ESSAYS ON THE ECONOMICS OF OPEN-SOURCE SOFTWARE

by

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As members of the Dissertation Committee, we certify that we have read the dissertation

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DEDICATION

To my mother

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ABSTRACT

This dissertation comprises three essays analyzing various economic questions relating to open-source software development. The common thread linking these essays is the long-term sustainability of the open-source software development model, which is largely built on unpaid contributions from individual developers scattered across the world.

The first essay develops a theoretical analysis of the market for operating systems as two-sided platforms, modeling the effects of competition and compatibility between a proprietary platform developed by a profit-maximizing firm, and an open platform (a public good developed by volunteers). Looking at the impacts on the proprietary platform firm, and application developer firms and users of both platforms, I find that under certain circumstances, a proprietary platform can find it profitable to become compatible with the open platform. However, it is always optimal in terms of social welfare to have compatibility between platforms.

The second essay uses a laboratory experiment to examine how these characteristics and levels of motivations that are heterogeneous across individuals interact to result in sustainable, non-zero levels of contribution to open source software. There is a pronounced "leadership effect," with subjects playing in the first position invariably contributing more frequently than those in the second position, and so on. Heterogeneity preserves the leadership effect, but increases contributions across the board, and eliminates the pattern of declining individual and total group contributions over time frequently observed in public goods experiments.

The third essay studies the micro-foundations of open-source software contributions and provides an empirical examination of developer motivations using survey data. If open-source contributions and education are both signals of ability, then their impact on income is likely to be linked. They may be complements if open source contributions reinforce the signal from education by showing that one stands out from the crowd, or they

might be substitutes if open-source development replaces expensive education in honing programming skills by offering more immediate feedback. Using an instrumental variables framework to deal with the endogeneity of the education and contribution choices, I find that leading an open-source project and completing college are complementary practices, so that the signaling and reputation-building aspect dominates.

CHAPTER 1

The effects of compatibility on competition between proprietary and open two-sided platforms

1.1 Introduction

Two-sided platforms can be defined as markets where the volume of transactions depends on how the total price charged to two different types of users is shared between them, not just on the total price (Rochet and Tirole, 2006). This captures the idea that in a two-sided market, the externalities accruing to one side of the market from the other side's transactions are not internalized by the other side. Examples include the typical intermediation service provider, online marketplace, or "matchmaker" studied by Caillaud and Jullien (2003), credit card systems as studied by Rochet and Tirole (2003), media and advertising markets, and operating systems or video game consoles, who need to get both developers and users on board.

Two-sided platforms provide a useful framework with which to study the particular pricing dynamics of computer operating systems, which need to be adopted by both users and application developers, and where the externality to users accrues from having a large number of applications available for the platform. The platform firm, in this case the operating system, can charge access fees to users, developers, or both, or even choose to subsidize one side of the market, thereby using its pricing strategies to eliminate the issues associated with what would otherwise be a coordination game. For example, Sony and Microsoft have been known to sell their Playstation and XBox video game consoles to users at a price below cost (CNet News, 2006), while charging game developers high fees to develop games for the respective consoles. On the other hand, Microsoft charges users a relatively high fee to use its Windows operating system, while charging application developers a low to zero fee to use its Application Programming Interface (API) to develop Windows applications. Linux, being an open platform developed for the most part by volunteers[1], does not charge access fees to users or developers; however, application developers such as Red Hat and Novell sell Enterprise editions of Linux that bundle the platform with a suite of applications.

On November 2, 2006, Microsoft and Novell, the makers of Suse Linux, entered into an agreement to enhance compatibility and interoperability between their respective operating systems. They will collaborate on research aimed towards enabling virtualization (a process which will allow, say, Windows, to be run as a virtual machine on computer with Linux as its native operating system, and vice versa) and document format compatibility, as well as provide patent protection to each others' customers and developers. (CNN-Money, 2006; Novell Inc. Press Release, 2006) The purpose of this paper is to analyze the implications of compatibility between a proprietary platform and the open platform that it competes with, and its implications on strategies, pricing, profits and welfare. It is clearly shown that under some cases, compatibility can increase profits for the proprietary platform, and there are situations where social welfare is improved by imposing compatibility even if the proprietary platform's profits are lowered.

1.2 Literature Review

Economides and Katsamakas (2006) have a theoretical analysis of a comparison of a proprietary software platform versus an open one. Approaching the issue as a study of two-sided platforms consisting of an operating system and applications, they find that the variety of applications is in the case of an open platform, but that the proprietary platform will dominate the open platform in terms of market share. Their specific result that the proprietary platform's market share increases as switching costs between platforms increase is borne out by this paper.

Rochet and Tirole (2003) and Hagiu (2006, 2004) also develop useful models of two-sided platforms in software markets, though the model of Rochet and Tirole (2003) is far more general and covers hardware/software two-sided platforms as well. Armstrong

[1]Firms like IBM which contribute to the development of Linux also do not receive any direct payment for their contributions. Their business model relies on selling related consulting services.

(2006) studies general models of competing two-sided platforms. They all find that the side, or user type, with a higher own price elasticity of demand for the platform is charged a lower proportion of the total platform price, while the side with a lower elasticity of demand pays a higher proportion of the price in equilibrium. This paper does not focus on demand elasticities. Instead, prices and purchase decisions are modeled as functions of the degree of differentiation between the two platforms, using a Hotelling model.

Gabszewicz, Laussel, and Sonnac (2006, 2002); Choi (2006) and Doganoglu and Wright (2006) use a Hotelling structure to model the two types of users in models of competing platforms, and Doganoglu and Wright (2006) model the effects of compatibility. However, their model does not accommodate transactions between the two types of users, which is a crucial feature of software markets, as well as marketplaces like shopping malls or online auction websites. They find that compatibility is always welfare-increasing relative to the case when users multihome (adopt both platforms simultaneously), but firms may have an excessive incentive to become compatible if users were singe-homing previously in the case of one-sided markets. When markets are two-sided but there is no product differentiation, they find that platforms have the correct (in terms of social welfare) incentive to choose compatibility as long as consumers cannot multihome. Otherwise, their incentive is insufficient. This paper's findings are in line with their result, in that the proprietary platform has an insufficient incentive to choose compatibility in some cases. However, in the model presented here, firms never have an excessive incentive to choose compatibility.

Katz and Shapiro (1985) examine the effects of compatibility on one-sided networks, and find that it improves social welfare as long as firm profits increase under compatibility, and that firms may fail to acheive it in some cases even when it is socially optimal. This paper has an even stronger result for the specific case of two competing two-sided platforms, where one is open and the other proprietary, since it is always socially optimal to impose compatibility even when it reduces the platform's profits.

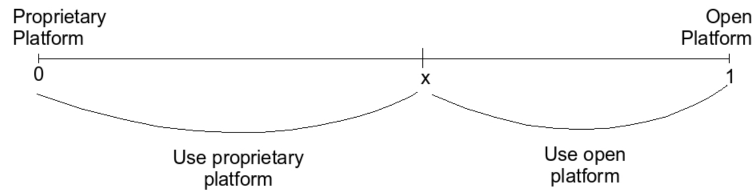

Figure 1.1: Division of users between two incompatible platforms.

1.3 The baseline model with incompatible platforms

There are two platforms, one proprietary and one open, denoted throughout by M and O respectively. The proprietary platform is developed by a strategic profit-maximizing firm, while the open platform is a freely accessible public good[2] which sets its user and developer prices equal to zero. The proprietary platform competes with the open platform in a modified Hotelling setup forming a single-agent game.

Consumers, or platform users, are uniformly distributed along a 0,1 interval as in Figure 1.1. The "transport" parameter t, where $t > 0$, represents their taste for a particular platform, while x represents the consumer's location. We assume the market is covered, so that all consumers purchase at least one platform. Users are not strategic agents.

Users must also purchase applications to use on the platform. We assume application developers are strategic, profit-maximizing firms, and differentiated by their fixed costs, which are uniformly distributed along a separate, unrelated 0,1 interval as in Figure 1.2. Each developer produces one type of application and there is a continuum of developers. The transport parameter c, where $c > 0$, represents their preference for a particular platform and θ represents their location. This captures the degree of differentiation between platforms from a developer's point of view (c), and the developer's degree of investment in, or preference for, coding for a particular platform (θ). $c\theta$ is a developer's fixed cost of developing an application for the proprietary platform, and $c(1 - \theta)$ is a developer's fixed cost of developing an application for the open platform. Developers choose one platform and do not multi-home. However, their location is exogenously determined. We

[2]The open platform is assumed to be developed by unpaid volunteers.

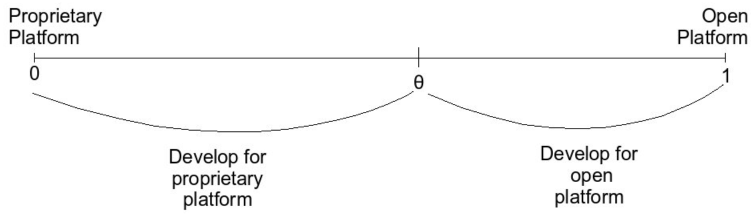

Figure 1.2: Division of developers between two incompatible platforms.

also assume all developers enter the market.[3]

The market proceeds in the following way, with the proprietary platform and all developers as strategic agents:

1. First, the proprietary platform sets user prices, denoted as p_u^M, and developer access fees, denoted as p_d^M. The prices for the open platform, p_u^o and p_d^o are zero by definition.

2. Next, developers choose which platform to develop for. Let n_M^d denote the number of developers choosing to work with the proprietary platform, and n_o^d the number of developers choosing to work with the open platform, given p_u^M (since the equilibrium proportion of users on each platform is a known function of p_u^M) and p_d^M.

3. After choosing a platform, developers set application prices, given p_u^M and p_d^M. For developer j, this is denoted by p_{Mj}^d for developers on the proprietary platform and p_{oj}^d for developers on the open platform.

4. Lastly, users decide which platform to adopt. Let n_M^u denote the number, or proportion of users who choose the proprietary platform, and n_o^u be the number of users choosing the open platform. Users also simultaneously purchase applications to use on the platform, choosing from among the available applications on the chosen platform and buying exactly one unit of every selected application.

[3]It can be shown that the case where some firms do not enter the market can only be supported when either the proprietary platform's application price or developer price is negative.

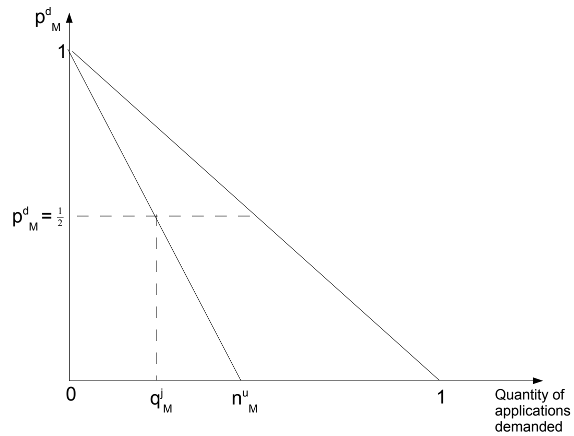

Figure 1.3: Application demand curve for a developer on the proprietary platform

Users are not strategic agents, but their values for each application available for the chosen platform are independent and uniformly distributed on the 0,1 interval. Each user's valuations for each application are independent. The probability that any user on platform k buys application j with a price p^d_{kj} is therefore the probabillity that their value for the application is greater than p^d_{kj}, which is $1 - p^d_{kj}$. Each developer then faces the following decision problem: the expected number of applications that developer j can sell is $\int_0^{n^u_M}(1 - p^d_{Mj})dj$ for a developer on the proprietary platform, and $\int_{n^u_M}^1(1 - p^d_{oj})dj$ for a developer on the open platform, since developers can only sell to users on their own platform. As a result, each application also faces the same demand curve: $(q_j|p^M_u, p^M_d) = (1-p^d_M)n^u_M$ for firm j on the proprietary platform, and $(q_j|p^M_u, p^M_d) = (1-p^d_o)n^u_o$ for firm j on the open platform.

