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Essays on managerial productivity and firm outcomes

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ESSAYS ON MANAGERIAL PRODUCTIVITY AND FIRM OUTCOMES

by

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ABSTRACT

This dissertation studies internal and external factors affecting firm outcomes. The first two chapters explore the sources of variation in managerial skill within an Indian life insurance firm. The existing literature has investigated the association between managerial productivity and management practices across firms, but has largely overlooked how individual traits and skills affect managerial performance. Intra-firm variation in managerial productivity allows us to study managerial skill without the confounded effects of variation in management practices. The third chapter models how external technological change affects competition between media firms, and what that implies for information availability in a society.

For the first two chapters, I use a novel dataset drawn from a life insurance firm in India, with 211 managers, each leading a sales team of insurance agents. Chapter 1 studies the sources of large variation in performance across teams. I find that the performance of newly recruited agents is positively correlated with the managers' past team productivity index. I also observe that when agents move across teams in the firm's internal labor market, there is no change in the output of such agents, except when they join the team of a high performing manager (in the top decile of team performance). This allows me to infer

that most managers differ from along their recruiting skill, whereas the high performers are able to provide some form of managerial contribution to productivity such as training, supervision or guidance.

Chapter 2 examines the dynamics of managerial skills in this firm. I distinguish between internally-hired managers who were working previously as agents in the firm, and externally-hired managers, who joined the firm directly as managers. I find that the teams of internally-hired managers are 14% more productive, but that the teams of externally-hired managers catch up in a span of six to seven years. Among different mechanisms, I find evidence that the managers differ in the recruitment of good workers and also in the contribution to the output of their workers. Further, I find evidence that the externally-hired managers learn how to recruit good workers. This is the first study to show evidence supporting learning-by-doing on part of managers.

The third chapter, co-authored with Benjamin Ogden, develops a model of endogenous media polarization—or, product differentiation among news sources—to study how this affects political outcomes. We show that under internet-based technology, where users provide additional values when they are served their preferred content, media firms would have an incentive to skew their content, leading to divergence. However, the degree of divergence will depend on the distribution of audience. Under reasonable restrictions on the distribution of voters, informed political choices are implemented and in no distribution. The model demonstrates why increasing media polarization does not necessarily lead to incorrect political outcomes and may in fact create conditions for correct policy choice.

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Chapter 1

What Do Good Managers Do? Evidence from an Insurance Firm in India

Do managers within a firm differ in productivity measures? Within-firm disparity in managerial performance holds significant implications. Many firms, such as multi-plant manufacturing units or multi-branch sales firms, employ several managers with access to the same management practices, identical incentives, and similar markets. Dispersion in performance within this selected group of managers would throw light on how managerial skill impacts firm outcomes. Syverson (2011) emphasizes this distinction by asking whether the ”skills of those who implement” managerial practices, rather than just the practices themselves, may also have a role in explaining firm-level productivity. If managerial productivity does vary within a firm, this poses another question - what are the productive skills of the managers? The role of managers in any firm is broadly defined, and managers perform various, sometimes intangible, tasks. Discovering which skills separate managers from on another or which manager performs which tasks better may hold crucial value for firms regarding job design, the transmission of information on productive skills, etc.

To answer the questions mentioned above—viz., Do managers within a firm differ in productivity and, if so, what do good managers do?—I use four years of panel data on 211 sales-teams, each led by one manager, in a life insurance firm in India. Although the managers are subject to the same incentives and management practices, their teams differ vastly in performance - the average output in the team at the 90th percentile is five times the average output of the team at the 10th percentile. Further, output per worker and team size are significantly and positively correlated: larger teams have, on average, more productive workers.

The subject firm provides much discretion to the managers and the output gap can arise for several reasons. For example, managers might be heterogeneous in recruiting agents, in training and supervising them, or in formulating product and market strategy. To explore heterogeneity in managerial skill, I correlate output per worker for each team in 2012 with outcomes of managerial tasks in the years 2013-2015. I find the following -

1. The output of new recruits is significantly and positively correlated with the output per worker in 2012; new recruits of better teams outperform the new recruits of teams with lower output per worker. This positive correlation could be potentially due to two main causes—good managers recruit good agents, or good managers provide more valuable training, supervision, and/or motivation.

2. To isolate one channel from the other, I observe those agents who move across teams due to an internal agent-manager matching policy. When a manager exits the firm, remaining agents of her team, known as “orphaned agents”, are quasi-randomly matched with other managers over time. Assignment of these agents occurs in an as-if random manner. This variation in teams for the same agent allows me to compute the manager value-addition to an agent’s output. Using empirical Bayes shrinkage on a manager dummy in the change in the output of allotted agents, I find that the output of an agent allotted this way increases only when the agent joins the team of a manager in the upper 10th percent of ability, whereas output is unchanged for agents joining other teams.

3. I also find that when a high performing manager exits, the output of her agents falls but no change is observed for agents of other exiting managers.

4. Output can also be a result of market conditions, which may vary across managers. Using a coarse menu, value and cost of products sold by the agents, I rule out differences in market heterogeneity.

Evidence 1, 2, and 3 above state that: (a)output of new recruits varies across managers; (b) except for the top 10%, managers are unable to increase the output of agents that they receive quasi-randomly; and (c), except for high-performing managers, output of agents does not decline when their manager exits. Collectively, these results imply that for 90% of the managers, skill differential exists in the recruitment of agents, whereas managers in the upper 10th percentile can add value to their agents' output in the form of motivation, guidance, or supervision, etc. Evidence 4 rules out market or customer heterogeneity as well as team-specialization.

To explore the implications of heterogeneity in recruitment skill, I develop a model where managers differ in the noisiness (or precision) of the signal they receive regarding an agent's productivity before recruiting him. Agents receive a stochastic outside option in every period. The model provides four implications- 1) The separation rate of agents working under more able managers is lower due to better selection; 2) Smaller separation of agents implies a bigger team of more able managers, keeping tenure of manager constant; 3) The team size of a manager increases at a decreasing rate with respect to the tenure of the manager. Concavity arises due to two opposing forces: addition of new agents to the team remains constant as only one agent is recruited each period, but combined deterioration of the team increases as previously recruited workers exit with a non-zero probability; 4) Since bigger teams are composed of more productive workers, team output is convex with respect to team size. All the implications are confirmed in the data.

The paper's primary contribution is to provide evidence that the managerial skill of recruitment is a significant reason for intra-firm disparity in managers'/supervisors' performance. Most studies have documented the divergence in managerial performance as due either to the effect of incentives within firms (Bandiera et al. (2009); Shearer (2004) Bandiera et al., [2007]) or to management practices across firms (Huselid (2016), Ichniowski and Prennushi, [1997]; Bloom and Reenen (2010); Bloom et al. (2010)). Lazear et al. (2015) and Adhvaryu et al. (2016) are recent studies that document managers' productivity as a result of her skill - in the former, training workers in a US-based technology firm, and, in the latter, in reassigning workers to protect from pollution shocks in an Indian textile plant in the latter.

This study is distinct from Lazear et al. (2015) and Adhvaryu et al. (2016) in two ways. First, the firms studied in the other two papers do not allow managers to recruit agents, whereas in contrast, I find the main skill differential to lie in recruitment. In addition, I can also observe in my data the managerial roles studied in the other two papers. In this sense, in this chapter I will provide a more comprehensive analysis than the other two papers. Second, output dispersions across managers recorded in this study are higher than those seen in other papers. One potential reason for higher output dispersion in the subject firm might be that good managers perform the task of recruitment outside the firm where other managers cannot observe them. As such, diffusion in the knowledge of recruitment could be slower, keeping the output gap larger. This is consistent with the theory of tacit versus codified knowledge, which is usually invoked to explain why knowledge flow remains slow in Multi-National Companies (Gupta and Govindarajan (2000)).

The theoretical foundation for links between managerial traits and firm outcomes has been explored previously(Hambrick and Mason (1984), Ocasio (1997), Dessein and Santos (2016) and Steen (2016)). Bertrand and Schoar (2002) and Cho and Hambrick (2006) provide empirical evidence for links between the background traits of CEOs and their impact on firm outcomes. However, these papers study the behavior of senior executives engaging in high-level strategic decisions. In contrast, I study the role of mid-level (or lower-level) managers, who are closest to the production process.

In the firm, 90% of managers vary in their skill of recruiting productive workers, creating output dispersion across teams. Many studies of sales-force management reveal that the individual skill of a salesperson is a stronger determinant of his performance than other factors such as motivation, personality traits, organizational factors, etc. (Churchill et al. (1985)). In other settings as well, workforce selection and retention has also been found to be closely related to firm-level productivity. For instance, Heath (2016) and Beaman and Magruder (2012) study the positive effects of recruitment through referrals in garment firms in Bangladesh and among low-skilled urban workers in India, respectively. Bender et al. (2016) find that high-productivity manufacturing firms in Germany are better at retaining high human capital workers.

I find evidence that the top 10% of managers increase the output of their allotted workers. This evidence suggests the presence of "superstars" in the firm. Malmendier and Tate (2009) and Desai and Jain (1995) study the consequent performance of award-winning CEOs and the investment advice by prominent money managers, respectively. However, these studies show that the impact of such superstars is insignificant compared to the non-superstars.

Finally, the current study can be put into the category of "insider econometrics" - a term first coined in Ichniowski and Shaw (2003) - which refers to the study of a firm's internal organization to test theories of personnel economics. While what we may lose in the generalization of the results, we gain in precision. Lazear (1999) provides a survey of the field.

Throughout the chapter, I use the masculine pronouns (he, his, him) for the agent and the feminine pronouns (she, her) for the manager. I will use agents, salespersons, and workers interchangeably.

1.1 Institutional Background

The subject firm is a life insurance firm that operates across India. The life insurance industry in India is highly concentrated: the top six firms out of 24 comprise 85% of the market with the subject firm being one of them[1].

1.1.1 Organization Structure of the Firm

Figure 1·1 represents the organizational chart of the subject firm. The firm has a divisional organization structure, with three hierarchies: zones, divisions, and branches.

Zonal and divisional supervisors implement the strategy laid out by Central Headquarters (located in Mumbai) They also act as information intermediaries - relaying outcomes to the levels above and transmitting outlay to tiers below[2].

Branches are local administrative units populated with one administrator monitoring several manager-led teams of salespersons. These teams are responsible for selling insurance products. The central authority of the firm determines the product characteristics. Managers receive a performance-linked payment along with a monthly basic pay. Agents face a piece-rate compensation.

In this paper, the data comes from one division in the city of Delhi. This division has 24 branches with 211 managers and around 9000 sales agents. Demographically, this division covers a population of around 7 million people with a per capita income of US $4300. Further, the market for this division is highly competitive with all of other 23 firms operating in the same geographic zone covered by the division.

[1]More information on the subject firm is available on request since identity of the firm cannot be fully revealed.

[2]Despite the diversity of the market, decision-making in the firm is highly centralized. Alonso et al. (2008) demonstrate, theoretically, adaptation to local needs can be met by centralization conditional on the alignment of manager's incentives.

1.1.2 Managers' and Agents' Incentives

In the subject firm, managers' monthly compensation comprises a fixed pay and a performance-based variable pay. Variable pay increases in the total output of a manager's team and decreases in the operational expenses incurred by the manager. These operational expenses include items such as activation costs of newly recruited agents, travel, and office-related expenses, etc. On average, the variable component comprises of 50% of the manager's monthly compensation and goes as high as 68% for the most productive managers.

Agents face a piece-rate compensation scheme where they receive a fixed share of the value of the products they sell. The piece rate varies across products, but the overall incentive structure is uniform for all agents[3].

Appendix A.1 provides more details for the incentives structure.

1.1.3 Role of Managers

When a manager joins the firm, her responsibility is to build the team. She has the following discretion:

- Full discretion in recruiting agents: To qualify as an agent, a candidate must undergo 50 hours of training and pass an online exam. The cost of training and the online exam are incurred by the firm and billed as an operational expense for the manager. Conditional on these requirements, a manager has the full responsibility and sole authority to choose candidates. The responsibility entails searching and assessing a candidate for the agency and appraising him of the expectations. The firm neither assists nor intervenes in the process[4].

- Guidance and supervision: Qualified agents receive a basic insurance-specific education by the firm before joining the team. Once an agent joins the team, training,

[3]Homogeneous compensation scheme for heterogeneous sales agents is the norm in many industries. See Daljord et al. (2014), Misra and Nair (2011) and Lo et al. (2011)

[4]Appendix A.2 provides more details on the recruitment procedure.

guidance, and supervision of the agent is the manager's responsibility.

- Conditional discretion on terminating an agency: If, in the first year of an agent's career, the agent sells less than 12 products or the total value of his sales is less than Rs. 100,000 (USD1,554), then such an agency is terminated. The manager of such an agent has the discretion to overrule this termination.

- Product and market strategy: The menu of products is decided by the firm's central authority and undergoes frequent revisions. Managers can decide the balance of their portfolio from the menu available. They can also judge how best to distribute their agents over the menu of products.

All managers, irrespective of tenure or branch, have the same responsibilities.

What can managers not do? A newly-recruited manager cannot join an existing team or replace some other manager. She is responsible for building the team. The manager cannot influence or vary compensation schemes for the agents in her team. A manager cannot alter the product features either, such as by altering premium rates or term limits on insurance products. A manager cannot move to another branch within the same division. Agents are associated with the branch only through their manager and cannot choose to move to some other team unless their manager exits.

1.2 Data Description

I use four years of panel data of 211 managers, each leading one team, from 2012-2015, comprising of around 9000 salespersons across 24 branches in Delhi. For performance measures of each agent, I can observe number, revenue, and amount insured of total products sold. Products of the firm can be classified into two broad categories—single-premium, where customers pay premium only once (at the beginning), and multi-premium, where the premium is paid at regular intervals. For each of the product categories, I can observe revenue obtained by the agent. I can also observe team size, the tenure of agents and managers and the gender of managers. Entry of new recruits in the years 2013-2015, exit of agents in the years 2012- 2014, and allotment of agents from 2013-2015 can be inferred from unique alpha-numeric codes of agents[5].

For an agent's (and consequently team's) product portfolio, I can construct three variables. These are:

- Type of product: I use the ratio of revenue from single premium products over total revenue as a proxy for type of product sold by each agent.
- Average value of product: To compute value of product, I use the ratio of total revenue over number of products sold by each agent.
- Average cost of product: For an insurance firm, the cost of a product is the total amount insured that the firm is liable to pay in the future. To compute average cost of product, I use the ratio of total amount insured over quantity of product sold by each agent.

Table 1.1 gives summary statistics on managers and agents. Figure 1·2 plots the histogram of output per worker of the teams. The spread of distribution is substantial: the team at the 90th percentile has an average output five times that of the team at the 10th percentile. This measure of spread is comparable in magnitude to average 90-10 total factor productivity (TFP) ratios across firms in developing countries (Syverson, 2011).

In Figure 1·3, I provide the binned scatter plot between the log of team size and the log of output per worker, along with the linear fit of the conditional expected function. The slope is significantly positive, suggesting that bigger teams are also, on average, more productive.

Positive correlation between output per worker and team size translates into even more amplified differences in team output, defined as the number of products sold by the

[5] Appendix A.4 provides details on construction of key variables

agents of a team. Figure 1·4 plots the histogram of team output. Now, the team output at the 90th percentile of output is 20 times than team output at the 10th percentile.

Figure 1·5 plots the histogram of agent output. The ratio of 90-10 productivity level is close to 20, similar in magnitude to team-level output disparity.

To observe within-team variance in agent's output, I regress the log of output on manager fixed effects. Table 1.2 displays the results. On using manager fixed effects, R^2 is 9% and the adjusted R^2 is 8.2[6]. An R^2 of this magnitude is large when compared to other studies of salesperson's performance. For instance, a meta-analysis conducted by Churchill et al. (1985) shows that, on average, "*less than 4% of the variation in salesperson's performance is explained by a single predictor of that performance*". Thus, in the subject firm, managers are responsible for a substantial variation in the performance of agents.

1.2.1 Index of Team Productivity

As a measure of team productivity, I use the ratio of total team output and team size for each manager in 2012. This method of arriving at productivity is analogous to estimating TFP for a manufacturing firm, where residual productivity is recorded after controlling for major inputs, viz., capital and labor. Further, output per worker for each team has the following desirable properties:

- Residual output: For a sales-team, labor is the major input in the production function. Dividing team output by total team size controls for the factor of production. The residual variance productivity can be attributable to manager's effectiveness.

- Relevance: Correlation between this metric of managerial ability and log of team output is high. Total team output is the relevant data point from the firm's perspective, against which the manager is rewarded. Owing to this property, output per

[6] I also run 100 simulations with log of agent output allocated randomly to managers but keeping the team size the same as in the actual data. The average R^2 and adjusted R^2 for these 100 simulations is 0.01 and 0.001, respectively.

worker is a good index of manager's productivity and firm's incentives.

- Stability: Output per worker for managers displays high serial correlation.This property indicates the robustness of this metric to idiosyncratic shocks.

Table 1.1 provides summary statistics on this index.

1.3 Tasks of Productive Managers

In this section, I try to discern the tasks of the productive managers. To do so, I correlate the index of team productivity, i.e., output per worker for each team in the year 2012, with variables in the years 2013-2015 that are outcomes of managerial tasks.

1.3.1 Performance of New Recruits

Figure 1·6 shows the log of output of a newly recruited agent in years 2013 to 2015 as a local polynomial curve of the log of team output per worker in 2012. The slope, which is positive, can be interpreted as the elasticity between a new recruit's performance and his team's output per worker in 2012.

I regress the log of output of new recruits from 2013-2015 on manager-specific variables. Table 1.3 shows the results. Column (1) controls for log of output per worker in 2012 as an explanatory variable. In Column (2), I control for tenure, square of tenure, and gender of the manager. Both specifications include year and branch fixed effects. The coefficient on log of output per worker in 2012 is significant and between 0.23-0.25 in both specifications.

The above results suggest that the output of a new recruit and average output in a team are correlated. Many hypotheses could be consistent with this outcome. For instance, managers may differ in selection of agents, or they may vary in training. It may also be due to factors independent of managers' efforts such as peer effects or positive assortative matching of agents with teams.

1.3.2 Output Change for Allotted Agents

To isolate selection from other channels, I observe variation in team-assignment for the same agent. This variation is obtained from an internal agent-manager matching policy. In the subject firm, when a manager exits, the recruited agents of her team, now termed "orphaned," stay with the firm. Such orphaned agents are then matched to other existing managers. These agents, who change teams, are known as allotted agents.

According to the allotment rule, an orphaned agent chooses a team in the order of his revenue in the year before allotment; thus, an orphaned agent with higher revenue chooses his team first. A potential issue here is that the matching between alloted agents and managers may not be random, as agents may choose to go to good managers. To address that, I plot the log of output per worker in 2012 of the team an orphaned agent is matched with against the log of revenue of that allotted agent in the pre-allotment year in Figure 1·7. Table 1.4 provides the results of linear regression. Figure 1·7 shows that there is no correlation between an agent's productivity and the output per worker of the matched team; agent-manager matching due to the allotment policy appears random [7]. In Appendix A.5, I conduct more robustness checks to test the random allocation of allotted workers to the managers.

I use this policy to observe the difference in the output of orphaned agents before and after they join a new team. The difference in the output of the allotted agent eliminates year fixed effect. Any change in agent's output thus has the interpretation of the manager's contribution to an agent's productivity[8]. I use the following empirical model:

$$\log y^A_{amb} - \log y^O_{ab} = \beta \log k_m + \kappa X_m + \phi_t + \epsilon_{ambt}$$

[7] Another takeaway from Figure 1·7 is that orphaned agents appear indifferent among the managers. Since they are more likely to know the productivity and features of these teams, this apparent indifference makes the hypothesis of assortative matching between agents and managers weaker.

[8] The implicit assumptions are that manager and agent effect are separable and agent effect is time-invariant

where y^A_{ambt} and y^O_{ab} are, respectively, output of an agent a after and before being allotted to manager m in branch b at time t. k_m is team output per worker in 2012. X_m are manager-specific controls and, ϕ_t is year fixed effects, respectively. The coefficient on $\log k_m$ is the elasticity of the change in output of an allotted agent with respect to the log of team output per worker in 2012. An interpretation of positive β is the value added by a manager to her agents.

Table 1.5 presents the results of the above empirical model. Value of β is 0.88, which appears strikingly high; a manager with a one percent point higher ability increases the output of allotted workers by 88%. An effect of this magnitude requires further exploration.

I investigate the distribution of the above result in Figure 1·8. The vertical axis represents the change in the log output of allotted agents, and the horizontal axis is the log of team output per worker of the team in 2012 to whom such agents were allotted. I also impose a linear fit on the scatter plot.

The linear curve has a positive slope. However, Figure 1·8 suggests that the manager effect is noisy. A few outliers could be driving the positive slope. The spike in the performance of such agents might also be due to idiosyncratic productivity shock and not due to the managers. Further, the average number of allotted agents per manager is 2.15, adding more evidence for the noisiness of the effect.

To address this concern and to arrive at a result robust to such noise, I compute empirical Bayes estimates of the manager fixed effects. These manager fixed effects are obtained from the following regression:

$$\log y^A_{amb} - \log y^O_{amb} = \phi_m + \phi_t + \epsilon_{amt}$$

An empirical Bayes (EB) estimate for each manager is a weighted average of manager's fixed effect, $\hat{\phi_m}$, and the mean of $\hat{\phi_m}$. In the current context, weight on manager fixed effect would vary proportionately with the number of allotted agents per manager and inversely with within-manager variation in output change of allotted workers. Thus, managers which provide more information about alloted agents would receive higher weight and the ones which provide noisier information would receive lower weight. Appendix A.6 provides details for derivation of empirical Bayes estimator. For a detailed discussion and application of empirical Bayes estimator, see Guarino et al. (2015).

Figure 1·9 plots the EB estimator as a local polynomial curve of log of team output per worker in 2012. A scatter plot is also provided. The mean of EB estimates (represented by a red line) for the manager in the upper 10th percentile is significantly greater than zero, indicating that these managers are able to add value to the productivity of the allotted agent. Thus, guidance, supervision, or monitoring by very high-performing managers may be a significant component in the productivity of her agents.

Heterogeneity of manager effect between the bottom 90% and top 10% of the managers can also be explored using the following model:

$$\Delta \log y^{A}_{amb} = \beta_1 \log k_m * \mathbb{1}\{Bottom90\%\} + \beta_1 \log k_m * \mathbb{1}\{Top90\%\} + \mathbb{1}\{Top90\%\} + \kappa X_m + \phi_t + \epsilon_{ambt}$$

where, $\Delta \log y^{A}_{amb}$ is the change in log output of allotted agents, $\mathbb{1}\{Bottom90\%\}$ and $\mathbb{1}\{Top10\%\}$ are indicators for managers in the bottom 90% and top 10%, respectively. In column (2) of Table 1.5, $\beta_1 \neq \beta_2$ and $\beta_2 > 0$, suggesting that the top 10% managers are able to increase the output of their allotted agents whereas the bottom 90% are unable to do so[9].

1.3.3 Output Change for Orphaned Agents

Managers might also differ in their ability to track, monitor, and enforce agents to work continuously. Equivalently, managers might accompany agents to "pitch" a product to a potential client. To test this hypothesis, one can record the change in an agent's output

[9]Alternatively, I use the estimator from Gregory and Hansen (1996) to endogenously find structural breaks in level and slope of change in output of allotted agents with respect to the index of managerial productivity. Results are similar.

when his manager leaves.

In the year 2015, six managers in the firm exited. In Figure 1·10, I plot the change in the log of output of each orphaned agent when his manager left against the log of output per worker in 2012. Out of the six managers who exited, only one was a high-performing manager. The output of the agents of this manager decreased whereas the output of other agents did not change. This result adds weight to the view that high performing managers provide some form of supervision or guidance to their workers.

1.3.4 Manager's Product and Market Strategy

Managers have considerable decision-making power in choosing which product to sell and which customer demographics to target. Differences in the richness of information over sub-local demand conditions may drive output dispersion across managers. Such customer heterogeneity will be reflected in the product features of the agents and teams of the managers. As described in Section 1.2, I construct three metrics of product portfolios: type, average value, and average cost of products sold.

In Table 1.6, I regress these three variables for newly recruited agents on the log of team output per worker in 2012, along with other manager-specific controls and branch and time fixed effects. In each model, the coefficient on log output per worker in 2012 is close to zero with a small standard error, ruling out customer and demand heterogeneity across managers.

Managers might also differ in specializing their workforce. For instance, a manager might be good at discerning her agent's propensity of selling to a consumer group based on age, class, caste, etc. If so, a manager would get more out of such an agent than the one with no particular group to target, potentially contributing to output dispersion[10].

To test this hypothesis, I construct a metric of each agent's specialization, which is the

[10]Implicit assumption being differences in agent's propensity to target a customer group. This propensity can be considered as one dimension of productivity

following:

$$s^f_{ambt} = |f_{ambt} - E_m(f_{ambt})|$$

where f_{ambt} is agent a's product feature (type, cost and value) and $E_m(f_{ambt})$ is the intra-team mean of that product feature. An agent's specialization is thus the mean absolute deviation of the agent's product feature. I regress new agent's specialization of each product feature on the log of managerial output in 2012 along with other manager-specific controls and branch and time fixed effects. I also control the team's mean of the product features in each model which holds the point of reference of standard deviation constant. A positive (negative) coefficient on log of output per worker in 2012 would indicate higher specialization (generalization) of her agents by the manager. Table 1.7 provides the results. The coefficient on the log of output per worker in 2012 remains close to zero for each of the product features.

Thus, to the extent that the data allows, market and product heterogeneity can be ruled out within and across teams[11].

Summary of Key Results

I find that: 1) performance of new recruits is strongly correlated with the metric of manager's ability; 2) when an orphaned agent is allotted a manager, his output increases only when joining a manager in the top 10% of output per worker whereas no change is observed for others; 3) when an agent becomes orphaned due to the exit of his manager, his output declines only when his manager was in the top 10% of output per worker in 2012; and 4) agents within or across teams are not heterogeneous in their product features. Evidence 1, 2 and 3 indicate that 90% of the managers vary in the selection of their agents, whereas the top 10% also contribute to an agent's productivity[12]. Evidence 4 rules

[11]Same result holds true when I consider the sample of all agents as seen in Table 1.8 and Table 1.9.

[12]Peer effects may also be a plausible reason for this result. While peer effects cannot be fully ruled out, average team size is 42 and agents seldom work together. This makes peer effects less likely in the given context.

out market heterogeneity or agent specialization across managers as a potential source of output dispersion.

How likely is the managerial skill of agent selection to be the primary reason for the difference in team output? Similarly, how likely is it that top performers stand out in their skill of increasing an agent's output? Through a meta-analysis of 116 empirical studies, Churchill et al. (1985) found the productivity of the salesperson was the second most important determinant of sales performance in terms of average correlation with sales outcome. However, the same study mentions that no single predictor is sufficient to explain significant variation in a salesperson's performance. Thus, multiple factors collectively contribute to an agent's output. These other factors might be the contribution of the managers in the form of supervision, guidance, monitoring, etc.

These results and the brief discussion above do not disallow other competing mechanisms. Any hypotheses where the output is a function of agent-manager match quality, rather than agent effect, can provide these results. For instance, consider that managers can only train the agents that they recruit and not the ones they receive through allotment. In such cases, selection of agents and training are intertwined and cannot be separated.

A conclusive test to differentiate between agent's productivity and manager's contribution in the output of an agent is possible if a new recruit of a manager is randomly assigned to a different team at the date of joining. Institutional mechanics do not allow this experiment. Nevertheless, in Appendix A.7, I test some alternative hypotheses of managerial contribution in an agent's output and some robustness tests. For instance, if managers differ only in the selection of agents, then the output gap between their recruited agents should appear immediately and then remain stable over time. On the other hand, if managers differ in training, then the output gap between new recruits should diverge. In Appendix A.7.1, I test this hypothesis to show that the output gap across new recruits remains stable over time. If an agent's production were a function of individual attention provided by managers, then output and number of new recruits in a team should be negatively related (rejected in appendix A.7.2); or, if training were effective only at the beginning of an agent's career, then managers must be using discretion to retain some workers to train them next year (rejected in Appendix A.7.3).

1.4 Theoretical Framework

In this section, I will present a model of agent screening by managers. I focus only on the screening role of the managers since, from the results above, I find that 90% of managers vary in their skill of recruiting productive workers. The model serves two purposes. First, given the institutional settings, it rationalizes how managers may differ in the screening of their new recruits, as found above. Second, given this comparative static result, the model provides implications on empirical patterns that should hold true across managers.

Consider a firm where managers recruit an agent in each period, who carries out production. An agent's production function takes the following form:

$$y_a = \theta_a$$

where θ_a is the productivity of the agent (unknown to the agent before being recruited). The agent's pay-off is sy and the manager receives $(1 - s)y$, where $0 < s < 1$ [13]. Agents are of two types: θ_L with mass q and $\theta_H (> \theta_L)$ with mass $1 - q$.

Before recruiting an agent, a manager assesses a candidates on the basis of a noisy signal of his true productivity. This signal takes two values, $\hat{\theta}_a \in \{\hat{\theta}_L, \hat{\theta}_H\}$. Consider this signal to consist of all information about the candidate's suitability for employment in the firm, such as a description of previous work experience, schooling, temperament,

[13] Rao (1990) demonstrates that an optimal compensation scheme for heterogeneous sales force consists of a commission rate and quota-based bonus.

behavior etc.. The signal is observed with the following conditional probability:

$$Pr(\hat{\theta}_k|\theta_j, k \neq j) = p \tag{1.1}$$

(1) can be interpreted as the probability of a "wrong" signal; i.e. if the agent's actual productivity is $\theta_L(\theta_H)$ then with probability p, the manager receives a non-corresponding signal $\hat{\theta}_H(\hat{\theta}_L)$.

I make the following assumptions

Assumption-1: Signals are independent across workers and over time.

Assumption-2: $0 < p < \frac{1}{2}$

Assumption-3: Signals are costless to managers.

Assumption-4: Manager recruits one agent in each period.

Assumption-5: At each time period t, agent receives $y_o^A + \epsilon$ as outside option where $\epsilon \sim N(0, \sigma^2)$ is iid.

Assumptions 1 simplifies the analysis. Assumption 2 puts a bound on the noisiness of the signal; it states that, while neither signal determines the agent type with certainty, $\hat{\theta_L}$ ($\hat{\theta_H}$) is more likely to come from θ_L (θ_H). Assumption 3 states that the manager can observe as many candidates as possible before choosing someone for recruitment.

