Selling Platforms

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Abstract

Network goods and platform-enabled marketplaces are a dominant part of industry and entrepreneurship today. Firms selling these products task selling agents to recruit network participants. This creates a novel agency problem, distinct from one encountered with traditional goods because of externalities created by network effects. We analyze this managerial problem within a principal-agent framework, aiming to understand the impact of network effects on compensation design and also to identify new insights regarding compensation strategies for network and platform goods. Our analyses articulate a spectrum of ways in which these externalities influence the optimal design of compensation plans, depending on whether network effects are direct or indirect and on what metrics are used to determine performance incentives. For instance, for network goods, an increase in the intensity of network effects should increase the agent's share of the firm's total revenues, but a smaller fraction should be paid as incentive-based payments. The firm's net profit always increases as direct network effects increase, but profit levels for a platform can decrease as cross platform effects increase. Overall, the salesforce effort is strategically more important when selling network and platform goods than when selling traditional goods as sellers of such goods should dedicate a higher share of revenues to salesforce compensation.

1   Introduction

Thanks to network effects, platforms and network goods differ fundamentally from traditional products in how they create and provision value for users. Customers 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; *OpenTable*, which connects restaurants with patrons; 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, i.e., how managers should design performance-based compensation plans for agents tasked with recruiting network participants. 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; Hagiu 2007). But the intellectual framework of the extant research primarily revolves around one lever for influencing market outcomes, namely *price*—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 through the efforts of selling agents. This is commonly seen in two-sided markets, but is also observed in single-sided markets. *Kyruus*, which provides coordination technology to multi-point health systems, hires sales staff to sign up provider organizations. Among two-sided markets, *OpenTable* 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. 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, i.e., creating network growth, is a critical activity for managers of network goods, hence the problem of suitably managing and incentivizing sales agents is particularly acute. As with all goods, 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 Mantrala 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 comes from how network effects alter the outcome of the agent's efforts, and hence his incentives to work and take risks. As a result, series of strategic issues follow from this feature. First, how should network effects cause managers to change the lever with which they control the agent's effort, i.e., the commission rate? On one hand, there is support for an increase in sales commissions because stronger network effects amplify the agent's selling effectiveness. On the other hand, network goods "sell themselves" (i.e., sales occur on account of network size, less dependent on agent's efforts) suggesting a decreasing in commission. Second, how do network effects alter the mix between guaranteed and performance based compensation awarded to sales and business development staff? Third, do stronger network effects cause profit levels for platform companies to increase or decrease when sales forces are used to recruit network participants? Finally, what fraction of revenues should be allocated to the agent's compensation and in which way?

Neither the platform nor the salesforce literatures examine the design of compensation plans and performance-based incentives 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 analyze a series of models covering both direct and indirect effects, and (for two-sided network goods) with performance metrics on both sides vs. just the side that the agent is tasked with recruiting. 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, and most importantly, based on the nature of externalities they generate. A key insight 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.

We first consider the case of a network good characterized solely by direct network ef-

fects, 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. Yet, cross platform network effects affect compensation design differently than direct network effects, because they generate externalities that differ from the network good case, i.e., externatilies between the two sides of the market (absent in the network good case). Specifically, we find that the optimal commission rate decreases with the intensity of network effects.

Surprisingly, for platform goods the firm's profit may decrease once the intensity of cross-network effects gets too large, even though the agent works harder. This emphasizes the need to incorporate cross platform network effects differently, and discerningly, in the agent's compensation plan. More importantly, this result highlights that the firm must deploy an appropriate number of instruments (metrics which are linked to performance-based incentives) to manage the externalities created by network effects. We show that compensation plans that meter network size on *both* sides of the market create an always-positive relationship between network effects and the firm's profit. Finally, we find that when multiple agents are employed to sell either a network good or a platform good, network effects *always* alter commission rates because of the externalities generated *between* agents.

The remainder of the paper evolves as follows. §2 presents a benchmark case of salesforce compensation without network effects. § 3 extends to network goods characterized by direct network effects, while §4 examines platforms or two-sided markets with cross platform network effects. In § 5, we generalize our results to two-sided compensation plans and multiple agents. §6 concludes.