Assuming developers only face fixed costs and have a zero marginal cost, we obtain $(p^d_M|p^M_u, p^M_d) = \frac{1}{2}$ as the equilibrium price for all applications on the proprietary platform, and $(p^d_o|p^M_u, p^M_d) = \frac{1}{2}$ as the equilibrium price for all applications on the open platform. Figure 1.3 shows the demand curve faced by any single proprietary application developer. At a price $p^d_M = \frac{1}{2}$ as shown, it can expect to sell one application each to $\frac{n^u_M}{2}$ users.

Since each user's valuation for any given application is independent and does not depend on the prices or valuations for the other applications, the equilibrium price for any one application does not depend on the prices charged by the other applications.

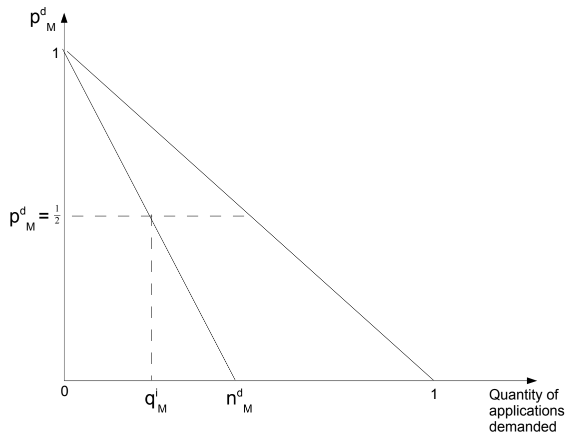

Figure 1.4: Application demand curve for a user on the proprietary platform

Therefore, no developer has an incentive to deviate from a price of $\frac{1}{2}$, since by doing so they would neither increase their own profit, nor lower the profits of the other developers, and setting any other price is a strictly dominated strategy.

Since all application prices are the same, the expected mass of applications any user on the proprietary platform purchases is $\int_0^{n^d_M}(1-p^d_M)dz$, and $\int_{n^d_M}^1(1-p^d_o)dz$ for any user on the open platform. Each user therefore has an application demand: $q_i = (1-p^d_M)n^d_M$ for user i on the proprietary platform (Figure 1.4), and $q_i = (1-p^d_o)n^d_o$ for user i on the open platform. However, the demand curve in Figure 1.4 is not typical, since each application is different from the others. At the same time, it denotes the total mass of applications purchased by any single user, which, at an equilibrium application price of $\frac{1}{2}$, equals $\frac{n^d_M}{2}$.

User utility is a function of the base utility from using a platform, V, the price paid for the platform, the user's location (i.e. preference for the chosen platform), and the net consumer surplus from consumption of the applications, which is the willingness to pay for each application less its price, integrated over the quantity of applications purchased. This is increasing in the number of available applications (or application variety) and decreasing in their price. User utility is therefore:

$$U_i^M = V - p_u^M - tx + \int_0^{(1-p^d_M)n^d_M}(1-\frac{z}{n^d_M} - p^d_M)dz$$

for a user who adopts the proprietary platform, and

$$U_i^o = V - t(1-x) + \int_0^{(1-p_o^d)n_o^d} (1 - \frac{z}{n_o^d} - p_o^d)dz$$

for a user who adopts the open platform. The utility from using a platform, V, is assumed to be high enough that in equilibrium all consumers purchase at least one platform. At this point it is assumed that users cannot multihome, or purchase both applications.

Since we know that $p_M^d = p_o^d = \frac{1}{2}$ in equilibrium, we can substitute that price into user utility functions to obtain:

$$U_i^M = V + \frac{(1-p_M^d)^2 n_M^d}{2} - p_u^M - tx$$

and

$$U_i^o = V + \frac{(1-p_o^d)^2 n_o^d}{2} - t(1-x)$$

Consumer surplus, and therefore user utility, is increasing in the proportion of developers on the chosen platform. This constitutes the indirect network effect that makes the operating system a two-sided platform. By locating the indifferent consumer, we get:

$$x = n_M^u = \frac{1}{2} + \frac{n_M^d - n_o^d}{16t} - \frac{p_u^M}{2t}$$

and since $n_o^u = 1 - n_M^u$ by definition,

$$n_o^u = \frac{1}{2} - \frac{n_M^d - n_o^d}{16t} + \frac{p_u^M}{2t}$$

In the limit, we see that as $t \rightarrow \infty$, $n_M^u \rightarrow \frac{1}{2}$. If $t \rightarrow 0$, then, $n_M^u \rightarrow 0$ (solving through for $n_M^d - n_o^d$).

Developer profits, for a developer j who chooses to develop for the proprietary platform, are represented by:

$$\pi_{Mj}^d = p_{Mj}^d(1-p_{Mj}^d)n_M^u - p_d^M - c\theta$$

where $c\theta$ is the fixed cost of developing the application, θ represents a developer's location with regards to the preference for developing for a particular platform, and c is a transport parameter indicating the level of differentiation between the platforms from a developer's perspective. This can be understood as the investment a developer makes in learning to code for, and becoming comfortable with, a particular platform. Similarly, profits for a developer j who chooses the open platform are:

$$\pi^d_{oj} = p^d_{oj}(1 - p^d_{oj})n^u_o - c(1 - \theta)$$

Since all developer prices must equal $\frac{1}{2}$ in equilibrium, we can substitute this and the values obtained for n^u_p and n^u_o back into the profit functions to obtain:

$$\pi^d_p = \frac{1}{8} + \frac{n^d_M - n^d_o}{64t} - \frac{p^M_u}{8t} - p^M_d - c\theta$$

and

$$\pi^d_o = \frac{1}{8} - \frac{n^d_M - n^d_o}{64t} + \frac{p^M_u}{8t} - c(1 - \theta)$$

To calculate the proportion of application developers entering the market on each platform, we find the indifferent developer, and we see that:

$$\theta = n^d_M = \frac{1}{2} - \frac{4p^M_u}{32ct - 1} - \frac{16tp^M_d}{32ct - 1}$$

and

$$n^d_o = \frac{1}{2} + \frac{4p^M_u}{32ct - 1} + \frac{16tp^M_d}{32ct - 1}$$

Platform profits can be represented as:

$$\Pi_M = p^M_u n^u_M + p^M_d n^d_M - C$$

for the proprietary platform, where C is the platform's fixed cost. Substituting for n^d_M and n^d_o, we get:

$$\Pi_M = p^M_u \left[\frac{1}{2} - \frac{p^M_u}{2t(32ct - 1)} - \frac{2p^M_d}{32ct - 1} - \frac{p^M_u}{2t}\right] + p^M_d \left[\frac{1}{2} - \frac{4p^M_u}{32ct - 1} - \frac{16tp^M_d}{32ct - 1}\right] - C$$

This gives us:

$$p^{p*}_u = \frac{32ct - 1}{64c} - \frac{3p^M_d}{16c}$$

and

$$p_d^{p*} = \frac{32ct - 1}{64t} - \frac{3p_u^M}{16t}$$

Substituting, we get:

$$p_u^{M*} = \frac{(32ct - 1)(16t - 3)}{4(256ct - 9)}$$

and

$$p_d^{M*} = \frac{(32ct - 1)(16c - 3)}{4(256ct - 9)}$$

We see that the sum of p_u^M and p_d^M is a constant for fixed values of c and t. As the platform raises one price it must lower the other; however for given values of t and c there is a unique equilibrium pair of prices. The proprietary platform's market share, n_M^u, is increasing in t as long as $c > \frac{3}{16}$. This is in line with the findings of Economides and Katsamakas (2006), since the proprietary platform dominates the market as switching costs (represented by levels of differentiation, in this model) increase.

Currently, Microsoft sets its developer price at or close to zero. In this paper's framework, a value of $c = \frac{3}{16}$ rationalizes this price as long as $t > \frac{3}{16}$. A low level of platform differentiation with respect to developers and a high level of differentiation with respect to users justifies a zero developer price (since the developers need to be brought on board) and a positive user price (since there are enough users with a strong preference for the proprietary platform even when it has a positive price). Negative prices, or subsidies to either side are also possible if the level of differentiation for that side is especially low.

1.4 Compatible platforms

Compatibility is defined as giving users the ability to use applications made for any platform, having installed either platform. Platforms can achieve this at some additional fixed cost C_2. Each user now can purchase any of the applications from 0 to 1 (Figure 1.3), not just from 0 to n_M^d for proprietary platform users and n_o^d to 1 for open platform users, as was the case when platforms were incompatible. Developers now have a potential market of all users from 0 to 1 (Figure 1.4). Each developer on platform k can now expect to sell to $\int_0^1 (1 - p_{kj}^d) dj$ users. The demand curve faced by any developer, regardless of the platform, is now $q_j = (1 - p_k^d)$ for developer j on platform k. User demand curve for applications does not depend on the platform chosen by the application developer and is $q_i = (1 - p_k^d)$ for user i. The equilibrium application price does not change, since the developers still have a zero marginal cost and positive fixed cost indexed by their location (preference for a platform), and we have $p_M^d = p_o^d = \frac{1}{2}$.

User utility is now:

$$U_i^M = V - p_u^M - tx + \int_0^{(1-p_M^d)} (1 - z - p_M^d) dz$$

for a user who adopts the proprietary platform, and

$$U_i^o = V - t(1-x) + \int_0^{(1-p_o^d)} (1 - z - p_o^d) dz$$

for a user who adopts the open platform. As in the previous section, the utility from using a platform, V, is assumed to be high enough that in equilibrium all consumers purchase at least one platform. Since we know that $p_M^d = p_o^d = \frac{1}{2}$ in equilibrium, we can substitute that price into user utility functions to obtain:

$$U_i^M = V + \frac{1}{8} - p_u^M - tx$$

and

$$U_i^o = V + \frac{1}{8} - t(1-x)$$

By locating the indifferent consumer, we get:

$$x = n_M^u = \frac{1}{2} - \frac{p_u^M}{2t}$$

and

$$n_o^u = \frac{1}{2} + \frac{p_u^M}{2t}$$

Since the demand for any given developer's application is $1 - \frac{1}{2} = \frac{1}{2}$, developer profits are:

$$\pi_{Mj}^d = \frac{p_{Mj}^d}{2} - p_d^M - c\theta = \frac{1}{4} - p_d^M - c\theta$$

for developers working on the proprietary platform, and

$$\pi_{oj}^{d} = \frac{1}{4} - c(1-\theta)$$

for developers working on the open platform. As earlier, c represents the fixed cost and the location parameter θ represents a developer's taste for a particular platform. Note that since platforms are now compatible, developers can potentially sell to all users by choosing any platform. So if $p_d^M > c$, no developers will choose to develop for the proprietary platform, since even the developers located at $\theta \to 0$ will find it more profitable to switch to the open platform; as the platforms are compatible the demand for their application will be unchanged. The proportion of developers choosing each platform can be written as:

$$n_M^d = \frac{1}{2} - \frac{p_d^M}{2c}$$

and

$$n_o^d = \frac{1}{2} + \frac{p_d^M}{2c}$$

The platform's profit can now be written as:

$$\Pi_M = p_u^M \left(\frac{1}{2} - \frac{p_u^M}{2t}\right) + p_d^M \left(\frac{1}{2} - \frac{p_d^M}{2c}\right)$$

The platform's prices are now:

$$p_u^M = \frac{t}{2}$$

and

$$p_d^M = \frac{c}{2}$$

Platform profit is now $\frac{c+t}{8}$.

1.5 Welfare analysis

Since this framework leads to the conclusion that Microsoft's zero price for developers when platforms are incompatible requires $c = \frac{3}{16}$, the developer and platform profits and consumer welfare are compared for that particular case.

When the platforms are incompatible, the proprietary platform makes a profit of:

$$\Pi_M = \frac{32ct - 1}{4(256ct - 9)} \left[(16t - 3)n_M^u + (16c - 3)n_M^d\right]$$

This is greater than $\frac{c+t}{8}$ when $c = \frac{3}{16}$ if $t > 0.263$. However, if $t < 0.263$, then the proprietary platform is better off choosing to be compatible with the open platform. So as the differentiation with respect to users falls, compatibility becomes a better option.

