Online Appendix
A Kinky Consistency: Experimental Evidence of Behavior under Linear and Non-Linear Budget Constraints

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This online appendix includes the experiment instructions in Appendix A; details on the procedure Aejto benchmark our test of rationality in Appendix B; details on the structural estimation in Appendix C; decision plots for every experiment participant in Appendix D; additional results on the consistency of preferences in Appendix E; additional details of our analyses of alternative explanations in Appendix F; and additional tables and figures in Appendix G.

A Experiment Instructions

See below for the full experimental instructions and the computer interface used.

Sample instructions

Introduction

This is an experiment in decision-making. Research foundations have provided funds for conducting this research. Your payoffs will depend only on your decisions and on chance. It will not depend on the decisions of the other participants in the experiments. Please pay careful attention to the instructions as a considerable amount of money is at stake. After you read this part of the instructions, it will also be read aloud by the instructor, and you may also ask any questions.

The entire experiment should be complete within an hour and a half. At the end of the experiment you will be paid privately. At that time, you will receive \$5 as a participation fee (simply for showing up on time). Details of how you will make decisions and receive payments will be provided below.

During the experiment we will speak in terms of experimental tokens instead of dollars. Your payoffs will be calculated in terms of tokens and then translated at the end of the experiment into dollars at the following rate:

3 Tokens = 1 Dollar

Your participation in the experiment and any information about your payoffs will be kept strictly confidential. Each participant will be assigned a participant ID number. This number will be used to record all data. Only the Xlab administrator but not the experimenter will have both the list of participant ID numbers and names.

Please do not talk with anyone during the experiment. In order to keep your decisions private, please do not show your choices to any other participant. We also ask everyone to remain silent until the end of the experiment. At the end of the experiment you will be paid privately according to your participant ID number.

This experiment consists of two parts. At the end of Part I you will be given the instructions for Part II.

Part I

In this part of the experiment, you will participate in 50 independent decision problems that share a common form. This section describes in detail the process that will be repeated in all decision problems and the computer program that you will use to make your decisions.

In each decision problem you will be asked to allocate tokens between two accounts, labeled x and y. The x account corresponds to the x-axis and the y account corresponds to the y-axis in a two-dimensional graph. Each choice will involve choosing a point on a line representing possible token allocations. Examples of lines that you might face appear in Attachment 1.

In each choice, you may choose any *x* and *y* pair that is on the line. For example, as illustrated in Attachment 2, choice *A* represents a decision to allocate *q* tokens in the *x* account and *r* tokens in the *y* account. Another possible allocation is *B*, in which you allocate *w* tokens in the *x* account and *z* tokens in the *y* account.

Each decision problem will start by having the computer select such a line randomly from the set of lines that intersect with at least one of the axes at 50 or more tokens but with no axis exceeding 100 tokens. The lines selected for you in different decision problems are independent of each other and of the lines selected for any of the other participants in their decision problems.

To choose an allocation, use the mouse to move the pointer on the computer screen to the allocation that you desire. When you are ready to make your decision, left-click to enter your chosen allocation. After that, confirm your decision by clicking on the Submit button. Note that you can choose only *x* and *y* combinations that are on the line. To move on to the next round, press the OK button. The computer program dialog window is shown in Attachment 3.

Your payoff at each decision round is determined by the number of tokens in your *x* account and the number of tokens in your *y* account. At the end of the round, the computer will randomly select one of the accounts, *x* or *y*. It is equally likely that account *x* or account *y* will be chosen. You will only receive the number of tokens you allocated to the account that was chosen.

Next, you will be asked to make an allocation in another independent decision. This process will be repeated until all 50 rounds are completed. At the end of the last round, you will be informed the first part of the experiment has ended.

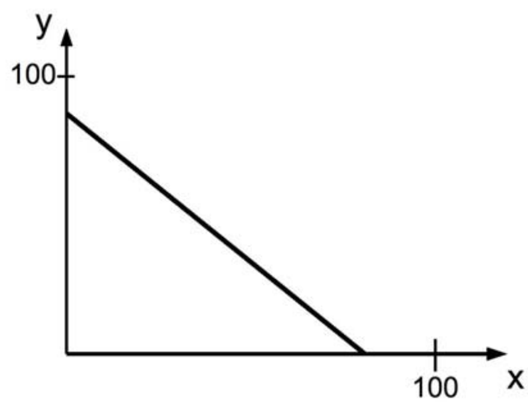
Your earnings for this part of the experiment will be determined as follows. At the end of the experiment, the computer will randomly select one decision round to carry out (that is, 1 out of 50) for payoffs. The round selected depends solely upon chance. For each participant, it is equally likely that any round will be chosen.

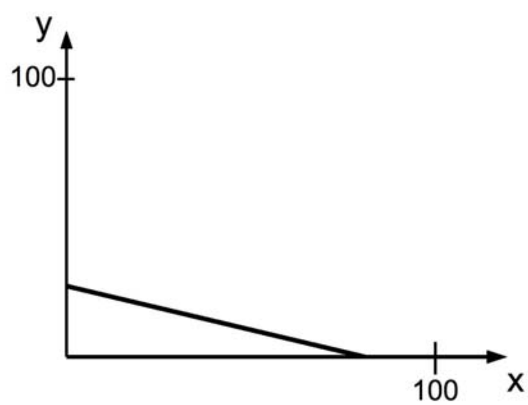
For example, suppose that in the round the computer chose to carry out for payoffs, you chose allocation *A*, as illustrated in Attachment 2, and that the computer chose account *y* for you in that round. In that case you would receive *r* tokens in total. Similarly, if the computer chose account *x* for you in that round then you would receive *q* tokens in total. If you chose allocation *B* and the computer chose account *y* you would receive *z* tokens in total, and if the computer chose account *x* then you would receive *w* tokens in total.

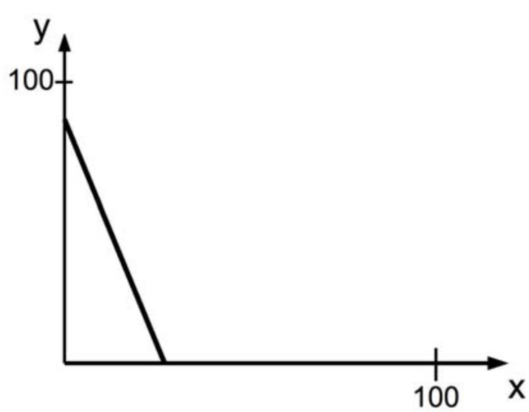
At the end of the experiment, the tokens will be converted into money. Each token will be worth 0.33 Dollars. You will receive your payment as you leave the experiment.

If there are no further questions, you are ready to start. At the end of this part of the experiment, you will receive further instructions.

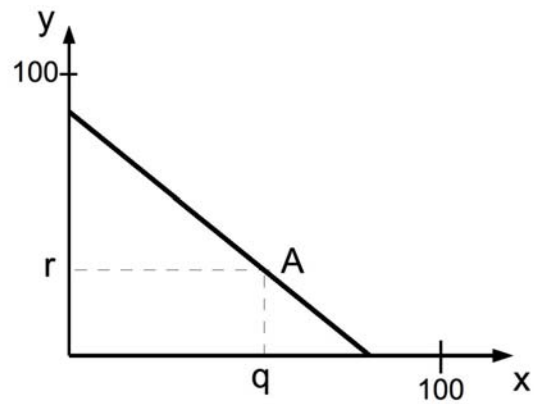
Attachment 1

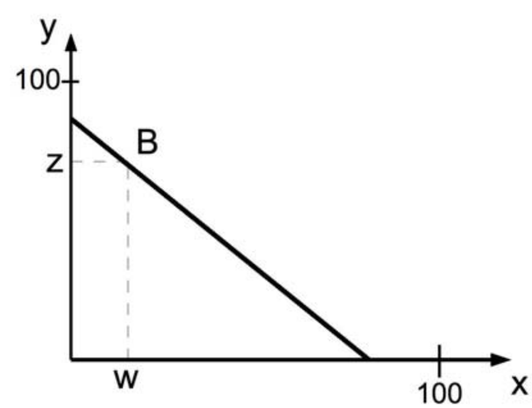




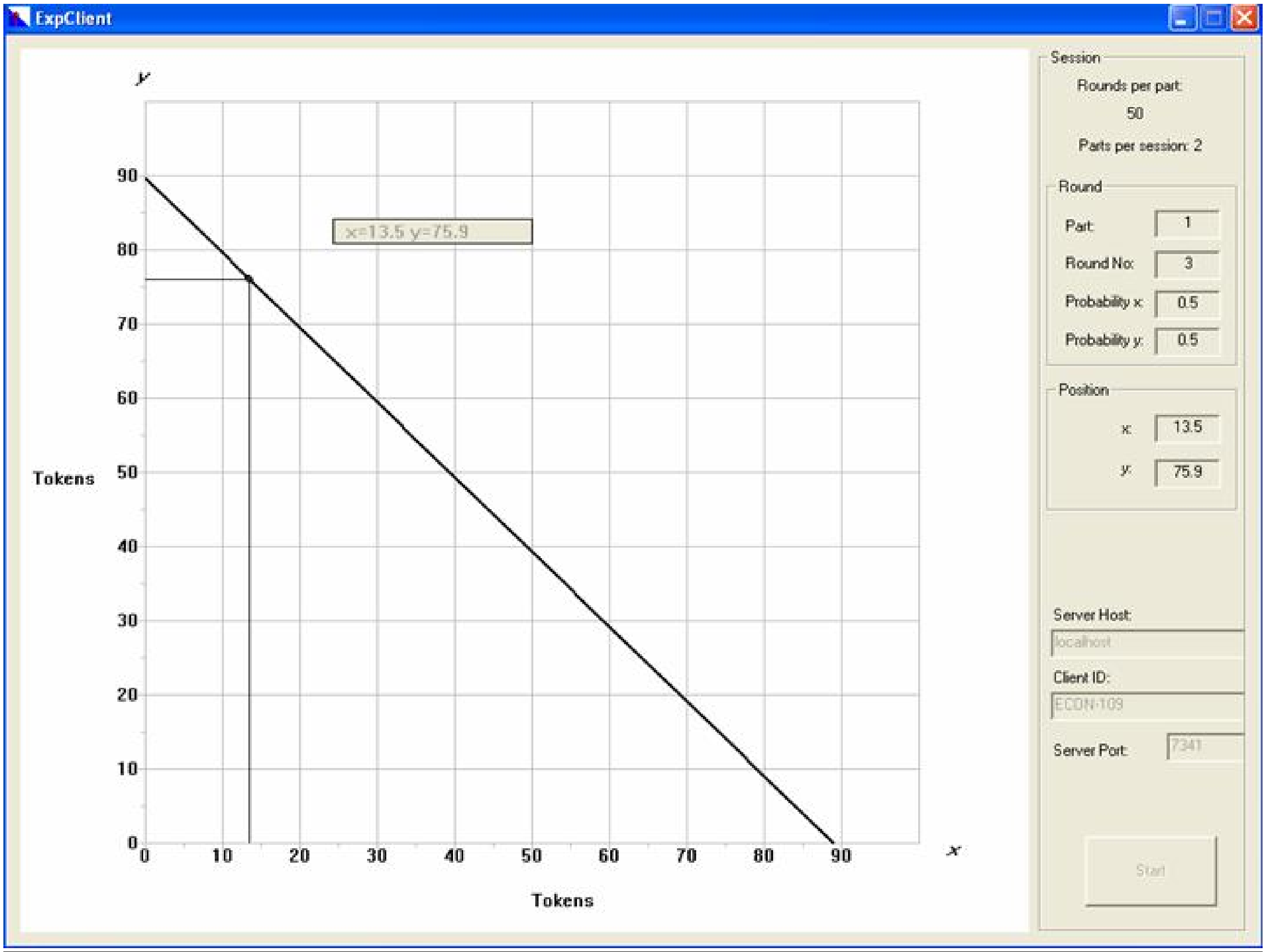


Attachment 2





Attachment 3



Part II

This part of the experiment employs the same experimental computer program. In this part of the experiment, you will also participate repeatedly in 50 independent decision problems that share a common form. This section describes in detail the differences between the two parts of the experiment. After you read this part of the instructions, it will also be read aloud by the instructor, and you may also ask any questions.

In each decision problem you will again be asked to allocate tokens between two accounts, labeled *x* and *y*. The *x* account corresponds to the *x*-axis and the *y* account corresponds to the *y*-axis in a two-dimensional graph. Once again, each choice will involve choosing a point representing possible token allocations.

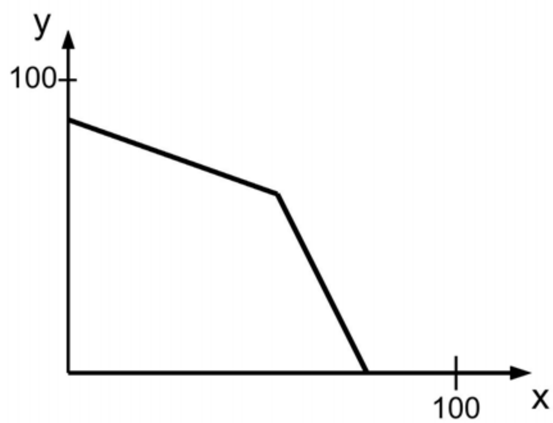
Again, each choice will involve choosing a point on a graph representing possible token allocations. The *x*-axis and *y*-axis are again scaled from 0 to 100 tokens. In each choice, you may choose any allocation that is on the kinked-shaped lines. Examples of lines that you might face appear in Attachment 4.

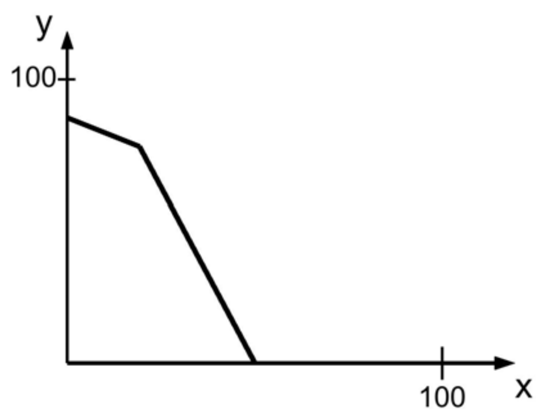
Each decision problem will start by having the computer select such a kinked-shaped line randomly. That is, the lines selected depend solely upon chance and it is equally likely that you will face any kinked-shaped line. The lines selected for you in different decision problems are independent of each other and of the lines selected for any of the other participants in their decision problems.

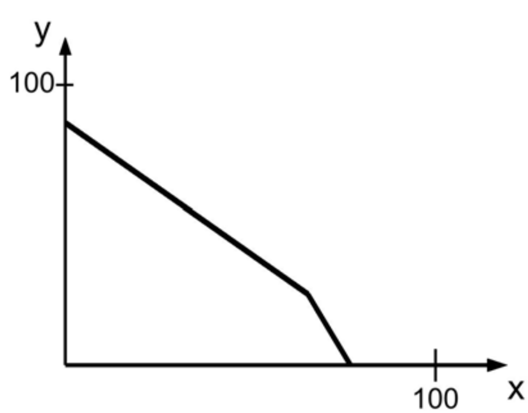
Recall that to choose an allocation, use the mouse to move the pointer on the computer screen to the allocation that you desire and click on your chosen allocation. Examples of possible choices appear in Attachment 5. For example, suppose that in the round the computer chose to carry out for payoffs, you chose allocation *A*, as illustrated in Attachment 5, and that the computer chose account *y* for you in that round. In that case you would receive *q* tokens in total. Similarly, if the computer chose account *x* for you in that round then you would receive *r* tokens in total. If you chose allocation *B* and the computer chose account *y* you would receive *z* tokens in total, and if the computer chose account *x* then you would receive *w* tokens in total.

In this part of the experiment, the method of determining payment is the same as in the previous part. Recall that in each round it is equally likely that account *x* or account *y* will be chosen. Once again, at the end of this part of the experiment, the computer will randomly select one of the fifty decision rounds from each participant to carry out for payoffs. You will receive your payment for this part of the experiment, together with your payment for the previous part, and the $5 participation fee, as you leave the experiment.

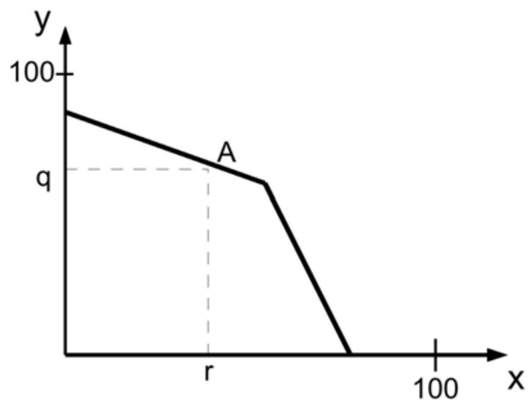
Attachment 4

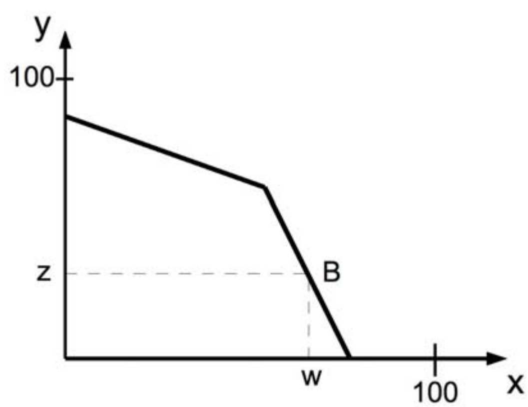






Attachment 5





B Benchmark Randomization and Type Taxonomy

This appendix presents the results of the benchmarking procedure used to determine the critical values for categorizing rationality types. We closely follow the methods of Choi et al. (2007a). We start with an individual whose behavior is determined by maximization of a CRRA (ρ set to 0.5, following Choi et al. (2007a)) expected utility function subject to logistic taste shocks, where the relative importance of the taste shock is determined by parameter γ (if $\gamma = 0$, the decisions are purely random, while when $\gamma \to \infty$, the decisions are purely the result of expected utility maximization by a rational agent). For each panel presented in the the first four figures in this appendix, we simulate 1300 subjects with these tastes for each combination of γ and n (the number of choice observations per subject) that we use.[43] The figures then plot the resulting distributions of the HM measure for each case, with Figure 11 showing the HM distributions derived from maximization subject to linear constraint sets and Figure 12 showing the HM distributions derived from kinked constraint sets.

In the first panel of Figures 11 and 12, we consider decision makers whose choices are completely random ($\gamma = 0$) and assess how the resulting distributions of the HM measure change as the number of observations increases. The results indicate that a larger number of decisions increases the statistical power to detect whether a set of data was generated by pure randomization, as is to be expected. Moreover, 50 decisions ($n = 50$) give us significant power against the weak hypothesis of pure randomization. Note that draws of 50 observations are just as powerful for the case of linear budget sets as for the case of kinked budget sets.

Stronger hypotheses can be formulated by comparing the experimental data to expected utility maximization subject to a random taste shock determined by non-zero γ values. For each combination of n and γ, one can test the null hypothesis that the observed behavior and resulting HM measure come from a distribution of individuals whose maximizing behavior is modulated with a degree of random shocks defined by level γ.

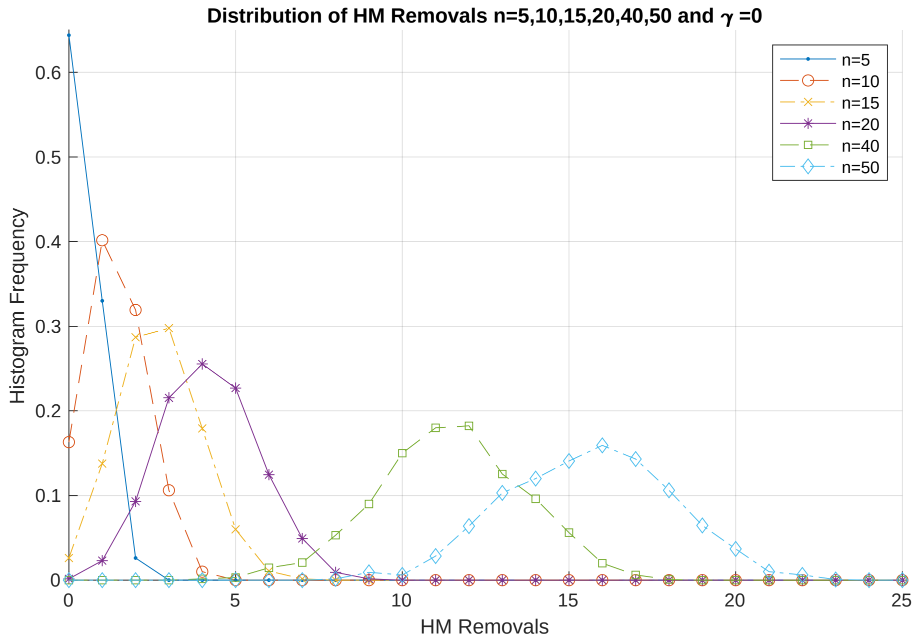
[43]Each of the choice observations from a simulated subject come from a scenario with a randomly generated budget set that is generated in the same way as those faced by the actual decision makers in our experiment.

The bottom panels of Figures 11-12 show the distributions (for $n = 50$ observations) in each budget context for differing degrees of γ. For instance, if one wanted to test the hypothesis of consistency equivalent to that from a distribution that has $\gamma = 5$ at the 95% level, one would compare the value of the HM score with the critical value 6. An HM score *greater* than 6 leads one to conclude that $\gamma < 5$ at the 95% confidence level or, equivalently, that the observed behavior is less rational, or consistent, than would be the case for 95% of a population that maximizes utility with only a moderately sized random taste shock. An individual with an HM greater than 6 would thus be said to be less consistent, with a 95% confidence level, than would be expected from individuals who only occasionally allow deviations from an otherwise rational CRRA utility maximization due to a moderate ($\gamma = 5$) random logistic taste shock. Similarly, for a somewhat higher standard of rationality ($\gamma = 10$), 4 HM removals becomes the critical value (i.e., an individual with an HM greater than 4 would thus be said to be less consistent, with a 95% confidence level, than would be expected from individuals who only occasionally allow deviations from an otherwise rational CRRA utility maximization due to a random logistic taste shock with parameter $\gamma = 10$).[44]

Table 2 (in the main text) shows the type distribution using the critical value of 4. Individual type assignments using this critical value can be seen in Table 3. Figure 4 (in the main text) explores the robustness of the type distribution to the choice of critical value. Importantly, the proportion of Type 4s remains quite large as the critical value deviates from 4. The proportion of Type 5s increases as the critical value increases. This increase is due mostly to the decrease in Type 1s, Type 2s, and Type 3s. This is purely a mechanical effect of lowering the bar of rationality.

[44] It is also of note that these same critical values result when performing this benchmarking procedure with 50 pooled choices selected for the simulated subjects in the same way as for the actual experimental subjects (with 25 linear and 25 matched kinked budget sets); see Figure 13. The fact that the simulation for 50 pooled choices yields virtually the same distribution of HM removals as for either the 50 linear or 50 kinked choices justifies using the same critical value for linear, kinked, and pooled settings, as we do throughout the paper.

Figure 11: HM Randomization Results (Linear)



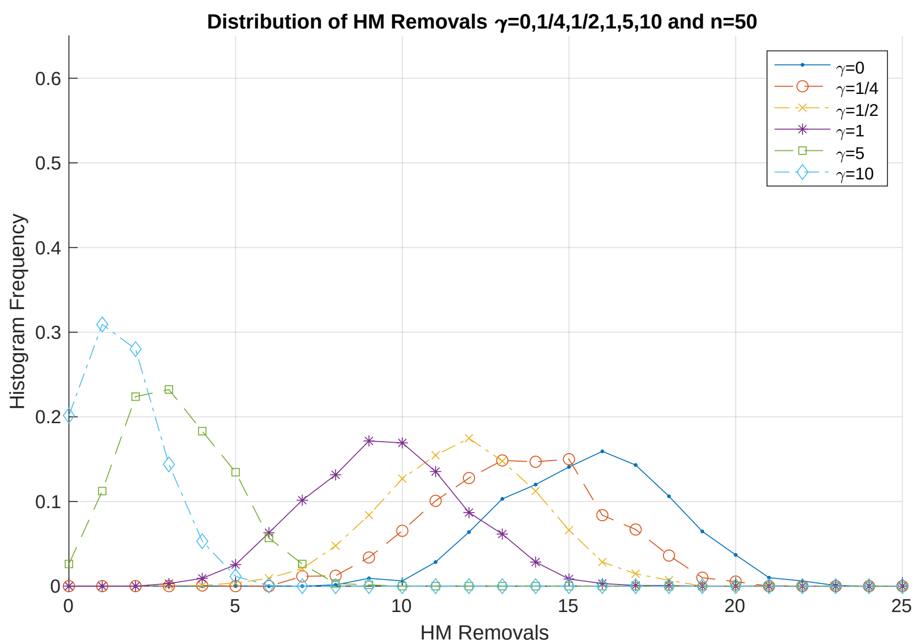
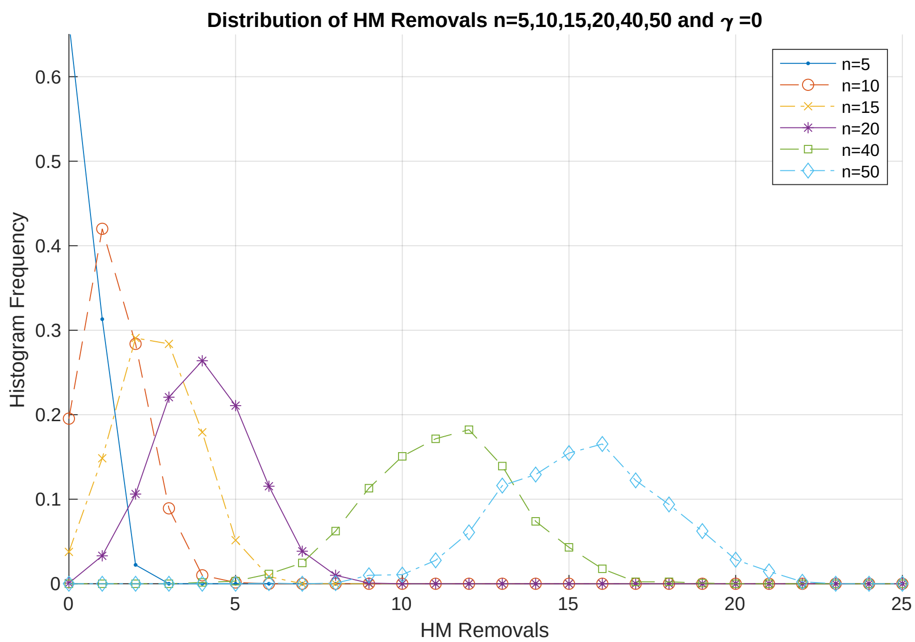


Figure 12: HM Randomization Results (Kinked)



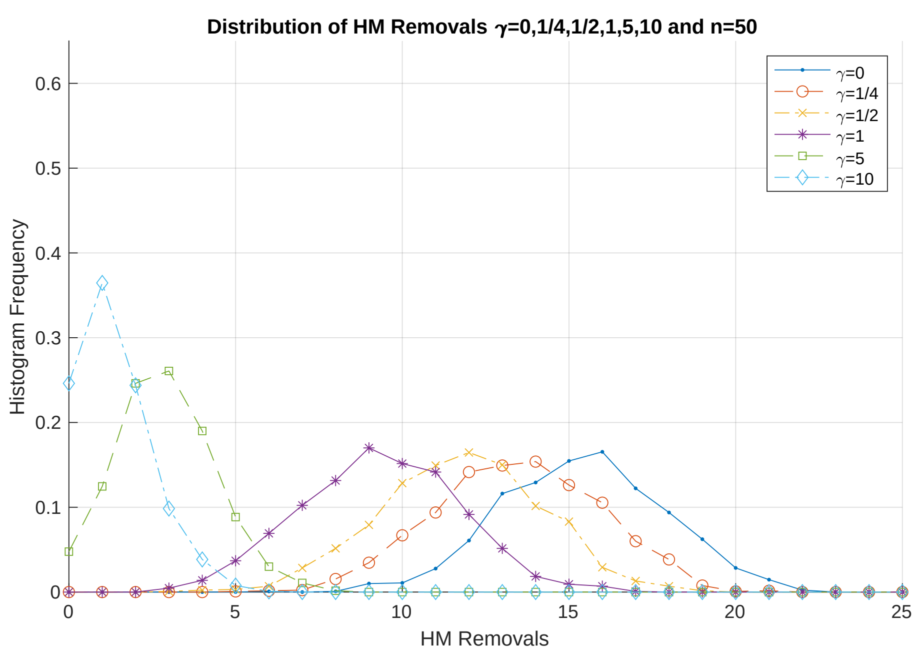


Figure 13: HM Randomization Results (Pooled)

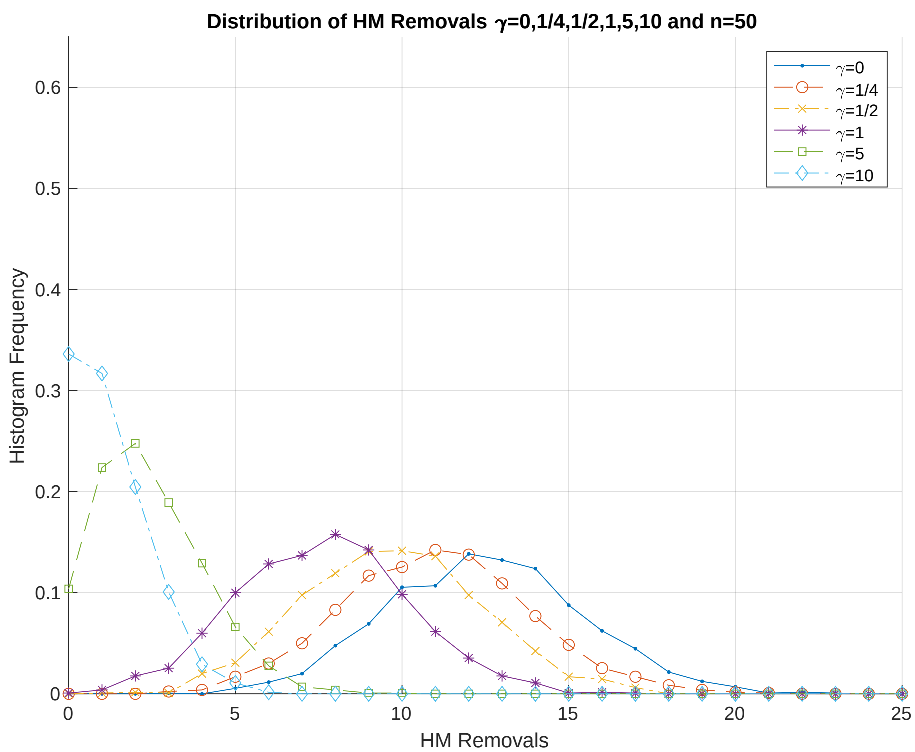


Table 3: Individual Type Listing

	Session 1	Type	Session 2	Type	Session 3	Type	Session 4	Type
	101	4	201	3	301	4	401	5
	102	1	202	2	302	4	402	4
	103	4	203	4	303	1	403	1
	104	3	204	3	304	5	404	4
	105	4	205	4	305	2	405	4
	106	3	206	3	306	4	406	2
	107	4	207	4	307	2	407	1
	108	2	208	3	308	4	408	4
	109	4	209	4	309	3	409	4
	110	5	210	1	310	4	410	2
	111	4	211	4	311	5	411	5
	112	5	212	3	312	2	412	2
	113	5	213	4	313	2	413	2
	114	4	214	3	314	4	414	1
	115	4	215	4	315	2	415	4
	116	3	216	5	316	5	416	1
	117	2	217	4	317	4	417	3
	118	5	218	3	318	3	418	4
	119	4	219	4	319	4	419	3
	120	4	220	4	320	4	420	2
	121	5	221	3	321	1	421	1
	122	2	222	4	322	5	422	4
	123	1	223	1	323	4	423	4
	124	4	224	5	324	1	424	5
	125	4	225	4	325	4	425	5
	126	4	226	1	326	4	426	1
	127	4	227	4	327	5	427	1
	128	5	228	4	328	4	428	1
	129	4	229	4	329	3	429	4
	130	4	230	4	330	4	430	2
	131	3	231	4	331	5	431	4
	132	1	232	1	332	4	432	4
	133	5	233	3	333	2	433	2
	134	4	234	4	334	4	434	1
	-	-	235	2	335	2	435	5
	-	-	236	3	336	4	436	4

C Parametric Estimation

Moffitt (1990) discusses difficulties in estimating models with kinked budget sets. An advantage of our setting is that the experiment generates random variation in the size and location of the kink. Our parametric estimation in the linear and non-linear settings builds upon Choi et al. (2007a). Like them, we estimate the following disappointment aversion utility function from Gul (1991) with the inclusion of a multiplicative stochastic component:

$$\min\left\{\alpha u(x)e^{\varepsilon_1}+u(y)e^{\varepsilon_2},u(x)e^{\varepsilon_1}+\alpha u(y)e^{\varepsilon_2}\right\} \tag{2}$$

where the function $u(x)$ has the CRRA form $u(x)=\frac{x^{1-\rho}}{1-\rho}$. We specify in this Appendix the NLLS problem—which forms the basis for the structural estimates used throughout the paper—for the estimation in the kinked treatment case (as the estimation of the linear treatment is included as a special case). Furthermore, for exposition purposes, we illustrate the case where the kink point is to the left of the 45 degree line. The opposite case requires a trivial symmetric modification.