Assumptions 4 and 5 reflect institutional features of the subject firm and the Indian insurance industry. In the subject firm, a manager chooses a candidate for agency in the firm who has to undergo a 50-hour training program and an online exam organized by the insurance regulator. The firms bills the training cost for each recommended candidate as a manager's operational expense and the online exam is held only four times a year[14]. Since recruitment opportunities are costly and infrequent, each managers wants to assess many agents (Assumption 3) but is restricted in the number of agents she can finally recommend (Assumption 4). This latter assumption also has empirical support - Table 1.10 shows that

[14] Appendix A.2 provides more institutional details.

managers do not vary significantly in the number of agents they hired in the years 2013-2015. Assumption 5 states that the productivity of the agents is firm-specific. This feature can also be ensured if agents face a transaction cost while moving away from the subject firm. Appendix A.9 describes some features of the firm that differentiate it from others in the industry.

1.4.1 Comparative Statics

Manager observes signals of agents and chooses an agent who would maximize the expected output; i.e. manager's problem is :

$$Max_{\hat{\theta_a} \in \{\hat{\theta_L}, \hat{\theta_H}\}} E(\theta|\hat{\theta_a}) \tag{1.2}$$

Given Assumption-3, $E(\theta|\hat{\theta_H}) > E(\theta|\hat{\theta_L})$[15]. Since signals are costless (Assumption-2), managers would wait until an agent with signal θ_H is observed. Assumption-1 implies that the manager will recruit the first worker with signal $\hat{\theta_H}$, since any other agent with $\hat{\theta_H}$ would have the same expected outcome.

Thus,

$$Max_{\hat{\theta_a} \in \{\hat{\theta_L}, \hat{\theta_H}\}} E(\theta|\hat{\theta_a}) = E(\theta|\hat{\theta_H}) = \alpha\theta_H + (1-\alpha)\theta_L \tag{1.3}$$

where

$$\alpha = Pr(\theta_H|\hat{\theta_H}) = \frac{(1-p)(1-q)}{(1-p)(1-q)+pq}$$

Thus, expected outcome for a manager is the weighted average of an agent's true productivity, where the weights are posterior distribution of the agent's type given his signal $\hat{\theta_H}$. Given Assumption-3, α increases as p decreases. Thus, if a manager has a less noisy signal, she is expected to recruit better workers and thus have higher $E(\theta|\hat{\theta_H})$.

[15]Proof provided in the Appendix

1.4.2 Dynamics

In each period, managers observe a new worker[16]. Given Assumptions 1, 2, 3, and 4, the manager repeats the same decision-making process in each period as in the static case. Thus, for each t, average productivity of the recruits of a manager stays the same as equation (3).

Testable Implications

Under the dynamic setting, the model provides four testable implications. I will provide the intuition for the results here. Proof can be found in the Appendix A.8.

Testable Implication-1:

The exit rate of agents of better informed managers is lower.

Under Assumption-5, an agent's outside option in each period is $y_o^A + \epsilon$. An agent realizes his productivity after working for one period. An agent would exit if his outside option is greater than his payoff in the firm; i.e., $s\theta_a < y_o^A + \epsilon$. Given that more able managers—ones with lower p (or higher α)—recruit more productive workers, teams of such managers would observe lower exit rate of agents.

Testable Implication-2:

The team size of better-informed managers is bigger.

The team of a manager at a given time is the set of agents who were recruited by that manager. Team size is the number of agents in this set. By Testable Implication-1, managers with better prior recruit more productive workers who are less likely to exit. Thus, with time, managers with better prior would have bigger teams.

Testable Implication-3:

Team size is increasing and concave with respect to the tenure of managers.

[16] In this paper, I abstract away from any learning or experimentation by managers.

Under Assumption-4, managers recruit only one worker each period. However, each agent faces a non-zero probability of exit. Initially, team size grows as the number of new recruits is greater than the exiting agents. Over time, as team size grows, the proportion of exiting agents counter-weighs the inflow of recruited agents. Thus, the team size of a manager increases initially and then plateaus as tenure increases[17].

Testable Implication-4:

Team output exhibits increasing returns to scale with respect to team size.

This result follows from the result of comparative statics, testable implication 1 and 2. Managers with better prior recruit more productive workers who are less likely to exit and thus form bigger teams. Bigger teams are, therefore, composed of more productive workers. Hence, team-output will increase more than proportionately with the size of the agents in the team, leading to convexity in the relationship between output and input.

Discussion of the Model

This model has some explanatory power that other models of recruitment do not. For example, if managers recruited workers until marginal productivity of the last worker was equal to the wage, then the positive relation between average output of the team and team size would depend on the functional form of the production function. In Appendix A.10, I provide an example. Further, models where managers acted as private good (Lazear et al. (2015)) or were engaged in monitoring (Calvo and Wellisz (1979)) will also not provide implication 2.

In the subject firm, recruitment is delegated to the managers and the cost incurred in training is also transferred to the managers (Appendix A.2). The subject firm, thus, rewards a manager if her private information over agent productivity is good and penalizes her if this information turns out to be poor. In this sense, the above model serves to capture the essence of private information of the manager over agent productivity. Any

[17] Calvo and Wellisz (1979) and Garicano and Rossi-hansberg (2005) are other studies which investigate the reasons for limits to span of control.

other model where managers possessed private information about the selection of agents may provide the results without adding any significant explanatory power.

1.5 Results on Testable Implications

I will use the following notation: k_m for output per worker in 2012, X_m for manager-specific controls and X_a for agent-specific controls (which will be described in the given context), ϕ_b and ϕ_t for branch and time-fixed effects.

1.5.1 Exit Rate

Consider the following model:

$$\mathbb{1}_{ambt}\{Exit\} = \beta \log k_m + \kappa K_m + \gamma K_a + \phi_b + \phi t + \epsilon_{ambt}$$

where $\mathbb{1}_{ambt}\{Exit\}$ is an indicator variable for exit of agent a (equal to 1 if agent left the firm and 0 otherwise) under manager m in branch b at time t. K_m and K_a are manager and agent-specific variables, respectively. The hypothesis is $\beta < 0$, i.e., agents of more able managers (higher k_m) are less likely to exit.

Table 1.11 provides the results. In Column (1), I use only the log of output per worker as an explanatory variable. Column (2) controls for tenure, tenure squared, and gender of the manager. In both regressions, the coefficient on the log of output per worker in 2012 is significantly negative: a manager with a one percent higher output per worker observes 4.7 -7.4% lower exits of agents. This coefficient is close to zero when I control the output and revenue of products sold by the agent (Column (3)), which is consistent with differential selection of agents by managers. A reflection problem exists in Column 3 since k_m is composed of the agent's output in 2012. To avoid this concern, in Column 4, I use the leave-one-out output per worker for each team as a proxy for k_m; i.e. I regress each agent's exit indicator on the log of team output per worker, leaving out that agent's output from the computation. Results are similar to those in column 3.

Tenure of the agent is endogenous to exit propensity, which may also drive output. To address this concern, I explore the exit propensity of only newly recruited workers[18]. By design, tenure is the same for all the agents in this sample. Table 1.12 provides the results. In Columns (1) and (2), when agent's performance variables are not included, coefficient on log of output per worker in 2012 is significantly negative and comparable to Columns (1) and (2) of Table 1.12. The significance of this coefficient vanishes in Column (3), when output and value of agent's sales are included (although the magnitude is still large). Exit rates of agents are different across managers and explained by productivity of the agent.

Agent's output drives exit propensity. In the firm, agents receive piece-rate compensation. Lazear (2000) shows how a piece-rate incentive scheme in a large auto glass company attracts and retains high productivity workers. However, in the subject firm, good managers form the conduit for the entry of productive workers, thereby adding to the effectiveness of piece-rate compensation. This can be interpreted as reduction in transaction costs by managers (Crook et al., 2012). Stability of the match between workers and firms is also an important resource for the firm if productivity increases during the tenure of the worker[19].

1.5.2 Team Size Growth

Consider the following model:

$$\log n_{mbt} = \beta \log k_m + \kappa_1 t_m + \kappa_2 t_m^2 + \phi_b + \phi_t + \epsilon_{mbt}$$

[18]As explained above, when a new recruit sells less than 12 products or total products less than Rs. 100,000, she can be fired by the manager. Thus, in Table 1.12 I restrict analysis to those new recruits who clear this cut-off since exit of such an agent is solely her decision and not confounded by manager's decision.

[19]The model can be extended to include this aspect of productivity without any substantial gains in its explanatory power about current empirical facts.

where n_{mbt} is team size of manager m and t_m is tenure of the manager. I use robust standard errors. Hypotheses are $\beta > 0$ and $\kappa_2 < 0 < \kappa_1$: teams of more able managers are bigger and team size exhibits concavity in manager's tenure.

Table 1.13 provides the results. The coefficient on the log of team output per worker in 2012 is significantly positive, suggesting a strong correlation between manager's prior on agent productivity and team size. Further, in Column (2), the coefficient on tenure and tenure square are significant, with $\kappa_2 < 0 < \kappa_1$. Thus, controlling for manager's ability, team size grows faster initially, but growth decreases as managers acquire tenure.

These results illustrate the role of the manager in determining the size of the input for production. While managers may not differ in size of input at the beginning of their careers, input inequality across managers arises over time. Thus, the scale of operation can vary across units even without any variation in management practice. Growth in the size of the operation is limited by the tenure of managers. Teams grow initially with tenure of the manager. Eventually, enough agents exit each year limiting the growth of teams. Correlation between tenure and output, thus, may arise without the need of invoking human capital or match quality theories of tenure, though this does not refute the presence of managers' human capital.

Growth in team size may also occurs due to variation in number of recruits. In Table 1.10, I show that managers do not differ significantly in their number of entrants, suggesting that team size growth occurs primarily due to agents' exit propensity of agents as posited in the model.

1.5.3 Team Output and Team Size

Consider the following model:

$$\log Y_{mbt} = \beta_1 \log n_{mbt} + \kappa X_m + \phi_b + \phi_t + \epsilon_{ambt}$$

where Y_{mbt} is team output of manager m and X_m consists of polynomial terms of tenure and gender of the manager. I use robust standard errors. The hypothesis is $\beta > 1$.

Table 1.14 provides the results. In Column (1), I use the log of team size as an explanatory variable. The coefficient on the log of team size is significantly greater than 1. In Column (2), I control for tenure and tenure square as well. Production function still exhibits increasing returns to scale. In Column (3), I use manager fixed effects. Coefficient on log team size is 1.17 and cannot be rejected from being greater than 1.

The results provide a novel explanation for increasing returns to scale. Such convexity of production may also occur due to other reasons. For example, each agent may target a specific market segment, thereby acquiring the expertise to make more sales. A team with more agents can, thus, target more segments. However, as described in Table 1.9, agents within a team do not differ in the nature, value, and cost of products they sell. Another cause of convexity in team output and team size is economies of scale, where a threshold of agents are required to attain a dominating production function. However, the individuality of the tasks performed by salesmen makes such positive spillovers within a team less likely.

This result and the result on team size growth hold interesting implications regarding variation in income payments across managers within firms. While there is growing inequality in both input and output across managers over time, output increases more than proportionately with team size. Since managers' income is linked to aggregate team output, income inequality across managers is more pronounced.

1.6 Conclusion

In this paper, I show wide dispersion in the output of manager-led teams of salespersons in a life insurance firm in India, even after controlling for team size, tenure, gender, and the office location of the manager. Managers perform several tasks when organizing and building their teams. Output dispersion could be a result of any of these managerial tasks or an aggregate effect of a combination of these tasks. Differences in the performance of new recruits across managers are significantly positive with respect to the index of managerial productivity and remain robust to different specifications. Evidence for managers providing training, supervision, or guidance (Section 1.3.2 and 1.3.3) is substantial, but only for managers in the upper 10th percentile (high-performing managers). These two results taken together indicate that differences in the selection of workers could be a potential reason for differences in productivity for most managers. However, managerial contribution in the form of training, supervision, or guidance by high-performing managers cannot be ruled out.

Given the institutional details of the subject firm, I develop a model of agent screening by managers. The model provides a mechanism of how the managers in the firm may differ in selection of their new recruits. Given this comparative static, the model provides testable implications that should hold across teams. These implications are: 1) a differential exit rate of workers across managers,; 2) team size growth with respect to manager's expertise and tenure, and 3) a convex functional relation between team-output and team size. All implications hold true in the data. Thus, the agent- and team-level empirical patterns observed in the firm are consistent with a model of agent screening.

This chapter is agnostic about learning by managers, i.e., whether the managerial skill of recruiting improves over time. In Chapter 2, I categorize the managers of this firm into two types: internally-hired, those who were agents before becoming managers, and externally-hired, those who joined from outside the firm. I find that teams of internally-hired managers are 14% more productive. Further, I find evidence that externally-hired managers learn how to recruit better agents, diffusing the output gap. This result sheds light on human capital, in the form of tenure, as one component of managerial productivity.

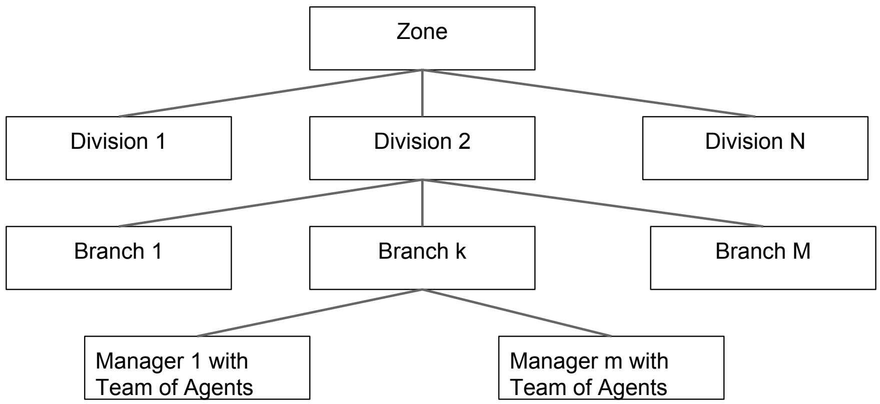
In the subject firm, a small set of managers can increase the output of their allotted agents. Thus, some managers differ in their skill-set, not merely along one skill. If managers within a firm differ in their areas of capabilities, can gains be obtained from specialization? For instance, can the firm divide their managerial pool into two types depending on the tasks they perform - one that specializes in recruiting and the other that specializes in supervision or guidance? This exercise would result in variation in management practices within a firm—an observation which was recently documented in Bloom et al. (2017). Furthermore, many organizations do have functional hierarchies with specialized managers, e.g., sales, marketing, etc., which are perhaps exploiting managers specialized in a skill. Functional hierarchies may thus be considered as an endogenous outcome of the differences in managerial skills.

The chapter's main contribution, however, is to demonstrate that what managers can do (individual know-how) is essential alongside what managers are allowed to do (management practices). Whether the skills of managers matter more than the tools themselves, or vice versa, cannot be answered by the chapter in its present form. The literature on management practices exploits its variation across firms. In the subject firm, management practices do not undergo a significant change during the period of observation. However, a hypothetical exercise may throw light on the connection between heterogeneity in managerial skill and management practice. In the firm, managers cannot alter the incentive/compensation scheme of the agents (one of the practices recorded in World Management Survey (WMS)). Assume that managers were allocated a budget to reward their agents for good performance. What would we expect? One prediction is that all managers could increase the output of their agents through incentives, thereby increasing the aggregate output in the firm. But managers may differ in how they reward agents, thereby increasing the variance of performance. Managers may also vary in providing incentives within a team. For instance, if they differ in spotting talent (as postulated here), they may attract even higher quality workers. Or agents within a team may engage in influence activity, leading to wasteful outcomes (Milgrom (1987) and Milgrom and Roberts (1987)).

This hypothetical exercise raises another question: How would changes in management practice affect the managerial pool? For instance, the subject firm does not allow managers to alter compensation schemes. Does this prevent some managerial candidates from joining the firm? More generally, if managers know their talents and skills, do they sort themselves in the firm that provides them with the power to exploit their capabilities? If yes, then the firms with a higher management score may attract more able managers where these managers can exploit their skill. If managerial talent is in short supply, productivity dispersion across firms may persevere—a mechanism (one of many) for Persistence Performance Differences across Seemingly Similar Enterprises (Gibbons and Henderson, 2014). This line of reasoning finds theoretical (Bond, 2017) and empirical support (Friedrich, 2015).

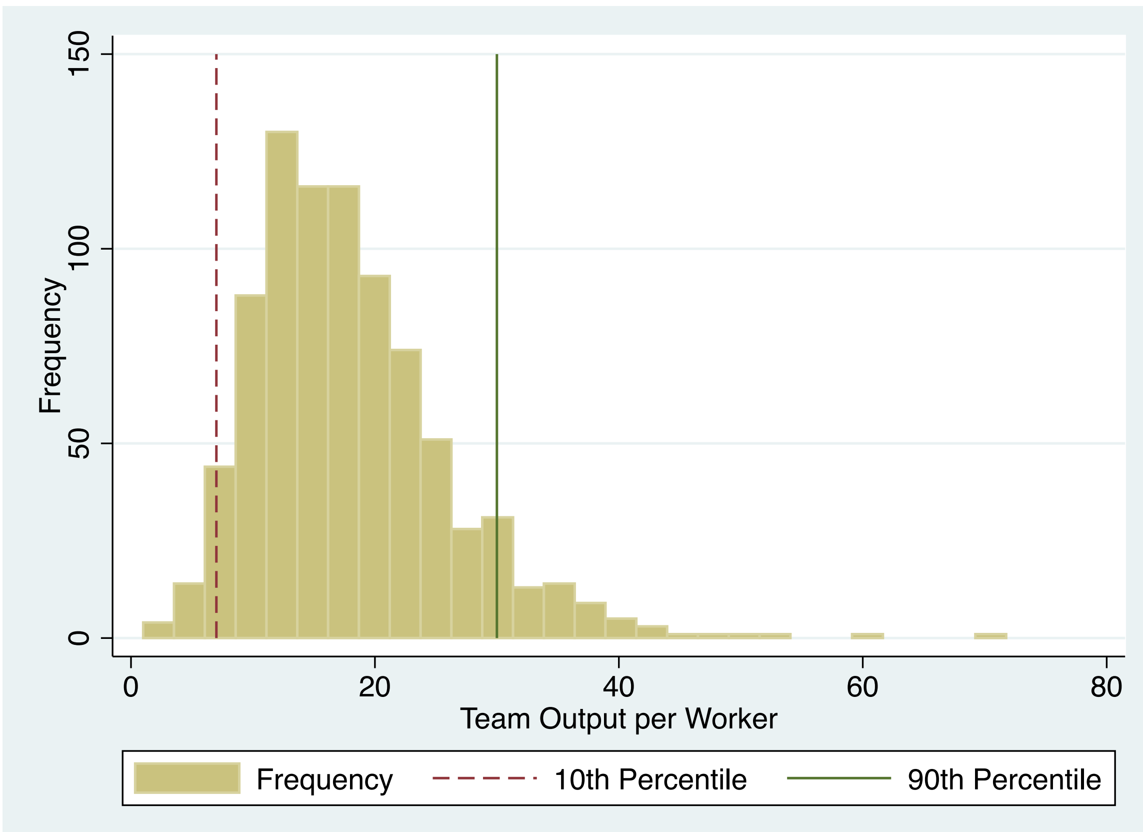
1.7 Figures

Figure 1·1: Organization Structure



The firm is divided into nine geographic zones across India which have in total 133 divisions with 2048 local-level branches. A branch is the smallest administrative unit of the firm with multiple manager-led teams of salespersons. In this paper, all data comes from one division in the city of Delhi with 24 branches and 211 manager-led teams.

Figure 1·2: Distribution of Output per Worker



Observations are at the manager-year level. This figure is the distribution of output per worker of teams. The solid green line represents the team at the 90th percentile and the dotted red line denotes the team at the 10th percentile. Ratio between team output at 90th to 10th percentile is five.

Figure 1·3: Binned Scatter Plot between Output per Worker and Team Size

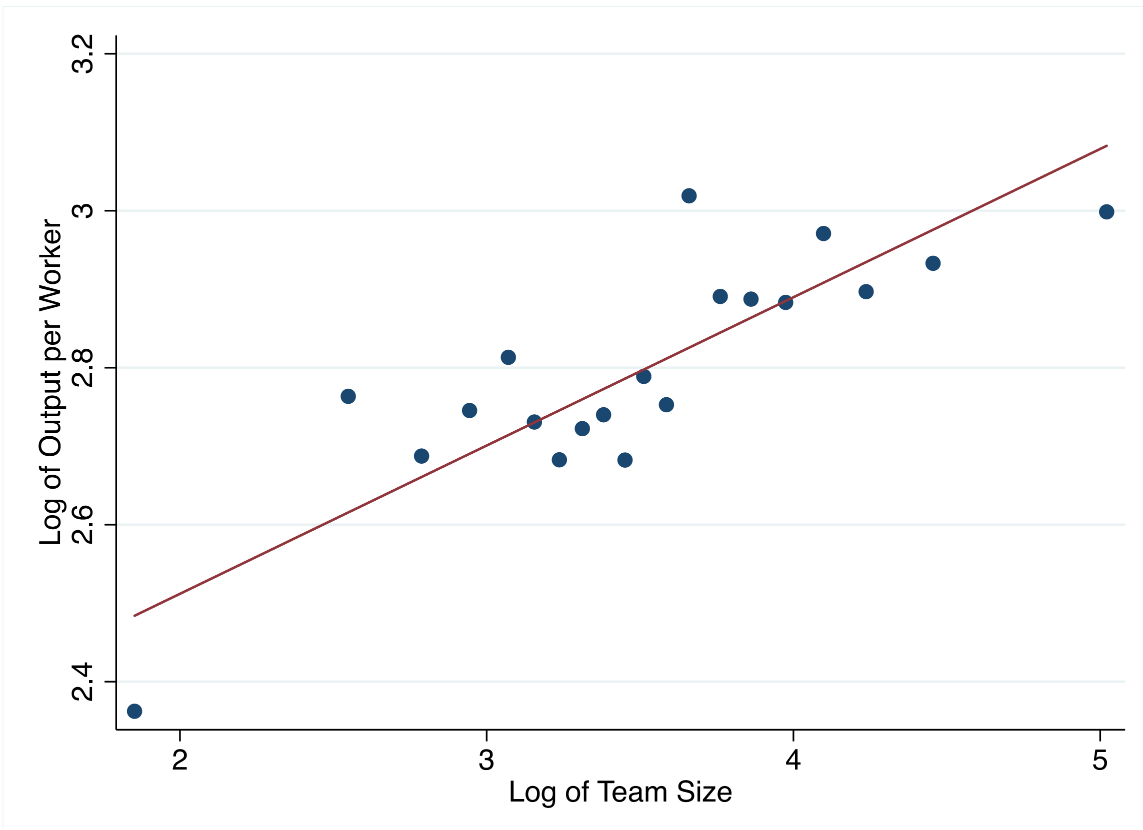
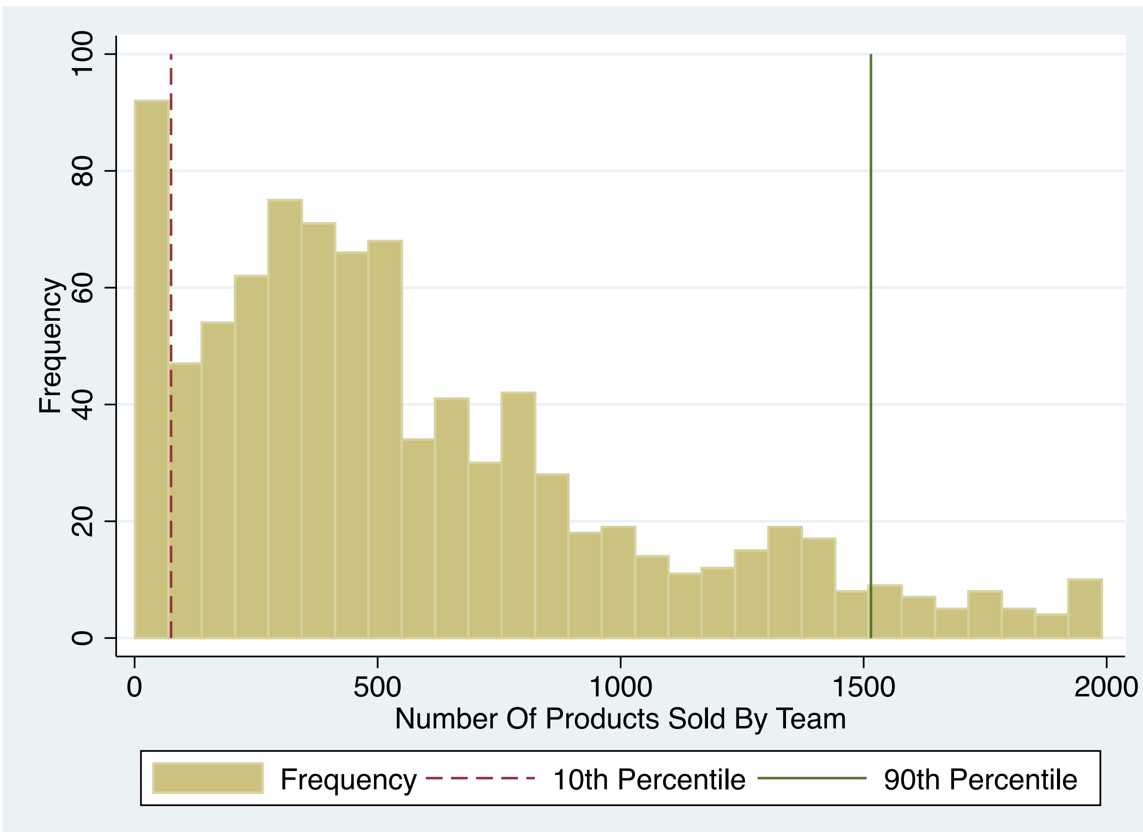
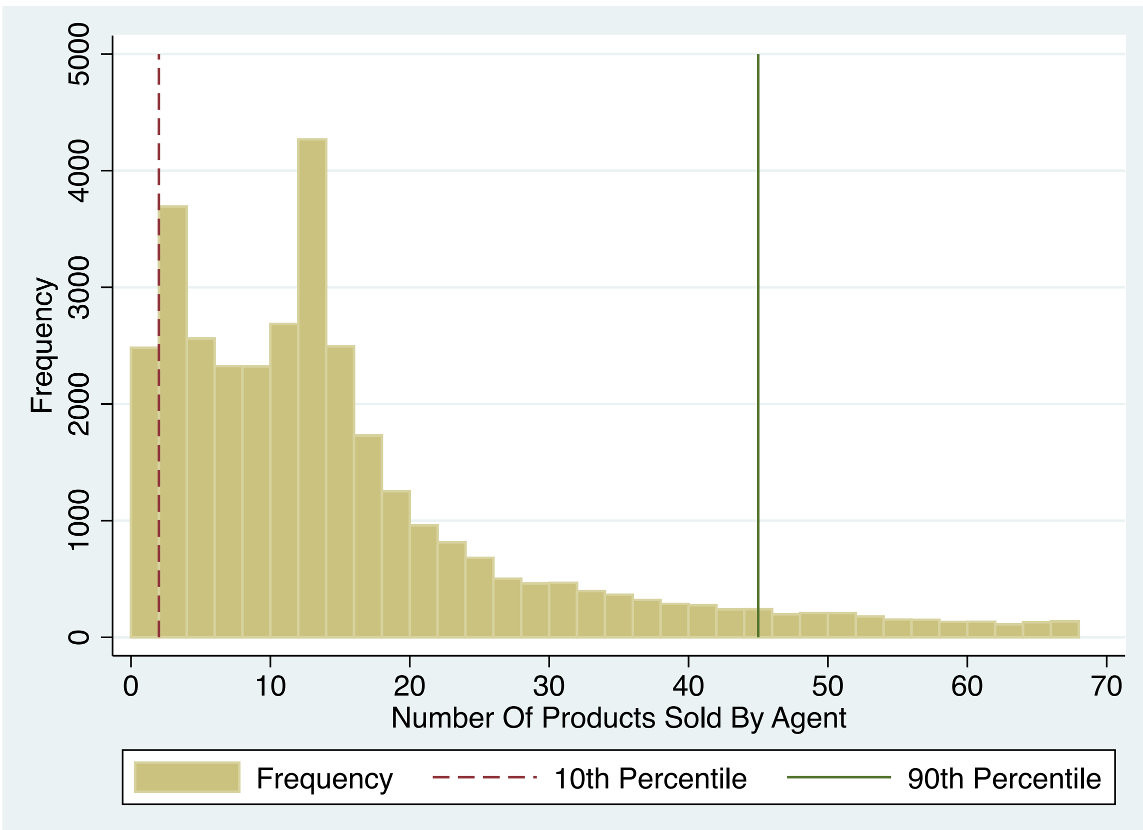


Figure 1·4: Distribution of Team Output



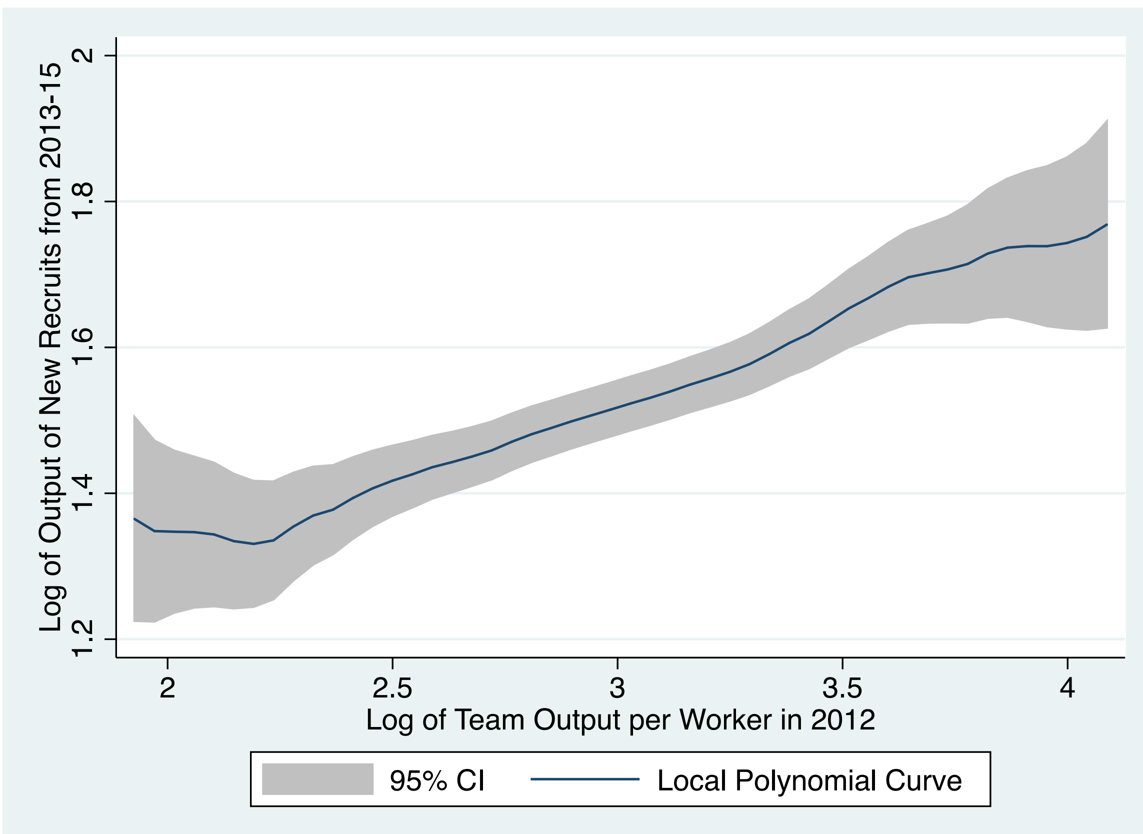
Observations are at the manager-year level. The solid green line represents the team at the 90th percentile and the dotted red line denotes the team at the 10th percentile. Ratio between team output at 90th to 10th percentile is twenty.