Total profits for the developers on the proprietary platform when platforms are incompatible can be written as:

$$\int_0^{n_M^d} (\frac{1}{8} + \frac{2n_M^d - 1}{64t} - \frac{p_u^M}{8t} - p_d^M - c\theta)d\theta$$

When the platforms are compatible, developers on the proprietary platform have a total profit of $\frac{4-3c}{32}$, which equals 0.1074 when $c = \frac{3}{16}$. In this case, total profits for developers on the proprietary platform are always higher when the platforms are compatible. This results from the higher demand for their application, even though the price the developers pay the platform is higher when they are compatible.

Total profits for developers on the open platform are always higher in the case of compatibility, since demand for their product increases and they face no change in the platform price they pay – it is always equal to zero. Consumer welfare for all users under incompatibility is:

$$\int_0^{n_M^u} (V - p_u^M + \frac{n_M^d}{8} - tx)dx + \int_{n_M^u}^1 (V + \frac{(1 - n_M^d)}{8} - t(1 - x))dx$$

Consumer welfare for all users when platforms are compatible can be expressed as $\frac{16V+2-7t}{16}$. When $c = \frac{3}{16}$, consumer welfare is always greater when the platforms are compatible.

1.5.1 Social Welfare

Under incompatibility, we sum up proprietary platform profits, developer profits for open and proprietary developers, and consumer welfare, and find that total social welfare is:

$$\frac{32ct - 1}{4(256ct - 9)} \left[(16t - 3)(\frac{1}{2} + \frac{15 - 16(c + 4t)}{2(256ct - 9)}) + (16c - 3)(\frac{1}{2} + \frac{15 - 16(t + 4c)}{2(256ct - 9)})\right]$$

$$+\int_0^{n_M^d}(\frac{1}{8}+\frac{2n_M^d-1}{64t}-\frac{p_u^M}{8t}-p_d^M-c\theta)d\theta+\int_{n_M^d}^1(\frac{1}{8}-\frac{2n_M^d-1}{64t}+\frac{p_u^M}{8t}-c(1-\theta))d\theta$$

$$+\int_0^{n_M^u}(V-p_u^M+\frac{n_M^d}{8}-tx)dx+\int_{n_M^u}^1(V+\frac{(1-n_M^d)}{8}-t(1-x))dx$$

When $c=\frac{3}{16}$, this equals:

$$\frac{21t+3V+1}{144}+\frac{17t-5}{192t}$$

When platforms are compatible and $c=\frac{3}{16}$, we find that total welfare equals:

$$\frac{256V+81-80t}{256}$$

which is always greater than total welfare when platforms are incompatible and $c=\frac{3}{16}$, assuming the platform has the same fixed cost in both cases. However, we know that the proprietary platform will only choose compatibility of its own accord when $t<0.263$, so if there is a comparatively high level of differentiation between platforms with regards to consumer preferences, the proprietary platform has no incentive to choose to be compatible with the open platform. Within this framework, then, if $c=\frac{3}{16}$ so that $p_d^p=0$, it is welfare-improving to impose compatibility on the platforms as a matter of policy. This is an even stronger result than that of Katz and Shapiro (1985), since in this case social welfare rises under compatibility even if the proprietary platform's profits are lower, which is when $t>0.263$.

1.6 Conclusion

Compatibility between platforms can be a sustainable equilibrium, and as the level of differentiation between the platforms falls from the user's perspective, a proprietary platform is better off choosing to be compatible with the open platform. In this light, Microsoft's action can potentially be explained as a result of efforts within the Linux community to make the Linux operating system user interface more conventionally user-friendly, dare one say more Windows-like – effectively lowering t. As has been demonstrated, this would make compatibility the better option in terms of profits as well as social welfare. In addition, in this particular case it is also *always* welfare-improving to impose compatibility on the proprietary platform.

There are interesting implications for other two-sided platforms, including cases where both the platforms are proprietary, such as video game consoles. That remains a subject for future research, as does the impact of variation in c, the measure of differentiation from the point of view of developers.

CHAPTER 2

An experimental analysis of teamwork and open-source software development (with Utteeyo Dasgupta)

2.1 Introduction

Open-source software is, perhaps, the most successful example of a public good relying on voluntary contributions in the modern world. For firms like Red Hat, Novell, and IBM, all of whom have made it a cornerstone of their business model, the motive to develop open-source code and contribute it to the community at large is clear – they rely on the ancillary services required by firms to set up and maintain complex information systems, and giving away the operating system and code is simply a way to ensure a reliable revenue stream in an industry with enormous network externalities.

However, this raises the even more interesting question of why the “community” itself – independent developers from around the world who write open source software in their spare time and proceed to give it away for free along with the source code – exists at all, contributing a large proportion of the available applications. The rapid growth and success of a method of software development that relies on widely scattered individuals contributing their time and effort for little to no immediate financial gain deserves explanation, not just as an intriguing economic puzzle, but as an idea which may hold worthwhile lessons for other aspects of both intellectual property and public goods in general. Are there any specific features of the open-source development process that contribute to its success, and can this success be replicated for other public goods relying on voluntary contributions?

There are a number of hypotheses attempting to explain open-source contributions, which need not be mutually exclusive. These include both intrinsic motivation (enjoyment, prestige effects, or altruism), and extrinsic motivation, which tends to involve job-market signaling – high-quality open-source code serves as a signal of ability to prospective employers – and/or human capital effects. These stem from the very openness of the code written, which allows immediate feedback as to its quality and serves as a useful way for coders to teach themselves new programming skills or improve an existing skill set, and can in turn later serve as a job market signal. These hypotheses, both intrinsic and extrinsic, can all be empirically tested (Hertel et al., 2003; Lakhani and Wolf, 2003; Orman, 2006). Across the board, enjoyment and the various extrinsic motivations have been found to matter much more than altruism.

In addition to these is the fact that open-source code is frequently written in response to a need – a task exists for which no software is available, or existing software is insufficient. Once the code has been written, it may well be too difficult or expensive to release it as proprietary code due to the risk of copyright infringement and the costs associated with patent filing.

In all these circumstances, heterogeneity in the above motivations and characteristics among developers and potential users of the project is hypothesized as the main driving force behind contributions, as there is a larger number of people on the outer tails of the distribution of motivations and chracteristics. Those with the highest levels of ability, the lowest opportunity cost of time, or the greatest personal benefit from seeing the project completed are the most likely to do so (Weber, 2004). However, heterogeneity is much more difficult to test empirically, even through surveys. It is in this situation that experiments become useful as a way to shed some light on the underlying question – does heterogeneity among users increase contributions to open-source software, and is this increase sustainable? Crucially, does this increase stem from the idea that with a sufficiently high variance in the distribution of characteristics, there will be some individuals for whom contribution is a dominant strategy, or is the mere presence of heterogeneity enough to increase contributions even if no single person has a dominant strategy to contribute?

In this paper, the second heterogeneity hypothesis is tested. The question being asked is, can heterogeneity in some crucial characteristic increase contributions to the public good even if it is never a dominant strategy to contribute? What mechanism drives the observed contributions – random, individual-specific unobservables, or reciprocity between agents?

The process of open-source development frequently follows the following trajectory – a developer programs the software, releasing the code under one of many open-source licenses, most commonly the General Public License, or GPL. Other developers choose whether or not to join the project by participating in coding, testing, or documentation. Most contributions are signed, and all are public, and sequential. Whether the project grows in terms of users and contributors is largely function of its quality and usefulness. In this manner, the open-source development process reflects the process of teamwork. Every team member has an incentive to free-ride off the efforts of others, but if no-one contributes, the task remains undone. Once again, heterogeneity in team members may well increase contributions to the team effort.

Laboratory experiments with voluntary contribution mechanisms in public goods games have consistently shown that subjects contribute significantly higher amounts than the Subgame Perfect Nash Equilibrium amount, and while contributions tend to decline over time, they almost never reach the SPNE prediction. A number of theories have been developed to explain this phenomenon, including Quantal Response Equilibrium and various altruism and reciprocity theories. It remains to be seen how relevant these theories are to individual decisions outside the laboratory, and that is the aim of this paper – to set up a laboratory experiment that reflects some crucial aspects of open-source software and team production, and to test the results against two competing theories of public goods contribution – Agent Quantal Response Equilibrium (McKelvey and Palfrey, 1998), and Sequential Reciprocity (Dufwenberg and Kirchsteiger, 2004). These two theories have very different priors. For example, since AQRE predicts that people play their SPNE strategy but with error, it implies that other people's decisions should have no effect on one's strategy. The behavioral predictions of Sequential Reciprocity, on the other hand, depend on the fact that one makes a decision in response to another person's actions. The two theories also have different testable implications for contributions in the presence of heterogeneity – AQRE predicts heterogeneity increases contributions only for low levels of random error, while SRE predicts that heterogeneity causes increased contributions across the board. With this experiment we can attempt to test their real-world relevance in the context of the impact of heterogeneity on open-source software contributions.

2.2 Literature Review

Most of the work done in recent times to answer the question of why people contribute, and continue to contribute to open-source and free software development has examined the issue in terms of intrinsic motivation (Bitzer et al., 2004) – people contribute because they enjoy writing code, and writing good code that is public enhances their reputation. At the same time, it has also been hypothesized (Lerner and Tirole, 2002) that open-source contributions act as a form of job-market signaling – they permit prospective employers to judge a person's ability directly. Reputation also obviously is a positive job-market signal, but at the same time there may well be some additional utility purely from having a good reputation as a programmer and being well-known within the community. Orman (2006) tests the job-market signaling hypothesis using a complementarity framework – if open-source contributions and education are both forms of job-market signaling, then they are likely to be linked in some way. They are found to be complementary, supporting the job-market signaling hypothesis as well as the idea that there may be human capital development effects from writing open-source code.

Apart from the job-market signaling, there is the evidence that releasing a piece of software one has written as open-source may actually help build a business around it, offering ancillary services like training and consulting. Open-source creates a community of like-minded people in the same field who can help the network around a particular application to grow, which is why even large firms like IBM are careful to maintain good will within the community.

It has also been hypothesized (Heckathorn, 1993; Oliver, Marwell, and Teixeira, 1985) that heterogeneity should increase average and total contributions to a public good, given that it increases the probability that a critical mass of agents who value the good enough to provide it even when the others free-ride will exist – those at the tail of the distribution for whom contribution is a dominant strategy. The findings of Palfrey and Prisbrey (1997) do not appear to bear this out – not everyone contributed when it was a dominant strategy to do so, though total contributions increased. While there is a large body of evidence showing that contributions increase with returns to the public good, Anderson, Mellor, and Milyo (2004) and Chan, Mestelman, Moir, and Muller (1999) find that heterogeneity in endowments in a simultaneous-contribution VCM public goods game significantly reduces contributions across the board. However, it remains to be seen if these results are artifacts of the simultaneous contribution protocol, since the results of Oliver et al. (1985) rely on sequential contributions.

In terms of experimental design, Erev and Rapaport (1990) find that a sequential mechanism in a step-level public good achieves the socially efficient level of provision more often than a simultaneous mechanism. Potters et al. (2005) have a similar finding where a strong leadership effect comes through even when the sequence is exogenously imposed – however, this is due to differential information as to the quality of the public good possessed by the leader. This is useful to know, since in the real world, in most forms of group or team production including open-source development, previous contributions are observed when an individual makes their own contribution decision. Palfrey and Prisbrey (1997) find that contributions increase as the difference in public and private return increases, as do Goeree et al. (2002), who find that contributions increase as "internal" return, public return, and group size increase. This supports the idea that those with a greater return from or lower cost of contributing should do so.

In this case, we wish to look at the pure effects of heterogeneity *without* altering subjects' dominant strategy to not contribute. Since, in a linear public goods game, the difference between public and private return is what matters, varying benefit levels is exactly the same as varying opportunity costs. For the sake of simplicity, we therefore vary opportunity costs. Empirical evidence (Orman, 2006) shows that contributions, while not significantly correlated with income, do in fact depend on opportunity costs.

