Selling Platforms

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Abstract

Firms selling network goods and two sided platforms often employ agents to sell their products. This paper explores how network effects alter the agency relationship between the firm (principal) and the salesperson (agent). We first show that compensation plans differ depending on the nature of network effects, i.e., direct or indirect and on the number of sales agents. This result implies that ignoring network effects in salesforce compensation would hurt profits. We then find that a firm selling network good or a platform should provision a higher share of its revenues to compensating its salesforce, compared to a firm selling a traditional good. Finally, we learn that profit levels for platform can decrease as cross platform effects increase, whereas profit levels for network goods always increase as direct network effects increase.
1 Introduction

Thanks to network effects, platforms and network goods differ fundamentally from traditional products in how they create and provision value for users. Users value these products not only for product features, but also for the networks that they enable to participate and interact with. These include “direct” or “same-side” network goods (e.g., freecycle.org or Skype) which facilitate interactions between one network of users, and platforms—which also enable “indirect” or “cross platform” network benefits by facilitating exchange between multiple networks (e.g., smartphone platforms, electronic payment platforms, which connect end-users with app developers and retail stores, respectively). Platform and network goods occupy a central position in today’s economy across sectors such as information technology, health care and banking. Firms like Apple, Google or Microsoft for instance surpass more traditional companies like Coca Cola or General Electric, not only in terms of brand value, but also in terms of shareholder value. The unique economic characteristics of platforms and network goods have led to the discovery of novel competitive strategies engendered by network effects (Shy 2001; Eisenmann et al. 2006; Bhargava 2014).

This paper examines a vital aspect of network goods that has thus far not received attention. Research into platforms has covered a rich set of issues such as pricing strategies (Liu and Chintagunta 2009), product design (Bakos and Katsamakas 2008), product launch (Lee and O’Connor 2003), seeding strategies (Dou et al. 2013), compatibility and competition (Farrell and Klemperer 2007), competition across platforms (Rochet and Tirole 2003; Chakravorti and Roson 2006), competition between incumbents and entrants (Katz and Shapiro 1992; Eisenmann et al. 2011), segmentation (Bhargava and Choudhary 2004; Jing 2007), timing of product introduction (Bhargava, Sun, et al. 2013), and business model design (Parker and Van Alstyne 2005; Hagtui 2007). But the intellectual framework on this work primarily revolves around one lever for influencing market outcomes, namely pricing—
how much to charge, whom to charge, what to charge for, how to vary price over time, etc.

Platform firms, however, use levers other than price to influence market outcomes. In particular, sellers of network goods often achieve network growth by employing sales agents to actively recruit market participants. This is commonly seen in two-sided markets, but is also observed in single-sided markets. *OpenTable* for instance, a two-sided online platform connecting restaurants with patrons, employs sales people to sell the platform to restaurants managers. *Credit Karma* hires sales staff to acquire financial provider firms, rounding out its business objective of serving customers who seek financial products. *American Well*, an online platform connecting physicians with patients, employs sales agents to reach out to health insurance companies that contract with these physicians. *Kyruus*, which provides coordination technology to multi-point health systems, hires sales staff to sign up provider organizations. Another important example is advertising oriented platforms such as media companies, which employ advertising sales agents to sell advertising space to advertisers (Sridhar et al. 2011).

Network mobilization is a critical activity for managers of network goods, hence the problem of suitably managing and incentivizing sales agents is particularly acute. The compensation structures for employees in sales or business development roles tend to differ from structures in other job categories. The main challenge in sales force compensation strategy originates from the unobservability of the sales agent’s selling efforts, which managers circumvent by linking observed performance to compensations. This issue is very well studied in the case of traditional goods (Basu et al. 1985; Coughlan and Sen 1989; Lal and Srinivasan 1993; Joseph and Kalwani 1995; Joseph and Thevaranjan 1998; Krishnamoorthy et al. 2005; Steenburgh 2008; Albers and Matrala 2008; Mantrala et al. 2010; Misra and Nair 2011; Jain 2012; Coughlan and Joseph 2012; Rubel and Prasad 2016), but not in the case of network goods and platforms.
A distinctive feature of agency relationships in the case of network goods and platforms is that network effects alter the outcome of the agent’s efforts, and hence impact the agent’s productivity. This raises a series of strategic issues. First, how should managers account for network effects in the design of compensation plans? For instance, since stronger network effects amplify the agent’s selling effectiveness, should managers increase sales commissions? Or, should they do the opposite because network effects also increase the value of the good independently of the agent’s effort? Second, how are profit levels altered when sales forces are used to sell network goods and platforms? Finally, what fraction of potential profit gains should be allocated to the agent’s compensation and in which way?

Neither the platform literature, nor the personal selling literature for traditional goods, examines salesforce compensation design under network effects. To address these questions and discover novel actionable managerial guidelines relevant to platform firms, we propose a principal-agent model of platform sales. We find that network effects indeed influence the design of compensation plan, but in a spectrum of ways depending on whether network effects are direct or indirect.

