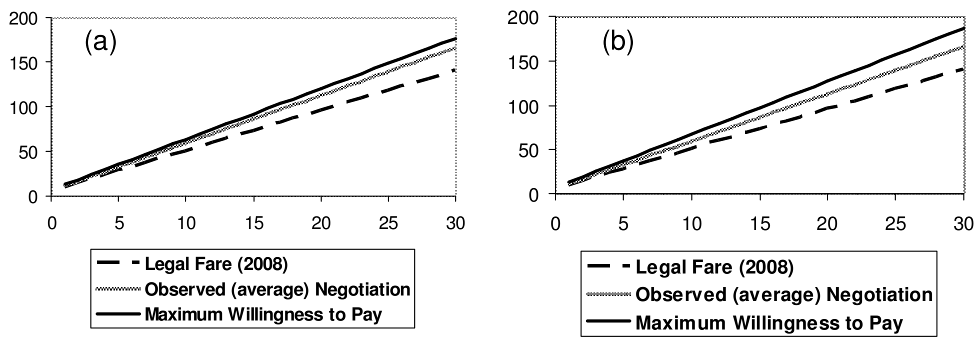


Figure 4.8: Type 1 Pricing Rules: (a) Nash; (b) Dictatorial; (c) Raiffa (discrete); and (d) Yu Solutions – horizontal axis is measured in kilometres and vertical axis in Rs.

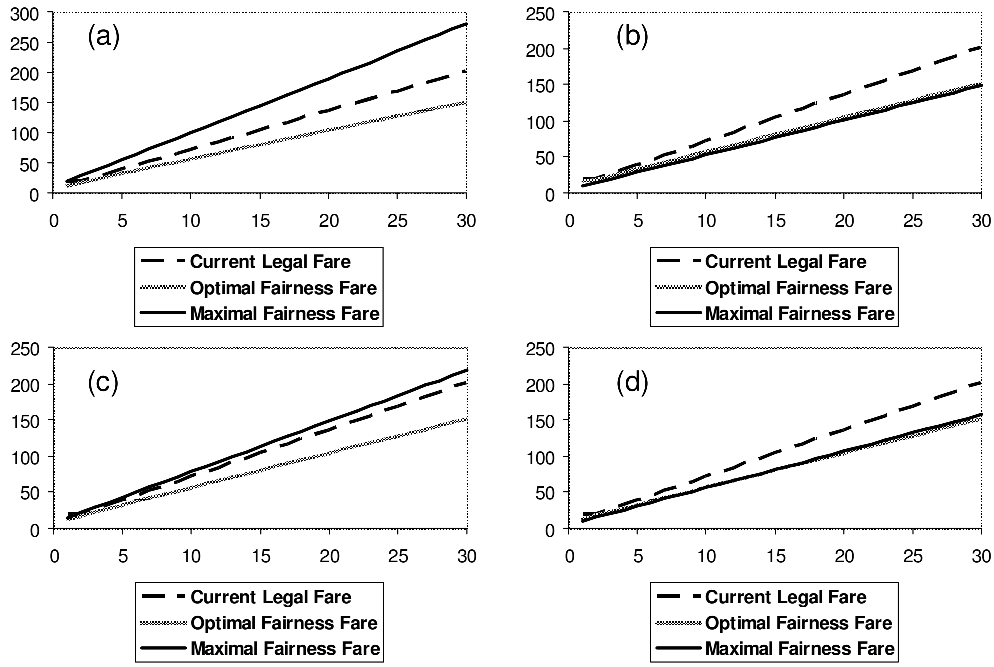
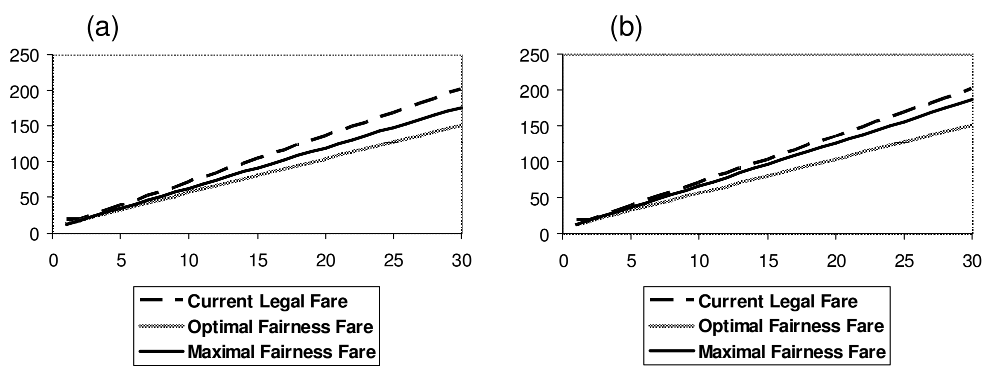


Figure 4.9: Type 2 and 3 Pricing Rules: (a) Kalai-Smorodinski (Type 2); and (b) Equal Area (Type 3) Solutions – horizontal axis is measured in kilometres and vertical axis in Rs.



4.7. Conclusion

This paper focuses on the possibility that fairness considerations could influence regulatory decisions. In the implicit discussion on the determinants of bargaining power, there is some evidence that those unemployed, perhaps, tend to haggle more and hence end up with better deals. This paper also makes a case for better connectivity enhanced by metro rail construction by providing evidence that it acts as a strong substitute to auto rickshaws. The effect of metro construction has been significant in bringing down negotiated auto prices closer to existing regulated fares.

I have abstracted away from driver heterogeneity and have capitalised on the theoretical setting based on identical material utilities. This is because the unit of observation in the available data is the customer. However, the observed behaviour of the drivers in this market – that everyone prefers to haggle for a mark-up over the legal fare, is explained and justified well by our theoretical setting. The only source of heterogeneity on the customers' side is their individual characteristics. Although this is not a central point, the results may be better interpreted with the additional assumption that each customer takes the same route ten times, and the excesses he pays over the legal fare when not travelling by the meter is averaged out. In general, this may not be true since two different places of destination from the same origin (the individual's residence here) will involve travelling different distances and hence different legal fares (and possibly different bargaining positions). Fortunately, as I have demonstrated, it is sufficient to deal with data on just the mark-up levels as proportions of the legal fare (rather than the absolute values of the mark-ups), for the purposes central to this research. While some people did report these figures (on actual distances covered, time of the day, destination and so forth) for each travel, information on them remained scanty (since they were not required for the original purpose). Some element of heterogeneity in the factors mentioned above would have given us more flexibility in terms of modelling individual transactions – more data is obviously better, for it leads to more information (for example, data on income level, time of transaction among other details, although such determinants of bargaining outcomes were not the key focus areas of this paper). One must, however, acknowledge the merit in the available data that, in my belief, overcomes the loss of heterogeneity – this is the only data source I am aware of that documents illegal (or more aptly, 'not-legal') payments to a great degree of accuracy stemming from the information and the data collection strategy.

For future research, the question addressed in this chapter can directly extend to the cycle-rickshaw market. It will be interesting to address what price, for instance, can be deemed 'fair' for a given distance. It is worth noting that there is no well-defined legal fare and the travel distance is not measured automatically for cycle rickshaw pullers (see Hyodo et al 2011, where GPS details of all services were recorded in a day by cycle rickshaws in Dhaka, in order to facilitate research by observing travel distance). So far, all the research on the cycle rickshaw markets focuses on the rental payments made by cycle rickshaw pullers to the owners of cycle rickshaws (see Kurosaki, 2012; Kurosaki et al, 2012; and Jain and Sood, 2012). One of the points made in this research, that the negotiated fares are lower near metro stations, compared with the finding of Kurosaki (2012), that the gross earnings of cycle rickshaw pullers are higher near metro stations suggests that auto taxi services are substitutes to metro railways whereas, cycle rickshaws are compliments to them.

Appendices to Chapter 4

Appendix 4A: Derivation of Rabin Fairness Utilities

Introduction to Rabin's Framework:

Let $a_i \in A_i$ be a strategy for player i, and $a = \{a_1, a_2\}$. $b_i \in A_i$ is player *j's* belief about player *i's* strategy. $c_i \in A_i$ is player *i's* belief about what player j believes about player *i's* strategy. *A strategy $a \in A$ is a fairness equilibrium if for $i = 1, 2$ if*

$$a_i \in arg\ max_{a_i \in A_i} U_i\ (a_i, a_j, b_j, c_i) \quad \text{and } a_i = b_i = c_i$$

We define the following payoffs given that player i plays a_i and believes that player j will play b_j

$\Pi_j\ (b_j, a_i)$ = player j's payoff if j plays strategy b_j and i plays strategy a_i

$\Pi_j^h(b_j)$ = player j's highest payoff if j plays strategy b_j

$\Pi_j^l(b_j)$ = player j's lowest Pareto efficient payoff if j plays strategy b_j

$\Pi_j^e(b_j)$ = $[\Pi_j^h(b_j) + \Pi_j^l(b_j)]/2$ is player j's equitable payoff

$\Pi_j^{min}(b_j)$ = player j's worst possible payoff if j plays strategy b_j

Player i's kindness to player j is given by

$$F_i(a_i, b_j) = \frac{\Pi_j\ (b_j, a_i) - \Pi_j^e(b_j)}{\Pi_j^h(b_j) - \Pi_j^{min}(b_j)}$$

Given the above specifications, player i's belief about how kind player j is being to player i when player i believes firstly, that player j plays b_j and secondly, that player j believes that player i plays c_i, is given by

$$\tilde{F}_j(b_j, c_i) = \frac{\Pi_i(c_i, b_j) - \Pi_i^e(c_i)}{\Pi_i^h(c_i) - \Pi_i^{min}(c_i)} = F_j(a_j, b_i) = \frac{\Pi_i(b_i, a_j) - \Pi_i^e(b_i)}{\Pi_i^h(b_i) - \Pi_i^{min}(b_i)}$$

The latter set of equalities holds in the equilibrium because expectations are correct.