To start, denote the price ratio p_x^i/p_y^i for the lines to the left and right of the kink point by p_1 and p_2, the kink point by $\log(y_k^i/x_k^i)=K^i$, and $\varepsilon=\varepsilon_1-\varepsilon_2$. As boundary observations are not well defined with the power function, we incorporate them (following Choi et al. (2007a)) by replacing the zero component of a boundary choice with a very small consumption level such that the ratio of choices (x^i/y^i) is truncated to be between ω and $1/\omega$, where $\omega=0.001$. A decision maker with preferences determined by equation (1) who faces a kinked budget set (defined by prices (p_1^i,p_2^i) and kink point K^i) will have their optimal choice (x^{i*},y^{i*}) determined by the following log demand ratio schedule[45]:

[45] Accounting for the multiplicative stochastic component in (2) results in an additive error term ε in the log demand ratio expressions and underlies the criterion function minimized in (3) via NLLS.

$$\log(x^{i*}/y^{i*}) = f(\log(p_1^i), \log(p_2^i), K^i; \alpha, \rho) =$$

$$\begin{cases} \log(\omega) & \text{for } -\rho\log(\omega) \leq \log(p_1^i) - \log(\alpha) \\ -\dfrac{\log(p_1^i) - \log(\alpha)}{\rho} & \text{for } \rho K^i < \log(p_1^i) - \log(\alpha) < -\rho\log(\omega) \\ -\log(y_k^i/x_k^I) & \text{for } \log(p_1^i) - \log(\alpha) < \rho K^i < \log(p_2^i) - \log(\alpha) \\ -\dfrac{\log(p_2^i) - \log(\alpha)}{\rho} & \text{for } 0 < \log(p_2^i) - \log(\alpha) < \rho K^i \\ 0 & \text{for } \log(p_2^i) - \log(\alpha) < 0 < \log(p_2^i) + \log(\alpha) \\ -\dfrac{\log(p_2^i) + \log(\alpha)}{\rho} & \text{for } \rho\log(\omega) < \log(p_2^i) + \log(\alpha) < 0 \\ -\log(\omega) & \text{for } \log(p_2^i) + \log(\alpha) \leq \rho\log(\omega) \end{cases}$$

Then, for each subject, we choose the parameters α, ρ to minimize:

$$\sum_{i=1}^{50} (\log(x^i/y^i) - f(\log(p_1^i), \log(p_2^i), K^i; \alpha, \rho))^2 \tag{3}$$

using NLLS with standard errors computed using a robust variance estimator. Tables 19-26 in Appendix G present the estimates $(\hat{\alpha}, \hat{\rho})$ that result for each individual in each of the linear and kinked treatments. In Section E.2 of this Appendix, we go into greater detail about some of the finer points and particulars of the estimation procedure that generates these tables, but before that, in Section E.1, we discuss the rationale for our use of the NLLS estimation strategy.

C.1 Choice of Estimation Strategy

Non-linear least squares estimation was chosen over maximum likelihood estimation (MLE) for two reasons.[46] First, NLLS more accurately recovers structural parameters for simu-

[46] The MLE estimator comes about from the maximization problem for an individual with utility defined by equation (2), which yields the following conditions used to define the log-likelihood function (with the

lated subjects, especially as the variance of the stochastic component increases. We generated the simulated subjects using the utility function in (2) with $\varepsilon \sim N(0, \sigma_\varepsilon)$ for a suite of structural parameter combinations (α, ρ) (which span the plurality of the structural parameters estimated in the data). We randomly choose 50 linear and 50 corresponding kinked budget sets from the actual budget sets offered to subjects in the study and then simulated the choices that 100 simulated subjects would make in each budget set as dictated by their assumed parameter values and the specified error-generating process. Using these choices, we could then reverse engineer (with either NLLS or MLE) a recovery of the implied structural parameters that would be expected to generate the choices of each of the simulated subjects, calculate the average of these estimated structural parameters, and then compare them to the average of the true values that generated the choices. For small values of σ_ε (0.01), both MLE and NLLS perform similarly well, judged by a

log price ratio defined as p and other terms defined as above):

$$\begin{aligned}
p &\geq \log\alpha + \rho\log(1/\omega) + \varepsilon \text{ for } x/y = \omega \\
p &= \log\alpha + \rho\log(y/x) + \varepsilon \text{ for } \omega < x/y < 1 \\
-\log\alpha + \rho\log(y/x) + \varepsilon &\leq p \leq \log\alpha + \rho\log(y/x) + \varepsilon \text{ for } x = y \\
p &= -\log\alpha + \rho\log(y/x) + \varepsilon \text{ for } 1 < x/y < 1/\omega \\
p &\leq -\log\alpha + \rho\log(\omega) + \varepsilon \text{ for } x/y = 1/\omega
\end{aligned}$$

For the equality conditions, the probability that ε satisfies that relation is well defined. The inequality conditions characterize an interval of values that ε can take to satisfy that relation. Denoting by ϕ and Φ the normal PDF and CDF, respectively, of the error term's distribution (mean zero with variance σ), the log-likelihood function is given by:

$$\begin{aligned}
\mathscr{L} = & \prod_{\text{for } x^i/y^i=\omega} \Phi[p - \log\alpha - \rho\log(1/\omega)] \\
\times & \prod_{\text{for } \omega<x^i/y^i<1} \phi[p - \log\alpha - \rho\log(y^i/x^i)] \\
\times & \prod_{\text{for } x^i=y^i} [\Phi[p + \log\alpha] - \Phi[p - \log\alpha]] \\
\times & \prod_{\text{for } 1<x^i/y^i<1/\omega} \phi[p + \log\alpha - \rho\log(y^i/x^i)] \\
\times & \prod_{\text{for } x^i/y^i=1/\omega} [1 - \Phi[p + \log\alpha - \rho\log(\omega)]]
\end{aligned}$$

The maximum likelihood estimators $(\hat{\alpha}_{MLE}, \hat{\rho}_{MLE}, \hat{\sigma}_{MLE})$ are then the parameters that maximize this log-likelihood function.

comparison of the average recovered structural parameter value and the average of the actual structural parameters used. However, increasing σ_ε even slightly (e.g., to 0.1 or higher; for reference, the average estimated σ found in the data is significantly greater than that for both MLE and NLLS) makes the NLLS estimation perform markedly better than MLE in recovering parameters. In particular, NLLS is better able to recover more extreme structural parameters for both the linear and non-linear budgets. Tables 17 and 18 in Appendix G contain the tests for $\sigma_\varepsilon = 0.1$. Moreover, the ability of NLLS to recover these parameters is not significantly impacted by the linearity of the budget, dovetailing with our second rationale for preferring NLLS detailed below.

The second reason NLLS estimation is preferred over MLE estimation is that the former appears to be less susceptible to bias in the parameter estimates that comes about strictly from switching from estimating choices over linear budget sets to estimating choices over non-linear budget sets.

Structural parameters are notoriously difficult to estimate using choices on non-linear budgets, and as we are particularly interested in identifying actual changes in structural parameters that result from a shift from linear to non-linear budget settings, we want to guard against differences in parameter estimates coming about solely because the estimation method itself leads to changes when applied to linear vis-a-vis non-linear budget settings (without there being any actual change in the structural parameters). To further assess whether NLLS/MLE estimation on non-linear budgets accurately recovers parameters without a bias in comparison to the parameters recovered for linear budgets, we translate subjects' linear choices on linear budgets into choices on pseudo-non-linear budgets with an imposed pseudo-kink and then use NLLS/MLE to recover the parameters in both scenarios. Specifically, we take participants' budgets and choices from the linear treatment and add the pseudo-kink by randomly choosing a point between the riskless point (the 45 degree line intersection with the budget set) and the corner of the cheaper asset and classify it as the kink point K^i above (though it does not in fact represent any actual convexity in the budget line). We then apply the non-linear budget set variation of NLLS and MLE to this budget with "kink" K^i to ensure that the same parameters are recovered with this method as with the linear budget set variation of NLLS and MLE (as they should be given that there is no actual change in the data-generating process). NLLS succeeds in this regard, while MLE fails. In particular, MLE biases the ρ values toward zero when non-linearizing linear budgets and choices.

C.2 Computational Particulars of the Estimation Strategy

We now address several particulars of our NLLS estimation strategy. First, to avoid arriving at a local minimum, we use a variety of initial parameter conditions to seed our NLLS optimization algorithm. In particular, for linear budget sets, three α values are used as initial guesses: the largest and smallest values of the relative prices offered to an individual and the average of the two.[47] Additionally, two ρ parameters are used as initial guesses, 0.5 and 1.5. Together, this creates a 3x2 matrix with six potential initial conditions. For the non-linear budgets, these six initial guesses are used and then the estimated structural parameters from the linear budget sets of each participant are used as a seventh initial guess. The program iterates through the initial guesses, performing a kind of branch-and-bound algorithm, keeping the estimated structural parameters that minimize the loss function.

Second, due to data limitations, for each participant, the estimation of α is capped at the largest value among the set of offered price ratios (p_x^i/p_y^i) and their inverse. To illustrate why this is necessary, suppose that a participant's true α is 4.5 but that the largest value of the price ratio (p_x^i/p_y^i) or its inverse that they is ever offered is 4. This participant would choose the riskless asset for every budget he or she is offered (see the fifth line of the log demand function $\log(x^{i*}/y^{i*})$ defined above to see this), and thus any value of $\alpha \geq 4$ would be consistent with their choices, but estimating $\alpha > 4.5$ would be inconsistent with the true α. To discipline the model, we minimize the loss function under the constraint that α cannot exceed the maximum of (p_x^i/p_y^i) or (p_y^i/p_x^i) offered to the participant (as would be expected given the randomization procedure for

[47]This maximum and minimum of the relative prices offered are the maximum and minimum values (across all 50 budget sets) of the ratio of the commodity with the higher price (for a given budget set) over the commodity with the lower price (for the same budget set). See the second point in this subsection for why this range bounds alpha.

assigning budget constraints, there is no significant difference in the distribution of these maximum prices across types). In essence, data limitations restrict what can be known about subjects' structural parameters. Importantly, the maximum prices in the linear and non-linear budgets differ, with the non-linear budgets having larger maximum prices by construction. Thus, *after* estimating α for the non-linear budget, we restrict it to not exceed the α constraint from the linear budgets; otherwise, the α values would be biased when we compare the structural parameters across the linear and non-linear treatments.

Third, choices at or near the riskless point on the budget are reclassified. The structural estimation is sensitive to small deviations around the riskless point on the budget curves. For example, suppose a participant chooses the point $(x^i, y^i) = (33.5, 33)$ for a linear budget $(x^{\text{Max}}, y^{\text{Max}}) = (50, 100)$. While this choice is close to the riskless point of the budget, the participant has chosen a higher portion of the expensive good, resulting in an upward-sloping demand curve. Moreover, suppose a participant chooses the point $(x^i, y^i) = (33.3, 33.4)$ for the same linear budget $(x^{\text{Max}}, y^{\text{Max}}) = (50, 100)$. While this choice is consistent with a downward-sloping demand curve, the deviation from the pure riskless choice of $(x^i, y^i) = (33.33, 33.33)$ could be due to price sensitivity or computational rounding of choices to the nearest tenth place when subjects are offered choices. Additionally, subjects may be myopic when making decisions around the riskless point, perceiving $(x^i, y^i) = (33.3, 33.4)$ and $(x^i, y^i) = (33.33, 33.33)$ as negligibly different choices (on the visual interface, they appear very much the same). The structural estimation procedure, on the other hand, treats these alternative choices as fundamentally different, with the potential to markedly change the estimated parameters. Thus, to be conservative about subjects' price sensitivity, we reclassify all choices such that $|x^i - y^i| \leq 1$ as if they are at the riskless point, $x^i = y^i$, on the linear and non-linear budgets.

Fourth, extreme outliers are removed from the structural estimation using quartile outlier detection. As noted in Choi et al. (2007a), the structural estimation is sensitive to outliers. This sensitivity is especially pronounced for participants with a majority of points around the riskless point of each budget. To make our estimation robust to extreme outliers in a formal and non-ad hoc manner, we employ quartile outlier detection, an outlier detection method used for choices that are not distributed normally (Hodge and Austin, 2004; Rousseeuw and Hubert, 2011). Specifically, we calculate the interquartile region of the absolute value of the log choice ratio $iqr = |\log(x^i/y^i)|_{.75} - |\log(x^i/y^i)|_{.25}$ for each subject and remove all choices that exceed $20iqr$ below the lower quartile or $20iqr$ above the upper quartile of choices from the structural estimation. This process is performed on both the linear and non-linear treatments separately. This large band was chosen to identify choices that seem to be outliers (e.g., see ID 220) but to not remove choices for other participants whose extreme choices may result from dramatic changes in prices. For instance, if a participant's true structural parameters were a large value of α and a zero value of ρ, a utility-maximizing subject would pick the riskless point of the budget for prices below a certain α and the corners for prices above α. The outlier detection outlined here would not remove the corner choices of this individual, as shown in Figure 24 in Appendix G, which presents the choice plots for two individuals: one whose outlier choice is removed by the procedure and one whose choice is not. In any case, the modal and median number of outliers removed for an individual in the linear and non-linear treatments is zero, and the mean is less than 1 in both treatments.

Fifth, to make the estimation robust to smaller outliers and larger error processes, σ_ε, we use weighted non-linear least squares on subjects' choices. Specifically, we employ bi-square weighting with the common tuning parameter $\kappa = 4.685, w(r, \kappa) = 1(|r < \kappa|)(1 - (r/\kappa)^2)^2$, where r is the estimated residual (Huber (2004)). As is common with weighted non-linear least squares, this weighting process is evaluated iteratively as in Holland and Welsch (1977). We use the residuals from the last iteration of non-linear least squares estimation process to weight the loss function in the current iteration. This iteration continues until the loss function is below a function tolerance or the normed difference between the last iteration's estimated structural parameters and the current iteration's estimated structural parameters are below a tolerance band.

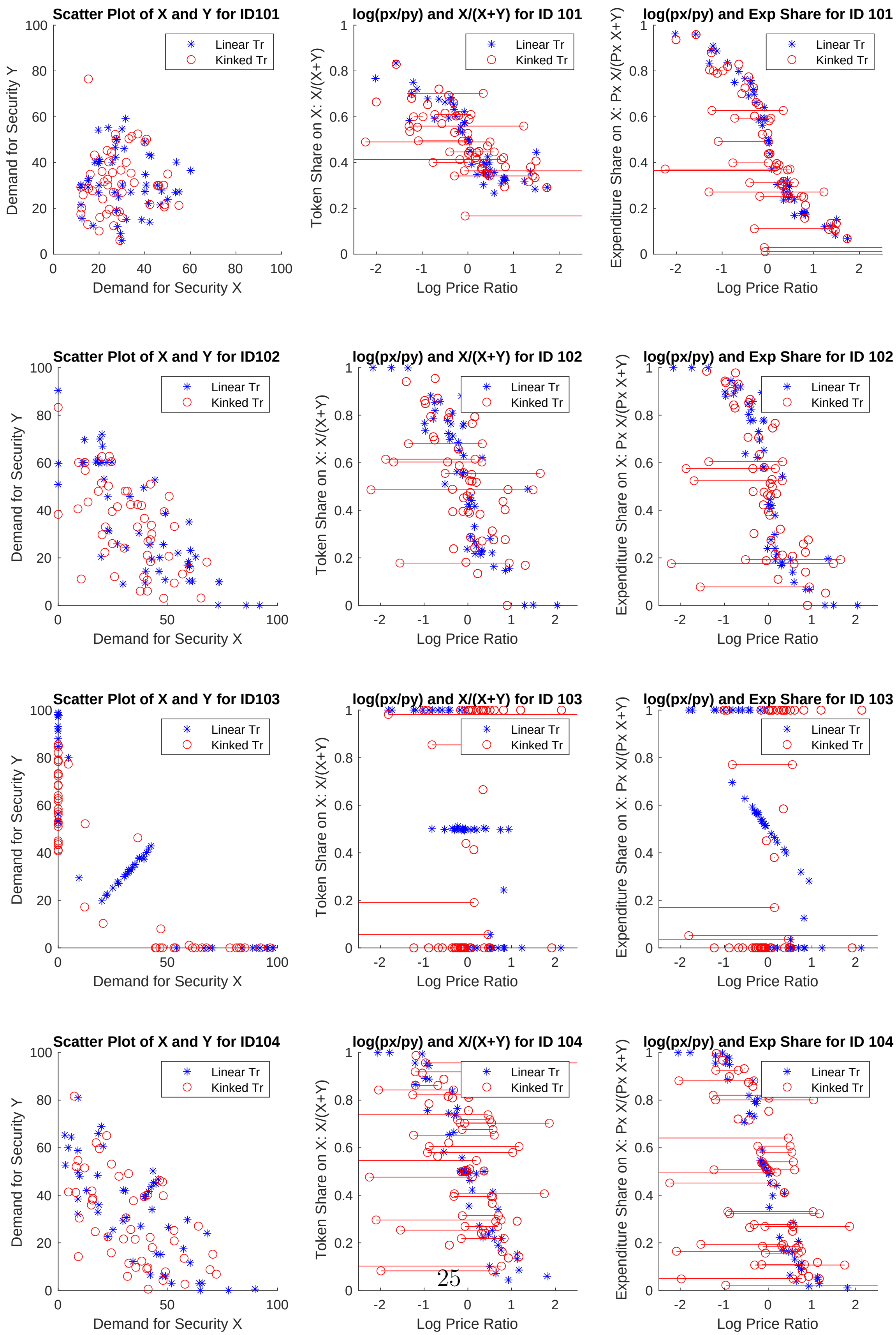
Thus, for each subject, we choose the parameters α, ρ to minimize:

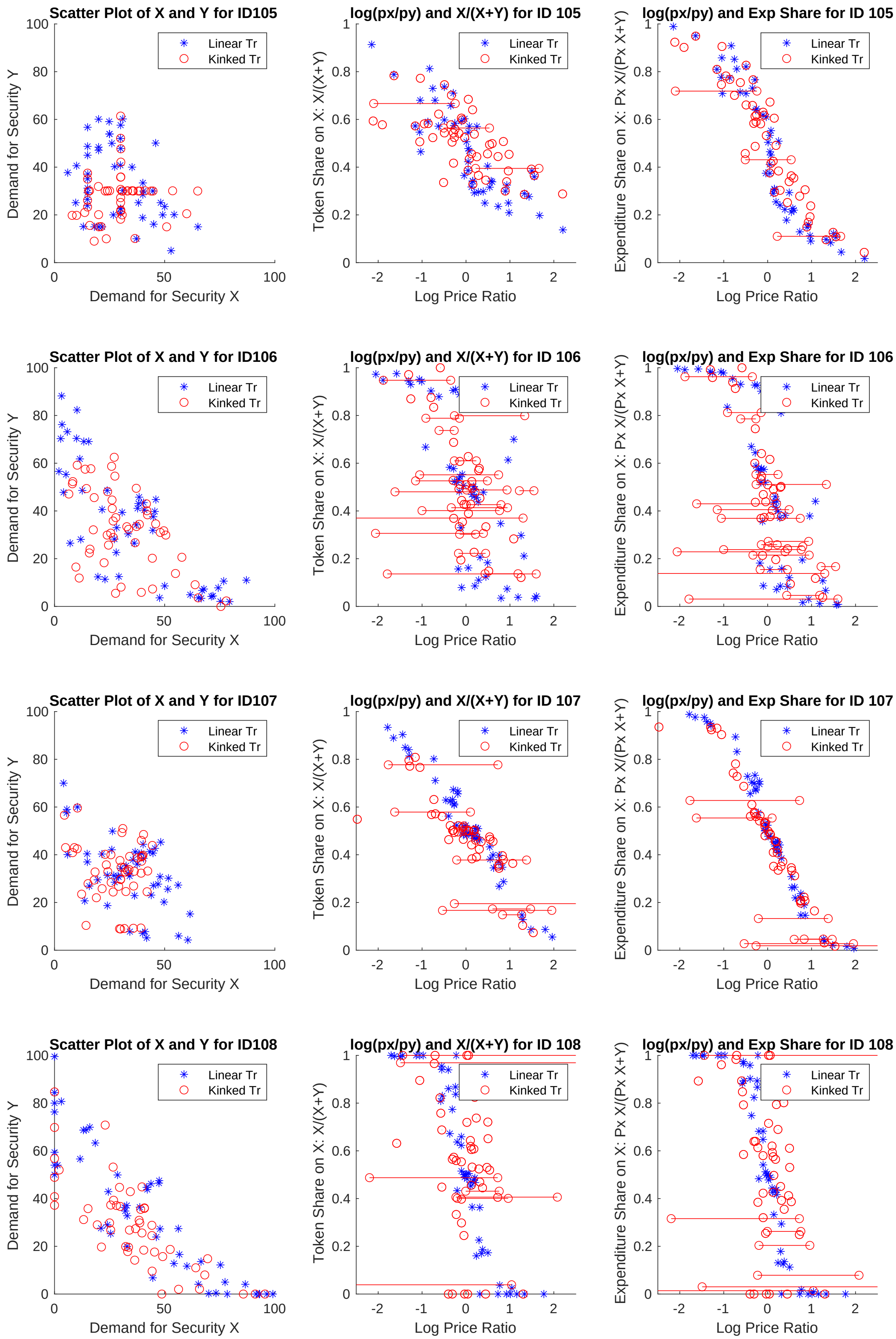
$$\sum_{i \notin \mathbb{O}}^{50} w(r_{k-1}, \kappa)_i (\log(y^i/x^i) - f(\log(p_1^i), \log(p_2^i), K^i; \alpha_k, \rho_k, \omega))^2$$

$$\text{s.t. } \alpha_k \leq \max\{p_1^i, p_2^i, (p_1^i)^{-1}, (p_2^i)^{-1}\}_{i=1 \notin \mathbb{O}}^{50}$$

Where $\mathbb{O}$ is the set of outliers for each subject and $w(r_{k-1}, \kappa)$ is the bi-square weighting vector, $r_{k-1} = \log(y^i/x^i) - f(\log(p_1^i), \log(p_2^i), K^i; \alpha_{k-1}, \rho_{k-1}, \omega)$ is the vector of residuals from the previous iteration of non-linear least squares, and k denotes the iteration of the weighted non-linear least squares algorithm. As noted, Tables 19-26 in Appendix G present the results of this estimation, $(\hat{\alpha}, \hat{\rho})$, for each individual in each of the linear and kinked treatments.

D Decision Plots

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log(px/py) and Exp Share for ID 108
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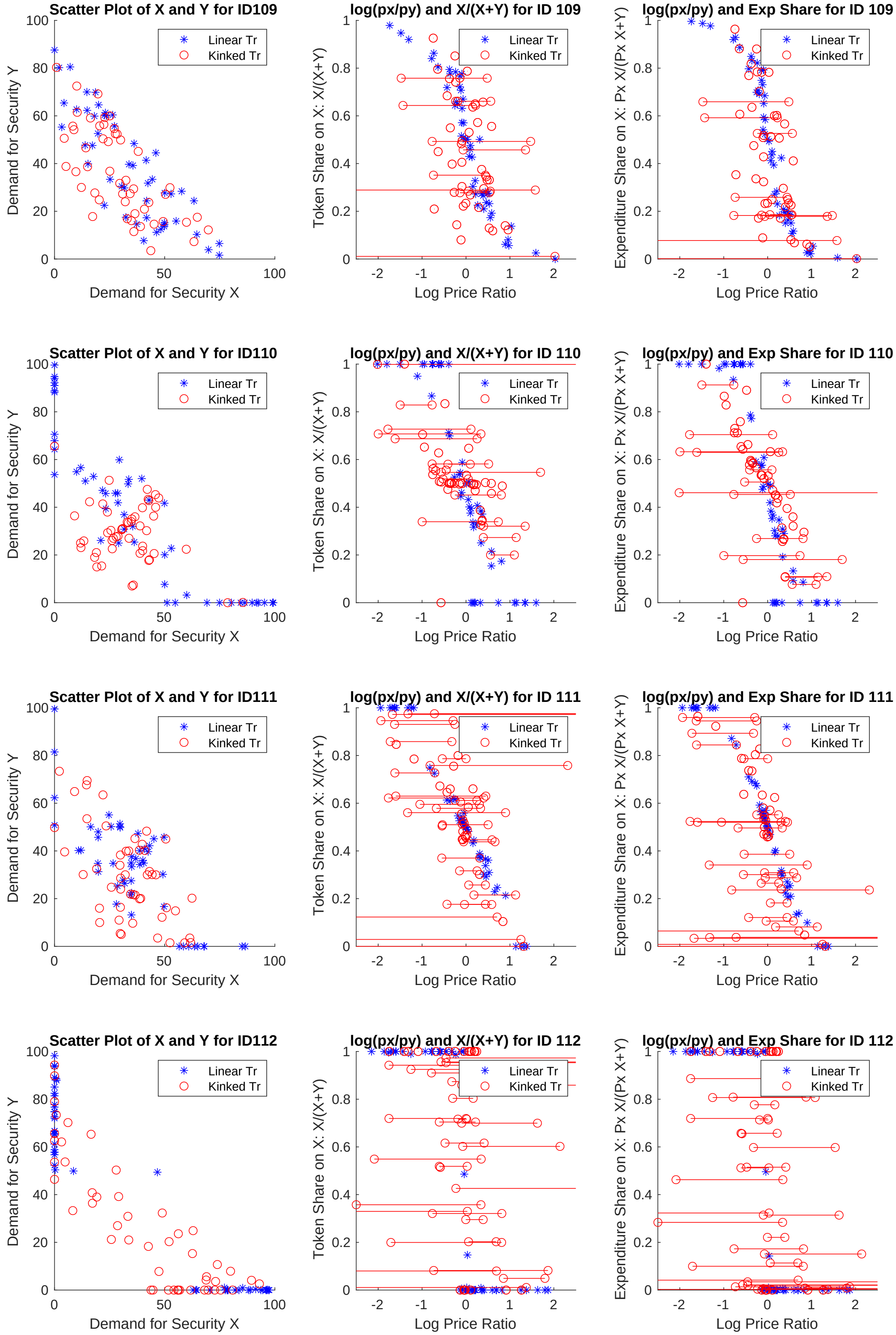
Log Price Ratio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Scatter Plot of X and Y for ID112
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log(px/py) and Exp Share for ID 112
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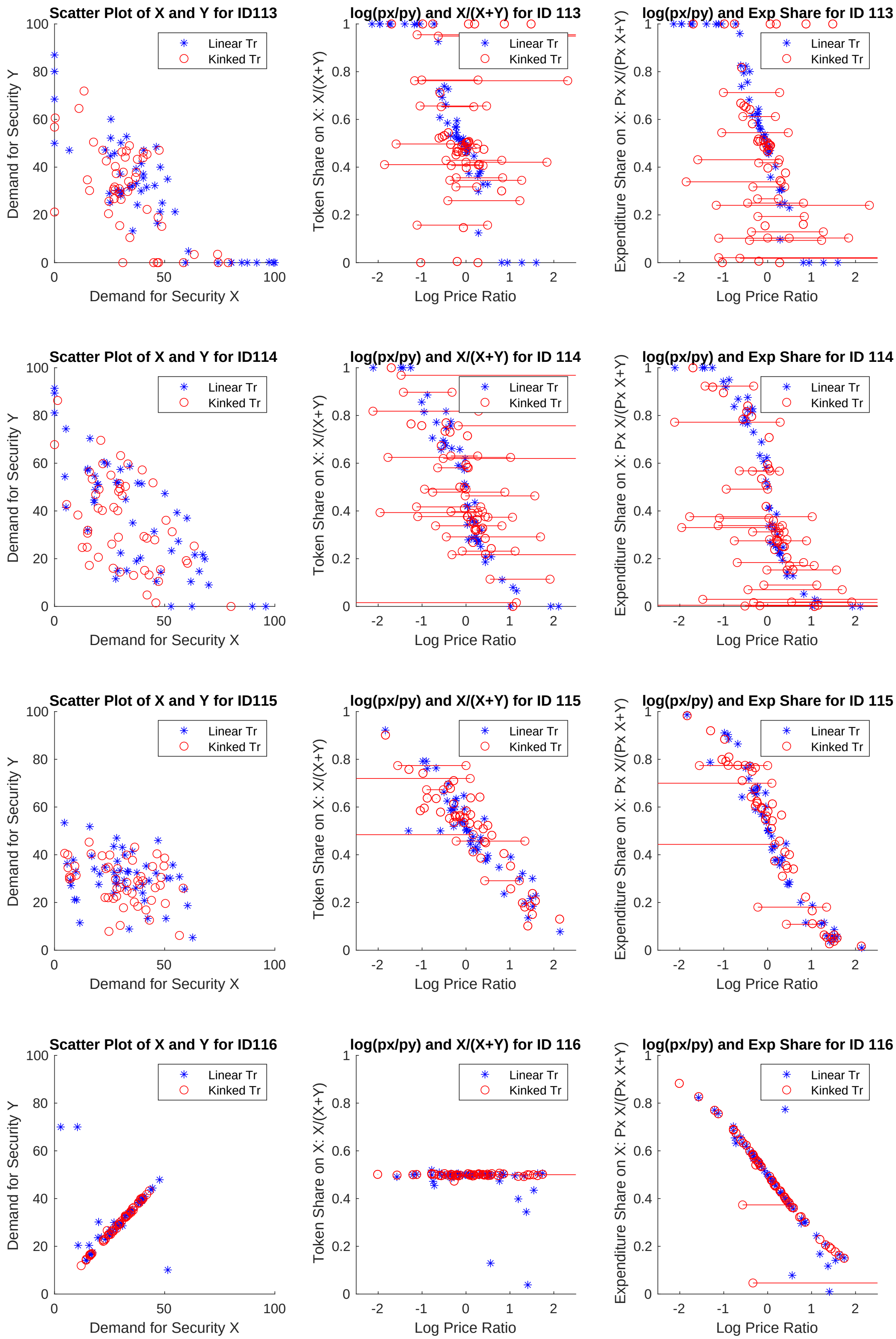
Log Price Ratio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log(px/py) and X/(X+Y) for ID 116
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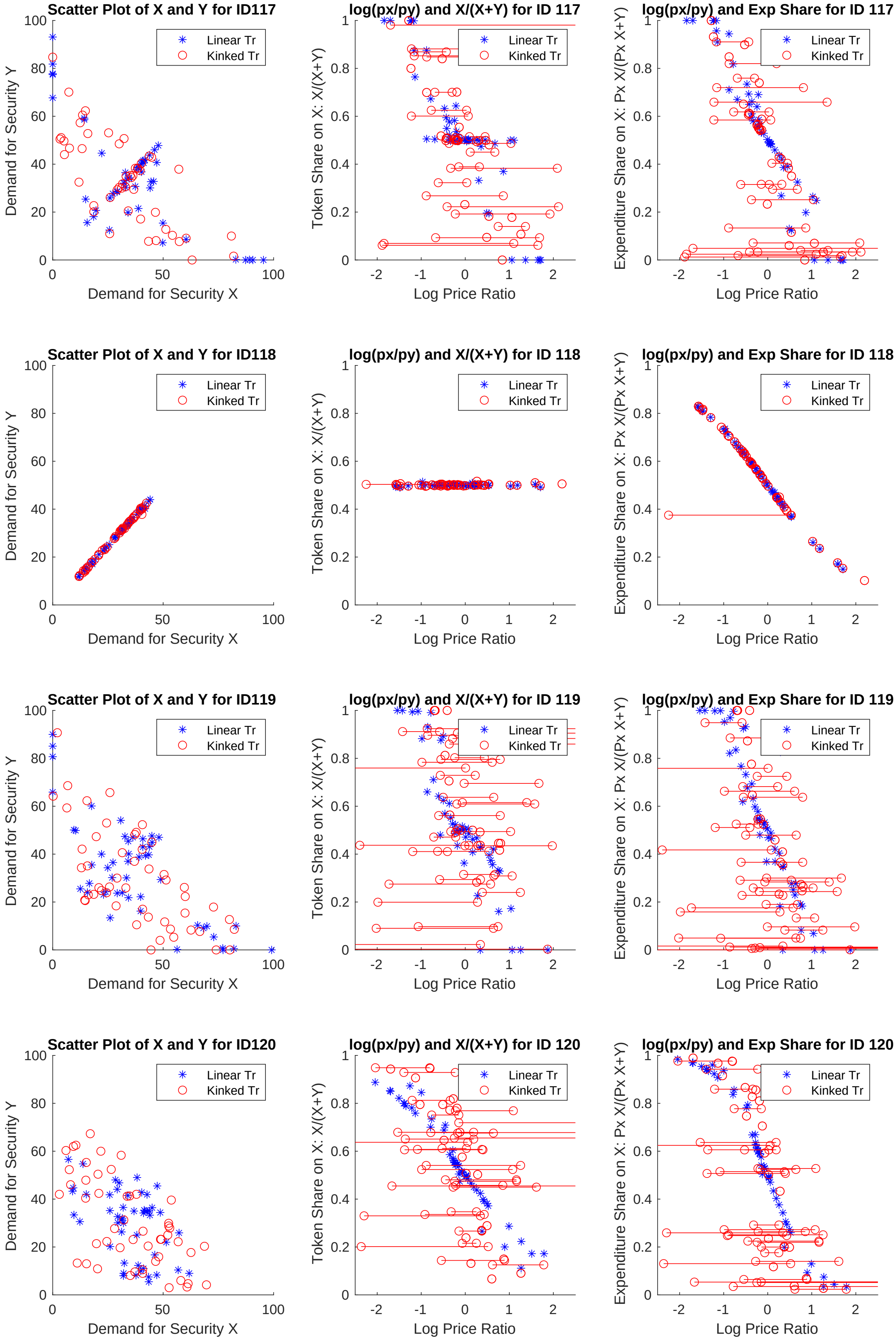
Log Price Ratio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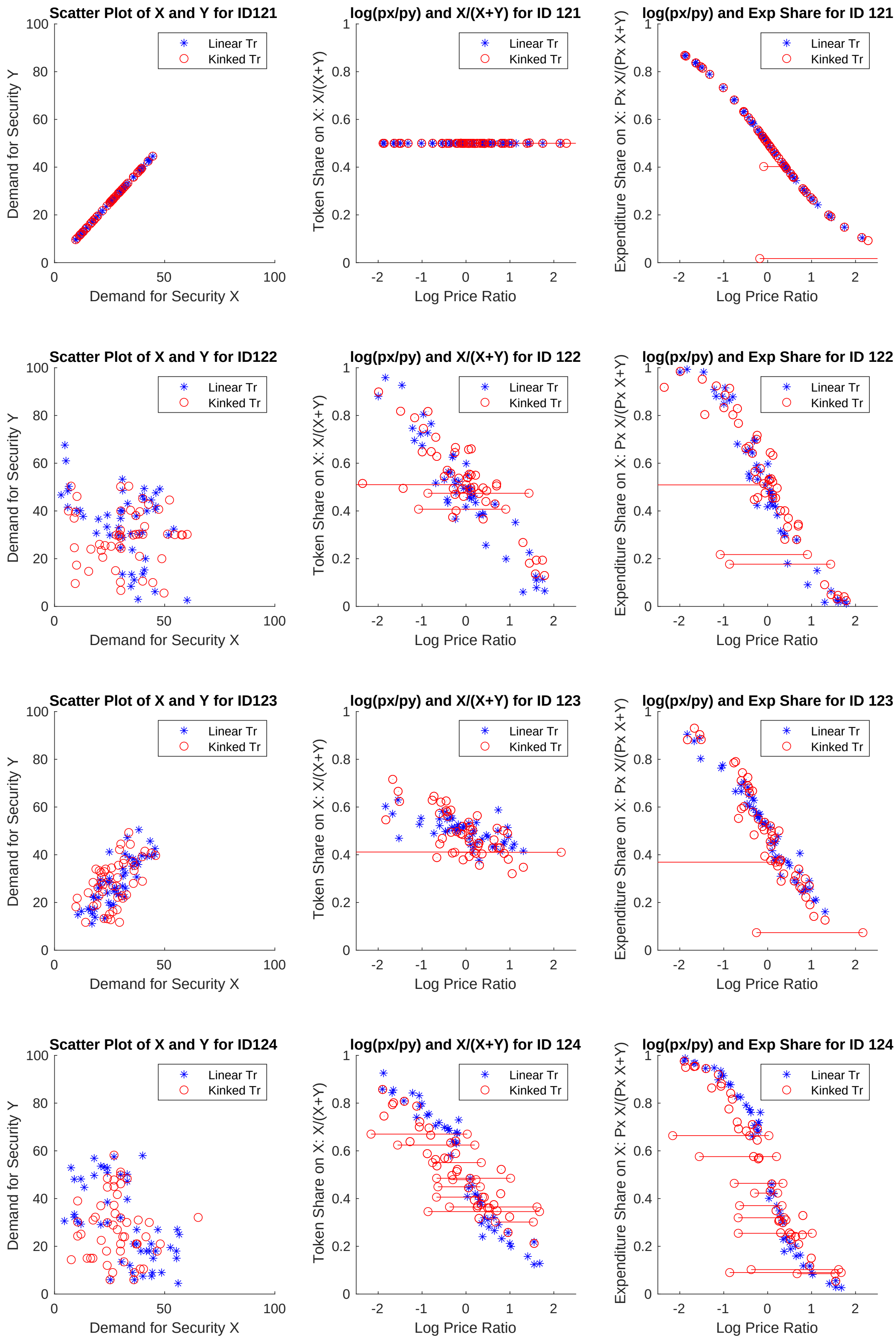
Log Price Ratio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Log Price Ratio
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Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio
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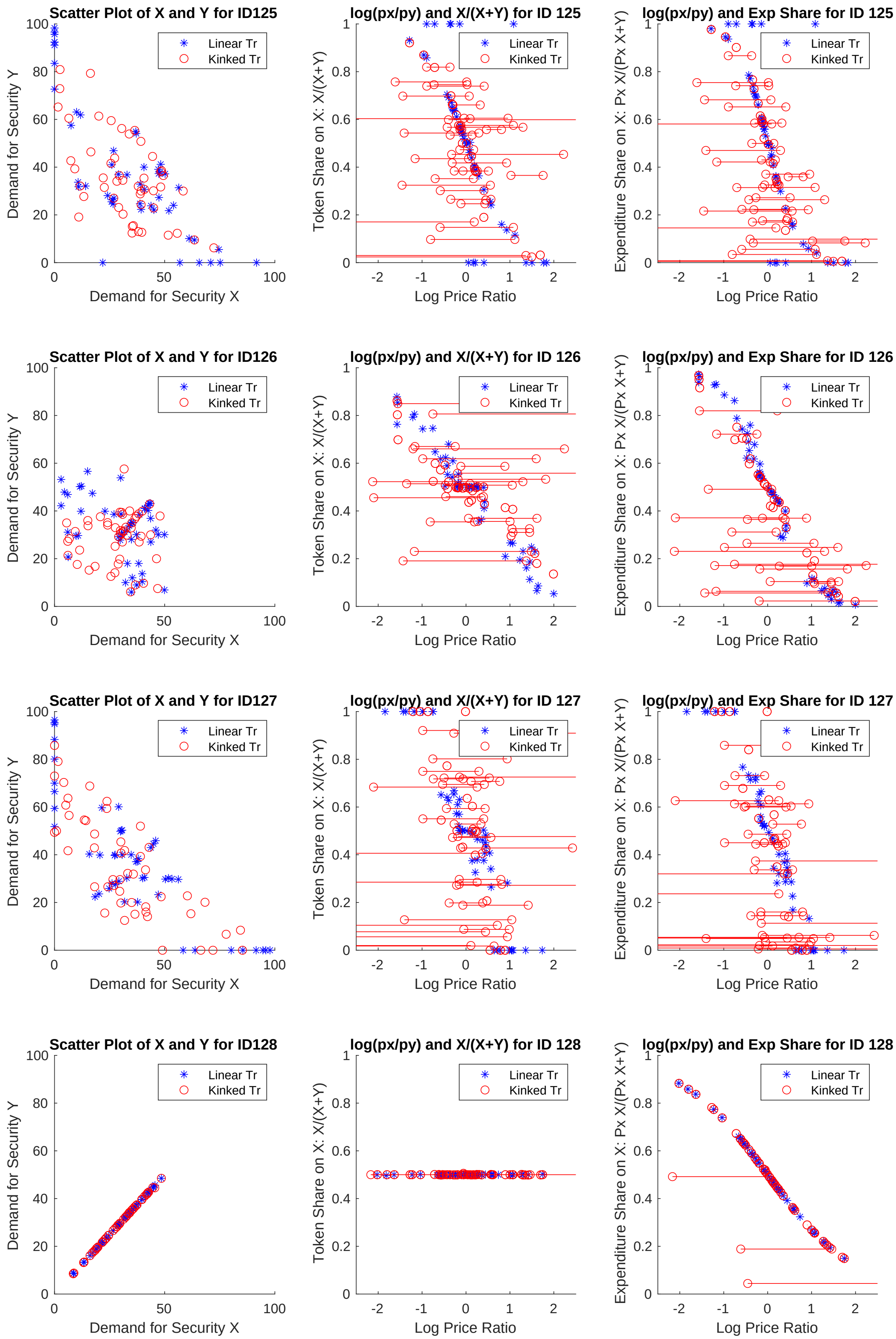

