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Aligning Capacity Decisions in Supply Chains When Demand Forecasts Are Private Information: Theory and Experiment (Supplemental Material)

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1. Alternative Assumptions on Noise

Recall that in Section 4 we assumed that demand, x, was uniformly distributed over $\mathbb{R}$ and that firms received a signal $\theta_i = x + \epsilon_i$, where ϵ_i was uniformly distributed over $[-\eta, \eta]$. In this section, we continue to assume that demand is uniformly distributed $\mathbb{R}$ but now assume that $\epsilon_i \sim N(0, \sigma^2)$. Then, given a signal θ_i, firm i believes that demand is normally distributed with mean θ_i and variance σ^2. Denote the distribution and density of firm beliefs given signal θ by $F_{x|\theta}$ and $f_{x|\theta}$, respectively.

We look for an equilibrium in monotone strategies. That is, each firm i's capacity choice is given by a function $K_i(\theta_i)$, which is strictly increasing in θ_i. Given this, we can write the expected profits of the sales firm who received a signal θ and is considering a capacity choice $k \geq 0$ as:

$$\Pi(\theta, k|K_m(\cdot)) = -\gamma k + \pi \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} \min\{K_m(\theta_m), k, x\} f_{\theta_m|x}(\theta_m|x) d\theta_m \right] f_{x|\theta}(x|\theta) dx,$$

where $f_{\theta_m|x}(\theta_m|x)$ is the density, conditional on demand, of possible signals of the manufacturing firm, and has a normal distribution with mean x and standard deviation σ.

We first show that there are signal realisations low enough such that it is a dominant strategy to choose a capacity of zero. To see this, suppose that $K_m(\theta_m) \geq 0$ for all $\theta_m \in \mathbb{R}$ and sales is contemplating a capacity of $k = 0$. This implies that for all possible signal realisations for the manufacturing firm, sales' choice of 0 will be at or below that of manufacturing. Therefore, it is not difficult to see that the derivative of sales' expected profit function evaluated at $k = 0$ is given by:

$$\frac{\partial \Pi_s}{\partial k}|_{k=0} < -\gamma + \pi \int_0^{\infty} f_{x|\theta}(x|\theta) dx,$$

which will be strictly less than zero for θ sufficiently small, since the integral goes to zero as $\theta \to -\infty$. Thus there exists $\underline{\theta}$, such that for all $\theta < \underline{\theta}$, it is a dominant strategy to choose a capacity of 0.

Therefore, we look for a symmetric equilibrium of the following form: Each firm has a capacity choice function given by $K(\theta)$, where, for some θ^*, $K(\theta) = 0$ for all $\theta \leq \theta^*$ and $K'(\theta) > 0$ for all $\theta > \theta^*$.

Let $K_m(\theta_m)$ denote the capacity choice function of manufacturing. We assume that it satisfies the two basic properties outlined above. In this case, the derivative of the expected profit function is given by:

$$\frac{\partial \Pi_s}{\partial k} = -\gamma + \pi \int_k^\infty \int_{\max\{\theta^*, K_m^{-1}(k)\}}^\infty f_{\theta_m|x}(\theta_m|x) f_{x|\theta}(x|\theta) d\theta_m dx.$$

Observe that in a symmetric equilibrium, it must be that $K_m(\theta) = K_s(\theta)$, which means that at the optimal solution to the above equation, we require that $K_m^{-1}(k) = \theta$.

We can actually characterise θ^* fairly easily. In particular, θ^* solves:

$$-\gamma + \pi \int_0^\infty (1 - F_{\theta|x}(\theta^*|\theta^*)) f_{x|\theta}(x|\theta^*) dx = 0.$$