We first consider the case of a network good characterized solely by direct network effects, which increase not only the mean but also the variance of sales. We find that as the intensity of network effects increases, so does the firm’s profit, but the firm gives up a greater percentage of earnings to the agent, and also increases the fraction of guaranteed salary. We then consider platforms or two-sided markets, where cross platform network effects between two sides (e.g., between restaurants and patrons in the case of OpenTable), drive the firm’s profit. Again, cross platform network effects (on the side that the agent is hired to sell) increase both the mean and the variance of sales, but they affect compensation design differently than direct network effects. The commission rate increases with the intensity of network effects. Surprisingly, the firm’s profit may decrease once the intensity gets too large, even though the agent works harder. On the opposite side of the market, if cross-network effects are negative,
that can cause the agent to work less. Hence, we show that cross platform network effects should be incorporated differently, and discerningly, in the agent’s compensation plan by the manager. An important insight of the proposed model is that ignoring network effects in the design of compensation plans would lead to profit losses because managers would over estimate the effectiveness of the agent and under-estimate the optimal level of risk to which the agent should be exposed to through the performance based incentives.

The remainder of the paper evolves as follows. In Section 2, we analyze the case of network goods, which are characterized by direct network effects. In Section 3, we focus on platforms or two-sided markets which are characterized by cross platform network effects. Finally, we conclude in Section 5.

2 Salesforce Strategy for Network Goods

We first study one-sided network goods that exhibit direct network effects, i.e., users’ benefit increases with the presence of other “similar” users. This occurs for instance in systems designed for communication, community, and sharing (e.g., Skype, online tennis clubs, “meetup” groups, eBay, freecycle). To develop this model, first consider the interplay between sales and sales effort for a traditional good with no network effects.

2.1 Benchmark Case: No Network Effect

In the literature, this interplay is commonly captured with the following relationship between sales level and the agent’s effort \( Q = V + \beta w + \epsilon \) (Holmstrom and Milgrom 1987; Salanié 2005), where \( Q \) is the sales level for the good when the agent’s sales effort level is \( w \) and selling effectiveness \( \beta \), \( V \) is the baseline sales (also a proxy for the quality of the good), and \( \epsilon \) is Normally distributed with zero mean and variance \( \sigma^2 \), capturing demand shocks. These shocks imply that the firm cannot directly observe or infer the agent’s effort, who
can shirk due to moral hazard. The managerial problem is to find the compensation plan, i.e., \( \omega(Q) \), that optimally incentivizes the agent to work. In line with the extant salesforce compensation literature, we adopt the commonly used the LEN framework (see, e.g., Bolton and Dewatripont (2005)), which stands for Linear plan and Exponential utility function. Specifically, the manager offers a linear plan \( \omega = \alpha_0 + \alpha_1 Q \) (a base salary \( \alpha_0 \), and commission rate \( \alpha_1 \) on sales) to an agent having an exponential utility function,

\[
U(\omega(Q), w) = -e^{-\rho(\omega(Q) - C(w))},
\]

where \( \rho \) is the agent’s risk aversion coefficient and \( C(w) \) is the cost of effort (with \( C'(w) > 0 \) and \( C''(w) > 0 \)). Linear contracts received much attention because of their robustness (demonstrated by Holmstrom and Milgrom (1987)) and simplicity in practice. Given the linear plan, the optimal level of effort is chosen to maximize the certainty equivalent of the agent’s utility, i.e.,

\[
w^* = \arg \max \ E[\omega(Q)] - \frac{\rho}{2} Var[\omega(Q)] - C(w).
\]

Assuming that the agent’s cost of effort is of the form \( C(w) = w^2/2 \), we obtain that the level of effort exerted by the agent is \( w^* = \beta \alpha_1 \).

The manager then determines the parameters of the contract to maximize the firm’s profit, i.e.,

\[
E[\Pi] = E[Q] - (\alpha_0 + \alpha_1 E[Q]),
\]

where \( E[Q] = V + \beta w \), subject to the agent’s incentive compatibility constraint, i.e., \( w = w^* \), and \( E[\omega(Q(w^*))] - \frac{\rho}{2} Var[\omega(Q(w^*))] - C(w^*) > R \), respectively, where \( R \) is the value of the agent’s outside option. As a result, \( \alpha_1^* = \frac{\beta^2}{\beta^2 + \rho \sigma^2} \) and \( w^* = \frac{\beta^3}{\beta^2 + \rho \sigma^2} \) (see Bolton and Dewatripont (2005)), and as it might be expected, a more effective agent (higher \( \beta \)) works more, and the firm sets a higher commission rate for an agent who is more effective or less
risk averse ($\rho$).

### 2.2 Salesforce Compensation with Direct Network Effects

When direct network effects exist, the influence of the agent’s effort on demand is given by

$$Q = V + \beta w + \eta Q^e + \epsilon, \quad (4)$$

where $0 < \eta < 1$ measures the strength of network effects and $Q^e$ is the market’s expectation regarding $Q$. If consumers form rational expectations, i.e., $Q = Q^e = q$, the equilibrium demand becomes

$$q = \frac{V + \beta w}{1 - \eta} + \frac{\epsilon}{1 - \eta}. \quad (5)$$

This setup satisfies important properties of network goods. First, volatility of market outcomes increases with network effects. The theoretical literature on network goods notes that equilibrium outcomes can vary between total market failure and a highly successful outcome. Competitive markets display even higher variance due to standards wars and the possibility of a winner-take-all outcome. Stock prices of companies that make network goods tend to exhibit higher volatility. Second, network effects exaggerate the potential impact of each unit of selling effort, because if the product becomes popular, high adoption levels can further propel sales.