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2 Salesforce Compensation Design: Benchmark Case

Salesforce compensation design has been extensively studies for traditional goods, with no network effects. In the extant literature, the interplay between sales and selling effort is commonly captured by the relationship $Q = V + \beta\mathtt{w} + \epsilon$ (Holmstrom and Milgrom 1987; Salanié 2005), where Q is the sales level for the good when the agent's sales effort level is $\mathtt{w}$ and selling effectiveness β, V is the baseline sales (also a proxy for the quality of the good), and ϵ is Normally distributed with zero mean and variance σ^2, capturing demand shocks. These shocks prevent the manager from directly observing the agent's effort, hence the agent may decide to shirk. To circumvent this issue, the manager ties the agent's payment to his performance, i.e., $\omega(Q)$, to incentivize him to optimally work from the firm's perspective. The literature on salesforce compensation design is built around the LEN framework (Linear Plan, Exponential Utility, Normally distributed performance, see, e.g., pp. 137-139 in Bolton and Dewatripont (2005)). Specifically, the manager offers a linear plan $\omega = \alpha_0 + \alpha_1 Q$ (a base salary α_0, and commission rate α_1 on sales) to an agent having an exponential utility function,

$$U(\omega(Q), \mathtt{w}) = -e^{-\rho(\omega(Q) - C(\mathtt{w}))}, \tag{1}$$

where ρ is the agent's risk aversion coefficient and $C(\mathtt{w})$ is the cost of effort (with $C'(\mathtt{w}) > 0$ and $C''(\mathtt{w}) > 0$). 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.,

$$\mathtt{w}^* = \arg\max_{\mathtt{w}} \mathbb{E}[\omega(q)] - \frac{\rho}{2} Var[\omega(q)] - C(\mathtt{w}). \tag{2}$$

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

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

$$\mathbb{E}[\Pi] = \mathbb{E}[Q] - (\alpha_0 + \alpha_1 \mathbb{E}[Q]), \tag{3}$$

where $\mathbb{E}[Q] = V + \beta\mathtt{w}$, subject to the agent's incentive compatibility constraint (IC), i.e., $\mathtt{w} = \mathtt{w}^*$, and the agent's individual rationality condition (IR), i.e., $\mathbb{E}[\omega(Q(\mathtt{w}^*))] - \frac{\rho}{2}Var[\omega(Q(\mathtt{w}^*))] - C(\mathtt{w}^*) > R$, respectively, where R is the value of the agent's outside option. As a result, we obtain that the optimal commission rate and effort level are $\alpha_1^* = \frac{\beta^2}{\beta^2 + \rho\sigma^2}$ and $w^* = \beta\alpha_1^* = \frac{\beta^3}{\beta^2 + \rho\sigma^2}$, respectively (see Bolton and Dewatripont (2005) for similar results). Furthermore, the share of performance based incentives in the agent's total cash compensation, i.e., $\Lambda_0 = \frac{\alpha_1 \mathbb{E}[Q]}{\alpha_0 + \alpha_1 \mathbb{E}[Q]}$, is equal to $\frac{2\beta^2}{\beta^2 + \rho\sigma^2} \frac{\beta^4 + V(\beta^2 + \rho\sigma^2)}{\beta^4 + 2R(\beta^2 + \rho\sigma^2)}$.

These results allow us to make three observations regarding compensation design for traditional goods. First, the agent expends effort proportionally to his commission rate. Second, as it might be expected, a more effective agent (higher β) works more, and the firm sets a higher commission rate for an agent who is more effective or less risk averse (ρ). Finally, the standalone value of the product, i.e., V, does not alter the commission rate but does change the share of performance based incentives received by the agent, such that $\frac{\partial\Lambda_0}{\partial V} > 0$. Next, in the core of the paper, we investigate how these quantities, and others, change as sales are also driven by network effects.

3 Compensation Design with Direct Network Effects

In this section we consider one-sided network goods that exhibit direct network effects, i.e., users' benefit increases with the presence of other "similar" users. Common examples include systems designed for communication, community, coordination and sharing (e.g., Skype, online tennis clubs, "meetup" groups, freecycle, Kyruus). Then, the product's sales growth is influenced, besides product quality and the agent's effort, by existing network size.

We augment the sales equation in the traditional good case as follows $Q = V + \beta\mathtt{w} + \eta Q^e + \epsilon$, 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

$$q = \frac{V + \beta\mathtt{w}}{1 - \eta} + \frac{\epsilon}{1 - \eta}. \tag{4}$$

This setup satisfies important properties of network goods. First, volatility of market outcomes increases with network effects as $Var(q) = \frac{Var(\epsilon)}{(1-\eta)^2} = \frac{\sigma^2}{(1-\eta)^2}$. 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. As a result, we obtain that the optimal effort exerted by the agent is

$$\mathtt{w}^* = \beta \frac{\alpha_1}{1 - \eta}. \tag{5}$$

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 and for $\eta > 0$, the agent is motivated to work more for any value of the commission rate α_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 man-

ager 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

$$
\mathbb{E}[\Pi] = \frac{V + \beta \mathtt{w}}{1 - \eta} - \left(\alpha_0 + \alpha_1 \frac{V + \beta \mathtt{w}}{1 - \eta} \right) \tag{6a}
$$

$$
= \underbrace{\frac{V + \beta \mathtt{w}}{1 - \eta}}_{sales\ revenue} - \underbrace{(R + C(\mathtt{w}))}_{basic\ compensation} - \underbrace{\frac{\rho}{2} Var(\omega)}_{compensation\ for\ risk} \tag{6b}
$$

where $\mathbb{E}[q] = \frac{V + \beta \mathtt{w}}{1 - \eta}$ is the expected revenue generated by the agent and $\alpha_0 + \alpha_1 \frac{V + \beta \mathtt{w}}{1 - \eta}$ is the cost of compensating this agent.