Hence, for $\theta \leq \theta^*$, we have that $K(\theta) = 0$. On the other hand, for $\theta > \theta^*$, it can be shown that:

$$K(\theta) = \theta + \sqrt{2}\sigma \mathrm{Erfc}^{-1}\left(\frac{2\left(\pi - \sqrt{\pi^2 - 2\pi\gamma}\right)}{\pi}\right),$$

where $\mathrm{Erfc}(x) = 1 - \frac{2}{\sqrt{\pi}} \int_0^z e^{-t^2} dt$ and $\mathrm{Erfc}^{-1}(\cdot)$ is the inverse function. Notice that just as with the uniform case, if $\gamma > \frac{\pi}{2}$, then the term inside the square root is negative, which means that we don't have an equilibrium in monotone strategies. This result follows since one can show that: $\int_0^\infty (1 - F_{\theta|x}(\theta|x)) f_{x|\theta}(x|\theta) dx$ is increasing in θ and that the limit as $\theta \to \infty$ is $\frac{1}{2}$. Therefore, if $\gamma > \frac{\pi}{2}$, the derivative of the expected profit function is always negative. This actually shows that not only do we not have an equilibrium in monotone strategies, but also that the unique equilibrium is that of the complete coordination failure.

1.1. Truthful Information Sharing With Normally Distributed Signals

Consider now the CI-2S game with normally distributed signals. Given two signals, θ_1 and θ_2, it is easy to see that the firms' common belief about demand is $N(0.5(\theta_1 + \theta_2), 0.5\sigma^2)$. Thus, the efficient equilibrium corresponds to firms choosing capacity $K^{\text{CI-2S}}(\theta_1, \theta_2) = F_{\theta_1,\theta_2}^{-1}((\pi - \gamma)/\pi)$. It is also not difficult to see that, at the efficient equilibrium, expected profits are given by:

$$\mathbb{E}[\pi^{\text{CI-2S}}(\theta_1, \theta_2)] = \pi \int_{-\infty}^{F_{\theta_1,\theta_2}^{-1}((\pi-\gamma)/\pi)} x f_{\theta_1,\theta_2}(x) dx.$$

On the other hand, the expected profits for firms in the CI game, upon receiving a signal $\hat{\theta} = 0.5(\theta_1 + \theta_2)$ (so that expected demand is identical) is similar:

$$\mathbb{E}[\pi^{\text{CI}}(\hat{\theta})] = \pi \int_{-\infty}^{F_{\hat{\theta}}^{-1}((\pi-\gamma)/\pi)} x f_{\hat{\theta}}(x) dx$$

which is the same expression as for the CI-2S game, but for the fact that the variance is twice as high. To complete the analogy for Proposition 2 from the text, one simply news to note that the above expressions are decreasing in the variance of beliefs. Thus, $\mathbb{E}[\pi^{\text{CI-2S}}(\theta_1, \theta_2)] > \mathbb{E}[\pi^{\text{CI}}(\hat{\theta})]$.

1.2. Cheap-Talk Communication With Normally Distributed Signals

We note here that Proposition 3 continues to hold under the assumption of normally distributed signals. The main difference is that because signals have infinite support, every message is *on the equilibrium path*. That is, upon receiving a message M_i, firm j can **never** know with certainty that firm i lied. However, this does not matter since, as we argued in the main text, so long as firms expect to coordinate on the efficient equilibrium of the post-communication subgame, the firms' interests are perfectly aligned. Moreover, as before, a firm never strictly benefits by inflating its signal and strictly suffer by deflating its signal.

2. Example: Truthful but Inefficient Equilibria May Not Exist

Suppose that there is a truthful equilibrium in which firms' capacity choices are given by $K_i(\theta_\ell, \theta_h) = 0.5[s^*(\theta_\ell + \eta) + (1 - s^*)(\theta_h - \eta)]$. That is, they only choose half of the efficient equilibrium quantities. To further simplify matters, let $\pi = 10$, $\gamma = 3$ and $\eta = 5$. Next suppose that firm 1 sends $M_1 = 20.1 > \theta_1 = 20$. To see whether this represents a profitable deviation, we calculate the expected profits of firm 1, taking into consideration capacities in the next stage, which are given by:

$$K = \begin{cases} 0, & \text{if } |\theta_2 - 20.1| > 10 \\ \frac{1}{2}[\frac{7}{10}(\min\{20.1, \theta_2\} + 5) + \frac{3}{10}(\max\{20.1, \theta_2\} - 5)], & \text{o.w.} \end{cases} .$$