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Demand for Security Y
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log(px/py) and X/(X+Y) for ID 128
Token Share on X: X/(X+Y)
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log(px/py) and Exp Share for ID 126
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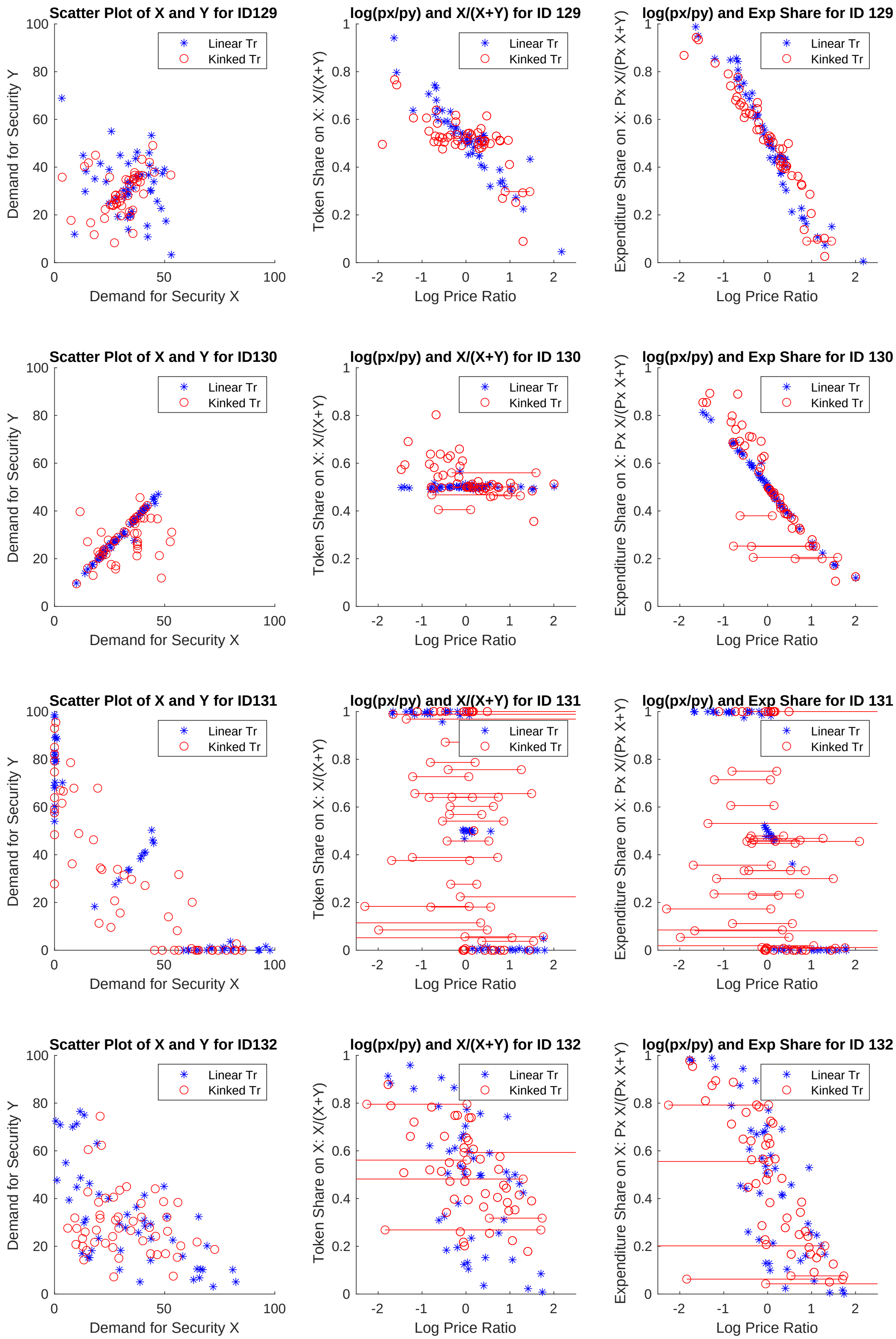
Log Price Ratio
Linear Tr
Kinked Tr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log(px/py) and X/(X+Y) for ID 131
log(px/py) and Exp Share for ID 131
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log(px/py) and X/(X+Y) for ID 132
log(px/py) and Exp Share for ID 132
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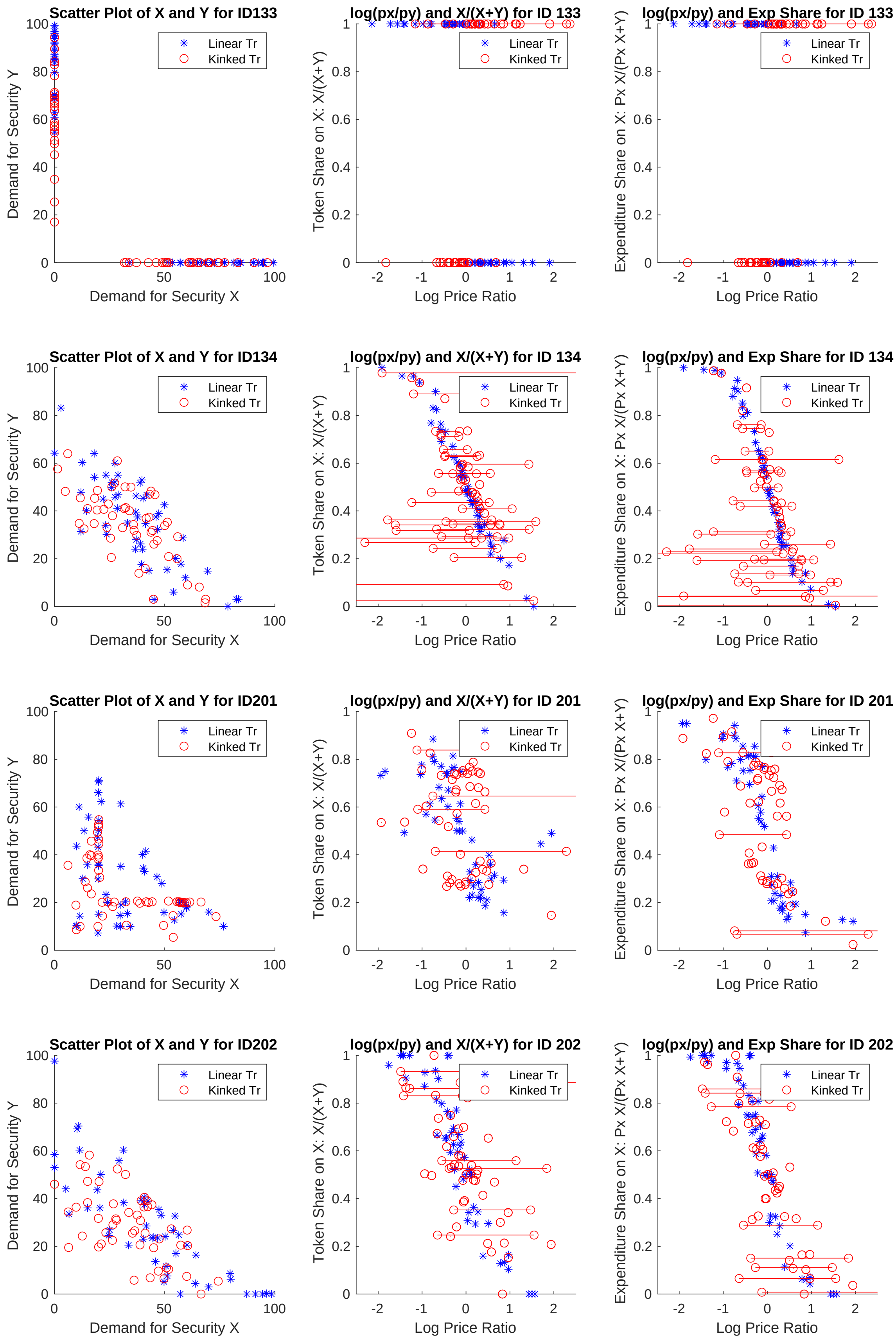
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio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log(px/py) and Exp Share for ID 134
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log(px/py) and X/(X+Y) for ID 201
log(px/py) and Exp Share for ID 201
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log(px/py) and Exp Share for ID 202
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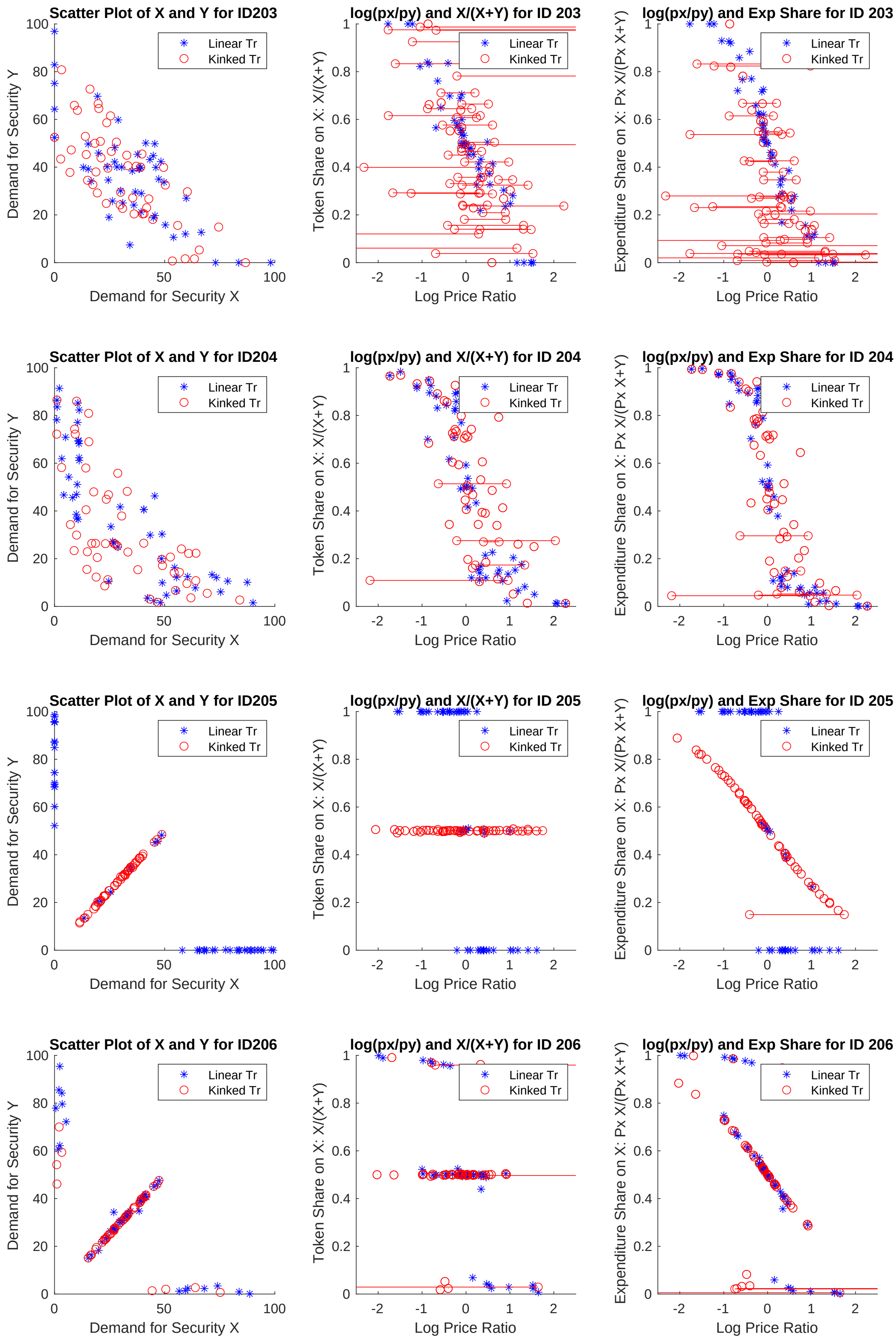
Log Price Ratio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Expenditure Share on X: Px X/(Px X+Y)
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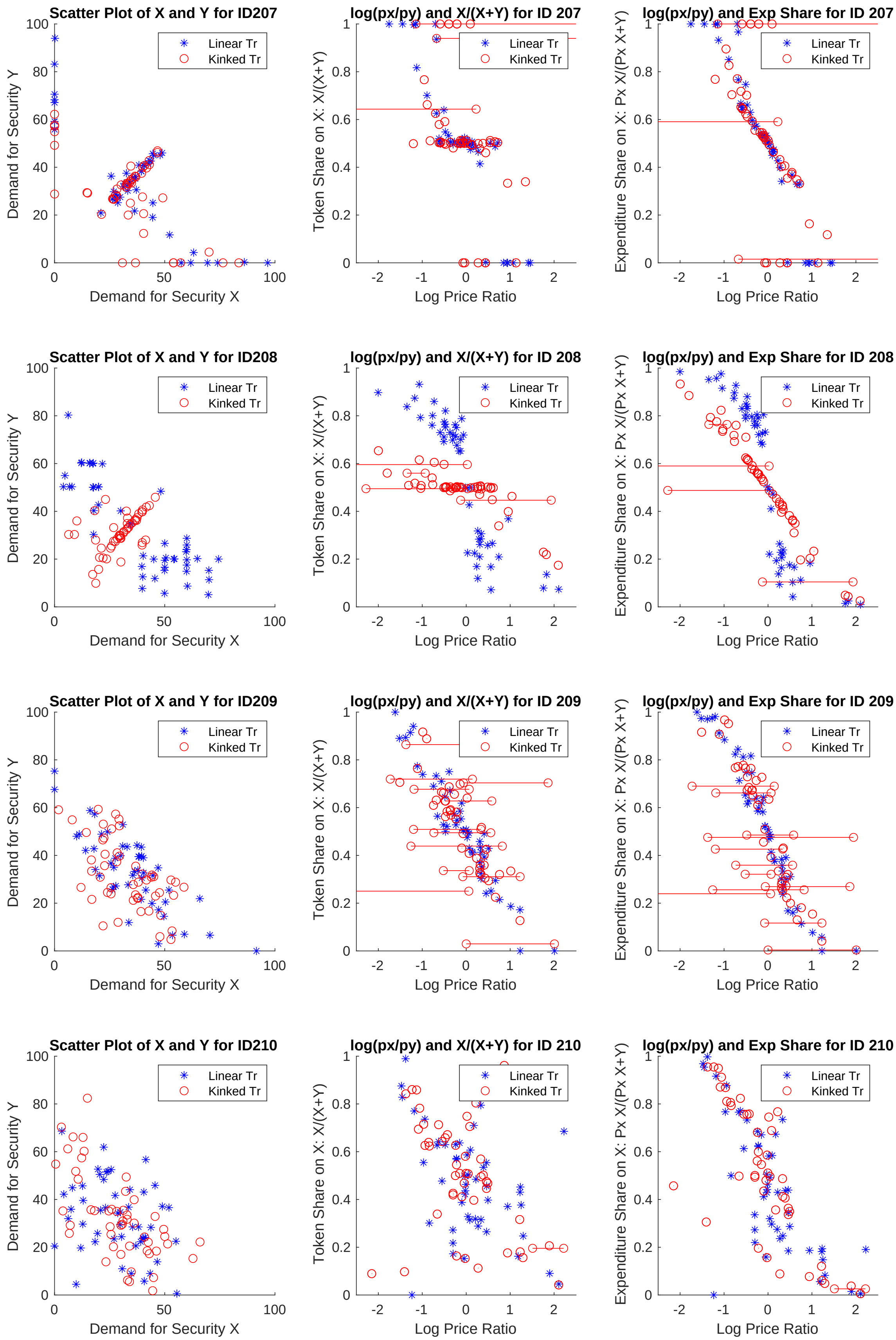
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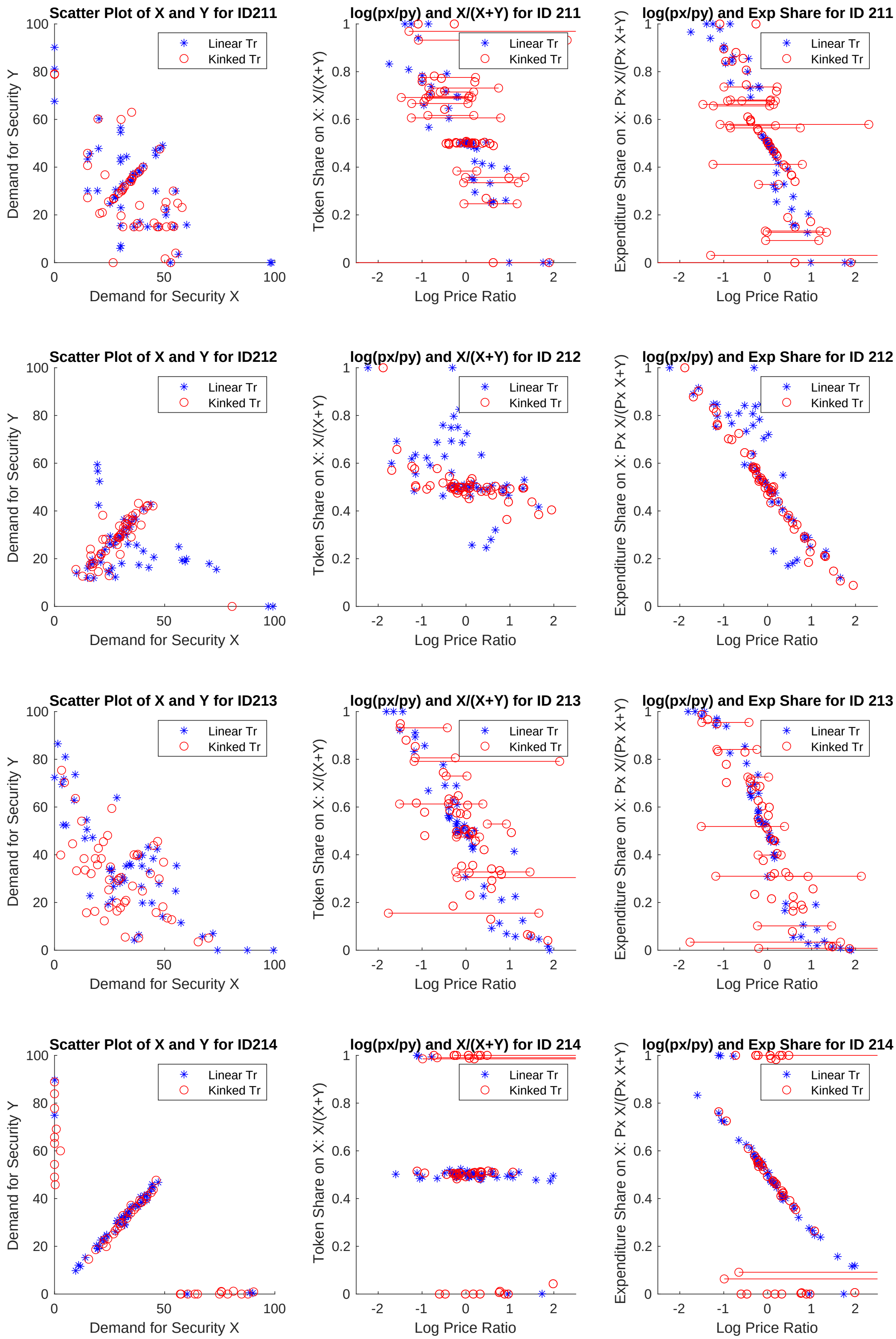
Log Price Ratio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log(px/py) and Exp Share for ID 214
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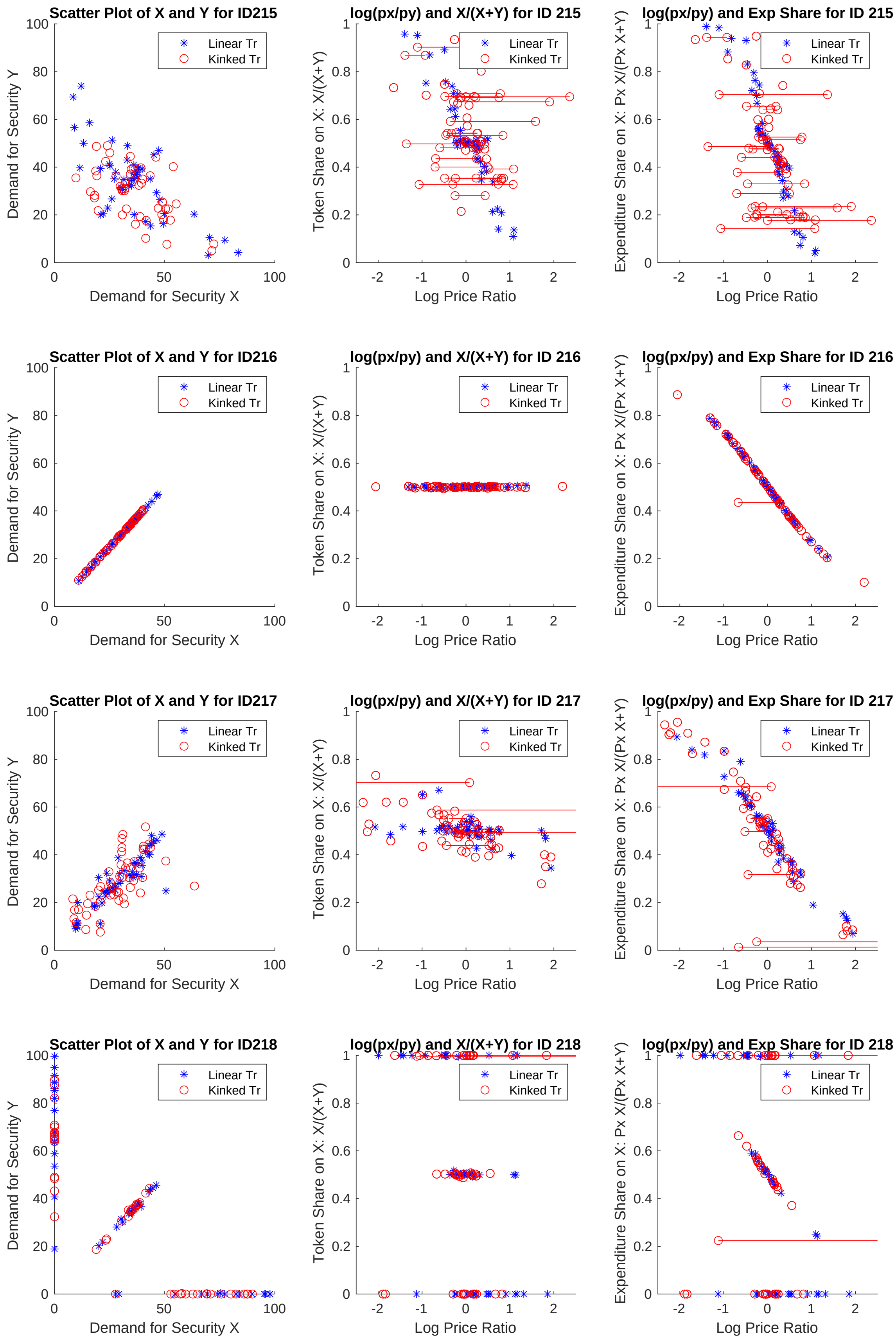
Log Price Ratio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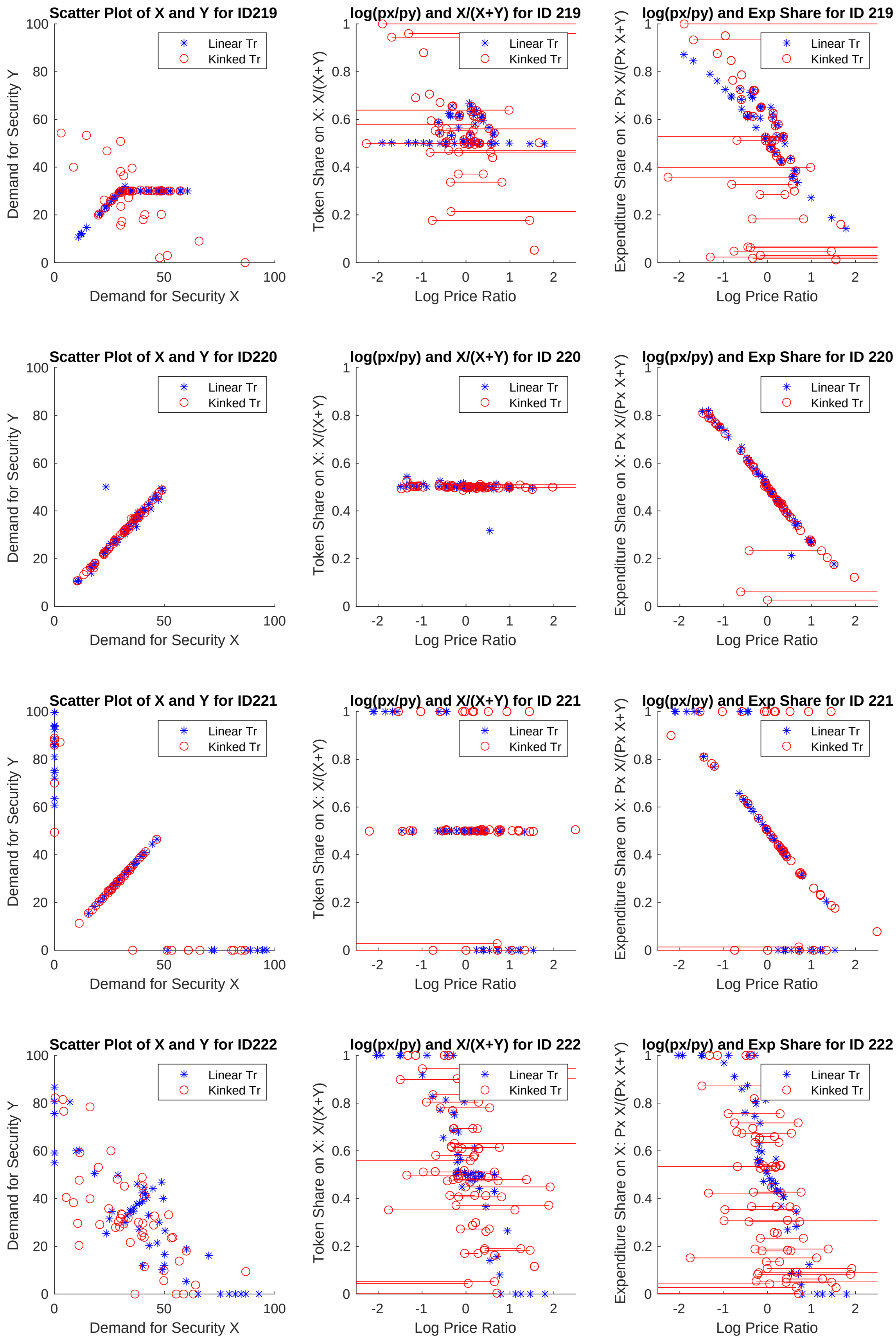
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Expenditure Share on X: Px X/(Px X+Y)
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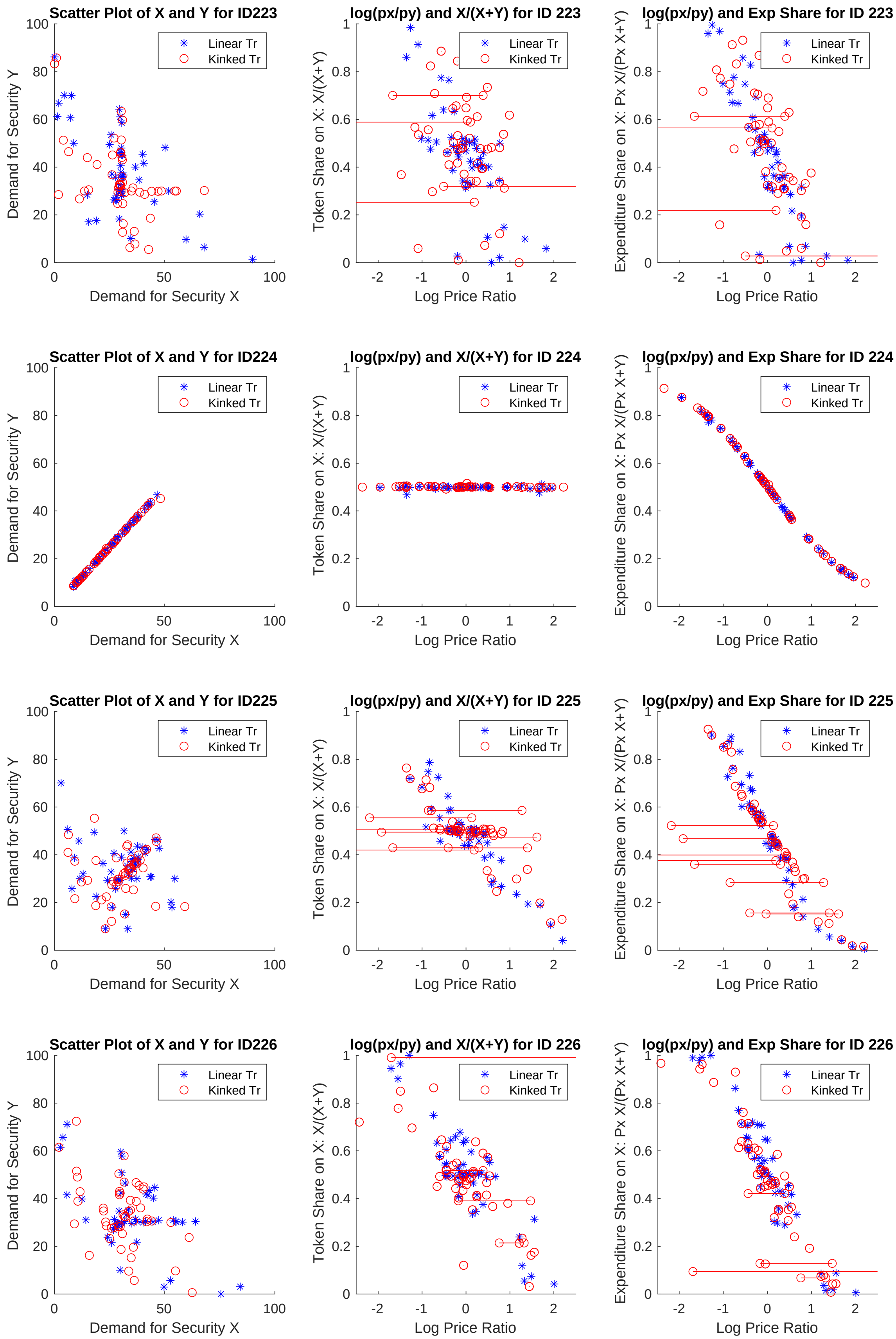
log(px/py) and Exp Share for ID 222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Expenditure Share on X: Px X/(Px X+Y)
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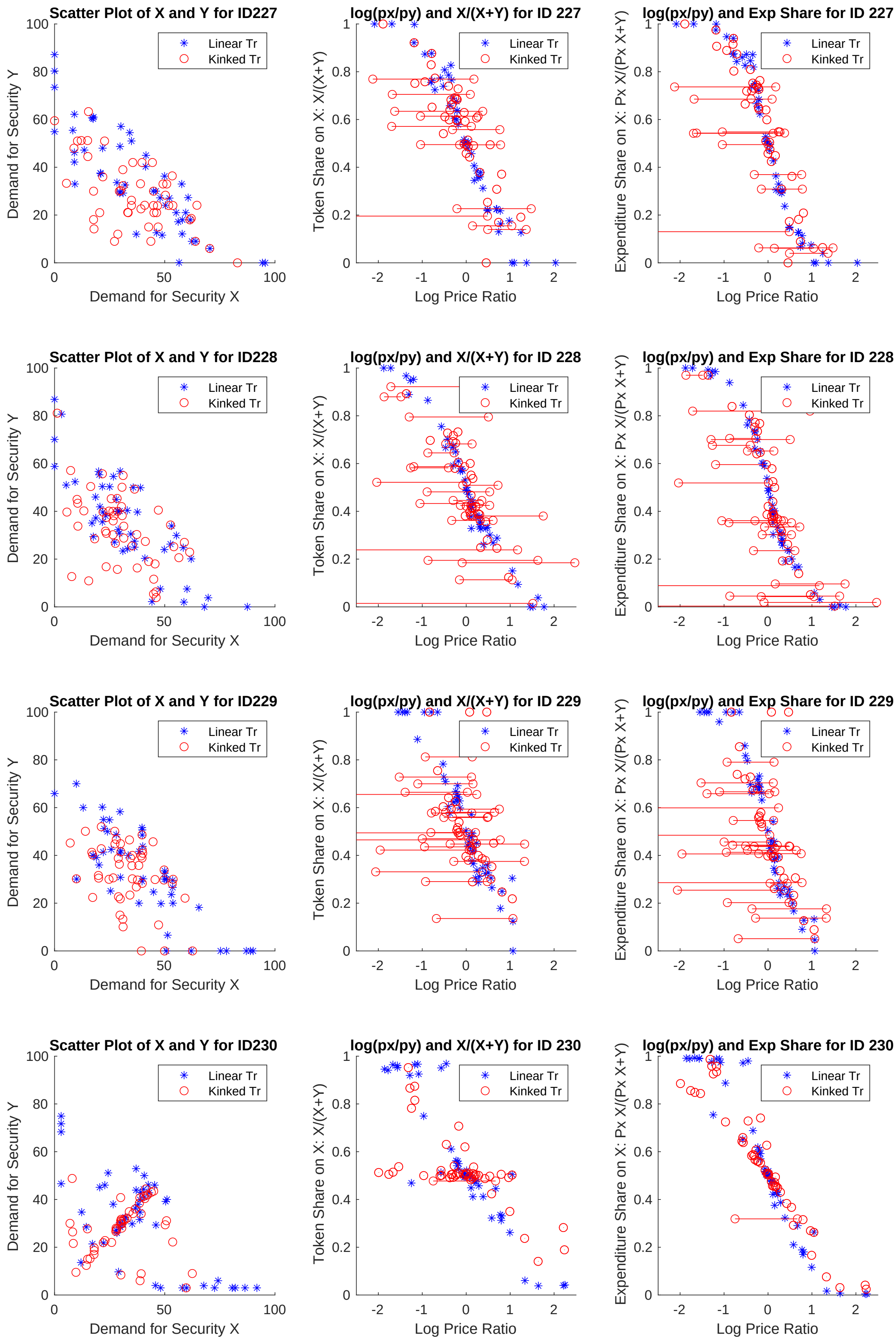
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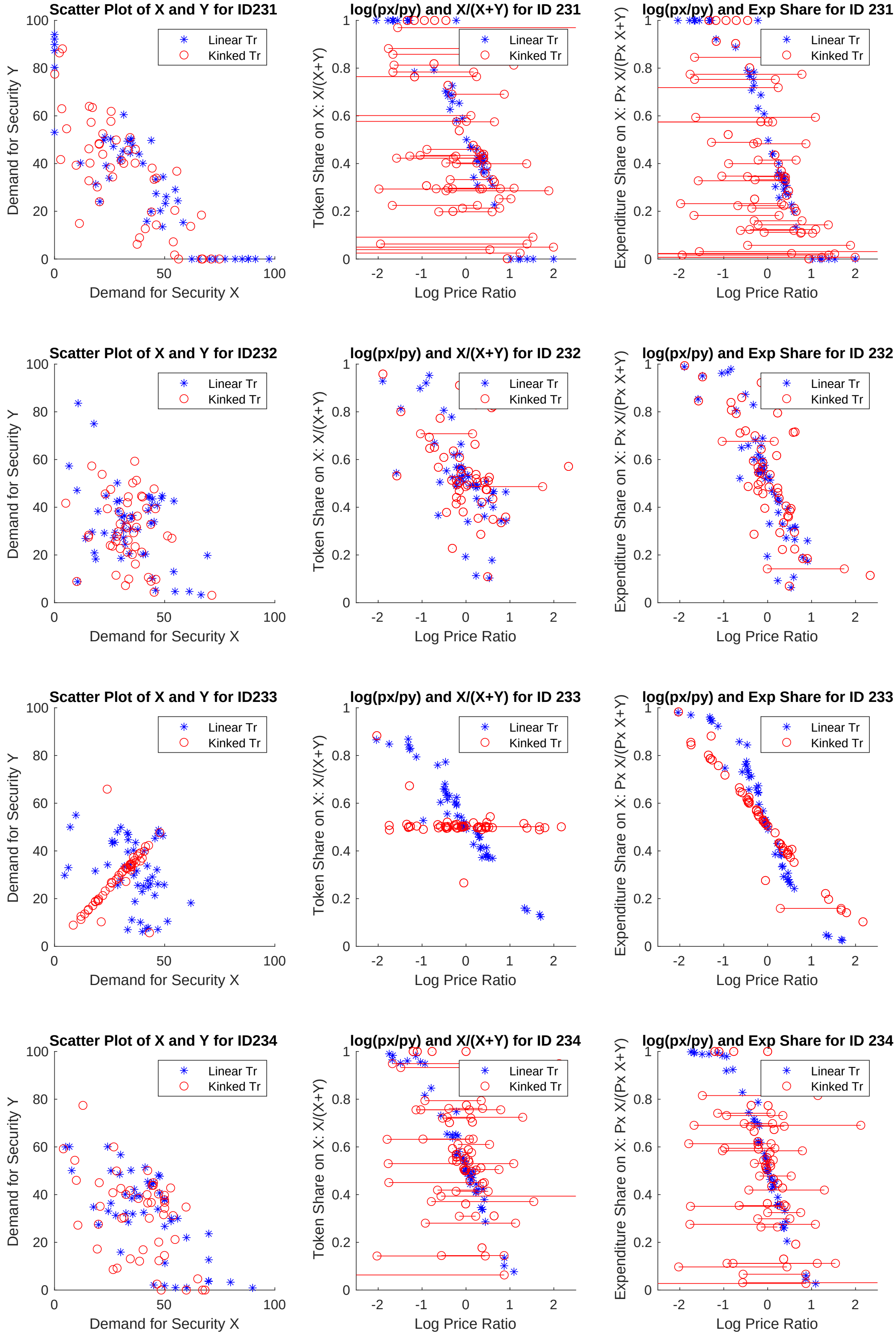
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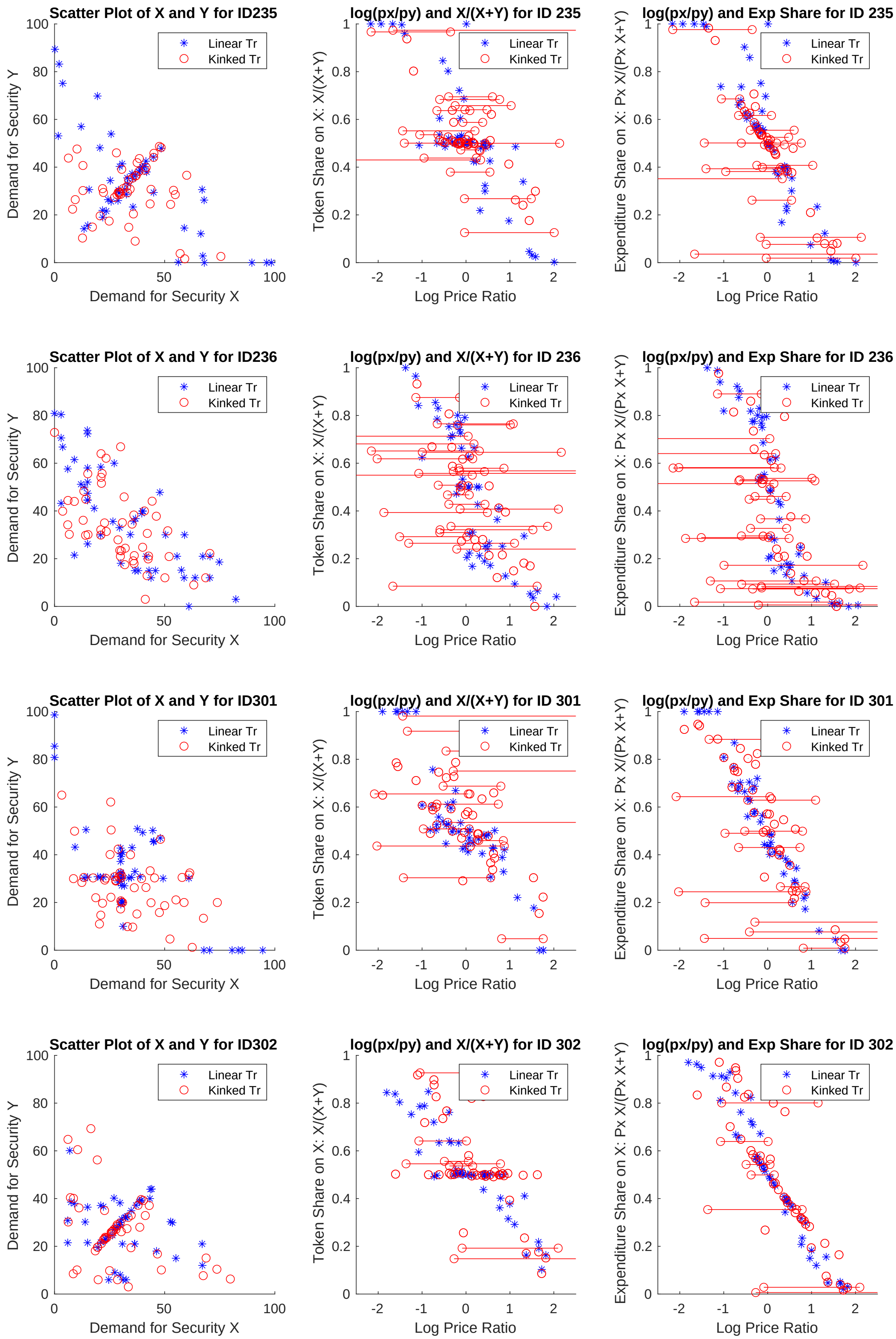
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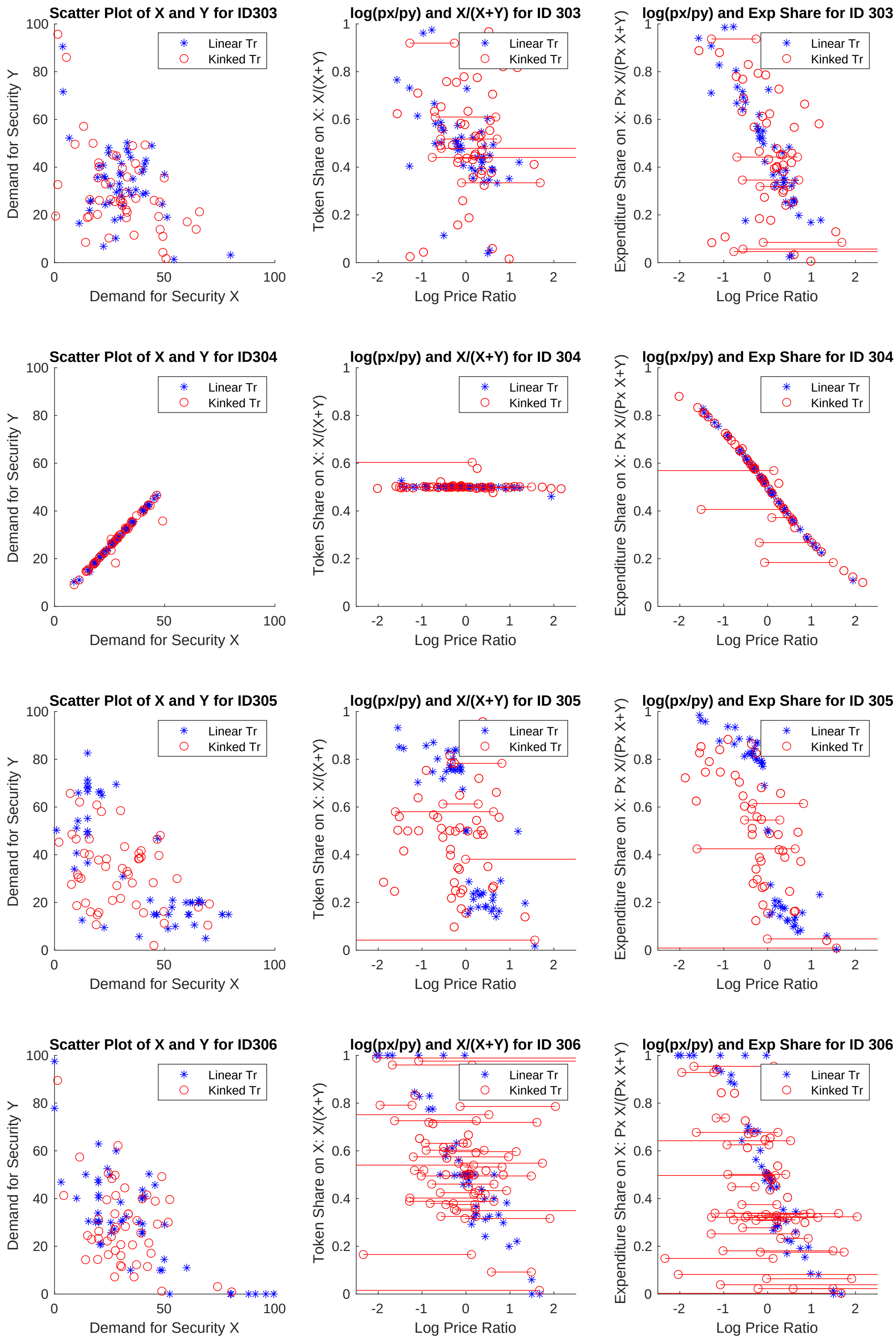
Expenditure Share on X: Px X/(Px X+Y)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Log Price Ratio
log(px/py) and Exp Share for ID 303
Expenditure Share on X: Px X/(Px X+Y)
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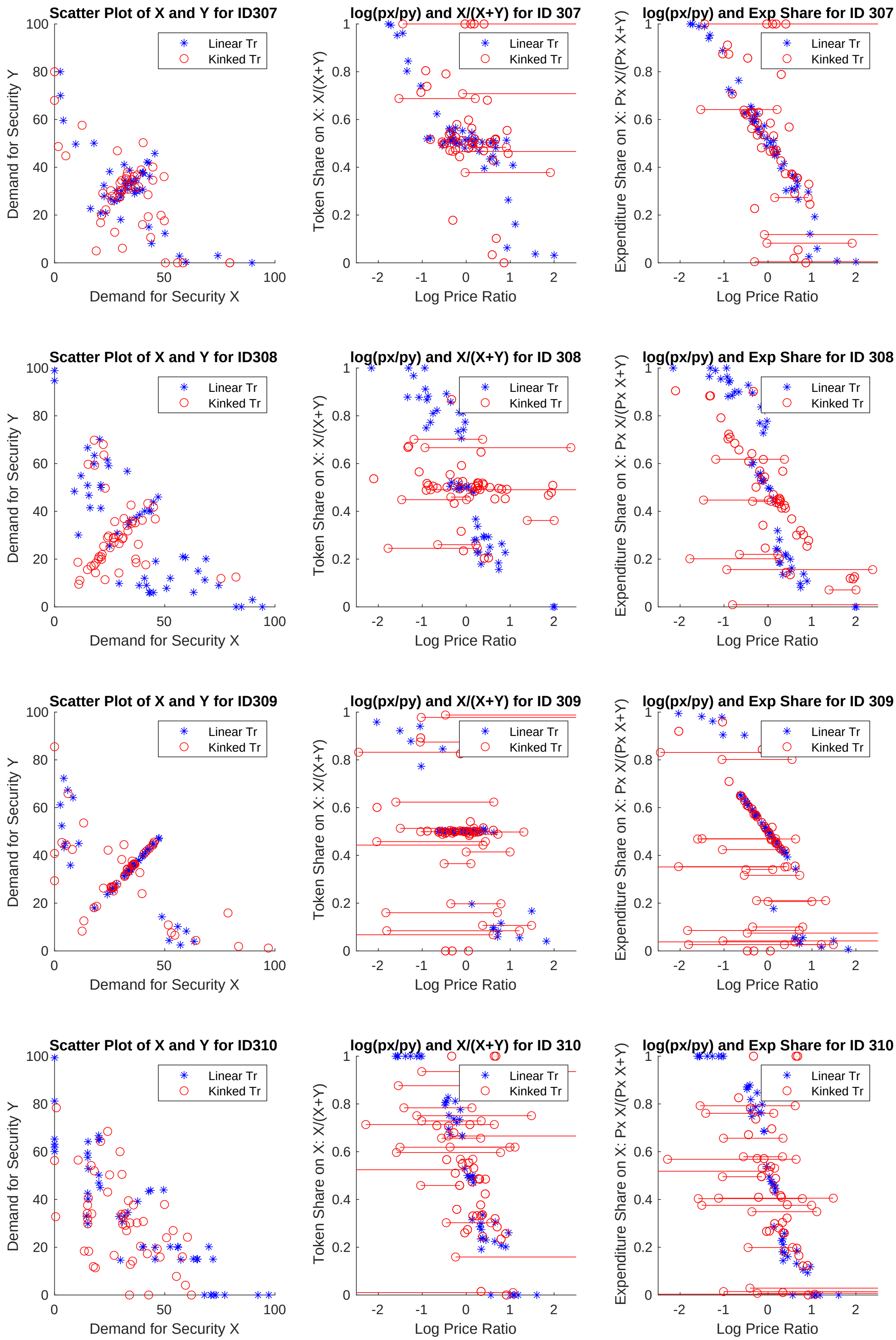
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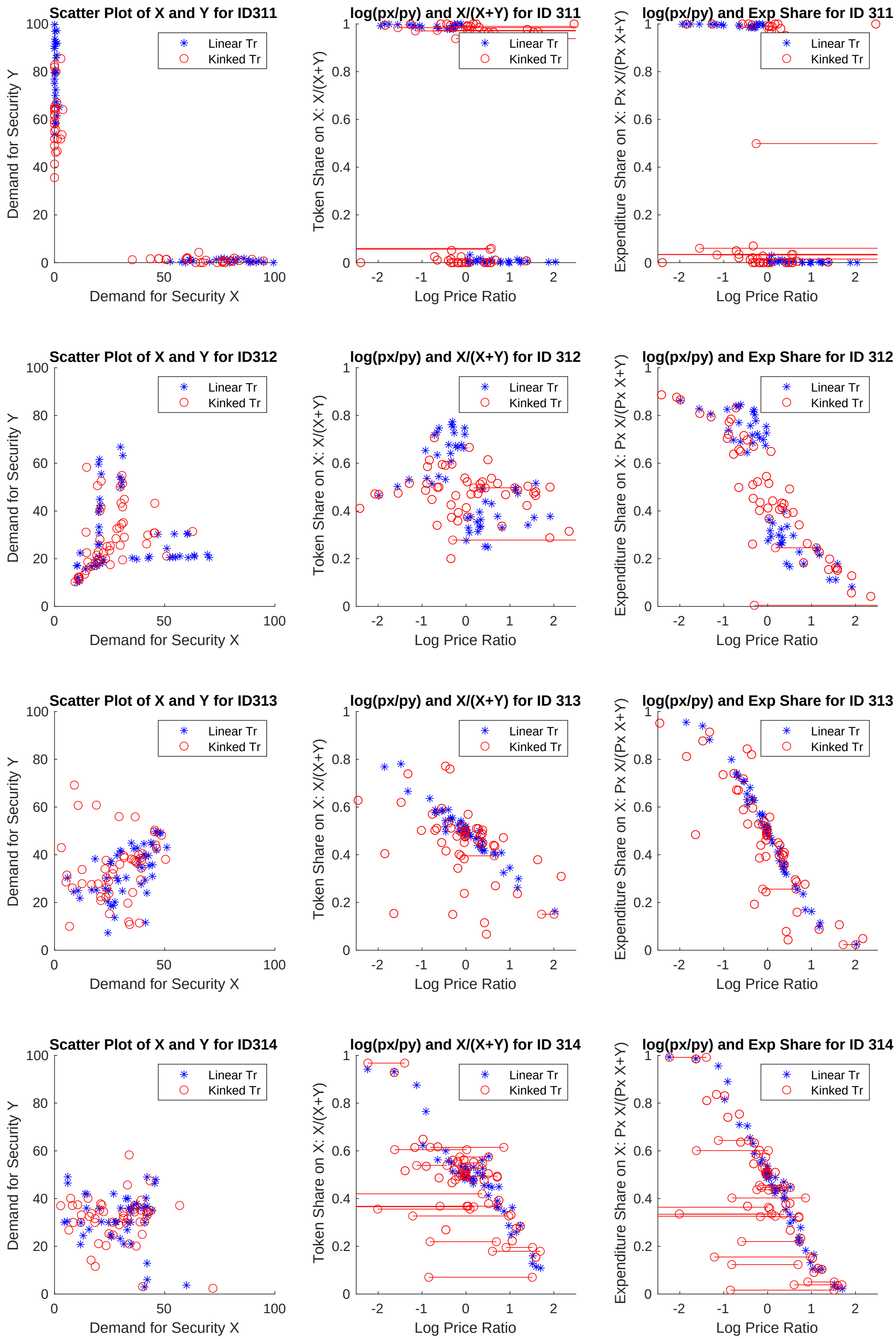
log(px/py) and Exp Share for ID 309
Scatter Plot of X and Y for ID310
log(px/py) and X/(X+Y) for ID 310
log(px/py) and Exp Share for ID 310
Linear Tr
Kinked Tr
Demand for Security Y
Demand for Security X
Token Share on X: X/(X+Y)
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio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Log Price Ratio
log(px/py) and Exp Share for ID 311
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio
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log(px/py) and X/(X+Y) for ID 312
log(px/py) and Exp Share for ID 312
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log(px/py) and X/(X+Y) for ID 313
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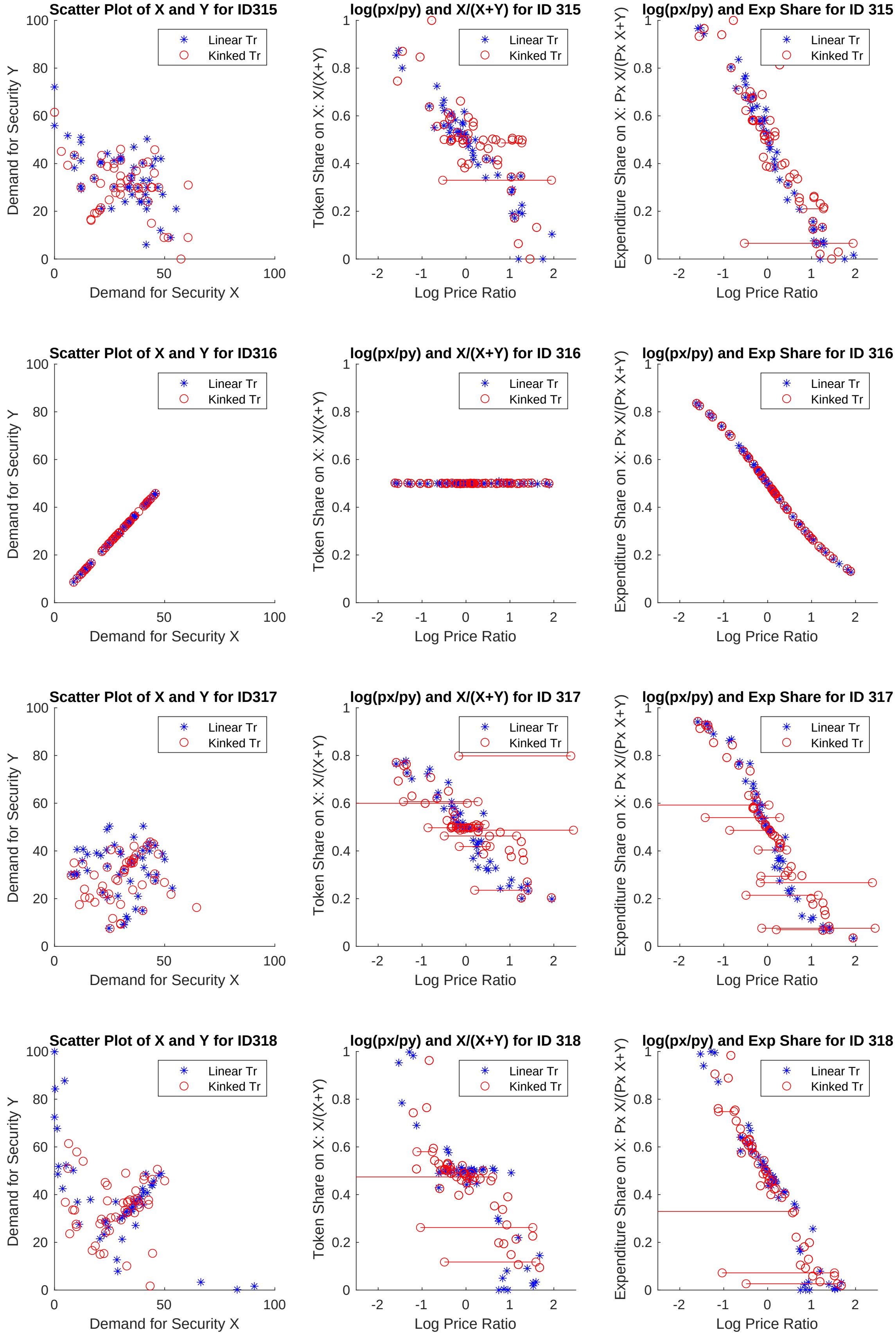
log(px/py) and Exp Share for ID 314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log(px/py) and Exp Share for ID 317
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log(px/py) and X/(X+Y) for ID 318
log(px/py) and Exp Share for ID 318
Linear Tr
Kinked Tr
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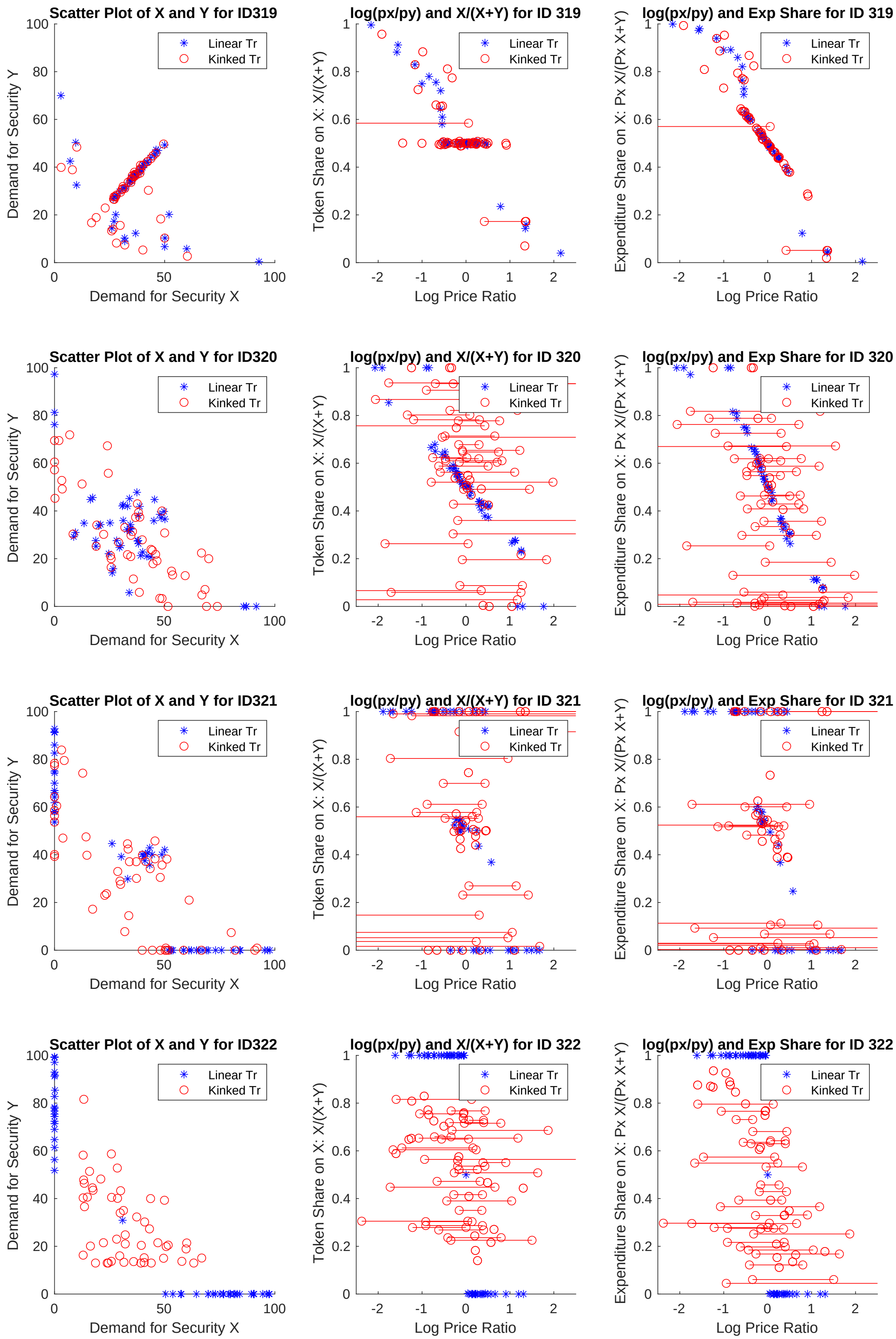