How does the intensity of network effects influence the optimal commission rate α_1^* that the firm should offer the agent? An increase in η implies higher expected sales, but also higher sales volatility, thereby increasing the agent's exposure to compensation risk. Hence the agent demands higher payment to compensate for this increased risk. Consider if, on top of this, the firm were to increase the commission rate and motivate the agent to work even more, leading to even higher sales volatility. In return, the firm would need to compensate the agent for the extra cost of effort as well as for the greater risk. This additional compensation

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cost caused by higher commission rate must be balanced against the gains from higher sales. The combined effect of η on α_1^* (i.e., $\frac{\partial \alpha_1^*}{\partial \eta}$) has the same sign as $\frac{\partial^2 \pi}{\partial \alpha_1 \partial \eta}$. Computing the effect of α_1 on profit,

$$\frac{\partial \pi}{\partial \alpha_1} = \underbrace{\frac{\beta^2}{(1-\eta)^2}}_{\text{change in revenue}} - \underbrace{\left(\frac{\alpha_1 \beta^2}{(1-\eta)^2} + \frac{\rho \sigma^2 \alpha_1}{(1-\eta)^2} \right)}_{\text{change in compensation costs}} \tag{7}$$

we see that η affects both revenue and compensation costs in a similar way, specifically, the effect is purely a multiple of the general tradeoff between revenue and (compensation) costs. Hence, a change in η does not alert this tradeoff (i.e., $\frac{\partial^2 \pi}{\partial \alpha_1 \partial \eta} = \frac{\partial \pi}{\partial \alpha_1} \times \frac{\partial \pi}{\partial \eta}$), because the revenue-cost tradeoff is already set optimally (i.e., numerators in Eq.7 cancel out at α_1^*, where $\frac{\partial \pi}{\partial \alpha_1} = 0$). Therefore the optimal commission rate is independent of η (formally, $\frac{\partial^2 \pi}{\partial \alpha_1 \partial \eta} = 0 = \frac{\partial \alpha_1^*}{\partial \eta}$).

Proceeding with the compensation design, we compute the optimal commission rate by solving the first order condition ($\frac{\partial \pi}{\partial \alpha_1} = 0$). This leads to the following result.

Proposition 1. *Under direct network effects, 1) the optimal commission rate is independent of η, and 2) the share of incentive payment in the agent's total compensation is reduced as η increases. Formally,*

$$\alpha_1^* = \frac{\beta^2}{\beta^2 + \rho \sigma^2}, \tag{8a}$$

$$\Lambda_1^* = \frac{2V(1-\eta)}{\beta^2} + \frac{2\beta^2}{(\beta^2 + \rho \sigma^2)} \quad \text{simplified, at } R = 0 \tag{8b}$$

An increase in η increases the agent's compensation risk. For the firm, it is less expensive to mitigate this risk through fixed salary than through higher incentives (because the latter itself creates risk). Therefore, while the commission rate remains unchanged, the agent's total compensation increases along with the share of fixed salary in this total compensation. This result is not motivated by concern 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,

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i.e., $\frac{\partial \mathbf{w}^*}{\partial \eta} > 0$. The firm enjoys an increase in expected sales ($\mathbb{E}[q(\mathbf{w}^*)] = \frac{V}{1-\eta} + \frac{\beta^4}{(1-\eta)(\beta^2 + \rho\sigma^2)}$) and, being less risk-averse, is better off shifting more of the risk to itself. Although the absolute value of the agent's incentive compensation increases on account of increased sales, his fixed compensation increases in a greater proportion than $\mathbb{E}[q(\mathbf{w}^*)]\alpha_1^*$, thereby reducing the share of performance-based incentives in the agent's total salary.

Proposition 1 demonstrates that 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. This suggests, due to synchronicity between risk and reward, that the firm should keep an increasing share of sales revenues as network effects increase. Surprisingly, that is not the case, as can be verified easily because $\frac{\partial \omega(q(\mathbf{w}^*;\eta))}{\partial \eta} < 0$.