2.3 The Model

We set up a simple 3-person sequential public goods game. All three players have the same endowment, and decide in a predetermined ordered sequence whether or not to

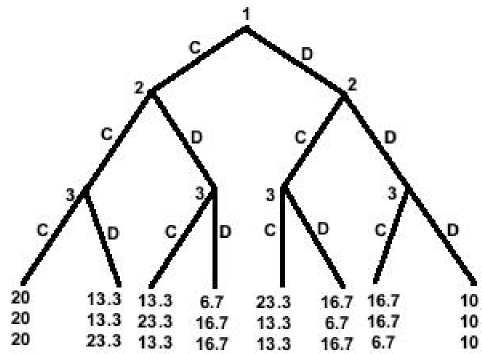

Figure 2.1: Constant Opportunity Costs

contribute it – their choice is binary. Whether the game is a sequential or simultaneous contribution VCM mechanism, the selfish preferences subgame perfect Nash equilibrium is to have zero contributions from all subjects.

Let each individual's endowment be w. There are N persons in a group, and each contributes x tokens to the public good, $x \in \{0, w\}$, so that the contribution decision is binary. x_i is the amount contributed by individual i, which in this case is either 0 or 10. All contributions to the public good are multiplied by a factor B and divided among the entire group, so that the Marginal Per Capita Return (MPCR), which is the gain received by an individual player from the contribution of one additional dollar, equals $\frac{B}{N}$. The private return on tokens not contributed is c, so that in a one-shot game, each subject solves the following:

$$\underset{x_i}{Max} \; \frac{B(x_i + \sum_{j \neq i} x_j)}{N} + c_i(w - x_i) \tag{2.1}$$

So that we get a corner solution, with $(x_i^*|x_j^*) = w$ if $\frac{B}{N} \geqslant c_i$, and $(x_i^*|x_j^*) = 0$ otherwise, for all $j \neq i$. This applies to both simultaneous and sequential contribution mechanisms. Since we restrict $c_i > \frac{B}{N}$, the subgame perfect equilibrium is to have zero contributions. Figure 2.1 shows the game tree for the case when $N = 3$, $w = 10$, and $B = 2$, and $c_i = c_j = 1 \forall j \neq i$, which is the configuration used in the baseline treatment of the experiment. In this case, the SPNE is for all players to defect. However, there is a Sequential Reciprocity Equilibrium (Dufwenberg and Kirchsteiger, 2004) where

$(x_i|x_j^*) = 10$ for all $i \neq j$, even if $\frac{B}{N} < c_i$.

2.3.1 The Logit AQRE

McKelvey and Palfrey (1998) develop a version of logit quantal response equilibrium for sequential games, which they call the logit agent quantal response equilibrium. Following their model, we have for two possible levels of contribution x and y, the probability of contributing x given by:

$$P(x) = \frac{e^{\frac{\pi(x)}{\mu}}}{e^{\frac{\pi(x)}{\mu}} + e^{\frac{\pi(y)}{\mu}}} \tag{2.2}$$

where $\pi(x)$, the material benefit, is defined as:

$$\frac{B(x_i + \sum_{j \neq i} x_j)}{N} + c_i(w - x_i) \tag{2.3}$$

and μ refers to an "error parameter" that ranges from 0 to infinity. The higher the value of μ, the closer behavior is to being purely random, and the lower the value of μ, the closer behavior gets to pure Nash dominant strategy behavior.

Due to the particular logit functional form, the predicted strategies have the following features:

1. The probability of contributing any amount does not depend on the actions, observed or anticipated, of the other players, since they cancel out of the numerator and denominator. This is a testable implication.

2. In the same manner, the order or position at which a player makes their contribution decision should not affect the probability of contributing any amount or the optimal strategy.

3. Expected contributions are significantly higher than the subgame perfect equilibrium.

   Table 2.1 shows the simulated probabilities of contributing for a constant opportunity cost of 1, versus a randomly drawn opportunity cost for each player which is 0.75 with a probability of 0.5 and 1.25 with a probability of 0.5, with 3-person groups. From this table, we see that, additionally:

4. For sufficiently small values of μ, i.e. $\mu < 3$, predicted contributions are higher in the heterogenous cost case, even though they do not affect dominant strategies. However, as behavior becomes increasingly random, these differences are wiped out. This difference results from the convexity of the exponential function.

Table 2.1: Expected contributions in the Logit AQRE

	$P(x = 10)$	
μ	Constant opportunity cost	Heterogenous opportunity costs
1	0.034	0.15
2	0.16	0.22
3	0.25	0.27
10	0.417	0.417
∞	0.5	0.5

2.3.2 Sequential Reciprocity

Developed by Dufwenberg and Kirchsteiger (2004), the theory of sequential reciprocity builds on Rabin (1993) and defines the game as a psychological game Γ, with N players, the set H of choice profiles or histories, a set of actions A, a set B_{ij} of player i's beliefs about j's strategy, and a set C_{ijk} of i's beliefs about j's beliefs about player k's strategy . A utility function for each player i is defined, which depends on i's material payoffs, a reciprocity coefficient, i's "kindness" towards other players, and other players' perceived "kindness" towards i. Kindness towards is defined as the difference between the payoff received by i as a result of the others' actions and the "equitable" payoff (which is the average of the possible payoffs i could have received as a result of the others' actions). Correspondingly i's kindness towards the other players is defined as the difference between the payoffs they receive as a result of i's actions, and the average of the payoffs they could have received as a result of i's actions.

The utility function is therefore:

$$U_i = \pi_i + \Sigma_{j \neq i} Y_i \kappa_{ij} \lambda_{iji} \tag{2.4}$$

π_i is defined as above, in equation 2.

Y_i refers to the individual coefficient of reciprocity, where $Y_i \in [0, \infty)$. The higher it is, the more reciprocally motivated is an individual.

$\kappa_{ij} : A_i \times \Pi_{j \neq i} B_{ij} \rightarrow R$ at history $h \in H$ refers to i's kindness to j. It is defined as follows:

$$\kappa_{ij}(a_i(h), (b_{ij}(h))_{j \neq i}) =$$
$$\pi_j(a_i(h), (b_{ij}(h))_{j \neq i}) - \frac{1}{2}\{\pi_j^{max}((b_{ij}(h))_{k \neq j}) + \pi_j^{min}((b_{ij}(h))_{k \neq j})\}$$

$\lambda_{iji} : B_{ij} \times \Pi_{k \neq j} C_{ijk} \rightarrow R$ refers to i's belief about how kind player j is to i at history $h \in H$. It is defined as:

$$\lambda_{iji}(b_{ij}(h), (c_{ijk}(h))_{k \neq j}) =$$
$$\pi_j(b_{ij}(h), (c_{ijk}(h))_{k \neq j}) - \frac{1}{2}\{\pi_j^{max}((c_{ijk}(h))_{k \neq j}) + \pi_j^{min}((c_{ijk}(h))_{k \neq j})\}$$

λ_{iji} is mathematically equivalent to κ_{ji}.

Utility is maximized by ensuring that the signs of κ_{ij} and λ_{iji} are the same. In this 3-player game, since one action affects both the other players equally, when there is a tie, the material payoff provides a tie-breaking mechanism. Since the players in the experiment are anonymous, we can safely assume that a player has exactly the same Y towards both the other members of her group.

Since beliefs are required to be correct in equilibrium, there are exactly two pure strategy equilibria, but multiple mixed strategy equilibria. We find the following[1]:

1. If players 1 and 2 do not contribute, player 3 will not contribute.

2. If either player 1 or 2 contributes, but the other does not, player 3 will not contribute. In this case, the reciprocity-weighted terms in player 3's utility function cancel out, and the material payoff from not contributing is higher. So it acts as a tie-breaker.

[1]All proofs are in Appendix A.

3. If players 1 and 2 both contribute, player 3 will contribute as long as $Y_3 > 0.05$. If $Y_3 < 0.0375$, she will not contribute. For $0.0375 \leqslant Y_3 \leqslant 0.05$, player 3 contributes with probability $4 - \frac{0.15}{Y_3}$.

4. If player 1 contributes, player 2 will not contribute for $Y_2 < 0.05$, OR if $Y_3 < 0.039$ regardless of the value of Y_2, since that would imply player 3 contributes with a probability less than 0.17. If $0.05 \leqslant Y_2 \leqslant 0.3$, player 2 contributes with probability $26.7 - \frac{1}{Y_3} - \frac{0.3}{Y_2}$. If $Y_3 > 0.05$, so that player 3 will contribute if she does, and $Y_2 > 0.06$, then player 2 will always contribute if player 1 does.

5. If $\frac{0.038}{Y_3} + \frac{0.01}{Y_2} > 1$, so that the sum of the probabilities with which players 2 and 3 contribute is less than $\frac{1}{2}$, then player 1 will not contribute. If $0.004 \leqslant Y_1 \leqslant 0.5$, and $\frac{0.038}{Y_3} + \frac{0.01}{Y_2} < 1$, player 1 contributes with probability $\dfrac{\frac{2.3}{Y_3} + \frac{0.6}{Y_2} - 59.7}{Y_1(\frac{4}{Y_3} + \frac{1}{Y_2} - 77.7)} - 28.2 + \frac{1.15}{Y_3} + \frac{0.3}{Y_2}$.

Knowing this, and the fact that beliefs about kindness are correct in equilibrium, we see that if player 1 does not contribute, player 2 will never contribute in equilibrium. In equilibrium, we should therefore never see a case where player 1 does not contribute and either of the other two do. The only pure strategy equilibria are where either everyone defects or everyone contributes in equilibrium.

For heterogeneous costs with $c_i \in \{0.75, 1.25\}$, the pure strategy equilibria do not change. However, the different opportunity costs will change the values of κ_{ij} and λ_{iji}, as well as the material payoffs, so while the structure of the mixed-strategy equilibria will be the same – contribute for sufficiently high values of Y_1, Y_2, and Y_3, contribute with some probability for intermediate values, and defect for low values – the exact parameters and ranges are different.

We find that when 3's opportunity cost is 1.25, then if 1 and 2 contribute, she will contribute if $Y_3 > 0.117$, and will defect for $Y_3 < 0.066$, contributing with a probability $p_3 = 2.29 - \frac{0.15}{Y_3}$ if $0.066 \leqslant Y_3 \leqslant 0.117$. When her opportunity cost is 0.75, and if 1 and 2 contribute, she will contribute if $Y_3 > 0.016$, and will defect for $Y_3 < 0.015$, contributing with a probability $p_3 = 10.375 - \frac{0.15}{Y_3}$ if $0.015 \leqslant Y_3 \leqslant 0.016$. So not only does she need a lower reciprocity coefficient to contribute when her opportunity cost is lower, but when she plays a mixed strategy, her probability of contributing is higher. This holds for all three players, since beliefs about others' kindness and contribution probabilities will be correct in equilibrium, and we should therefore see higher contributions when player 3's opportunity cost is low. This will lead to more mixed strategies being played and overall higher contributions in the heterogeneity case even if one player in the group has a high opportunity cost. Of course, if 3's reciprocity coefficient is low, we may observe defection even if 1 and 2 contribute, and this is not a violation of the mixed strategy equilibrium.

This clearly differs from the logit AQRE in that higher contributions in the case of heterogenous opportunity costs are predicted across the board, not only for cases of very low μ, like logit AQRE. In the sequential reciprocity model, one player's contributions are explicitly conditional on the expected and actual contributions of the others, unlike in the logit AQRE.

2.4 Experimental Design

A sequential-contribution mechanism is used in all treatments, in order to more closely parallel the actual process, in which contributions of others are frequently observed before one makes ones own contribution decision. The procedure is similar to Erev and Rapaport (1990), with the crucial difference that we do not use a step-level public good. Instead, the public good is provided as long as total contributions are greater than 0, so that at least one person contributes, given that contributions are binary.

The experiment was programmed and conducted with the software z-Tree (Fischbacher, 1999).

2.4.1 Baseline

Subjects play in N-person groups; we have set $N = 3$, since 3 is the smallest number for which the game constitutes a public goods game and the models are tractable. Subjects are randomly reassigned to groups in each round, and they never know the identities of the others in their group. Since the moves are sequential, the order in which moves are made is also randomly reassigned in each round. Subjects observe the contribution decisions of the others in their group.