Similar to the benchmark case, the manager offers the salesperson a linear compensation plan that links payment and observed performance $q$, i.e., $\omega(q) = \alpha_0 + \alpha_1 q$, and the agent determines his utility-maximizing selling effort. Thus, we obtain that the optimal effort
exerted by the agent is

\[ w^* = \beta \frac{\alpha_1}{1 - \eta}. \]  

(6)

When direct network effects exist, i.e., \( 0 < \eta < 1 \), the effectiveness of the agent’s effort is enhanced by the intensity of network effects. As a result, the agent is motivated to work more for any value of the commission rate \( \alpha_1 \).

Given this insight, what is the profit maximizing commission rate and how should the agent’s exposure to risk be varied with network effects? Alternatively, should the manager increase or decrease the share of performance based rewards in the agent’s total cash compensation? On the one hand, the intensity of the network augments the agent’s selling effectiveness, which means that the firm should increase the commission rate to capitalize on the motivational effects of network effects on the agent’s behavior, similar to what would happen when the agent’s selling effectiveness increases in the case of traditional goods. But on the other hand, and contrary to traditional goods, the intensity of the network also allows the agent to benefit from the “free” sales engendered by the size of the network, irrespective of the agent’s exerted effort, which should call for lower incentives in the agent’s cash compensation.

To formally explore how the manager should fractionally allocate the total compensation between performance-based incentives and the fixed salary, we again write the firm’s expected profit as

\[ E[\Pi] = \frac{V + \beta w}{1 - \eta} - \left( \alpha_0 + \alpha_1 \frac{V + \beta w}{1 - \eta} \right) \]  

(7)

where \( E[q] = \frac{V + \beta w}{1 - \eta} \) is the expected revenue generated by the agent and \( \alpha_0 + \alpha_1 \frac{V + \beta w}{1 - \eta} \) is the cost of compensating this agent. Maximizing Eq. 7, subject to the agent’s IC and IR conditions, we obtain the following proposition.
Proposition 1. The optimal commission rate is

$$\alpha_1^* = \frac{\beta^2}{\beta^2 + \rho \sigma^2}. \quad (8)$$

This first proposition provides two insights. First, it reveals that the commission rate for a network good sold by one agent does not depend on the intensity of direct network effects and is actually identical to the commission rate offered to an agent selling a traditional good. Even though this result appears surprising, it can be easily explained by comparing how revenues and the cost compensating the agent vary when the manager changes the commission rate. Specifically, the total revenues generated by the agent as a function of $\alpha_1$ equals $V(1-\eta)+\frac{\beta^2 \alpha_1}{(1-\eta)^2}$, whereas the cost of compensation the agent is $R + \alpha_1^2 \frac{\beta^2 + \rho \sigma^2}{(1-\eta)^2}$. Therefore, the marginal benefit of varying the commission rate and the corresponding marginal cost of agent’s compensation are both impacted similarly by the intensity of direct network effects, which yield an optimal commission rate that is independent of $\eta$. We will show later how this insight change in the case of platforms and when multiple agents are employed by the firm.

The second insight pertains to how network effects influence the allocation of risk between the agent and the firm, as captured by the share of performance-based incentives in the agent’s total cash compensation. Specifically, assuming for simplicity that $R = 0$, we find that the share of performance-based incentives in the agent’s total compensation, i.e., $\Lambda_1^* = \frac{\alpha_1^* q}{\alpha_0^* + \alpha_1^* q}$, is

$$\Lambda_1^* = \frac{2V(1-\eta)}{\beta^2} + \frac{2\beta^2}{(\beta^2 + \rho \sigma^2)}, \quad (9)$$

which means that the manager should decrease the share of performance-based incentives in
the agent’s total cash compensation as the intensity of network effects increases as \( \frac{\partial \Lambda^*}{\partial \eta} < 0 \).\(^1\) This result is not motivated by the expectation that the agent would shirk due to the free sales generated by the size of the network. On the contrary, the agent works more as network effects increase, i.e., \( \frac{\partial w^*}{\partial \eta} > 0 \).

Instead, to explain why \( \frac{\partial \Lambda^*}{\partial \eta} < 0 \), we first note that network effects increase the mean value of sales, i.e., \( \mathbb{E}[q(w^*)] = \frac{V}{1-\eta} + \frac{\beta^4}{(1-\eta)(\beta^2 + \rho^2)} \), and as a result so does the total performance based commission received by the agent, i.e., \( \mathbb{E}[q(w^*)]\alpha^* = \left( \frac{V}{1-\eta} + \frac{\beta^4}{(1-\eta)(\beta^2 + \rho^2)} \right) \frac{\beta^2}{\beta^2 + \rho \sigma^2} \). However, from the agent’s perspective an increase in \( \eta \) also exposes him to increased compensation risk due to the higher volatility in sales and commission payment. Consequently, the manager raises the agent’s fixed salary to compensate for this risk-induced disutility. Specifically, \( \alpha_0 \) increases at a greater proportion than \( \mathbb{E}[q(w^*)]\alpha^* \), thereby reducing the share of performance-based incentives in the agent’s total salary.

Thus in equilibrium, the manager decreases the agent’s risk exposure as the intensity of direct network effect increases, increasing at the same time the firm’s exposure, which could suggest that the firm should keep an increasing share of sales revenues as network effects increase. We examine this possibility in the next result.