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

Thanks to the agent's effort and the intensity of network effects, the firm's revenues equal $q^* = \frac{V + \beta \mathbf{w}^*}{1-\eta}$ (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 η increases. Specifically, computing the share of the agent's compensation in the firm's sales revenues, i.e., $\Omega_1 = \frac{\alpha_0 + \alpha_1^* q^*}{q^*}$, i.e., $\Omega_1^* = \frac{\beta^4}{2((\beta^4 + V(1-\eta)(\beta^2 + \rho\sigma^2)))}$, we find that $\frac{\partial \Omega_1^*}{\partial \eta} > 0$.

Fig. 1 encapsulates the two main findings discussed above regarding the mix of compensation given to the agent, and the agent's share of total revenues from sales. 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
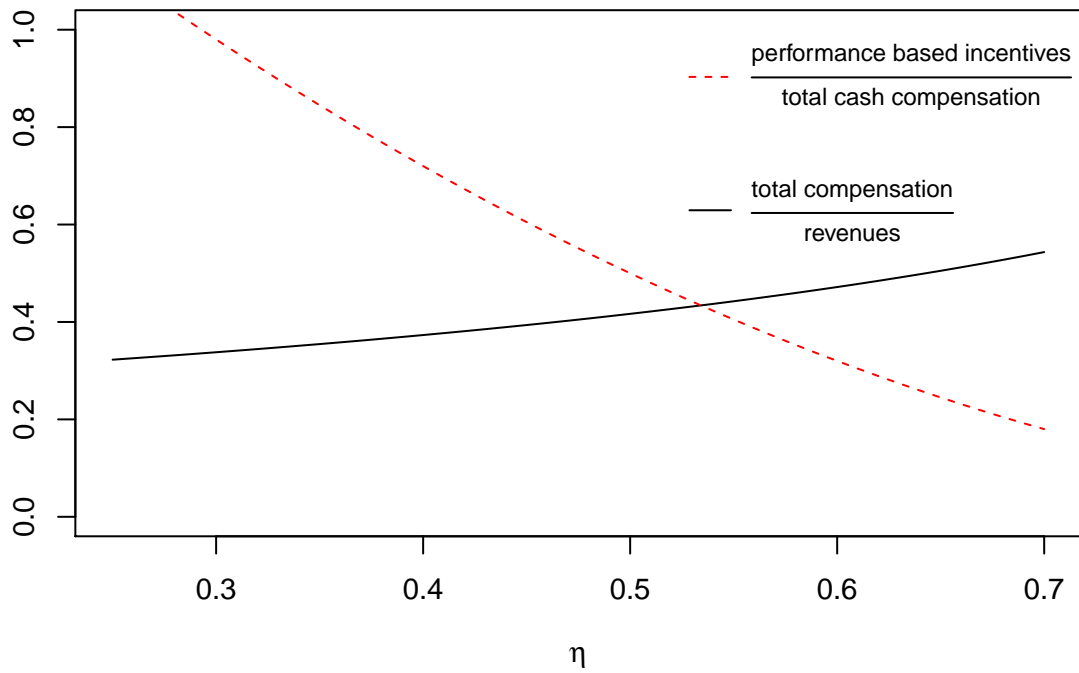
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Figure 1: How network effects influence nature of compensation, and sharing of gains between agent and firm. Total compensation (relative to firm's profit) increases with intensity of network effects, while share of commission (dashed line) decreases.

to strategically choose the intensity of the network effect, the optimal intensity η^* could be found by maximizing the marginal revenues generated by the network good (net of the compensation costs) to the marginal cost of varying η. Again, the inference that the firm's profit increases with an increase in η 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, ie., $\frac{\partial \Pi^*}{\partial \eta} > 0$.*

The key insight from Propositions 2 and 3 is that when selling a product with (positive) direct network effects, it is in the firm's interest to compensate the sales agent handsomely for selling a product whose sales depend greatly on factors outside the agent's control. Network effects increase both the mean and the variance of sales, altering the agency relationship between the firm and the selling agent hired to sell the good. Consequently, 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. These results create new insights on how network effects impact the firm's management of its salesforce. Most importantly, these findings highlight the strategic importance of personal selling for network goods, and suggest that owners of the firm be more actively engaged in early-stage business development (with less reliance on sales agents), thereby creating better alignment between risk and reward.

4 Salesforce Strategy in Two-Sided Markets

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 on that side, installed base on the other side (the cross-network effect), and stand-alone features of the product. For instance, a smartphone has stand-alone value due to its in-built features (e.g., processor, voice and data capabilities, storage, calendar, mail etc.) and cross-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, influenced by stand-alone benefits (V_b and V_s, respectively) and cross-network benefits ($\eta_b Q_s$ and $\eta_s Q_b$). Here, η_b reflect the intensity of cross-network effects for buyers, i.e., measures the value that buyers place on size of the seller network; similarly, η_s reflects the intensity of cross-network effects for sellers. Plugging all other influences into the error terms ϵ_b and ϵ_s (on the two sides of the platform), the sales model in existing literature may be described as follows.