Figure 1·5: Distribution of Agent Output



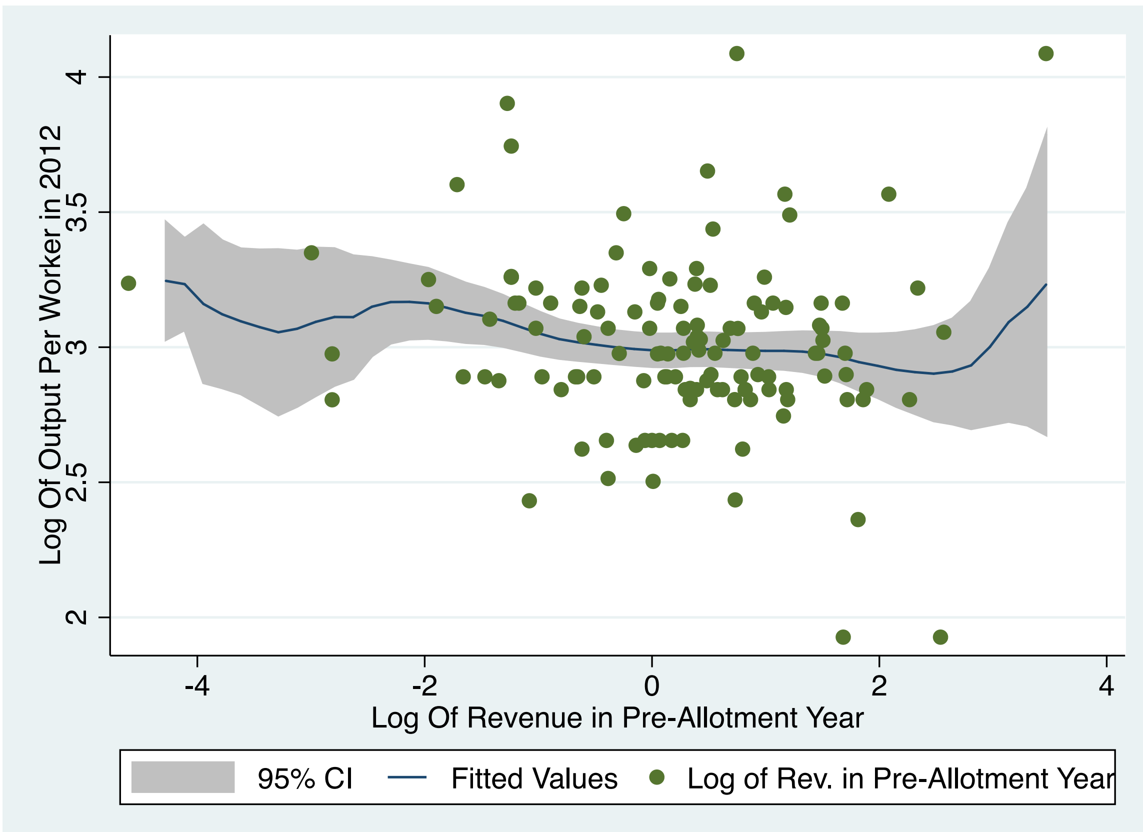
Observations are at the agent-year level. The solid green line represents the agent at the 90th percentile and dotted red line represents the agent at the 10th percentile. The ratio between agent output at 90th to 10th percentile is 20.

Figure 1·6: Performance of Newly Recruited Agents (2013-2015)



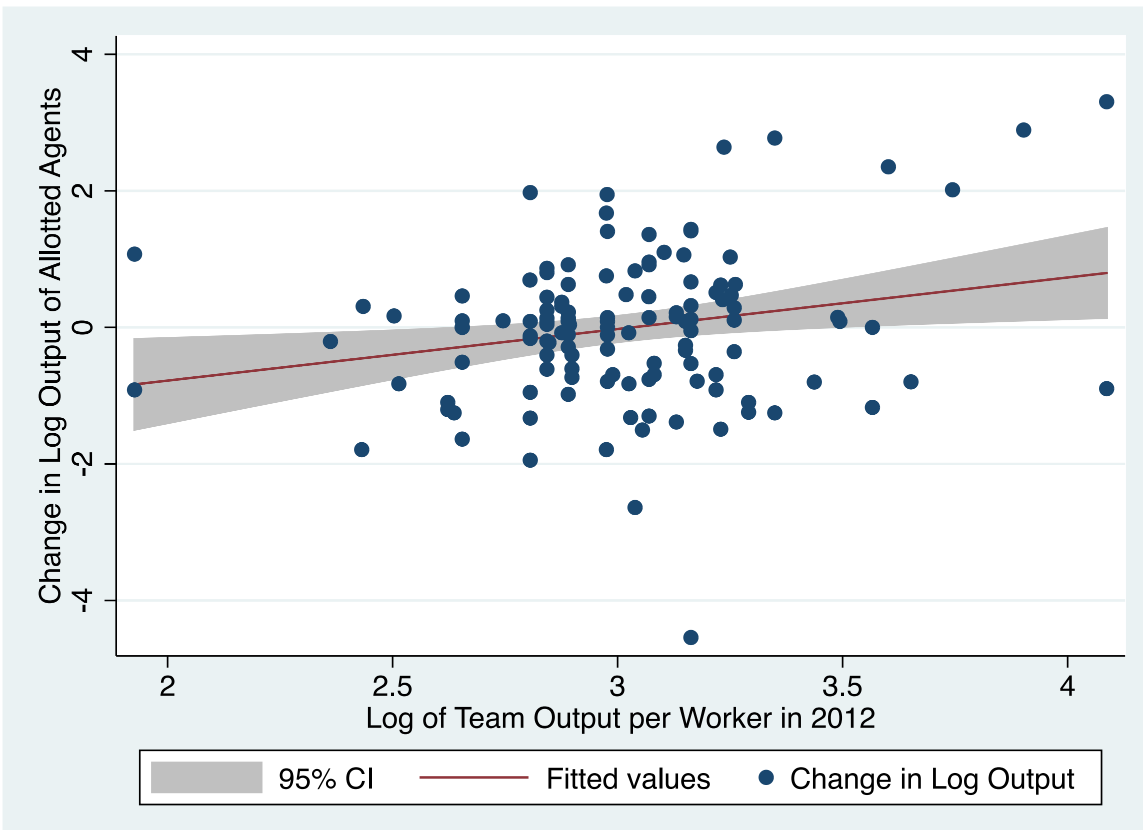
Vertical axis measures the log of output of newly recruited agents in the first year of his career. Horizontal axis measures the log of output per worker in 2012 of the team that the new recruit joins.

Figure 1·7: Matching between Orphan Agents and Managers



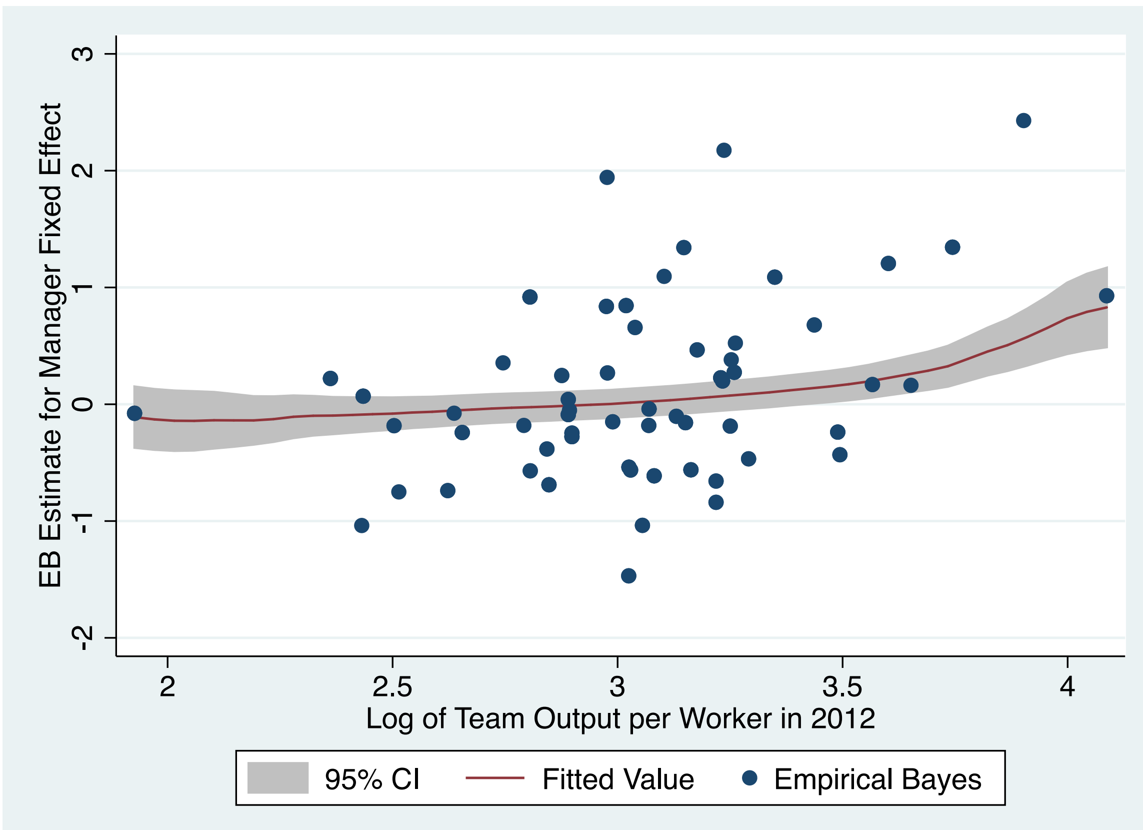
Horizontal axis measures the log of revenue of allotted agents in the year prior to allotment. Vertical axis measures the log of output per worker in 2012 of the team that the orphan agent joins.

Figure 1·8: Change in Output of Agents before and after allotment (2013-2015)



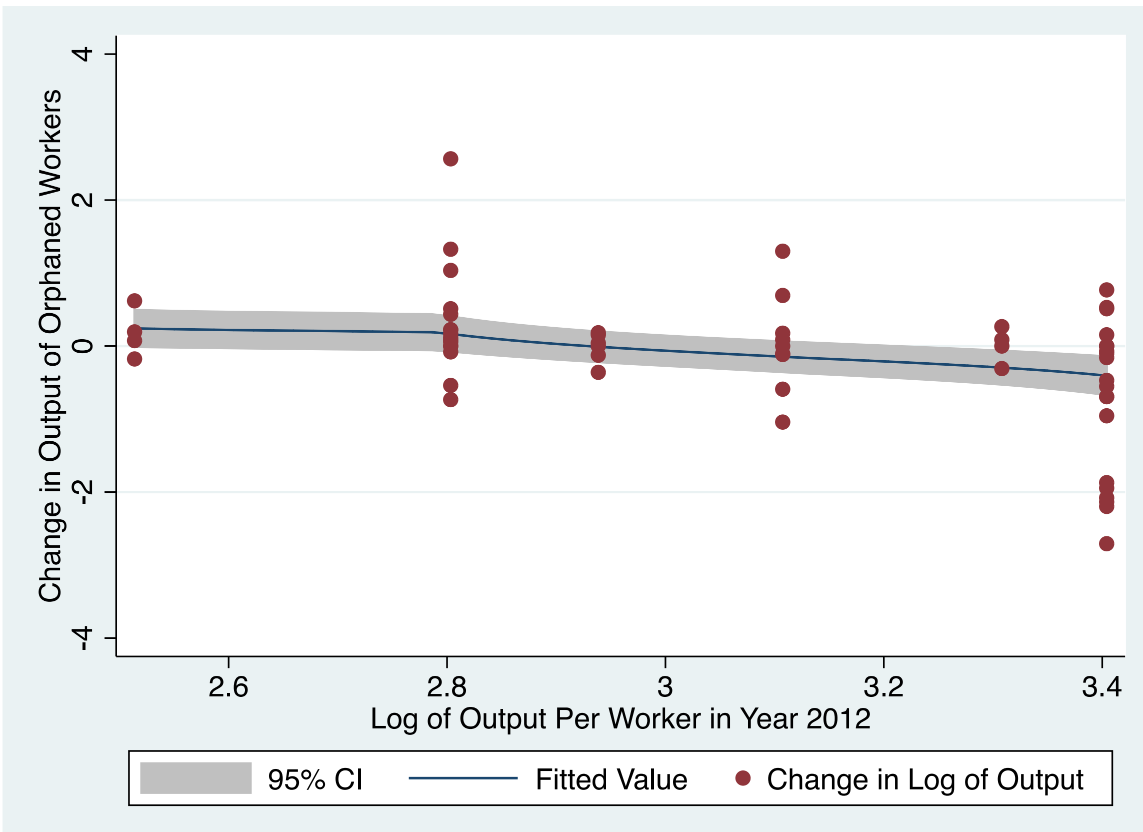
Vertical axis measures the difference between the log of output of allotted agents before and after allotment in the years 2013-2015. Horizontal axis measures the log of output per worker in 2012 of the team which the alloted agent joins.

Figure 1·9: Empirical Bayes Estimators of Manager Effect in Output Change of Allotted Agents



Vertical axis measures Empirical Bayes Estimator of Manager-Value Added to allotted agents. Horizontal axis measures the log of team output per worker in 2012.

Figure 1·10: Change in Output of Agents before and after being orphaned



Vertical axis measures the difference between the log output of orphaned agents before and after being orphaned in year 2015. Horizontal axis measures the log of team output per worker of the managers who exit. Note: 3 of the 6 exiting managers were hired in 2013.

1.8 Tables

Table 1.1: Summary Statistics

Panel A: Managers			
	Mean	SD	Observations
Output	834.306	1391.763	841
Revenue (Rs.)	158.718	272.663	841
Amount Insured (Rs.)	22.319	39.302	841
Manager Tenure	16.264	8.952	841
Team size	42.551	41.246	841
Output per Worker	17.792	7.805	841
Panel B: Agents			
	Mean	SD	Observations
Output	20.066	36.899	39875
Revenue (Rs.)	4.101	17.238	39875
Amount Insured (Rs.)	0.554	1.457	39875
Agent Tenure	7.759	7.444	38811
Panel C: Output Per Worker in 2012			
	Mean	SD	Observations
Output per Worker	20.800	7.644	211

Output is the number of products sold. In Panel A and Panel B, observations are at the manager-year and agent-year level, respectively.

Table 1.2: Decomposition of Agent Output

Dpdt. Var. : Log of Agent Output				
	(1)	(2)	(3)	(4)
Year Fixed Effect	Yes	No	No	Yes
Branch Fixed Effect	No	Yes	No	No
Manager Fixed Effect	No	No	Yes	Yes
Observations	39875	39875	39875	39875
R^2	0.022	0.011	0.089	0.106
Adjusted R^2	0.022	0.011	0.082	0.099

Sample of all agents from 2012-15.

Table 1.3: Performance of Newly Recruited Agents (2013-2015)

Dpdt. var.: Log of Output of a New Recruit		
	(1)	(2)
Log(Team Output Per Worker in 2012)	0.246***	0.237***
	(0.048)	(0.058)
Manager Tenure		0.012
		(0.014)
Manager Tenure Square/100		-0.038
		(0.044)
$\mathbb{1}\{Male\}$		0.061
		(0.343)
Observations	4382	4382

Sample of newly recruited workers from 2013-2015. Output is the number of products sold by an agent in the first year of his career. Standard errors are clustered by manager. Branch and year fixed effects are provided for each specification. Square of the manager tenure has been normalized by 100. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 1.4: Matching between Orphan Agents and Managers

Dpdt. var.: Log of Revenue of Allotted Agents in pre-allotment year	
	(1)
Log(Team Output Per Worker in 2012)	-0.566
	(0.422)
Manager Tenure	-0.120
	(0.078)
Manager Tenure Square/100	0.284
	(0.233)
$\mathbb{1}\{Male\}$	-0.217
	(0.605)
Observations	127
Branch Fixed Effect	Yes
Time Fixed Effect	Yes

Sample consists of orphan agents in 2012-2014. Branch and year fixed effects are provided for each specification. */**/*** denotes significance at the 10/5/1 percent levels, respectively. Standard errors, shown in parenthesis, are clustered by managers. Square of the manager tenure has been normalized by 100.

Table 1.5: Change In Output of Allotted Agents (2013-2015)

	(1)	(2)
Log(Team Output per Worker in 2012)	0.881***	
	(0.326)	
Log(Team Output per Worker in 2012)*$\mathbb{1}\{Bottom 90\%\}$		0.264
		(0.309)
Log(Team Output per Worker in 2012)*$\mathbb{1}\{Top 10\%\}$		3.173***
		(0.932)
$\mathbb{1}\{Top 10\%\}$		-9.894***
		(3.646)
Observations	127	127

Dependent variable is the change in log of output of allotted agents before and aftera allotment. Sample consists of agents alloted in years 2013-15. Standard errors, shown in parentheses, are clustered by manager. Both models control for tenure, tenure square, and gender of the manager. Year fixed effects are provided for each specification. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 1.6: Product Features of New Recruits

	Product Type	Avg.Cost	Avg.Value
Log(Team Output Per Worker in 2012)	-0.001	-0.003	-0.029
	(0.022)	(0.002)	(0.020)
Mean	0.133	0.027	0.144
SD	(0.29)	(0.045)	(0.402)
Observations	4356	4382	4382

Results of OLS regression of product features of new recruits from 2013-2015 on the log of team output per worker in 2012. Tenure and squared tenure of the manager, gender of the manager, and branch and year fixed effects are controlled for in each specification. Mean and standard deviation of each product feature for all newly recruited agents are shown in the table. Standard errors, shown in parentheses, are clustered by manager. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 1.7: Specialization of New Recruits

	MAD(Prod. Type)	MAD(Avg. Cost)	MAD(Avg. Value)
Log(k_m)	0.006	0.000	0.010
	(0.012)	(0.001)	(0.007)
Mean	0.017	0.007	0.040
(SD)	(0.071)	(0.005)	(0.74)
Observations	4356	4382	4382

Results of OLS regression of mean absolute deviation for product feature of new recruits from the mean of the corresponding product feature of new recruits of a manager on the log of team output per worker in 2012. k_m is Team Output Per Worker in 2012. Each model controls for tenure, tenure squared and gender of the manager, team mean of the corresponding product feature, branch and year fixed effect. Mean and standard deviation of specialization in each product feature of all newly recruited agents are shown in the table. Standard errors, shown in parentheses, are clustered by manager. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 1.8: Product Features of All Agents

	Product Type	Avg.Cost	Avg.Value
Log(Team Output Per Worker in 2012)	-0.025	-0.001	-0.018
	(0.022)	(0.001)	(0.014)
Mean	0.285	0.026	0.186
(SD)	(0.35)	(0.042)	(0.632)
Observations	34393	34553	34553

Results of OLS regression of product features of all agents on the log of team output per worker in 2012. Tenure, squared tenure, gender of the manager, tenure of agents, squared tenure of agents, branch and time fixed effects are controlled for in each specification. Mean and standard deviation of each product feature for all agents are shown in the table. Standard Errors, shown in parentheses, are clustered by manager. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 1.9: Specialization of All Agents

	MAD(Prod. Type)	MAD(Avg. Cost)	MAD(Avg. Value)
Log(k_m)	0.006	-0.000	0.006
	(0.007)	(0.001)	(0.007)
Mean	0.119	0.054	0.007
(SD)	(0.148)	(0.029)	(0.002)
Observations	33734	33858	33858

Results of OLS regression of mean absolute deviation for product feature of all agents from the mean of the corresponding product feature of agents in the team of a manager on the log of team output per worker in 2012. k_m is Team Output Per Worker in 2012. Tenure of managers, squared tenure of manager, gender of manager, tenure of agents, squared tenure of agents, branch and time fixed effects are controlled for in each specification. Mean and standard deviation of specialization in each product features of all agents are shown in the table. Each specification also contains mean of the product feature. Standard Errors are clustered by manager. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 1.10: Number of New Recruits

Dpdt. Var. : Log of Number of New Recruits		
	(1)	(2)
Log (Team Output per Worker in 2012)	0.146	0.137
	(0.134)	(0.153)
Manager Tenure		0.056^{**}
		(0.024)
Manager Tenure Square/100		-0.221^{***}
		(0.075)
$\mathbb{1}\{Male\}$		0.537^{***}
		(0.188)
Observations	549	549

Branch and year fixed effects are provided for each specification. Standard errors, shown in parentheses, are robust. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 1.11: Exit Probability of Agents

Dpdt. Var.: $\mathbb{1}\{Exit\}$				
	(1)	(2)	(3)	(4)
Log(Team Output Per Worker in 2012)	-0.074***	-0.047***	-0.014	
	(0.011)	(0.013)	(0.013)	
Log(Leave One Out Output Per Worker)				-0.002
				(0.012)
Manager Tenure		-0.008***	-0.008***	-0.009***
		(0.003)	(0.003)	(0.003)
Manager Tenure Square/100		0.019*	0.019*	0.021**
		(0.010)	(0.010)	(0.010)
$\mathbb{1}\{Male\}$		0.016	0.019	0.020
		(0.027)	(0.027)	(0.028)
Output			-0.017***	-0.017***
			(0.004)	(0.004)
Revenue			0.018	0.018
			(0.042)	(0.042)
Observations	26490	26490	26490	26490

Sample of all agents from 2012-2014. Square of tenure term has been normalized by 100. Output and revenue of the agent has been normalized by 10 and 100, respectively. Branch and year fixed effects are provided for each specification. Standard errors, shown in parentheses, are clustered at the manager level. */**/*** denotes significant at the 10/5/1 percent significance levels. For the newly recruited agents in column 4, I impute the leave-one-out output per worker by team output per worker in 2012.

Table 1.12: Exit Probability of Newly Recruited Agents

Dpdt. var.: $\mathbb{1}\{Exit\}$			
	(1)	(2)	(3)
Log(Team Output Per Worker in 2012)	-0.073*	-0.081*	-0.068
	(0.040)	(0.042)	(0.041)
Manager Tenure		0.013	0.012
		(0.009)	(0.009)
Manager Tenure Square/100		-0.039	-0.039
		(0.027)	(0.027)
$\mathbb{1}\{Male\}$		-0.015	-0.012
		(0.065)	(0.066)
Output in Year 1			-0.008***
			(0.002)
Revenue in Year 1			-0.027
			(0.141)
Observations	506	506	506

Sample of newly recruited agents who cleared the cut-off of mandatory retention. Square of tenure term is normalized by 100. Output and revenue of the agent has been normalized by 10 and 100, respectively. Branch and year fixed effects are provided for each specification. Standard errors, shown in parenthesis, are clustered by manager. */**/*** denotes significant at the 10/5/1 percent significance levels.

Table 1.13: Team Size Growth

Dpdt. Var.: Log of Team Size		
	(1)	(2)
Log of Output per Worker	0.575***	0.439**
	(0.210)	(0.217)
Manager Tenure		0.104***
		(0.020)
Manager Tenure Square/100		-0.353***
		(0.082)
$\mathbb{1}\{Male\}$		0.315**
		(0.147)
Observations	841	841

Branch and year fixed effects are provided for each specification. Square of manager tenure is normalized by 100. Standard errors, shown in parentheses, are clustered by branch. */**/*** denotes significant at the 10/5/1 percent significance levels.

Table 1.14: Team Output and Team Size

Dpdt. var. : Log(Team Output)			
	(1)	(2)	(3)
Log(Team size)	1.144***	1.106***	1.170***
	(0.034)	(0.036)	(0.160)
Manager Tenure		0.041***	
		(0.007)	
Manager Tenure Square/100		-0.099***	
		(0.025)	
$\mathbb{1}\{Male\}$		-0.039	
		(0.105)	
MFE	No	No	Yes
Observations	841	841	841

Branch and year fixed effects are provided for each specification. Square of manager tenure is normalized by 100. Standard errors, shown in parentheses, are clustered by branch. */**/*** denotes significant at the 10/5/1 percent significance levels.

Chapter 2

Managerial Productivity and Tenure: Evidence from an Insurance Firm in India

Managers have a significant impact on worker and firm productivity. Empirical evidence for this comes from extensive cross-firm studies (Friedrich (2015); Bloom et al. (2013)) and recent within-firm research (Lazear et al. (2015); Adhvaryu et al. (2016)). However, this line of investigation begets the question, What makes a good manager? More particularly, do traits such as prior firm experience or tenure on the job increase managerial productivity?

In this chapter, I explore the above mentioned questions using a panel dataset of 248 manager-led teams of salespersons in a life insurance firm in India. I find that, after controlling for the tenure, gender and workplace location of the managers, a team supervised by a manager hired from within the firm (internally-hired) is 14% more productive than a team led by a manager hired from the external labor market (externally-hired). Further, I find that the gradient of productivity with respect to tenure is steeper for the externally-hired managers. Thus, while internally-hired managers start out at a higher productivity level, the externally-hired managers are able to grow faster, leading to convergence in the output of the two teams.

I consider three mechanisms to explain higher productivity of internally-hired managers and the eventual catch-up by the externally-hired ones. These three mechanisms are:

- Recruitment: Under this hypothesis, the internally-hired managers, having worked in the firm, may have better information on the productivity of their new recruits.

Thus, they may recruit better workers, creating the initial productivity gap. However, externally-hired managers may learn how to recruit good workers as they acquire tenure, closing out the gap.

- Training: Under this mechanism, the internally-hired managers may provide better training, supervision, guidance, etc. to their agents, creating the initial output gap. For example, they may teach their agents sales tricks that they learned when they themselves worked as agents. As externally-hired managers acquire tenure, they may learn how to provide useful contribution to their agents, closing the output gap.
- Retention: Under this mechanism, the internally-hired managers change the composition of their teams by preventing the exit of their more productive workers and/or letting go the bad ones. Externally-hired managers learn these skills as they acquire tenure.

To test the recruitment mechanism, I regress the output of newly recruited agents on their manager's characteristics. I find that the new recruits of internally-hired managers are more productive, after controlling for manager characteristics. Further, the gradient of output of new recruits is higher with respect to the tenure of externally-hired managers. This provides support for the recruitment mechanism but is also consistent with the training mechanism.

To separate the two channels, I carry out two tests. First, using the firm's internal labor market, which allows agents to move across teams, I find that the output of such agents increases when they join the team of an internally-hired managers. Second, I explore the returns to tenure for the agents in the two types of teams. I find that the agents of externally-hired managers exhibit a higher return to tenure, but the difference is not significant. These two tests provide weak evidence for the training mechanism, although they do not have significant power.

I do not find any difference in the attrition rate in the two types of teams after controlling for the agent's output. Hence, I rule out the retention mechanism.

Thus, while I find strong evidence of a productivity gap and differential tenure gradient between the two types of the managers, no single mechanism can explain all of the results.

The main contribution of the chapter is to record the productivity difference between the internally-hired and externally-hired managers in a life insurance firm in India. Extensive theoretical works (Rosen and Lazear (1982), Chan (1996), Garicano and Rossi-hansberg (2005), Bose and Lang (2017)) and empirical works Murphy and Zabojnik (2007) have already established conditions when a firm would promote an employee from within instead of recruiting a new employee from outside. In the subject firm, the internally-hired managers have more productive teams, but they form only 20% of the managerial fleet. In this sense, the chapter provides empirical support for Bond (2017) where a firm promotes an employee from within but faces a binding constraint on the stock of high productivity candidate. Thus, the firm falls back on the external labor market to fill managerial vacancies.

I explore the mechanisms through different models of learning by managers. There is a vast literature on learning within a firm. Some of the classic papers include Harris and Holmstrom (1982), Holmstrom (1999), Farber and Gibbons (1996), Waldman (1984) and Murphy (1986). However, these papers demonstrate the process of learning a worker's true productivity by observing her output over time. In this chapter, the learning process model is similar to the Beckerian view of human capital accumulation as a function of tenure in the firm—managers learn to perform tasks better as they acquire tenure. Most papers in this field pertain to the process of learning-by-doing in the manufacturing sector (Hatch and Mowery (1998), Argote and Epple (1990)).

Naeem and Woodruff (2013) and Chen (2017) are some recent papers which have studied productivity differences between male and female managers. To the best of my knowledge, the present study is the first to compare performance of managers hired from within a firm against that of managers hired from outside it.

This study also contributes to the classic debate between the role of human capital vis-á-vis match quality in the relation between employee productivity and tenure. Using a bounding procedure similar to that of Topel (1991), I am able to attribute at least 30% of the productivity gap to the higher human capital of internally-hired managers. Given that an internally-hired manager works for around 3-5 years as an agent in the firm before becoming managers, this lower bound is higher than the 25% of wage growth in 10 years estimated by Topel (1991). I also use number of products sold and revenue collected as measures of performance, as these are less susceptible to the biases to which other metrics, such as wage, are prone

Throughout the chapter, I use feminine pronoun (she, her) for managers and masculine pronouns (he, his, him) for salesperson. I will use agent and worker interchangeably.

2.1 Institutional Overview

The firm under analysis is the same firm that was discussed in Chapter 1. For most of the institutional details of the firm, such as the market in which it operates, etc., please refer to Section 1.1 above. Here I will discuss in more detail the specific features of the firm that are relevant for this chapter

2.1.1 Manager Hiring

Figure 1·1 provides the organizational chart for the firm. Allocation of the managers to the branches is carried out by the Zonal Officers. Demand and supply of managers is balanced at the divisional level; i.e. demand for managers at the divisional level is absorbed by the supply of managers at the divisional level.