Demand for Security Y
Log Price Ratio
Token Share on X: X/(X+Y)
Expenditure Share on X: Px X/(Px X+Y)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Kinked Tr
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Kinked Tr
log(px/py) and Exp Share for ID 319
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio
Linear Tr
Kinked Tr
Scatter Plot of X and Y for ID320
Demand for Security Y
Demand for Security X
Linear Tr
Kinked Tr
log(px/py) and X/(X+Y) for ID 320
Token Share on X: X/(X+Y)
Log Price Ratio
Linear Tr
Kinked Tr
log(px/py) and Exp Share for ID 320
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio
Linear Tr
Kinked Tr
Scatter Plot of X and Y for ID321
Demand for Security Y
Demand for Security X
Linear Tr
Kinked Tr
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Token Share on X: X/(X+Y)
Log Price Ratio
Linear Tr
Kinked Tr
log(px/py) and Exp Share for ID 321
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio
Linear Tr
Kinked Tr
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Demand for Security Y
Demand for Security X
Linear Tr
Kinked Tr
log(px/py) and X/(X+Y) for ID 322
Token Share on X: X/(X+Y)
Log Price Ratio
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log(px/py) and Exp Share for ID 322
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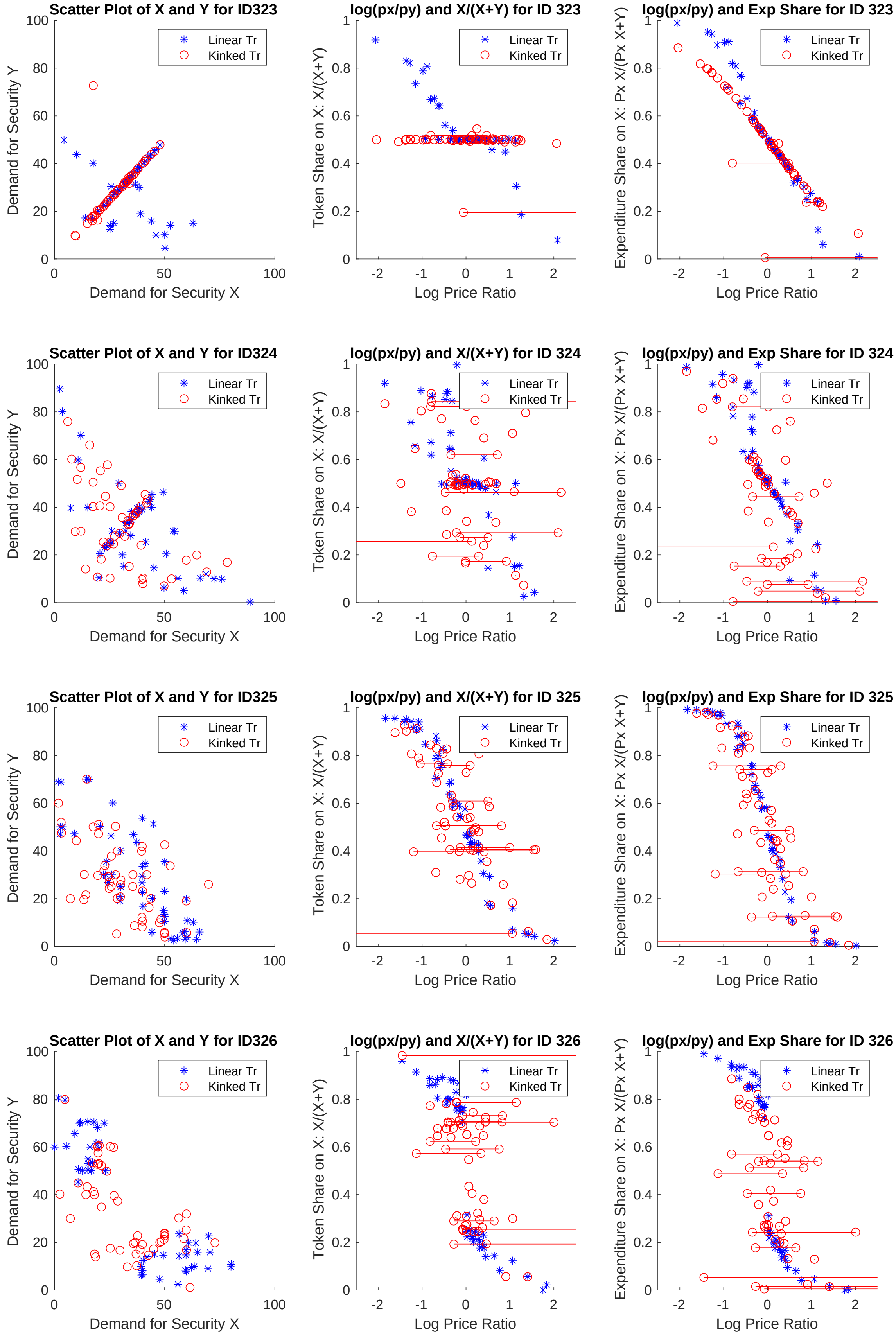
Kinked Tr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log(px/py) and Exp Share for ID 324
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log(px/py) and X/(X+Y) for ID 325
log(px/py) and Exp Share for ID 325
Scatter Plot of X and Y for ID326
log(px/py) and X/(X+Y) for ID 326
log(px/py) and Exp Share for ID 326
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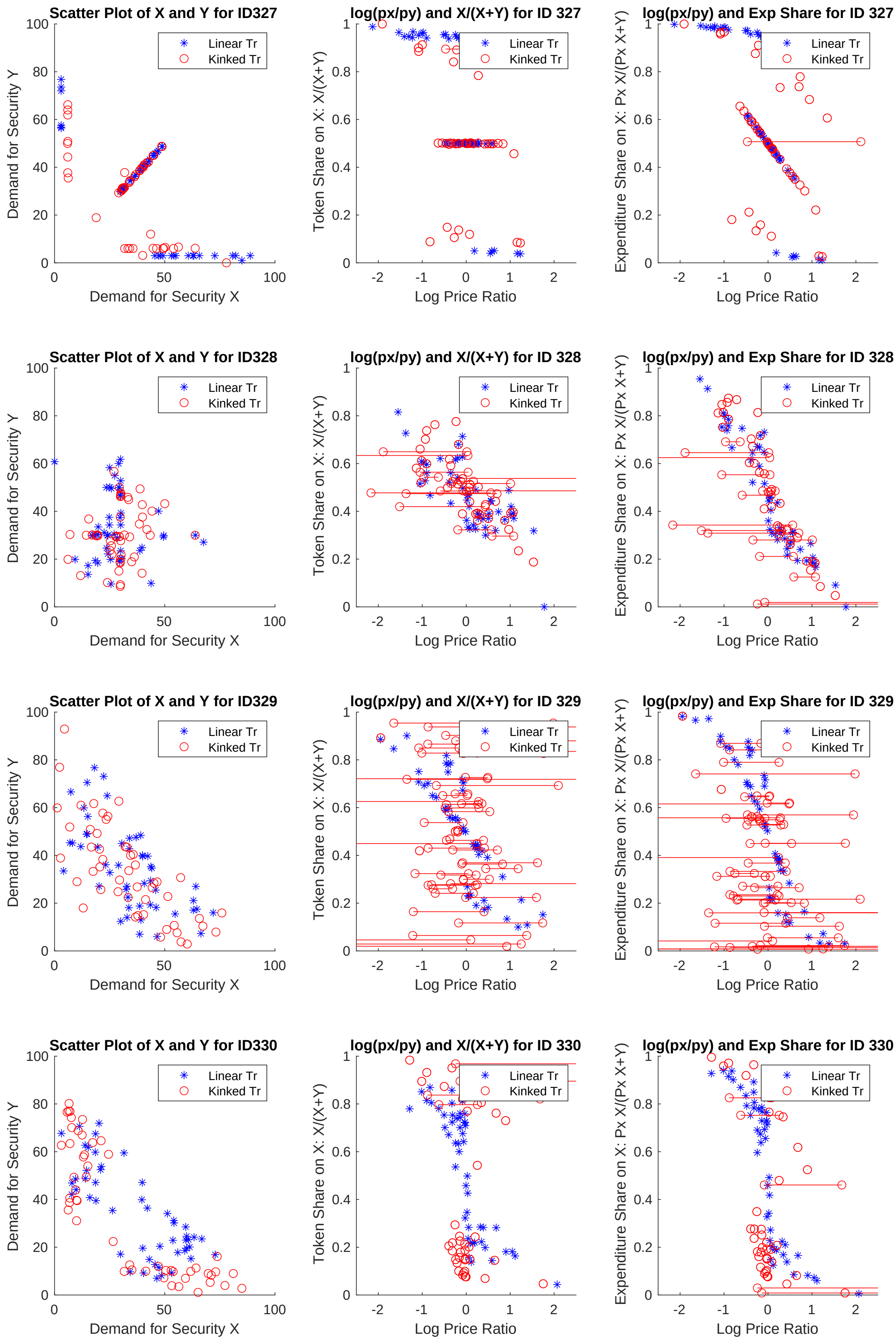
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio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log(px/py) and Exp Share for ID 328
Scatter Plot of X and Y for ID329
log(px/py) and X/(X+Y) for ID 329
log(px/py) and Exp Share for ID 329
Scatter Plot of X and Y for ID330
log(px/py) and X/(X+Y) for ID 330
log(px/py) and Exp Share for ID 330
Demand for Security Y
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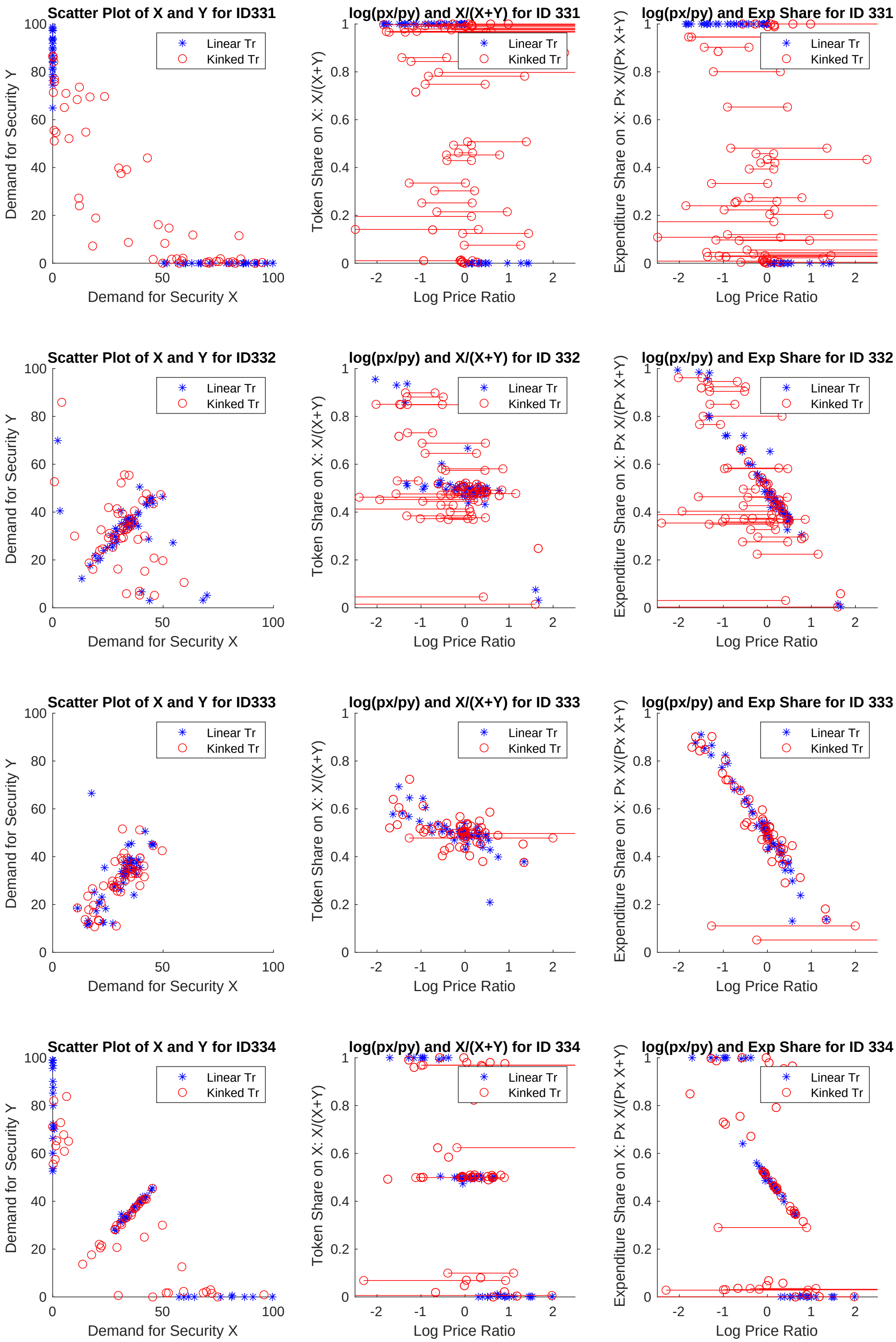
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio
Linear Tr
Kinked Tr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log(px/py) and Exp Share for ID 332
Scatter Plot of X and Y for ID333
log(px/py) and X/(X+Y) for ID 333
log(px/py) and Exp Share for ID 333
Scatter Plot of X and Y for ID334
log(px/py) and X/(X+Y) for ID 334
log(px/py) and Exp Share for ID 334
Demand for Security Y
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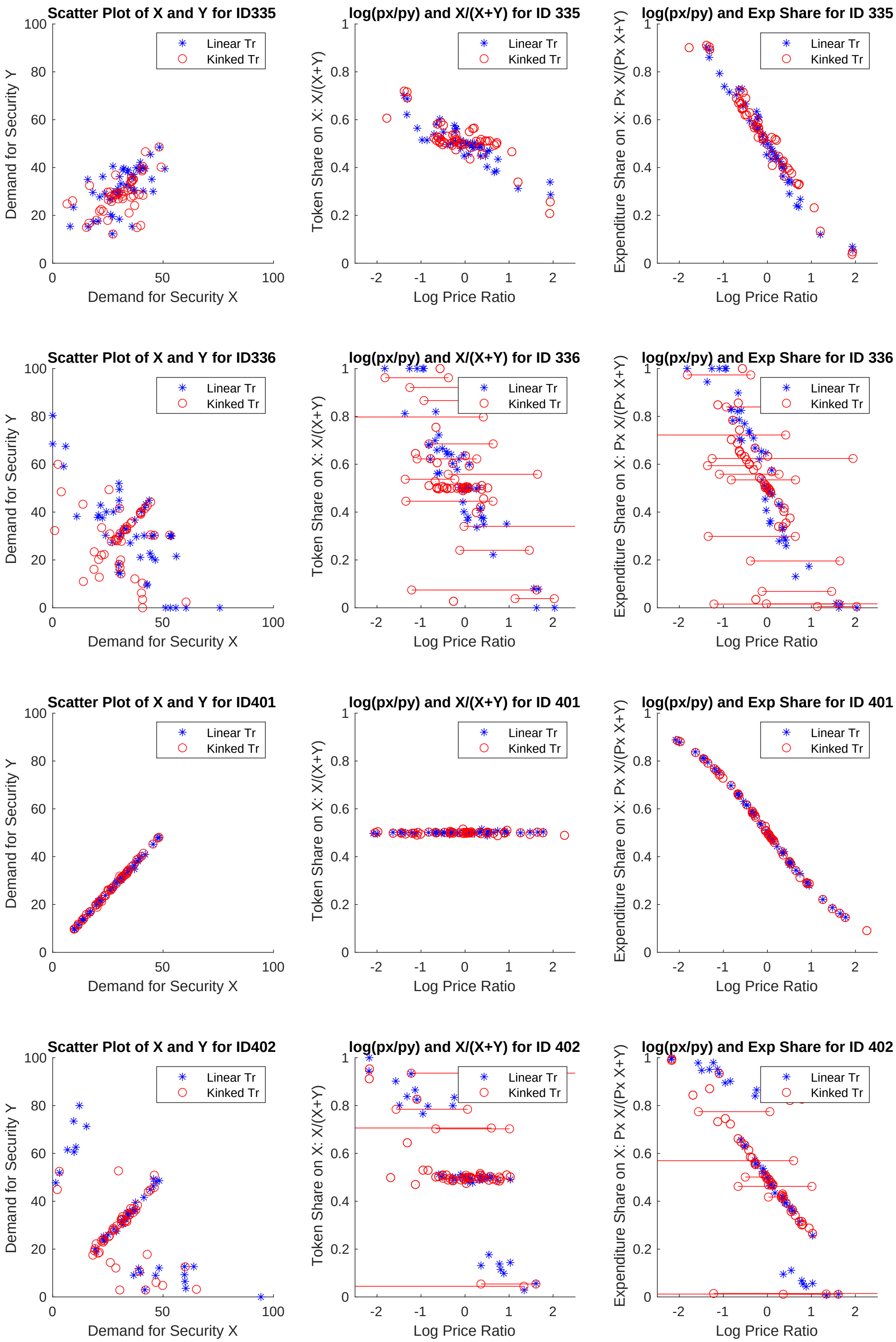
Token Share on X: X/(X+Y)
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio
Linear Tr
Kinked Tr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Demand for Security X
Linear Tr
Kinked Tr
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Token Share on X: X/(X+Y)
Log Price Ratio
log(px/py) and Exp Share for ID 335
Expenditure Share on X: Px X/(Px X+Y)
Scatter Plot of X and Y for ID336
log(px/py) and X/(X+Y) for ID 336
log(px/py) and Exp Share for ID 336
Scatter Plot of X and Y for ID401
log(px/py) and X/(X+Y) for ID 401
log(px/py) and Exp Share for ID 401
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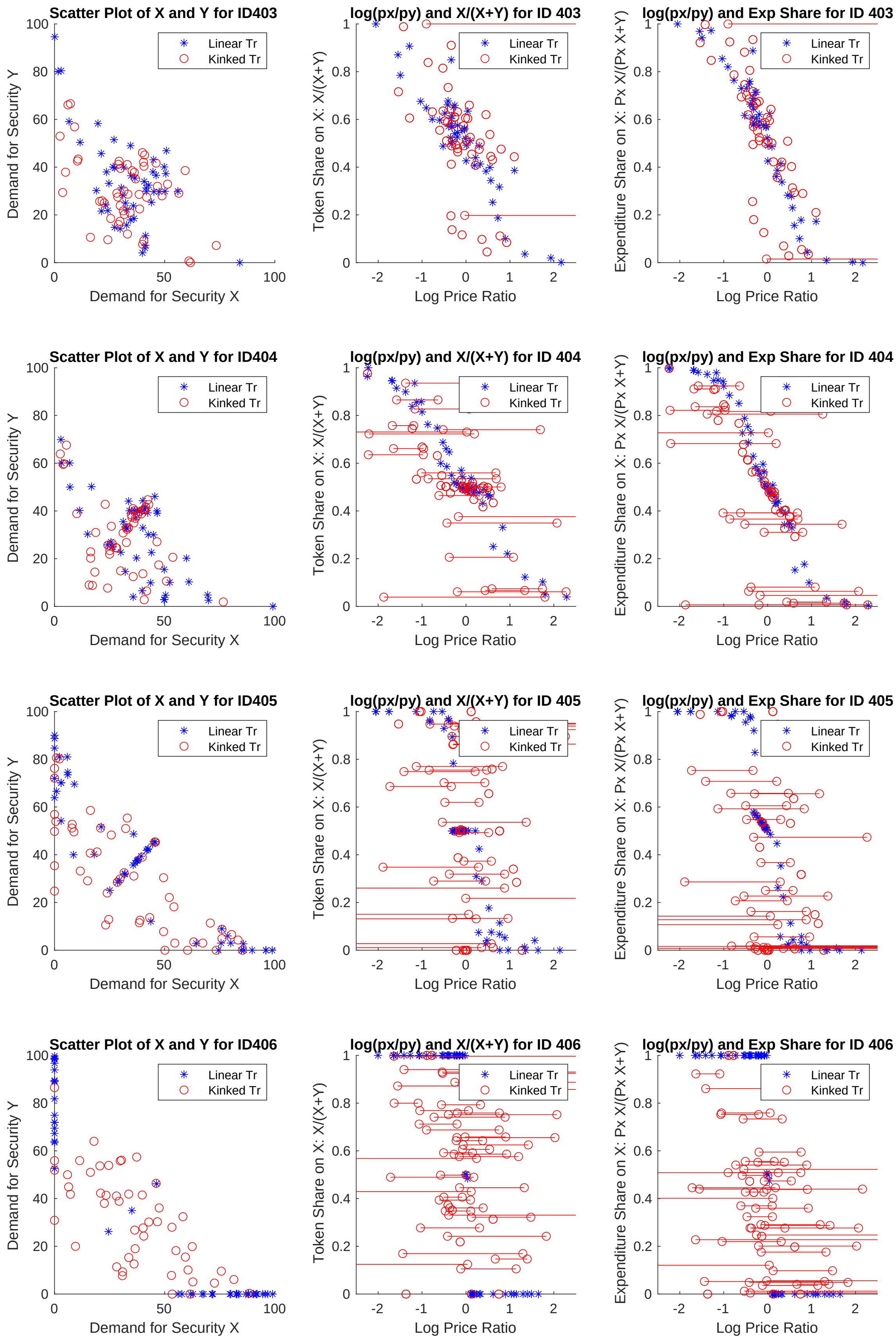
log(px/py) and X/(X+Y) for ID 402
log(px/py) and Exp Share for ID 402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Kinked Tr
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Log Price Ratio
log(px/py) and Exp Share for ID 403
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio
Scatter Plot of X and Y for ID404
log(px/py) and X/(X+Y) for ID 404
log(px/py) and Exp Share for ID 404
Scatter Plot of X and Y for ID405
log(px/py) and X/(X+Y) for ID 405
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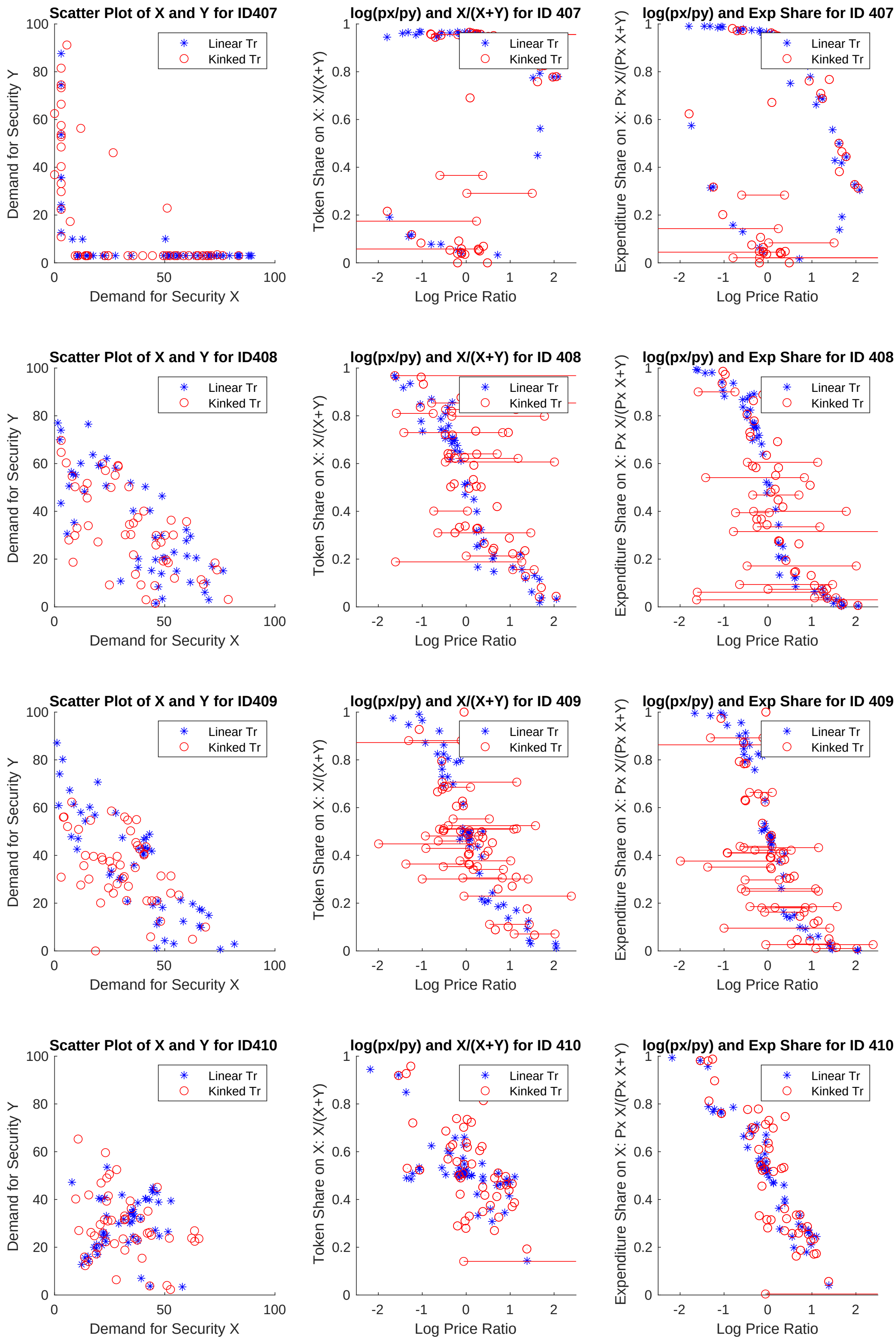