Each subject is endowed with $w = 10$ tokens and can contribute all or none of the tokens. We refer to each subject's contribution as x_i. The tokens retained, $w - x_i$, are multiplied by a private return factor c_i, representing each player's opportunity cost of contribution. In the baseline, c_i is set equal to 1 for all players, so that opportunity costs are homogenous. After each player has decided whether to contribute, the total amount contributed is multiplied by 2 and divided amongst the players, such that the MPCR is $\frac{2}{3}$. This constitutes our baseline treatment where the subgame perfect equilibrium is not to contribute anything.

According to logit AQRE, the expected value of contributions ranges between 0.34 tokens and 5 tokens, depending on the value of μ. We should expect to see contributions randomly distributed across the subjects, with anywhere from 3% to half of the subjects contrbuting. Estimates of μ have differed widely across various experiments, but if it is fairly high, we would expect to see just over 40% of the subjects contributing.Crucially, one subject's contribution decision should not be affected by, or correlated with, the prior contributions of other subjects in the group. It should also not depend on their position in the group.

On the other hand, if sequential reciprocity holds, we should never see a situation where player 3 contributes and only one of the other two players does. Other equilibria may well be observed.Note that Player 1 mixes strategies over a wider range of Y than player 2, who in turn mixes over a wider range of Y than player 3. So we are likely to observe more random behavior from player 1 than from player 2, and from player 2 than from player 3.

2.4.2 Heterogeneity Treatment

Here, we will test the hypothesis that heterogeneity among subjects is by itself sufficient to ensure contributions to the public good. Unlike Palfrey and Prisbrey (1997), we do not allow the opportunity cost for some subjects to be below $\frac{2}{N}$. We restrict $c_i \in \{0.75, 1.25\}$, so that once again, the subgame perfect equilibrium is to not contribute anything. The opportunity cost is randomly redrawn for each player in each round, and there is a 50% probability of a player's opportunity cost in any round being 0.75 and a 50% probability of it being 1.25.

Logit AQRE in this case predicts higher contributions than in the homogeneous cost case, as was demonstrated earlier. The expected value of contributions ranges between 1.5 tokens and 5 tokens, depending on the value of μ. We should expect to see contributions randomly distributed across the subjects, with anywhere from 15% to half of the subjects contributing.If μ is fairly high, we would expect to see no difference in the proportion of subjects contributing in the two treatments. Since estimates of μ have ranged widely in previous experiments, it would remain to be estimated from the data.

In order to test the predictions of the Sequential Reciprocity model, each subject's opportunity cost is known by the others in the group, so that opportunity costs are perfect information. In this case, we would expect to see greater contributions from subjects with low opportunity costs, and lower contributions from subjects with high opportunity costs. We should see higher overall contributions as players 1 and 2 mix strategies more often even when their own opportunity costs are higher.

Results

The results of the two treatments, each run over 20 periods with 33 (different) subjects who were randomly rematched into 11 groups of 3 in every round, run counter to the predictions of the subgame perfect equilibrium and logit AQRE. However, we fail to reject the sequential reciprocity hypothesis.

Overall, across all periods, total contributions per group in the baseline averaged 8.9 across all periods, with a standard deviation of 8.57. In the heterogeneity treatment, however, total contributions per group averaged 13.5, with a standard deviation of 10.06. From Figure 2.2, we see that total contributions show a clear pattern of decline over time in the baseline, as is standard in public goods games. However, this pattern of decline is clearly absent from the treatment.

Average individual contributions show the same behavior (Figure 2.3). There is a steep decline in individual contributions in the baseline, which is absent in the treatment,

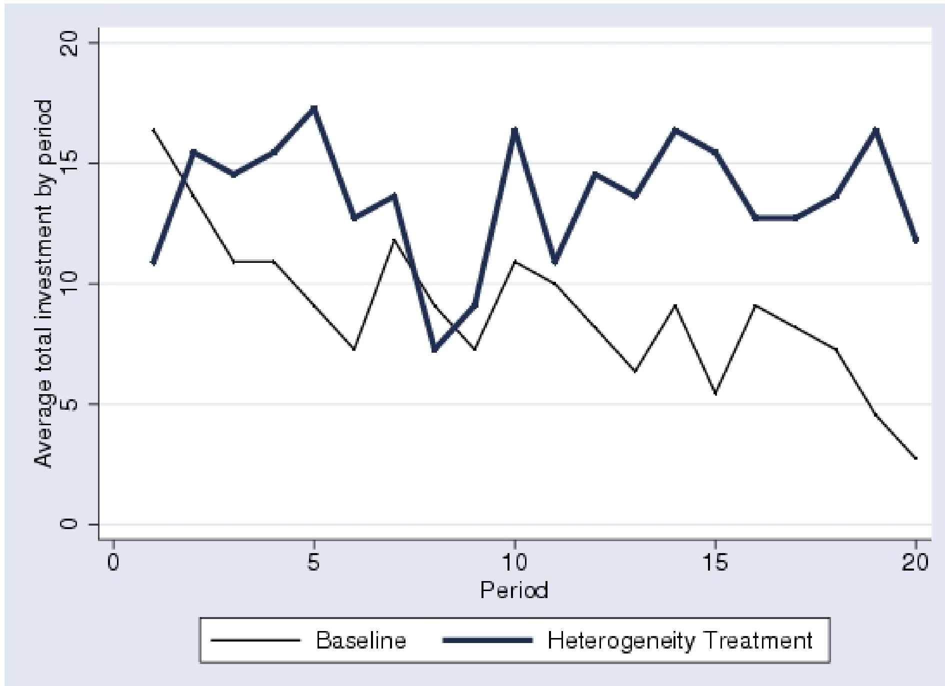

Figure 2.2: Mean of Total Contributions by Period

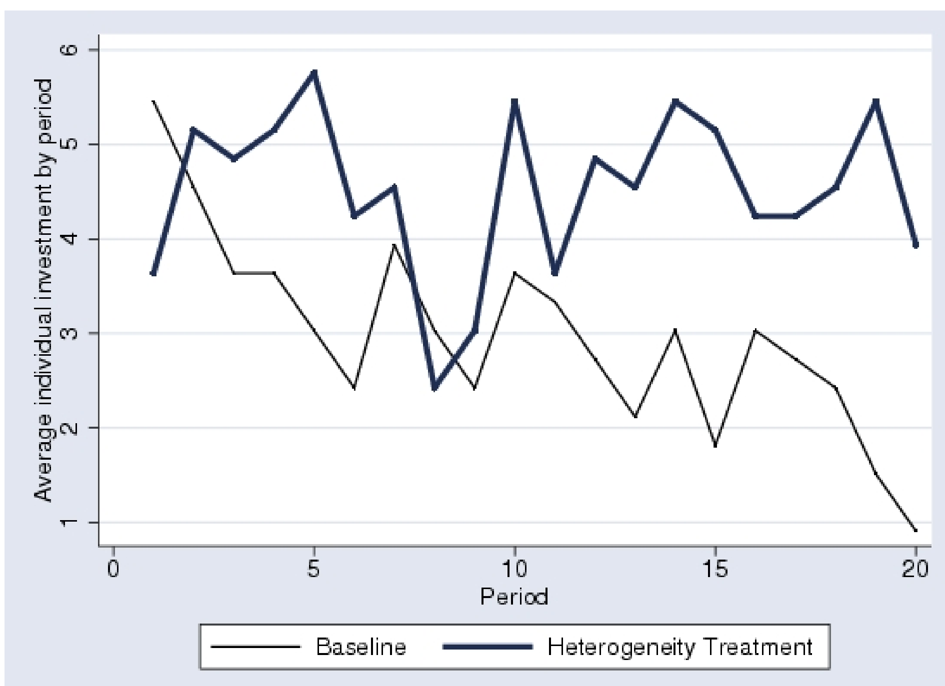

Figure 2.3: Mean of Individual Contributions by Period

on the whole contributions are much higher. However, once we break up the data by player type, a striking pattern becomes clear – as player 1 or 2, subjects tend to contribute much more than they do as player 3. In both treatments and in all rounds, the bulk of the contributions come from player 1 and 2, not from player 3. This is immediately clear when we see Table 2.2, which looks at how many times players in different roles contributed, and Figures 2.4 and 2.5, which show the average contribution for each player type by period. The effect of order in the sequence is less pronounced in the treatment (Figure 5) but is still present, as is shown in Table 2.2.

Table 2.2: Contributions by player type

Type	0	10	Contribution %	Total
Baseline:				
1	116	104	47.3%	220
2	151	69	31.4%	220
3	197	23	10.5%	220
Total	464	196	29.7%	660
Treatment:				
1	97	123	55.9%	220
2	117	103	46.8%	220
3	148	72	32.7%	220
Total	362	298	45.2%	660

Logit AQRE predicts that the choices made by the others should not affect an individual's choice, and that an individual's position in the group should not influence the choices made. However, as we have seen, this is clearly refuted as well. Inevitably, and right till the very end, people in the first position tend to contribute, those in the second position contribute but a little less, and those in the third position tend to defect. This holds for both treatments, only in the heterogeneity treatment we see far higher contributions overall.

Most fascinating is the observation that subjects themselves behave differently when in different playing positions, and the pattern is more pronounced in the baseline (Figure 6). The same individuals who defect when playing in the third position frequently contribute when playing as Player 1 or 2. In fact, very few subjects show a consistent pattern of behavior across playing roles – the majority adapt their behavior to their circumstances

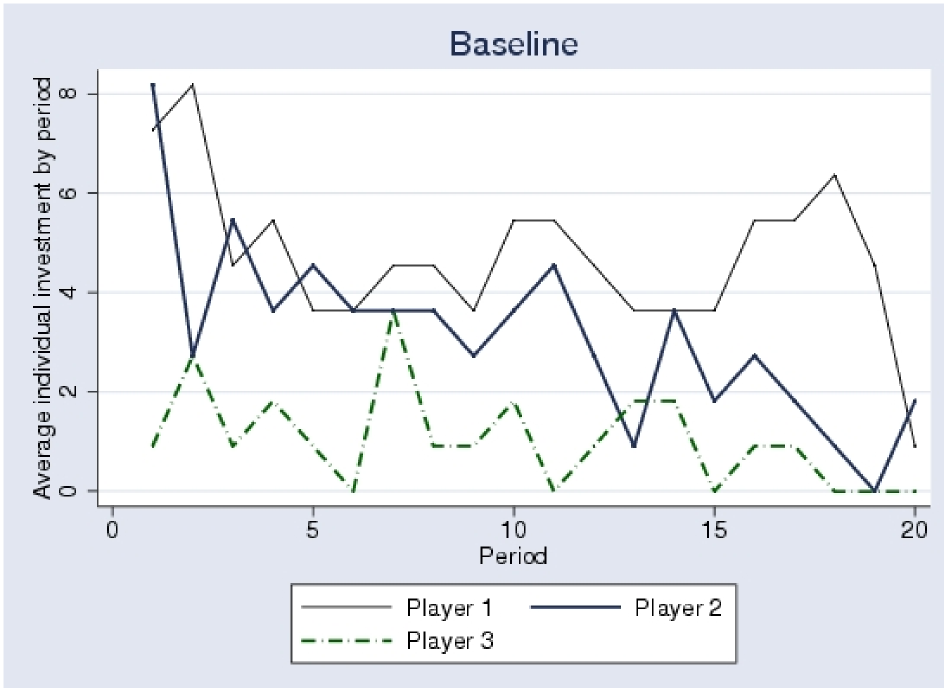

Figure 2.4: Mean of Individual Contributions by Period and Player Type, Baseline

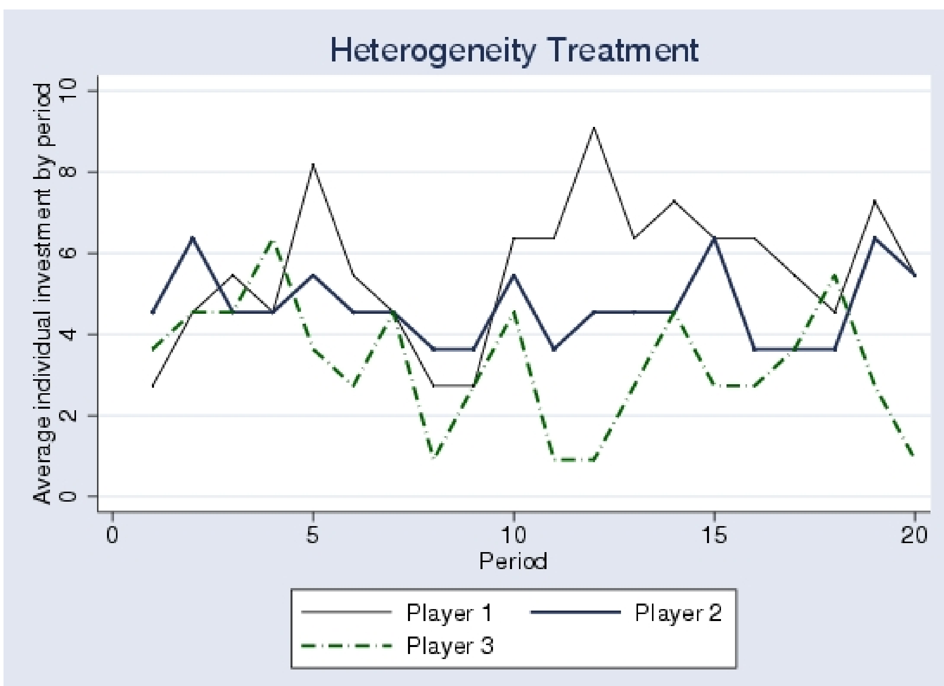

Figure 2.5: Mean of Individual Contributions by Period and Player Type, Heterogeneity Treatment

[2].