**Proposition 2.** As the intensity of the network effect increases, the manager should dedicate a higher share of revenues to sales force compensation.

Thanks to the agent’s effort and the intensity of network effects, the firm’s revenues equal \( q^* = \frac{V + \beta w^*}{1-\eta} \) (recall, we normalized the unit profit margin to 1). Trivially, the total profit potential of the network good increases as network effects get stronger. But the increased intensity of network effects also implies greater volatility in outcomes, making the agent more concerned about his salary, and causing the firm to increase the agent’s total compensation as \( \eta \) increases. Specifically, computing the share of the agent’s compensation in the firm’s sales revenues, i.e., \( \Omega = \frac{\alpha_0 + \alpha^* q^*}{q^*} \), i.e., \( \Omega^* = \frac{\beta^4}{2(\beta^4 + V(1-\eta)(\beta^2 + \rho^2))} \), we find that \( \frac{\partial \Omega^*}{\partial \eta} \).

\(^1\)which also holds for \( R > 0 \)
Figure 1: How network effects influence nature of compensation, and sharing of gains between agent and firm. Total compensation (relative to firm’s profit) increases with intensity of network effects, while share of commission (dashed line) decreases.

The key insight from Proposition 2 is that when network effects are strong, it is in the firm’s interest to compensate the sales agent handsomely for selling a product whose sales depend greatly on factors outside his control. The firm is better able, in expectation, to realize the higher profit potential of the network good by not only relieving the agent’s increased compensation risk, but also passing a greater share of its earnings to the sales agent, compared to a firm selling a traditional good. Proposition 2 thus adds to our understanding of how network effects impact the firm’s management of its salesforce. We encapsulate the two main findings of the two results in Fig. 1.

Our final result in this section shows that the increase in the share of earnings paid to the sales agent, as network effects increase, does not happen at the expense of lower profits. This result is insightful because firms can control the intensity of network effects through
product design, e.g., by controlling the level of openness in the system, or by altering the
tools for search, discovery, matching and transactions with other users. The result reveals
that if the manager were to strategically choose the intensity of the network effect, the
optimal intensity $\eta^*$ could be found by maximizing the marginal revenues generated by the
network good (net of the compensation costs) to the marginal cost of varying $\eta$. Again, the
inference that the firm’s profit increases with an increase in $\eta$ is most evident for $R=0$, where
$$\Pi^* = \frac{V}{1-\eta} + \frac{\beta^4}{2(\beta^2+\rho\sigma^2)(1-\eta)^2}.$$ 

**Proposition 3.** The firm’s profit, net of salesforce compensation costs, increases with the
intensity of network effects, i.e., $\frac{\partial\Pi^*}{\partial\eta} > 0$.

To summarize our analysis of a one-sided network good, direct network effects increase
both the mean and the variance of sales, which alters the agency relationship between the
firm and the selling agent hired to sell the good. The natural question that ensues is then
how should the manager optimally incentivize the agent such that to determine the profit-
maximizing allocation of risk and rewards between the firm and the salesperson. Proposition 1 implies that even though the commission rate does not vary with the intensity of
direct network effects, both the fixed payment and performance based rewards (i.e., sales
times commission rate) received by the agent will increase, but that the fixed salary will in-
crease in a greater proportion. As a result, the share of performance based incentives in the
agent’s total cash compensation decreases as the intensity of direct network effects increases.
Proposition 2 shows that for products with stronger network effects, the firms should propor-
tionally sacrifice (allocate) more of its revenues to compensate the agent. This insight allows
us to highlight that personal selling has a greater strategic importance in this case than in
the case of products without network effects. Nevertheless, Proposition 3 demonstrates that
* ceteris paribus, profit levels always increase in the intensity of network effects.
We now consider a two-sided platform marketplace, characterized by cross platform network effects between two sides. We label these two sides as $B$ (buyers) and $S$ (sellers). The platform firm creates the infrastructure and business rules that enable transactions between buyers and sellers. In this stylized interpretation, a transaction involves the seller transferring some product or service that creates value for the buyer, in exchange for a fee. The platform may capture a commission on the transaction or it may set membership fees for buyers and/or sellers. Research on business models for two-sided market platforms has highlighted the tensions between pricing (monetization) and sales (Bhargava, Sun, et al. 2013). One crucial insight from this research is that often the optimal strategy for the platform is to subsidize one side of the market while monetizing the other (Parker and Van Alstyne 2005; Eisenmann et al. 2006). These are labeled the “subsidy” (or “free”) and the “paying” sides. Commonly, the subsidy side corresponds to buyers, while the paying side corresponds to sellers.