Utility Function for Player i is given by

$$U_i(a_i, b_j, c_i) = \Pi_i(a_i, b_j) + \tilde{F}_j(b_j, c_i)[1 + F_i(a_i, b_j)]$$

The idea is simple, if player i feels that player j is being mean to him (that is player j's fairness function is negative) player i would also want to be mean to player j (make his own fairness function negative), and vice versa.

Let $L = L(k)$ for k kilometres. Let f denote the fuel costs per kilometre travelled. Thus $F = fk$

We write material payoffs as follows

$$\Pi_c = \begin{cases} W_c^* - p_a, & if\ p_a \leq r_c \\ 0, & otherwise \end{cases} \tag{4A.1}$$

$$\Pi_a = \begin{cases} p_a - fk, & if\ p_a \leq r_c \\ 0, & otherwise \end{cases} \tag{4A.2}$$

According to Rabin, there exists a fairness equilibrium $z_{ac} = p_a = r_c$ such that $z_{ac} \in [L(k), W_c^*]$.

We write the kindness functions as follows.

i) Kindness function for how the customer treats the driver = $F_c(r_c, p_a)$

a) if customer sets $r_c \geq p_a$

$$F_c(r_c,p_a) = \frac{\Pi_a(p_a,r_c) - \Pi_a^e(p_a)}{\Pi_a^h(p_a) - \Pi_a^{min}(p_a)} = \frac{p_a - fk - (\frac{p_a - fk}{2} + \frac{p_a - fk}{2})}{p_a - fk - (L(k) - fk)} = 0 \qquad (4A.3)$$

where,

$\Pi_a^h(p_a)$ = the auto driver's highest payoff when he plays strategy p_a

$\Pi_a^l(p_a)$ = the auto driver's lowest Pareto efficient payoff when he plays strategy p_a

$\Pi_a^e(p_a)$ = the auto driver's equitable payoff defined as the arithmetic mean of the above two expressions

$\Pi_a^{min}(p_a)$ = the auto driver's worst possible payoff when playing p_a

for $z_{ac} = p_a = r_c$,

$$F_c(z_{ac}) = 0 \qquad (4A.4)$$

Given p_a, the driver always receives a payoff of $(p_a - fk)$, regardless of the choice of r_c (conditional on $r_c \geq p_a$). The customer is being neutral to the driver.

b) if $r_c < p_a$

$$F_c(r_c,p_a) = \frac{\Pi_a(p_a,r_c) - \Pi_a^e(p_a)}{\Pi_a^h(p_a) - \Pi_a^{min}(p_a)} = \frac{0 - (\frac{p_a - fk}{2} + \frac{p_a - fk}{2})}{p_a - fk - (L(k) - fk)} = -\frac{p_a - fk}{p_a - L(k)} < 0 \qquad (4A.5)$$

ii) Kindness function for how the auto-driver treats the customer = $F_a(p_a,r_c)$

a) if auto driver sets p_a such that $r_c \geq p_a$

$$F_a(p_a,r_c) = \frac{\Pi_c(r_c,p_a) - \Pi_c^e(r_c)}{\Pi_c^h(r_c) - \Pi_c^{min}(r_c)} = \frac{W_c^* - p_a - (\frac{W_c^* - L(k)}{2} + \frac{W_c^* - r_c}{2})}{W_c^* - L(k) - 0} = \frac{L(k) + r_c - 2p_a}{2(W_c^* - L(k))}$$

(4A.6)

where,

$\Pi_c^h(r_c)$, $\Pi_c^l(r_c)$, $\Pi_c^e(r_c)$, *and* $\Pi_c^{min}(r_c)$ have definitions analogous to that of the auto driver's case discussed above.

for $z_{ac} = p_a = r_c$,

$$F_a(z_{ac}) = \frac{L(k) - z_{ac}}{2(W_c^* - L(k))} \tag{4A.7}$$

b) if $r_c < p_a$

$$F_a(p_a, r_c) = \frac{\Pi_c(r_c, p_a) - \Pi_c^e(r_c)}{\Pi_c^h(r_c) - \Pi_c^{min}(r_c)} = \frac{0 - (\frac{W_c^* - L(k)}{2} + \frac{W_c^* - r_c}{2})}{W_c^* - L(k) - 0} = \frac{L(k) + r_c - 2W_c^*}{2(W_c^* - L(k))} < 0$$

(4A.8)

Using all the information above, we now construct the Rabin-utility functions for the customer and the auto-driver as follows.

iii) Customer's payoff {we will set $p_a = z_{ac}$ here}[37],

$$\widetilde{\Pi}_c = \Pi_c + F_a(p_a, r_c)[1 + F_c(r_c, p_a)] \tag{4A.9}$$

a) When customer sets $r_c = z_{ac}$

We use (4A.4) and (4A.7) in (4A.9) above to get

$$\widetilde{\Pi}_c = W_c^* - z_{ac} + \frac{L(k) - z_{ac}}{2(W_c^* - L(k))}[1 + 0]$$

[37] The utility representation apart from capturing the stylised facts, also points out one bit of realism: whenever a player is treating the other unkindly, the other individual's overall utility will be lower than his material payoffs. It's a bitter experience.

$$\leftrightarrow \qquad \widetilde{\Pi}_c = W_c^* - z_{ac} + \frac{L(k) - z_{ac}}{2(w_c^* - L(k))} \tag{4A.10}$$

b) When customer sets $r_c < z_{ac}$

We use (4A.5) and (4A.8) in (4A.9) above to get

$$\widetilde{\Pi}_c = 0 + \left[\frac{L(k) + r_c - 2w_c^*}{2(w_c^* - L(k))}\right]\left[1 - \frac{p_a - fk}{p_a - L(k)}\right]$$

$$\leftrightarrow \qquad \widetilde{\Pi}_c = \left[\frac{L(k) + r_c - 2w_c^*}{2(w_c^* - L(k))}\right]\left[1 - \frac{z_{ac} - fk}{z_{ac} - L(k)}\right]$$

$$\leftrightarrow \qquad \widetilde{\Pi}_c = \left[\frac{L(k) + r_c - 2w_c^*}{2(w_c^* - L(k))}\right]\left[\frac{fk - L(k)}{z_{ac} - L(k)}\right]$$

$$\leftrightarrow \qquad \widetilde{\Pi}_c = \left[\frac{2w_c^* - L(k) - r_c}{2(w_c^* - L(k))}\right]\left[\frac{L(k) - fk}{z_{ac} - L(k)}\right] \tag{4A.11}$$

Evaluating the 'Fair' Price: We calculate the price that maximises the benefit from travelling (agreement) over not travelling (disagreement) using Rabin-utilities.

The customer travels when $r_c = z_{ac}$ and does not travel when $r_c < z_{ac}$. Thus, for him to prefer travelling, it must be the case that

$\widetilde{\Pi}_c(r_c = z_{ac}) \geq \widetilde{\Pi}_c(r_c < z_{ac})$, so we define the following net-benefit function $NB(z_{ac})$ by subtracting (4A.11) from (4A.10)

$$NB(z_{ac}) = \widetilde{\Pi}_c(r_c = z_{ac}) - \widetilde{\Pi}_c(r_c < z_{ac})$$

$$NB(z_{ac}) = W_c^* - z_{ac} + \frac{L(k) - z_{ac}}{2(w_c^* - L(k))} - \left[\frac{2w_c^* - L(k) - r_c}{2(w_c^* - L(k))}\right]\left[\frac{L(k) - fk}{z_{ac} - L(k)}\right]$$

Further, let $r_c = z_{ac} - \varepsilon;\ \varepsilon \in [0,1]$ so that the customer is at the margin, hence being almost indifferent between travelling and not travelling. The above expression becomes

$$NB(z_{ac}) = W_c^* - z_{ac} + \frac{L(k) - z_{ac}}{2(w_c^* - L(k))} - \left[\frac{2w_c^* - L(k) - z_{ac} + \varepsilon}{2(w_c^* - L(k))}\right]\left[\frac{L(k) - fk}{z_{ac} - L(k)}\right]$$

Taking limits as ε approaches zero and taking derivative of $NB(z_{ac})$ with respect to z_{ac}, and equating it to zero gives us the following first order condition

$$\frac{\partial NB(z_{ac})}{\partial z_{ac}} = -1 - \frac{1}{2(w_c^* - L(k))} + \left[\frac{2w_c^* - L(k) - z_{ac}}{2(w_c^* - L(k))}\right]\left[\frac{L(k) - fk}{(z_{ac} - L(k))^2}\right] +$$

$$\frac{1}{2(w_c^* - L(k))}\left[\frac{L(k) - fk}{z_{ac} - L(k)}\right] = 0$$

On multiplying throughout by $2(W_c^* - L(k))$, we get

$$-2(W_c^* - L(k)) - 1 + \left[\frac{(2w_c^* - L(k) - z_{ac})(L(k) - fk)}{(z_{ac} - L(k))^2}\right] + \left[\frac{L(k) - fk}{z_{ac} - L(k)}\right] = 0$$