Observe that firm 1 will choose a capacity of 0 if $|\theta_2 - 20.1| > 10$ because, in this case, it is common knowledge that firm 1 lied and that firm 2 will, therefore, choose a capacity of 0. Taking expectations over the set of states and the possible signals of firm 2, the expected profits of firm 1 from inflating its signal by 0.1 are: 74.8352. On the other hand, the expected profits from faithfully reporting its signal are: 74.6643. Therefore, firm 1's deviation is profitable, and so the equilibrium in this example cannot be truthful.

3. Supplemental Data Analysis

3.1. The CP and NCP Treatments

3.1.1. Learning We now discuss whether subjects are able to learn. We focus on two potentially different forms of learning: (i) does alignment improve over time and (ii) do profits increase over time?

Do subjects learn to align their choices? Recall that subjects played the game for 30 or 40 periods with random rematching in each round. In Table 1 we show the results of a series of random-effects regressions where we regress d_t^j on the round and other control variables. Learning is indicated by a negative coefficient on round, which is generally what we see. Except for the PI$(10, 6)$ game, the coefficient is negative, and is significant at the 1% level in four of five of these games, and at the 10% level in the fifth game. Next, note that learning appears to be stronger in the CI games than in the PI games. If we pool the data across the CI and PI treatments for each of the three parameter values, the coefficient on `round` is significantly smaller (meaning faster learning) in the CI game than the PI game for $(\pi, \gamma) \in \{(10, 3), (10, 6)\}$.

Although the evidence is not conclusive, Table 1 also suggests that alignment may be more difficult to achieve when demand is higher. This seems intuitive because, when demand is high, there is more scope to be undercut. This could be due to heterogenous risk preferences among subjects. It is unclear to us what is driving the significantly negative coefficient in the PI$(10, 3)$ game.

Table 1 Random-effects regressions of d_t^j on round

	Demand $\sim U[20,50]$ $\pi=5;\ \gamma=2$		Demand $\sim U[100,400]$ $\pi=10;\ \gamma=3$		Demand $\sim U[100,400]$ $\pi=10;\ \gamma=6$	
	CI	PI	CI	PI	CI	PI
`round`	-0.159***	-0.136***	-0.823***	-0.283*	-0.287***	-0.0605
	[0.0217]	[0.0234]	[0.191]	[0.146]	[0.0727]	[0.0659]
`demand`	0.0840***	0.181***	-0.0228	-0.0192**	0.00955	0.0257**
	[0.0195]	[0.0250]	[0.0154]	[0.00836]	[0.00774]	[0.0117]
`cons`	4.168***	1.753**	47.61***	39.42***	17.34***	18.08***
	[0.857]	[0.851]	[7.438]	[5.320]	[3.129]	[2.596]
N	600	540	960	960	880	800
R^2	0.090	0.144	0.069	0.013	0.033	0.009

Standard errors in brackets, clustered at subject level. *** significant at 1%; ** significant at 5%; * significant at 10%

Do subjects earn more in later rounds? Table 1 shows a tendency towards improved coordination in capacity choices as the experiment proceeds. We now analyze whether subject's earnings increased as the experiment proceeds. We regress profits on round and round^2, the (unknown) state of demand and also on the match's choice. The results are reported in Table 2. We focus our attention on the coefficients involving `round`. As can be seen, the coefficient on `round` is positive and statistically significant in all games. Thus, at least for initial rounds, profits tend to increase. However, it is also true that the coefficient on `round`^{2} is negative and also always significant. Thus, at some point, learning reaches a maximum and profits begin to decline. What is generally true is the following: the decline in profits in late rounds is more pronounced in the PI games than in the CI games, especially in the PI$(10,6)$ game. This could be indicate that subjects were learning to play the equilibrium of the game (i.e., the complete coordination failure).