In the extant research on platforms, sales on each side of the platform are described primarily as a function of pricing and product features on that side, and installed base on the other side (the cross-network effect). On each side, in principle, the product creates value to users via a combination of stand-alone features and cross-network effects. For instance, a smartphone has stand-alone value due to its in-built features (e.g., processor, SIM card, storage, calendar, mail etc.) and network benefits depending on the third-party apps available on its app store. Let $Q_b$ and $Q_s$ represent sales on the buyer and seller sides, respectively. Then these are affected by stand-alone benefits ($V_b$ and $V_s$) and cross-network benefits ($\eta_b Q_s$ and $\eta_s Q_b$, where $\eta_b$ and $\eta_s$ reflect the intensity of cross-network effects). Plugging all other influences into the error terms $\epsilon_b$ and $\epsilon_s$ (on the two sides of the
platform), sales on the two sides may be described as follows.

\[ Q_b = V_b + \eta_b Q_s + \epsilon_b \]  \hspace{1cm} (10)
\[ Q_s = V_s + \eta_s Q_b + \beta w + \epsilon_s. \] \hspace{1cm} (11)

Research on network goods and platforms has not examined the effect of other instruments that affect sales, such as advertising and sales force. However, deployment of these other instruments is a crucial element of the business strategy for platforms, especially because network effects amplify volatility in market outcomes. We introduce a sales force instrument on one side of the two-sided market, namely the paying side. This structure is motivated by many real-world platform products where growth on the non-paying side is primarily achieved by word-of-mouth as well as the inherent value (both stand-alone benefits and cross-network benefits) that customers on this side receive from participation. A simple prototypical example to illustrate this idea is the two-sided market created by CreditKarma which provides consumers with a free credit report, and earns revenue by directing these “users” to firms that seek to provide financial products to them. CreditKarma captures consumer-users through word-of-mouth and online advertising, and has an in-house sales team responsible for signing up financial service providers. Another example is advertising selling agents in media companies who are responsible for selling advertising space to advertisers and not for growing eyeballs.

Specifically, we examine the effect of having one selling agent, on the seller side, who puts in effort (or work) level \( w \) to persuade more sellers to join the platform. Then, the sales levels on the two sides of the platform marketplace are given by

\[ Q_b = V_b + \eta_b Q_s + \epsilon_b \] \hspace{1cm} (12a)
\[ Q_s = V_s + \eta_s Q_b + \beta w + \epsilon_s. \] \hspace{1cm} (12b)
The terms $\epsilon_b$ and $\epsilon_s$, corresponding to sales influences, not observed by the firm, are assumed to be normally distributed (with mean 0 and variance $\sigma_b^2$ and $\sigma_s^2$, respectively). The parameters $\eta_b$ and $\eta_s$ representing cross-network effects are each assumed to be less than 1, which can be achieved without loss of generality by scaling other parameters in the model. Further, in the analysis below, we will employ $\eta_s > 0$ (representing that the paying side values the platform for the access it provides to the subsidy side, which eventually pays the “paying” side for some service), while $\eta_b$ can be positive or negative, indicating that the subsidy side may not be necessarily perceived positively by the paying side, e.g., advertising on a newspaper can be seen negatively by readers, while advertisers value the number of readers.

Similar to the previous section, we employ a rational expectations framework. We cross-substitute $Q_s$ and $Q_b$ in Eq. 24 to obtain the equilibrium levels $q_s$ and $q_b$ on the two sides,

\begin{align}
q_b &= \frac{V_b + \eta_b(V_s + \beta w + \epsilon_s) + \epsilon_b}{1 - \eta_b \eta_s} \\
q_s &= \frac{V_s + \eta_s(V_b + \epsilon_b) + \beta w + \epsilon_s}{1 - \eta_b \eta_s}.
\end{align}

(13a) \quad (13b)

Now consider the design of a salesforce compensation strategy, where the firm pays the agent, hired to acquire customers on the paying side, a guaranteed salary plus a commission linked to sales on the paying side. As in the network good case, we consider a linear compensation plan of the form $\omega(q_s) = \alpha_0 + \alpha_1 q_s$.

The agent’s expected total utility corresponding to work level $w$ comprises the compensation $\omega(q_s(w))$, net of the agent’s cost of work $\frac{w^2}{2}$ and the cost of risk $\frac{\rho}{2} Var[\omega(q_s(w))]$, where $Var[\omega(q_s(w))] = \frac{\alpha_1^2 (\sigma_b^2 \eta_s^2 + \sigma_s^2)}{(1 - \eta_b \eta_s)^2}$. Its certainty equivalent expression is given by

$$
\mathbb{E}[U(w)] = \alpha_0 + \alpha_1 q_s(w) - \frac{w^2}{2} - \frac{\rho \alpha_1^2 (\sigma_b^2 \eta_s^2 + \sigma_s^2)}{2 (1 - \eta_b \eta_s)^2}.
$$

(14)
The agent’s optimal effort strategy is determined such that \( w^* = \arg \max_w \mathbb{E}[U(w)] \), which yields that

\[
w^* = \beta \frac{\alpha_1}{1 - \eta_b \eta_s}.
\]  

(15)

Similar to the network good case, cross platform network effects increase the agent’s selling effectiveness, causing the agent to work more for a given sales commission as network effects increase. The firm, in turn, gets a greater payoff for each unit of agent compensation. Intuitively, then, following the logic of Proposition 2, the firm would be expected to set aside a greater share of its revenues to salesforce compensation when network effects are stronger. We examine this intuition formally by identify the optimal parameters of the compensation plan, i.e., the guaranteed payment and commission rate, subject to the agent’s IC and IR conditions.