On multiplying throughout by $(z_{ac} - L(k))^2$, we get

$$[-2(W_c^* - L(k)) - 1](z_{ac} - L(k))^2 + (2W_c^* - L(k) - z_{ac})(L(k) - fk) +$$

$$(L(k) - fk)(z_{ac} - L(k)) = 0$$

$$\leftrightarrow \quad [-2(W_c^* - L(k)) - 1](z_{ac} - L(k))^2 + [2(W_c^* - L(k)) - (z_{ac} - L(k))]\ (L(k) - fk) +$$

$$(L(k) - fk)(z_{ac} - L(k)) = 0$$

$$\leftrightarrow \quad [-2(W_c^* - L(k)) - 1](z_{ac} - L(k))^2 + 2(W_c^* - L(k))(L(k) - fk) -$$

$$(L(k) - fk)(z_{ac} - L(k)) + (L(k) - fk)(z_{ac} - L(k)) = 0$$

The last two terms on the L.H.S cancel out and we're left with

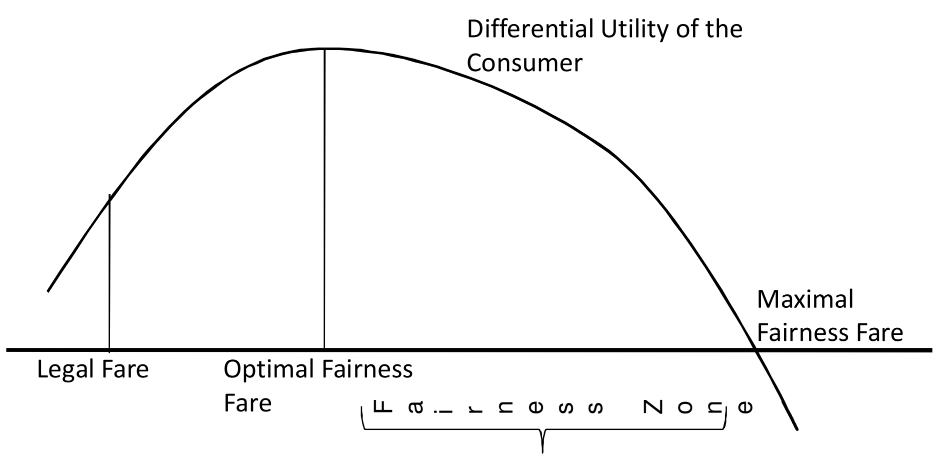
$$[2(W_c^* - L(k)) + 1](z_{ac} - L(k))^2 = 2(W_c^* - L(k)\,)\,(L(k) - fk)$$

$$\leftrightarrow \qquad (z_{ac} - L(k))^2 = \frac{2(w_c^* - L(k)\,)\,(L(k) - fk)}{[2(w_c^* - L(k)) + 1]}$$

$$\leftrightarrow \qquad z_{ac} = L(k) + \sqrt{\frac{2(w_c^* - L(k))\,(L(k) - fk)}{[2(w_c^* - L(k)) + 1]}} \qquad (4A.12)$$

(4A.12) above is yet another fairness-equilibrium. In Appendix 4E, it is shown that the above expression maximizes the net benefit curve.

Figure 4A.1: The 'fair' fares



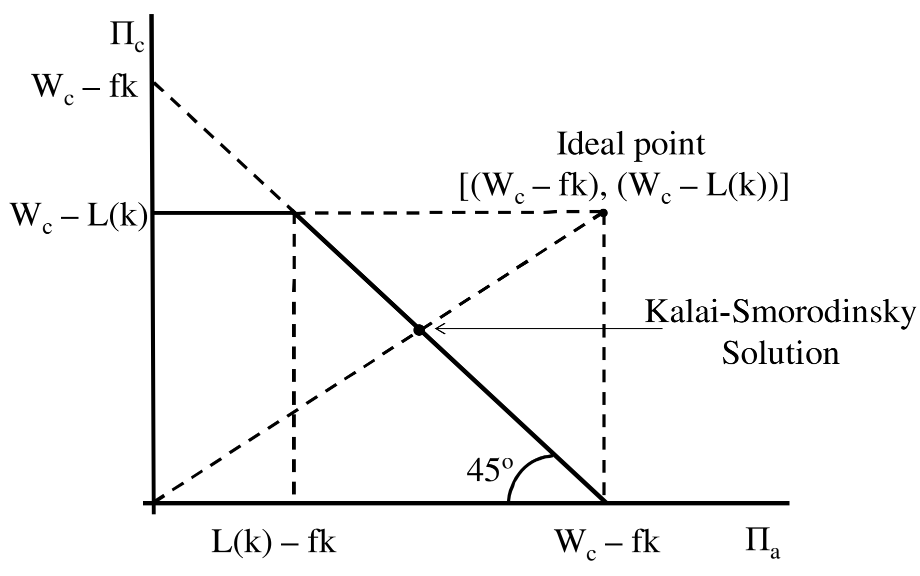
2

Appendix 4B: Derivation of Equilibrium Conditions for the Kalai-Smorodinsky Solution

The derivation

I shall assume a (0, 0) disagreement payoff profile throughout this subsection to keep the explanation of derivations of equilibrium (and the related structural equation) simple. The regressions account for availability of substitutes. The KS solution sets utility gains from the disagreement point proportional to the agents' most optimistic expectations (see Figure 4B.1). For each agent, the latter is defined as the highest utility he can attain in the feasible set.[38]

Figure 4B.1: Kalai-Smorodinsky Solution: This solution is obtained by finding the maximal point on the feasible set connecting the disagreement point to the 'ideal' point represented by the highest utility levels that either agent can reach in the feasible set as its coordinates.



[38] This is of course, subject to the constraint that no agent should receive less than his coordinate of the disagreement point.

The equation of the straight line joining $((W_c - fk), (W_c - L(k)))$ and $(0, 0)$ is given by

$$\Pi_c = \frac{W_c - L(k)}{W_c - fk} \cdot \Pi_a \tag{4B.1}$$

We work out the point of intersection of this line with the utility frontier as follows

$$\left[\frac{W_c - L(k)}{W_c - fk} + 1\right] \cdot \Pi_a = W_c - fk$$

$$\leftrightarrow \qquad [(W_c - L(k)) + (W_c - fk)] \cdot \Pi_a = (W_c - fk)^2$$

We replace Π_a above using (4.3) and rearrange to obtain

$$[(1 + \theta_{ac})L(k) - fk] = \frac{(W_c - fk)^2}{[(W_c - L(k)) + (W_c - fk)]}$$

$$\leftrightarrow \qquad (1 + \theta_{ac})L(k) = \frac{(W_c - fk)^2 + [(W_c - L(k)) + (W_c - fk)] \cdot fk}{[(W_c - L(k)) + (W_c - fk)]} \tag{4B.2}$$

On dividing (4B.2) throughout by L(k) and solving the numerator of RHS, we get

$$(1 + \theta_{ac}) = \frac{1}{L(k)} \cdot \frac{W_c^2 - fk \cdot L(k)}{[(W_c - L(k)) + (W_c - fk)]} \tag{4B.3}$$

$$\leftrightarrow \qquad (1 + \theta_{ac}) \cdot L(k) \cdot [2W_c - fk - L(k)] = W_c^2 - fk \cdot L(k)$$

$$\leftrightarrow \qquad 2(1 + \theta_{ac}) \cdot L(k) \cdot W_c - (1 + \theta_{ac}) \cdot L(k) \cdot (fk + L(k)) = W_c^2 - fk \cdot L(k)$$

$$\leftrightarrow \qquad W_c^2 - 2(1 + \theta_{ac}) \cdot L(k) \cdot W_c + L(k) \cdot [(1 + \theta_{ac})(fk + L(k)) - fk] = 0$$

$$\leftrightarrow \qquad W_c^2 - 2(1 + \theta_{ac}) \cdot L(k) \cdot W_c + L(k) \cdot [\theta_{ac} fk + (1 + \theta_{ac})L(k)] = 0$$

Adding $[(1 + \theta_{ac})L(k)]^2$ on both sides, we get,

$$W_c^2 - 2(1+\theta_{ac})\cdot L(k)\cdot W_c + [(1+\theta_{ac})L(k))]^2 + L(k)\cdot[\theta_{ac}fk + (1+\theta_{ac})L(k)] = [(1+\theta_{ac})L(k))]^2$$

$$\leftrightarrow \quad [W_c - (1+\theta_{ac})L(k)]^2 = [(1+\theta_{ac})L(k))]^2 - \theta_{ac}fkL(k) - (1+\theta_{ac})L_k^2$$

$$\leftrightarrow \quad [W_c - (1+\theta_{ac})L(k)]^2 = [(1+\theta_{ac})^2 - (1+\theta_{ac})]L_k^2 - \theta_{ac}fkL(k)$$

$$\leftrightarrow \quad [W_c - (1+\theta_{ac})L(k)]^2 = (\theta_{ac}^2 + \theta_{ac})L_k^2 - \theta_{ac}fkL(k)$$