Table 2 Random-effects regressions of profits on round

	Demand $\sim U[20,50]$ $\pi=5;\ \gamma=2$		Demand $\sim U[100,400]$ $\pi=10;\ \gamma=3$		Demand $\sim U[100,400]$ $\pi=10;\ \gamma=6$	
	CI	PI	CI	PI	CI	PI
`round`	0.953***	1.637***	12.700***	9.389***	4.818***	4.278***
	[0.250]	[0.284]	[3.312]	[2.450]	[1.308]	[1.477]
`round`^{2}	-0.016**	-0.040***	-0.209***	-0.202***	-0.074***	-0.090***
	[0.007]	[0.008]	[0.063]	[0.054]	[0.027]	[0.032]
`demand`	0.542***	-0.192*	3.881***	3.349***	0.262	-0.428
	[0.143]	[0.108]	[0.450]	[0.394]	[0.524]	[0.615]
`m.c.`†	2.104***	2.699***	2.990***	3.555***	3.673***	4.339***
	[0.183]	[0.174]	[0.454]	[0.394]	[0.531]	[0.623]
`cons`	-12.142***	-11.890***	-269.282***	-228.062***	-120.973***	-134.606***
	[1.749]	[2.973]	[38.503]	[31.553]	[18.315]	[19.911]
N	600	540	960	960	880	800
R^2	0.774	0.752	0.929	0.935	0.929	0.882

Clustered standard errors (at subject level) in brackets. *** significant at 1%; ** significant at 5%; * significant at 10%.
† `m.c.` denotes one's match's choice.

3.1.2. Autocorrelation in choices To examine whether subjects use history-dependent strategies, we estimate the capacity choice function as a function of the current signal and other lagged variables. We include the lagged choice and lagged demand as well as the lagged difference between a subject's choice and her opponent's choice. We have no *a priori* prediction about the relationship between current choice and lagged choice. On the other hand, because the demand was i.i.d. across rounds we might expect a negative correlation between current choice and lagged demand. Concerning the lagged difference between own choice and opponent's choice, we do not have a clear prediction. On one hand, because subjects were randomly matched each period, the previous choice by one's opponent need not be informative about the current choice. On the other hand, one might expect a negative relationship. If $c \neq m.c.$ then it is very likely that the subject suffered from lost earnings, either because she was undercut by her opponent or because she lost out on potential earnings by choosing too conservatively. In the former case, this negative feedback causes subjects to lower their capacity choice, while in the latter case she chooses a higher capacity, all else equal, in the next period — hence the negative relationship. The results of this exercise are on display in Table 3.

Table 3 Random-effects Tobit regressions of choice on estimate and lagged variables

	Demand $\sim U[20,50]$ $\pi=5$; $\gamma=2$		Demand $\sim U[100,400]$ $\pi=10$; $\gamma=3$		Demand $\sim U[100,400]$ $\pi=10$; $\gamma=6$	
	CI	PI	CI	PI	CI	PI
θ	0.821***	0.841***	0.945***	0.958***	0.968***	0.964***
	[0.0199]	[0.0213]	[0.0116]	[0.0103]	[0.00593]	[0.00732]
`lagged choice`	0.118**	0.111**	0.0994**	0.0149	0.104***	0.0744*
	[0.0485]	[0.0547]	[0.0405]	[0.0417]	[0.0300]	[0.0387]
`lagged demand`	-0.0662	-0.0649	-0.0936**	-0.0226	-0.108***	-0.0765**
	[0.0425]	[0.0448]	[0.0390]	[0.0406]	[0.0291]	[0.0376]
`lagged c − m.c.`	-0.0704**	-0.131***	-0.0114	-0.0248	-0.0272	-0.0681**
	[0.0345]	[0.0345]	[0.0297]	[0.0289]	[0.0275]	[0.0265]
`cons`	1.583	0.648	13.48***	12.92***	-7.366***	-2.37
	[1.209]	[1.278]	[4.754]	[4.479]	[2.702]	[3.559]
N	580	522	936	936	858	780
LL	-1568	-1387	-4390	-4279	-3391	-3272

Standard errors in brackets. *** significant at 1%; ** significant at 5%; * significant at 10%.
The variable `lagged c − m.c.` denotes the lagged difference between the subjects choice and his/her match's choice.