$$Q_b = V_b + \eta_b Q_s + \epsilon_b \tag{9}$$

$$Q_s = V_s + \eta_s Q_b + \epsilon_s. \tag{10}$$

To this existing model, and following the structure introduced in §3, we apply a salesforce

instrument on one side of the two-sided market, namely the paying side (usually businesses, or, "sellers"). If the agent puts in effort w to recruit sellers, the sales levels on the two sides of the platform marketplace are modified to add the term βw, reflecting the contribution of the agent.

$$Q_b = V_b + \eta_b Q_s + \epsilon_b \tag{11a}$$

$$Q_s = V_s + \eta_s Q_b + \beta\text{w} + \epsilon_s. \tag{11b}$$

This seller-side agent structure is motivated by many real-world platform products which deploy salesforce to recruit paying-side participants, while relying on word-of-mouth and inherent value (both stand-alone benefits and cross-network benefits) to create growth on the non-paying side (often, consumers or "buyers"). 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.

As before, ϵ_b and ϵ_s, are assumed to be normally distributed (with means 0 and variance σ_b^2 and σ_s^2, respectively). Both η_b and η_s are each assumed to be less than 1, which can be achieved without loss of generality by scaling other parameters in the model. Further, $\eta_s > 0$ (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 η_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 and consider a linear compensation plan. Specifically, cross-substituting Q_s and Q_b in Eq. 11 yields the equilibrium levels q_s and q_b on the two sides,

$$q_b = \frac{V_b + \eta_b(V_s + \beta\mathtt{w} + \epsilon_s) + \epsilon_b}{1 - \eta_b\eta_s} \tag{12a}$$

$$q_s = \frac{V_s + \eta_s(V_b + \epsilon_b) + \beta\mathtt{w} + \epsilon_s}{1 - \eta_b\eta_s}, \tag{12b}$$

and the agent's compensation is $\omega(q_s) = \alpha_0 + \alpha_1 q_s$, which comprises a guaranteed salary, α_0, plus a commission rate α_1 linked to sales on the paying side. As a result, the certainty equivalent of the agent's utility is given by

$$\mathbb{E}[U(\mathtt{w})] = \alpha_0 + \alpha_1 q_s(\mathtt{w}) - \frac{\mathtt{w}^2}{2} - \frac{\rho}{2}\frac{\alpha_1^2(\sigma_b^2\eta_s^2 + \sigma_s^2)}{(1 - \eta_b\eta_s)^2}. \tag{13}$$

The agent's optimal effort strategy is then determined such that $\mathtt{w}^* = \arg\max_{\mathtt{w}} \mathbb{E}[U(\mathtt{w})]$, which yields that

$$\mathtt{w}^* = \beta\frac{\alpha_1}{1 - \eta_b\eta_s}. \tag{14}$$

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.

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4.1 Optimal Linear Plan with Cross Platform Effects

Let $\mathbb{E}[\Pi]$ be the expected profit of the firm such that

$$\mathbb{E}[\Pi] = \frac{V_s + \eta_s V_b + \beta \mathtt{w}}{1 - \eta_b \eta_s} - \left(\alpha_0 + \alpha_1 \frac{V_s + \eta_s V_b + \beta \mathtt{w}}{1 - \eta_b \eta_s} \right), \tag{15}$$

where, similar to the direct network effects case, $\frac{V_s + \eta_s V_b + \beta \mathtt{w}}{1 - \eta_b \eta_s}$ is the expected revenue generated by the agent's effort and network effects, and $\alpha_0 + \alpha_1 \frac{V_s + \eta_s V_b + \beta \mathtt{w}}{1 - \eta_b \eta_s}$ is the expected compensation paid to the agent. The optimal commission rate is characterized by $\alpha_1^* = \underset{\alpha_1}{\arg\max}\, \mathbb{E}[\Pi]$, subject to the agent's incentive compatibility and individual rationality conditions, i.e., $\mathtt{w}^* = \beta \frac{\alpha_1}{1 - \eta_b \eta_s}$ and $\mathbb{E}[U(\mathtt{w}^*)] > 0$, respectively. For single-sided network goods with direct network effects only, Proposition 1 established that commission rate is independent of η while the share of incentive payment in the agent's total compensation reduces with η (i.e., $\frac{\partial \alpha_1^*}{\partial \eta} = 0$ and $\frac{\partial \Lambda_1^*}{\partial \eta} < 0$). Our next result examines the same questions under cross-platform effects, solving the first-order condition ($\frac{\partial \mathbb{E}[\Pi]}{\partial \alpha_1} = 0$) to obtain optimal commission rate. Recall that η_s measures the importance of the size of buyer network to sellers, while η_s is the importance of seller network size to buyers.