Demand for managers arises from vacancies created in the branches due to the resignation, retirement, termination or promotion of existing managers. Total demand for managers is added up to the divisional level.

Supply of managers is channelled through a two-stage process. Candidates must appear for an aptitude-based test. Having qualified on the test, candidates appear for an interview. The test is conducted by an independent agency at the behest of the firm, whereas interviews are conducted by the Zonal Officers.

Zonal managers then allocate the qualified managers to the branches in a division.

2.1.2 Manager-Type

In this study, I will classify the managers into two categories:-

- **Internally-hired** are those managers who had worked as agents in the firm prior to becoming managers;
- **Externally-hired** are those managers who come from the external labor market.

The process of hiring a manager is identical for both types of manager. Whether from within the firm or from outside, a candidate goes through the same two-stage process. The firm does not provide incentives to current agents to participate in the test. In this way, managers choose to appear for the test[1].

2.2 Data And Empirical Facts

2.2.1 Summary Statistics

I use a four-year long panel dataset of 248 manager led-teams from 24 branches located in Delhi. I can observe total number, value of products sold, and amount insured by each

[1] This is not to say that Zonal Officers do not know whether a candidate was an agent in the firm or not or an agent may not be encouraged by his superiors to appear for the test. Zonal Officers do see the resumé but the test evaluates the candidates on the same metrics. Further, I will show in Section 2.4 how innate productivity of the two types of managers cannot explain all the results.

agent as performance variables. I aggregate these three measures for all agents in the team to obtain performance metrics of the team. I can also observe tenure of the agents and managers in the firm, and total team size under each manager[2].

Tables 2.1 and 2.2 provide summary statistics at the team and agent level, respectively. In Figures 2·1 and 2·2, I plot the density of log of output per worker and log of revenue per worker, respectively, for each type of manager. In both figures, the distribution for internally-hired managers stochastically dominates the distribution for externally-hired managers—the team productivity of the internally-hired managers has a larger mean with a lower dispersion. Similar patterns are obtained in Figures 2·3 and 2·4, where I plot the density of output and revenue of agents of each type of manager, respectively.

2.2.2 Team Productivity

Figure 2·5 provides the binned scatter plot between the log of output per worker for each type of manager and manager tenure, along with a quadratic fit of the conditional expected function. The curve for the externally-hired managers is concave and starts out at a lower level than the curve for internally-hired managers, which remains invariant with tenure.

To investigate the productivity gap and differential growth of team productivity, I use the following model:

$$\log y_{mbt} = f(I_m, T_m) + \phi_b + \phi_t + \epsilon_{mbt} \tag{2.1}$$

where y_{mbt} is the output per worker for manager m in branch b in year t, T_m is tenure of manager m, I_m is an indicator for a manager which takes a value of 1 for an internally-hired manager and 0 otherwise. ϕ_b and ϕ_t are branch and time fixed effects, respectively.

Table 2.3 shows the results. I explore the returns to tenure for internally- and externally-hired managers in Columns (1) and (2), respectively, using a quadratic functional form for $f(I_m, \cdot)$. Consistent with Figure 2·5, the team productivity of externally-hired managers

[2]Appendix A.4 provides details on the construction of key variables.

exhibits an increasing and concave relationship with the tenure of its managers, whereas the trajectory for the teams of internally-hired managers appears flat.

In Columns (3)-(5), I pool the observations of the two types of teams and explore the extrapolated productivity gap at the beginning of the managers' careers. Column (3) shows that after controlling for tenure, gender, branch and year fixed effects, teams of internally-hired managers are 14% more productive. I impose a linear and quadratic functional form on $f(\cdot)$ in Columns (4) and (5), respectively, and interact tenure terms with I_m to allow for different returns from tenure for the two types of managers. Steeper returns for externally-hired managers with respect to tenure is evident in both columns.

The coefficient on I_m in columns (4) and (5) has the interpretation of the productivity gap at zero tenure for each manager. However, in the data, there are no internally-hired managers who were freshly recruited[3]. Thus, the coefficient is based on an extrapolation. With this caveat in mind, I interpret from column (5) that the extrapolated productivity gap at the beginning of the managers' career is 0.908 in log points, which shrinks to 0.041 for managers with ten years of tenure with a standard error of 0.046; within 10 years, productivity gap dissipates.

In Table 2.4, I conduct the same analysis as in Table 2.3, but use the mean of agent's average tenure in each team as an additional control. Results are qualitatively similar to Table 2.3, but now the extrapolated gap at the beginning of the career in each specification is slightly smaller, indicating the role of agents' quality (proxied by tenure) in team productivity.

Differential tenure trajectory for the managers, recorded in Tables 2.3 and 2.4, may be driven by cohort effects (Baker et al. (1994)). For instance, externally-hired managers of recent cohorts may have come from a low-talent pool due to a shock specific to the external labor market. Such selection mechanisms imply a higher productivity gap between the two types of managers with low tenure, and a smaller gap for the earlier cohorts (higher

[3]There were some freshly recruited externally-hired managers

tenure). To address this issue, I explore the year-on-year growth rate for the managers. Specifically, I use the following model:

$$\Delta \log y_{mt} = f(I_m, T_m) + \phi_t + \nu_{mt} \tag{2.2}$$

where $\Delta \log y_{mt}$ is the change in log of team productivity of manager m between t and $t-1$. Using the first difference eliminates the time-invariant manager fixed effects[4]. Results are provided in Table 2.5. Column (1) shows that after eliminating cohort-based factors, the team productivity of externally-hired grows at a 5% faster rate. This is in contrast with 1.2% differential in growth rate seen in Column (4) of Table 2.3, which does not account for time-invariant effects—the gap in time-invariant factors between the two types of managers was bigger in earlier cohorts.

2.3 Mechanisms

Internally-hired managers operate a more productive team, but the teams of externally-hired managers exhibit a faster growth in productivity. To understand the reasons for these empirical facts, I will consider three mechanisms: (1) the internally-hired managers recruit more productive workers and the externally-hired managers learn how to do this; (2) managers differ in the training they provide to their workers and the difference dissipates as externally-hired managers acquire knowledge with tenure; and, finally, (3) the internally-hired managers retain more productive workers and the externally-hired managers learn this skill. Appendix B provides theoretical foundations for these mechanisms. In the next section, I will provide empirical tests for the three mechanisms.

[4]The implicit assumption is that time-varying and time-invariant effects are independent.

2.3.1 Mechanism-1: Recruitment

Under this mechanism, the internally-hired managers recruit more productive agents. Externally-hired managers learn to recruit better agents.

Since the database has observations from 2012-2015, I identify the newly hired agents in 2013, 2014 and 2015. I then use the following model :

$$\log y_{ambt} = f(I_m, T_m) + \phi_b + \phi_t + \epsilon_{ambt}$$

where $\log y_{ambt}$ is the log of output of agent a under manager m in branch b in year t. Table 2.6 provides the results.

In Columns (1) to (4), I explore the effect of manager tenure on output of new recruits, separately for internally- and externally-hired managers, using a quadratic fit on $f(I_m, \cdot)$. Whether with or without manager fixed effects, I find that the output of new recruits increases with the tenure of the externally-hired managers, whereas the internally-hired manager's tenure has much lower explanatory power.

In Columns (5) and (6), I pool the two samples together to measure the extrapolated performance gap between the new recruits of the two types of managers at the beginning of the manager's career. I allow for different returns from manager tenure by interacting I_m with tenure terms. In both columns, performance of the new recruit rises at a faster rate with respect to the tenure of the externally-hired managers.

As argued above, the coefficient on I_m may not hold much interpretation since its based on an extrapolation at the beginning of the manager's career. The extrapolated gap between the new recruits of the two types of managers at the beginning of the manager's career is 0.40 in log output, which reduces to 0.039 with a standard error of 0.086, for managers with 10 years of tenure. Thus, the performance gap between new recruits of the two types of managers dissipates within 10 years of manager tenure.

Results in Table 2.6 may imply that the managers differ in recruiting productive workers, but these results are also consistent with the training mechanism. For instance, all new agents may come from the same talent pool but managers differ in training, supervision, guidance, etc of their agents.

2.3.2 Mechanism-2: Training

To isolate the recruiting mechanism from training, I conduct two tests.

Output Change of Alloted Agents

In the first test, I observe agents moving across teams. Appendix A.3 provides institutional details of this internal labor market of the firm. If the internally-hired managers provide better training initially, then the agents alloted to them should exhibit an increase in their output.

From 2013-2015, 127 agents move across teams. I use the following model:

$$\log y_{ambt} - \log y_{ambo} = f(I_m, T_m) + \phi_t + \epsilon_{amt}$$

where y_{ambt} is the output of the orphaned agent a after being allotted to manager m in branch b in year t and y_{abo} is the output of this agent before being alloted. Table 2.7 provides the results.

The coefficient on I_m in column (1), where I control for manager tenure, is positive and fairly large, although insignificant. This indicates support for the mechanism of initial training, although estimates are noisy. However, tenure remains negative in all specifications, and in columns (2) and (3), interaction between tenure terms and I_m are insignificant, suggesting implausibility of this mechanism in explaining convergence.

Output Growth of Agents

For the second test, I observe the output growth of agents with respect to their tenure for each type of manager. If the externally-hired managers are learning how to provide training, then the growth of an agent's output should be higher for the agents of externally-hired managers.

In Figure 2·6, I provide binned scatter plot between the log output of agents in each type of team and the agent's tenure, along with a quadratic fit of the conditional expected function. The agents of the internally-hired managers are more productive but the returns from tenure are similar for the two types of agents; the two curves do not exhibit convergence.

To explore this effect, I estimate the effect of tenure on agent productivity separately for agents of internally- and externally-hired managers. Consider the following model:

$$\log y_{amt} = f(T_a) + \phi_m + \phi_t + \epsilon_{amt}$$

where, y_{amt} is output of agent a under manager m in year t, T_a is agent a's tenure and ϕ_m is manager fixed effect.

In Columns (1) and (2) of Table 2.8, I impose a quadratic fit on $f(\cdot)$. Results show that the output trajectory with respect to tenure is slightly steeper for the agents of externally-hired managers, although, the two coefficients are not significantly different from each other. Similar results are obtained when I include manager fixed effects (Columns (3) and (4)). Thus, for any given manager, the output growth of agents is not correlated with manager fixed effects.

In Columns (5) and (6), I pool the samples together and use the following model:

$$\log y_{ambt} = f(I_m, T_a, T_m) + \phi_b + \phi_t + \epsilon_{ambt}$$

where T_m is manager tenure and ϕ_b and ϕ_t are branch and time fixed effects, respectively. In Column (5), I impose a linear fit on $f(\cdot)$ with interactions between tenure terms and I_m, whereas Column (6) uses a quadratic fit with interactions. In Column (5), the interaction between I_m and agent tenure is not significant, indicating parallel growth rate between the agents in the two types of teams.

As with managers, cohort effects for agents may confound the coefficient on tenure of agents. For example, true returns from tenure may be higher for the agents of externally-hired managers, but if earlier cohorts of such agents were drawn from low productivity distributions, then the process of convergence may get attenuated. To address this issue, I regress the change in the log of output of the two agents on I_m in Table 2.9. Taking first differences eliminates cohort effects. Results show that the output of the agents of externally-hired managers exhibit a 1.2% faster growth rate (column (1)), but the difference is not significant.

2.3.3 Mechanism-3: Retention

Internally-hired managers may provide non-pecuniary utility (dis-utility) to their high output (low output) workers that prevents (increases) their turnover to monetarily equivalent outside options. For instance, the internally-hired managers may socialize with and treat their more productive agents better, potentially reducing their exit, and increasing team productivity. Hoffman and Tadelis (2018) provides empirical evidence for this managerial behavior in a high-tech firm.

Figure 2·7 provides the binned scatter plot between the exit probability of an agent and the agent's output, along with the linear fit of the conditional expected function. The binned scatter plot appears similar for the agents in both types of team, but the slope of the conditional expected function is flatter for the internally-hired.

To test this hypothesis further, I use the following model:

$$\mathbb{1}_{ambt}\{Exit\} = f(y_{ambt}) + \phi_m + \phi_t + \epsilon_{ambt}$$

where $\mathbb{1}\{Exit\}$ is the exit indicator for agent a under manager m in branch b in year t. It takes value 1 if the agent exited and 0 otherwise. y_{ambt} is the output of this agent and ϕ_m

and ϕ_t are manager and year fixed effects, respectively. Table 2.10 provides the results.

Columns (1) and (2) quantify the relationship between the exit probability and output of the agents of the internally- and externally-hired managers, respectively. The coefficient on y_{ambt} is significantly negative in both columns, but the gradient is steeper for the agents of the externally-hired managers. This may be driven by two factors: (a) since output and exit rate are inversely related, higher average output in the teams of internally-hired managers keeps the average exit rate of their agents low[5], or (b) the externally-hired managers provide more non-pecuniary utility to their high output agents.

To account for manager-provided non-pecuniary utility, I conduct this analysis with manager fixed effects in Columns (3) and (4). The coefficient on y_{ambt} for each type of agent remains unchanged. Thus, the managers do not provide more non-pecuniary utility to their high output agents.

Columns (1)-(4) collectively show that the managers are unable to prevent the exit of their high output worker, over and above what is determined by the agent's output. However, this non-pecuniary utility may be a public good that affects all the agents equally and reduces the level of exit rate for all workers. We know already that the managers differ in recruiting/training their agents (Table 2.6 and 2.7), this added public good utility may create a larger team of more productive workers for the internally-hired managers generating higher per capita output, consistent with the results in Table 2.3.

To test this hypothesis, I pool all the observations together and regress the exit rate of the workers on I_m, along with other controls. The effect of the public good utility would be observed as a difference in the level of exit rate of agents. Column (5) shows that after controlling for the output of the agents, the coefficient on I_m is not different from zero; the two types of managers do not differ in the provision of non-pecuniary public good utility.

[5]This hypothesis requires the agent's outside option to be independent of current earnings. Appendix A.9 provides arguments for why that may be true.

In columns (6)-(8), I interact I_m with agent output and tenure terms to allow for differential relationships between the exit rate of each type of agent and their output and the tenure of their manager. If the internally-hired managers are better at preventing the exit of their high output worker, the interaction between agent output and I_m should be negative. However, this hypothesis can be ruled out since the coefficient on this term is positive. The coefficient on I_m is an extrapolation of the difference in exit rate of agents with zero output in the two types of teams. Due to the absence of any mass at that point, this coefficient does not hold informative value. However, using the extrapolated coefficient on I_m in column (6), the projected difference between the attrition rate at average agent output (20) is -0.01 with a standard error of 0.012; an average worker in each team is almost equally likely to stay in the firm. Interactions between tenure terms and I_m do not have explanatory power, disallowing convergence/differential learning in this skill.

Summary of Results

Results on the mechanisms tell a multi-faceted story. Table 2.6 indicates that the new recruits of the internally-hired managers perform better, and that the magnitude of the performance gap attenuates as the externally-hired managers acquire tenure. This lends support to both the recruitment and initial training mechanisms. Table 2.7 shows that on being alloted to a team of the internally-hired managers, an orphaned agent's output goes up, providing weight to the training mechanism.

Many other hypotheses may be consistent with these results. Managers may differ in imparting one-time non-deteriorating initial training, which creates an immediate impact on the new recruits and alloted agents. However, initial training and recruitment mechanisms may be present simultaneously. One may not rule out confounding effects orthogonal to managerial skill. For instance, the results in Table 2.7 could be driven by peer effects—as agent joins a more productive team, he gets to work with more productive agents, thereby learning from them. Further, the weak evidence of convergence among agents, shown in Table 2.9, could be interpreted as agents learning salesman skills by themselves, instead of guidance by managers. An ideal test would be if a candidate chosen by one manager is randomly reallocated to some other manager/team before the candidate joins the firm. Such a test is not possible under current firm mechanics[6].

2.4 Other Identification Checks

2.4.1 Bounding Information Differential

From Column (3) of Table 2.3, we find that on controlling for tenure, branch, and the gender of the manager and year fixed effects, the internally-hired managers operate a 14% more productive team. However, empirical models in Table 2.3 do not control for ability-related manager characteristics such as education, test scores, industry experience etc. These confounding effects suggest that human capital or information differentials might only be partly responsible for the productivity gap.

To understand the above argument, consider the following: Let $k_t^I(k_t^E)$ be the human capital of internally-hired managers (externally-hired managers) with tenure t and let $\bar{\theta}^I(\bar{\theta}^E)$ be the innate productivity of internally-hired managers (externally-hired managers). Thus, after controlling for tenure of the managers, the projected output gap between the two types of managers at the beginning of their career can be written as:

$$\hat{\beta}_0 = k_0^I + \bar{\theta}^I - (k_0^E + \bar{\theta}^E)$$

$$\hat{\beta}_0 = k_0^I - k_0^E + (\bar{\theta}^I - \bar{\theta}^E)$$

$\bar{\theta}^I - \bar{\theta}^E$ reflects innate differences between the two types of managers, which are not controlled, whereas $k_0^I - k_0^E$ captures the human capital differential.

To address these time-invariant effects, I use the year-on-year difference in team pro-

[6]An issue with random allocation of agents would be that the incentives for managers to recruit would have to be altered. But, then the managers may respond to the newer incentives, thereby disallowing an apple-to-apple comparison.

ductivity in Table 2.5, which allows me to eliminate θ. Consider Column (1) of Table 2.5.

$$\Delta \log y_{mt} = \gamma I_m + \phi_t + \nu_{mt}$$

In the above model, γ is the difference in the output gap between the two managers between $t = 0$ and $t = 1$, i.e.,

$$\hat{\gamma} = \hat{\beta}_1 - \hat{\beta}_0$$

$$\hat{\gamma} = k_1^I + \bar{\theta}^I - (k_1^E + \bar{\theta}^E) - (k_0^I + \bar{\theta}^I - (k_0^E + \bar{\theta}^E))$$

$$\hat{\gamma} = (k_1^I - k_1^E) - (k_0^I - k_0^E)$$

$$(k_0^I - k_0^E) = (k_1^I - k_1^E) - \hat{\gamma}$$

If the difference in human capital between two managers remains positive at the end of the first year, then $-\hat{\gamma}$ is the lower bound on the information gap between two managers at the beginning of their career, i.e., $k_1^I - k_1^E > 0 \implies k_0^I - k_0^E > -\hat{\gamma}$

From Table 2.5,we know that $\hat{\gamma} = -0.051$. By the above reasoning, $(k_0^I - k_0^E) > -\hat{\gamma}$. Thus, $(k_0^I - k_0^E) > 0.051$. Further, from Table 2.3, we know that $\hat{\beta}_0 = 0.148$. Hence, at least 30% of the productivity gap between two managers can be attributed to human capital[7].

For the above reasoning to be valid, $\hat{\gamma}$ should be unbiased, i.e., $E(\nu_{mt} * I) = 0$. Given that $\nu_{mt} = \epsilon_{mbt+1} - \epsilon_{mbt}$, $E(\nu_{mt} * I) = 0 \implies E[(\epsilon_{mbt+1} - \epsilon_{mbt}) * I] = 0$. Therefore, the unbiasedness of $\hat{\gamma}$ is equivalent to no serial co-relation in $\log y_{mbt}$ for the internally-hired managers. This condition is satisfied.

2.4.2 Market and Customer Heterogeneity

A potential cause of productivity dispersion between the teams and agents could be market or customer heterogeneity. For instance, some managers may have more precise information over demand characteristics of customers, which allows them to sell more. Such

[7] $\hat{\beta}$ and $-\hat{\gamma}$ are statistically different.

information heterogeneity will be reflected in the product portfolio of the agents. As detailed in Section 1.2, I observe three product features. To test this hypothesis, I regress these three product features of an agent's portfolio on manager and agent characteristics.

Table 2.11 presents the results; agents of the two types of managers do not differ in the type, value and cost of products.

2.4.3 Specialization Within Teams

Managers are provided full discretion to allocate their agents across different products. Assume that the agents differ in their propensity to sell a particular type of product or to cater to a particular customer demographic, and that the managers differ in identifying this talent among their agents. Under this hypothesis, a manager who makes her agents specialize will have a more productive team.

To test this hypothesis of intra-team specialization of agents, I regress the absolute distance between an agent's three product features and the team-level mean of these product features on agent and manager characteristics along with branch and time fixed effects.

Table 2.12 presents the results. The two types of managers do not differ in the degree of specialization within teams.

2.5 Conclusion

In this chapter, I find a high productivity gap between the sales teams of the internally-hired managers and externally-hired managers in an Indian insurance firm. Further, I find evidence of convergence between the productivity of these two types of teams.

No single mechanism can fully explain the reason for the productivity gap and eventual catch-up. Among different channels, I find evidence of differential effects at the recruiting stage and training by managers; internally-hired managers recruit good workers and are also able to increase the output of the alloted agents who join them from other teams. Further, the output gap between the new recruits of the two types of managers attenuates as the externally-hired managers acquire tenure. One may interpret this as the result of the externally-hired managers learning how to recruit good agents. While it is acknowledged that these effects remain open to different interpretations, the main contribution of the chapter is to record the productivity gap between internally- and externally-hired managers in a firm and the fact that this gap closes as externally-hired managers acquire tenure. The eventual convergence of externally-hired managers with tenure can be attributed to accumulation of human capital.

The exact nature of the human capital is unclear. For instance, some of the externally-hired managers may come from another insurance firm. In such cases, human capital is firm-specific. But they may also come from a different industry, or they may be fresh graduates who are in their first job. The human capital gap may then be industry-specific in the former case, or simply the result of experience in the latter case.

Generalization of the results to other settings remains limited. However, in the context studied, managers improve their operation of some management practices over time. This is in contrast to the current literature which considers certain key management practice as the source of managerial productivity (Bloom et al. (2010), Bloom and Reenen (2010)). The results indicate that the adoption of management practices might itself be endogenous to manager specific traits or firm policies.