For the treatment, along with player order, we see that opportunity cost is one of the main determinants of the contribution decision, as predicted by the sequential reciprocity model. Contributions are significantly higher when the opportunity cost is low. This is immediately apparent when we look at Figure 7, which depicts average individual contributions in the heterogeneity treeatment by opportunity cost. When it is equal to 1.25, contributions are, on average, 2.97 – almost exactly the same as the baseline. In fact, for player 1, the contributions when the opportunity cost is 1.25 are 4.22 – exactly the same as the baseline. When the opportunity cost is equal to 0.75, average contributions are 6.13. Also, out of the 123 occasions when player 1 contributes in the treatment, 70 of those, or 57% are when player 3 has a low opportunity cost, as predicted by sequential reciprocity. Of the 103 occasions when player 2 contributes, 61 or 59.2% of those are when player 3 has a low opportunity cost – once again, in line with the predictions of sequential reciprocity.

To measure the different impacts of the factors affecting contribution, we estimate the contribution decision using logit as a function of opportunity cost, player type, contribution decisions of the previous players in the group, and the profit earned in the previous period. Table 2.3 shows the results of the logit estimation. We see that all are significant. From an opportunity cost of 1, increasing the opportunity cost to 1.25 decreases the contribution probability by 0.52, holding all else constant. What is interesting is that being in the treatment, holding everything else constant, increases the contribution probability by 0.172 at the mean, showing an increase in contribution probability *purely* as a result of heterogeneity.

It is important to note, however, that the observations are not independent, since the same subjects played for 20 rounds, making a total of 66 unque subjects. Panel data techniques help to account for the subject-specific unobserved heterogeneity. Since the independent variables, being experimental parameters, are completely exogenous and in no way correlated with subject-specific effects, the random effects estimator is more ef-

[2]Note that since roles were randomly assigned in each round, each subject got to be in each position on at least 3 separate occasions, except for subject 33 in the baseline, who played as Player 1 only once.

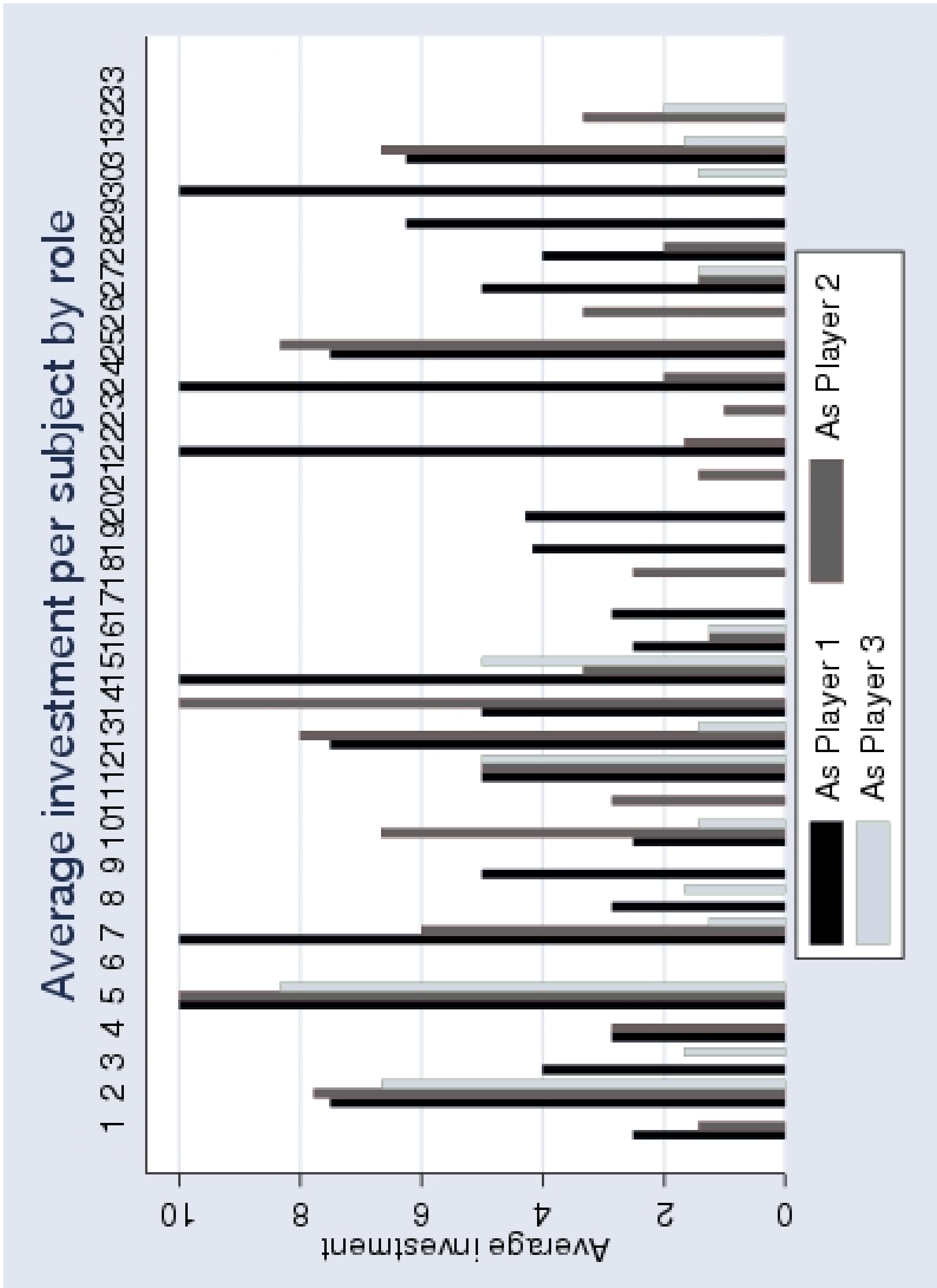

Figure 2.6: Mean of Individual Contributions by Period and Player Type, Baseline Treatment

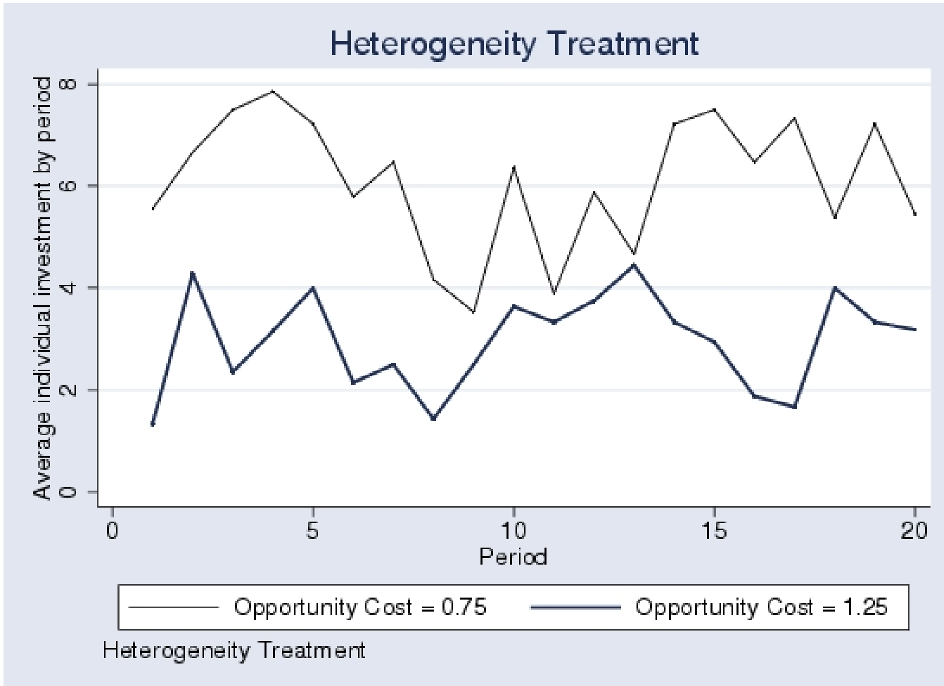

Figure 2.7: Mean of Individual Contributions by Period and Opportunity Cost, Heterogeneity Treatment

ficient and therefore preferred. A Hausman (1978) test comparing the fixed effects and random effects logit was conducted, and since there was no significant difference between the fixed-effects and random-effects estimators, only the random effects results are reported. Since ρ, the proportion of total variance contributed by panel-level variance, is positive and significant, we know that the panel-level effects, namely the unobserved subject-level heterogeneity, cannot be ignored.

Qualitatively, the logit results are confirmed by the random effects logit estimation – see table 2.4. Contributions are significantly higher in the treatment, when opportunity cost is low, and when the others in the group contribute. Profit in the previous period ceases to be significant, but this is due to the fact that subject random effects are now picking up all the subject-level heterogeneity.

The μ error parameter in the logit AQRE model is potentially identified. However, since the data do not match the model, it would be meaningless to estimate it, and therefore we do not.

Table 2.3: Estimation results : Logit, dependent variable is investment decision

Variable	Coefficient	Marginal Effect at Mean
Opportunity cost	-2.71***	-.52
	(0.45)	(0.087)
Player type = 3	-1.49***	-0.285
	(0.3)	(0.055)
Treatment	0.904***	0.172
	(0.173)	(0.033)
Previous investment faced by 2	0.067***	0.013
	(0.022)	(0.004)
Previous investment faced by 3	0.088***	0.017
	(0.018)	(0.003)
Own profit in previous period	-0.031**	-0.006
	(0.016)	(0.003)
Intercept	1.809	–
	(0.544)	–

*significant at 90% level ** significant at 95% level ***significant at 99% level
Standard errors in parentheses

Table 2.4: Estimation results : Logit with Random Effects, dependent variable is investment decision

Variable	Coefficient	(Std. Err.)
Opportunity Cost	-3.203***	(0.519)
Player type = 3	-1.831***	(0.346)
Treatment	1.212***	(0.369)
Previous investment faced by 2	0.081***	(0.025)
Previous investment faced by 3	0.105***	(0.021)
Own profit in previous period	-0.019	(0.019)
Intercept	1.742	(0.667)
Log(variance)	0.397	(0.277)
Standard deviation σ_u	1.219	(0.169)
ρ	0.311	(0.059)

*significant at 90% level ** significant at 95% level ***significant at 99% level

There are a few violations of equilibrium strategy, but not many. Player 3's violate their equilibrium strategy by contributing when either of the previous players has not. Out of the 23 times that player 3 contributes in the baseline, 11 of these occur when one of the previous players has contributed, and 3 when neither has. Since there are a total of 91 occasions where one of the two players contributes, and 149 occasions where neither does, that leads to a violation rate of 7.8%. For player 2, there are 28 occasions in the baseline when player 1 does not contribute and player 2 does out of 116 times when player 1 does not contribute, which is a violation rate of 24.1%.