log(px/py) and X/(X+Y) for ID 406
log(px/py) and Exp Share for ID 406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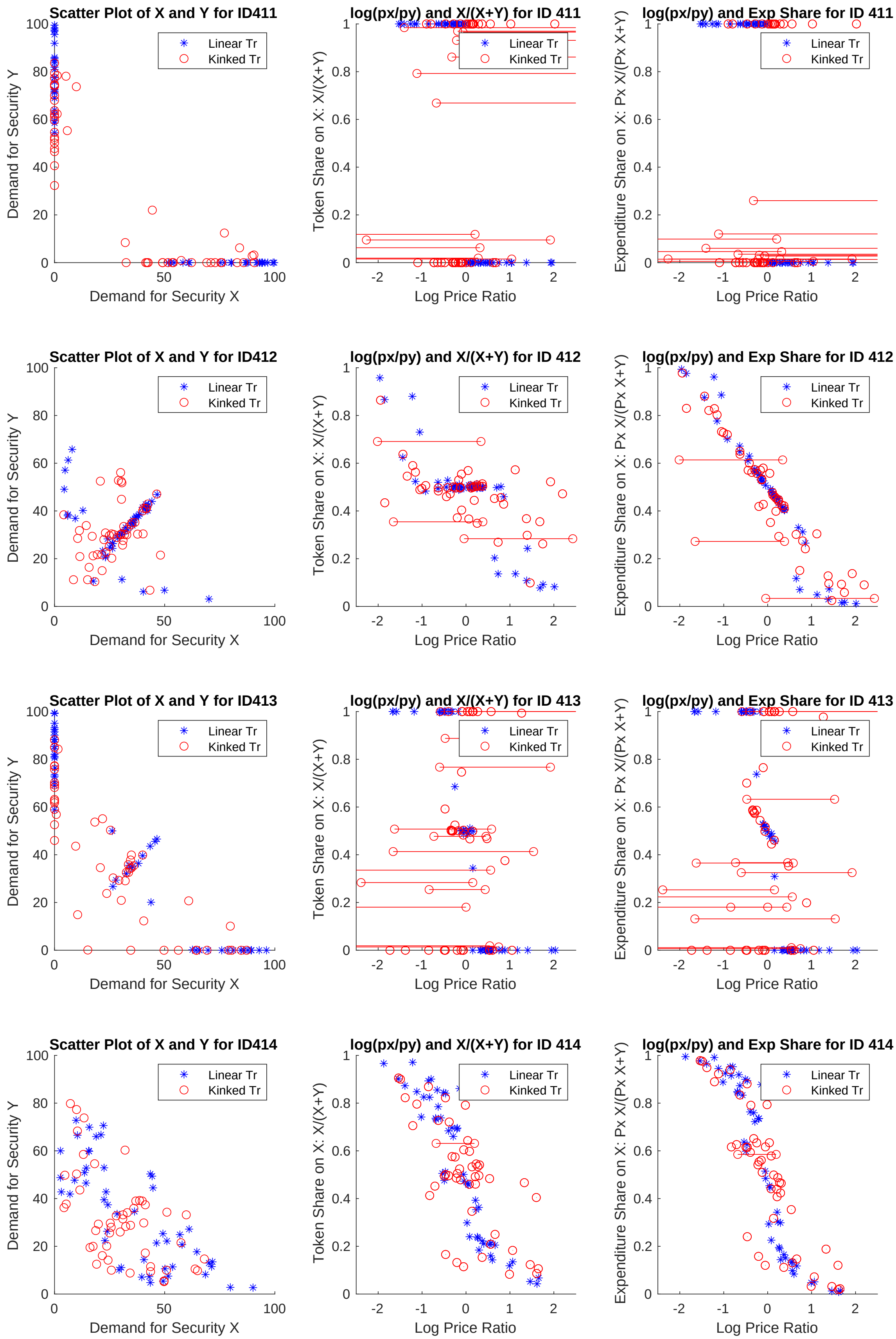
log(px/py) and X/(X+Y) for ID 408
log(px/py) and Exp Share for ID 408
Scatter Plot of X and Y for ID409
log(px/py) and X/(X+Y) for ID 409
log(px/py) and Exp Share for ID 409
Scatter Plot of X and Y for ID410
log(px/py) and X/(X+Y) for ID 410
log(px/py) and Exp Share for ID 410
Linear Tr
Kinked Tr
Demand for Security X
Demand for Security Y
Log Price Ratio
Token Share on X: X/(X+Y)
Expenditure Share on X: Px X/(Px X+Y)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Scatter Plot of X and Y for ID413
log(px/py) and X/(X+Y) for ID 413
log(px/py) and Exp Share for ID 413
Scatter Plot of X and Y for ID414
log(px/py) and X/(X+Y) for ID 414
log(px/py) and Exp Share for ID 414
Linear Tr
Kinked Tr
Demand for Security Y
Demand for Security X
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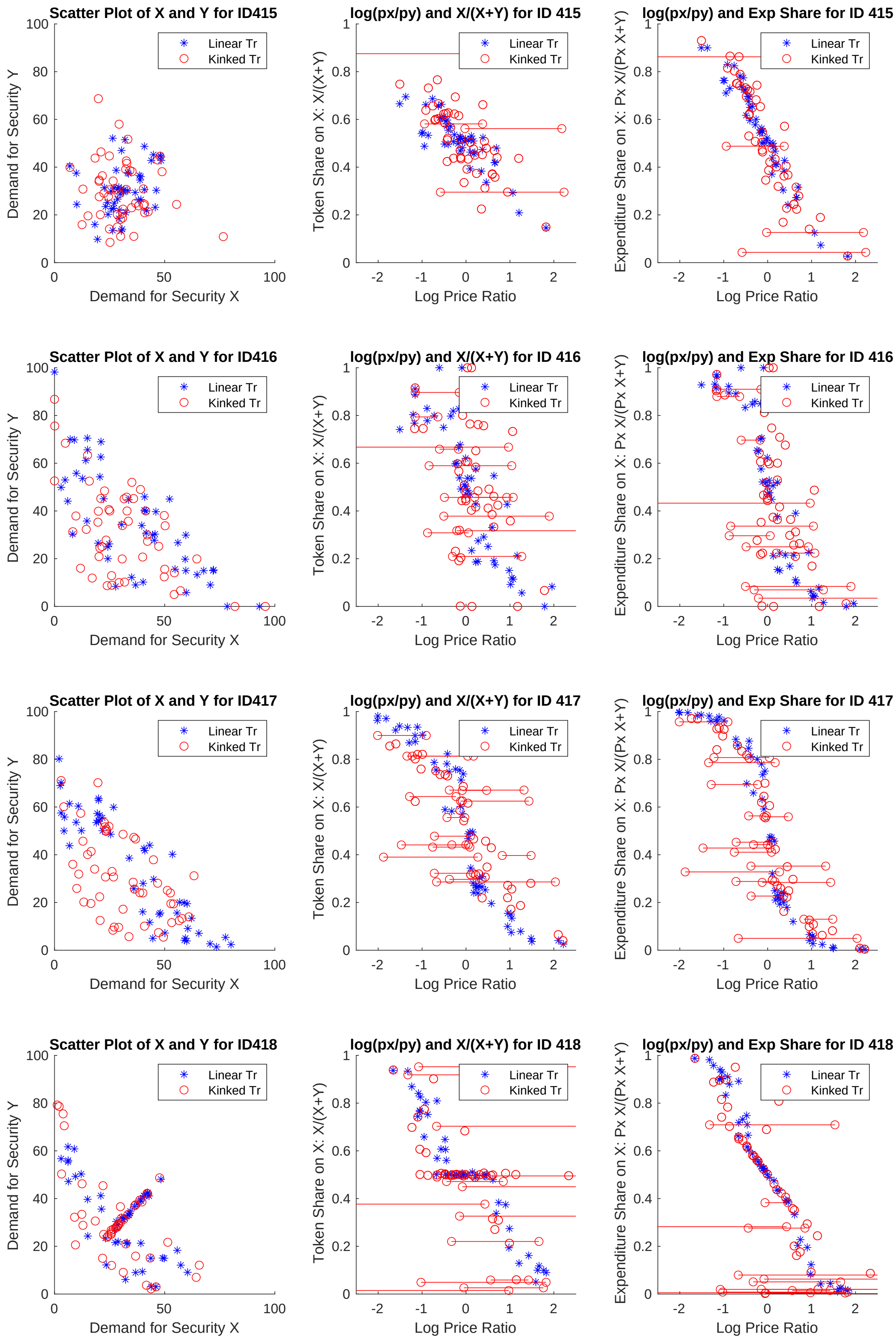
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio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log(px/py) and Exp Share for ID 416
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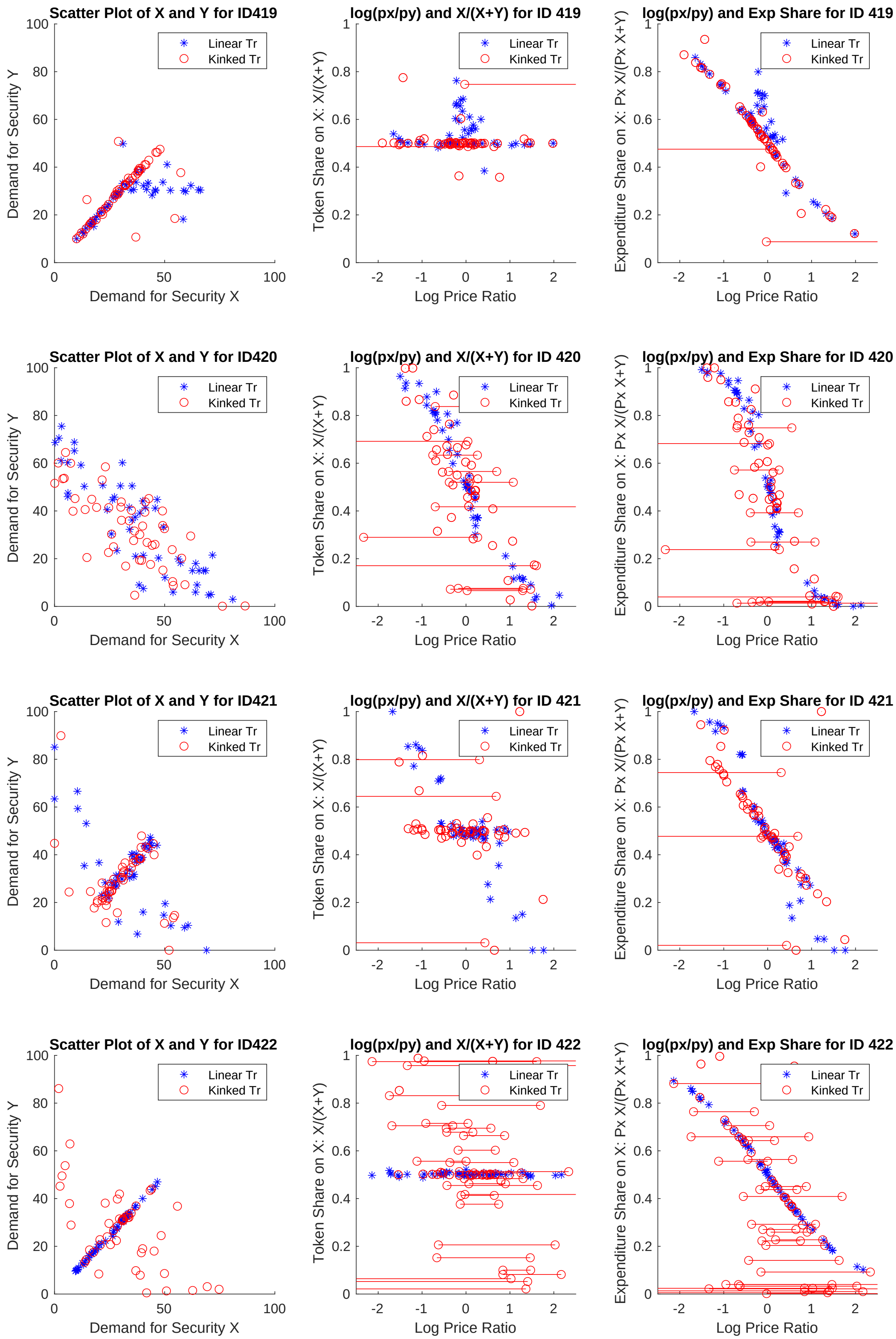
log(px/py) and X/(X+Y) for ID 417
log(px/py) and Exp Share for ID 417
Scatter Plot of X and Y for ID418
log(px/py) and X/(X+Y) for ID 418
log(px/py) and Exp Share for ID 418
Linear Tr
Kinked Tr
Demand for Security Y
Demand for Security X
Token Share on X: X/(X+Y)
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio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log(px/py) and Exp Share for ID 420
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log(px/py) and X/(X+Y) for ID 421
log(px/py) and Exp Share for ID 421
Scatter Plot of X and Y for ID422
log(px/py) and X/(X+Y) for ID 422
log(px/py) and Exp Share for ID 422
Linear Tr
Kinked Tr
Demand for Security Y
Demand for Security X
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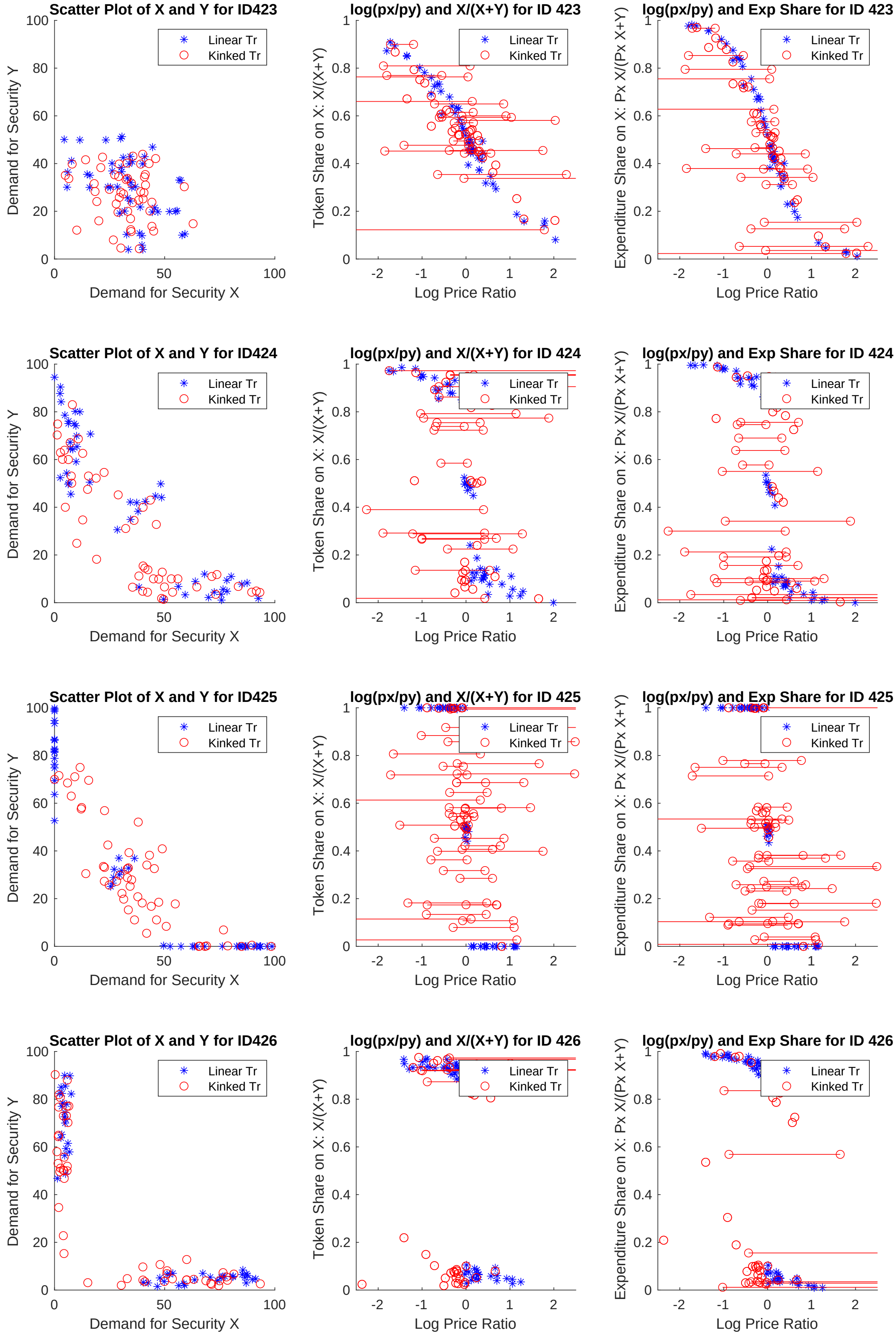
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio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log(px/py) and Exp Share for ID 425
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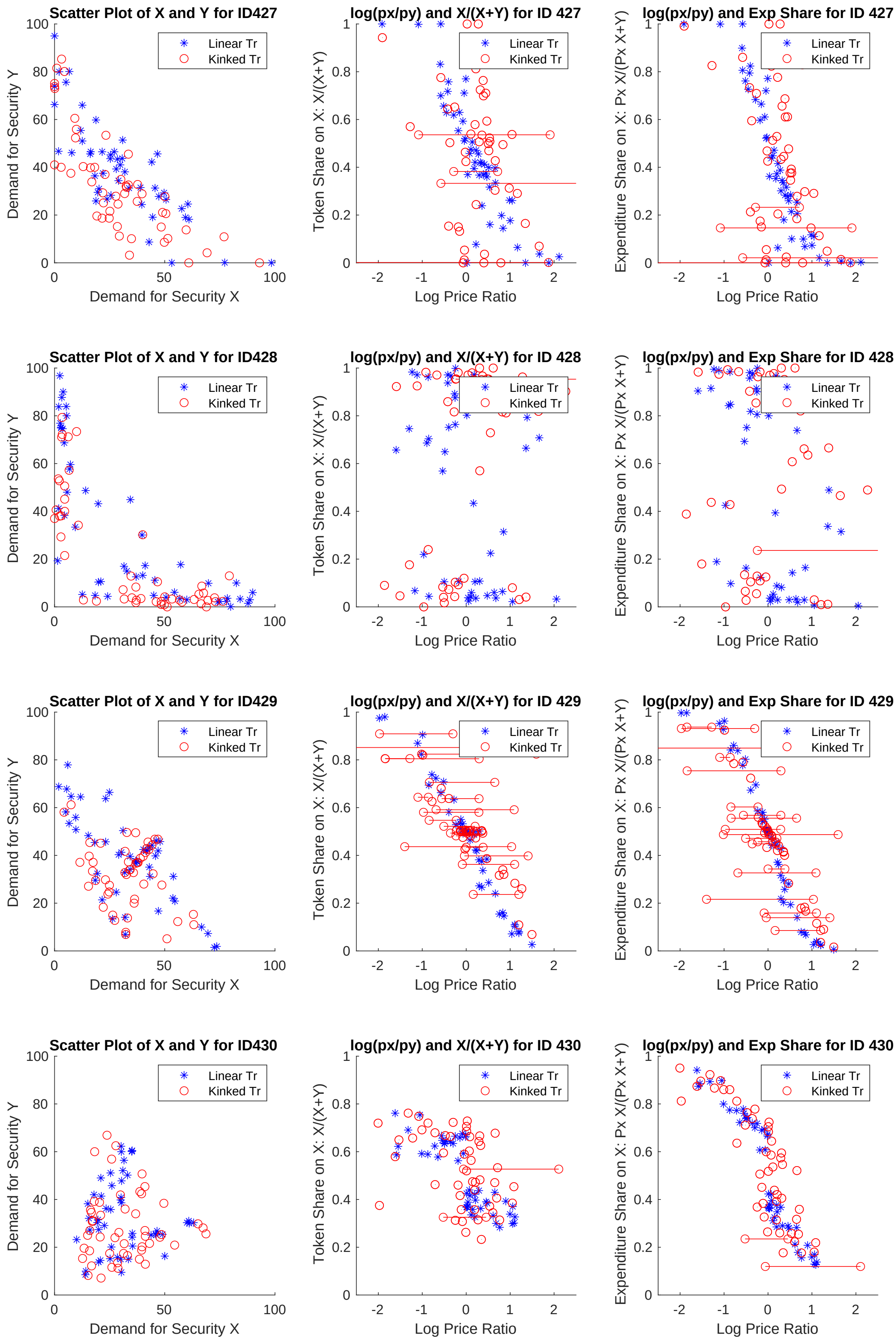
log(px/py) and X/(X+Y) for ID 426
log(px/py) and Exp Share for ID 426
Linear Tr
Kinked Tr
Demand for Security X
Demand for Security Y
Log Price Ratio
Token Share on X: X/(X+Y)
Expenditure Share on X: Px X/(Px X+Y)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Demand for Security X
Linear Tr
Kinked Tr
log(px/py) and X/(X+Y) for ID 427
Token Share on X: X/(X+Y)
Log Price Ratio
log(px/py) and Exp Share for ID 427
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio
Scatter Plot of X and Y for ID428
log(px/py) and X/(X+Y) for ID 428
log(px/py) and Exp Share for ID 428
Scatter Plot of X and Y for ID429
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log(px/py) and Exp Share for ID 429
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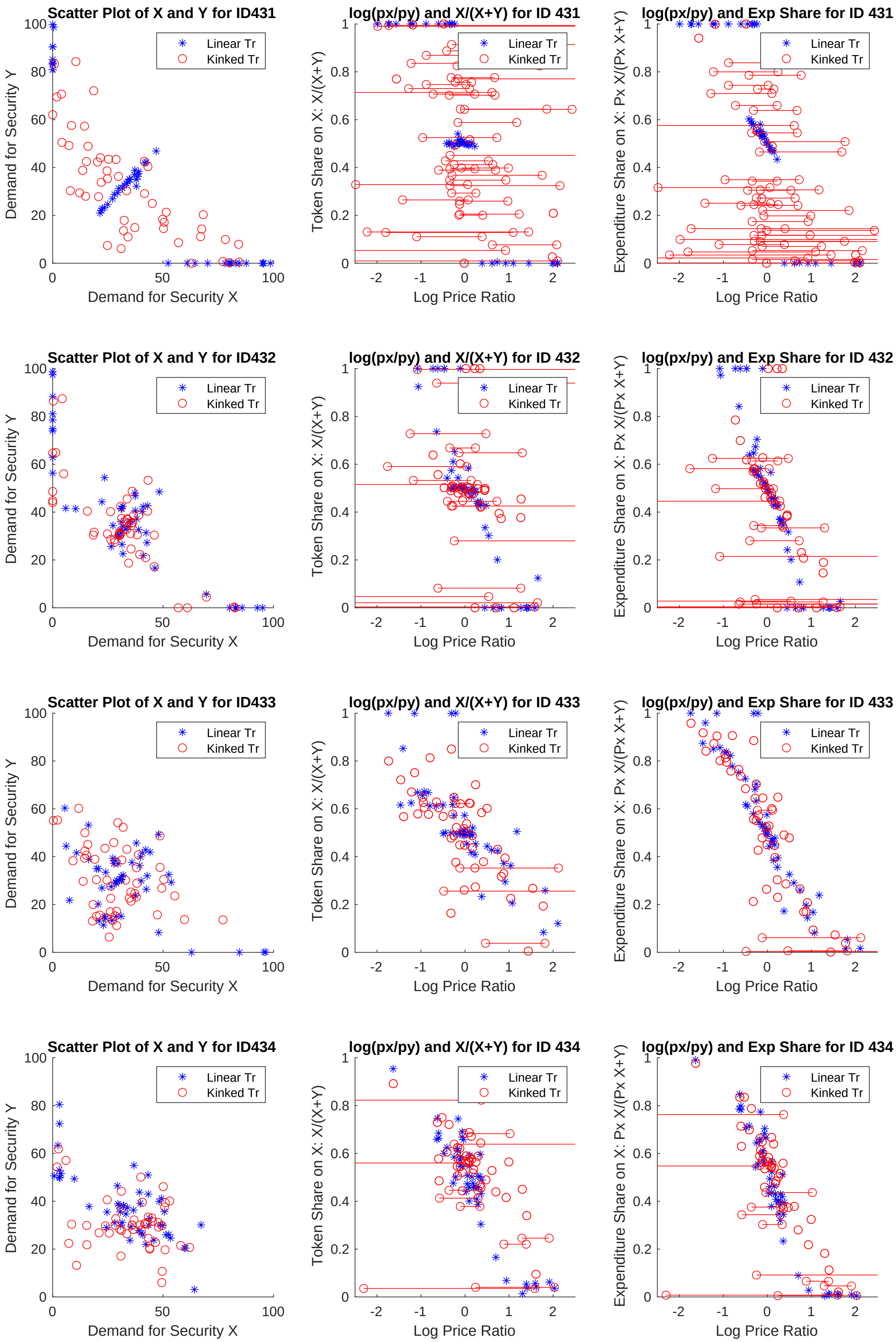
log(px/py) and Exp Share for ID 430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Scatter Plot of X and Y for ID433
log(px/py) and X/(X+Y) for ID 433
log(px/py) and Exp Share for ID 433
Scatter Plot of X and Y for ID434
log(px/py) and X/(X+Y) for ID 434
log(px/py) and Exp Share for ID 434
Linear Tr
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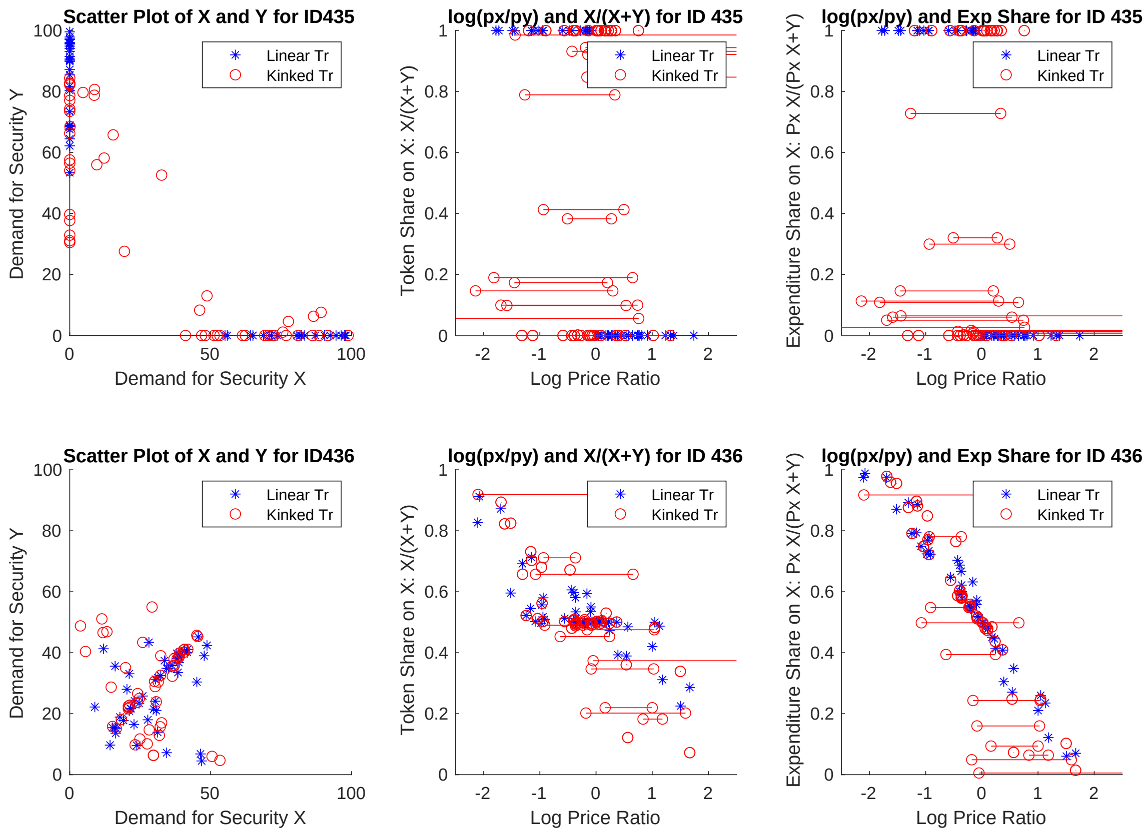
Token Share on X: X/(X+Y)
Expenditure Share on X: Px X/(Px X+Y)
Log Price Ratio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Demand for Security Y
Demand for Security X
Linear Tr
Kinked Tr
log(px/py) and X/(X+Y) for ID 435
Token Share on X: X/(X+Y)
Log Price Ratio
log(px/py) and Exp Share for ID 435
Expenditure Share on X: Px X/(Px X+Y)
Scatter Plot of X and Y for ID436
log(px/py) and X/(X+Y) for ID 436
log(px/py) and Exp Share for ID 436