2.6 Figures

Figure 2·1: Distribution of Log of Output per Worker by Manager

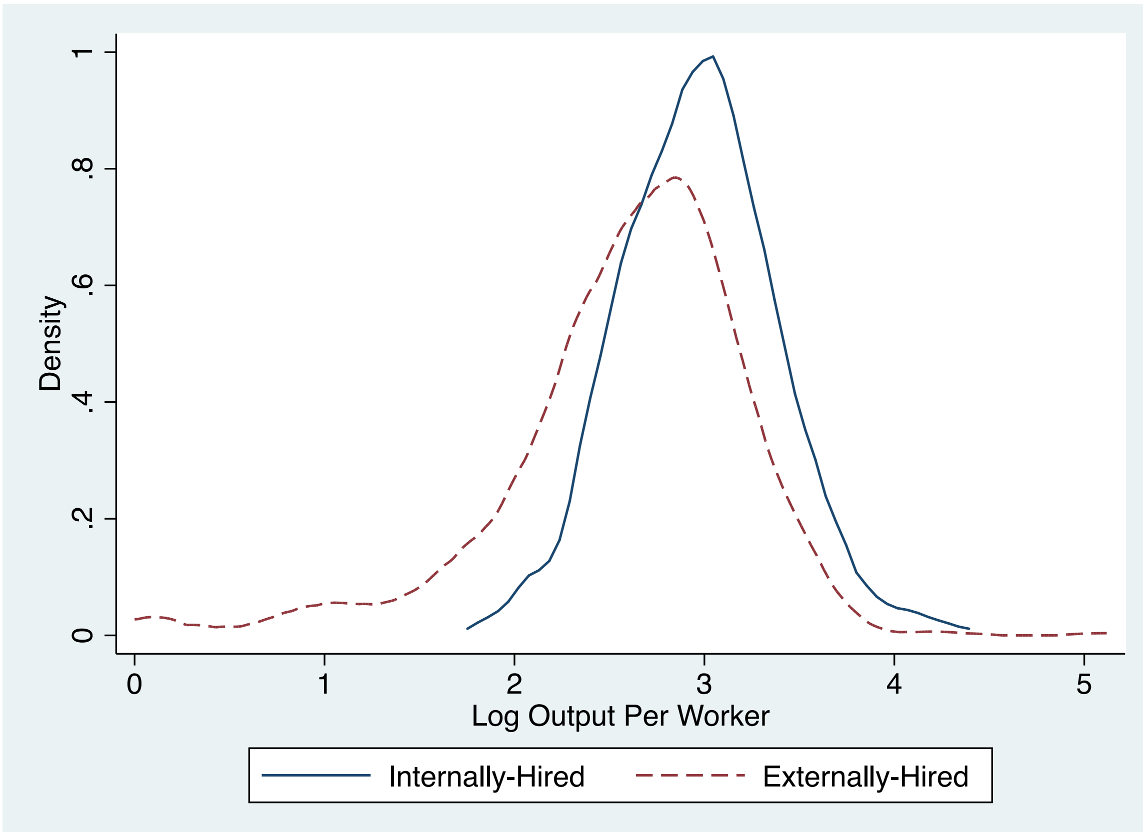


Figure 2·2: Distribution of Log of Revenue per Worker by Manager

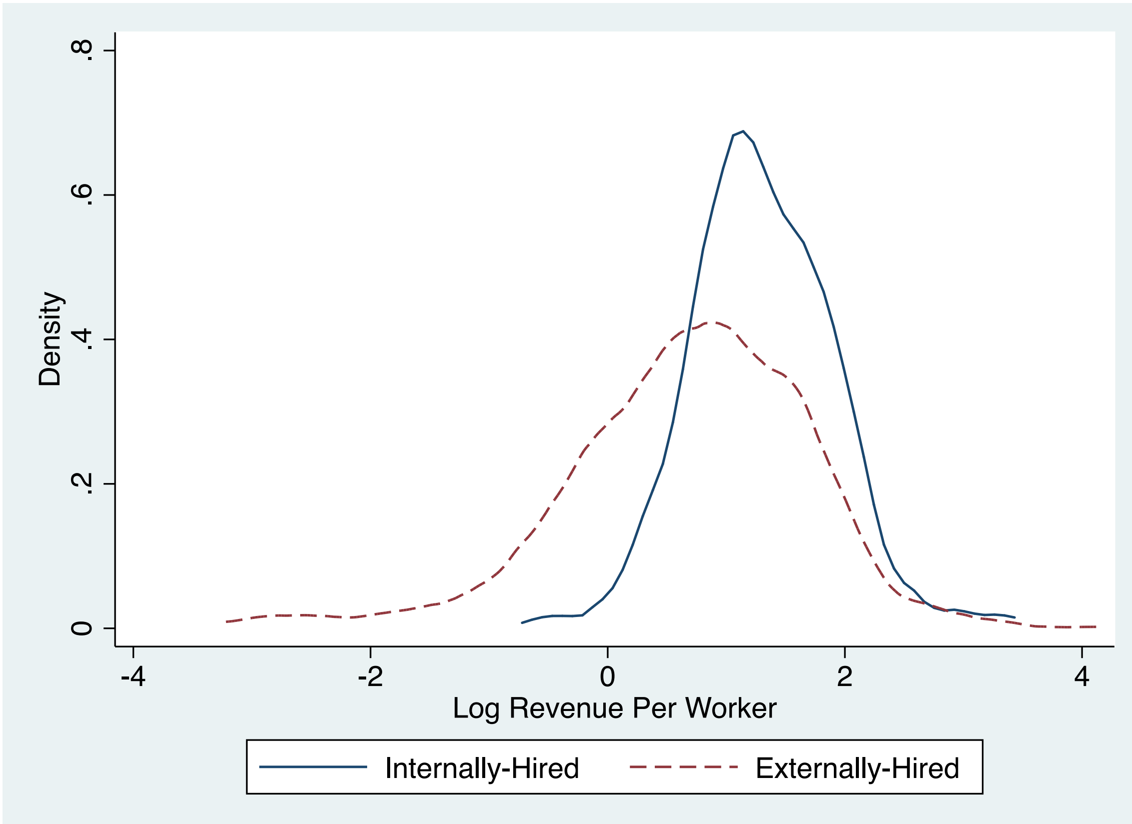


Figure 2·3: Distribution of Log of Output by Agents

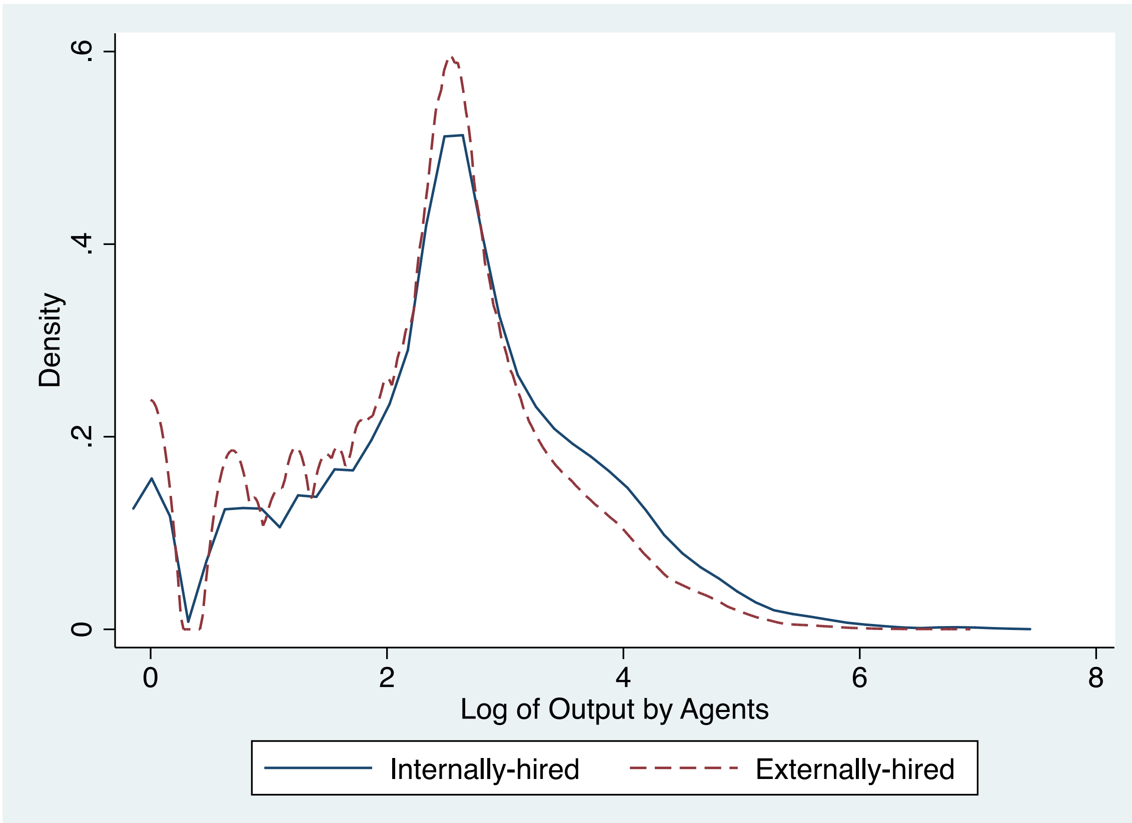


Figure 2·4: Distribution of Log of Revenue by Agents

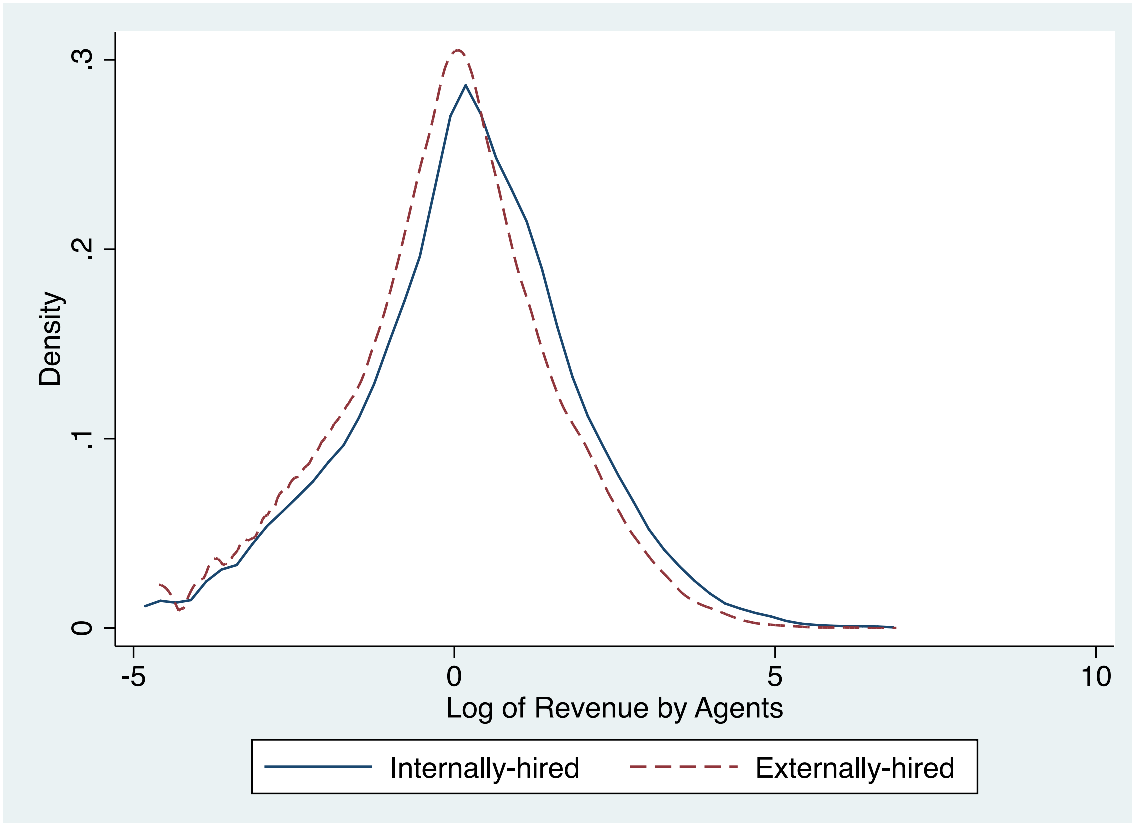
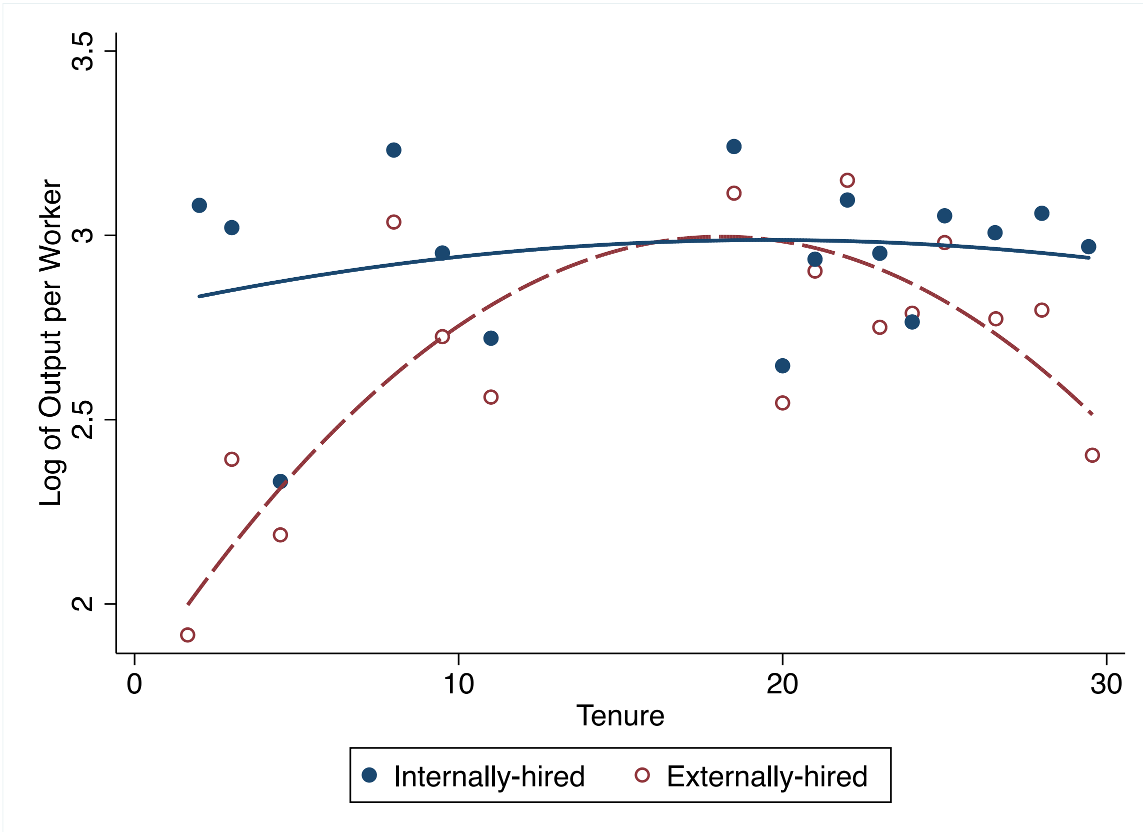
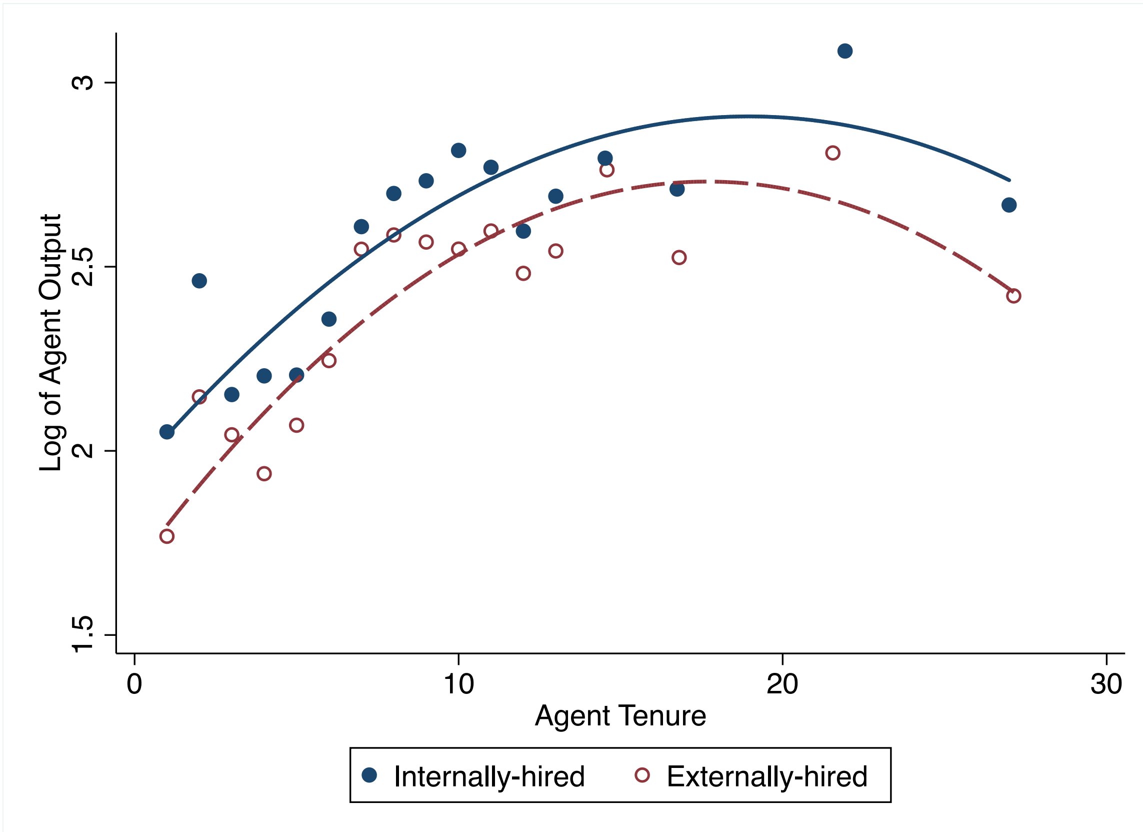


Figure 2·5: Output per Worker



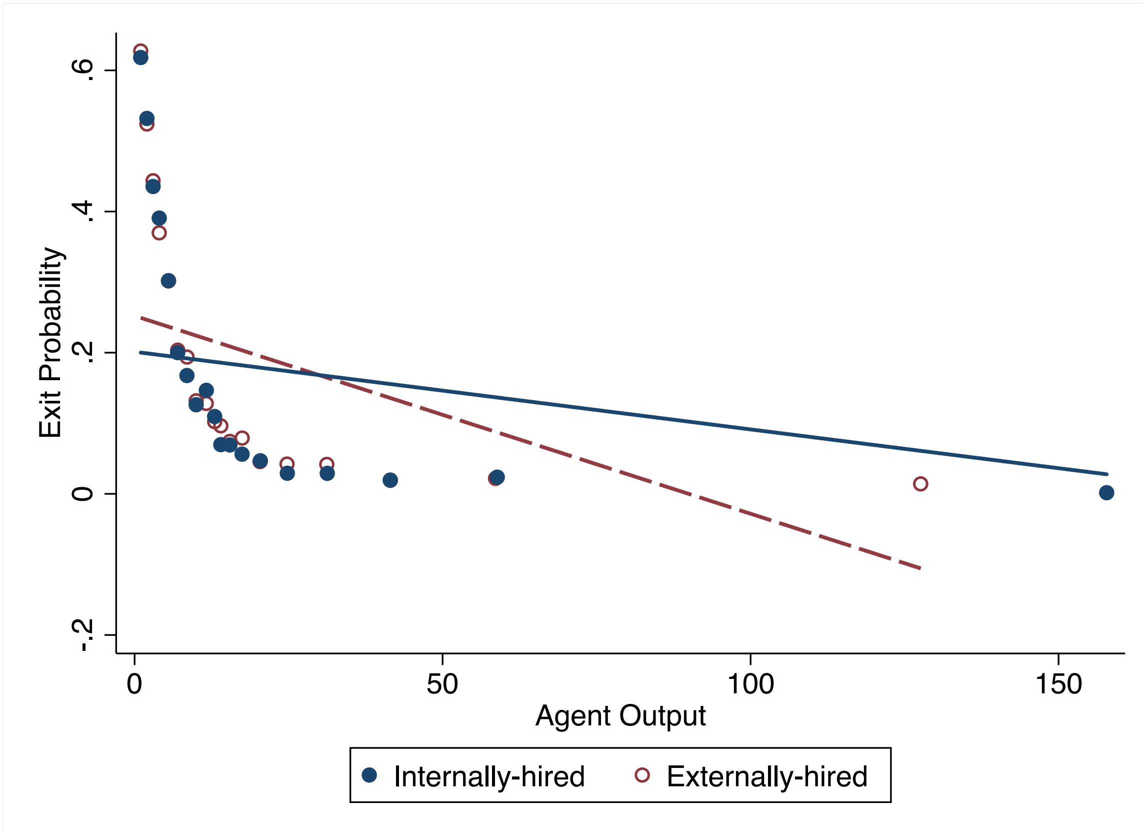
This figure is a binned scatter plot between the log of output per worker and the tenure of managers of each type. Solid blue curve is the quadratic fit of the conditional expected function for the internally-hired managers. Dashed red curve is the quadratic fit of the conditional expected function for the externally-hired managers.

Figure 2·6: Agent Output



This figure is a binned scatter plot between the log of agent output and the tenure of agents in each type of team. Solid blue curve is the quadratic fit of the conditional expected function for the agents of the internally-hired managers. Dashed red curve is the quadratic fit of the conditional expected function for the agents of the externally-hired managers.

Figure 2·7: Exit Propensity by Team



This figure is a binned scatter plot between the exit probability of an agent and his output. Solid blue curve is the linear fit of the conditional expected function for the agents in the teams of internally-hired managers. Dashed red curve is the linear fit of the conditional expected function for the agents in the teams of externally-hired managers.

2.7 Tables

Table 2.1: Summary Statistics—Managers

	Mean	Standard Deviation	Minimum	Median	Maximum	Observations
Panel A: Internally-hired						
Output	1478.909	2619.787	39	830	21614	197
Revenue	300.989	541.125	9.880	166.390	3400.530	197
Team Size	55.838	55.691	6	45	381	197
Output per Worker	21.134	9.319	6.500	19.030	71.759	197
Revenue per Worker	4.407	3.274	0.581	3.574	25.845	197
Manager Tenure	19.827	6.116	2	21	29	197
$\mathbb{1}\{Male\}$	0.959	0.198	0	1	1	197
Panel B: Externally-hired						
	Mean	Standard Deviation	Minimum	Median	Maximum	Observations
Output	581.800	627.887	1	404.000	5788	740
Revenue	106.725	126.257	0.040	62.745	1106.930	740
Team Size	34.701	35.221	1	26	280	740
Output per Worker	15.783	9.995	1.000	14.743	167	740
Revenue per Worker	3.083	3.776	0.040	2.128	61.496	740
Manager Tenure	13.426	9.932	1	17	30	740
$\mathbb{1}\{Male\}$	0.968	0.177	0	1	1	740

Output is the number of products sold. Observations are at the manager-year level in Panel A and B, for internally- and externally-hired managers, respectively.

Table 2.2: Summary Statistics—Agents

	Mean	Standard Deviation	Minimum	Median	Maximum	Observations
Panel A: Agents of Internally-hired						
Output	24.960	51.053	1	13	1473	11498
Revenue	5.088	22.021	0.000	1.230	752.640	11498
Agent Tenure	8.027	7.394	1	8	28	11498
Panel B: Agents of Externally-hired						
	Mean	Standard Deviation	Minimum	Median	Maximum	Observations
Output	17.588	27.443	1	12	1028	24233
Revenue	3.274	12.609	0.000	0.950	982.290	24233
Agent Tenure	7.015	6.930	1	6	28	24233

Output is the number of products sold. Observations are at the agent-year level in Panel A and B, for internally- and externally-hired managers, respectively.

Table 2.3: Team Productivity

Dpdt. Var.: Log of Output per Worker	(1)	(2)	(3)	(4)	(5)
I_m			0.148^{***}	0.543^{***}	0.908^{***}
			(0.035)	(0.090)	(0.129)
Manager Tenure	0.000	0.123^{***}	0.031^{***}	0.033^{***}	0.125^{***}
	(0.017)	(0.011)	(0.003)	(0.003)	(0.011)
Manager Tenure Square/100	0.037	-0.346^{***}			-0.350^{***}
	(0.047)	(0.041)			(0.039)
Manager Tenure*I_m				-0.021^{***}	-0.125^{***}
				(0.005)	(0.018)
Manager Tenure Square*$I_m/100$					0.383^{***}
					(0.059)
$\mathbb{1}\{Male\}$	-0.057	0.482^{***}	0.389^{**}	0.377^{**}	0.309^{**}
	(0.150)	(0.178)	(0.157)	(0.156)	(0.146)
Observations	197	740	937	937	937
Manager Type	Internal	External	NA	NA	NA

Branch and time fixed effects are included in all specifications. Manager Tenure Square and interaction of Manager Tenure Square with I_m are normalized by 100. Standard errors are robust to heteroscedasticity.

Table 2.4: Team Productivity—Controlling Agents' Average Tenure

Dpdt. Var.: Log of Output per Worker	(1)	(2)	(3)	(4)	(5)
I_m			0.131***	0.491***	0.840***
			(0.034)	(0.085)	(0.124)
Manager Tenure	-0.001	0.105***	0.018***	0.020***	0.110***
	(0.017)	(0.011)	(0.004)	(0.005)	(0.011)
Manager Tenure Square/100	0.039	-0.332***			-0.340***
	(0.048)	(0.039)			(0.037)
Manager Tenure*I_m				-0.019***	-0.119***
				(0.004)	(0.018)
Manager Tenure Square*$I_m/100$					0.367***
					(0.057)
$\mathbb{1}\{Male\}$	-0.051	0.447**	0.369**	0.358**	0.294**
	(0.147)	(0.175)	(0.152)	(0.151)	(0.142)
Agents' Average Tenure	0.003	0.046***	0.047***	0.045***	0.040***
	(0.011)	(0.012)	(0.011)	(0.011)	(0.010)
Observations	197	740	937	937	937
Manager Type	Internal	External	NA	NA	NA

Branch and time fixed effects are included in all specifications. Manager Tenure Square and interaction of Manager Tenure Square with I_m are normalized by 100. Standard errors are robust to heteroscedasticity. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 2.5: Team Productivity Growth

Dpdt. Var.: Change in Log Output per Worker		
	(1)	(2)
I_m	-0.051**	-0.247***
	(0.026)	(0.073)
ΔManager Tenure Square/100		-0.349***
		(0.125)
ΔManager Tenure Square*I_m/100		0.603***
		(0.186)
Observations	689	689

Time fixed effects are included in both specifications. Change in Manager Tenure Square and interaction of change in Manager Tenure Square with I_m are normalized by 100. Standard errors are robust to heteroscedasticity. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 2.6: Output Of Newly Recruited Agents

Dpdt. Var.: Log Output of Newly Recruited Agents	(1)	(2)	(3)	(4)	(5)	(6)
I_m					0.241*	0.397**
					(0.128)	(0.181)
Manager Tenure	0.010	0.061***	-0.009	0.072	0.012***	0.055***
	(0.021)	(0.014)	(0.072)	(0.057)	(0.003)	(0.013)
Manager Tenure Square/100	-0.031	-0.169***	0.034	-0.196		-0.152***
	(0.068)	(0.048)	(0.222)	(0.184)		(0.045)
Manager Tenure*I_m					-0.011*	-0.049*
					(0.006)	(0.028)
Manager Tenure Square*I_m/100						0.129
						(0.090)
$\mathbb{1}\{Male\}$	0.514**	-0.095			0.035	-0.054
	(0.214)	(0.143)			(0.159)	(0.153)
Observations	1343	3947	1343	3947	5290	5290
Manager Fixed Effects	No	No	Yes	Yes	NA	NA
Manager Type	Internal	External	Internal	External	NA	NA

Samples in columns (1) and (2) contain newly-recruited agents of the internally-hired and externally-hired managers, respectively, and include branch and year fixed effects. Samples in columns (3) and (4) contain newly-recruited agents of the internally-hired and externally-hired managers, respectively, and include manager and year fixed effects. For columns (5) and (6), all observations of newly-recruited agents are pooled and include branch and year fixed effects. Manager Tenure Square and interaction of Manager Tenure Square with I_m are normalized by 100. Standard errors are clustered at manager-level. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 2.7: Change In Output Of Allotted Agents

Dpdt. Var.: Change in Log Output of Alloted Agents			
	(1)	(2)	(3)
I_m	0.190	0.846	0.120
	(0.136)	(0.662)	(0.940)
Manager Tenure	-0.031**	-0.026*	-0.156***
	(0.014)	(0.014)	(0.044)
Manager Tenure*I_m		-0.032	0.097
		(0.030)	(0.122)
Manager Tenure Square/100			0.396**
			(0.151)
Manager Tenure Square*$I_m/100$			-0.407
			(0.385)
$\mathbb{1}\{Male\}$	0.655***	0.661***	0.598***
	(0.140)	(0.144)	(0.159)
Observations	127	127	127

Sample consists of the orphaned agents who were allotted to other managers in 2013-2015. Branch and year fixed effects are included for all specifications. Manager Tenure Square and interaction of Manager Tenure Square with I_m are normalized by 100. Standard errors are clustered at the manager-level. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 2.8: Output Trajectory Of Agents

	(1)	(2)	(3)	(4)	(5)	(6)
I_m					0.258*	0.408***
					(0.142)	(0.139)
Agent Tenure	0.111***	0.125***	0.113***	0.116***	0.045***	0.125***
	(0.011)	(0.008)	(0.011)	(0.010)	(0.004)	(0.010)
Agent Tenure Square/100	-0.291***	-0.347***	-0.297***	-0.326***		-0.352***
	(0.031)	(0.029)	(0.032)	(0.033)		(0.033)
Agent Tenure*I_m					-0.003	-0.017
					(0.007)	(0.013)
Manager Tenure					0.010***	0.028**
					(0.003)	(0.012)
Manager Tenure*I_m					-0.007	-0.040
					(0.006)	(0.027)
Agent Tenure Square*I_m/100						0.071*
						(0.041)
Manager Tenure Square/100						-0.076*
						(0.042)
Manager Tenure Square*I_m/100						0.115
						(0.084)
$\mathbb{1}\{Male\}$	-0.155	0.114			-0.024	-0.052
	(0.167)	(0.114)			(0.086)	(0.075)
Observations	11498	24233	11498	24233	35731	35731
Manager Fixed Effects	No	No	Yes	Yes	NA	NA
Manager Type	Internal	External	Internal	External	NA	NA

Samples in columns (1) and (2) contain agents of the internally-hired and externally-hired managers, respectively, and include branch and year fixed effects. Samples in columns (3) and (4) contain agents of the internally-hired and externally-hired managers, respectively, and include manager and year fixed effects. For columns (5) and (6), all observations of agents are pooled and, include branch and year fixed effects. Manager Tenure Square and interaction of Manager Tenure Square, Agent Tenure Square, and interactions of Manager Tenure Square and Agent Tenure Square with I_m is normalized by 100. Standard errors are clustered at manager-level. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 2.9: Output Growth Of Agents

	(1)	(2)
I_m	-0.012	-0.025
	(0.016)	(0.022)
ΔAgent Tenure Square/100		-0.124**
		(0.054)
ΔAgent Tenure Square*I_m/100		-0.017
		(0.049)
ΔManager Tenure Square/100		-0.034
		(0.039)
ΔManager Tenure Square*I_m/100		0.069*
		(0.041)
Observations	20900	20900

Year fixed effects are included in both specifications. Change in Manager Tenure Square, Agent Tenure Square, and interactions of change in Manager Tenure Square and Agent Tenure Square with I_m are normalized by 100. Standard errors are clustered at the manager-level. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 2.10: Exit Rate

Dpdt. Var.: $\mathbb{1}\{Exit\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I_m					-0.007	-0.042***	-0.082**	-0.053
					(0.012)	(0.016)	(0.035)	(0.045)
Agent Output/10	-0.010***	-0.027***	-0.010***	-0.026***	-0.017***	-0.027***	-0.026***	-0.026***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Agent Output*I_m/10						0.016***	0.016***	0.016***
						(0.004)	(0.004)	(0.004)
Manager Tenure							-0.004***	-0.012***
							(0.001)	(0.003)
Manager Tenure*I_m							0.003	0.002
							(0.002)	(0.007)
Manager Tenure Square/100								0.027***
								(0.009)
Manager Tenure Square*I_m/100								-0.001
								(0.023)
$\mathbb{1}\{Male\}$					-0.013	-0.010	-0.002	-0.001
					(0.031)	(0.030)	(0.027)	(0.027)
Observations	8973	18766	8973	18766	27739	27739	27739	27739
Manager Type	Internal	External	Internal	External	NA	NA	NA	NA
Manager Fixed Effects	No	No	Yes	Yes	NA	NA	NA	NA

Sample consists of exiting agents in years 2012-2014. Standard errors are clustered at manager-level. Columns (3) and (4) include Manager Fixed Effects. Branch & Year fixed effects are provided for all other specifications. Output and interaction of output with manager dummy are normalized by 10. Manager tenure square and interaction of manager tenure square with manager dummy are normalized by 100. Standard errors are clustered at the manager-level. */**/*** denotes significance at the 10/5/1 percent levels, respectively.

Table 2.11: Market Heterogeneity

	Type of Products	Avg. Cost	Avg. Revenue
I_m	-0.014	-0.000	-0.018
	(0.013)	(0.001)	(0.015)
Observations	35731	35731	35731

Each specification includes branch and time fixed effects, second order polynomial tenure terms of manager and agents, and gender of manager. Standard errors are clustered at the manager-level.

Table 2.12: Team Specialization

	MAD(Type of Prod.)	MAD(Cost)	MAD(Value)
I_m	0.003	-0.000	0.007
	(0.004)	(0.001)	(0.007)
Observations	35731	35731	35731

Each specification includes branch and time fixed effects, second order polynomial tenure terms of manager and agents, and gender of manager and team-level mean of product features. Standard errors are clustered at the manager-level.

Chapter 3

Internet-based Media Competition and Political Outcomes

The media plays an important role in how voters acquire information regarding policy proposals. Voters absorb the expert-recommended analysis from a news source in order to weigh the costs and benefits of a policy. Owing to this, truthfulness and the quality of information conveyed by the media remains an important issue. In recent years, concern about the media landscape has become even more pronounced, as the rise in media polarization—diverging viewpoints among news sources on the same issues—is considered as one reason for the concurrent rise in political polarization (e.g., McCarty et al. (2006)), which may be leading to inefficient political outcomes.

Media polarization is often attributed to the new internet-based technology, where users interact with the opinion pieces they read. This interaction includes sharing, tweeting, liking, and, more broadly speaking, circulating the content to the audience that would not have seen it otherwise, and attracting these new audiences to the news site. For instance, Stocking et al. (2018) analyzes 9.7 million immigration-related tweets to find that around 75% of tweets contained at least one link redirecting readers to a news organization. If the propensity of user interaction is a function of one's preference for opinions, the benefits of the new technology increase the incentives for news firms to skew their opinion towards the users' bias, and further away from reporting the true state of the world. This divergence and skew is worrying since it could distort the availability of information in the society, leading to sub-optimal policy choices. The concern over catering and pandering to partisan viewers has been raised in prior theoretical (Bernhardt et al. (2008)) and empirical literature (DellaVigna and Kaplan (2007)), but with a focus upon cable news.

In order to test these concerns, we build a formal model in which citizens receive opinions on some policy issues and also vote for a policy in an election. We call these citizens voter-consumers, who are heterogeneous in their preference over policy and opinion. While unbiased information-seekers want to receive state-relevant information to choose the correct policy, the biased voter-consumers exhibit confirmation bias, consistent with Gentzkow et al. (2014); i.e. left-biased (right-biased) voter-consumer prefers, ex ante, a liberal (conservative) policy and also prefers to listen to more left-wing (right-wing) commentators. Voter-consumers receive information from one of two media firms, which observe the state of the world and compete by committing to a profile of message for each possible realization of the state. These messages may endorse a policy by providing opinions or may provide a bland, uninformative reporting, endorsing none of the available policy options. Having observed (possible) state-relevant messages from their chosen sources, voter-consumers then update their priors to form their preferences over policies.

We carry out the analysis in two parts. First, we consider the case of old technology where the primary source of politics-related opinion was cable networks and user interaction was absent. In this setting, firms converge to offer the same expected bias. However, if most consumers exhibit a confirmation bias, then the media firms would refrain from always reporting the truth as it would create disutility for at least one group. Instead, with a positive probability, the media firms would endorse no policy. One can interpret this as reporting the headlines without providing opinions, similar to the style of a press release. When both firms choose to send no opinions, voters receive no information about the underlying causes of the news and, as such, choice of policy remains uninformed.

In the second part, we consider the case of new technology, where users provide additional rents to the media firms by circulating an article when it endorses the policy they prefer. We show that with the increase in value from the new technology, the incentive for divergence increases. One firm would provide a state-invariant slant to gain rents from the biggest biased group, leaving the other firm to cater to the remaining population. The degree of divergence, however, would depend on the relative mass of unbiased consumers. If the unbiased viewers are present in sufficient quantity, the second firm would reveal the truth to attract them. In this case, new technology increases the aggregate level of information in society leading to informed policy choices. However, if these unbiased viewers are too small, the firm would divert to the other extreme by providing state-invariant slant. Now, the unbiased viewers would be unable to update their priors as messages from either of the firms remain state-invariant. Thus, the concerns regarding internet-based media are contingent on the electorate, and requires further investigation.

The literature on media bias and political outcomes is vast and growing (e.g., Groseclose and Milyo (2005) Mullainathan and Shleifer (2005), Prior (2005), Gentzkow and Shapiro (2006), Duggan and Martinelli (2010), Gentzkow and Shapiro (2010), Puglisi (2011)). For a general overview of the field, see Prat and Stromberg (2011). By focusing upon media firms which report information about the state of the world, we differentiate ourselves fully from one subset of the literature which focuses on media as endorsement heuristics for voters (e.g., Chiang and Knight (2011); Castaneda and Martinelli (2016)).

The literature on endogenous media bias can be divided according to supply driven bias or demand driven bias. Under supply driven media bias, political capture of media firms, either through direct bribes (McMillan and Zoido (2004)) or editor/owner bias (Gentzkow and Shapiro (2010)), drives the skew of the content. In such settings, political bias and efficiency is reducing due to competition and specialization (e.g., Besley and Burgess (2006); Gentzkow et al. (2006); Anderson and Mclaren (2012); Sobbrio (2014); see Baron (2006) for an exception). In contrast, we show that under the new technology, as one firm specializes its content, the incentives to reveal state-relevant information increases for the media.