As can be seen, for all games there is a positive relationship between the current and previous capacity choice, and the effect is significant (at the 5% level or better) in four of the six games. Moreover, when significant, the effect seems to be fairly large in magnitude at more than 10% of the effect on one's signal. This positive correlation indicates that subjects are prone to some inertia in their decision making. For lagged demand, the coefficient is always negative (as expected), but is only significant for three of the games. Finally, as expected, we also see a negative relationship between current choice and the lagged difference between c and $m.c.$; however, the effect is only significant in 3 games. Thus, it would seem that there is some evidence that players adopt an adaptive learning strategy and react to lagged variables.

3.2. The CP-2S and MS Treatments

3.2.1. Do subjects learn to align their choices? In Table 4 we replicate Table 1, which looks at the question of whether subjects become better-aligned as the experiment progressed. As can be seen, in all games we find a negative and significant coefficient on `round`, which indicates that alignment is improving over time. Consistent with the results from the main text, the coefficients on `round` appear to be smaller in magnitude for the $(\pi,\gamma) = (10,6)$ games than for the $(\pi,\gamma) = (10,3)$ games.

Table 4 **Random-effects regressions of d_t^j on round**

	Demand $\sim U[20,50]$ $\pi = 5;\ \gamma = 2$		Demand $\sim U[100,400]$ $\pi = 10;\ \gamma = 3$		Demand $\sim U[100,400]$ $\pi = 10;\ \gamma = 6$	
	CI-2S	PI-MS	CI-2S	PI-MS	CI-2S	PI-MS
`round`	-0.0496*	-0.108***	-0.341***	-0.412***	-0.314***	-0.505***
	[0.0265]	[0.0197]	[0.091]	[0.0968]	[0.087]	[0.109]
`demand`	0.100***	-0.0119	-0.003	-0.029	0.037**	0.01
	[0.0285]	[0.0115]	[0.006]	[0.0211]	[0.017]	[0.009]
`cons`	0.568	5.359***	21.192***	34.87***	17.054***	26.536***
	[0.703]	[0.644]	[3.774]	[7.823]	[3.999]	[3.976]
`N`	660	660	880	914	960	880
R^2	0.077	0.0777	0.0377	0.0284	0.0263	0.0686

Standard errors in brackets, clustered at subject level. *** significant at 1%; ** significant at 5%; * significant at 10%

3.2.2. Do subjects earn more in later rounds? Table 5 replicates Table 2, examining the relationship between profits and `round` in the CI-2S and PI-MS treatments. The only difference from our previous results is that we fail to find a learning effect in the CI-2S(5,2) game and that in the CI-2S(10,3) game, the learning effect is positive over all rounds.

Table 5 **Random-effects regressions of profits on round**

	Demand $\sim U[20,50]$ $\pi = 5;\ \gamma = 2$		Demand $\sim U[100,400]$ $\pi = 10;\ \gamma = 3$		Demand $\sim U[100,400]$ $\pi = 10;\ \gamma = 6$	
	CI-2S	PI-MS	CI-2S	PI-MS	CI-2S	PI-MS
`round`	0.191	0.881***	7.319***	10.416***	3.935**	9.259***
	[0.158]	[0.197]	[1.513]	[1.707]	[1.887]	[2.542]
$\texttt{round}^2$	-0.002	-0.020***	-0.133***	-0.215***	-0.058	-0.176***
	[0.006]	[0.005]	[0.030]	[0.037]	[0.038]	[0.052]
`demand`	-0.085	0.617***	2.701**	4.832***	-0.668	-0.607
	[0.262]	[0.161]	[1.119]	[0.490]	[1.108]	[0.455]
`m.c.`†	2.917***	2.397***	4.264***	2.135***	4.605***	4.640***
	[0.281]	[0.176]	[1.141]	[0.498]	[1.116]	[0.473]
`cons`	-6.348**	-18.011***	-162.733***	-206.923***	-145.149***	-207.364***
	[2.535]	[1.847]	[21.491]	[32.002]	[20.581]	[32.647]
`N`	660	660	880	914	960	880
R^2	0.865	0.904	0.972	0.959	0.835	0.91

Clustered standard errors (at subject level) in brackets. *** significant at 1%; ** significant at 5%; * significant at 10%.
† `m.c.` denotes one's match's choice.