E Consistency of Preferences

This appendix presents individual-level measures of deviations from SARP. In Tables 4-15, the data are divided by data source (linear treatment, kinked treatment, or pooled across the two treatments). The second column of each table is Afriat's CCEI. The third column is the measure of Varian (1982), and the next two are the estimated and exact deviations as measured by Houtman and Maks (1985), used to compute the HM measure. Figures 14-16 present histograms of HM removals, Afriat's CCEI, and Varian's CCEI for the linear, kinked, and pooled choices. The results are broadly consistent across the figures, regardless of which measure of consistency is used: the difference between the pooled distribution and either the linear or kinked distribution is statistically significant in the expected direction (the CCEI scores shift left in the pooled case, consistent with the rightward shift of HM removals in the pooled case).

Table 4: Linear Treatment – Session 1

User ID	E	E+V	Estimated V ($\leq$)	Violations	Data size
101	0.9988	0.9956	1	2	50
102	0.9877	0.9299	6	21	50
103	0.9886	0.9419	3	12	50
104	0.9693	0.9493	4	14	50
105	0.9914	0.9681	3	6	50
106	0.7545	0.4039	22	370	50
107	0.9977	0.9904	2	4	50
108	0.9714	0.9638	1	9	50
109	1.0000	1.0000	0	0	50
110	0.9862	0.8922	1	13	50
111	1.0000	1.0000	0	0	50
112	0.9951	0.9921	1	2	50
113	1.0000	1.0000	0	0	50
114	0.9927	0.9824	1	2	50
115	0.9833	0.9643	2	10	50
116	0.8590	0.6629	17	292	50
117	0.9873	0.9429	2	4	50
118	0.9839	0.9767	3	9	50
119	0.8421	0.8232	2	96	50
120	0.9996	0.9976	1	2	50
121	0.9995	0.9962	2	4	50
122	0.9940	0.9651	1	2	50
123	0.9925	0.9090	4	16	50
124	0.9948	0.9948	1	2	50
125	0.9663	0.7500	5	20	50
126	0.9979	0.9682	1	2	50
127	1.0000	1.0000	0	0	50
128	0.9991	0.9971	2	4	50
129	0.9728	0.9654	1	2	50
130	0.9928	0.9757	2	6	50
131	0.9267	0.8615	3	40	50
132	0.7453	0.4518	31	604	50
133	0.9662	0.6634	1	2	50
134	0.9995	0.9987	1	2	50

Table 5: Linear Treatment – Session 2

User ID	E	E+V	Estimated V ($\leq$)	Violations	Data size
201	0.9805	0.9443	4	11	50
202	0.9823	0.8624	8	56	50
203	1.0000	1.0000	0	0	50
204	0.9772	0.9746	4	14	50
205	0.9676	0.6551	17	131	50
206	0.9252	0.7808	7	36	50
207	0.9939	0.8730	11	51	50
208	0.8991	0.8880	8	25	50
209	0.9966	0.9795	3	6	50
210	0.3585	0.1744	38	862	50
211	0.9769	0.9347	1	4	50
212	0.9577	0.9428	9	41	50
213	0.9576	0.8331	3	6	50
214	0.8659	0.4619	6	50	50
215	0.9990	0.9946	3	9	50
216	0.9989	0.9957	4	8	50
217	0.9979	0.9857	2	4	50
218	0.4727	0.2004	26	710	50
219	0.9982	0.9959	2	4	50
220	0.9994	0.9983	2	4	50
221	0.7756	0.4163	31	524	50
222	0.9960	0.9577	2	4	50
223	0.7981	0.7421	16	149	50
224	0.9982	0.9940	4	8	50
225	1.0000	1.0000	0	0	50
226	0.9721	0.9485	7	17	50
227	0.9986	0.9972	1	2	50
228	1.0000	1.0000	0	0	50
229	0.9986	0.9898	3	6	50
230	0.9907	0.9875	1	2	50
231	0.8998	0.7858	5	33	50
232	0.9143	0.8845	5	15	50
233	0.9975	0.9792	4	10	50
234	0.9995	0.9980	2	4	50
235	0.9757	0.7497	10	119	50
236	0.9633	0.9346	6	34	50

Table 6: Linear Treatment – Session 3

User ID	E	E+V	Estimated V (≤)	Violations	Data size
301	0.9956	0.9916	3	6	50
302	0.9992	0.9961	1	2	50
303	0.8312	0.5354	21	424	50
304	1.0000	0.9957	1	2	50
305	0.9999	0.9963	1	2	50
306	0.9743	0.9540	1	2	50
307	0.9922	0.9771	4	12	50
308	0.9677	0.9163	2	12	50
309	0.9552	0.8547	7	29	50
310	0.9836	0.9718	3	6	50
311	0.9957	0.9800	2	6	50
312	0.9537	0.9017	2	4	50
313	1.0000	1.0000	0	0	50
314	0.9893	0.9497	3	20	50
315	0.9977	0.9966	1	2	50
316	0.9996	0.9971	1	4	50
317	0.9918	0.9597	2	4	50
318	0.8967	0.7233	6	62	50
319	1.0000	1.0000	0	0	50
320	0.9990	0.9975	1	2	50
321	0.7007	0.5826	17	486	50
322	1.0000	1.0000	0	0	50
323	0.9977	0.9947	2	4	50
324	0.9157	0.7064	21	282	50
325	1.0000	1.0000	0	0	50
326	0.9975	0.9795	1	2	50
327	0.9985	0.9976	1	2	50
328	0.9995	0.9986	1	2	50
329	0.9813	0.9272	5	15	50
330	0.9921	0.9816	2	4	50
331	1.0000	1.0000	0	0	50
332	0.9965	0.9908	2	7	50
333	0.9970	0.9909	3	6	50
334	0.9296	0.9094	3	32	50
335	0.9977	0.9923	1	2	50
336	0.9821	0.9770	2	7	50

Table 7: Linear Treatment – Session 4

User ID	E	E+V	Estimated V ($\leq$)	Violations	Data size
401	0.9928	0.9783	5	10	50
402	0.9770	0.8818	10	63	50
403	0.9323	0.9256	5	12	50
404	0.9950	0.9862	1	2	50
405	0.9865	0.9612	3	9	50
406	1.0000	1.0000	0	0	50
407	0.4106	0.1589	23	1078	50
408	0.9977	0.9716	1	2	50
409	0.9921	0.9841	2	13	50
410	0.9834	0.9521	3	19	50
411	1.0000	1.0000	0	0	50
412	0.9991	0.9857	2	4	50
413	0.9989	0.9979	2	4	50
414	0.9668	0.9019	5	29	50
415	0.9878	0.9611	2	7	50
416	0.8682	0.7321	16	214	50
417	0.9957	0.9682	4	8	50
418	1.0000	1.0000	0	0	50
419	0.9902	0.8696	10	52	50
420	1.0000	1.0000	0	0	50
421	0.9429	0.9254	4	28	50
422	0.9985	0.9967	1	2	50
423	1.0000	1.0000	0	0	50
424	1.0000	0.9992	1	2	50
425	0.9993	0.9977	1	2	50
426	0.9942	0.9665	7	16	50
427	0.9435	0.6465	23	396	50
428	0.4604	0.2036	40	985	50
429	0.9998	0.9990	1	2	50
430	0.9938	0.9805	2	4	50
431	0.9990	0.9964	1	2	50
432	0.9483	0.9081	2	51	50
433	0.9369	0.7892	12	127	50
434	0.9831	0.9578	5	27	50
435	1.0000	1.0000	0	0	50
436	0.9743	0.9584	2	7	50

Table 8: Kinked Treatment – Session 1

User ID	E	E+V	Estimated V (≤)	Violations	Data size
101	0.9997	0.9735	2	4	50
102	0.9730	0.8969	8	42	50
103	1.0000	1.0000	0	0	50
104	1.0000	1.0000	0	0	50
105	0.9890	0.9062	2	4	48
106	0.9894	0.8814	2	16	50
107	0.9989	0.9960	1	2	50
108	0.9716	0.8418	9	67	50
109	0.9980	0.9788	2	4	50
110	0.9768	0.9083	1	28	50
111	0.9866	0.9647	3	9	50
112	0.9341	0.8885	3	30	50
113	0.9981	0.9939	1	2	50
114	1.0000	1.0000	0	0	50
115	0.9982	0.9832	1	2	50
116	0.9965	0.9903	3	6	50
117	0.9760	0.9445	6	19	50
118	0.9982	0.9979	1	2	49
119	0.9800	0.9768	2	4	50
120	1.0000	1.0000	0	0	50
121	0.9982	0.9982	1	2	49
122	0.9788	0.9462	4	21	50
123	0.9549	0.9392	4	17	50
124	0.9881	0.9870	1	4	50
125	1.0000	1.0000	0	0	50
126	0.9913	0.9663	3	6	50
127	0.9815	0.9203	2	10	50
128	0.9994	0.9962	2	4	50
129	0.9830	0.9207	4	43	50
130	0.9921	0.8335	9	51	50
131	1.0000	1.0000	0	0	50
132	0.9349	0.6914	15	108	50
133	1.0000	1.0000	0	0	50
134	1.0000	1.0000	0	0	50

Table 9: Kinked Treatment – Session 2

User ID	E	E+V	Estimated V (≤)	Violations	Data size
201	0.9623	0.9025	2	12	50
202	0.9333	0.8472	6	49	50
203	0.9548	0.9514	2	4	50
204	0.9987	0.9770	1	2	50
205	0.9967	0.9884	2	6	50
206	0.9995	0.9977	1	2	50
207	0.9559	0.7424	4	13	50
208	0.9978	0.9959	2	4	50
209	0.9883	0.9742	3	13	50
210	0.8584	0.6717	14	120	49
211	0.9936	0.9614	2	4	50
212	0.9963	0.9911	2	4	50
213	0.9353	0.8522	3	16	49
214	0.9815	0.9561	3	9	50
215	0.9986	0.9930	2	4	50
216	0.9973	0.9955	2	4	50
217	0.9874	0.9415	4	8	50
218	0.9998	0.9971	1	2	50
219	0.9961	0.9633	3	6	50
220	0.9968	0.9905	3	6	50
221	0.9575	0.9486	4	15	50
222	1.0000	1.0000	0	0	50
223	0.9504	0.8712	10	75	50
224	0.9992	0.9931	3	8	50
225	0.9967	0.9705	2	9	50
226	0.9686	0.9330	8	39	50
227	0.9780	0.9647	2	9	50
228	1.0000	1.0000	0	0	50
229	1.0000	1.0000	0	0	50
230	0.9906	0.9716	2	7	50
231	0.9989	0.9942	1	2	50
232	0.9150	0.7148	26	319	50
233	0.9823	0.9466	4	8	50
234	0.9877	0.9876	1	2	49
235	0.9906	0.9525	7	19	50
236	0.9597	0.9311	1	8	50

Table 10: Kinked Treatment – Session 3

User ID	E	E+V	Estimated V (≤)	Violations	Data size
301	0.9687	0.8834	5	47	50
302	0.9632	0.7702	2	4	50
303	0.8704	0.6691	17	411	50
304	0.9963	0.9916	2	4	50
305	0.5932	0.5095	31	289	50
306	0.8905	0.8475	7	39	50
307	0.9840	0.9200	4	19	50
308	0.9463	0.7130	15	113	50
309	0.9555	0.7508	4	10	50
310	0.9776	0.9556	3	9	50
311	0.9901	0.9790	2	4	50
312	0.9438	0.8280	5	48	50
313	0.9316	0.8419	4	21	50
314	0.9955	0.9325	1	4	50
315	0.9876	0.9458	6	12	50
316	1.0000	1.0000	0	0	50
317	0.9708	0.8817	5	29	50
318	1.0000	1.0000	0	0	50
319	1.0000	1.0000	0	0	50
320	0.9319	0.7744	1	5	50
321	0.9869	0.9234	4	18	50
322	0.9596	0.9433	2	8	50
323	0.9822	0.9456	2	9	50
324	0.8122	0.6954	20	221	50
325	0.9905	0.9610	1	4	50
326	1.0000	1.0000	0	0	50
327	1.0000	1.0000	0	0	50
328	0.9989	0.9962	1	2	50
329	0.9751	0.9317	1	2	50
330	0.9867	0.9424	4	8	50
331	0.9852	0.9487	1	4	50
332	0.9765	0.9704	2	7	50
333	0.9430	0.8955	11	99	50
334	0.9252	0.9077	4	10	50
335	0.9870	0.9786	7	16	50
336	0.9971	0.9955	2	4	50

Table 11: Kinked Treatment – Session 4

User ID	E	E+V	Estimated V (≤)	Violations	Data size
401	0.9984	0.9970	2	4	50
402	0.9922	0.9732	6	23	50
403	0.9674	0.9193	5	19	50
404	0.9862	0.9708	4	8	50
405	0.7742	0.6776	4	46	50
406	0.9884	0.8858	5	13	50
407	0.4124	0.1413	42	1093	50
408	0.9919	0.9872	2	4	48
409	0.9984	0.9892	2	10	50
410	0.8985	0.8305	6	14	50
411	1.0000	1.0000	0	0	50
412	0.9755	0.9624	5	19	50
413	0.8917	0.7542	4	53	50
414	0.9576	0.7602	14	85	50
415	0.9724	0.9149	3	26	50
416	0.9307	0.6428	11	102	50
417	0.9657	0.9540	3	9	50
418	0.9615	0.8919	4	15	50
419	0.9648	0.8931	6	32	50
420	0.9948	0.9690	5	10	50
421	0.9573	0.8257	9	26	50
422	0.8801	0.6336	5	78	49
423	0.9983	0.9838	2	4	50
424	0.9922	0.8595	1	14	50
425	0.9992	0.9982	1	2	50
426	0.5912	0.4709	7	41	50
427	0.8749	0.6450	24	316	50
428	0.4772	0.1684	42	1199	49
429	1.0000	1.0000	0	0	50
430	0.9561	0.9324	4	17	50
431	0.7891	0.7133	5	10	50
432	0.9964	0.7582	3	24	50
433	0.9157	0.7713	7	58	50
434	0.9917	0.9413	9	31	50
435	1.0000	1.0000	0	0	50
436	0.9995	0.9974	1	2	50