The above strand of literature studies how political factors, such as influence of political parties, affect media environment through the supply side. We, on the other hand, analyze demand-driven endogenous media bias to study the relationship in the opposite direction—how media polarization affects political outcomes. Similar to our primary setting, papers in this sphere focus on biased consumers and profit-maximizing firms which respond to the demand for bias, generating media polarization (Mullainathan and Shleifer (2005); Gentzkow and Shapiro (2006); see Oliveros (2015) for an exception where consumer preferences are inversely related to media preferences). However, they considered neither the trade-off for voters between preference for slant and preference for information, the technology shift that would lead to a specialized media, nor the ex-post political outcome. Chan and Suen (2008) consider media that are exogenously limited in their ability to report the full truth, while Stromberg (2004) considers an increasing returns to scale technology (broadcast media), which provides incentive to cater to the group based on its size, but does not yield divergence in the media space.

3.1 Model

There exists a state of the world (unobserved to the voter), $\omega \in \{-1, 1\}$, each of which is equally likely. There exists a policy space $a \in \{-1, 1\}$.

For example, consider the issue of whether minimum wage should be increased to \$15 per hour or not. The underlying state of the world is the elasticity of labor demand; if elasticity is greater than 1, then the correct policy is to not raise minimum wage whereas if labor demand is fairly inelastic, then minimum wage should be increased.

Denote by $\hat{a}$ the policy function that maps from state space $\omega \in \{-1, 1\}$ to policy space $a \in \{-1, 1\}$. Thus, $\hat{a}$ determines the chosen policy for each state of the world.

3.1.1 Media Firms

There are two media firms, $\tau \in \{1,2\}$[1], which observe the true state of the world and send a message m. Message, m, belongs to the set $\{-1,1,0\}$, where $m = -1$ is interpreted as endorsing policy $a = -1$, whereas $m = 1$ corresponds to recommending policy $a = 1$. Message $m = 0$ represents a neutral content that merely states the headlines, without providing any opinions or analysis for recommended policy. Here, one can consider the example of the Associated Press or Reuters.

Firms commit in advance to a strategy that specifies a deterministic message to be sent in each state. They can randomize ex ante over different strategies. The realization of these strategies is observable to voters, who then choose one media firm. Denote a media strategy by $\hat{m}$. Let $\mathcal{M} = \{m_T, m_v, m_r, m_l, m_R, m_L\}$ be the set of strategies for media firms, defined as follows:

Truth-telling, m_T where

$$m_T = \begin{cases} m = -1 & : \omega = -1 \\ m = 1 & : \omega = 1 \end{cases}$$

Moderate Right Slant, m_r, where

$$m_r = \begin{cases} m = 0 & : \omega = -1 \\ m = 1 & : \omega = 1 \end{cases}$$

Moderate Left Slant, m_l, where

$$m_l = \begin{cases} m = -1 & : \omega = -1 \\ m = 0 & : \omega = 1 \end{cases}$$

Extreme Right Slant, m_R, where $m = 1 \, \forall \, \omega$

[1] In Appendix C, we provide an extension with N firms.

Extreme Left Slant, m_L, where $m = -1 \, \forall \, \omega$

Moderation, m_v, where $m = 0 \, \forall \, \omega$

When firms commit to m_T, the recommended policy changes with the state of the world, whereas m_v provides headlines without any opinions/analysis. With m_r (m_l), a media firm provides a detailed opinion piece for a policy whenever $\omega = 1(-1)$ but refrains from holding any position when $\omega = -1(1)$. m_R and m_L represent extreme skew where the news firm takes a stand on policy matters that remains invariant to the state of the world[2].

Firms stick to the committed message when the state of the world is revealed. However, before the state is realized, firms can potentially randomize over media strategies in $\mathcal{M}$. The realized strategy from randomization is revealed before the state occurs.

3.1.2 Voters/Consumers

The population is composed of a unit mass of voter-consumers of types $i \in \{L, R, U\}$. Voter-consumers are heterogeneous in their preference over policy $a \in \{-1, 1\}$ and media strategies $\mathcal{M}$.

The utility function for voter type i, $U_i(\hat{a}, \hat{m}; \omega)$, takes the following form:

$$U_i(\hat{a}, \hat{m}; \omega) = -(m(\omega) - b_i(\omega))^2 - (a(\omega) - b_i(\omega))^2,$$

where, $b_R(\omega) = 1 \, \forall \omega$, $b_L(\omega) = -1 \, \forall \omega$, and $b_U(\omega) = \omega$. $m(\omega)$ is the message in $\hat{m}$ and $a(\omega)$ is the implemented policy when state is ω.

Let $P(i)$ be the mass of voter type i. Define $P(i = L) = \lambda$, $P(i = R) = \rho$ and $P(i = U) = \mu$. In order to make the problem interesting, we make the following assumption:

Assumption 1: $\frac{1}{2} > max\{\rho, \lambda, \mu\}$, $\rho > \mu$ and $\rho > \lambda$

[2]For eg; consider conspiracies about 'Deep State' propagated by conservative news sources in the US, with respect to Mueller investigation.

Thus, none of the groups compose by itself a majority. Second and third inequalities state that the right-biased group is the largest group. This simplifies the analysis without any loss of generality.

For any given message, m, voter types $i = L$ or $i = R$ have state-invariant preference for policies, where $i = L(R)$ prefers $a = -1(1)\,\forall\,\omega$. In this sense, $i \in \{L, R\}$ are biased voter-consumers who have made up their minds regarding the policy solution and are uninfluenced by any state-relevant information. We call them biased groups with $i = L(R)$ defined as the left-biased(right-biased) group. On the other hand, preference of $i = U$ over policy varies with the true state of the world. This group does not exhibit a strong ideological predisposition for policy solution. We call these voters "updaters", since their preference are capable of changing over the state of the world. Updaters are then the pivotal voters. We assume the prior beliefs of the updaters are uniform. Thus, if the state remains unknown, then the updaters are indifferent between the two policies. In that case, we assume the updaters choose either policy with equal probability, and split evenly between them.

The biased groups prefer opinions that reflect their ex post preference for policy, whereas the updaters treat any state-relevant information as useful. One can consider that the biased viewers receive a strong signal for one state before the media firms reveal their messages. This induces them to believe that only one state is possible, and any messages by the media firms to the contrary are given less or no weight at all. Updaters, on the other hand, do not receive such signals and rely solely on the messages from the media firms to become informed about the state of the world. Having no pre-determined information, the updaters consider each state to be equally likely, generating uniform priors.

3.1.3 Timeline

1. Media firms commit to a strategy, which is revealed to the voter-consumers. If firms randomize over strategy, the realized strategy pair from this randomization is revealed to the voter-consumers.

2. Voter-consumers choose one and only one media firm depending on its strategy profile[3].

3. A state is realized, which is observed by the media firms. A message is issued, and the voter-consumers update their priors to form preferences over policy.

3.1.4 Preference Ordering Of Voter/Consumers Over News Source

Let $a(\omega) \in \{-1, 1\}$ be the eventual policy chosen by the majority of voters for a given ω. Since the updaters are pivotal, if they consider $\omega = -1$ to be more likely than $\omega = 1$, then $a(\omega) = -1$. Otherwise, $a = 1$ is chosen.

Define

$$V_i(\hat{m}) = -E_\omega(m(\omega) - b_i(\omega))^2 - E_\omega(a(\omega) - b_i(\omega))^2,$$

as the ex ante utility of a voter-consumer i from a media strategy $\hat{m}$. Each voter takes the equilibrium $a(\omega)$ as given. The additive separability of the utility function implies that the voter-consumer's preference for media firm depends only on the first term of $V_i(\hat{m})$. Thus, $V_i(\hat{m})$ determines i's preferences over $\mathcal{M}$.

Since biased groups do not change their policy preference after receiving messages, $V_i(\hat{m})$ for $i \in \{L, R\}$ can be written as:

$$V_i(\hat{m}) = -E_\omega(m(\omega) - b_i)^2 + K_i$$

[3]Constraints on the choice over media firm stems from the opportunity cost of voters, rather than the price of following news. Indeed, whether it is the old technology or the new, choice of news is infra-marginal to the price of accessing the news.

where K_i is independent of $\hat{m}$ chosen by $i \in \{L, R\}$.

Updaters, on the other hand, can alter their policy preference on receiving messages. Further, updaters change their beliefs over ω after observing messages. Thus, for the updaters, ex ante utility from $\hat{m}$ is:

$$V_U(\hat{m}) = -E_{\omega;\hat{m}}(m(\omega) - \omega)^2 - E_{\omega;\hat{m}}(a(\omega) - \omega)^2,$$

where $E_{\omega;\hat{m}}$ denotes the updated beliefs over ω for the chosen $\hat{m}$.

We can order i's preference over $\mathcal{M}$ as the following:[4]

for $i = R$, $m_R \succ m_r \succ m_v \succ m_T \succ m_l \succ m_L$

for $i = L$, $m_L \succ m_l \succ m_v \succ m_T \succ m_r \succ m_R$

for $i = U$, $m_T \succ m_r \sim m_l \succ m_v \succ m_R \sim m_L$

When the updaters are indifferent between two media strategies, we assume they split evenly between the two options.

3.1.5 Profit Function for Media Firms

Given the above preferences of the voter-consumers, media firms compete to maximize profits, which depend on the size of each group and value from each group (Stromberg (2004)). We will consider the following linear profit function, π:

$$\pi_\tau = \Sigma_i v_i f_i(\tau)$$

where v_i is the value provided by group $i \in \{L, R, U\}$ and $f_i(\tau)$ is the share of group i watching news channel τ. In particular, v_i will depend on the technology of the media firms, which will be described later.

[4]Preference ordering derived in Appendix C

3.2 Equilibrium

Media firms pick their strategy $\hat{m}_1$ and $\hat{m}_2$ to maximize their profits given the preference of voter-consumers. The pair of media strategies which forms a Nash Equilibrium between media firms will be the ***media equilibrium***.

Having chosen the news sources, the updaters observe messages and then update their beliefs regarding the state of the world to form preferences about policies. A policy preferred by the majority of the voters will be the chosen policy defined as the ***political equilibrium***. Given Assumption-1, the updaters are the pivotal voters. Thus, the policy preferred by the updaters determines the political equilibrium.

The following analysis is divided into two parts. First, we describe the old technology, where user interaction was limited. We explore media and political equilibria in that situation. Then, we explain how the new technology that allows user interaction differs from the old technology in terms of the value provided by the users. With the new value schedule, we characterize media and political equilibria under the new technology.

3.3 Old Technology

Under the old technology, the mode of news delivery is the mass media, such as cable networks. The viewers are passive and any endorsements or dissemination of opinion is limited. Recall the profit function for media firm:

$$\pi_\tau = \Sigma_i v_i f_i(\tau)$$

We make the following assumption:

Assumption 2: Under old technology, $v_i = 1 \,\forall\, i \in \{L, R, U\}$.

Assumption 1 implies that the profits of media firm τ increase in the aggregate viewership of the news channel. Table C.1 provides the payoff for firms for each possible media strategy pair.

3.3.1 Media Equilibria Under Old Technology

Theorem 1: Under the old technology, there is a unique Nash equilibrium where both firms select an identical mixed strategy that assigns positive probability weights to m_T, m_v, m_r.

The proof is provided in Appendix C. The intuition is as follows. A moderate slant such as m_r will dominate an extreme slant, since the updaters prefer state-varying messages since it has informative value, whereas m_R or m_L is preferred by only one biased group when m_r is available. Given that $\rho > \lambda$, m_r will also dominate m_l. The best response to m_r is m_T as it attracts all the updaters and the left-baised group, which is greater than half. But, the best response to m_T is m_v since it attracts both sets of biased audience, again greater than half. However, the best response to m_v is m_r, since it attracts the right-biased group and the updaters. Thus, we seek a mixed strategy Nash Equilibrium in these three strategies.

3.3.2 Political Equilibrium Under Old Technology

Theorem 2: Under old technology,

$a = 1$ is chosen by majority with probability 1 when $\omega = 1$.

$a = -1$ is chosen by majority with a positive probability less than 1 when $\omega = -1$.

The proof is provided in Appendix C. Whenever both firms play m_v, the updaters receive no state-contingent information. Thus, their posterior beliefs remain the same as their priors. Updaters evenly split between the two policies. Given $\rho > \lambda$, $a = 1$ is chosen whenever both firms play m_v.

3.4 New Technology

Under the new technology, news sources exist online and users interact with opinion pieces through liking, commenting, providing feedback, and more generally disseminating opinion pieces further. By interacting with the news website in this manner, the audience is involved in spreading the recommendation beyond the audience that arrives on the site directly (Stocking et al. (2018)). In this manner, the viewers act as vehicle of endorsement for the news firm. Hence, media firms receive additional traffic and viewership, resulting in higher value.

However, viewers vary in their degree of interaction after observing the content of the news sites. For instance, a biased viewer who finds an opinion piece opposed to (aligned with) her view is unlikely (likely) to endorse it on her social network. Evidence for this behavior is recorded in Kalogeropoulos et al. (2017), where using a cross-national sample of online news users, the authors find positive and negative spiral of user interaction depending upon engagement with the news.

Owing to this behavior of the voter-consumer, the value provided by i, v_i, is contingent on the transmitted messages of the media firms. We make the following assumptions about v_i under the new technology:

For $i = R$,

$$v_R = \begin{cases} v(>1) & : m = 1 \text{ for any } \omega \\ 1 & : \text{otherwise} \end{cases}$$

For $i = L$,

$$v_L = \begin{cases} v(>1) & : m = -1 \text{ for any } \omega \\ 1 & : \text{otherwise} \end{cases}$$

For $i = U$,

$$v_U = \begin{cases} v(>1) & : m = 1 \; s.t. \; Pr(\omega = 1 | m = 1; \hat{m}) = 1 \\ v(>1) & : m = -1 \; s.t. \; Pr(\omega = -1 | m = -1; \hat{m}) = 1 \\ 1 & : \text{otherwise} \end{cases}$$

Biased groups provide value when their ex post preferred policy is endorsed regardless of the state of the world. Updaters, on the other hand, require a policy endorsement to reveal the true state of the world without any uncertainty. Note that the updaters do not provide any value when $m = 0$, even when it reveals the true state of the world (eg; when

$m = 0$ for a firm that chooses $\hat{m} = m_r$). This is consistent with the interpretation of $m = 0$ as reporting without providing opinions which does not get retweeted, liked or circulated.

Consider the following example of profit realization for two firms under the new technology. Let firm-1 choose m_R and firm-2 commit to m_T. Given the preference ordering of voter-consumers, $i = R$ choose m_R, whereas the remaining groups follow firm-2. Now, expected profits for firm-1, π_1, are given by:

$$\pi_1 = E_\omega(v_R \rho)$$

$$\pi_1 = Pr(\omega = 1)\Sigma_m Pr(m|\omega = 1; m_R)v_R\rho +$$
$$Pr(\omega = -1)\Sigma_m Pr(m|\omega = -1; m_R)v_R\rho$$

Since $m(\omega) = 1\,\forall\omega$ under m_R, $v_\rho = v\,\forall\omega$. Thus, $\pi_1 = \frac{1}{2}v\rho + \frac{1}{2}v\rho = v\rho$.

Firm-2 attracts $i \in \{L, U\}$. Thus, its profits are:

$$\pi_2 = E_\omega(v_U\mu + v_L\lambda)$$

$$\pi_2 = Pr(\omega = 1)\Sigma_m Pr(m|\omega = 1; m_T)(v_U\mu + v_L\lambda) +$$
$$Pr(\omega = -1)\Sigma_m Pr(m|\omega = -1; m_T)(v_U\mu + v_L\lambda)$$

Under m_T, $m(1) = 1$, and $m(-1) = -1$. Therefore, $v_L = v$ when $\omega = -1$ and $v_L = 1$ otherwise. Further, from posterior probabilities derived above, $Pr(\omega = 1|m = 1; m_T) = Pr(\omega = -1|m = -1; m_T) = 1$. Thus, we get $v_U = v\,\forall\,\omega$. Hence, expected profits for firm-2 are: $\pi_2 = \frac{1}{2}(v\mu + \lambda) + \frac{1}{2}(v\mu + v\lambda) = v\mu + \frac{v+1}{2}\lambda$.

Table C.2 provides the payoff for firms for each possible media strategy pair.

3.4.1 Media Equilibria under the New Technology

We make the following assumption:

Assumption 3: $max\{2\mu, 2\lambda\} > \rho$

Assumption 3 provides a sufficient condition to disallow the equilibrium where both media firms cater to the right biased group.

Theorem 3: Under the new technology with Assumption 3,

If $\mu \geq \frac{\lambda}{2}$, then for a sufficiently high value of v, the unique pure strategy Nash Equilibrium is of the form $(\hat{m}_{\tau}, \hat{m}_{-\tau}) = (m_R, m_T)$ where $\tau \in \{1, 2\}$ indexes firms.

If $\mu < \frac{\lambda}{2}$, then for a sufficiently high value of v, the unique pure strategy Nash Equilibrium is of the form $(\hat{m}_{\tau}, \hat{m}_{-\tau}) = (m_R, m_L)$ where $\tau \in \{1, 2\}$ indexes firms.

Appendix C provides the proof. The intuition is the following. One firm acquires the biggest group. The rents from the biggest group restrict the firm from deviating and losing value from this group. This is consistent with DellaVigna and Kaplan (2007), which analyses the entry of Fox News Network in capturing the conservative audience. Another firm faces a trade-off between attracting rents from all the updaters or slanting towards left to gain more rents from left-biased group. If the updaters constitute a sufficient mass ($\mu \geq \frac{\lambda}{2}$), then the incentive to not lose the updaters outweighs the additional rents from the left-biased group for a sufficiently high value of v. However, if the updaters constitute a small mass, and if the value from user interaction is high enough, then firm-2 would have an incentive to gain value from the left-biased group at the cost of losing the value from the updaters.

Note that (m_R, m_T) as an equilibrium can be obtained even if $\mu < \lambda$; revelation of truth is possible even when the updaters are the smallest group.

3.4.2 Political Equilibrium under the New Technology

Theorem 4: Under Assumptions 2 and 3, and with new technology,

If $\mu \geq \frac{\lambda}{2}$, then $a = \omega$ is chosen by majority for each $\omega \in \{-1, 1\}$.

If $\mu < \frac{\lambda}{2}$, then $a = 1$ is chosen by majority $\forall \omega \in \{-1, 1\}$.

When $\mu \geq \frac{\lambda}{2}$, the strategy profile in the media equilibrium is (m_R, m_T). Updaters receive true information about the state of the world. Thus, for each state of the world, the updaters are fully informed. Since the updaters are the pivotal voters in this case, the policy preferred by them is the chosen policy.

On the other hand, if $\mu < \frac{\lambda}{2}$, the media strategy profile is (m_R, m_L). Updaters choose m_T and receive state-invariant messages whichever news channel they watch and, hence, do not improve their beliefs about the state of the world, staying indifferent between the two policies. Since $\rho > \lambda$, $a = 1$ is chosen irrespective of the state of the world and the policy choice remains uninformed.

3.5 Conclusion

In this chapter, we provide a possible explanation of how the internet-based interactive technology of media firms may induce firms to diverge their stand on political issues. Further, how such divergence affects information availability depends discontinuously on the mass of unbiased viewers. If the electorate is already ideologically polarized with little demand for state-contingent information, then profit-motivated media firms would only confirm what the majority considers preferable. However, the preference of unbiased viewers cannot be overlooked if they constitute a big enough consumer bloc (even though they may be the smallest group). In such a case, one media firm would alway report the true state of the world.

This chapter identifies two incentives for media firms that have been overlooked in the previous literature. First, with confirmation bias among voter-consumers, convergence of content among media firms need not imply truth-telling. This is because sufficiently strong confirmation bias deters firms from displeasing biased consumers. Second, under the new technology, media firms would gain additional rents from the biased groups and thus can afford to let go of the other biased group by providing state-contingent slant. Therefore, specialization and competition could lead to better information availability, contrary to some of the theoretical models, but consistent with the empirical evidence, e.g., Gentzkow and Shapiro (2011), Gentzkow et al. (2014), and Schroeder and Stone (2015).

Appendix A

Appendices to Chapter-1

A.1 Managerial Incentives

A manager's incentives are governed by a comparison of her annual remuneration and the total revenue collected by her team in that year. Annual remuneration consists of a fixed composition such as basic pay, dearness allowance, and other refundable expenses such as work-related expenses, travel allowance, etc.. Total revenue consists of premium payments on products sold in a given year, known as First Year Premium. The ratio of annual remuneration and total revenue is known as the cost ratio. If cost ratio is lower than a predetermined limit (19% in this division), the manager becomes eligible for increments in fixed components and other incentive schemes. On the other hand, penalties and disincentives are levied on the manager if the cost ratio exceeds the predetermined limit. These penalties increase with respect to the amount the Cost Ration exceeds this limit and with respect to the duration it persists above this limit.

If the cost ratio is lower than 19% for a manager, then she receives an incremental raise in her basic pay, fixed pay, and travel-related expenses. Further, she becomes eligible for other incentive schemes. For example, if on the team of a manager the number of agents who sell more than 20 products in a year, defined as productive agents, is more than 18, then the manager receives 2.5% of the bonus for each productive agent over 18. Also, if a manager fails to recruit at least five agents in the previous year, then the performance based bonus is reduced by 0.5%. Managers are also rewarded on the persistence of their teams, i.e,. if a manager is able to retain 90% of her agents from the previous year, then the manager receives Rs.100-Rs.200 per agent.

As mentioned above, If the cost ratio exceeds 19%, then the manager becomes ineligible for incentive schemes and faces decrement in basic pay in the following manner.

Table A.1: Table of Disincentive

	1st Occasion	**2nd Occasion**	**3rd and Subsequent Occasion**
2%<CR - EL <4%	No Increment	No Increment	No Increment
CR - EL >4%	No Increment	No Increment	1 Decrement
32% <CR <35%	No Increment	1 Decrement	2 Decrement
CR >35%	1 Decrement	1 Decrement	1 Decrement

The magnitude of the cost ratio also determines service termination for managers. A manager is fired if any of the following are true:

- her cost ratio exceeds 50% in any year;
- her cost ratio exceeds 45% in any year and the aggregate cost ratio of the preceding two years exceeds 50%;
- her cost ratio exceeds 40% in any year and the aggregate cost ratio of the preceding two years exceeds 47.50%;
- her cost ratio exceeds 38% in any year and the aggregate cost ratio of the preceding two years exceeds 38%.

The structure of the incentive scheme forces a manager to keep her cost ratio low; i.e., keep total revenue high without increasing annual remuneration too much. Low-productivity workers increase operational costs, which constitute a variable part of annual remuneration. For example, agents can bill the firm for work-related expenses such as traveling or client service. Further, agents receive a commission even on premium payments of products sold previously, but that amount does not form a part of the total revenue. As such, some less motivated agents have a lower incentive to bring First Year Premium as compared to a manager. Thus, without highly motivated and productive workers on her team, it is difficult for the manager to keep the cost ratio low. All of this implies that managers have a strong incentive to increase the productivity of their team.

A.2 Recruitment Procedure

To recruit an agent into the firm, a manager has to follow this process :

- A manager chooses a candidate for agency and enrolls him with the firm.
- Once enrolled with the firm, the agent is registered for a 50-hour training and an online exam. The training and online exam is conducted by the Insurance Regulatory and Development Authority (IRDA) of India.
- The firm incurs the cost of training and the online exam. However, the cost is billed as an operational expense of the manager.
- If the agent qualifies on the test, he receives a certificate to conduct agency and sell the firm's insurance products.
- The test is held once in each quarter. Further, in each quarter, exams are held only on four days. Thus, effectively, the exams are held 16 times each year.

The managers incur a cost for each attempted recruitment and the time window to recruit agents is limited. Such restrictions imply that managers have an incentive to recruit good agents.

A.3 Allotment Policy for Orphaned Workers

Orphaned workers are defined as those agents whose managers have exited the firm. These workers are allotted to other managers. The following procedure is used for matching:

- Allotable agents are ranked by the total revenue they obtained in the previous year. Preference of selecting a manager is given according to this ranking.
- The consent of a manager is required for the allotment to be carried out. If an orphaned agent does not get allotted due to lack of consent of the manager, then this agent is allotted to the next preferred manager.
- Allotment is conducted by Divisional Officers.
- The output of the allotted agent after being matched to a new manager is counted in the total team output of the manager. As such, the manager receives the compensation defined by the incentive scheme.
- An allotted agent may ask to be detached from the team within three years of the allotment. Once separated from the team, a now-orphaned agent would not be re-allotted to the team of the manager from whom he requested to be detached.

A.4 Construction of Key Variables

The data was obtained from the management information system of the firm. In this system, each employee is identified through a unique numeric or alpha-numeric code assigned at the time of entry that stays constant throughout the employee's career. An exited employee's codes are not reassigned to new entrants. Further, the dataset includes the manager's code alongside each agent's code, which is used to match each agent with his manager and identify teams of each manager.

A.4.1 Tenure of Managers and Agents

The codes for managers are numeric and in reverse-chronological order, i.e., a more recent entrant is assigned a numerically higher code than a manager recruited before her.

I use this reverse-chronological property of the codes to construct tenure. First, for a randomly picked sample of codes, I inquired about the exact joining date, which the firm was generously willing to provide. This allowed me to construct an incomplete mapping between codes and tenure. For the codes, which were out of the initial sample, I imputed tenure by putting it equal to the tenure of the numerically nearest code for which tenure was obtained. (The mapping is available on request).

For agents, codes are alpha-numeric, with the alphabetical component represents the branch code for the agent. The rest of the code exhibits the reverse-chronological property and thus, a similar procedure was applied.

A.4.2 Entering, Exiting, and Allotted Agents

To identify entrants, I matched the codes of all agents in one year to the codes in the preceding year. Given that a new code is assigned to each entrant, the codes that were not matched were considered new entrants. This procedure, thus, gave me entrants for the second, third, and fourth year of my dataset (2013-2015). For exiting agents, codes from one year were matched to the succeeding year, giving me unmatched codes (exiters, this time) for years 2012, 2013, and 2014.

When an agents becomes orphaned, he is assigned a numeric code in place of the code of his previous manager. This numeric code is common for all such orphaned agents. When an orphaned agent is allotted to a manager, this “orphan" code is replaced by the new manager’s numeric code. I isolated all those orphaned agents whose orphan codes changed from one year to another.

A.4.3 Team Size

As explained above, each agent is tagged with the code of his manager. A team can be defined as a set of agents with a common manager code. The size of this set was defined and used as team size.

A.5 Robustness Checks for Random Allocation of Allotted Agents

I provide more tests on random allocation of allotted agents to the managers.

Comparison of Receiving Managers and Non-Receiving Managers

During the time of this study, 59 managers, out of 211, received allotted agents. The set of 59 managers who received allotted agents could be different from the 152 managers who did not. I check if these two sets are balanced across the observable covariates—tenure, team output per worker, team output, and team size. I define the set of 59 managers as the Receiving Managers and the remaining set of 152 as the Non-Receiving Managers.

Figure A·1: Receiving versus Non-Receiving Managers

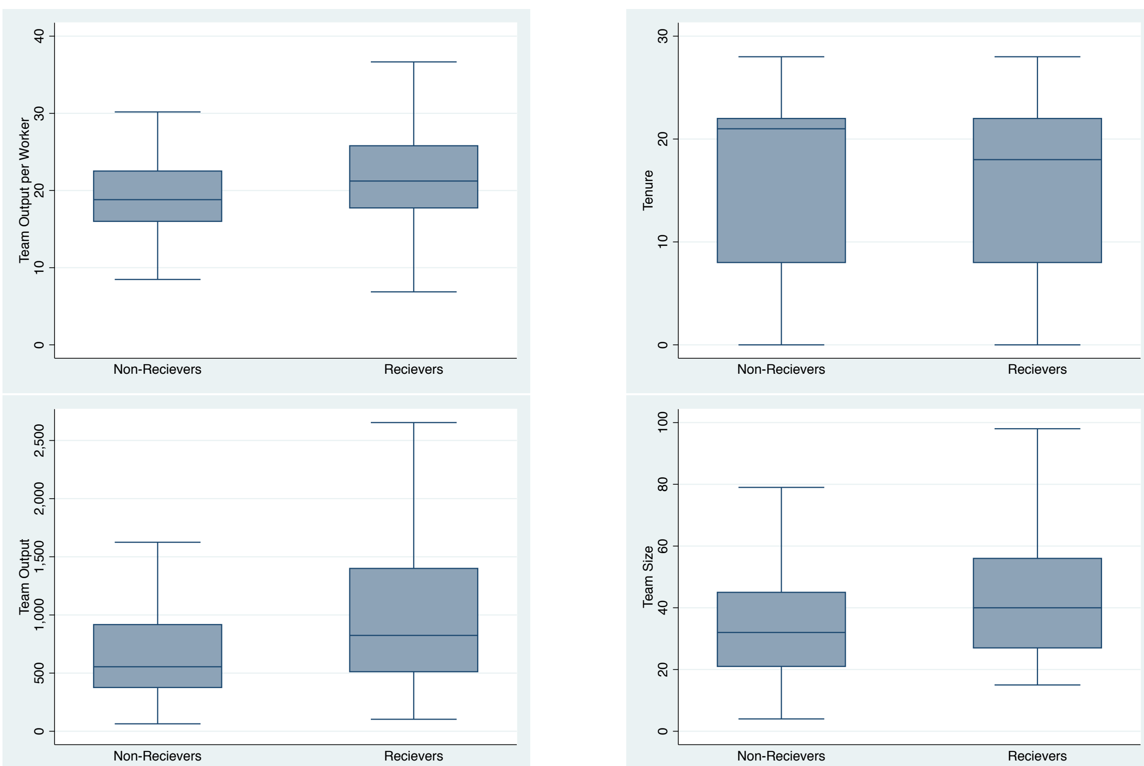


Figure ?? displays the box plot for the two sets of managers. The middle line in each box represents the median value for the observable covariates of that set. Each box contains 50% of the observations for each set of the managers.

For tenure and team output per worker, the two sets overlap. Team output and team size are slightly larger for the Receiving managers, but not without considerable overlap.

Thus, managers who receive allotted agents are not too different from the ones who do not.

Revealed Preference of Allotted Agents

Allotted agents are allowed to choose any manager they want. I observed only the realized choices of the allotted agents and not the full preference ordering of the allotted agents over the managers. Informal interactions reveal that allotted agents prefer to stay within the branch with which they started out. This inclination is due to commuting concerns. If so, agents may have lexicographic preference; allotted agents choose a branch and then choose the best manager from the available set of managers in that branch.

To explore this concern, I compared the realized choices of the allotted agents with the quality of other managers in that branch.