Taking square root on both sides we get

$$[W_c - (1+\theta_{ac})L(k))] = \sqrt{(\theta_{ac}^2 + \theta_{ac})L_k^2 - \theta_{ac}fkL(k)}$$

$$\leftrightarrow \quad (1+\theta_{ac})L(k) + \sqrt{(\theta_{ac}^2 + \theta_{ac})L_k^2 - \theta_{ac}fkL(k)} = W_c$$

Finally, we divide throughout by $L(k)$ to get the KS equilibrium condition

$$(1+\theta_{ac}) + \sqrt{\theta_{ac}(1+\theta_{ac}) - \theta_{ac}\left(\frac{fk}{L(k)}\right)} = \frac{W_c}{L(k)}$$

Using (4.4) in the above expression (and accounting for the disagreement payoff) gives us[39]

$$(1+\theta_{ac}) + \sqrt{\theta_{ac}(1+\theta_{ac}) - \theta_{ac}\left(\frac{fk}{L(k)}\right)} = \boldsymbol{X_c}\left(\frac{\boldsymbol{\alpha}}{L(k)}\right) - \left(\frac{\gamma_s}{L(k)}\right)S_c + \frac{\nu_c}{L(k)} \qquad (4B.4)$$

Let, $h(\boldsymbol{X_c}; \boldsymbol{\alpha}) = \boldsymbol{X_c\alpha}$

This leads us to the following structural equation which we call as Type 2.

$$\Omega_{KS}(\theta_{ac}) = (1+\theta_{ac}) + \sqrt{\theta_{ac}(1+\theta_{ac}) - \theta_{ac}\left(\frac{fk}{L(k)}\right)} = \boldsymbol{Y_c\beta} + \eta_c$$

where,

[39] $\left(\frac{\boldsymbol{\alpha}}{L(k)}\right)$ simply denotes that each element of $\boldsymbol{\alpha}$ is divided by $L(k)$.

Ω_{KS}: $R \rightarrow R$ is a monotonic transformation such that

$$\Omega_{KS}(\theta_{ac}) = (1 + \theta_{ac}) + \sqrt{\theta_{ac}(1 + \theta_{ac}) - \theta_{ac}\left(\frac{fk}{L(k)}\right)}.$$

$\boldsymbol{Y_c} = [\boldsymbol{X_c} \vdots S_c]$ is the partition matrix of the exogenous variables.

$\boldsymbol{\tau}^{\boldsymbol{T}} = [\boldsymbol{\alpha}^{\boldsymbol{T}} \vdots \gamma_s]$ is the partition vector of coefficients.

g: $R^j \rightarrow R^j$ is an invertible map such that $\boldsymbol{\beta} = g(\boldsymbol{\tau}) = (\frac{1}{L(k)})\boldsymbol{\tau}$. So that $\hat{\boldsymbol{\tau}} = g^{-1}(\widehat{\boldsymbol{\beta}}) = L(k)\widehat{\boldsymbol{\beta}}$

u: $R \rightarrow R$ is an invertible map such that $\eta_c = u(L(k))\cdot v_c$ where $u(L(k)) = (\frac{1}{L(k)})$.

Let $H(\boldsymbol{Y_c};\boldsymbol{\beta}) = \boldsymbol{Y_c}\boldsymbol{\beta}$.

Equation (4B.4) above can be explicitly written in relation to the observed coefficients as follows.

$$(1 + \theta_{ac}) + \sqrt{\theta_{ac}(1 + \theta_{ac}) - \theta_{ac}\left(\frac{fk}{L(k)}\right)} = \boldsymbol{Y_c}\underbrace{(\frac{\boldsymbol{\tau}}{L(k)})}_{\boldsymbol{\beta}} + \underbrace{\frac{v_c}{L(k)}}_{\eta_c} \qquad (4B.5)$$

Appendix 4C: Evaluation of Comparable Residuals for RMSE (with arbitrary errors)

For ease of notation, I define

$\boldsymbol{X} = \boldsymbol{Y_c}$ the partition matrix of independent variables

$\boldsymbol{B} = \boldsymbol{\beta}$ the partition vector of coefficient vectors

$y = (1 + \theta_{ac})$ the outcome variable in Type 1 structural equation

$$\Psi_2(y) = \sqrt{\theta_{ac}(1 + \theta_{ac}) - \theta_{ac}\left(\frac{fk}{L(k)}\right)}; \quad \Psi_3(y) = \sqrt{\theta_{ac}(2 + \theta_{ac}) - 2\theta_{ac}\left(\frac{fk}{L(k)}\right)}$$

$\Phi_i(y) = y + \Psi_i(y)$ the outcome variable in *Type i* $(i \in \{2,3\})$ structural equation

The three *types (1, 2 and 3)* can now be written as

Type 1: $\boldsymbol{y} = \boldsymbol{XB_1} + \boldsymbol{v_1}$ (4C.1)

Type i: $\boldsymbol{\Phi_i(y)} = \boldsymbol{XB_i} + \boldsymbol{v_i}$ $\quad i \in \{2,3\}$ (4C.2)

We note that $\Phi_i(y)$ is a quasi-linear transformation of y, with a non-linear component $\Psi_i(y)$ and is also linear at the limit. Now,

$\boldsymbol{v_1} = \boldsymbol{y} - E[\boldsymbol{y}|\boldsymbol{X}] = \boldsymbol{y} - \boldsymbol{X\hat{B}_1}$ {from (4C.1)} (4C.3)

To provide an intuition, here we ask the question that if we were to predict the values of the outcome variables of Type 2 and Type 3 structural equations, using the regression estimates of Type 1 equation, will we do a better job. We use the expected values of the dependent variable of Type 1 (mark up over the legal fare) equation to obtain the (implied) expected values of its quasi linear (and monotonic) transformations (the dependent variables of Type 2 and Type 3 structural equations). We then find out the differences between the observed transformations (by which we mean transformations $\Phi_i(y)$ of the actually observed mark-ups y) and their expected values obtained (directly) from regressions of Type 2 and Type 3 structural equations and implied (indirectly) by Type 1 structural equation. Formally,

From (4C.1) above,

$$\hat{\boldsymbol{y}} = \boldsymbol{X}\hat{\boldsymbol{B}}_1$$

$$\leftrightarrow \qquad \boldsymbol{\Phi_i(\hat{y}) = \Phi_i(X\hat{B}_1)} \; ; i \in \{2,3\} \quad \{\text{the quasi linear transformations are also monotonic}\}$$

The residual implied by Type 1 structural equation comparable with Type i $(i \in \{2,3\})$ structural equation is obtained as follows

$$\boldsymbol{v_1^i = \Phi_i(y) - \Phi_i(\hat{y}) = \Phi_i(y) - \Phi_i(X\hat{B}_1)} \; ; \qquad i \in \{2, 3\} \tag{4C.4}$$

And the residuals obtained by *Type i* structural equation come directly from (4C.2).

$$\boldsymbol{v_i = \Phi_i(y) - \widehat{\Phi_i(y)} = \Phi_i(y) - X\hat{B}_i} \; ; \qquad i \in \{2, 3\}$$

We then use the residuals obtained to calculate comparable RMSEs. These have been reported in Tables 4.6 and 4.7. It should be noted that for the range of values of y we observe, the transformation $\Phi_i(y)$ is almost linear. Thus although, ideally in (4C.4), we'd be interested in

$$\boldsymbol{v_1^i = \Phi_i(y) - \widehat{\Phi_i(y)} = \Phi_i(y) - \widehat{\Phi_i(XB_1)}} \; ; \qquad i \in \{2, 3\} \tag{4C.5}$$

and arrive at estimates of $\boldsymbol{B_1}$ using non-linear estimation (minimizing the sum of squared errors in (C.5)). This is where the almost linearity of $\Phi_i(y)$ comes in. Fundamentally, let

$$\Phi_i(y) \cong \tau + \lambda y \; ; (\lambda > 0) \tag{4C.6}$$

From (4C.5), then,

$$\boldsymbol{v_1^i} = \boldsymbol{\Phi_i(y)} - \widehat{\boldsymbol{\Phi_i(y)}} \cong \lambda(\boldsymbol{y} - \boldsymbol{\hat{y}})$$

that is, the $\boldsymbol{B_1}$ that minimises the sum of squared terms above (shown below)

$$\sum_j (v_{1j}^i)^2 = (\lambda^2)\sum_j (y_j - \hat{y}_j)^2 \quad (4C.7)$$

where j denotes the summation across the observations. Clearly, (since $\lambda > 0$) the $\boldsymbol{B_1}$ that minimises (4C.7) is also the one that minimises

$$\sum_j (v_{1j})^2 = \sum_j (y_j - \hat{y}_j)^2$$

which is precisely the $\boldsymbol{B_1}$ that is represented by (4C.3 and 4C.4) that is the one obtained from the Nash solution. This exercise is just to show that the non-linear estimates will be deadly close to the linear estimates and running a separate non-linear estimation will add no value.

Finally, the only issue with the approach discussed in this appendix is that we can only draw comparisons between Types 2 and 3 individually against Type 1. We cannot compare Type 2 and Type 3 against each other. So we look into the following appendix where a universal comparison can be made.