Table 12: Pooled across Both Treatments (Avg. of 10 Repetitions) – Session 1

User ID	E	E+V	Estimated V (≤)	Violations	Data size
101	0.997	0.991	12.2	25.1	50
102	0.964	0.777	15.3	71.2	50
103	0.735	0.509	24.3	459.5	50
104	0.976	0.941	8.4	23.8	50
105	0.959	0.906	13.0	35.1	50
106	0.895	0.711	16.1	137.2	50
107	0.997	0.981	10.4	26.5	50
108	0.968	0.903	11.9	65.1	50
109	0.990	0.957	7.8	20.2	50
110	0.988	0.940	6.5	21.9	50
111	0.996	0.983	9.2	22.0	50
112	0.976	0.943	4.3	14.9	50
113	0.998	0.996	4.8	10.8	50
114	0.996	0.990	9.5	20.3	50
115	0.985	0.967	13.3	33.8	50
116	0.925	0.846	19.7	116.4	50
117	0.964	0.879	8.4	44.1	50
118	0.994	0.988	15.7	35.9	50
119	0.944	0.883	15.2	89.9	50
120	0.955	0.896	12.2	35.5	50
121	0.999	0.996	2.8	9.8	50
122	0.982	0.960	15.8	48.1	50
123	0.973	0.916	16.7	55.3	50
124	0.992	0.977	9.1	20.1	50
125	0.982	0.879	8.3	20.4	50
126	0.993	0.976	11.5	27.0	50
127	0.944	0.905	6.1	42.7	50
128	0.996	0.995	6.7	15.4	50
129	0.986	0.959	16.6	42.1	50
130	0.973	0.920	18.1	63.5	50
131	0.946	0.855	9.3	54.4	50
132	0.823	0.570	31.6	393.3	50
133	0.845	0.730	3.2	39.9	50
134	0.997	0.987	9.3	19.9	50

Table 13: Pooled across Both Treatments (Avg. of 10 Repetitions) – Session 2

User ID	E	E+V	Estimated V (≤)	Violations	Data size
201	0.968	0.910	14.4	46.8	50
202	0.949	0.871	13.0	57.8	50
203	0.965	0.955	9.7	27.7	50
204	0.990	0.980	10.6	26.7	50
205	0.794	0.445	25.2	442.7	50
206	0.953	0.837	14.4	45.8	50
207	0.979	0.830	15.2	76.2	50
208	0.938	0.884	12.1	66.3	50
209	0.987	0.940	12.5	39.3	50
210	0.674	0.349	34.1	513.5	50
211	0.983	0.944	9.9	28.1	50
212	0.969	0.927	20.9	77.2	50
213	0.966	0.895	12.0	39.1	50
214	0.710	0.341	36.4	634.2	50
215	0.997	0.995	10.2	27.1	50
216	0.997	0.994	12.7	30.1	50
217	0.979	0.935	17.6	48.9	50
218	0.580	0.274	36.6	645.3	50
219	0.937	0.885	16.6	42.1	50
220	0.968	0.936	17.1	53.0	50
221	0.795	0.477	28.0	487.3	50
222	0.948	0.922	8.5	31.9	50
223	0.892	0.790	19.4	106.2	50
224	0.986	0.971	14.8	35.3	50
225	0.993	0.983	13.8	35.6	50
226	0.978	0.936	15.5	71.4	50
227	0.992	0.981	10.1	27.3	50
228	0.998	0.996	9.5	19.0	50
229	0.996	0.991	8.9	23.5	50
230	0.919	0.874	12.4	33.6	50
231	0.977	0.948	7.9	22.7	50
232	0.894	0.783	21.4	122.8	50
233	0.990	0.911	12.4	36.3	50
234	0.988	0.931	8.6	21.0	50
235	0.986	0.938	16.7	58.4	50
236	0.974	0.936	8.7	28.1	50

Table 14: Pooled across Both Treatments (Avg. of 10 Repetitions) – Session 3

User ID	E	E+V	Estimated V ($\leq$)	Violations	Data size
301	0.965	0.897	13.8	64.9	50
302	0.969	0.868	12.5	42.8	50
303	0.819	0.343	35.6	642.2	50
304	0.998	0.988	11.4	27.3	50
305	0.747	0.544	18.9	153.3	50
306	0.957	0.913	6.8	26.9	50
307	0.989	0.837	14.5	48.0	50
308	0.906	0.804	15.8	98.4	50
309	0.926	0.745	14.3	112.2	50
310	0.988	0.972	7.3	18.8	50
311	0.993	0.983	1.9	7.3	50
312	0.953	0.854	12.5	65.6	50
313	0.936	0.840	13.6	44.5	50
314	0.991	0.921	15.4	43.3	50
315	0.991	0.911	11.6	31.3	50
316	0.994	0.990	11.8	30.1	50
317	0.990	0.963	14.0	38.2	50
318	0.940	0.829	13.2	48.5	50
319	0.998	0.995	13.2	26.4	50
320	0.968	0.843	11.9	42.4	50
321	0.795	0.640	14.0	226.0	50
322	0.913	0.817	3.6	31.2	50
323	0.965	0.928	13.3	47.8	50
324	0.894	0.601	33.7	491.4	50
325	0.996	0.985	6.1	15.1	50
326	0.990	0.973	9.0	20.6	50
327	0.993	0.970	7.0	15.6	50
328	0.993	0.988	11.7	25.0	50
329	0.969	0.861	10.4	35.7	50
330	0.953	0.790	19.6	137.4	50
331	0.986	0.964	1.2	3.7	50
332	0.985	0.976	15.0	44.1	50
333	0.975	0.943	19.2	81.1	50
334	0.937	0.840	12.1	64.4	50
335	0.990	0.981	14.9	37.9	50
336	0.994	0.967	12.5	33.9	50

Table 15: Pooled across Both Treatments (Avg. of 10 Repetitions) – Session 4

User ID	E	E+V	Estimated V (≤)	Violations	Data size
401	0.995	0.989	17.7	40.9	50
402	0.977	0.902	15.5	67.1	50
403	0.969	0.921	12.8	41.0	50
404	0.991	0.985	11.4	29.2	50
405	0.907	0.771	13.3	72.0	50
406	0.994	0.960	1.9	4.4	50
407	0.414	0.152	44.1	1167.5	50
408	0.992	0.985	10.3	21.2	50
409	0.994	0.981	10.1	33.8	50
410	0.946	0.811	17.1	62.5	50
411	1.000	1.000	0.0	0.0	50
412	0.963	0.909	16.4	48.8	50
413	0.931	0.831	5.4	27.9	50
414	0.968	0.869	12.2	53.5	50
415	0.971	0.938	16.4	53.1	50
416	0.891	0.572	28.7	453.0	50
417	0.991	0.973	10.9	26.7	50
418	0.957	0.903	9.9	36.4	50
419	0.968	0.883	20.9	78.5	50
420	0.988	0.980	10.6	27.8	50
421	0.966	0.820	19.2	112.1	50
422	0.719	0.393	26.0	254.0	50
423	0.997	0.987	10.3	21.5	50
424	0.977	0.921	4.4	17.0	50
425	0.999	0.995	3.5	9.1	50
426	0.807	0.776	9.5	38.2	50
427	0.884	0.643	27.7	367.0	50
428	0.486	0.220	42.1	1049.0	50
429	0.994	0.993	10.8	22.6	50
430	0.968	0.942	9.9	29.6	50
431	0.987	0.968	7.4	19.5	50
432	0.943	0.852	13.8	84.7	50
433	0.934	0.776	20.7	169.6	50
434	0.984	0.929	15.0	71.6	50
435	1.000	1.000	0.0	0.0	50
436	0.983	0.966	18.1	44.1	50

Figure 14: Histogram of HM Removals by Treatment

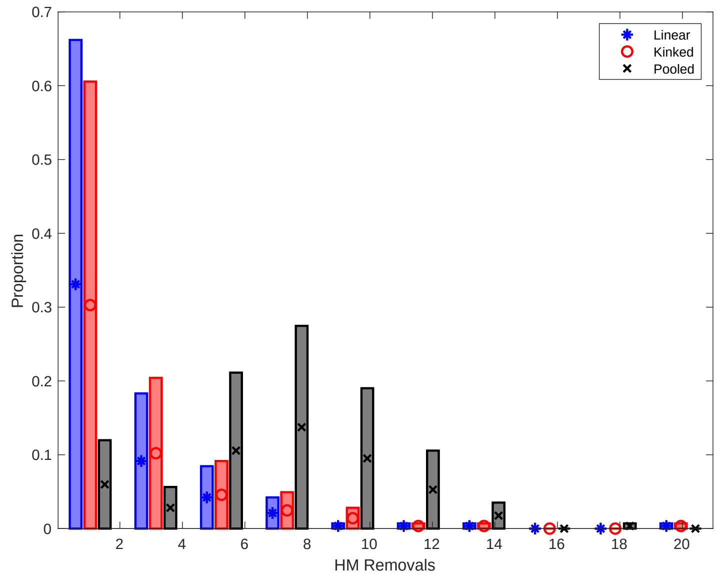


Figure 15: Histogram of CCEI Score by Treatment

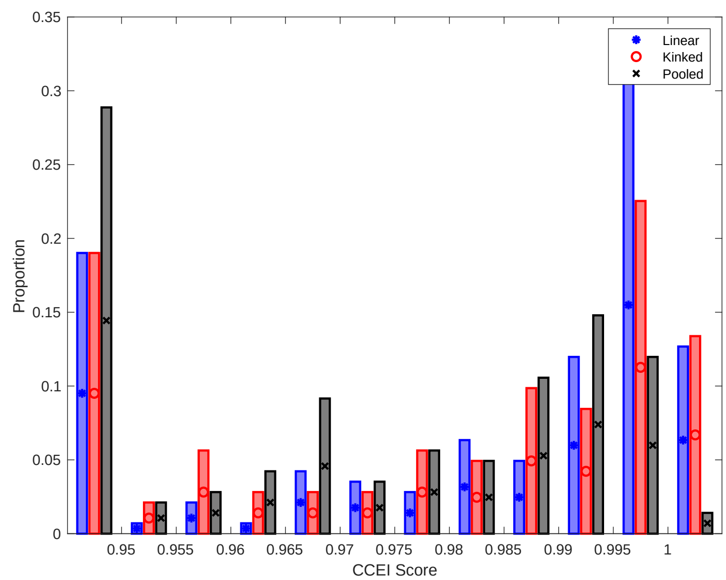


Figure 16: Histogram of CCEI E+V Score by Treatment

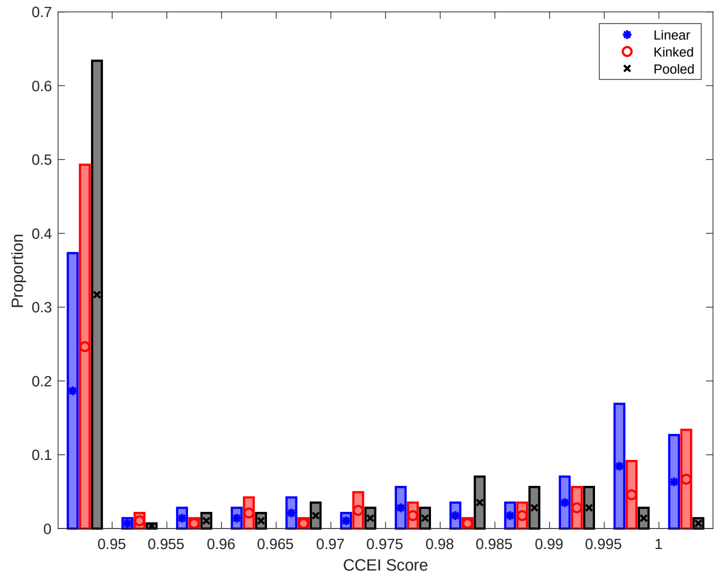


Figure 17: CDF of CCEI by Treatment

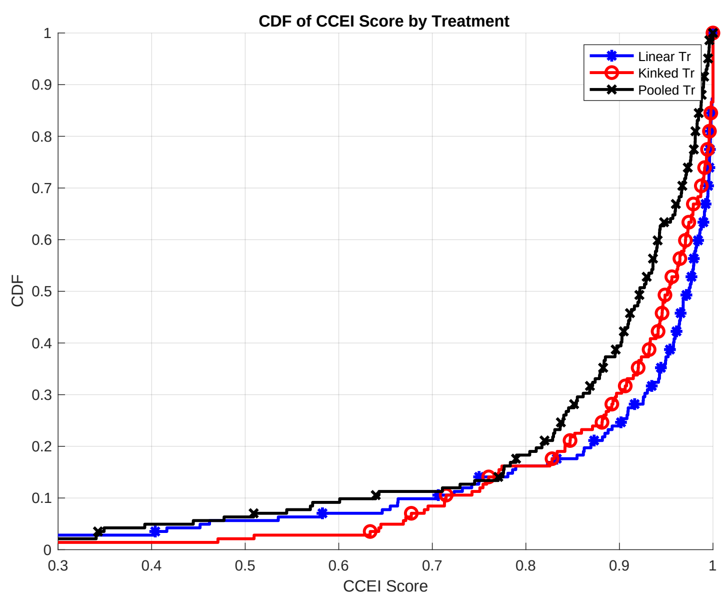


Figure 18: CDF of CCEI E+V by Treatment

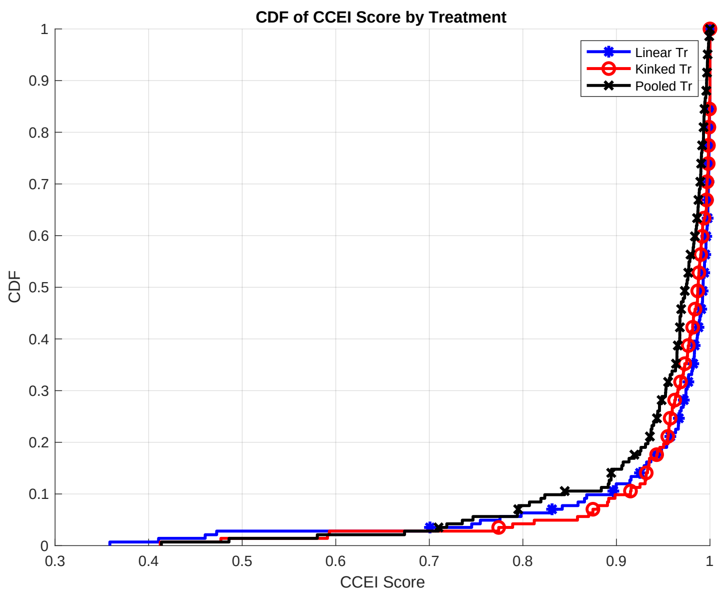
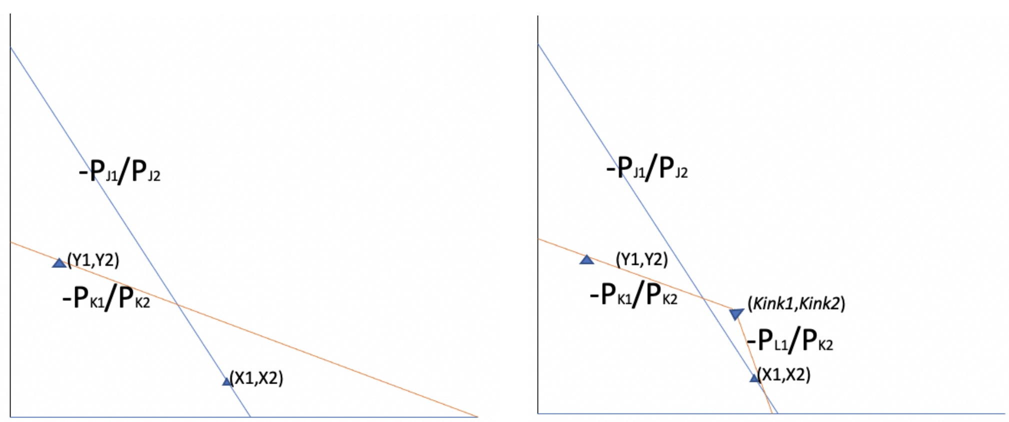


Figure 19: Comparing CCEI for Two Kinds of Violations



Notes: The figure presents two possible violations of GARP. In the first, in the left panel, bundle (X_1, X_2) is chosen facing linear prices (P_{J1}, P_{J2}), and bundle (Y_1, Y_2) is chosen facing linear prices (P_{K1}, P_{K2}). In the other violation, in the right panel, the same bundle (X_1, X_2) is chosen facing the same prices (P_{J1}, P_{J2}), while the same bundle (Y_1, Y_2) is chosen facing instead the kinked schedule where the prices are (P_{K1}, P_{K2}) if good 1 is to the left of kink point $(Kink_1, Kink_2)$ and (P_{L1}, P_{L2}) if good 1 is to the right of this kink (with P_{L1} set equal to P_{K1} and P_{L2} adjusted accordingly to preserve the relative price ratio). Without loss of generality, imagine that the most cost-efficient way to relax one of the budget constraints to remove an inconsistent choice involves relaxing the constraint containing choice (Y_1, Y_2) in both the linear-linear violation case and the linear-kink violation case. This implies that the CCEI for the linear-linear violation can be found by solving for e_{LL} such that $e_{LL}(P_{K1}Y_1 + P_{K2}Y_2) \leq (P_{K1}X_1 + P_{K2}X_2) = P_{K1}(Kink_1 + (X_1 - Kink_1) + P_{K2}((Y_{InterceptK} - Kink_2) + (Kink_2 - X_2)) = P_{K1}(Kink_1 + (X_1 - Kink_1) + P_{K2}(Y_{InterceptK} - Kink_2) + P_{K2}(Kink_2 - X_2)$ and that the CCEI for the linear-kink violation can be found by solving for e_{LK} such that $e_{LK}(P_{K1}Y_1 + P_{K2}Y_2) \leq P_{K1}(Kink_1 + (X_1 - Kink_1) + P_{K2}(Y_{InterceptK} - Kink_2) + P_{L2}(Kink_2 - X_2)$. As $P_{K2} \neq P_{L2}$ while all other terms from the two expressions are identical, e_{LK} will generally not be equal to e_{LL} even though the choices underlying each violation are the same, (X_1, X_2) and (Y_1, Y_2), and are made with the same governing prices local to the choice, (P_{J1}, P_{J2}) for (X_1, X_2) and (P_{K1}, P_{K2}) for (Y_1, Y_2).

F Alternative Explanations

Figure 20: CDF of Fraction of Per-Person Choice at 45 degree or Maximum Intercept Heuristic

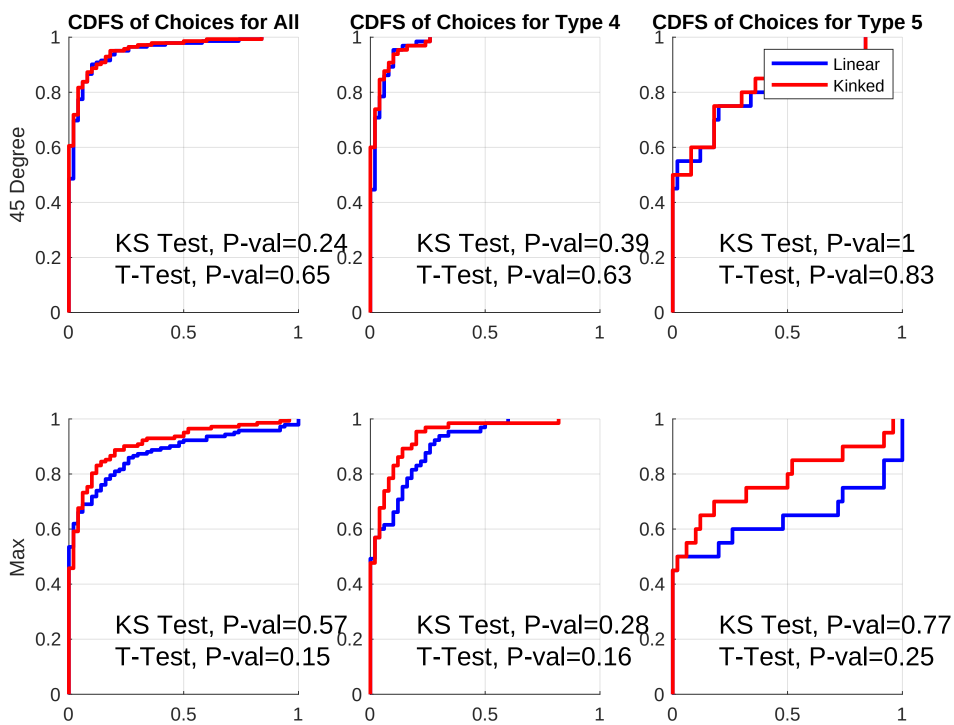


Figure 21: CDF of HM Removals by Treatment after Dropping FOSD Observations

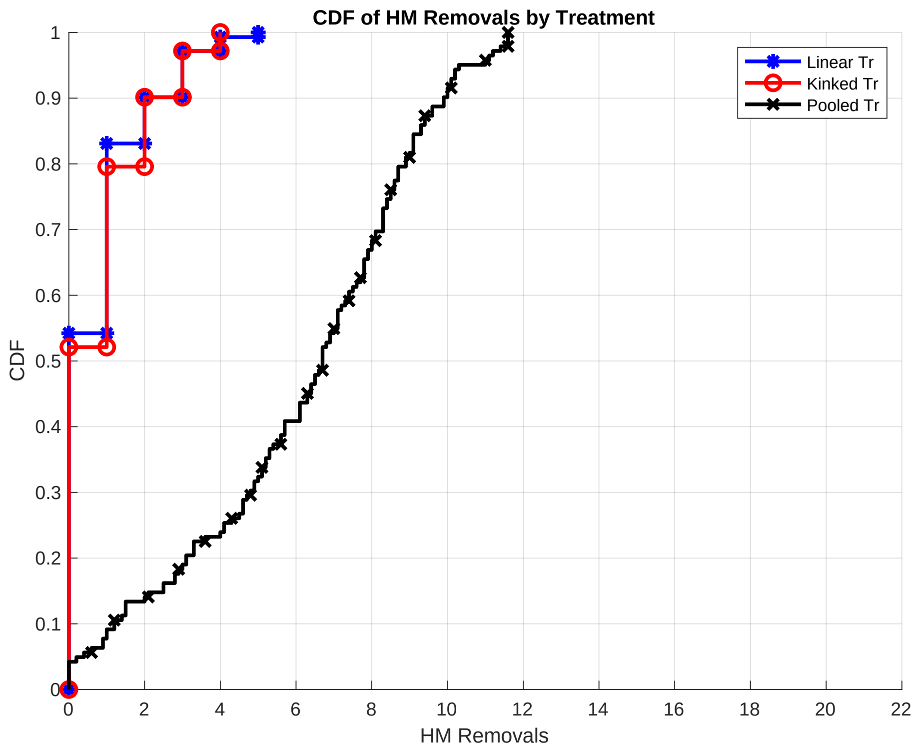


Figure 22: Histogram of HM Removals by Treatment after Dropping FOSD Observations

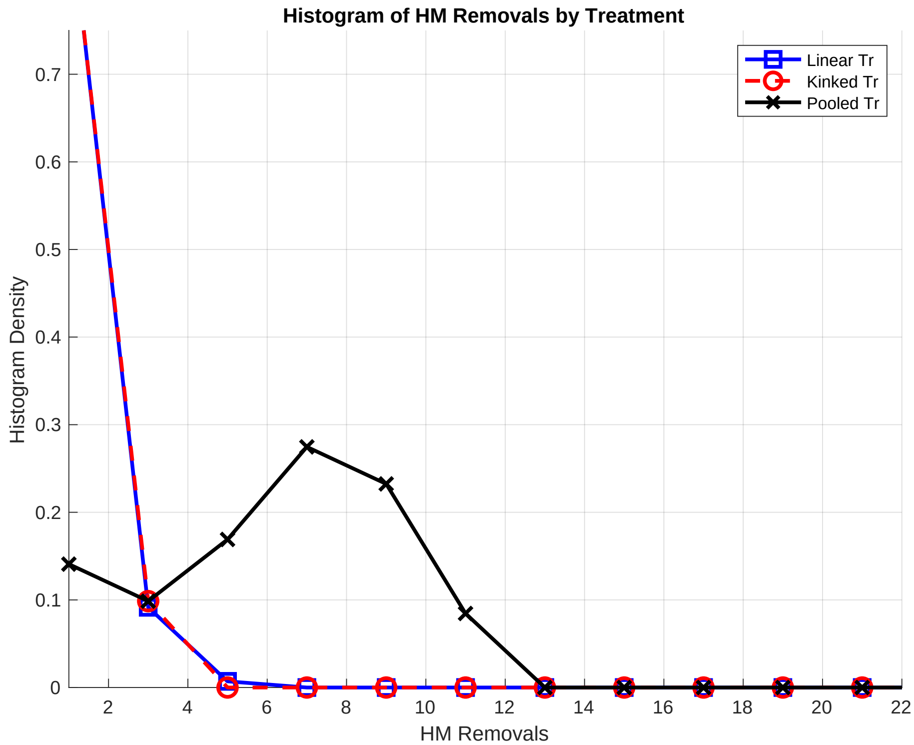
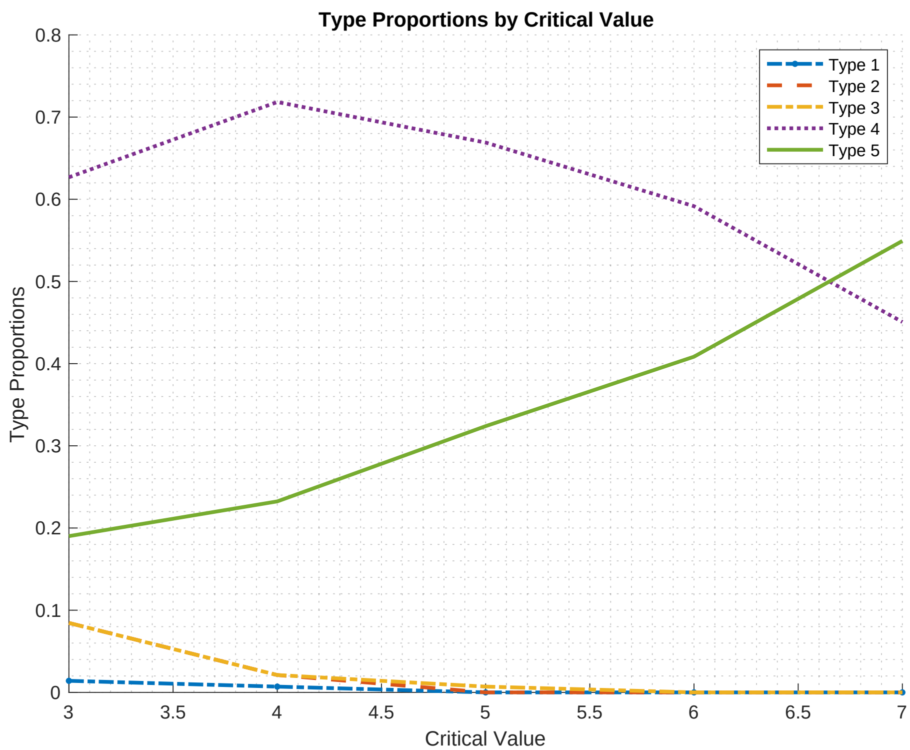


Table 16: Type Proportions for Critical Value of 4 after Dropping FOSD Observations

Type	Proportion
1	0.007
2	0.021
3	0.021
4	0.718
5	0.232

Figure 23: Type Distribution by Critical Value after Dropping FOSD Observations



G Additional Tables and Figures

Table 17: Comparison of Parameters Recovered Using NLLS Estimation to Simulated Parameters for Linear and Non-linear Budgets (with Stochastic Volatility $\sigma_e = .1$)

	α					ρ					$r(1)$				
	True	Est. L	std	Est. K	std	True	Est. L	std	Est. K	std	True	Est. L	std	Est. K	std
	1.000	1.000	0.000	1.011	0.033	0.000	0.002	0.002	0.008	0.008	0.000	0.001	0.001	0.009	0.016
	1.000	1.049	0.006	1.202	0.241	1.000	1.002	0.009	1.005	0.183	0.500	0.525	0.003	0.581	0.057
	1.000	1.049	0.006	1.333	0.214	2.000	2.004	0.017	1.791	0.272	1.000	1.025	0.007	1.014	0.097
	1.649	1.609	0.030	1.564	0.158	0.000	0.007	0.007	0.030	0.030	0.245	0.237	0.008	0.231	0.044
	1.649	1.732	0.021	1.709	0.234	1.000	1.001	0.019	1.101	0.233	0.715	0.733	0.006	0.771	0.070
	1.649	1.732	0.021	1.861	0.367	2.000	2.003	0.038	1.996	0.417	1.185	1.197	0.016	1.207	0.159
	2.718	2.588	0.113	2.503	0.398	0.000	0.016	0.012	0.054	0.096	0.462	0.449	0.016	0.443	0.062
	2.718	2.858	0.058	2.516	0.646	1.000	1.002	0.042	1.188	0.618	0.855	0.866	0.013	0.918	0.207
	2.718	2.859	0.058	2.220	0.706	2.000	2.002	0.084	2.541	1.319	1.249	1.250	0.032	1.490	0.572
	4.482	4.164	0.323	4.109	0.754	0.000	0.025	0.016	0.119	0.324	0.635	0.619	0.022	0.641	0.089
	4.482	4.730	0.234	3.735	1.613	1.000	0.995	0.354	2.389	3.242	0.933	0.940	0.105	1.551	1.468
	4.482	4.780	0.327	2.684	1.641	2.000	1.918	0.789	4.970	4.939	1.232	1.210	0.237	2.664	2.348
	1.000	1.049	0.006	1.491	0.357	5.000	5.009	0.043	4.071	0.914	2.500	2.527	0.019	2.144	0.421
	1.000	1.049	0.006	1.586	0.413	10.000	10.019	0.086	7.871	1.702	5.000	5.031	0.041	3.962	0.842
	1.000	1.049	0.006	1.594	0.616	20.000	20.038	0.172	15.331	4.729	10.000	10.037	0.085	7.518	2.357

Table 18: Comparison of Parameters Recovered Using MLE to the Simulated Parameters for Linear and Non-linear Budgets (with Stochastic Volatility $\sigma_e = .1$)

	α					ρ					$r(1)$				
	True	Est. L	std	Est. K	std	True	Est. L	std	Est. K	std	True	Est. L	std	Est. K	std
	1.000	1.002	0.001	1.356	0.306	0.000	0.010	0.070	0.000	0.000	0.000	0.006	0.035	0.138	0.101
	1.000	1.055	0.006	1.281	0.196	1.000	0.995	0.009	0.239	0.114	0.500	0.524	0.003	0.236	0.039
	1.000	1.058	0.007	1.446	0.191	2.000	1.986	0.017	0.346	0.131	1.000	1.020	0.007	0.345	0.055
	1.649	1.649	0.033	6.098	1.837	0.000	0.000	0.000	0.000	0.000	0.245	0.245	0.009	0.687	0.133
	1.649	1.744	0.021	1.847	0.419	1.000	0.991	0.020	0.299	0.091	0.715	0.730	0.006	0.427	0.037
	1.649	1.753	0.021	2.084	0.430	2.000	1.971	0.036	0.380	0.135	1.185	1.185	0.015	0.512	0.050
	2.718	2.719	0.133	6.391	2.140	0.000	0.000	0.001	0.000	0.000	0.462	0.462	0.019	0.695	0.124
	2.718	2.894	0.057	3.007	0.515	1.000	0.977	0.040	0.101	0.101	0.855	0.859	0.013	0.534	0.045
	2.718	2.914	0.060	3.021	0.571	2.000	1.932	0.087	0.119	0.141	1.249	1.224	0.033	0.541	0.053
	4.482	4.522	0.520	6.045	1.743	0.000	0.000	0.001	0.000	0.000	0.635	0.635	0.030	0.699	0.071
	4.482	4.981	0.516	5.135	0.934	1.000	1.314	3.410	0.008	0.032	0.933	1.039	0.978	0.669	0.050
	4.482	5.352	0.901	4.574	0.912	2.000	2.501	5.204	0.015	0.052	1.232	1.394	1.497	0.636	0.059
	1.000	1.067	0.008	1.831	0.219	5.000	4.924	0.045	0.316	0.184	2.500	2.492	0.020	0.435	0.074
	1.000	1.088	0.010	2.229	0.395	10.000	9.691	0.108	0.407	0.177	5.000	4.879	0.052	0.549	0.074
	1.000	1.166	0.029	3.960	1.073	20.000	18.754	0.364	0.662	0.344	10.000	9.398	0.185	0.795	0.128

Table 19: NLLS Structural Linear Session 1

ID	Type	α	se(α)	ρ	se(ρ)	$r(1)$	Elas $\log pr = 0$	Elas $\log pr = 1$
101	4	1	0	1.3739	1.1703e-16	0.68695	-1.3739	-1.3739
102	1	1	0	0.3189	2.9257e-17	0.15945	-0.31868	-0.31857
103	4	2.5432	NaN	0.013716	2.999e-160	0.4411	-0.0076514	-0.0076514
104	3	1.0821	2.3406e-16	0.37921	0	0.22876	-0.35132	-0.35392
105	4	1	2.3406e-16	1.2181	1.1703e-16	0.60906	-1.2181	-1.2181
106	3	1	0	0.52826	5.8514e-17	0.26413	-0.52746	-0.52657
107	4	1.1397	2.3406e-16	0.6764	1.1703e-16	0.40204	-0.38973	-0.66993
108	2	1.1709	0	0.13368	1.4628e-17	0.14517	-0.12165	-0.12166
109	4	1	0	0.40303	5.8514e-17	0.20151	-0.40303	-0.40303
110	5	1.398	0	0.034036	1.1269e-50	0.18253	-0.026123	-0.026122
111	4	1.9054	2.3406e-16	0.080859	1.4628e-17	0.34813	-0.015828	-0.016302
112	5	1	0	0.059793	0	0.029897	-0.044497	-0.044493
113	5	1.8255	2.3406e-16	0.012441	1.4628e-17	0.29785	-0.0026247	-0.0026266
114	4	1.0876	2.3406e-16	0.29351	2.9257e-17	0.18848	-0.27392	-0.27472
115	4	1	2.3406e-16	1.0381	1.1703e-16	0.51905	-1.0381	-1.0381
116	3	5.7101	NaN	0.5	5.8514e-17	0.82876	0	0
117	2	3.081	4.6811e-16	0.016388	7.3142e-18	0.51599	-0.006068	-0.0060686
118	5	5.5172	NaN	0.5	0	0.82302	0	0
119	4	1.9432	2.3406e-16	0.093097	1.4628e-17	0.36224	-0.059304	-0.059369
120	4	1	0	0.91347	0	0.45673	-0.91347	-0.91347
121	5	8.614	NaN	0.5	5.8514e-17	0.88517	0	0
122	2	1.2593	2.3406e-16	0.66545	1.1703e-16	0.44311	-0.38368	-0.57822
123	1	1	0	5.1527	1.4628e-17	2.5763	-5.1527	-6.9202e-13
124	4	1	2.3406e-16	0.82364	0	0.41182	-0.82364	-0.82364
125	4	1.2742	2.3406e-16	0.24195	6.9754e-24	0.23979	-0.18146	-0.18119
126	4	1.1607	0	0.76952	1.1703e-16	0.457	-0.45589	-0.75995
127	4	1.7509	2.3406e-16	0.01165	0	0.27835	-0.0062595	-0.0062599
128	5	7.57	NaN	0.5	0	0.8697	0	0
129	4	1.2256	2.3406e-16	0.813	1.1703e-16	0.5037	-0.43854	-0.78706
130	4	7.4336	NaN	0.5	5.8514e-17	0.86737	0	0
131	3	1.1375	0	0.035588	0	0.082034	-0.031164	-0.031163
132	1	2.5159	2.3406e-16	0.26958	1.4628e-17	0.54088	-0.1311	-0.13349
133	5	1	2.3406e-16	0.054047	0	0.027024	-0.037202	-0.037199
134	4	1.1947	2.3406e-16	0.31421	5.8514e-17	0.24458	-0.2356	-0.24678