Proposition 4. *Under cross-platform network effects, 1) the optimal commission rate decreases in η_s but is independent of η_b, and 2) an increase in η_b reduces the share of incentive payment in the agent's total compensation, while increase in η_s may cause the optimal share to either increase or decrease. Formally,*

$$\alpha_1^* = \frac{\beta^2}{\beta^2 + \rho\left(\sigma_s^2 + \sigma_b^2 \eta_s^2\right)} \tag{16a}$$

$$\Lambda_2^* = 2 \frac{(V_s + V_b \eta_s)(1 - \eta_b \eta_s)}{\beta^2} + \frac{2\beta^2}{\beta^2 + \rho(\sigma_s^2 + \sigma_b^2 \eta_s^2)} \tag{16b}$$

Proposition 4 elucidates that cross-platform effects, contrary to direct network effects, do impact the commission rate received by the agent. Specifically, for an agent hired to recruit sellers, only the externality generated by the number of buyers on the number of

sellers, as captured by η_s, matters. This result has several implications. First, it reveals that network effects should enter the commission rate as a way to internalize the externalities that they generate, a result that we generalize in Section 5. Second, it provides the insight that for cross-platform network goods (when an agent is hired to recruit on the seller-side), it is the network effect perceived by *buyers* that affects commission design. In contrast, the seller-side network effect η_b does not affect commission rate. In this sense, it behaves like V (core product value), because its impact on the agent's benefit from the platform depends on q_b which, as with V, is a metric that the agent does not directly influence.

Taking a deeper look at the role of network effects we note that the commission rate now decreases in η_s. To understand why this is the case, recall that η_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 varies with η_s, because even though η_s increases the value of the platform, it also channels the uncertainty that exists in the buyer's side to the seller's side. Thus, cross platform effects create a negative externality (increased risk) that the firm internalizes through the commission rate. To further understand this insight, we contrast the respective role of η_b and η_s on sales generated in the sellers' side, i.e., $q_s = \frac{V_s + \eta_s(V_b + \epsilon_b) + \beta \mathbf{w} + \epsilon_s}{1 - \eta_b \eta_s}$. When η_b increases, it impacts in a similar way the agent's effectiveness and sales variance, that is by a factor equal to $\frac{1}{1 - \eta_b \eta_s}$. This is not true when η_s varies as it increases the agent's effectiveness by $\frac{1}{1 - \eta_b \eta_s}$, but its impact on sales variance is $\eta_s \frac{1}{1 - \eta_b \eta_s} \epsilon_b + \frac{1}{1 - \eta_b \eta_s \epsilon_b} \epsilon_s$. This asymmetry creates the negative externality that the manager must internalize by adjusting the commission rate accordingly.

Turning to the mix of guaranteed and performance-based payments in the agent's compensation plan reveals that Λ_2^* (fraction of performance-based incentives to total compensation) shares both similarities and differences with respect to Λ_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, Λ_2^* contrasts with respect to Λ_1^* in that an increase η_s can lead to both an increase or a decrease in Λ_2^*. Why? Because an increase in η_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 $\frac{\partial \Lambda_2^*}{\partial \sigma_b}$.

4.2 Cross-Network Effects: Size and Split of Profits

Next we examine how the intensity of the two cross-network effects, η_s and η_b, affects the absolute value of the firm's profit (net of agent compensation) as well as the fraction of earnings that the firm shares with the agent. After replacing the optimal commission rate and salary in the firm's profit, we obtain that

$$\Pi^* = \frac{V_s + \eta_s V_b}{1 - \eta_s \eta_b} + \frac{\beta^4 (1 - \eta_s \eta_b)^{-2}}{\beta^2 + \rho\left(\sigma_s^2 + \eta_s^2 \sigma_b^2\right)}. \tag{17}$$

Furthermore, the share of sales revenues that should be allocated to sales force compensation is $\Omega_2 = \frac{\alpha_0^* + \alpha_1^* q_s^*}{q_s^*}$, i.e., $\Omega_2^* = \frac{\beta^4}{2\left(2\beta^4 - 2V_b h_1^2 \eta_s \rho + h_1(2(V_s \beta^2 + V_b \beta^2 \eta_s) + 2V_s h^2 \rho)\right)}$, where $h_1 = 1 - \eta_b \eta_s$ and $h_2 = \sigma_s^2 + \sigma_b^2 \eta_s^2$. As a result, we obtain the following proposition.