### 3.1 Optimal Linear Compensation Plan with Cross Platform Effects

Formally, let \( \mathbb{E}[\Pi] \) be the expected profit of the firm such that

\[
\mathbb{E}[\Pi] = \frac{V_s + \eta_b V_b + \beta w}{1 - \eta_b \eta_s} - \left( \alpha_0 + \alpha_1 \frac{V_s + \eta_b V_b + \beta w}{1 - \eta_b \eta_s} \right),
\]  

(16)

where, similar to the network good case, \( \frac{V_s + \eta_b V_b + \beta w}{1 - \eta_b \eta_s} \) is the expected revenue generated by the agent’s effort and network effects, and \( \alpha_0 + \alpha_1 \frac{V_s + \eta_b V_b + \beta w}{1 - \eta_b \eta_s} \) is the expected compensation paid to the agent. The optimal commission rate is characterized by \( \alpha_1^* = \arg \max_{\alpha_1} \mathbb{E}[\Pi] \), subject to the agent’s incentive compatibility and individual rationality conditions, i.e., \( w^* = \beta \frac{\alpha_1}{1 - \eta_b \eta_s} \) and \( \mathbb{E}[U(w^*)] > 0 \), respectively. We obtain the following proposition.
Proposition 4. The optimal commission rate for an agent selling a platform good is

$$\alpha^*_1 = \frac{\beta^2}{\beta^2 + \rho(\sigma_s^2 + \sigma_b^2 \eta_s^2)}$$  \hspace{1cm} (17)$$

Proposition 4 elucidates that cross-platform effects, contrary to the network good case, partially impact the commission rate received by the agent, i.e., specifically, only the externalities generated by the number of buyers on the number of sellers matters. Such an externality was not present in the network good case, which explains why the optimal commission rate for a network good case does not vary as the intensity of direct network effects vary.

In particular, we note that the commission rate now decreases in $\eta_s$. To understand why this is the case, recall that $\eta_s$ captures how sensitive sellers are to the number of buyers participating in the platform, which increases the value of platform for sellers, not unlike $V_s$. However, contrary to $V_s$, the optimal commission rate should account for $\eta_s$. Why? Because even though $\eta_s$ increases the value of the platform, it also channels the uncertainty that exists in the buyer’s side to the seller’s side, which matters as the agent is risk averse.

Building on the result of Proposition 4, we find that the share of performance based incentives in the agent’s total cash compensation is

$$\Lambda^*_2 = 2\frac{(V_s + V_b \eta_s)(1 - \eta_b \eta_s)}{\beta^2} + \frac{2\beta^2}{\beta^2 + \rho(\sigma_s^2 + \sigma_b^2 \eta_s^2)},$$

which reveals that $\Lambda^*_2$ shares both similarities and differences with respect to $\Lambda^*_1$. Specifically, we note that the share of performance based incentives in the agent’s total cash compensation always increase as the stand-alone values increase and always decrease in the agent’s risk aversion and sales variance, i.e., $\frac{\partial \Lambda^*_2}{\partial V_s} > 0$, $\frac{\partial \Lambda^*_2}{\partial V_b} > 0$, $\frac{\partial \Lambda^*_2}{\partial \sigma_s} < 0$ and $\frac{\partial \Lambda^*_2}{\partial \sigma_b} < 0$. Furthermore, $\frac{\partial \Lambda^*_2}{\partial \eta_b} < 0$, which also comports with the insight obtained from the network good case.

Yet, $\Lambda^*_2$ contrasts with respect to $\Lambda^*_1$ in that an increase $\eta_s$ can lead to both an increase
or a decrease in $\Lambda_2^*$. Why? Because an increase in $\eta_s$ leads to two effects. It increases the value of the platform for buyers, as an increase in $V_s$ would do, but it also increases sales uncertainty, which would comport as $\frac{\partial \Lambda_2^*}{\partial \sigma_s}$ and $\frac{\partial \Lambda_2^*}{\partial \sigma_b}$.

### 3.2 Impacts of Cross Platform Effects on the Firm’s Profit

Specifically, after replacing the optimal commission rate and salary in the firm’s profit, we obtain that

$$\Pi^* = \frac{V_s + \eta_s V_b}{1 - \eta_s \eta_b} + \frac{(1 - \eta_s \eta_b)^{-2}}{2(1 + 2 \rho (\sigma_s + \eta_s^2 \sigma_b))},$$

which allows us to obtain the following proposition

**Proposition 5.** The firm’s profit always increases as $\eta_b$ increases, but can decrease as $\eta_s$ increases.

The surprising part of this result is that the platform’s profit can go down as $\eta_s$ increases. The intuition for this insight comes from the fact that $\eta_s$ creates some externalities that the manager cannot perfectly internalize in the agent’s compensation plan, similar to $\eta_b$ in the case the platform good and $\eta$ in the network good case.

### 4 Extensions

We next consider to interesting extensions to our core model. The first extension investigates the use of two-sided compensation plans in the case of platform goods. The second extension investigates how accounting for more than one agent would impact our results.
4.1 Two Sided Compensation Plan

A novel element of two-sided markets is the cross-market network effect. That is, participation in side $B$ (say, buyers) is influenced by the “network”—the level and nature of members—on side $S$ (say, sellers), and vice versa. This motivates a question in sales force incentive design, i.e., should an agent who is hired to acquire customers on side $S$ be paid based on the outcome on side $S$ only, or also incentivized based on outcome on side $B$? Note that, if $\eta_s > 0$, the $S$-side agent will free-ride these positive network effects, because side $S$ membership will grow in part based on increase in side $S$ membership. Conversely, the efforts of the agent in growing side $S$ will also, if $\eta_b > 0$, have a spillover effect in terms of growing side $B$ (which, in turn, will contribute to growth in side $S$)? Does the firm need to explicitly account for these cross-network effects by setting two separate commission rates, representing sales in sides $B$ and $S$ respectively? Will that help the firm achieve a better outcome? Or, can these benefits be achieved merely by setting a (possibly higher) single-sided commission rate, because it automatically internalizes cross-network effects? We examine this issue by developing a model which consists of a compensation plan with a cross-side commission rate $\alpha_2$ in addition to the (previously introduced) guaranteed salary $\alpha_0$ and same-side commission rate $\alpha_1$. Formally the commission structure is $\omega(q_s, q_b) = \alpha_0 + \alpha_1 q_s + \alpha_2 q_b$.