3.2.3. The Consequences of Lying We briefly take a deeper look on the consequences of lying. Table 6, reports the results of a series of random-effects regression of profits on variables related to messages. Specifically, we include two dummy variables, one for sending a dishonest message and one for receiving a dishonest message. We also include variables which capture the extent to which one sent (or received) an inflated message, and variables which indicate whether one sent (or received) a deflated message.

Table 6 Random-effects regressions of profits on round and the misrepresentation of signals

		Dem. $\sim U[20,50]$ $\pi=5$; $\gamma=2$		Dem. $\sim U[100,400]$ $\pi=10$; $\gamma=3$		Dem. $\sim U[100,400]$ $\pi=10$; $\gamma=6$	
	round		0.176***		1.238***		1.426**
			[0.0370]		[0.273]		[0.597]
	demand	0.757***	0.763***	4.289***	4.274***	-0.253	-0.226
		[0.169]	[0.163]	[0.373]	[0.366]	[0.583]	[0.558]
	m.c.	2.273***	2.258***	2.650***	2.669***	4.279***	4.248***
		[0.175]	[0.171]	[0.372]	[0.364]	[0.592]	[0.567]
message sent	$(M_i-\theta_i)1_{(M_i>\theta_i)}$	-0.338*	-0.333**	-2.034***	-2.022***	-0.811***	-0.756***
		[0.174]	[0.167]	[0.332]	[0.315]	[0.205]	[0.222]
	$(M_i-\theta_i)1_{(M_i<\theta_i)}$	0.845*	0.747	3.457**	3.343**	1.646***	1.475***
		[0.451]	[0.457]	[1.520]	[1.535]	[0.363]	[0.392]
	$1_{(M_i\neq\theta_i)}$	0.26	0.268	25.69	21.11	34.56	36.87
		[0.820]	[0.718]	[15.68]	[15.46]	[35.77]	[33.98]
message rec'ed	$(M_j-\theta_j)1_{(M_j>\theta_j)}$	-0.291***	-0.288***	-1.792***	-1.802***	-1.177***	-1.127***
		[0.099]	[0.092]	[0.341]	[0.339]	[0.294]	[0.300]
	$(M_j-\theta_j)1_{(M_j<\theta_j)}$	0.759***	0.664***	3.288**	3.180**	1.432***	1.264***
		[0.227]	[0.223]	[1.468]	[1.491]	[0.301]	[0.287]
	$1_{(M_j\neq\theta_j)}$	0.262	0.27	22.36***	20.55***	15.01	15.26
		[0.763]	[0.713]	[7.023]	[7.478]	[13.58]	[13.90]
	cons	-9.052***	-11.74***	-84.91***	-105.7***	-118.7***	-151.90*
		[1.183]	[1.385]	[16.09]	[18.13]	[45.05]	[53.68]
	N	660	660	914	914	880	880
	R^2	0.911	0.914	0.973	0.974	0.914	0.916

Clustered standard errors (at subject level) in brackets. *** significant at 1%; ** significant at 5%; * significant at 10%.
† m.c. denotes one's match's choice.