Table 20: NLLS Structural Linear Session 2

ID	Type	α	se(α)	ρ	se(ρ)	$r(1)$	Elas $\log pr = 0$	Elas $\log pr = 1$
201	3	1	2.3406e-16	1.1793	0	0.58963	-1.1793	-1.1791
202	2	1	2.3406e-16	0.28521	0	0.1426	-0.28217	-0.28178
203	4	1	2.3406e-16	0.74978	1.4628e-17	0.37489	-0.70512	-0.69264
204	3	1	0	0.45763	5.8514e-17	0.22882	-0.45763	-0.45763
205	4	1	2.3406e-16	0.0034775	0	0.0017387	-0.0024102	-0.0024102
206	3	1.282	0	0.31955	7.3142e-18	0.28092	-0.26905	-0.27053
207	4	1.9235	4.6811e-16	0.029738	0	0.32928	-0.020716	-0.020717
208	3	1	2.3406e-16	0.6427	5.8514e-17	0.32135	-0.6427	-0.6427
209	4	1.1651	0	0.53489	2.9257e-17	0.34217	-0.47615	-0.48228
210	1	1.4475	2.3406e-16	0.79798	0	0.56849	-0.63841	-0.65419
211	4	1	4.6811e-16	0.86229	0	0.43115	-0.82581	-0.80776
212	3	3.7692	0	0.66602	5.4495e-26	0.80138	-0.23027	-0.26458
213	4	1.143	2.3406e-16	0.42352	0	0.27754	-0.38154	-0.38457
214	3	2.8667	4.6811e-16	16.1243	0	6.666	-5.022e-149	0
215	4	1.1551	0	0.42425	0	0.28301	-0.29878	-0.35499
216	5	3.9203	NaN	0.5	5.8514e-17	0.75545	0	0
217	4	1	0	9.0933	0	4.5466	-9.0933	-1.568e-184
218	3	3.0937	NaN	0.0045383	0	0.51311	-0.0022701	-0.0022701
219	4	6.7376	4.6811e-16	0.5	0	0.85406	-1.2906e-10	-7.7128e-07
220	4	4.5276	NaN	0.5	5.8514e-17	0.78636	0	0
221	3	4.308	4.6811e-16	0.010591	3.406e-27	0.62645	-0.0056869	-0.0056868
222	4	1.5587	2.3406e-16	0.13464	6.9754e-24	0.28248	-0.10635	-0.10638
223	1	1.2255	0	0.57145	0	0.38411	-0.49914	-0.50479
224	5	7.0965	NaN	0.5	0	0.86123	0	0
225	4	1.2885	2.3406e-16	0.76988	0	0.50489	-0.28301	-0.74442
226	1	1.5528	2.3406e-16	0.46527	0	0.43828	-0.28294	-0.30589
227	4	1.1594	2.3406e-16	0.29273	0	0.2194	-0.26208	-0.26304
228	4	1.2369	0	0.27858	0	0.24362	-0.22138	-0.22454
229	4	1	2.3406e-16	0.57277	0	0.28639	-0.54216	-0.53669
230	4	1.078	2.3406e-16	0.58189	5.8514e-17	0.32807	-0.53771	-0.54822
231	4	1.4852	0	0.11687	0	0.25143	-0.090082	-0.090169
232	1	1	2.3406e-16	0.89796	5.8514e-17	0.44898	-0.89796	-0.89795
233	3	1	2.3406e-16	0.89872	1.1703e-16	0.44936	-0.89872	-0.89872
234	4	1.0814	2.3406e-16	0.39472	0	0.23616	-0.3244	-0.35743
235	2	3.3568	0	0.072225	0	0.56649	-0.022561	-0.022624
236	3	1	0	0.54243	2.9257e-17	0.27122	-0.54228	-0.54196

Table 21: NLLS Structural Linear Session 3

ID	Type	α	se(α)	ρ	se(ρ)	$r(1)$	Elas $\log pr = 0$	Elas $\log pr = 1$
301	4	3.1016	2.3406e-16	0.029511	7.3142e-18	0.52327	-0.011129	-0.011133
302	4	1.3031	0	0.91715	5.8514e-17	0.58223	-0.44373	-0.87925
303	1	1.0201	2.3406e-16	1.4931	1.4628e-17	0.75641	-1.4679	-1.479
304	5	6.9709	NaN	0.5	5.8514e-17	0.8588	0	0
305	2	1	0	0.5308	5.8514e-17	0.2654	-0.5308	-0.53079
306	4	2.056	2.3406e-16	0.15413	3.4877e-24	0.41341	-0.10271	-0.10287
307	2	2.191	2.3406e-16	0.24013	0	0.47658	-0.055867	-0.063226
308	4	1	2.3406e-16	0.36971	0	0.18486	-0.36958	-0.36947
309	3	1.3039	0	0.47965	3.4877e-24	0.36754	-0.33059	-0.36329
310	4	1.272	2.3406e-16	0.12742	0	0.18253	-0.109	-0.10907
311	5	1	2.3406e-16	0.0061909	3.4877e-24	0.0030954	-0.0058894	-0.0058894
312	2	1	2.3406e-16	2.6054	8.5149e-28	1.3027	-2.6054	-2.5591
313	2	1.0891	0	1.3346	2.3406e-16	0.70876	-0.6102	-1.3346
314	4	1.5435	2.3406e-16	0.59757	1.1703e-16	0.49883	-0.040924	-0.4504
315	2	1	2.3406e-16	0.98748	0	0.49374	-0.98696	-0.98278
316	5	6.6525	NaN	0.5	5.8514e-17	0.85225	0	0
317	4	1	2.3406e-16	1.1352	2.3406e-16	0.56761	-1.1352	-1.1352
318	3	1.6864	0	0.35141	0	0.41975	-0.26117	-0.26264
319	4	1.4882	0	0.46252	5.8514e-17	0.41856	-0.093946	-0.27074
320	4	2.7935	2.3406e-16	0.11402	0	0.51705	-0.066426	-0.066486
321	1	1.7827	2.3406e-16	0.0066299	0	0.28432	-0.0040018	-0.0040018
322	5	1	0	0.050933	0	0.025466	-0.044267	-0.044263
323	4	1.6681	4.6811e-16	0.64645	0	0.55337	-0.060591	-0.4335
324	1	1.0943	0	0.67473	1.4628e-17	0.38171	-0.62855	-0.63669
325	4	1	2.3406e-16	0.49545	5.8514e-17	0.24773	-0.49545	-0.49545
326	4	1	2.3406e-16	0.36334	5.8514e-17	0.18167	-0.36334	-0.36333
327	5	1.002	0	0.40371	0	0.20284	-0.40301	-0.40292
328	4	2.1494	0	0.68639	0	0.66244	-0.27107	-0.3558
329	3	1	2.3406e-16	0.77779	5.8514e-17	0.38889	-0.77779	-0.77779
330	4	1	2.3406e-16	0.55416	0	0.27708	-0.55416	-0.55416
331	5	1	2.3406e-16	0.054262	0	0.027131	-0.042567	-0.042563
332	4	3.1736	0	0.16578	5.8514e-17	0.5812	-0.00030463	-0.00066276
333	2	1.1245	2.3406e-16	2.5781	1.1703e-16	1.3432	-1.4901	-2.5781
334	4	1.9241	0	0.016551	0	0.32349	-0.011896	-0.011896
335	2	1.0696	2.3406e-16	2.2297	0	1.1472	-1.4508	-2.2297
336	4	1.096	0	0.69326	1.4628e-17	0.3917	-0.63929	-0.63204

Table 22: NLLS Structural Linear Session 4

ID	Type	α	se(α)	ρ	se(ρ)	$r(1)$	Elas $\log pr = 0$	Elas $\log pr = 1$
401	5	8.036	NaN	0.5	5.8514e-17	0.87708	0	0
402	4	1.3778	2.3406e-16	0.47713	2.9257e-17	0.39144	-0.32893	-0.35182
403	1	1.3158	2.3406e-16	0.41486	5.8514e-17	0.33993	-0.29858	-0.31386
404	4	1.2546	0	0.5448	1.1703e-16	0.38185	-0.36735	-0.43504
405	4	1.1213	4.6811e-16	0.18691	0	0.15034	-0.17409	-0.17413
406	2	1	2.3406e-16	0.053584	0	0.026792	-0.046417	-0.046412
407	1	8.0727	0	0.5	1.3951e-23	0.87763	-0.20587	-0.20854
408	4	1	0	0.56159	0	0.2808	-0.56159	-0.56159
409	4	1	0	0.47028	0	0.23514	-0.47028	-0.47028
410	2	2.8334	4.6811e-16	0.34931	0	0.61298	-0.0040011	-0.016348
411	5	1	0	0.058336	0	0.029168	-0.048047	-0.048042
412	2	1.6343	0	0.58835	5.8514e-17	0.51791	-0.15708	-0.3496
413	2	1.2787	0	0.0096948	0	0.12707	-0.0083369	-0.0083369
414	1	1	2.3406e-16	0.53049	5.8514e-17	0.26525	-0.53049	-0.53049
415	4	1.0961	2.3406e-16	1.418	0	0.75336	-1.0079	-1.418
416	1	1	0	0.63943	1.4628e-17	0.31972	-0.63163	-0.6268
417	3	1	0	0.53583	1.1703e-16	0.26792	-0.53583	-0.53583
418	4	1.4315	0	0.53629	5.8514e-17	0.43716	-0.14099	-0.38233
419	3	1	4.6811e-16	24.7791	0	12.3895	-24.7791	0
420	2	1	0	0.51362	5.8514e-17	0.25681	-0.51362	-0.51362
421	1	1.3869	2.3406e-16	0.5693	0	0.43928	-0.4468	-0.4591
422	4	8.7818	NaN	0.5	0	0.88732	0	0
423	4	1	2.3406e-16	0.8252	1.1703e-16	0.4126	-0.8252	-0.8252
424	5	1	2.3406e-16	0.32218	5.8514e-17	0.16109	-0.32218	-0.32217
425	5	1	0	0.048073	0	0.024037	-0.046609	-0.046606
426	1	1	2.3406e-16	0.29545	0	0.14773	-0.2904	-0.28987
427	1	1	2.3406e-16	0.53139	1.4628e-17	0.26569	-0.51565	-0.51184
428	1	5.4024	2.3406e-16	0.10814	0	0.71612	-0.052806	-0.052828
429	4	1.1156	0	0.46606	1.1703e-16	0.28699	-0.31743	-0.43117
430	2	1	2.3406e-16	1.4502	1.1703e-16	0.72508	-1.4502	-1.4502
431	4	1.5212	2.3406e-16	0.026225	3.4877e-24	0.21929	-0.019985	-0.019984
432	4	1.5629	2.3406e-16	0.12116	1.3951e-23	0.2773	-0.09306	-0.093034
433	2	1.0623	0	1.2294	6.9754e-24	0.64436	-1.1598	-1.1181
434	1	1.1092	2.3406e-16	0.50169	0	0.30195	-0.42197	-0.45159
435	5	1	2.3406e-16	0.055957	0	0.027978	-0.04752	-0.047515
436	4	2.4893	0	0.60913	1.1703e-16	0.6759	-0.00038098	-0.077973

Table 23: NLLS Structural Kinked Session 1

ID	Type	α	se(α)	ρ	se(ρ)	$r(1)$	Elas $\log pr = 0$	Elas $\log pr = 1$
101	4	1	0	1.7577	4.6811e-16	0.87886	-1.7577	-1.7577
102	1	1	0	0.45119	5.8514e-17	0.2256	-0.45114	-0.45104
103	4	1	0.033739	0.0052069	0.0028407	0.0026035	-0.0024435	-0.0024435
104	3	1.0135	1.6051e-10	0.33337	1.4267e-07	0.17339	-0.32596	-0.32754
105	4	1	0	2.2088	4.6811e-16	1.1044	-2.2088	-2.2088
106	3	1	0	0.56457	0	0.28228	-0.56457	-0.56456
107	4	1.7047	0.00014214	0.40194	5.9149e-05	0.44787	-0.00066763	-0.088087
108	2	1.6437	0.14835	0.051012	0.023394	0.26747	-0.039315	-0.039314
109	4	1	0	0.38365	0	0.19183	-0.38365	-0.38365
110	5	2.4945	0	0.070642	1.4628e-17	0.45654	-0.014477	-0.01463
111	4	1.3993	0	0.17704	0	0.25248	-0.094194	-0.09804
112	5	1	0	0.017058	1.8286e-18	0.0085289	-0.013179	-0.013179
113	5	1.8141	2.3406e-16	0.012435	1.8286e-18	0.29499	-0.009261	-0.009261
114	4	1.1026	2.3406e-16	0.25009	2.9257e-17	0.17353	-0.21809	-0.22068
115	4	1	0	1.0087	0	0.50437	-1.0087	-1.0087
116	3	5.7101	0	0.5	0	0.82876	0	0
117	2	1.3207	0	0.37805	5.8514e-17	0.32359	-0.30212	-0.30638
118	5	5.5172	5.9918e-14	0.5	0	0.82302	0	0
119	4	1	2.3406e-16	0.36664	2.9257e-17	0.18332	-0.36436	-0.36372
120	4	1	0	0.37068	0	0.18534	-0.37068	-0.37068
121	5	8.614	0	0.5	0	0.88517	0	0
122	2	1.2418	2.3406e-16	0.86832	1.1703e-16	0.53696	-0.41122	-0.855
123	1	1	2.3406e-16	2.4732	4.6811e-16	1.2366	-2.4732	-2.4732
124	4	1	0	1.141	2.3406e-16	0.57052	-1.141	-1.141
125	4	1	0	0.47848	0	0.23924	-0.47848	-0.47848
126	4	1.3497	2.3406e-16	0.86593	0	0.5722	-0.17004	-0.85954
127	4	1.2519	2.3406e-16	0.092387	1.4628e-17	0.15747	-0.078804	-0.07884
128	5	7.57	5.9918e-14	0.5	0	0.8697	0	0
129	4	2.1409	4.6811e-16	0.3581	0	0.51867	-0.0022343	-0.026422
130	4	1	0	3.6763	0	1.8381	-3.6763	-2.9195
131	3	1.2535	2.3406e-16	0.031965	7.3142e-18	0.12827	-0.022487	-0.022487
132	1	1.1388	0	1.2705	2.3406e-16	0.69746	-1.0252	-1.2555
133	5	1	2.3406e-16	0.042508	1.1428e-19	0.021254	-0.020357	-0.020357
134	4	1.1874	2.3406e-16	0.33989	5.8514e-17	0.25436	-0.1967	-0.25685

Table 24: NLLS Structural Kinked Session 2

ID	Type	α	se(α)	ρ	se(ρ)	$r(1)$	Elas $\log pr = 0$	Elas $\log pr = 1$
201	3	1	2.3406e-16	0.9715	2.3406e-16	0.48575	-0.9715	-0.97149
202	2	1.0385	2.3406e-16	0.6205	1.1703e-16	0.32901	-0.60403	-0.60526
203	4	1	0	0.39179	2.9257e-17	0.19589	-0.3914	-0.39113
204	3	1	0	0.33603	5.8514e-17	0.16801	-0.33603	-0.33603
205	4	5.0146	1.1984e-13	0.5	0	0.80609	0	0
206	3	7.3089	0	0.5	0	0.86516	0	0
207	4	1.8086	4.6811e-16	0.086901	2.9257e-17	0.32776	-0.062214	-0.062206
208	3	1.5771	2.3406e-16	1.5321	2.3406e-16	0.95157	-0.051281	-1.5321
209	4	1	0	0.61817	1.1703e-16	0.30908	-0.61817	-0.61817
210	1	1.0042	0	0.73721	0	0.37068	-0.73443	-0.73515
211	4	1.4759	2.3406e-16	0.26962	1.4628e-17	0.32204	-0.20664	-0.20783
212	3	1.2862	2.3406e-16	4.4742	9.3622e-16	2.3272	-0.26185	-0.051626
213	4	1.0374	0	0.59219	1.1703e-16	0.31435	-0.55432	-0.57578
214	3	1.61	2.3406e-16	0.050515	7.3142e-18	0.25759	-0.036451	-0.036449
215	4	1.1678	2.3406e-16	0.44669	1.1703e-16	0.29941	-0.31461	-0.37193
216	5	3.9203	5.9918e-14	0.5	0	0.75545	0	0
217	4	1	0	4.2753	0	2.1377	-4.2753	-0.31629
218	3	1.6113	0	0.029124	0	0.24786	-0.017072	-0.017072
219	4	1.7	0	0.3022	5.8514e-17	0.4002	-0.09447	-0.11737
220	4	4.5276	0	0.5	0	0.78636	0	0
221	3	2.024	4.6811e-16	0.001297	0	0.3392	-0.00090792	-0.00090792
222	4	1	2.3406e-16	0.1935	0	0.096748	-0.19259	-0.19251
223	1	1.5139	0	0.31183	5.8514e-17	0.35382	-0.22235	-0.22553
224	5	7.0965	0	0.5	0	0.86123	0	0
225	4	1.4638	2.3406e-16	0.9161	1.1703e-16	0.63007	-0.10936	-0.90293
226	1	1.4721	2.3406e-16	0.50351	0	0.43355	-0.20092	-0.31552
227	4	1.1202	2.3406e-16	0.34275	0	0.22752	-0.30196	-0.3059
228	4	1	2.3406e-16	0.52267	1.1703e-16	0.26133	-0.52267	-0.52267
229	4	1.0051	2.3406e-16	0.71322	0	0.35917	-0.70788	-0.7039
230	4	1.3733	0	1.0574	2.3406e-16	0.6729	-0.54697	-0.99086
231	4	1.351	2.3406e-16	0.093772	0	0.19513	-0.072023	-0.072112
232	1	1.5389	2.3406e-16	0.44844	0	0.42638	-0.19492	-0.25473
233	3	7.6842	5.9918e-14	0.5	0	0.87159	0	0
234	4	1.3478	2.3406e-16	0.058402	7.3142e-18	0.1767	-0.041864	-0.041904
235	2	2.2871	4.6811e-16	0.34916	0	0.53937	-0.011944	-0.039036
236	3	1	0	0.41881	0	0.20941	-0.41881	-0.41881

Table 25: NLLS Structural Kinked Session 3

ID	Type	α	se(α)	ρ	se(ρ)	$r(1)$	Elas $\log pr = 0$	Elas $\log pr = 1$
301	4	1	0	0.88709	0	0.44355	-0.88709	-0.88709
302	4	1.1784	2.3406e-16	0.89057	0	0.52418	-0.71587	-0.81881
303	1	1.3603	2.3406e-16	0.16045	2.9257e-17	0.23101	-0.12585	-0.12619
304	5	6.9709	1.1984e-13	0.5	0	0.8588	0	0
305	2	1	0	2.2722	4.6811e-16	1.1361	-2.2718	-2.1377
306	4	2.0469	4.6811e-16	0.25271	0	0.45503	-0.054668	-0.065456
307	2	2.5532	0	0.10163	1.4628e-17	0.47823	-0.059668	-0.059723
308	4	1	0	3.5168	4.6811e-16	1.7584	-3.5168	-2.6632
309	3	1.4762	4.6811e-16	0.20535	2.9257e-17	0.29119	-0.16708	-0.16712
310	4	1.3718	0	0.090626	0	0.20097	-0.075354	-0.075371
311	5	1	0	0.0061909	0	0.0030954	-0.0044676	-0.0044676
312	2	1.9186	0	3.6551	9.3622e-16	1.9612	-0.2226	-3.6398
313	2	1	0	1.3798	0	0.68992	-1.3798	-1.3798
314	4	1.6014	0	0.54134	0	0.48738	-0.11251	-0.31298
315	2	1.8679	0	0.61072	2.9257e-17	0.58001	-0.36627	-0.39366
316	5	6.6525	1.1984e-13	0.5	0	0.85225	0	0
317	4	1.077	2.3406e-16	1.335	2.3406e-16	0.70366	-1.0418	-1.335
318	3	1.5891	2.3406e-16	0.48623	5.8514e-17	0.45806	-0.1211	-0.25866
319	4	1.5948	2.3406e-16	0.46467	1.1703e-16	0.44936	-0.083267	-0.23292
320	4	1	2.3406e-16	0.060255	0	0.030128	-0.060246	-0.060246
321	1	1.2242	2.3406e-16	0.07295	9.1428e-19	0.13689	-0.056693	-0.056685
322	5	1	0	0.88331	0	0.44166	-0.88331	-0.88331
323	4	8.0283	1.1984e-13	0.5	0	0.87697	0	0
324	1	1.3132	2.3406e-16	0.63505	0	0.44709	-0.45713	-0.50775
325	4	1	2.3406e-16	0.50441	0	0.25221	-0.50441	-0.50441
326	4	1	2.3406e-16	0.42875	1.1703e-16	0.21437	-0.42875	-0.42875
327	5	1.0705	2.3406e-16	0.39149	5.8514e-17	0.22958	-0.36971	-0.37135
328	4	1	0	1.3587	2.3406e-16	0.67936	-1.3587	-1.3587
329	3	1	2.3406e-16	0.36489	5.8514e-17	0.18244	-0.36489	-0.36489
330	4	1	0	0.3732	5.8514e-17	0.1866	-0.36969	-0.36886
331	5	1	2.3406e-16	0.043312	0	0.021656	-0.033948	-0.033946
332	4	2.8567	0	0.15208	2.9257e-17	0.53983	-0.011657	-0.013132
333	2	1.7577	0	2.1375	0	1.2628	-0.013451	-2.1375
334	4	1.1792	2.3406e-16	0.22599	2.9257e-17	0.19448	-0.20394	-0.2038
335	2	1.685	2.3406e-16	1.115	2.3406e-16	0.77633	-0.0037723	-1.1145
336	4	1.7967	2.3406e-16	0.26977	5.8514e-17	0.4088	-0.15869	-0.16177

Table 26: NLLS Structural Kinked Session 4

ID	Type	α	se(α)	ρ	se(ρ)	$r(1)$	Elas $\log pr = 0$	Elas $\log pr = 1$
401	5	8.036	0	0.5	0	0.87708	0	0
402	4	2.0395	2.3406e-16	0.40522	0	0.52091	-0.062648	-0.11441
403	1	1.2984	0	0.28874	0	0.27177	-0.22449	-0.22747
404	4	1.6435	2.3406e-16	0.43275	5.8514e-17	0.44699	-0.040605	-0.17971
405	4	1	0	0.12673	0	0.063366	-0.1053	-0.10524
406	2	1	2.3406e-16	0.11436	0	0.057181	-0.11302	-0.11299
407	1	8.0727	5.9918e-14	0.5	0	0.87763	-0.21697	-0.21878
408	4	1	0	0.56948	1.1703e-16	0.28474	-0.56948	-0.56948
409	4	1	2.3406e-16	0.68927	1.1703e-16	0.34464	-0.68915	-0.68856
410	2	2.5727	0	0.22031	0	0.52901	-0.015954	-0.021485
411	5	1	0	0.013011	3.6571e-18	0.0065053	-0.0064194	-0.0064194
412	2	3.114	4.6811e-16	0.53944	1.1703e-16	0.71236	-0.00073738	-0.025012
413	2	1.2858	0	0.010221	1.8286e-18	0.13007	-0.0070655	-0.0070655
414	1	1.0244	2.3406e-16	0.69792	1.1703e-16	0.36095	-0.67832	-0.68628
415	4	1	0	1.2903	0	0.64516	-1.2903	-1.2903
416	1	1.494	2.3406e-16	0.47712	2.9257e-17	0.42728	-0.38514	-0.3843
417	3	1	0	0.78991	1.1703e-16	0.39496	-0.78991	-0.78991
418	4	1.6777	2.3406e-16	0.3849	0	0.4332	-0.17462	-0.19998
419	3	7.2895	5.9918e-14	0.5	0	0.86481	0	0
420	2	1.0888	0	0.53234	2.9257e-17	0.30819	-0.49913	-0.50256
421	1	1	2.3406e-16	2.7066	4.6811e-16	1.3533	-2.7066	-2.6597
422	4	1	0	0.52949	1.1703e-16	0.26475	-0.52948	-0.52944
423	4	1.1486	2.3406e-16	0.86492	0	0.49956	-0.41863	-0.86481
424	5	1.0951	0	0.29355	0	0.19188	-0.27678	-0.27699
425	5	1	2.3406e-16	0.049761	3.6571e-18	0.02488	-0.049742	-0.049742
426	1	1	0	0.18516	0	0.092578	-0.17861	-0.17844
427	1	1	0	0.79855	2.9257e-17	0.39928	-0.72458	-0.70932
428	1	5.4024	0	0.10814	0	0.71612	-0.055905	-0.05591
429	4	1.3323	2.3406e-16	0.59545	1.1703e-16	0.43416	-0.11125	-0.5491
430	2	1	2.3406e-16	1.562	2.3406e-16	0.78102	-1.562	-1.562
431	4	1	2.3406e-16	0.20792	2.9257e-17	0.10396	-0.20695	-0.20686
432	4	1.5364	2.3406e-16	0.10159	1.4628e-17	0.26001	-0.081299	-0.081298
433	2	1.8742	4.6811e-16	0.36173	2.9257e-17	0.46829	-0.13518	-0.15679
434	1	1.2294	0	0.65306	1.1703e-16	0.42596	-0.43326	-0.56274
435	5	1	2.3406e-16	0.009801	0	0.0049005	-0.0059399	-0.0059399
436	4	1.3775	2.3406e-16	0.78056	1.1703e-16	0.53923	-0.33694	-0.68237

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Figure 24: Example of Quartile Outlier Detection Assessment of 2 Subjects

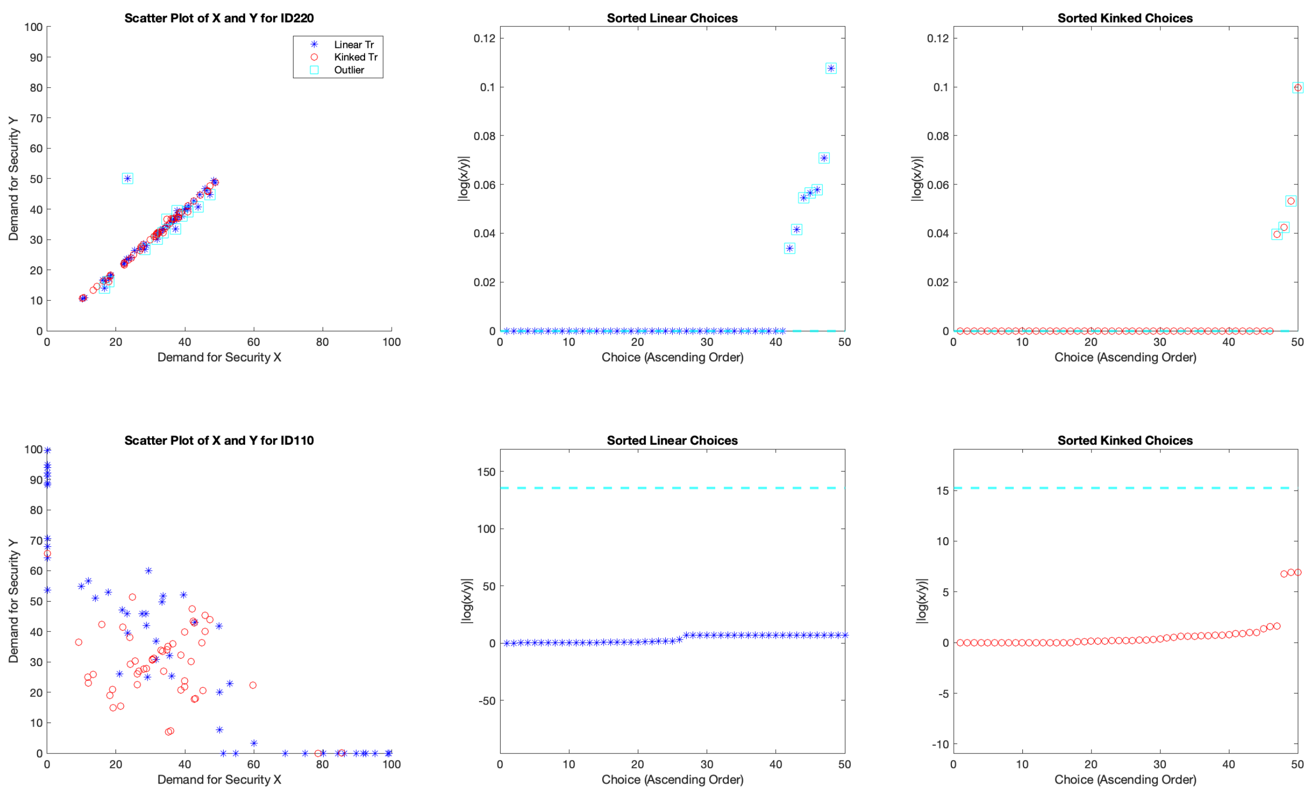


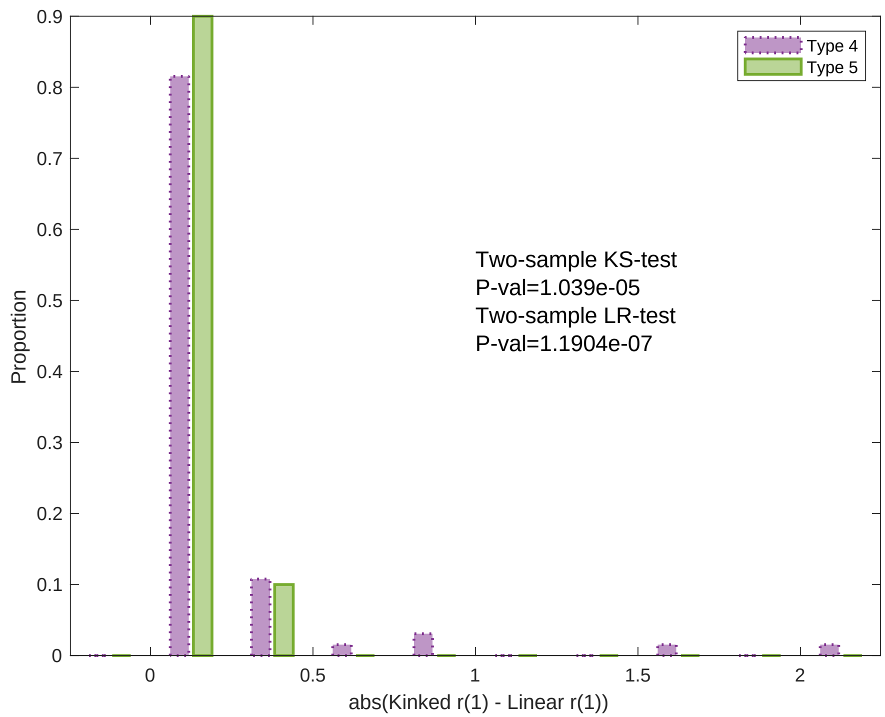
Table 27: Average Type 4 and Type 5 Population Parameters within Each Treatment

	Linear Type 4	Linear Type 5	2 sample p-val Type4Lmean = Type4Kmean	2 sample p-val Type4Lmean= Type5Lmean	Kinked Type 4	Kinked Type 5	2 sample p-val Type5Lmean= Type5Kmean	2 sample p-val Type4Kmean= Type5Kmean
α	1.73	3.38	0.27	0.001	1.48	3.44	0.95	0.000
ρ	0.62	0.26	0.69	0.159	0.69	0.29	0.67	0.036

Table 28: Average Type 4 and Type 5 Population Risk Premium and Elasticity within Each Treatment

	Linear Type 4	Linear Type 5	2 sample p-val Type4Lmean = Type4Kmean	2 sample p-val Type4Lmean= Type5Lmean	Kinked Type 4	Kinked Type 5	2 sample p-val Type5Lmean= Type5Kmean	2 sample p-val Type4Kmean= Type5Kmean
$r(1)$	0.47	0.39	0.93	0.571	0.46	0.42	0.79	0.729
$elas_{log(pr)=0}$	-0.48	-0.05	0.71	0.100	-0.54	-0.08	0.57	0.019
$elas_{log(pr)=1}$	-0.40	-0.05	0.15	0.000	-0.53	-0.08	0.56	0.002

Figure 25: Magnitude of Individual Change in Risk Premium Histogram by Type



Notes: The figure presents the histogram (separately for Types 4 and 5) of the magnitude of change (across the linear and kinked treatments) in individual estimates of the risk premium $r(1)$ (as defined in the text). Extremely large magnitude changes (in excess of 2) are grouped together in the last bin for presentation purposes. KS test p-values are reported for the null hypothesis that the Type 4 and Type 5 distributions are the same. LR test p-values are reported for the null hypothesis that the Type 4 and Type 5 sample means are the same.