Next, we follow the same steps as in the previous sections. We first find that under the two side compensation plan, the agent’s optimal effort is

$$w^* = \frac{\alpha_1 + \alpha_2 \eta_b}{1 - \eta_b \eta_s}, \quad (20)$$

The inclusion of the second commission rate in the compensation plan means that the firm is willing to provide incentives to the agent for the “free customers.” Specifically, the
platform’s profit function under the two commissions is

$$E[\Pi] = \frac{V_s + \eta_s V_b + w}{1 - \eta_b \eta_s} - \left( \alpha_0 + \alpha_1 \frac{V_s + \eta_s V_b + w}{1 - \eta_s \eta_b} + \alpha_2 \frac{V_b \eta_b + V_b + \eta_b w}{1 - \eta_s \eta_b} \right),$$

where $\beta$ has been normalized to 1. The manager determines the optimal commission rates to maximize the firm’s profit, subject to the agent’s IC and IR conditions. As a result we obtain the following proposition.

**Proposition 6.** The optimal commission rates are such that $\alpha_2^* = -\alpha_1^* \eta_s$, where

$$\alpha_1^* = \frac{1}{(1 - \eta_s \eta_b)(1 + \rho \sigma_b^2)}.$$

This new proposition yields two main insights. First, the commission rate on the side of the “free customers” (i.e., buyers) is negative, which means that the agent has to pay to play. This insight echoes a similar finding when price is the main lever of control, that is, the firm should “subsidize” one side at the expense of the other one. Note that such an arrangement is not uncommon, for instance real estate agents often pay brokers who provide a platform to access buyers and sellers. Second, the commission rate $\alpha_1$ under the two sided compensation plan differs, as it should, from the $\alpha_1$ under the one sided compensation plan. In particular, we note that $\alpha_1$ does not now depend on $\sigma_b$. This provides an interesting insight because it means that the performance based incentives provided to the agent now becomes independent from the risk of the buyer’s side, whereas this was not the case under the one sided compensation plan. This result happens because the second commission allows the manager to perfectly internalize the risk on both side through the compensation plan, whereas this was not the case when only one commission was allowed.
4.2 Multiple Agents

We now investigate situations where the manager assigns different salespeople to serve distinct customer segments or territories and analyze how compensation plans differ in such situations.

In the network good case, we generalize the case to two agents by assuming that each agent is assigned a specific sales territory. Sales in this territory are driven by the standalone value of the platform \(V\), the agent’s effort and its effectiveness \(w_i\) and \(\beta_i\), respectively, demand shocks \(\epsilon_i\) are Normally distributed with mean zero and variance \(\sigma_i^2\)) and finally network effects, which equals \(\eta_i \sum_{i=1}^2 Q_i^e\), such such that

\[
Q_1 = V + \beta_i w_i + \eta_i \left( Q_1^e + Q_2^e \right) + \epsilon_i, \tag{23}
\]

Similarly, in the platform good case, we assume that the firm’s business is divided into two different segments on the sellers’ side, i.e., \(i = \{1, 2\}\), served by a dedicated agent, such that

\[
Q_{si} = V_s + \eta_{si} Q_b + \beta_i w_i + \epsilon_{si}. \tag{24a}
\]

In the above equation, we assume that the standalone values are the same across the two segments, and each segment only differs on three dimensions, namely, how much the buyers’ side is valued by the sellers’ side \(i\), i.e., \(\eta_{si}\), the agent’s effort and effectiveness, i.e., \(\beta_i w_i\), and finally unobservable demand shocks, i.e., \(\epsilon_{si}\), which are Normally distributed with zero mean and variance \(\sigma_{si}^2\). Conversely, the demand function on the buyers’ side becomes

\[
Q_b = V_b + \eta_b (Q_{s1} + Q_{s2}) + \epsilon_b, \tag{25}
\]

Assuming rational expectations in both the network good case and the platform case, we
obtain the equilibrium demands, agents’ optimal effort strategies and obtain the optimal commissions rates such to maximize profits under the agents’ IC and IR conditions. As a result, we are to furnish the following table that summarizes our main results with respect to the optimal incentive strategies for agents selling goods characterized by network effects.