In the treatment, player 3 contributes 27 times out of the 92 occasions where one of the two previous players contributes, and 10 times out of the 61 that neither player does, leading to a violation rate of 24.18% – but 26 of these 37 violations were when player 3 had a low opportunity cost of 0.75. Player 2 contributes 36 out of the 97 times that player 1 does not, leading to a violation rate of 37.1%. However, out of these 36 occasions, 25 were when player 2 had a low opportunity cost. As is obvious from the regression results, the heterogenous opportunity cost makes a significant difference to contributions. However, while mean contributions by 1 are higher when players 2 and/or 3 have a low opportunity cost, this difference is not statistically significant by a t-test or a Mann-Whitney test.

2.4.3 Conclusions

A preliminary glance at the data shows that not only does the subgame perfect Nash equilibrium prediction not hold, which is fairly standard for public goods experiments, but logit AQRE, which is one of the most commonly used theories to predict contributions does not hold either. In fact, logit AQRE does not really explain the data at all. The high rate of defection by player 3 when players 1 and/or 2 contribute also precludes any explanation using theories of inequality-aversion. Sequential reciprocity can explain a lot of the data, particularly the differential contributions in different player roles and the higher overall contributions in the treatment. However, the only place where it falls short is in the lack of statistical significance in the increase in contributions by player 1 when players 2 and/or 3 have a low opportunity cost.

However, it is important to notice the downward trend in contributions in the baseline– there is a learning process, and in the last two rounds, only 5 and 3 people contributed respectively. With more rounds, subjects may well have reached the subgame perfect Nash equilibrium, or in this case, the particular sequential reciprocity equilibrium with universal defection. Then again, it may simply be an end game effect. The fact that this decline disappeared in the heterogeneity treatment has broad implications, showing that the combination of sequential contribution and heterogeneity goes a long way towards sustaining co-operation in a public goods scenario.

The most fascinating feature of the data is the consistently trusting behavior of the first and second players in a group. This can almost be said to mirror the particular characteristic of open-source development where the bulk of the work is done by a few select developers, mainly the project leaders, while there is a larger community which contributes comparatively little (Orman, 2006). Also, the hypothesis of heterogeneity in opportunity costs increasing contributions is borne out, and as predicted by sequential reciprocity, contributions are greater when the opportunity cost is low. Charness and Yang (2006) show that endogenous group formation dramatically increases public goods contributions and also eliminates the pattern of decline over time. As a real-world public good, open-source software possesses both these fundamental characteristics – endogenous group formation and heterogeneity of opportunity costs and benefits. Together, then, these two may well go a long way towards explaining its continued success, and the combination of the two remains open for further study.

CHAPTER 3

Giving It Away For Free? Motivations of Open-Source Software Developers

3.1 Introduction

Open-source software, sometimes referred to as Free software, (since they do not always refer to exactly the same concept, this paper will use the term OS/FS, which includes both) is software whose source code, written in C, C++, or any other programming language, is made available to any and all users of that software. According to the Free Software Foundation(Stallman, 2001), free software is software that comes with permission for anyone to use, copy, and distribute, either verbatim or with modifications, either gratis or for a fee. In particular, this means that source code must be available. In FSF founder Richard Stallman's more colloquial terms, it is free as in speech, not free as in beer. The Open Source Initiative (The Open Source Initiative, 2003) defines open-source software in the same way, but with much looser licensing restrictions, specifically, it allows proprietary software to be linked and distributed with free software programs. Both differ from proprietary software in that the users of a proprietary software program only have access to the binary files, i.e. the sequence of 0s and 1s that the computer itself reads in order to execute the program.

The most famous example of OS/FS software is the Linux operating system, first written in 1991 by a Finnish student named Linus Torvalds, and posted on the Internet for free download, since he wanted the assistance of as many people as possible in improving and developing it. However, there are many other widespread examples - the Apache web server, the Perl programming language, and so on. These and other OF/FS applications tend to be distributed under special licenses, like the General Public License (GPL), under which Linux is distributed, the Apache Software License, or the Mozilla Public License. Together they are popularly known as “copyleft” - an obvious play on ’copyright’. These licenses are legally binding (though none have been tested in court as yet) agreements detailing the OS/FS conditions listed above, and users must agree to their terms before installing the desired program.

Historically, when the computing industry was still nascent, most software development tended to follow an informal version of the OS/FS development model - code was freely shared between institutions and programmers. However, as the industry matured, the development of copyrighted, commercial software increased rapidly. The granting of the first software-related patent in 1981 in the Diamond v. Diehr case, and the rapid growth of software patents in the 1990s (though what is strictly patentable is not the software, but rather the "process" itself) further enabled the growth of an enormous industry based on proprietary software.

At first glance, the behavior of programmers who choose to write code for free, open-source projects runs counter to most of traditional economic theory. After all, what the idea of open source does is convert a normally proprietary product, i.e. software, into a public good, developed using a voluntary-contributions mechanism. Theory states this ought to result in under-provision, if not complete free-riding. The fact remains, however, that not only does OS/FS software exist, but that it has been embraced, in varying degrees, by what reads like a who's-who list of IT firms – including IBM, HP, Cisco, and Apple among others.[1] Apache server software runs close to two-thirds of all web servers (Netcraft.com, 2007).

Currently, there are two major modes of development for OS/FS software. It may be developed either in large firms which sell OS/FS software and consulting services, either as a primary or ancillary source of revenue, or by individual programmers, working on a largely volunteer basis, for a few hours a week in their spare time. The former is a different business model from the conventional approach of copyrighting and/or patenting software in order to sell it, and is a separate research topic by itself. It is the latter, however, which this paper focuses on.

There are many competing theories as to what motivates people to contribute to OS/FS

[1]With the notable exception of Microsoft, who nevertheless have a "Shared Source Initiative" under which they release portions of their source code to certain clients, including the governments of China and Russia.

projects, which need not be mututally exclusive. One is that they are altruistic - they believe in the ideal of software being free, of source code being open and editable, and of defeating software monopolies (Saint-Paul, 2002). This idea is also widely upheld by those in the Free Software community (Stallman, 2001), who have been known to liken buying proprietary software to “buying a car with the hood welded shut”.

Secondly, there is the view that OS/FS developers simply enjoy what they do - they are hobbyists, seeking challenges that they cannot find in their regular jobs (Raymond, 2000). Working on OS/FS projects enables them to feel creative (Lakhani and Wolf, 2003), and the recognition and fame they get within the community acts as a tremendous ego-boost.

Thirdly, there is the fact that a large number of OS/FS projects have come into being to fulfill a need that was not being met by proprietary software - the Apache web server is the best example of this, along with the PHP and Perl scripting languages, among many others.

Fourthly, there is the idea that developers can use OS/FS contributions as a form of job market signaling, since each person’s contributions are clearly documented, unlike the case of proprietary software, where companies ensure that the contribution of an individual developer is never revealed (Lerner and Tirole, 2002). In fact, the reason why most software companies keep this information private is to prevent their most talented developers from being “poached” by rival firms.

Lastly, there are learning effects - by developing OS/FS software and being part of a large developer community, programmers have the opportunity to share knowledge, and acquire and hone new skills (Ghosh and Glott, 2002). It is fairly common for developers to simply begin coding, writing an application in order to teach themselves programming. Releasing it to market is an expensive proposition, and expected returns would most likely not cover the costs of copyrights or patents, setting up a secure payments system, and piracy control measures. In these situations, it is rational for a developer to simply release the program as open-source, given all the other benefits of being a “part of the community”, including receiving feedback about the quality of the code, developing a social network, and not having to offer any warranty on the software.[2]

[2] The General Public License, under which the largest portion of OS/FS software is released, expressly

The larger, overall question which remains to be answered is: is the open-source development model a sustainable one? While there is already talk of applying it to other forms of research, including biotechnology (Lerner and Tirole, 2004), software is fundamentally different from most other industries in that the marginal cost of producing one additional unit of the application is zero, the only fixed costs of development are the time and effort required to write the application, and the only capital investment needed is a personal computer, which is already a common household item in developed countries. Even in the field of software, though, the question remains – are the incentives provided by open-source development sufficient to sustain and encourage innovation in the long run? A closer look at individual motivation is one step towards answering this question.

This paper examines the job-market signaling hypothesis in detail. If education is a form of job-market signaling (Spence, 1973), and so are contributions to OS/FS software, then we would expect to observe one of the following: talented coders choose to signal their type through high educational attainment and significant contributions to OS/FS software, making the two practices *complementary*. Cost constraints may also lead talented developers to choose OS/FS contributions over expensive college education as a signaling device, making them substitutes.

Since OS/FS contributions can also be a form of human capital investment, they may be either a *substitute* for education – a form of on-the-job training (Mincer, 1962), or they may complement it, as OS/FS code serves as proof of skills acquired – skills that, if they are self-taught, would have no other means of being convincingly conveyed to prospective employers and the larger community. In the latter case, we can say that ability, once again drives the adoption of the two. Finally, they may be independent of one another.

The data used for the analysis is from the Free/Libre and Open Source Software (FLOSS) online survey (Ghosh and Glott, 2002) of 2774 self-described OS/FS developers, conducted in the first half of 2002 at the Insititute for Infonomics at the University of Maastricht.

states that the software is provided without any warranty, express or implied.

3.2 Literature Review

3.2.1 Studies of OS/FS Developer Motivations

Lee, Moisa, and Weiss (2003) model the effect of OS/FS contributions on expected wages. They state that OS/FS developers do not earn wages, but they do earn "signals" which indicate their productivity. The value of a signal is the discounted value of the expected deferred payoff. Theirs is a purely theoretical model, which supports Lerner and Tirole's hypothesis of job-market signaling.

This hypothesis is not very clearly borne out by empirical studies, particularly developer surveys. Hertel, Niedner, and Herrmann (2003), in their internet-based survey of Linux kernel developers, find that the most important predictors for participants' engagement were a more specific identification as a Linux developer or with a subsystem (i.e. a feeling of identification and community), a considerable tolerance in respect to time losses due to Linux development activities, and a rather pragmatic interest in personal advantages due to improving the Linux kernel quality. They do not make it explicit, but it is likely that the last two motives are strongly related to each other - the more the "personal advantage" from kernel development, the more tolerant a developer is likely to be about time losses. They regressed time spent on Linux development on various characteristics of developers, and found that developers were willing to spend more time in the subsystem the higher they valued its goals and the higher they perceived their contribution as important for the project success.

However, Lakhani and Wolf (2003), in their survey of 684 developers from the Sourceforge.net OS/FS software repository, find that enjoyment-based intrinsic motivation, namely how creative a person feels when working on the project, is the strongest and most pervasive driver. They also find that user need, intellectual stimulation derived from writing code, and improving programming skills are top motivators for project participation. They, too, use a simple OLS model wherein they regress time spent on OS/FS development on developer characteristics. A number of their respondents, however, actually worked on OS/FS development as a part of their regular jobs. This is an important element that cannot be ignored - frequently, companies will encourage their employees to work on OS/FS applications if the company itself has some utility for the application, either as its main line of business, or simply to carry out its work. On the other hand, sometimes developers will work on OS/FS projects at their workplace, but without the approval or consent of the firm - their immediate supervisors may be either unaware of this “shirking”, or may tacitly let it continue.

Another theoretical model of intrinsic motivation has been developed by Bitzer, Schrettl, and Schröder (2004). They model the decision to develop or not to develop OS/FS software as a war of attrition, with each individual preferring to wait for someone else to develop the required software. The subgame perfect equilibrium of this game has all developers with one or more of the following: a higher gain from the software, a larger “gift” benefit, a longer time horizon (i.e. younger), a lower discount rate, a lower cost of software development, or a higher “play” value of developing software, contributing right at the start, at time t = 0, rather than waiting. Apart from the fact that they do not model network effects in the software developed, their predictions make sense intuitively, and the model has potentially testable implications.