	Mean	Count
$\mathbb{1}${If joining a team below max. of the branch}	0.960	121
$\mathbb{1}${If joining a team below mean of the branch}	0.520	66
$\mathbb{1}${If joining a team below med. of the branch}	0.457	58
Observations	127	

Table A.5 shows that 52% of the allotted agents choose a manager below the average manager in that branch, and 45% of the allotted agents choose a manager below the median manager in that branch. Thus, to the extent that the realized choices reveal the preferences of the allotted agents, it appears that the selection is orthogonal to the managerial quality as I define it.

A.6 Empirical Bayes Estimation

I use the following model:

$$\log y^A_{ambt} - \log y^O_{amb} = \phi_t + \phi_b + \phi_m + \nu_{ambt} \tag{A.1}$$

where ϕ_m is manager fixed effect, assumed to be random with a variance σ^2_m and ν_{ambt} is an idiosyncratic component with variance σ^2_ν. The above model can be rewritten as:

$$\log y^A_{ambt} - \log y^O_{amb} = \phi_t + \phi_b + \psi_{ambt} \tag{A.2}$$

where $\psi_{ambt} = \phi_m + \nu_{ambt}$ has variance $\sigma^2_\psi = \sigma^2_m + \sigma^2_\nu$. An estimator of σ^2_ψ is

$$\tilde{\sigma^2_\psi} = \frac{\Sigma_a \Sigma_t \tilde{\psi^2_{ambt}}}{N - K} \tag{A.3}$$

where $\tilde{\psi_{ambt}}$ is the predicted residuals of (3), N is the number of observations, and K is the degree of freedom.

The empirical Bayes (EB) estimator, ϕ^*_m, of manager fixed effect, ϕ_m, is defined as:

$$\phi^*_m = \frac{\sigma^2_m}{\sigma^2_m + \frac{\sigma^2_\nu}{N_m}} E_m(\hat{\psi_{ambt}}) \tag{A.4}$$

where $E_m(\hat{\psi_{ambt}})$ is the within-manager average of residuals and N_m is the number of allotted agents for each manager. To compute ϕ^*_m, estimators of σ^2_m and σ^2_ν are needed.

For an estimator of σ^2_ν, I compute:

$$\tilde{\sigma^2_\nu} = \frac{\Sigma_a \Sigma_t (\tilde{\psi_{ambt}} - E_m \tilde{\psi_{ambt}})^2}{N - M} \tag{A.5}$$

where $E_m \tilde{\psi_{ambt}}$ is within-manager average of OLS residuals and M is the number of managers.

I use

$$\tilde{\sigma}_m^2 = \tilde{\sigma}_\psi^2 - \tilde{\sigma}_\nu^2 \tag{A.6}$$

as an estimate of σ_m^2, where $\tilde{\sigma}_\psi^2$ is obtained from (5) and $\tilde{\sigma}_\nu^2$ is obtained from (7).

I plug (8) and (7) in (6) to obtain EB estimate.

A.7 Additional Tests for Manager's Contribution

In this section, I provide some robustness checks and tests for alternative hypotheses of the managerial contribution to an agent's productivity. Neither one single test conclusively, nor all of them collectively, rule out all forms of manager's contribution. However, these tests reject, to an extent, different hypotheses about the manager's contribution to an agent's productivity.

A.7.1 Output Gap Trajectory between New Recruits

Assume that the effect of training occurs over time. In particular, assume the production function of agent a under manager m at time t, y_a^m, to have the following form:

$$y_a^m(t) = \theta_a + \alpha_m t \tag{A.7}$$

where θ_a is the agent-specific productivity, $t > 0$ is the time for which the agent has been with the manager and α_m is the value added by a's manager in the form of training or guidance. If we impose $\alpha_m = 0$, we obtain the model in Section 3.

Now, if managers differ in the training of workers, then the output gap between newly recruited agents across managers would grow over time, i.e.,

$$\alpha_{m'} > \alpha_m \implies \frac{dy_a^{m'}(t)}{dt} > \frac{dy_a^m(t)}{dt}$$

On the other hand, if $\forall\, m$, $\alpha_m = 0$, then no such gap should be observed with time.

To test this hypothesis, I construct a balanced panel of new recruits from 2013 who survived until 2015 I observe the performance of new recruits of managers in each year. I then use the following model:

$$\log y_{ambt} = \beta \log k_m + \gamma tt + \theta \log k_m * tt + \phi_b + \epsilon_{ambt}$$

where $\log y_{ambt}$ is log of output of agent a under manager m in branch b at time t, t is time trend, and k_m is team output per worker in 2012 for the manager.

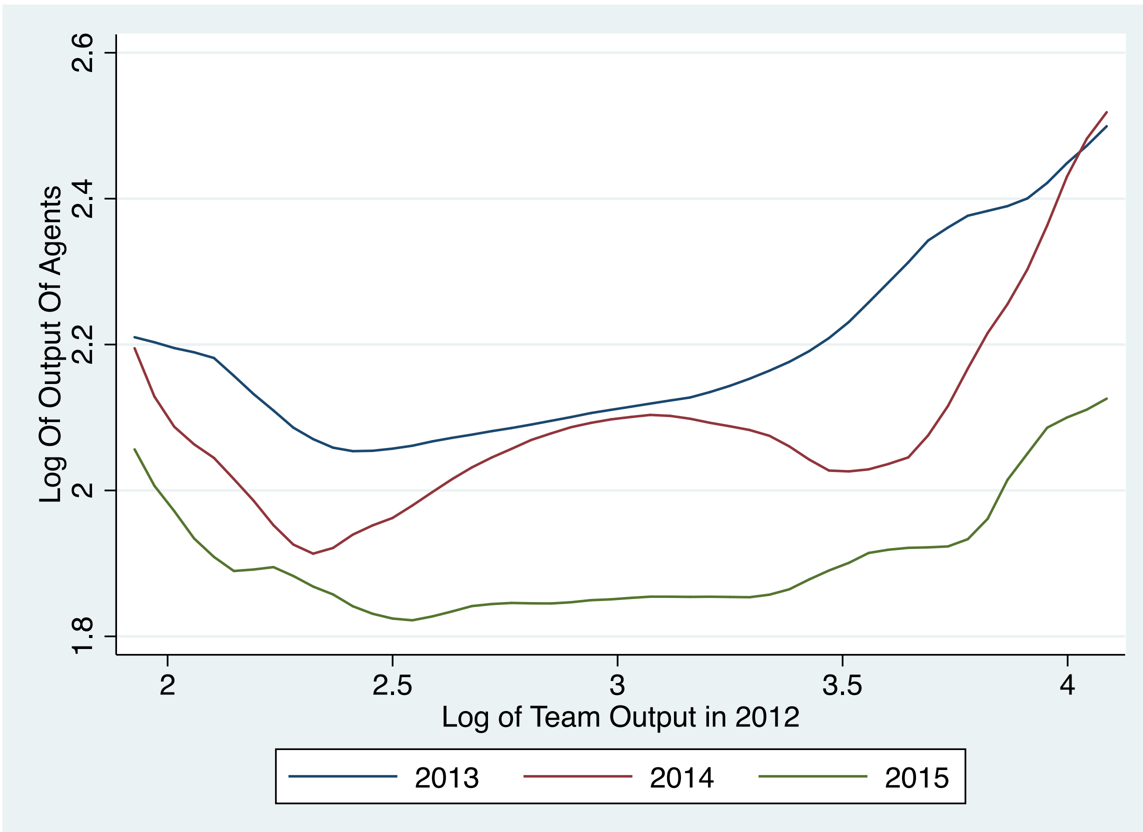
If managers differ in training and if training took some time to take effect, then output gap among agents should be larger in subsequent years; $\theta > 0$. Table **??** displays the results.

	Log of Agent Output
Log of Team Output per Worker in 2012	0.344**
	(0.147)
T	0.149
	(0.160)
Log of Team Output per Worker in 2012*T	-0.097*
	(0.055)
BFE	Yes
Observations	2025

Tenure, square of tenure of the manager, branch fixed effects and time fixed effects are controlled in the specification. Standard errors, shown in parentheses, are clustered by manager. Sample consists of those new recruits in 2013 who survived in the firm until 2015. */**/*** denotes significant at the 10/5/1 percent significance levels, respectively.

$\theta < 0$; variance in agent's output across managers appears to decrease with time. This result might suggest that managers are heterogeneous in training their workers. In Figure **??**, I explore the output gap semi-parametrically. Figure suggests that the output of new recruits remains stable in 2013 and 2014. In 2015, output gap for all agents goes down, leading to a contraction in output gap. Thus, one cannot conclude that managers are heterogeneous in training.

Figure A·2: Output Gap Trajectory of New Recruits



A.7.2 Agent Productivity and Managerial Attention

Assume that agent production is a function of the manager's attention that the agent receives in the first year of his career. Now, assume manager divides her attention equally among all newly recruited agents. Thus,

$$y_a = \frac{k_m}{n}$$

where n is the number of new recruits. In the firm, k_m and n both are decision variables of the manager; i.e. n is endogenous to manager's decision. Thus, *within a team*, the mean output of new recruits and number of new recruits are inversely related. I use the following model;

$$\log(\bar{y_{a|m}}) = \beta \log n + \phi_m + \phi_t + \epsilon_{amt}$$

where $\bar{y_{a|m}}$ is the mean output of new recruits a of manager m, n is the number of new recruits and ϕ_m is manager fixed effect. Table C.1 provides the results:

	Mean Output of New Recruits
Number of New Recruits	0.039
	(0.028)
Observations	561
Manager Fixed Effects	Yes

The coefficient on number of new recruits is positive and insignificant.

A.7.3 Subsequent Performance of Discretionary Retained Agents

In the firm, if any agent—in the first year of his career—fails to sell less than 12 products or sell products worth less than Rs. 100,000 (US 1,500), then such an agency is terminated. The manager,however, can decide to retain such to-be-fired agent.

If a manager decided to retain such agents and output of agents was functional only on training by manager, then she should provide more training to the retained agents. Thus, an increase in output should be observed in the second year of retained agents.

The figure below summarizes the result for this hypothesis. The blue curve is a local polynomial fit of log of retained agent's output in year 1 and log output per worker in 2012. The blue curve is the same but for agent's output in year 2. The grey band is the 95% CI. Output of the agent between two years does not undergo upward transition, rejecting this hypothesis.

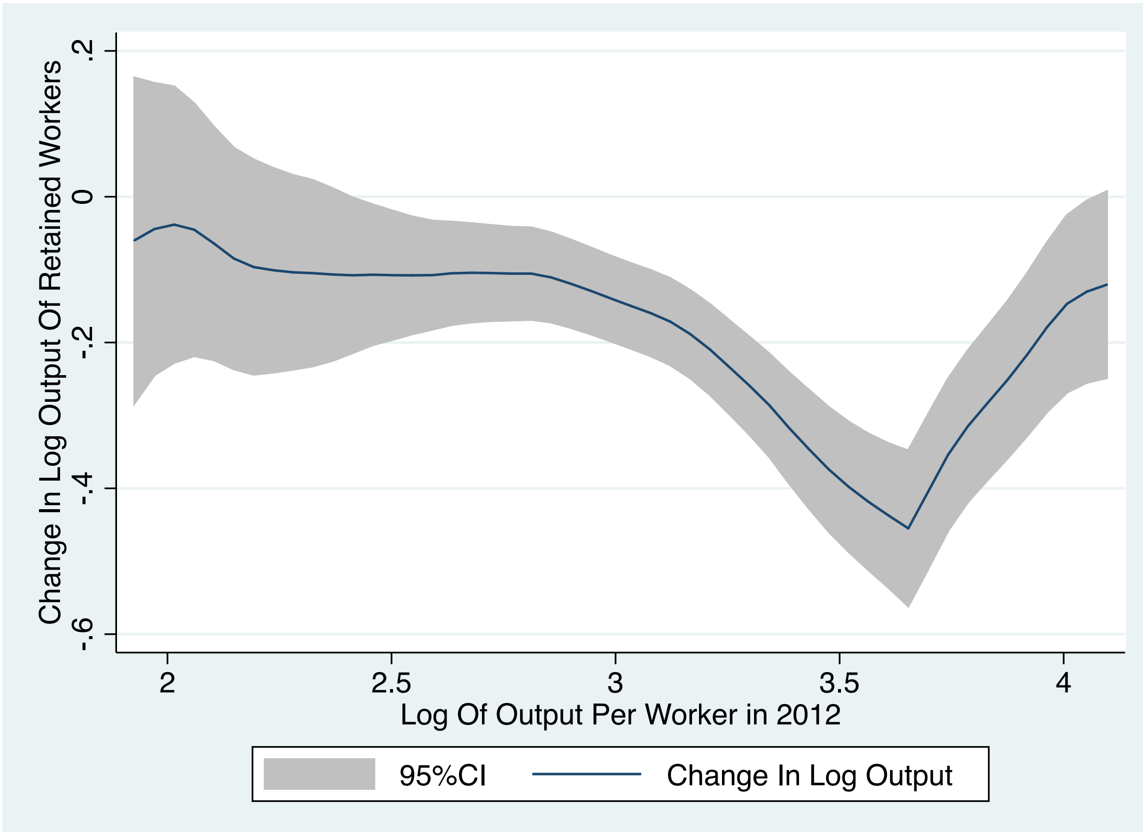


Figure A·3: Change in Output of Retained Workers

A.8 Proofs of Testable Implications

A.8.1 Exit Rate of Agents

For any given team of a manager with prior p; exit probability is given by :

$$Pr(Exit|\alpha) = \begin{cases} 0: & \Phi(\frac{s\theta_L - y_o^A}{\sigma}) \\ 1-\alpha: & \Phi(\frac{s\theta_H - y_o^A}{\sigma}) - \Phi(\frac{s\theta_L - y_o^A}{\sigma}) \\ 1: & 1 - \Phi(\frac{s\theta_H - y_o^A}{\sigma}) \end{cases}$$

where $\Phi(.)$ is the distribution function of standard normal and $1-\alpha$ is the probability of $\theta_a = \theta_L$.

Thus,

$$Pr(Exit|\alpha) = 1 - [\Phi(\frac{s\theta_L - y_o^A}{\sigma}) + \alpha(\Phi(\frac{s\theta_H - y_o^A}{\sigma}) - \Phi(\frac{s\theta_L - y_o^A}{\sigma}))] \tag{A.9}$$

(4) states that as α increases $Pr(Exit)$ decreases; if a manager has a better prior (lower p), then his team is less likely to have lower productivity workers (lower $1-\alpha$), and thus the probability of exit decreases.

A.8.2 Team Size Growth

The probability of an agent staying with the firm can be written as $1 - Pr(Exit|\alpha)$. Thus,

$$Pr(Stay|\alpha) = \Phi(\frac{s\theta_L - y_o^A}{\sigma}) + \alpha(\Phi(\frac{s\theta_H - y_o^A}{\sigma}) - \Phi(\frac{s\theta_L - y_o^A}{\sigma})) \tag{A.10}$$

Let Team size, N_t, be the total number of workers in the team of a manager at time t. Now,

$$N_t = \Sigma_{\tau=1}^{t}(Pr(Stay|\alpha))^{\tau}$$

i.e. expected team size at t is the sum of probability of an agent recruited at τ staying in the firm for $t-\tau$ periods.

$$N_t = \frac{1 - (Pr(Stay|\alpha)^t}{1 - Pr(Stay|\alpha)} \tag{A.11}$$

From (6), one sees that team size is higher for higher α. A manager with a better prior (higher α) would recruit better workers who are less likely to exit. Thus, for a given t (tenure of the manager), a manager with better prior would have a bigger team.

From (6), we can also see that controlling for α, team size is increasing and concave in tenure. This is because:

$$\frac{dN_t}{dt} = \frac{-1}{1 - Pr(Stay|\alpha)} Pr(Stay|\alpha)^t log(Pr(Stay|\alpha))$$

and

$$\frac{d^2N_t}{dt^2} = \frac{-1}{1 - Pr(Stay|\alpha)} Pr(Stay|\alpha)^t log(Pr(Stay|\alpha))^2$$

Since $log(Pr(Stay|\alpha)) < 0$, $\frac{d^2N_t}{dt^2} < 0 < \frac{dN_t}{dt}$

Intuition is the following. Managers recruit one worker every period but with some probability they lose the workers recruited in previous periods. Thus, initially team size grows but over time the growth starts tapering off.

A.8.3 Team Output and Team Size

Define total output of a team at t, Y_t, as the sum of output from each agent in a team.

$$Y_t = \frac{1 - (Pr(Stay|\alpha)^t}{1 - Pr(Stay|\alpha} E_\alpha(\theta)$$

$$Y_t = N_t E_\alpha(\theta)$$

Now, team size is an increasing function of α. By Implicit Function theorem, we can write $E_\alpha(\theta) = g(N_t)$ where $g' > 0$. Thus,

$$Y_t = N_t g(N_t) \tag{A.12}$$

(7) suggests that Y_t would exhibit increasing returns to scale with respect to N_t. Simply put, better managers recruit more productive agents who stay longer in the team. Thus, bigger teams are composed of more productive workers.

A.9 Potential Sources of Firm Specificity

Some of the unique characteristics of the subject firm are as follows:

- The subject firm relies on manager-led teams of agents for product distribution, which is known as a tied-agency model. Most other firms rely on corporate agency model, where firms sell products through partnership with other private firms. This unique distribution model has bestowed certain advantages onto the agents of the subject firm vis-a-vis other firms in the industry. For example, the regulator did not establish well-suited rules to prevent mis-selling by corporate agents[1]. Due to misselling and fraud committed by other firms, public trust in insurance firms is low in India. However, the subject firm remained immune to bad press due to very little reliance on the corporate agency model. Further, tied-agency models have been less susceptible to misselling since agents are usually active in their networks and have to remain accountable. It is worth mentioning here that the sales agents of the subject firm have exploited the news of unfair practices by other firms as a part of their sales pitch.

- The subject firm's product menu is differentiated from other firms. For instance, the firm regularly sells products geared towards increasing social welfare rather than just providing the highest possible returns.

- Another reason for firm-specificity is the following: According to regulations, for an agent to change firms, he has to undergo 25 hours of training. The cost of this re-training is incurred by the new firm. This training requirement of training imposes two constraints - 1), the agent has first to ensure his payoff in the new firm exceeds his payoff in the current firm net of foregone income due to training and 2), the firm has to ensure that the productivity of the incoming agent is more than the costs to be incurred on him. These constraints imply lower turnover of agents between firms.

A.10 Alternative Model

Consider the following production function:

[1] See: http://www.livemint.com/Money/Xo38Z0zzeKW7Ee8ddP0RWL/Im-calling-from-Irda-and-will-help-you-redeem-your-policy.html

$$Y = AL^{\alpha}$$

where L is the number of workers, A is the managerial contribution and $\alpha < 1$.

Each manager recruits until the marginal productivity of the last agent is equal to the wage, ω;

$$\alpha AL^{\alpha-1} = \omega$$

Now, L is increasing in A. However, average output in the team is $\frac{AL^{\alpha}}{L} = \frac{\omega}{\alpha}$ which remains constant. Thus, in this model, team size and output per worker are not positively correlated.

Appendix B

Appendices to Chapter-2

Consider the following production function:

$$y_{amt} = \theta_a + k_m + \nu_t$$

where, $\theta_a \in \{\theta_L, \theta_H\}$ is agent's productivity, and k_m is manager m's contribution. $\theta_L < \theta_H$ and $\nu_L < \nu_H$.

Let q be the mass of θ_L

Assume that the productivity shock is independent of the agent's productivity.

Managers may also provide costless non-pecuniary utility, η_m, to their agents.

B.1 Mechanism-1: Recruitment

Before recruiting an agent, a manager receives a noisy signal, $\hat{\theta}_a$, of the agent's productivity. The signal takes two values: $\hat{\theta}_a \in \{\hat{\theta}_L, \hat{\theta}_H\}$. The signal is observed with the following conditional probability:

$$Pr(\hat{\theta}_k|\theta_j; k \neq j) = p$$

i.e. if the candidate has a productivity of $\theta_L(\theta_H)$, then with probability p, the manager receives the signal $\hat{\theta}_H(\hat{\theta}_L)$. Consider the following assumptions:

Assumption-1a: Signals are independent across candidates.

Assumption-1b: $0 < p < \frac{1}{2}$

Assumption-1c: Signals are costless to managers.

Let $p_I(p_E)$ be the conditional probability signal received by internally-hired manager (externally-hired manager).

Assumption-1d: $p_I < p_E$

Assumption-1b states that the probability of making a mistake in assessing a candidate for the job is bounded above by $\frac{1}{2}$, whereas Assumption-1d implies that internally-hired managers are less likely to make mistakes than externally-hired managers.

Testable Implications

The manager's problem is:

$$Max_{\hat{\theta}_a \in \{\hat{\theta}_L, \hat{\theta}_H\}} E(\theta|\hat{\theta}_a)$$

Now,

$$E(\theta|\hat{\theta}_H) = \theta_L + Pr(\theta_H|\hat{\theta}_H)(\theta_H - \theta_L)$$

and,

$$E(\theta|\hat{\theta}_L) = \theta_L + Pr(\theta_H|\hat{\theta}_L)(\theta_H - \theta_L)$$

Given assumption-1b,

$$Pr(\theta_H|\hat{\theta}_H) = \frac{1}{1 + \frac{p}{1-p}\frac{q}{1-q}} > Pr(\theta_H|\hat{\theta}_L) = \frac{1}{1 + \frac{1-p}{p}\frac{q}{1-q}}$$

Thus, given costless signals and independence of signals over candidates, managers would recruit the first candidate with signal $\hat{\theta_H}$. Further, given that internally-hired managers assess candidates better than externally-hired managers, we have:

$$E(\theta|\hat{\theta}_H; I) > E(\theta|\hat{\theta}_H; E)$$

This provides us with the first implications:

Testable Implication - 1a: Newly recruited agents of internally-hired managers sell more output than the newly recruited agents of externally-hired managers.

In the subject firm, managers recruit their agents four times each year, and incur a cost for each potential recruitment (as described in Appendix A.2). Thus, managers may observe the signal of a candidate in one period but may not recruit that candidate. In the next period, the manager may observe this agent again (if he is still available on the job market). Thus, managers observe some agents multiple times before recruiting them.

Let $(\hat{\theta}_k)|_{k=1}^{\tau}$ be the history of signals for a candidate observed for τ periods and let $k_l(k_h)$ be the number of periods for which the signal was $\hat{\theta}_L(\hat{\theta}_H)$. Let,

$$\alpha_\tau = Pr(\theta_H|(\hat{\theta}_k)|_{k=1}^{\tau}, \tau) = \frac{1}{1 + (\frac{p}{1-p})^{k_h - k_l} \frac{q}{1-q}}$$

Now,

$$E(\theta|(\hat{\theta}_k)|_{k=1}^{\tau}, \tau) = \theta_L + \alpha_\tau(\theta_H - \theta_L)$$

As $k_h - k_l$ increases, $E(\theta|(\hat{\theta}_k)|_{k=1}^{\tau}, \tau)$ increases. Thus, as $\hat{\theta_H}$ signals accumulate more than $\hat{\theta}_L$, the manager's assessment of that candidate improves.

Characterize a candidate, a, by the difference between his high and low productivity signals; i.e. $x_\tau^a = k_h - k_l$

Result-1: $E(x^a; \tau, p, \theta_H)$ is increasing in τ

$E(x^a; \tau, p, \theta_H) = E(k_h - k_l; \tau, p, \theta_H) = \tau(1-p) - \tau p = \tau(1-2p)$

Since, $p < \frac{1}{2}$, then $\frac{\partial}{\partial \tau} E(x^a; \tau, p, \theta_H) = (1-2p) > 0$

Thus, $E(x^a; t, p, \theta_H)$ increases with τ for θ_H and decreases in time for θ_L.

Result-2: $\forall\, \tau \geq 2 \nexists\, a$ such that $x_\tau^a \leq -2$

Consider a candidate with $x_\tau^a \leq -2$. In the next period, the candidate would either receive a high or a low signal. Thus, $x_{\tau+1}^a \leq -3$ or $x_{\tau+1}^a \leq -1$. For a new candidate $a^{'}$, $x^{a^{'}} = -1$ or $x^{a^{'}} = 1$. Thus, a new candidate always weakly dominates a candidate who has 2 low signals more than high signals, and as such, a candidate with $x_\tau^a \leq -2$ is replaced.

Thus, if high productivity candidate is observed over time, he is more likely to be assessed as a high productivity by the manager, whereas a low productivity candidate is dropped. Hence, with each given year of tenure, managers would recruit better candidates; i.e. $\frac{\partial E(\theta|p)}{\partial \tau}$.

Testable Implication - 1b: Newly recruited agents of higher tenured managers sell more output.

While the internally-hired managers would recruit better agents initially, for each additional year of tenure (signals), externally-hired managers would learn to recruit more productive workers. Thus, by assumption-1d; i.e. $p_I < p_E \implies E(x^a; t, p_I, \theta_H) > E(x^a; t, p_E, \theta_H) \implies \frac{\partial E(\theta|\tau, p_I)}{\partial \tau} < \frac{\partial E(\theta|\tau, p_E)}{\partial \tau}$

Testable Implication - 1c: Gradient of output of newly recruited agents is higher with respect to the tenure of the externally-hired managers.

B.2 Mechanism-2: Training

For orphaned agents, the production function is:

$$y_{at} = \theta_a + v_t$$

As they are allotted to new managers, the change in output of such agents will be:

$$y_{amt+1} - y_{at} = k_m + v_{t+1} - v_t$$

Thus, change in the output of such allotted agents is attributable to managerial contribution. Let $k_m^I (k_m^E)$ be managerial capital of internally-hired manager (externally-hired manager).

Assumption - 2a: $k_m^I > k_m^E$

Assumption - 2b: k_m is increasing with tenure of the manager.

From assumptions 2a and 2b, we get

Testable Implication - 2a: Change in output is higher for orphaned agents allotted to the internally-hired managers.

Testable Implication - 2b: Change in output is higher for orphaned agents allotted to managers with higher tenure.

B.3 Mechanism-3: Retention

Let $U_{am} = f(y_a, \eta_m)$ be the utility function of agent a where y_a is agent's output, and η_m is the non-pecuniary utility provided by the agent's manager m.

Assumption - 3a: $f_1(y_a, \eta_m) > 0$ and $f_2(y_a, \eta_m) > 0$

Let $U_{ao} = G + \epsilon_a$ be the outside option for agent a where $\epsilon_a \sim N(0, \sigma^2)$ and G is some constant[1]. An agent exits if $U_{ao} > U_{am}$ or $\epsilon_a > f(y_a, \eta_m) - G$. Thus, the probability of an agent's exit is $Pr(\epsilon > f(y_a, \eta_m) - G) = 1 - \Phi(\frac{f(y_a,\eta_m)-G}{\sigma})$, where $\Phi(\cdot)$ is standard normal distribution function. Let $\eta^I_m(\eta^E_m)$ be the non-pecuniary utility provided by an internally-hired manager.

Assumption - 3b: $\eta^I_m > \eta^E_m$

Assumption-3b states that the internally-hired managers provide more utility to their agents. For example, they treat their agents better. Under Assumptions-3a and 3b, after controlling for an agent's output, the probability of exit is lower for the agent of an internally-hired manager.

Testable Implication - 3a: $Pr(exit; I) < Pr(exit; E)$

Now, consider that managers can distribute the non-pecuniary utility to the agents in a non-uniform manner. For example, managers attend to high output agents to prevent them from exiting; i.e. $\frac{\partial \eta_m}{\partial y_a} > 0$.

Assumption - 3c: $\frac{\partial \eta^I_m}{\partial y_a} > \frac{\partial \eta^E_m}{\partial y_a}$

Assumption-3c states that the internally-hired managers attend to their high output

[1]The constant value of G implies productivity to be firm-specific. Appendix A.9 provides arguments for why productivity could be firm-specific.

agents better than the externally-hired managers. Now,

$$\frac{\partial Pr(exit; y_a, \eta_m)}{\partial y_a} = -\frac{\partial \Phi(\frac{f(y_a,\eta_m)-G}{\sigma})}{\partial f(y_a, \eta_m)}(\frac{\partial f(y_a, \eta_m)}{\partial y_a} + \frac{\partial f(y_a, \eta_m)}{\partial \eta_m}.\frac{\partial \eta_m}{\partial y_a})$$

Under Assumption-3c, the gradient of the exit rate with respect to output is lower for an agent of the internally-hired managers.

Testable Implication - 3b: $\frac{\partial Pr(exit;I)}{\partial y_a} < \frac{\partial Pr(exit;E)}{\partial y_a} < 0$

Appendix C

Appendices to Chapter-3

C.1 Preference Ordering over Media Strategies

Let $a(\omega) \in \{-1, 1\}$ be the eventual policy chosen by the majority of voters for a given ω. Let $a(\omega) \sim F(\cdot;\omega)$ be the distribution of $a(\omega)$. $F(\cdot;\omega)$ depends on the ex post policy preference of each group in an equilibrium. Note that the biased groups do not change their policy preferences no matter what information they receive. However, updaters may vary their policy choice if they observe state-relevant information. Hence, $F(\cdot;\omega)$ is potentially altered by the choice of $\hat{m}$ of the updaters but is independent of $\hat{m}$ chosen by the biased group.

For $i \in \{L, R\}$, preference over $\mathcal{M}$ is determined by:

$$V_i(\hat{m}) = -E_\omega(m(\omega) - b_i(\omega))^2 + K_i,$$

where $K_i = -E_\omega(a(\omega) - b_i(\omega))^2$. K_L and K_R are independent of $\hat{m}$ chosen by the biased groups.

For $i = R, b_R(\omega) = 1\ \forall\omega$

$V_R(\hat{m}) = -Pr(\omega = 1)(m(1) - 1)^2 - Pr(\omega = -1)(m(-1) - 1)^2 + K_R$. Thus,

$V_R(m_T) = -2 + K_R$

$V_R(m_v) = -1 + K_R$

$V_R(m_r) = -\frac{1}{2} + K_R$

$V_R(m_l) = -\frac{5}{2} + K_R$

$V_R(m_R) = K_R$

$V_R(m_L) = -4 + K_R$

Hence, $V_R(m_R) > V_R(m_r) > V_R(m_v) > V_R(m_T) > V_R(m_l) > V_R(m_L)$.

For $i = L, b_L(\omega) = -1\,\forall\omega$

$V_L(\hat{m}) = -Pr(\omega = 1)(m(1) + 1)^2 - Pr(\omega = -1)(m(-1) + 1)^2 + K_L$. Thus,

$V_L(m_T) = -2 + K_L$

$V_L(m_v) = -1 + K_L$

$V_L(m_r) = -\frac{5}{2} + K_L$

$V_L(m_l) = -\frac{1}{2} + K_L$

$V_L(m_R) = -4 + K_L$

$V_L(m_L) = K_L$

Hence, $V_L(m_L) > V_L(m_l) > V_L(m_v) > V_L(m_T) > V_L(m_r) > V_L(m_R)$.