Proposition 5. *As η_b increases, both the firm's profit and the share of revenues allocated to compensating the salesforce increase. Formally $\frac{\partial \Pi^*}{\partial \eta_b} > 0$ and $\frac{\partial \Omega_2}{\partial \eta_b} > 0$. However, increase in η_s may either increase or decrease the firm's profit and the share of revenues allocated to compensating the salesforce. Formally, $\frac{\partial \Pi^*}{\partial \eta_s}$ and $\frac{\partial \Omega_2}{\partial \eta_s}$ can be positive or negative.*

The disparate effects of η_b and η_s can be explained by considering their role on the agent's compensation. Again, it is useful to compare with the direct network effects case. In that setting, η worked in step with Q (the agent's performance metric), thereby complementing the agent's own effort. Consequently, an increase in η yielded the firm higher profit despite

passing on a greater share of earnings to the agent. For the two-sided networks case, it is η_b that works with the agent's performance metric, Q_s. Therefore, the effect of η_b on what share of earnings the firm passes to the agent, and the firm's eventual profit, parallels that of η under direct network effects.

The surprising part of this result is that the platform's profit can go down as η_s increases. The intuition for this insight comes from understanding that η_s works in conjunction with Q_b, a metric that does not directly accounted for in the agent's compensation. As a result, the commission rate does not adequately internalize the negative externality generated by η_s, which is the augmented risk due sales uncertainty on the buyers' side, i.e., $\eta_s^2 \sigma_b^2$.

To summarize, network effects create externalities that need to be internalized by the firm in the agent's compensation, i.e., they alter the agent's effectiveness and sales' risk structure. In the network good case, these externalities pertain to the same market and the firm can internalize these externalities with two control variables, i.e., the fixed salary and the commission rate. In the platform good case, network effects generate externalities that pertain to both sides of the platform, they increase the value of the platform for both sides, but also increase the variance on both sides of the market. Yet, despite the higher number of externalities, the firm has still only two control variables at its disposal. As result, it faces a situation where there are more externalities than control variables to internalize them, which explains why profit can go down as η_s increases.

In the next Section, we provide two extensions to our core model. The first extension investigates the use of two-sided compensation plans in the case of platform goods, which allows us to explore how having an additional control variable changes the agent's incentive compensation plan, but most importantly the firm's profit. In the second extension, we generalize our findings to more than one agent.

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5 Extensions

5.1 Two Sided Compensation Plan

We first investigate whether an agent hired tasked to recruit network participants on one side, i.e., the sellers' side, should be compensated based on the two outcome metrics q_s *and* q_b? 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 α_2 in addition to the (previously introduced) guaranteed salary α_0 and same-side commission rate α_1. Formally the commission structure is $\omega(q_s, q_b) = \alpha_0 + \alpha_1 q_s + \alpha_2 q_b$.

Following the same analysis pattern as in the previous sections, the agent's optimal effort under the two-sided compensation plan is

$$\mathtt{w}^* = \beta \frac{\alpha_1 + \alpha_2 \eta_b}{1 - \eta_b \eta_s}. \tag{18}$$

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

$$\mathbb{E}[\Pi] = \frac{V_s + \eta_s V_b + \mathtt{w}}{1 - \eta_b \eta_s} - \left(\alpha_0 + \alpha_1 \frac{V_s + \eta_s V_b + \mathtt{w}}{1 - \eta_s \eta_b} + \alpha_2 \frac{V_s \eta_b + V_b + \eta_b \mathtt{w}}{1 - \eta_s \eta_b} \right), \tag{19}$$

where β 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*

$$\alpha_1^* = \frac{1}{(1 - \eta_s \eta_b)(1 + \rho \sigma_s^2)}. \tag{20}$$

This new proposition delivers four important insights. First, it reveals that 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. The second insight is that the agent's commission on the sellers' side, i.e., α_1, no longer depends on σ_b, which 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. Third, we learn that α_1 increases in both η_s and η_b. Together, these results comport with the intuition that by employing a two-sided compensation plan allows the firm can better internalize the externatlities generated by the network effects.

The firm's profit under the two sided compensation plan is $\Pi_{II}^* = \frac{V_s + V_b \eta_s}{1 - \eta_s \eta_b} + \frac{1}{2(1 + \rho \sigma_s^2)(1 - \eta_b \eta_s)^2}$. The shift from one-sided to two-sided performance-based incentives always increases the firm's profit, i.e., $\Pi_{II} - \Pi_I = \frac{\rho \sigma_b^2 \eta_s^2 (1 - \eta_s \eta_b)^{-2}}{2(1 + \rho \sigma_s^2)(1 + \eta_s^2 \rho \sigma_b^2 \sigma_s^2)}$ is positive. More importantly, Π_{II}^* now increases in both η_s and η_b, eliminating the previous potential (under the one-sided plan) of a negative relationship between profit and intensity of cross platform effect. Hence, using a two-sided compensation plan is better as it allows the firm to fully benefit from network effects, contrary to the single-sided compensation plan.