Appendix 4D: Evaluation of Comparable Residuals for RMSE (using inverses)

Intuitively speaking, here we ask a question opposite to that posed in the previous appendix. If we were to predict the mark-up over the legal fare (the dependent variable of Type 1 equation) using regression estimates of Types 2 and 3, will we do a better job than the regression estimates obtained from Type 1 itself? I again point out that $\Phi_i(y)$ are monotonically increasing in y, so we invert the relations to obtain Φ_i^{-1} and calculate residuals implied by structural equations of Type 2 and Type 3 that are comparable with that of Type 1. Formally, we calculate the following,

$$\boldsymbol{v_i^1 = y - \Phi_i^{-1}(\widehat{\Phi_i(y)}) = y - \Phi_i^{-1}(XB_i)} \qquad i \in \{2, 3\}$$

And we rewrite (4C.3) below

$$\boldsymbol{v_1 = y - E[y|X] = y - X\widehat{B}_1}$$

We finally calculate comparable RMSEs as before. We observe out that

$$y = \Phi_i^{-1}(t_i) = \frac{t_i^2 - [(i-1)(\frac{fk}{L(k)}) - (i-2)]}{2t_i + (i-3) - (i-1)(\frac{fk}{L(k)})} \qquad i \in \{2, 3\}$$

where t_i represents the outcome variable of Type i equation ($i \in \{2, 3\}$).

Appendix 4E: Additional Support Material

4E.1. NB(z_{ac}) is maximized

We re-write the specifications in the body of this article to evaluate the following inequality. For ease of notation, we write $L(k) = L_k$.

$$NB(z_{ac}) = \widetilde{\Pi}_c(r_c = z_{ac}) - \widetilde{\Pi}_c(r_c < z_{ac}) > 0$$

$$\leftrightarrow \qquad NB(z_{ac}) = W_c^* - z_{ac} - \frac{z_{ac} - L_k}{2(W_c^* - L_k)} - \left[\frac{2W_c^* - L_k - r_c}{2(W_c^* - L_k)}\right]\left[\frac{L_k - fk}{z_{ac} - L_k}\right] > 0$$

On multiplying throughout by $2(W_c^* - L_k)$, we get

$$2(W_c^* - z_{ac})(W_c^* - L_k) - (z_{ac} - L_k) > (2W_c^* - L_k - r_c)\left[\frac{L_k - fk}{z_{ac} - L_k}\right]$$

On multiplying throughout by $(z_{ac} - L_k)$ and defining $r_c = z_{ac} - \varepsilon;\ \varepsilon \in [0,1]$ so that the customer is at the margin, hence being almost indifferent between travelling and not travelling, the above expression becomes

$$2(W_c^* - z_{ac})(W_c^* - L_k)(z_{ac} - L_k) - (z_{ac} - L_k)^2 > (2W_c^* - L_k - z_{ac} + \varepsilon)\,(L_k - fk)$$

On taking limits as ε approaches zero, and rearranging terms, we get the following quadratic in z_{ac}.

$$G(z_{ac}) = Az_{ac}^2 + Bz_{ac} + C > 0$$

where, $A = -2(W_c^* - L_k)$; $B = [2(W_c^{*2} - L_k^2) + (L_k - fk)]$; and, $C = -2(W_c^* - L_k)[(W_c^* L_k) + (L_k - fk)]$. We then recognize that $A < 0$, $B > 0$ and $C < 0$ to conclude that $G(z_{ac})$ is concave throughout and therefore has a global maximum. This completes the proof.

4E.2. Derivations for other solutions.

Equilibrium Conditions and Structural Equations

Let $$W_c = \alpha_k + \boldsymbol{X_c \alpha} + v_c \qquad (4.4)$$

where α_k is a representative constant for a given distance k for *every* customer and $\boldsymbol{X}$ does not include the constant of regression.

Nash Solution: The Nash Solution is characterised as follows

Maximize: $\Pi_a(\Pi_c - D_c)$ with respect to θ_{ac}

Using (4.3) and (4.5) we work out the first order condition of the problem above as follows

$$(1 + \theta_{ac}) = \frac{W_c - D_c + fk}{2L(k)}$$

Using (4.4) along with the disagreement equation in the above expression and rearranging the terms, gives us

$$(1 + \theta_{ac}) = \left(\frac{\alpha_k + fk}{2L(k)}\right) + \boldsymbol{X}_c\left(\frac{\boldsymbol{\alpha}}{2L(k)}\right) - \left(\frac{\gamma_s}{2L(k)}\right)S_c + \frac{v_c}{2L(k)} \qquad (4E.1)$$ [40]

This leads us to the following structural equation depicting the average mark-up as a function of determinants of valuation and the availability of substitutes (Type 1).

[40] Note that $\boldsymbol{\alpha}$ is a vector. The expression $(\frac{\boldsymbol{\alpha}}{L_k})$ only means that each element of the $\boldsymbol{\alpha}$ vector is getting divided by L_k

$$(1 + \theta_{ac}) = \beta_0 + \boldsymbol{X_c\beta} + \mu_s S_c + \eta_c \qquad (4E.2)$$

Egalitarian Solution: It is characterised as follows

$$\Pi_a = \Pi_c = \frac{W_c - fk}{2} \qquad (4E.3)$$

Using (4E.3), we get

$$W_c - (1 + \theta_{ac})L(k) = \frac{W_c - fk}{2}$$

$$\leftrightarrow \qquad (1 + \theta_{ac}) = \frac{W_c + fk}{2L(k)}$$

This is (structurally) identical to the Nash Solution.

Dictatorial Solution (customer is the dictator): The maximal point of the customer's coordinate on the payoff frontier is

$$\Pi_c = W_c - L(k) \qquad (4E.4)$$

$$\leftrightarrow \qquad W_c - (1 + \theta_{ac})L(k) = W_c - L(k) \qquad \{\text{using (4.5)}\}$$

This gives us

$$\theta_{ac} = 0 \qquad (4E.5)$$

Naturally, if the customer were the dictator, he would not pay any mark-up over the legal fare to the auto driver. In this case, we do not need a structural equation. One can simply test for $\theta_{ac} = 0$ to validate or invalidate a claim that suggests this dictatorial solution.

Dictatorial Solution (auto-driver is the dictator): This solution is arrived at the maximal point of the auto driver's coordinate on the utility frontier.

$$\Pi_a = W_c - fk \qquad (4E.6)$$

$$\leftrightarrow \qquad (1 + \theta_{ac})L(k) - fk = W_c - fk \quad \{\text{using } (4.3)\}$$

This gives us

$$(1 + \theta_{ac}) = \frac{W_c}{L(k)}$$

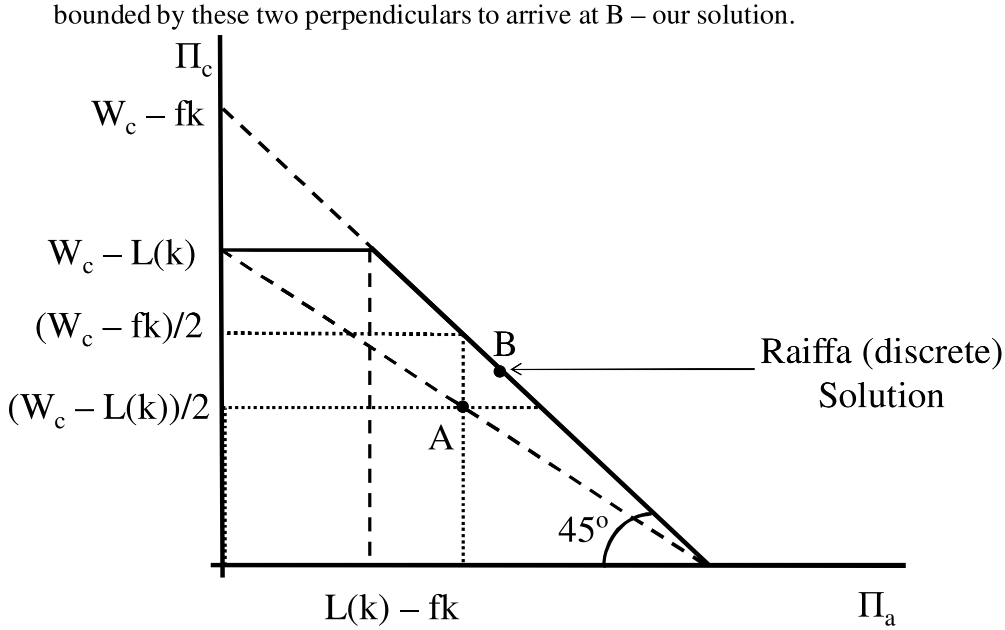
Thus, using (4.4) in the above expression gives us the following structural equation.

$$(1 + \theta_{ac}) = \left(\frac{\alpha_k}{L(k)}\right) + \boldsymbol{X_c}\left(\frac{\boldsymbol{\alpha}}{L(k)}\right) + \frac{\nu_c}{L(k)} \qquad (4E.7)$$

Clearly, our regression function is (structurally) a Type 1.

Raiffa Solution (discrete): The following figure explains the solution.

Figure 4E.1: The (discrete) Raiffa Solution:.We first bisect the line which has its intercepts as the maximum payoffs that can be derived by the customer and the auto driver. We call this point of bisection A. From A we draw lines perpendicular to the axes till they meet the utility frontier. Finally, we bisect the segment of the frontier bounded by these two perpendiculars to arrive at B – our solution.