For $i = U, b_U(\omega) = \omega$

$V_U(\hat{m}) = -Pr(\omega = 1)(m(1) - 1)^2 - Pr(\omega = -1)(m(-1) + 1)^2 + K_U$

where, $K_U = -E_\omega(a(\omega) - \omega)^2$. If updaters choose state-contingent message profiles, then $a(\omega) = \omega$ for each ω. Hence, whenever updaters choose $\hat{m} = \{m_T, m_l, m_r\}$, $K_U = 0$. Thus,

$V_U(m_T) = K_U = 0$

$V_U(m_r) = -\frac{1}{2} + K_U = -\frac{1}{2}$

$V_U(m_l) = -\frac{1}{2} + K_U = -\frac{1}{2}$

If updaters have to choose from m_v, m_R and m_L, their posterior beliefs are the same as their priors, since messages are state-invariant. In that case, they are split evenly between $a = 1$ and $a = -1$. Since we have assumed that $\rho > \lambda$, $a = 1$ is chosen by the majority. Now, $K_U = -\frac{1}{2}(1 - 1)^2 - \frac{1}{2}(1 + 1)^2 = -2$. Thus,

$V_U(m_v) = -1 + K_U = -3$

$V_U(m_R) = -2 + K_U = -4$

$V_U(m_L) = -2 + K_U = -4$

Hence, $V_U(m_T) > V_U(m_l) = V_U(m_r) > V_U(m_v) > V_U(m_R) = V_L(m_L)$.

C.2 Proof of Theorem-1

Table C.1 provides the payoffs for firms using the old technology as a normal form game.

Table C.1: Old Technology

	m_T	m_v	m_r	m_l	m_R	m_L
m_T	1/2, 1/2	$\mu, \rho + \lambda$	$\mu + \lambda, \rho$	$\mu + \rho, \lambda$	$\mu + \lambda, \rho$	$\mu + \rho, \lambda$
m_v	$\rho + \lambda, \mu$	1/2, 1/2	$\lambda, \rho + \mu$	$\rho, \mu + \lambda$	$\lambda + \mu, \rho$	$\rho + \mu, \lambda$
m_r	$\rho, \mu + \lambda$	$\rho + \mu, \lambda$	1/2, 1/2	$\rho + \frac{\mu}{2}, \lambda + \frac{\mu}{2}$	$\mu + \lambda, \rho$	$\rho + \mu, \lambda$
m_l	$\lambda, \mu + \rho$	$\mu + \lambda, \rho$	$\lambda + \frac{\mu}{2}, \rho + \frac{\mu}{2}$	1/2, 1/2	$\mu + \lambda, \rho$	$\rho + \mu, \lambda$
m_R	$\rho, \mu + \lambda$	$\rho, \lambda + \mu$	$\rho, \mu + \lambda$	$\rho, \mu + \lambda$	1/2, 1/2	$\rho + \frac{\mu}{2}, \lambda + \frac{\mu}{2}$
m_L	$\lambda, \rho + \mu$	$\lambda, \rho + \mu$	$\lambda, \mu + \rho$	$\lambda, \mu + \rho$	$\lambda + \frac{\mu}{2}, \rho + \frac{\mu}{2}$	1/2, 1/2

Assume there exists a pure strategy Nash Equilibrium. Since under old technology, profits are the same as the share of audience, $\pi_\tau + \pi_{\tau'} = 1$, where $\tau \in 1, 2$ indexes firms. If $\pi_\tau < \frac{1}{2}$, then firm-τ can deviate to firm-τ''s strategy, split the audience evenly, and increase profits to $\frac{1}{2}$. If $\pi_\tau = \pi_{\tau'} = \frac{1}{2}$, then either firm can unilaterally deviate to a strategy where two voter-consumer groups switch to the deviating firm, increasing profits to greater than half. Thus, no pure strategy Nash Equilibrium exists.

First, I will find the mixed strategy equilibrium where both firms assign the same positive probabilities to only m_T, m_v and m_r. Then, I will show that this is the unique equilibrium; no other equilibrium is possible where a firm assigns positive probability to a strategy $\hat{m} \in \mathcal{M} - \{m_T, m_v m_r\}$.

Let a_1, a_2 and a_3 be the probabilities of playing m_T, m_v and m_r, respectively by firm-2. Let $\pi_1(\hat{m})$ be the profit function for firm-1 on playing strategy $\hat{m}$. Given the mixed strategy of firm-2, the profits of firm-1 are given by:

$$E(\pi_1(m_T)) = a_1(\frac{1}{2} - \mu - \lambda) - a_2\lambda + \mu + \lambda$$

$$E(\pi_1(m_v)) = a_1(\rho) + a_2(\frac{1}{2} - \lambda) + \lambda$$

$$E(\pi_1(m_r)) = a_1(\rho - \frac{1}{2}) + a_2(\rho + \mu - \frac{1}{2}) + \frac{1}{2}$$

If firm-1 assigns positive probabilities to m_T, m_v and m_r, then $E(\pi_1(m_T)) = E(\pi_1(m_v)) = E(\pi_1(m_r))$. The system of equation in a_1 and a_2 has the following solution: $a_1 = 1 - 2\lambda$ and $a_2 = 2(\mu + \lambda) - 1$.

Let b_1, b_2 and b_3 be the probabilities of playing m_T, m_v and m_r, respectively by firm-1. Let $\pi_2(\hat{m})$ be the profit function for firm-2 on playing strategy $\hat{m}$. Given the mixed strategy of firm-1,

$$E(\pi_2(m_T)) = b_1(\frac{1}{2} - \mu - \lambda) - b_2\lambda + \mu + \lambda$$

$$E(\pi_2(m_v)) = b_1(\rho) + b_2(\frac{1}{2} - \lambda) + \lambda$$

$$E(\pi_2(m_r)) = b_1(\rho - \frac{1}{2}) + b_2(\rho + \mu - \frac{1}{2}) + \frac{1}{2}$$

If firm-2 assigns positive probabilities to m_T, m_v and m_r, $E(\pi_2(m_T)) = E(\pi_2(m_v)) = E(\pi_2(m_r))$. The system of equation in b_1 and b_2 has the following solution: $b_1 = 1 - 2\lambda$ and $b_2 = 2(\mu + \lambda) - 1$.

Thus, in the equilibrium, $a_1 = b_1$, $a_2 = b_2$ and $a_3 = b_3$; both firms use the same mixed strategy.

Uniqueness

First, note that if $\rho > \lambda$ then $\rho + \frac{\mu}{2} > \lambda + \frac{\mu}{2}$. Since $\rho + \frac{\mu}{2} + \lambda + \frac{\mu}{2} = 1$, therefore, $\rho + \frac{\mu}{2} > \frac{1}{2}$. Thus, m_r strictly dominates m_L. Hence, no equilibrium exists where m_L is played with positive probability.

Assume there exists a mixed strategy Nash Equilibrium where firm-2 assigns probabilities a_l and a_R to m_l and m_R, respectively, where $a_l \in (0,1)$, $a_R \in (0,1)$ and $a_l + a_R \leq 1$. Given these mixed strategies of firm-2, for firm-1, $E(\pi_1(m_r)) > E(\pi_1(m_R))$ and $E(\pi_1(m_r)) > E(\pi_1(m_l))$. Firm-1 will not play m_R and m_l, and may randomize over m_T, m_v and m_r with probabilities b_1, b_2 and b_3, respectively. Now, for firm-2,

$$E(\pi_2(m_r)) = b_1\rho + b_2(\rho + \mu) + b_3(\frac{1}{2})$$

$$E(\pi_2(m_R)) = b_1\rho + b_2\rho + b_3\rho$$

$$E(\pi_2(m_l)) = b_1\lambda + b_2(\lambda + \mu) + b_3(\lambda + \frac{\mu}{2})$$

For any possible randomization by firm-1, $E(\pi_2(m_r)) > E(\pi_2(m_l))$. If $b_1 = 1$, $\pi_2(m_v) > \pi_2(m_R)$. Otherwise, $E(\pi_2(m_r)) > E(\pi_2(m_R))$. This contradicts the hypothesis that firm-2 assigns positive probabilities to m_R and m_l. Analogous argument applies if $a_l = 0$ and $a_R \in (0,1)$ or if $a_l \in (0,1)$ and $a_R = 0$. Hence, no mixed strategy equilibrium exists where firm-2 assigns positive probabilities to m_R and m_l. Analogous argument applies for firm-1 as well. Hence, we can restrict attention to mixed strategy equilibria where firms randomize only over m_T, m_v and m_r.

Now, we show that in any mixed strategy Nash Equilibrium each firm assigns positive probabilities to m_T, m_v and m_r.

Assume there exists a mixed strategy Nash Equilibrium where firm-2 randomizes over m_v and m_r with probabilities a and $1 - a$, respectively, and plays m_T with 0 probability. Profits for firm-1 are:

$$E(\pi_1(m_T)) = \mu + \lambda - a\lambda$$

$$E(\pi_1(m_v)) = a(\frac{1}{2} - \lambda) + \lambda$$

$$E(\pi_1(m_r)) = a(\frac{1}{2} - \lambda) + \frac{1}{2}$$

Now, for firm-1, $E(\pi_1(m_r)) > E(\pi_1(m_v))$. Thus, firm-1 plays m_v with probability 0, and may randomize over m_T and m_r, with probabilities b and $1-b$, respectively.
For firm-2, $E(\pi_2(m_T)) = b(\frac{1}{2}) + (1-b)(\mu+\lambda)$ and $E(\pi_2(m_r)) = b\rho + (1-b)(\frac{1}{2})$. Since $\mu + \lambda > \frac{1}{2} > \rho$, for any value of $b \in [0,1]$, $E(\pi_2(m_T)) > E(\pi_2(m_r))$. Hence, a mixed strategy equilibrium where firm-2 plays m_T with probability 0 is not possible. Analogous argument applies for firm-1 as well.

Assume there exists a mixed strategy Nash Equilibrium where firm-2 randomizes over m_T and m_v with probabilities a and $1-a$, respectively, and plays m_r with 0 probability. Profits for firm-1 are:

$$E(\pi_1(m_T)) = a(\frac{1}{2} - \mu) + \mu$$

$$E(\pi_1(m_v)) = a(\frac{1}{2} - \mu) + \frac{1}{2}$$

$$E(\pi_1(m_r)) = -a\mu + \rho + \mu$$

Now, for firm-1, $E(\pi_1(m_v)) > E(\pi_1(m_T))$. Thus, firm-1 plays m_T with probability 0, and may randomize over m_v and m_r, with probabilities b and $1-b$, respectively.
For firm-2, $E(\pi_2(m_r)) = b(\rho+\mu) + (1-b)(\frac{1}{2})$ and $E(\pi_2(m_v)) = b(\frac{1}{2}) + (1-b)(\lambda)$. Since $\rho+\mu > \frac{1}{2} > \lambda$, for any value of $b \in [0,1]$, $E(\pi_2(m_r)) > E(\pi_2(m_v))$. Hence, a mixed strategy equilibrium where firm-2 plays m_r with probability 0 is not possible. Analogous argument applies for firm-1 as well.

Assume there exists a mixed strategy Nash Equilibrium where firm-2 randomizes over m_T and m_r with probabilities a and $1-a$, respectively, and plays m_v with 0 probability. Profits for firm-1 are:

$$E(\pi_1(m_T)) = a(\rho - \frac{1}{2}) + \mu + \lambda$$

$$E(\pi_1(m_v)) = a\rho + \lambda$$

$$E(\pi_1(m_r)) = a(\rho - \frac{1}{2}) + \frac{1}{2}$$

Now, for firm-1, $E(\pi_1(m_r)) < E(\pi_1(m_T))$. Thus, firm-1 plays m_r with probability 0, and may randomize over m_T and m_v, with probabilities b and $1-b$, respectively.

For firm-2, $E(\pi_2(m_v)) = b(\rho+\lambda) + (1-b)(\frac{1}{2})$ and $E(\pi_2(m_T)) = b(\frac{1}{2}) + (1-b)(\mu)$. Since $\rho + \lambda > \frac{1}{2} > \mu$, for any value of $b \in [0,1]$, $E(\pi_2(m_v)) > E(\pi_2(m_T))$. Hence, a mixed strategy equilibrium where firm-2 plays m_v with probability 0 is not possible. Analogous argument applies for firm-1 as well.

Now, consider an equilibrium where firm-2 plays a strategy, $\hat{m}_2$, with probability 1. For any $\hat{m}_2 \neq m_R$, there exists a unique best response for firm-1, $\hat{m}_1 \neq \hat{m}_2$, such that firm-1 receives more than half the audience. But, then firm-2 can deviate to the strategy of firm-1, split all the audience evenly, and increase profits to $\frac{1}{2}$. If firm-2 plays m_R with probability 1, then firm-1 is indifferent between m_T, m_v, m_r and m_l, and may randomize. For any non-degenerate randomization by firm-1, firm-2 can deviate to m_r profitably. For any degenerate randomization by firm-1, as argued above, firm-2 can deviate to firm-1's strategy and increase profits. Thus, no equilibrium exists where firm-2 plays a pure strategy and firm-1 plays a mixed strategy. Analogous argument applies for firm-1 as well.

C.3 Proof of Theorem-2

Firms randomize over m_T, m_v and m_r. The realized strategy from this randomization is revealed before the state occurs. Thus, updaters know which strategy is being played.

If either firm plays m_T, then updaters observe $m = 1$ when $\omega = 1$, and $m = -1$ and $\omega = -1$. Their posterior beliefs are: $Pr(\omega = 1|m = 1; m_T) = 1$ and $Pr(\omega = -1|m = -1; m_T) = 1$

If either firm plays m_r, then updaters observe $m = 1$ when $\omega = 1$, and $m = 0$ and $\omega = -1$. Their posterior beliefs are: $Pr(\omega = 1|m = 1; m_r) = 1$ and $Pr(\omega = -1|m = 0; m_r) = 1$

With probability a_2, firms play m_v. If both firms play m_v, updaters split evenly between both the firms and receive $m = 0$ as the message. Thus, posterior beliefs of all updaters are: $Pr(\omega = 1|m = 0; m_v) = Pr(\omega = -1|m = 0; m_v) = \frac{1}{2}$. Thus, updaters remain indifferent between $a = -1$ and $a = 1$, splitting evenly between the two policies. Since we assume $\rho > \lambda$, $a = 1$ would be chosen as the political equilibrium. Thus, $a = 1$ is chosen by the majority when $\omega = -1$ with probability $Pr(\omega = -1)a_2^2 = \frac{1}{2}a_2^2$, .

C.4 Proof of Theorem-3

Table C.2 provides the payoff for different strategy pairs under new technology.

C.4.1 Case-1: $\mu \geq \frac{\lambda}{2}$

Consider strategy profile (m_R, m_T). Profits for firm-1 are given by $v\rho$ and for firm-2 are $v\mu + \frac{v+1}{2}\lambda$, illustrated in the example in Section 3.4.

No unilateral profitable deviation for firm-1 exists if $\pi_1(m_R, m_T) > \pi_1(\hat{m}, m_T)\, \forall\, \hat{m} \in \mathcal{M} - \{m_R\}$i.e.:

$v\rho > \frac{v\mu}{2} + \frac{v+1}{4}(\rho + \lambda) \implies v > \frac{\rho+\lambda}{3\rho-2\mu-\lambda}$

$v\rho > \lambda + \rho \implies v > \frac{\rho+\lambda}{\rho}$

$v\rho > \frac{v+1}{2}\rho \implies v > 1$

$v\rho > \frac{v+1}{2}\lambda \implies v > \frac{\lambda}{2\rho-\lambda}$

$v\rho > v\lambda$

Given $\rho > \lambda$ and $\rho > \mu$, we obtain $3\rho - 2\mu - \lambda > 0$ and $2\rho - \lambda > 0$. Hence, for a sufficiently high positive value of v, all conditions are satisfied.

For firm-2, no unilateral profitable deviation exists if $\pi_2(m_R, m_T) > \pi_2(m_R, \hat{m})\, \forall\, \hat{m} \in \mathcal{M} - \{m_T\}$; i.e.

$v\mu + \frac{v+1}{2}\lambda > \lambda + \mu \implies v(\mu + \frac{\lambda}{2}) > \mu + \frac{\lambda}{2}$

$v\mu + \frac{v+1}{2}\lambda > \frac{v+1}{2}\mu + \lambda \implies v(\frac{\mu}{2} + \frac{\lambda}{2}) > \frac{\mu}{2} + \frac{\lambda}{2}$

$v\mu + \frac{v+1}{2}\lambda > \frac{v+1}{2}(\mu + \lambda) \implies v\frac{\mu}{2} > \frac{\mu}{2}$

$v\mu + \frac{v+1}{2}\lambda > \frac{v\rho}{2} + \frac{\lambda+\mu}{2} \implies v > \frac{\mu}{(2\mu+\lambda-\rho)}$

$v\mu + \frac{v+1}{2}\lambda > v\lambda + \frac{\mu}{2} \implies v > \frac{\mu-\lambda}{(2\mu-\lambda)}$

Since $\mu + \lambda = 1 - \rho > \frac{1}{2} > \rho$ and $\mu \geq \frac{\lambda}{2}$, all conditions are satisfied for a sufficiently high positive value of v.

Uniqueness

First, note that m_ν is dominated by m_R for a sufficiently high value of v. Thus, m_ν is never played.

From the above proof, when $\mu \geq \frac{\lambda}{2}$, m_R is the best response to m_T and vice versa. Thus, if a firm plays m_R, the other firm will not play $\hat{m} \in \mathcal{M} - \{m_T\}$ in a Nash Equilibrium. Similarly, if a firm plays m_T, the other firm will not play $\hat{m} \in \mathcal{M} - \{m_R\}$ in a Nash Equilibrium.

Now, if a firm plays a strategy $\hat{m}_\tau \in \{m_r, m_l, m_L\}$, given Assumption 3, Table C.2 shows that the best response for the other firm is either m_R or m_T. But, the best response to either of the two strategies is $\hat{m} \notin \{m_r, m_l, m_L\}$. Thus, a strategy profile of the form $(\hat{m}_\tau, \hat{m}_{-\tau})$, where $\hat{m}_\tau$ and $\hat{m}_{\tau'} \in \{m_r, m_l, m_L\}$, and $\tau \in \{1, 2\}$ indexes firm, cannot be a Nash Equilibrium.

Thus, no other strategy profile can be a pure strategy Nash Equilibrium.

C.4.2 Case-2: $\mu < \frac{\lambda}{2}$

Consider strategy profile (m_R, m_L), where firm-1 commits to extreme right slant and firm-2 chooses extreme left slant. All right-biased voter-consumers choose firm-1 and left-biased voter-consumers choose firm-2. Updaters are split evenly between the two firms. Profits for firm-1 are given by:

$$\begin{aligned}\pi_2(m_R, m_L) &= Pr(\omega = 1)\Sigma_m Pr(m|\omega = 1, m_R)(v_R\rho + v_U\frac{\mu}{2}) \\ &+ Pr(\omega = -1)\Sigma_m Pr(m|\omega = -1, m_R)(v_R\rho + v_U\frac{\mu}{2})\end{aligned}$$

Since $m(\omega) = 1\,\forall\omega$ under m_R, right-biased group provides value v in each state, whereas $v_U = 1$ in each state.

$$\pi_2(m_R, m_L) = \frac{1}{2}(v\rho + \frac{\mu}{2}) + \frac{1}{2}(v\rho + \frac{\mu}{2})$$

$$\pi_2(m_R, m_L) = v\rho + \frac{\mu}{2}$$

Similarly, profits for firm-2 are $\pi_2(m_R, m_L) = v\lambda + \frac{\mu}{2}$.

For firm-1, no unilateral profitable deviation exists if $\pi_1(m_R, m_L) > \pi_1(\hat{m}, m_L)\,\forall\,\hat{m} \in \mathcal{M} - \{m_R\}$i.e.:

$v\rho + \frac{\mu}{2} > v\mu + \frac{v+1}{2}\rho \implies v > \frac{\rho-\lambda}{\rho-2\mu}$

$v\rho + \frac{\mu}{2} > \rho + \mu \implies v > \frac{2\rho+\mu}{\rho}$

$v\rho + \frac{\mu}{2} > \frac{v+1}{2}(\mu + \rho) \implies v > \frac{\rho}{\rho-\mu}$

$v\rho + \frac{\mu}{2} > \frac{v+1}{2}\mu + \rho \implies v > \frac{2\rho}{2\rho-\mu}$

$v\rho + \frac{\mu}{2} > \frac{v\lambda}{2} + \frac{\rho+\mu}{2} \implies v > \frac{\rho}{2\rho-\mu}$

Given $\rho > \lambda > 2\mu > \mu$, all conditions are satisfied for a sufficiently high positive value of v.

For firm-2, no unilateral profitable deviation exists if $\pi_2(m_R, m_L) \geq \pi_2(m_R, \hat{m})\,\forall\,\hat{m} \in \mathcal{M} - \{m_L\}$; i.e.

$v\lambda + \frac{\mu}{2} > v\mu + \frac{v+1}{2}\lambda \implies v(\frac{\lambda}{2} - \mu) > \frac{\mu}{2} - \frac{\lambda}{2}$

$v\lambda + \frac{\mu}{2} > \lambda + \mu \implies v > \frac{2\lambda+\mu}{2\lambda}$

$v\lambda + \frac{\mu}{2} > \frac{v+1}{2}\mu + \lambda \implies v(\lambda - \frac{\mu}{2}) > \lambda$

$v\lambda + \frac{\mu}{2} > \frac{v+1}{2}(\mu + \lambda) \implies v > \frac{\lambda}{\lambda-\mu}$

$v\lambda + \frac{\mu}{2} > \frac{v\rho}{2} + \frac{\lambda+\mu}{2} \implies v > \frac{\lambda}{2\lambda-\rho}$

Given $\lambda > \frac{\lambda}{2} > \mu$ and $2\lambda = max\{2\lambda, 2\rho\} > \rho$, all conditions are satisfied for a sufficiently high positive value of v.

Uniqueness

First note that the above proof shows that when $\mu < \frac{\lambda}{2}$, m_L is the best response to m_R and vice versa. Thus, if a firm plays m_L, then the other firm will not play $\hat{m} \in \mathcal{M} - \{m_R\}$ in a Nash Equilibrium. Similarly, if a firm plays m_R, then the other firm will not play $\hat{m} \in \mathcal{M} - \{m_L\}$ in a Nash Equilibrium.

Now, if a firm plays a strategy $\hat{m}_\tau \in \{m_r, m_l, m_T\}$, given Assumption 3, Table C.2 shows that the best response for the other firm is m_R. But, the best response to m_R is $m_L \notin \{m_r, m_l, m_T\}$. Thus, strategy profiles of the form $(\hat{m}_\tau, \hat{m}_{-\tau})$, where $\hat{m}_\tau$ and $\hat{m}_{\tau'} \in \{m_r, m_l, m_T\}$, and $\tau \in \{1, 2\}$ indexes firm, cannot be a Nash Equilibrium.

Thus, no other strategy profile can be a pure strategy Nash Equilibrium.

Table C.2: New Technology

	m_T	m_ν	m_r	m_l	m_R	m_L
m_T	$\frac{\upsilon\mu}{2}+\frac{\upsilon+1}{4}(\rho+\lambda)$, $\frac{\upsilon\mu}{2}+\frac{\upsilon+1}{4}(\rho+\lambda)$	$\upsilon\mu, \lambda+\rho$	$\upsilon\mu+\frac{\upsilon+1}{2}\lambda$, $\frac{\upsilon+1}{2}\rho$	$\upsilon\mu+\frac{\upsilon+1}{2}\rho$, $\frac{\upsilon+1}{2}\lambda$	$\upsilon\mu+\frac{\upsilon+1}{2}\lambda$, $\upsilon\rho$	$\upsilon\mu+\frac{\upsilon+1}{2}\rho$ $\upsilon\lambda$
m_ν	$\lambda+\rho, \upsilon\mu$	1/2, 1/2	$\lambda, \frac{\upsilon+1}{2}(\rho+\mu)$	$\rho, \frac{\upsilon+1}{2}(\lambda+\mu)$	$\lambda+\mu$, $\upsilon\rho$	$\rho+\mu$, $\upsilon\lambda$
m_r	$\frac{\upsilon+1}{2}\rho, \upsilon\mu+\frac{\upsilon+1}{2}\lambda$	$\frac{\upsilon+1}{2}(\rho+\mu)$, λ	$\frac{\upsilon+1}{4}(\rho+\mu)+\frac{\lambda}{2}$, $\frac{\upsilon+1}{4}(\rho+\mu)+\frac{\lambda}{2}$	$\frac{\upsilon+1}{2}\rho+\frac{\upsilon+1}{4}\mu$, $\frac{\upsilon+1}{2}\lambda+\frac{\upsilon+1}{4}\mu$	$\frac{\upsilon+1}{2}\mu+\lambda, \upsilon\rho$	$\frac{\upsilon+1}{2}(\mu+\rho)$, $\upsilon\lambda$
m_l	$\frac{\upsilon+1}{2}\lambda, \upsilon\mu+\frac{\upsilon+1}{2}\rho$	$\frac{\upsilon+1}{2}(\lambda+\mu)$, ρ	$\frac{\upsilon+1}{2}\lambda+\frac{\upsilon+1}{4}\mu$, $\frac{\upsilon+1}{2}\rho+\frac{\upsilon+1}{4}\mu$	$\frac{\upsilon+1}{4}(\lambda+\mu)+\frac{\rho}{2}$, $\frac{\upsilon+1}{4}(\lambda+\mu)+\frac{\rho}{2}$	$\frac{\upsilon+1}{2}(\mu+\lambda)$, $\upsilon\rho$	$\frac{\upsilon+1}{2}\mu+\rho$, $\upsilon\lambda$
m_R	$\upsilon\rho, \upsilon\mu+\frac{\upsilon+1}{2}\lambda$	$\upsilon\rho, \lambda+\mu$	$\upsilon\rho, \frac{\upsilon+1}{2}\mu+\lambda$	$\upsilon\rho, \frac{\upsilon+1}{2}(\mu+\lambda)$	$\frac{\upsilon\rho}{2}+\frac{\lambda+\mu}{2}$, $\frac{\upsilon\rho}{2}+\frac{\lambda+\mu}{2}$	$\upsilon\rho+\frac{\mu}{2}$, $\upsilon\lambda+\frac{\mu}{2}$
m_L	$\upsilon\lambda, \upsilon\mu+\frac{\upsilon+1}{2}\rho$	$\upsilon\lambda, \rho+\mu$	$\upsilon\lambda, \frac{\upsilon+1}{2}(\mu+\rho)$	$\upsilon\lambda, \frac{\upsilon+1}{2}\mu+\rho$	$\upsilon\rho+\frac{\mu}{2}$, $\upsilon\lambda+\frac{\mu}{2}$	$\frac{\upsilon\lambda}{2}+\frac{\rho+\mu}{2}$, $\frac{\upsilon\lambda}{2}+\frac{\rho+\mu}{2}$

C.5 Proof of Theorem-4

Posterior probabilities are given by:

$$Pr(\omega = 1|m; \hat{m}) = \frac{Pr(m|\omega = 1; \hat{m})}{Pr(m|\omega = 1; \hat{m}) + Pr(m|\omega = -1; \hat{m})}$$

C.5.1 Case-1: $\mu \geq \frac{\lambda}{2}$

Updaters watch m_T, where they observe $m \in \{-1, 1\}$. Thus,

$Pr(\omega = 1|m = 1; m_T) = 1$

$Pr(\omega = 1|m = -1; m_T) = 0 \implies Pr(\omega = -1|m = -1; m_T) = 1$

Hence, updaters realize each state with full certainty and they prefer $a = \omega$ for each $\omega \in \{-1, 1\}$.

C.5.2 Case-2: $\mu < \frac{\lambda}{2}$

Updaters are indifferent between m_L and m_R. When they watch m_R, they observe $m = 1$ for each state. Thus, $Pr(\omega = 1|m = 1; m_R) = \frac{1}{2}$

Similarly, updaters who choose m_L observe $m = -1$ for each state. Thus, $Pr(\omega = 1|m = 1; m_L) = \frac{1}{2}$

Hence, updaters remain indifferent between $a = 1$ and $a = -1$. Since $\rho > \lambda$, $a = 1$ is chosen by the majority in each state.

C.6 Extension to N Firms

Let there be n firms. Let the strategy profile be

$$(\hat{m})_{i=1}^{n} = ((m_T)_{i=1}^{n_t}, (m_R)_{i=n_t+1}^{n_t+n_r}, (m_L)_{i=n_t+n_r+1}^{n}) \,\forall\, \omega \in \{-1, 0, 1\}$$

,

Profits for a truth-telling firm are $\pi_t(\hat{m})_{i=1}^{n} = \frac{v\mu}{n_t}$. If it deviates to m_R, then its profits are $\pi(m_R, (\hat{m})_{i=1}^{n-1}) = \frac{v\rho}{n_r+1}$. Thus, deviation is not profitable if $\mu > \frac{n_t\rho}{n_r+1}$. Similarly, deviation to $\hat{m} = m_L$ is not profitable if $\mu > \frac{n_t\lambda}{n_l+1}$.

Now, profits for a right-leaning firm are $\pi_\rho(\hat{m})_{i=1}^{n} = \frac{v\rho}{n_r}$. Deviation to m_T and to m_L is not profitable if $\mu < \frac{(n_t+1)\rho}{n_r}$ and $\frac{\rho}{\lambda} > \frac{n_r\lambda}{n_l+1}$, respectively.

Compiling all conditions, we get the following conditions as sufficient for $(\hat{m})_{i=1}^{n}$ to be Nash Equilibrium:

$$min\{\frac{\rho(n_t+1)}{n_r}, \frac{\lambda(n_t+1)}{n_l}\} > \mu > max\{\frac{\rho(n_t)}{(n_r+1)}, \frac{\lambda(n_t)}{(n_l+1)}\} \tag{C.1}$$

$$\frac{n_r+1}{n_l} > \frac{\rho}{\lambda} > \frac{n_r}{n_l+1} \tag{C.2}$$

Values of λ & ρ endogenously determine the number of firms for each content. Thus, even with arbitrary number of firms, truth-telling may be a Nash Equilibrium strategy, for appropriate distribution of preferences. This is consistent with Groseclose and Milyo (2005) finding that while media generally exhibits a left-shift, there still exist truthful reporting, such as ABC's Good Morning America and PBS' Newshour with higher average net ratings.

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