5.2 Multiple Agents

We now investigate compensation plans for situations where the manager assigns different salespeople to serve distinct customer segments or territories. Our multi-agent framework

is that each agent i ($\in \{1, 2\}$) is assigned a specific sales territory i. Sales in this territory are driven by the stand alone value of the platform (V), the agent's effort and effectiveness ($\mathbf{w}_i$ and β_i, respectively), demand shocks (ϵ_i are Normally distributed with mean zero and variance σ_i^2)), and finally network effects, ($= \eta \sum_{i=1}^{2} Q_i^e$). The "network" is the same as before, i.e., the entire set of user participants across sales territories.

The agent is compensated with a fixed salary α_0 plus a commission that depends on the sales metric Q_i. Thus, in this framework, each agent's effort exerts a positive externality on the other agent's compensation throug the size of the network. For the case of one-sided network goods with direct network effects only, the sales equation is

$$Q_i = V + \beta_i \mathbf{w}_i + \eta \left(Q_1^e + Q_2^e\right) + \epsilon_i, \tag{21}$$

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., $i = \{1, 2\}$, each served by a dedicated agent, such that

$$Q_{si} = V_s + \eta_s Q_b + \beta_i \mathbf{w}_i + \epsilon_{si}. \tag{22a}$$

In the above equation, we assume that the standalone values are the same across the two segments, and each segment only differs on two dimensions, namely, the agent's effort and effectiveness, i.e., $\beta_i \mathbf{w}_i$, and unobservable demand shocks, i.e., ϵ_{si}, which are Normally distributed with zero mean and variance σ_{si}^2. Conversely, the demand function on the buyers' side becomes

$$Q_b = V_b + \eta_b(Q_{s1} + Q_{s2}) + \epsilon_b, \tag{23}$$

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 that maximize profits under the agents' IC and IR conditions. Combining these solutions with the ones from the previous sections (with a single agent) we furnish the following table to compare and contrast the optimal incentive strategies for agents selling goods characterized by network effects.

Table 1: Optimal Commission Rates

	One Agent	Two Agents
Traditional Good	$\frac{\beta^2}{\beta^2+\rho\sigma^2}$	$\frac{\beta^2}{\beta^2+\rho\sigma^2}$
Network Good	$\frac{\beta^2}{\beta^2+\rho\sigma^2}$	$\frac{\beta^2(1-\eta)}{\beta^2(1-\eta)^2+\rho(1-2(1-\eta)\eta)\sigma^2}$
Platform Good	$\frac{\beta^2}{\beta^2+\rho(\sigma_s^2+\sigma_b^2\eta_s^2)}$	$\frac{\beta^2(1-\eta_b\eta_s)}{\beta^2(1-\eta_b\eta_s)^2+\rho(\sigma_s^2(1-\eta_b\eta_s)^2+\eta_s^2(\sigma_s^2\eta_b^2+\sigma_b^2))}$

The main insight from this table is that considering two agents alters the way network effects shape the design of compensation plans. For single-sided network goods, we show that the intensity of network effects does impact the optimal commission rate, even though such influence was absent when one agent managed the entire selling effort. Platform goods exhibit a similar contrast: η_b now influences the optimal commission rate, even though it did not in the case of a single agent.

The intuition for these findings ensues from how the firm deploys certain instruments available to it (fixed salary and commission) in response to the externalities created by network effects. Specifically, the firm's response must now take into account the externalities that are created between agents, in addition to the externalities within or across markets. Consider for example the platform good case. Here, 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

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triggers more effort as his selling effectiveness is enhanced by η_{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 time, this feedback loop also brings more risk, which necessitates to adjust the commission rate accordingly. A similar reasoning applies to the network good case.

6 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. Moreover, the firm must give up a higher share of its profit as network effects increase. The bottomline, though, is that with two levers (fixed and incentive salary) the firm can benefit from increased externalities that occur as the intensity of direct network effects increases.

Second, for two-sided network goods, externalities are created by two distinct cross-platform network effects. We study a compensation plan in which the agent is rewarded for sales on the side the agent is tasked with recruiting. 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 η_s (which measures how much sellers value the buy-side network) increases, and is independent of η_b. The agent's optimal effort, however, depends on both parameters, i.e., η_b positively impacts the agent's optimal effort, but η_s does so only when η_b is high enough. Finally, the firm's profit is no longer monotonic in η_s, i.e,, surprisingly, it can reduce when η_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.

Third, this potentially negative relationship between strength of network effects and the firm's profit motivates consideration of an alternate plan in which commission rates are 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. Although the agent does not directly recruit buyers, his effort will impact buyer participation through the cross-market effect. Crucially, this two-sided compensation structure gives the firm one extra lever with which to manage the externalities created by the two cross market effects. We show that this compensation strategy creates an always-positive relationship between strength of network effects and the firm's profit, and it dominates compensation plans based only on the paying side.

With these results in place, our work creates possibilities for future research. 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

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