The process of arriving at point A above and graduating to point B, essentially involves finding the midpoint of $\Pi_c^A = \left(\frac{W_c - L(k)}{2}\right)$ and $\Pi_c = \left(\frac{W_c - fk}{2}\right)$. We get

$$\Pi_c^B = \frac{1}{2}\left[W_c - \frac{fk + L(k)}{2}\right] \tag{4E.8}$$

Finally, using (4.5) in the above expression we get,

$$W_c - (1 + \theta_{ac})L(k) = \frac{1}{2}\left[W_c - \frac{fk + L(k)}{2}\right]$$

$$\leftrightarrow \qquad (1 + \theta_{ac}) = \frac{W_c}{2L(k)} + \frac{1}{4}\left[1 + \frac{fk}{L(k)}\right]$$

Using (4.4) in the above expression and rearranging the terms, gives us the following structural equation

$$(1 + \theta_{ac}) = \left(\frac{\alpha_k}{2L(k)} + \frac{1}{4}\left[1 + \frac{fk}{L(k)}\right]\right) + \boldsymbol{X}_c\left(\frac{\boldsymbol{\alpha}}{2L(k)}\right) + \frac{\nu_c}{2L(k)} \tag{4E.9}$$

This leads us to a regression equation of Type 1.

Equal-Area Solution: Figure 4E.2. below explains the process of obtaining the solution.

The equal area condition can be written as follows.

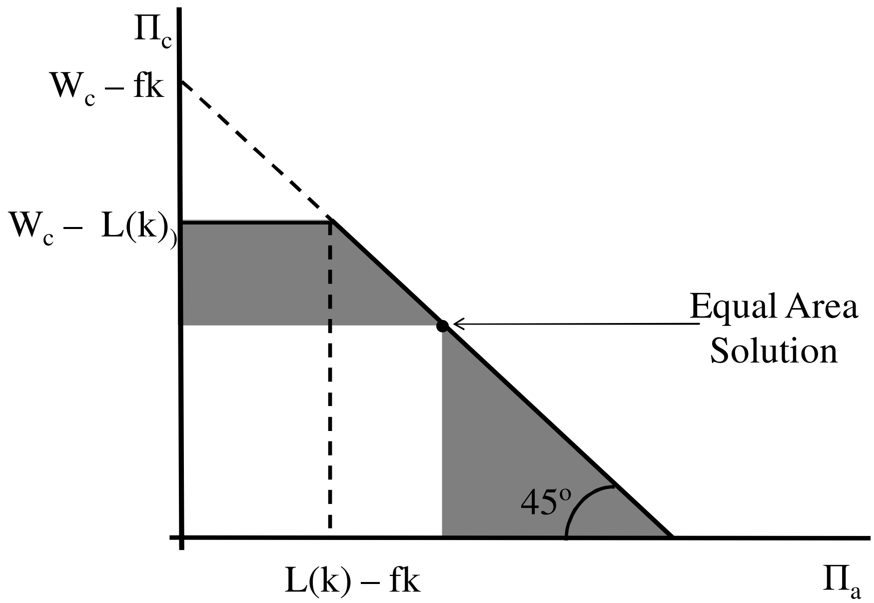
$$(W_c - L(k) - \Pi_c)(L(k) - fk) + \frac{1}{2}(\Pi_a - L(k) + fk)(W_c - L(k) - \Pi_c)$$

$$= \frac{1}{2}\Pi_c (W_c - fk - \Pi_a) \tag{4E.10}$$

Replacing Π_a and Π_c above by using (4.3) and (4.5), reduces (4E.10) to the following.

$$(\theta_{ac}L(k))(L(k) - fk) + \frac{1}{2}(\theta_{ac}L(k))^2 = \frac{1}{2}(W_c - (1 + \theta_{ac})L(k))^2$$

Figure 4E.2: Equal Area Solution: This solution picks the Pareto optimal point where the area of the individually rational part of the feasible set above the solution point is equal to the area to the right of that point (the area of the two shaded portions are equal).



Finally, dividing throughout by $(L(k))^2$ and rearranging terms, we arrive at

$$(1 + \theta_{ac}) + \sqrt{\theta_{ac}(2 + \theta_{ac}) - 2\theta_{ac}\left(\frac{fk}{L(k)}\right)} = \frac{W_c}{L(k)}$$

Using (4.4) in the above expression as before gives us the following structural equation.

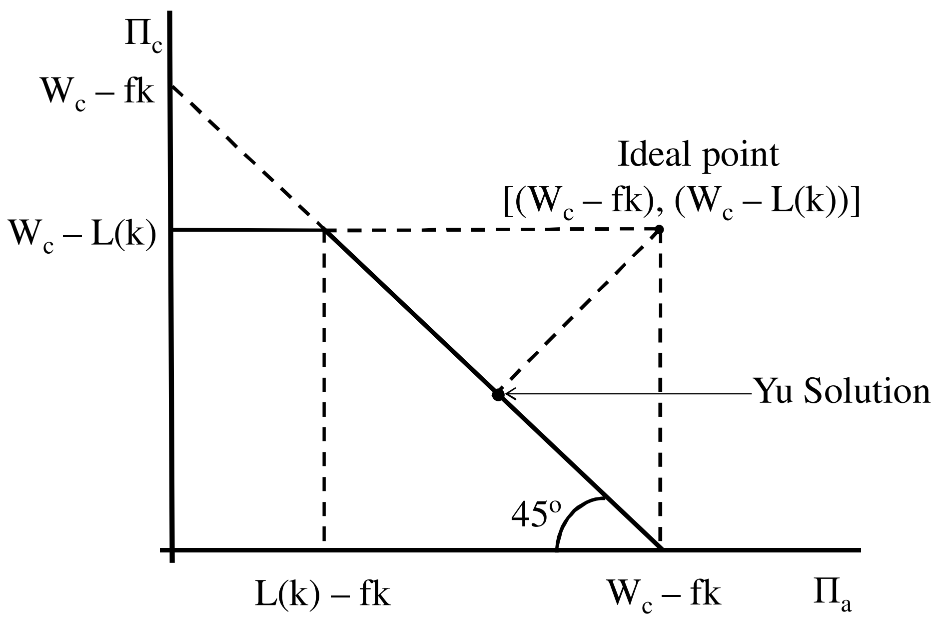
$$(1 + \theta_{ac}) + \sqrt{\theta_{ac}(2 + \theta_{ac}) - 2\theta_{ac}\left(\frac{fk}{L(k)}\right)} = \left(\frac{\alpha_k}{L(k)}\right) + \boldsymbol{X_c}\left(\frac{\boldsymbol{\alpha}}{L(k)}\right) + \frac{\nu_c}{L(k)} \qquad \text{(4E.11)}$$

This leads us to the following structural equation depicting a non-linear (and increasing) transformation (different from Kalai-Smorodinski) of the average mark-up as a function of determinants of maximum willingness to pay. We call this Type 3.

$$(1 + \theta_{ac}) + \sqrt{\theta_{ac}(2 + \theta_{ac}) - 2\theta_{ac}\left(\frac{fk}{L(k)}\right)} = \beta_0 + \boldsymbol{X_c\beta} + \eta_c$$

Yu Solution: Figure 4E.3, explains the derivation of the condition implied by the Yu Solution that we write below.

Figure 4E.3: Yu Solution: This solution is obtained by finding that point on the utility frontier the distance of which from the ideal point is minimum.



We use the fact that perpendicular distance is the shortest distance. The equation of the line with unit slope passing through the ideal point $[(W_c - fk), (W_c - L(k))]$ is given by

$$\Pi_c - (W_c - L(k)) = \Pi_a - (W_c - fk)$$

which simplifies to

$$\Pi_c = \Pi_a - (L(k) - fk)$$

We find the intersection point of this line with the utility frontier to get the following condition

$$\Pi_a = \frac{1}{2}W_c + \frac{1}{2}L(k) - fk \qquad (4E.12)$$

Finally replacing Π_a by using (4.3), above and solving for the mark-up, we get

$$(1 + \theta_{ac}) = \frac{W_c}{2L(k)} + \frac{1}{2} \tag{4E.13}$$

Now, just as before we use (4.4) to arrive at the following structural equation.

$$(1 + \theta_{ac}) = \left(\frac{\alpha_k}{2L(k)} + \frac{1}{2}\right) + \boldsymbol{X_c}\left(\frac{\boldsymbol{\alpha}}{2L(k)}\right) + \frac{\nu_c}{2L(k)} \tag{4E.14}$$

Which gives us an econometric equation indistinguishable from that of the Nash solution.

4E.3. Estimation of Maximum Willingness to Pay

The bargaining solutions discussed in the previous section lead to the following three different types of structural equations.

Type 1: $(1 + \theta_{ac}) = \beta_0 + \boldsymbol{X_c\beta} + \mu_s S_c + \eta_c$

Type 2: $(1 + \theta_{ac}) + \sqrt{\theta_{ac}(1 + \theta_{ac}) - \theta_{ac}\left(\frac{fk}{L_k}\right)} = \beta_0 + \boldsymbol{X_c\beta} + \mu_s S_c + \eta_c$

Type 3: $(1 + \theta_{ac}) + \sqrt{\theta_{ac}(2 + \theta_{ac}) - 2\theta_{ac}\left(\frac{fk}{L_k}\right)} = \beta_0 + \boldsymbol{X_c\beta} + \mu_s S_c + \eta_c$

In what follows, I discuss the process of estimating customer valuation for different solutions by explicitly stating the relationship between observed coefficients and quantities of interest. We start with the Type 1 solutions.