<table>
<thead>
<tr>
<th></th>
<th>One Agent</th>
<th>Two Agents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional Good</td>
<td>$\frac{\beta^2}{\beta^2 + \rho \sigma^2}$</td>
<td>$\frac{\beta^2}{\beta^2 + \rho \sigma^2}$</td>
</tr>
<tr>
<td>Network Good</td>
<td>$\frac{\beta^2}{\beta^2 + \rho \sigma^2}$</td>
<td>$\frac{\beta^2 (1 - \eta)(1 - \eta)^2 + \rho (1 - 2(1 - \eta)\eta) \sigma^2}{\beta^2 (1 - \eta)^2 + \rho (1 - 2(1 - \eta)\eta) \sigma^2}$</td>
</tr>
<tr>
<td>Platform Good</td>
<td>$\frac{\beta^2}{\beta^2 + \rho \sigma_s^2 + \rho \sigma_b^2 \eta_s^2}$</td>
<td>$\frac{\beta^2 (1 - \eta_b \eta_s) (1 - \eta_b \eta_s)^2 + \rho \sigma_s^2 (1 - \eta_b \eta_s)^2 + \rho \sigma_b^2 (1 - \eta_b \eta_s)^2 + \eta_s^2 (\sigma_b^2 \eta_s^2 + \sigma_b^2)}{\beta^2 (1 - \eta_b \eta_s)^2 + \rho \sigma_s^2 (1 - \eta_b \eta_s)^2 + \rho \sigma_b^2 (1 - \eta_b \eta_s)^2 + \eta_s^2 (\sigma_b^2 \eta_s^2 + \sigma_b^2)}$</td>
</tr>
</tbody>
</table>

The main insight from this table is that considering two agents change the optimal commission rates in the network good and platform cases. The intuition for these findings ensues from the externalities that are created between agents. Consider for example the platform good case.

In such situations, the effort of an agent has three effects on equilibrium sales. First, it has a direct effect on sales in his own market, which comports with traditional good, i.e., as his selling effectiveness increases, he works more. The second effect comes though increasing the size of the network on his end of the market, which also triggers more effort as his selling effectiveness is enhanced by $\eta_{si}$ as analyzed in Section 3. Finally, the third effect comes from the other market. As agent 1 works more, he increases $q_{s1}$, which in return increases the value of the platform good for buyers. As a result, agent 1’s effort in market 1 increases the value of the platform as well for sellers in market 2, which brings more sellers in this market. This creates a feedback loop since this effect then bring more buyers in, which consequently will increase even more sales in market 1 as well. At the same, this feedback loop also brings more risk, which necessitates to adjust the commission rate accordingly. A similar reasoning
applies to the network good case.

5 Conclusion

Platforms are an exciting aspect of business today. The positive feedback created by network effects, the immense popularity of many new platforms, e.g., Facebook, and excellent financial indicators, have created enormous interest this business model. However, setting up platforms and securing participation of key players, is difficult and requires concerted selling effort. To our knowledge, the present paper is the first to examine selling strategy and salesforce incentives for platforms and network goods. Our analysis demonstrates that the existence of network effects indisputably alters the management of sales force compensation plans.

There are three driving forces in economic analysis of selling strategies for platforms. First, to some extent, network goods “sell automatically,” increasing the agent’s mean reward relative to effort. Second, and conversely from the firm’s perspective, network effects make the agent more productive and every unit of compensation earns higher rewards for the firm. Third, network effects increase the volatility of market outcomes. Therefore, salesforce incentives—which inherently employ market outcomes—have to be adjusted for not only sales agents’ and the firm’s inherent rewards, but also for the additional risk placed on the sales agent due to higher volatility in outcomes. Mixing the three forces produces novel results.

First, for one-sided network goods, the effect of direct network effects is unequivocally positive, resulting in a win-win situation despite additional risk. Both the agent’s compensation and the firm’s profit increase in intensity of network effects. However, the optimal compensation design is altered, shifting more towards guaranteed compensation and away from commission, with the commission rate itself independent of the intensity of network effects.
effects. Moreover, the firm must give up a higher share of its profit as network effects increase.

Second, for two-sided network goods with cross-market effects, the compensation plan could potentially include commission rates linked to outcomes on both the seller or paying side, i.e., the one that the agent is responsible for, and the buyer or free side. Linking the agent’s compensation to performance on the free side seems reasonable because the agent’s effort on the seller-side will, due to the cross-market effect, reward the firm on the buyer side. We find that such compensation strategy actually dominates compensation plans based only on the paying side.

Third, we find several interesting insights regarding how cross-network effects influence optimal plan design and profitability. Unlike the case of direct network effects, now the commission rate does depend on the intensity of cross-network effects, i.e., it decreases as $\eta_s$ (which measures how much sellers value the buy-side network) increases, and is independent of $\eta_b$. The agent’s optimal effort, however, depends on both parameters, i.e., $\eta_b$ positively impacts the agent’s optimal effort, but $\eta_s$ does so only when $\eta_b$ is high enough. Finally, the firm’s profit is no longer monotonic in $\eta_s$, i.e., surprisingly, it can reduce when $\eta_s$ is high enough. This happens because higher outcome volatility forces the firm to substantially raise the agent’s guaranteed salary in order to compensate for the agent’s risk.

With these initial results in place, this research invites us to explore additional questions. For instance, it would be useful to endogenize the platform’s standalone quality $V$ and intensity of network effects, to explore the optimal design of platforms when selling them requires hiring sales agents under moral hazard. Second, considering price as well as personal selling would be crucial to see how moral hazard can change known pricing strategies for platform. Finally, managers use other marketing instruments such as advertising to grow the platform, often using different instruments on different sides. Hence, considering more than one marketing instruments would be valuable to design marketing budgeting and allocation strategies.
References