If inflated messages lead to lower profits, then, because $M_k - \theta_k > 0$, the coefficient on $(M_k - \theta_k)1_{(M_k>\theta_k)}$ will be negative. Similarly, if sending a deflated message leads to lower profits, then because $M_k - \theta_k < 0$, the coefficient on $(M_k - \theta_k)1_{(M_k<\theta_k)}$ will be positive. Indeed, this is precisely the pattern that we see. Across all games and specifications, the coefficients on $(M_k - \theta_k)1_{(M_k>\theta_k)}$, $k = 1, 2$, are negative and significant, indicating that it is not profitable to lie by inflating messages. In the game PI-MS$(10, 3)$, this effect is partially mitigated by the positive and significant coefficient on $1_{(M_j\neq\theta_j)}$. Therefore, for this game, small lies may be profitable, but big lies are counterproductive. We also see that the coefficient on $(M_k-\theta_k)1_{(M_k<\theta_k)}$ is positive across all games and specifications, though it loses significance in PI-MS$(5, 2)$ once we account for learning. Therefore, as with inflating messages, it is unprofitable to send or receive a deflated message. Finally, notice that the coefficients on $(M_k - \theta_k)1_{(M_k<\theta_k)}$ are generally larger in magnitude than are the coefficients on

$(M_k - \theta_k)1_{(M_k > \theta_k)}$. This suggests that it is *worse* to send a deflated message, which is intuitive because doing so can only cause one's opponent to choose a lower capacity, which can only lower profits.

3.3. Further Enhancements to Communication

In the text, we conjectured that one of the reasons why the PI-MS treatments worked so well, indeed, better than the CI-2S treatments, was because the ability to communicate allowed subjects to signal not just their private information but also their intended action. To further investigate this conjecture, we ran another experiment in which (i) subjects received private signals, (ii) subjects simultaneously sent messages to each other, (iii) subjects observed the messages and then sent a recommended capacity choice to each other, and (iv) subjects simultaneously choose capacities. We call this the PI-RP treatment, and we conducted two sessions (20 subjects in total) with prior demand support $[100, 400]$, $\eta = 25$ and $(\pi, \gamma) = (10, 3)$.

In the PI-RP$(10, 3)$ treatment, average profits are 1699.5, which is greater than the average profits of 1668.5 in the PI-MS$(10, 3)$ treatment, though the difference is not statistically significant ($t_{42} = 1.06$, $p = 0.294$). On the other hand, misalignment declines by more than half from 19.4 to 8.4 ($t_{42} = 5.76$, $p \ll 0.01$).

If, in the PI-MS treatments messages were being used, in part, to signal intended actions, then we might expect greater honesty by subjects in the communication phase of the PI-RP treatment. The frequency of honest messages does increase slightly (from 23.2% to 28.5%) as does the average correlation between messages and signals; however, in neither case is the difference significant. Furthermore, *conditional on lying*, subjects do so by *less* in the the PI-RP treatment ($p = 0.12$, though a rank-sum test gives $p = 0.03$).

In Table 7 we look at the relationship between the recommendation and the message sent and also between the capacity choice and the both the messages and recommendations (sent and received). We also include the results for the PI-MS$(10, 3)$ treatment for the sake of comparison. As can be seen, both the message sent and the message received have a positive effect on the recommendation. Thus, higher messages lead to higher recommendations. As can also be seen, recommendations also have a positive effect on final capacity choices. Notice now, however, that the effect on the message sent becomes small and negative (though still significant). This is in sharp contrast to the PI-MS$(10, 3)$ game where the message sent had a strong positive effect on one's own capacity choice. Thus, while the effect of the message sent has an *indirect* positive effect on capacity choice (working via the relationship between recommendation and message sent), the direct effect is severely diminished, even changing signs.

Table 7 **Messages and Recommendations in ms-rp**

	PI-RP(10, 3)		PI-MS(10, 3)
Ind. Vars. / Dep. Var.	`recommendation`	`capacity`	`capacity`
`estimate`	0.538***	0.650***	0.328***
	[0.030]	[0.024]	[0.034]
`message sent`	0.276***	-0.05***	0.390***
	[0.023]	[0.018]	[0.027]
`message received`	0.178***	0.048***	0.259***
	[0.019]	[0.015]	[0.021]
`recommendation sent`		0.152***	
		[0.023]	
`recommendation received`		0.196***	
		[0.022]	
`cons`	-2.960	-2.620*	1.921
	[2.391]	[1.444]	[3.075]
`N`	800	800	914
`LL`	-3334.9	-3014.8	-4013

Standard errors in brackets. *** significant at 1%; ** significant at 5%; * significant at 10%.