4E.3.1. Type 1 Solutions

Nash Solution: We identify the quantities of interest explicitly in relation to the observed coefficients in the structural equation (4E.1) below (after writing $L(k) = L_k$)

$$(1+\theta_{ac}) = \underbrace{\left(\frac{\alpha_k + fk}{2L_k}\right)}_{\beta_0} + \boldsymbol{X_c}\underbrace{\left(\frac{\boldsymbol{\alpha}}{2L_k}\right)}_{\boldsymbol{\beta}} - \underbrace{\left(\frac{\gamma_s}{2L_k}\right)}_{\mu_S} S_c + \underbrace{\frac{\nu_c}{2L_k}}_{\eta_c} \tag{4E.15}$$

We then invert the explicitly stated relations above to arrive at $\hat{\alpha}_k$, $\hat{\gamma}_s$, and the $\hat{\boldsymbol{\alpha}}$ vector as follows (note that running the Type 1 regression will lead us to estimates of β_0, μ_s, and $\boldsymbol{\beta}$).

$$\hat{\alpha}_k = 2\hat{\beta}_0 L_k - fk\,; \qquad \hat{\gamma}_s = -2\hat{\mu}_s L_k\,; \text{ and } \qquad \hat{\boldsymbol{\alpha}} = (2L_k)\hat{\boldsymbol{\beta}} \tag{4E.16}$$

We finally write customer valuation (using (4)) explicitly as a function of distance k (note that the egalitarian solution will have the exact same methodology).

$$\widehat{W}_c = \hat{\alpha}_k + \boldsymbol{X_c}\hat{\boldsymbol{\alpha}} \tag{4E.17}$$

Dictatorial Solution (auto driver is the dictator): We rewrite (4E.7) below and identify the quantities of interest explicitly in relation to the observed coefficients.

$$(1+\theta_{ac}) = \underbrace{\left(\frac{\alpha_k}{L_k}\right)}_{\beta_0} + \boldsymbol{X_c}\underbrace{\left(\frac{\boldsymbol{\alpha}}{L_k}\right)}_{\boldsymbol{\beta}} - \underbrace{\left(\frac{\gamma_s}{L_k}\right)}_{\mu_S} S_c + \underbrace{\frac{\nu_c}{L_k}}_{\eta_c}$$

We then, just as before invert the explicitly stated relations above as follows (valuation is estimated exactly as in (4E.17) above).

$$\hat{\alpha}_k = \hat{\beta}_0 L_k\,; \qquad \hat{\gamma}_s = -\,\hat{\mu}_s L_k\,; \quad \text{and} \qquad \hat{\boldsymbol{\alpha}} = (L_k)\hat{\boldsymbol{\beta}} \tag{4E.18}$$

Raiffa (discrete) Solution: We rewrite (4E.9) below and identify the quantities of interest explicitly in relation to the observed coefficients.

$$(1+\theta_{ac}) = \underbrace{\left(\frac{\alpha_k}{2L_k} + \frac{1}{4}\left[1 + \frac{fk}{L_k}\right]\right)}_{\beta_0} + \boldsymbol{X_c}\underbrace{\left(\frac{\boldsymbol{\alpha}}{2L_k}\right)}_{\boldsymbol{\beta}} - \underbrace{\left(\frac{\gamma_s}{2L_k}\right)}_{\mu_S} S_c + \underbrace{\frac{\nu_c}{2L_k}}_{\eta_c}$$

We then, just as before invert the explicitly stated relations above as follows (estimation of valuation remains the same as in (4E.17)).

$$\hat{\alpha}_k = (2\hat{\beta}_0 - \frac{1}{2})L_k - \frac{1}{2}fk; \qquad \hat{\gamma}_s = -2\hat{\mu}_s L_k; \text{ and } \qquad \hat{\boldsymbol{\alpha}} = (2L_k)\hat{\boldsymbol{\beta}} \tag{4E.19}$$

Yu Solution: We rewrite (4E.14) below and identify the quantities of interest explicitly in relation to the observed coefficients.

$$(1 + \theta_{ac}) = \underbrace{\left(\frac{\alpha_k}{2L_k} + \frac{1}{2}\right)}_{\beta_0} + \boldsymbol{X}_c\underbrace{(\frac{\boldsymbol{\alpha}}{2L_k})}_{\boldsymbol{\beta}} - \underbrace{(\frac{\gamma_s}{2L_k})}_{\mu_s}S_c + \underbrace{\frac{\nu_c}{2L_k}}_{\eta_c}$$

We then, just as before invert the explicitly stated relations above as follows (valuation is estimated just as (4E.17).

$$\hat{\alpha}_k = 2(\hat{\beta}_0 - \frac{1}{2})L_k; \qquad \hat{\gamma}_s = -2\hat{\mu}_s L_k; \text{ and } \qquad \hat{\boldsymbol{\alpha}} = (2L_k)\hat{\boldsymbol{\beta}} \tag{4E.20}$$

Within type 1, we could jointly classify, the Nash-Egalitarian, Raiffa and the Yu solutions as the non-dictatorial type, and the dictatorial solution as the dictatorial type.

4E.3.1. Type 2 Solution (Kalai-Smorodinski):

We identify the quantities of interest explicitly in relation to the observed coefficients (see Appendix 4B).

$$(1 + \theta_{ac}) + \sqrt{\theta_{ac}(1 + \theta_{ac}) - \theta_{ac}\left(\frac{fk}{L_k}\right)} = \underbrace{(\frac{\alpha_k}{L_k})}_{\beta_0} + \boldsymbol{X}_c\underbrace{(\frac{\boldsymbol{\alpha}}{L_k})}_{\boldsymbol{\beta}} - \underbrace{(\frac{\gamma_s}{L_k})}_{\mu_s}S_c + \underbrace{\frac{\nu_c}{L_k}}_{\eta_c}$$

We then, just as before invert the explicitly stated relations above (as we can see from the right hand side, the inversion relations are identical to (4E.18); valuation is estimated as in (4E.17)).

4E.3.3. Type 3 Solution (Equal Area):

We rewrite (4E.11) below and identify the quantities of interest explicitly in relation to the observed coefficients.

$$(1+\theta_{ac}) + \sqrt{\theta_{ac}(2+\theta_{ac}) - 2\theta_{ac}\left(\frac{fk}{L_k}\right)} = \underbrace{\left(\frac{\alpha_k}{L_k}\right)}_{\beta_0} + X_c\underbrace{\left(\frac{\boldsymbol{\alpha}}{L_k}\right)}_{\boldsymbol{\beta}} - \underbrace{\left(\frac{\gamma_s}{L_k}\right)}_{\mu_s}S_c + \underbrace{\frac{\nu_c}{L_k}}_{\eta_c}$$

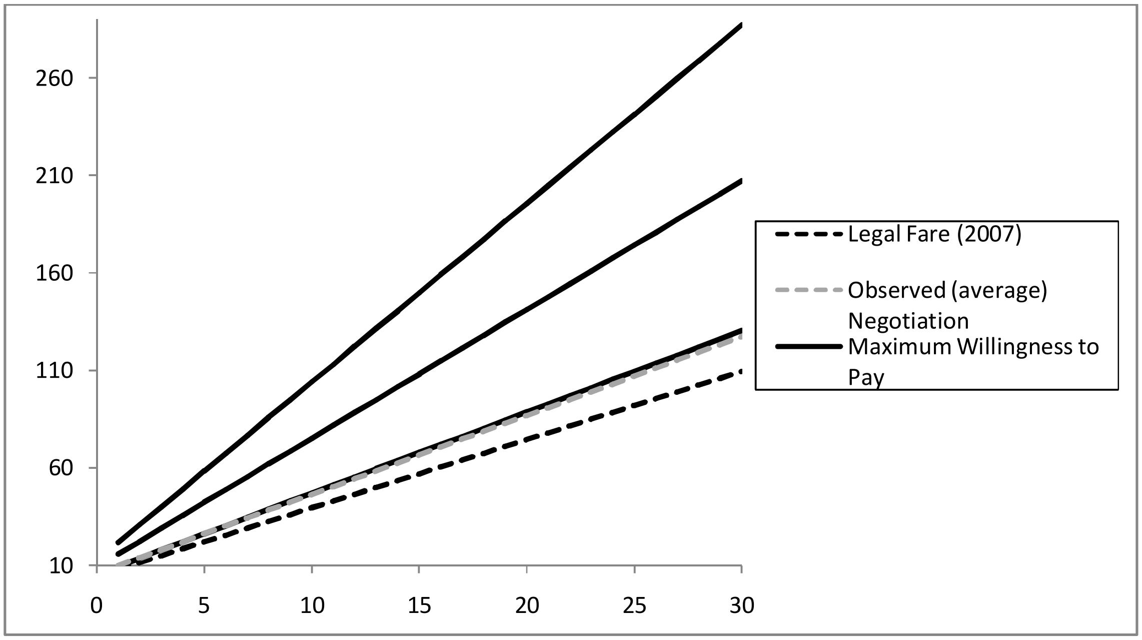
We immediately note that the inversion relations are identical to that of Type 2 above and the process of calculating valuation remains the same. Both the type 2 and type 3 solutions are non-dictatorial solutions.

4E.4. Specification checks

I let my regression estimates go through a set of (theoretical and observable) specification checks that should hold for the general public before accepting parameter values. For example, valuation is increasing in distance *k*, and the coefficient of *Metro* is negative (Tables 4.6 and 4.7) suggesting a substitution effect that reduces mark-up. Further, for both the years, the critical customer's estimated willingness to pay for distances up to three kilometres is very close to the actual metro fares for the same distances – for greater distances, the degree of substitutability between autos and metros tends to decline; one may have to change between different routes with the metro) thus revealing consistency with reality and therefore hinting at low degrees of bias in the predicted parameters for both the years.

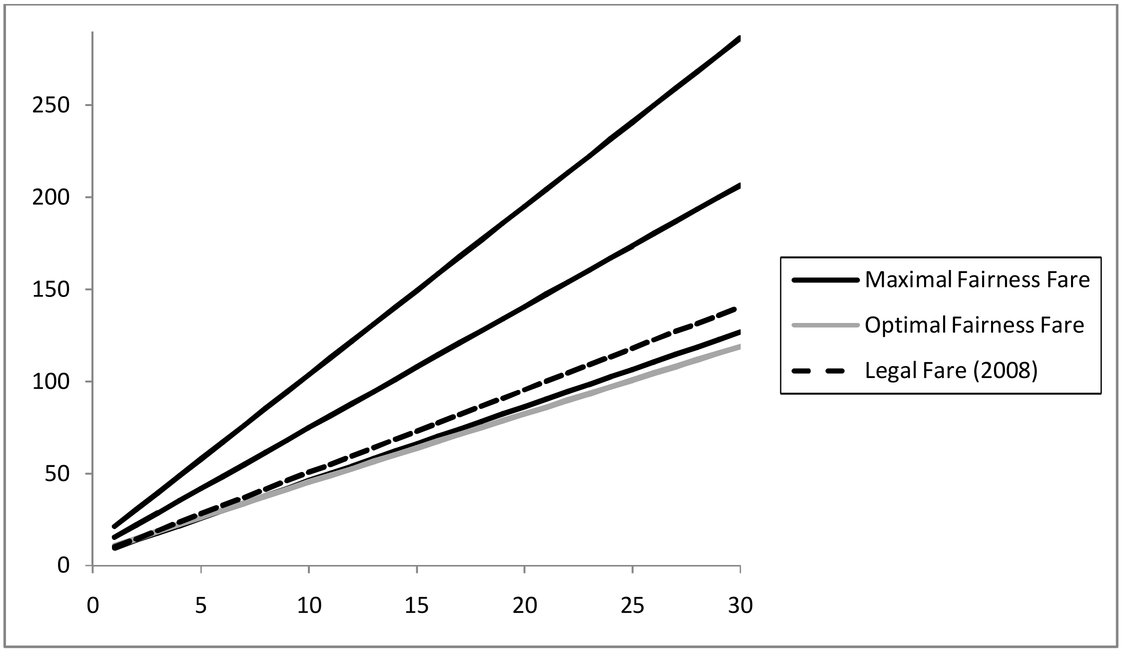
Appendix 4F: Analysis with Confidence Intervals

Figure 4F.1. Maximum willingness to pay in 2007 (Representative Model)



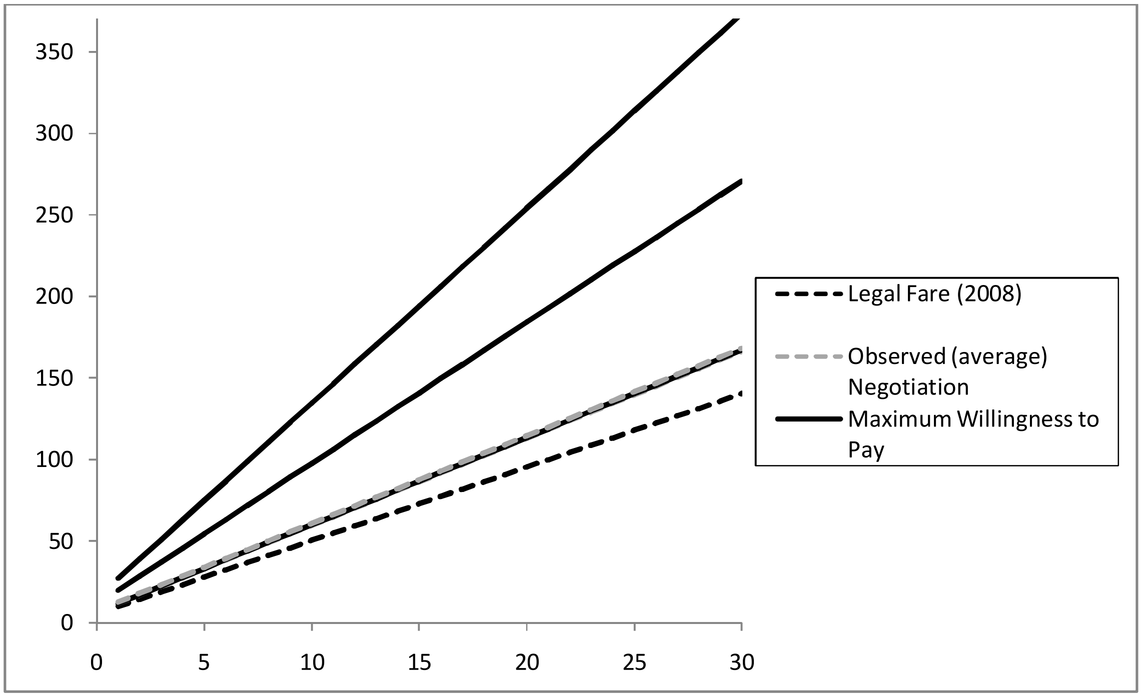
The horizontal axis is measured in kilometres and the vertical axis is measured in INR. Legal fare (2007) is shown in the black dashed line. The observed average negotiated share and its 95% confidence limits are shown by grey dashed lines. The estimated maximum willingness to pay for the critical customer and its 95% confidence limits are shown by the solid black lines. The conclusions remain the same as discussed in the main text.

Figure 4F.2. Pricing rules in 2007 (Representative Model)



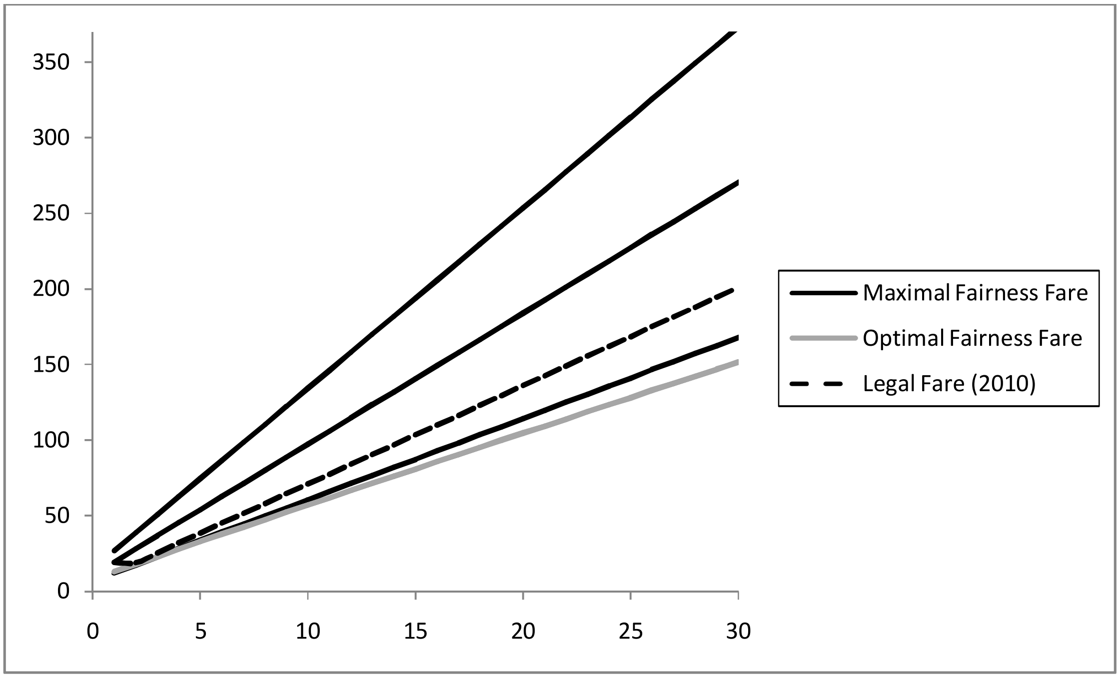
The horizontal axis is measured in kilometres and the vertical axis is measured in INR. Legal fare (2008) is shown in the black dashed line. The estimated maximal fairness fare and its 95% confidence limits are shown by the black solid lines. The estimated optimal fairness fare and its 95% confidence limits are shown by the solid grey lines. The conclusions remain the same as discussed in the main text.

Figure 4F.3. Maximum willingness to pay in 2008 (Representative Model)



The horizontal axis is measured in kilometres and the vertical axis is measured in INR. Legal fare (2008) is shown in the black dashed line. The observed average negotiated share and its 95% confidence limits are shown by grey dashed lines. The estimated maximum willingness to pay for the critical customer and its 95% confidence limits are shown by the solid black lines. The conclusions remain the same as discussed in the main text.

Figure 4F.4. Pricing rules in 2008 (Representative Model)



The horizontal axis is measured in kilometres and the vertical axis is measured in INR. Legal fare (2010) is shown in the black dashed line. The estimated maximal fairness fare and its 95% confidence limits are shown by the black solid lines. The estimated optimal fairness fare and its 95% confidence limits are shown by the solid grey lines. The conclusions remain the same as discussed in the main text.

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