Roberts, Hann, and Slaughter (2004) also develop a model of intrinsic and extrinsic motivations, and proceed to test it using a survey of 288 Apache web server developers. Their results – that extrinsic motivation, status and opportunistic motives, and education have a far greater impact on developer participation than intrinsic motivation – are further supported by the results of this paper. Most crucially, they find that various motivations to contribute to OS/FS are interrelated and complementary, and that extrinsic motivations do not crowd out intrinsic motivations, contrary to what has frequently been found in the psychology literature.

Roberts, Hann, Slaughter, and Fielding also test a Mincer wage regression for the panel of Apache developers, using both fixed and random effects. They find that skill, as measured by an individual’s rank in the Apache Software Foundation (a completely merit-based status ranking) has strongly positive effect on earnings, but that the actual amount of contributions do not. They therefore conclude that OS/FS contributions are more important for their signaling effects than their human capital effects. However, one crucial difference between their work and this paper is that they focus exclusively on

Apache developers. This is a very narrow subset of the over 100,000 projects listed on on Sourceforge.net alone. It is among the most successful OS/FS projects in existence, and therefore likely to attract more talent than almost any other – talent which is specifically focused on networking and web development. The vast majority of OS/FS projects cover almost all areas of computing and frequently go unnoticed. Whether or not the results they find apply across the board to all types of software developers is what this paper intends to find out.

3.2.2 Studies of Complementarity in Practices

Arora and Gambardella (1990) study complementarity in practices among linkages between biotechnology firms, i.e. testing whether agreements with other firms, research agreements with universities, investmentments in the capital stock of New Biotechnology Firms, and acquisitions of New Biotechnology Firms were complementary practices. Instead of merely testing for positive correlations, they test whether unobserved characteristics of the firms might lead to complementary adoption of a set of practices. They regress each of the practices on a set of observed firm characteristics, and then test the correlation between the residuals of each regression. Arora (1996) further elaborates the theoretical underpinnings of this model.

Ichniowski, Shaw, and Prennushi (1997) study Human Resource Management (HRM) practices on steel production lines. They estimate a productivity equation with dummy variables indicating adoption of sets of practices, using first a simple OLS regression on firm characteristics and the practice dummies, and then a fixed-effects model to difference out the impact of unobserved firm characteristics.

Athey and Stern (1998) then derive a complementarity measure from the productivity equation estimated by Ichniowski et al. (1997), and address the potential bias in the estimator, detailing the conditions required for it to be unbiased and the direction of bias. They then go on to derive a structural estimation framework for complementarity, using exclusion restrictions for the productivity equations across different practices.

The estimation that follows tests for complementarity using, first, the framework developed by Arora and Gambardella (1990), then that of Ichniowski et al. (1997), finally linking it with the analysis of Athey and Stern (1998).

3.3 The Data

The FLOSS survey, conducted between February and April 2002, surveyed 2784 OS/FS developers. After dropping respondents with missing data, the sample size is 2175.

The survey questions covered personal features of OS/FS developers, such as age, education, nationality, current country of residence, gross monthly income, marital status, employment status and job description, etc; characteristics of work in the OS/FS community, such as the type of project, hours per week devoted to OS/FS development, and number of projects the respondent is the leader of; and motivations, orientations, and expectations of OS/FS developers. The last involved a series of statements about attitudes and beliefs towards OF/FS and programming in general, and the degree of agreement with the statement.

With regard to the original hypotheses of job-market signaling and human-capital investment, a first look at the data appears to support either or both. (Descriptive statistics are in tables C.1 and C.2, and figures 1 through 6 in appendix C.) In the FLOSS survey, 61% of developers cited the chance to learn and develop new skills as their reason for joining the OS/FS community, about 26% stated they worked on OS/FS projects in order to solve a problem that could not be solved by proprietary software, while about a quarter cited improving their job opportunities as a reason, and about a third cited their belief that software should not be a proprietary good. If learning effects are indeed a primary motivation to contribute to OS/FS projects, then one can think of a developer's contributions as an investment in human capital – a form of on-the-job training (Mincer, 1974, 1962). This is especially plausible, given that over 85% of the respondents in the FLOSS survey agreed that expertise in the OS/FS community has a positive impact on job opportunities. Simple nearest-neighbor matching indicates that receiving a college education does increase the likelihood of being a project leader – the average treatment effect is 0.9 and the average treatment on the treated is 0.7, which are both significant at the 99% level. It remains to be seen if this is evidence of complementarity.

3.4 The Model

Two different models to estimate complementarity were tested. In both cases, the developer's monthly income was the outcome of interest. In each case, the practices being tested for complementarity were years of schooling, i.e. the level of educational attainment, and a measure of contribution to OS/FS software. The estimations were carried out using hours per week spent on OS/FS contributions, and then using number of projects the respondent was a leader of, as measures of contribution. The latter measure is more appealing, since it is a better indicator of ability, and perhaps even the quality of work produced, than mere time spent – different individuals are likely to have widely differing levels of per-hour productivity.

Using the framework developed by Athey and Stern (1998), we have:

Each individual i maximizes income Y, such that:

$$S_i^* = argmax_S Y(S_i, X_i, W_i) \tag{3.1}$$

Where S_i are practices, or strategies to be adopted. The X_i are the practice-specific exogenous variables affecting productivity, like the enjoyment from coding open-source software – the benefits from a practice. The W_i are practice-specific exogenous variables which do not affect productivity, like tuition as a cost of education – the costs of a practice.

Each X and W has an unobserved component, referred to as χ and ω respectively. We can think of these as unobserved returns to and costs of the practices, respectively.

If Y is supermodular in S, then for practices j and k, S^* is monotone nondecreasing in (X_j^1, W_j^1) and monotone nonincreasing in (X_j^0, W_j^0), so that if all the choice variables are complementary, an increase in the exogenous returns to one choice will lead to increases in all of the others, which will be endogenously determined. Two practices S_j and S_k are said to be *complements* if Y(.) is supermodular in S, so that the following holds:

$$Y(S_j^1, S_k^1) - Y(S_j^0, S_k^1) \geqslant Y(S_j^1, S_k^0) - Y(S_j^0, S_k^0) \tag{3.2}$$

where 1 and 0 refer to "high" and "low" levels of the practices respectively.

The unobserved benefits and costs – χs and ωs – are likely to lead to positive correlation between practices even after controlling for observables, so that merely testing a positive coefficient on an interaction term is not enough. While interpreting the results, we need to check whether whether the χs are present, independent, or correlated, and whether the ωs are independent, or correlated with each other.

Throughout, the practice “Education” will be said to have a high level if the respondent has completed an undergraduate education or higher, and a low level otherwise. The practice “F/OSS Contributions” will be said to have a high level if the respondent is the leader of at least one project, and a low level otherwise.

3.4.1 The Arora-Gambardella Model

Using the setup of Arora and Gambardella (1990), we have the following:

A developer has the payoff function $Y(s)$, which she[3] maximizes subject to her own (exogenous) characteristics, and strategies, which are under her control. Two strategies, s_j, s_k, are complementary if and only if:

$$\frac{\delta^2 Y}{\delta s_j \delta s_k} \geqslant 0, \forall i \neq j \tag{3.3}$$

Each developer solves the following optimization problem:

$$\underset{x}{Max} Y = f(\mathbf{s}; x) - (\mathbf{c} + \varepsilon).\mathbf{s} \tag{3.4}$$

where Y is income, s is the vector of available strategies, x is a vector of individual characteristics, and **c** is a vector of constant marginal costs associated with each strategy in s, and ε is a vector of stochastic disturbances in costs, representing the unobserved component.

The first-order condition for the problem can be written as:

$$Y_s = \mathbf{c} + \varepsilon \tag{3.5}$$

where Y_s is the matrix of first derivatives of $f(\mathbf{s}; x)$ with respect to $\mathbf{S}$. Let Y^* and $\mathbf{s}^*$ be the optimal quantities. Taking a Taylor expansion around $\widehat{\mathbf{s}}$, where $\widehat{s}(x)$ is defined such that $\widehat{Y_s}$ evaluated at $\widehat{\mathbf{s}}(x)$ is equal to **c**, we have:

$$Y_s \approx \widehat{Y_s} + \widehat{Y_{ss}}(\mathbf{s}^* - \widehat{\mathbf{s}}) \tag{3.6}$$

[3]Since 98% of the sample is male, the political correctness is slightly tongue-in-cheek.

where

$$\widehat{Y_{ss}}(\mathbf{s}^* - \widehat{\mathbf{s}}) \approx \varepsilon \tag{3.7}$$

where $\widehat{Y_{ss}}$ is a matrix of second-order derivatives.

Note that $\widehat{\mathbf{s}} \perp \varepsilon$, and assume $E(\varepsilon|x) = 0$. So $E(\mathbf{s}^*|x) = E(\widehat{\mathbf{s}}|x) = \widehat{\mathbf{s}}$. $\widehat{Y}$ is a function of x and can be removed from equation 7 once we condition on x.

From (7), postmultiplying each side by $(\mathbf{s}^* - \widehat{\mathbf{s}})'$ and after some algebraic manipulation, we get:

$$(\mathbf{s}^* - \widehat{\mathbf{s}})(\mathbf{s}^* - \widehat{\mathbf{s}})' = \widehat{Y_{ss}^{-1}} \cdot \varepsilon \cdot (\mathbf{s}^* - \widehat{\mathbf{s}})' \tag{3.8}$$

which leads us to:

$$(\mathbf{s}^* - \widehat{\mathbf{s}})(\mathbf{s}^* - \widehat{\mathbf{s}})' = \widehat{Y_{ss}^{-1}} \cdot \varepsilon \cdot \varepsilon' \cdot \widehat{Y_{ss}^{-1\prime}} \tag{3.9}$$

Finally, assuming $\Sigma \equiv E(\varepsilon \cdot \varepsilon|x)$ is a diagonal matrix and $Var(\varepsilon) = \sigma_\epsilon^2 I_n$, we can take expectations on each side of (9) and condition on x to get:

$$E[(\mathbf{s}^* - E(\mathbf{s}^*|x)) \cdot (\mathbf{s}^* - E(\mathbf{s}^*|x)')|x] = \widehat{Y_s^{-1}}\Sigma\widehat{Y_s^{-1\prime}} \tag{3.10}$$

Assuming concavity, $Y_{jj} < 0$. Σ is a non-negative matrix. So if $Y_{jk} > 0$, then we should have:

$$E[(s_j - E(s_k|x)) \cdot (s_k - E(s_k|x)')|x] \geqslant 0 \tag{3.11}$$

This is a testable implication of the theory.

3.4.2 The Ichniowski-Shaw-Prennushi Model

Using the setup of Ichniowski, Shaw, and Prennushi (1997), we have a basic productivity equation defined by:

$$lnY_i = \gamma' H_i + \beta' X_i + \xi_i \tag{3.12}$$

where lnY_i is the natural log of the income of individual i, D_i is a vector of dummy variables indicating which of the possible practice combinations has been adopted, and X_i is a vector of characteristics of individual i.

In this simple two-practice model, there are a total of four interaction dummies – high education and high contribution, low education and low contribution, low education and high contribution, or high education and low contribution, so that we have:

$$Y_i = \gamma^{00} D_i^{00} + \gamma^{01} D_i^{01} + \gamma^{10} D_i^{10} + \gamma^{11} D_i^{11} + \beta' X_i + \xi_i \tag{3.13}$$

Here, D_i^{00} (lnolead in the estimations) takes on a value of 1 if we observe the individual does not complete college, and does not lead any OS/FS projects. D_i^{01} (llead in the estimations) takes on a value of 1 if the individual has not completed college, but does lead at least one OS/FS project. D_i^{10} (hnolead in the estimations) equals 1 if the individual has completed college, and does not lead any OS/FS projects. Finally, D_i^{11} (hlead in the estimations) equals 1 if the individual has completed college and leads at least one OS/FS project.

The corresponding test statistic for complementarity is $\kappa = (\gamma^{11} - \gamma^{01}) - (\gamma^{10} - \gamma^{00})$. If $\widehat{\kappa}$, the estimated value of κ, is greater than zero, we have complementarity between practices. If $\widehat{\kappa} = 0$, the practices are independent, and if $\widehat{\kappa}$ is less than zero, they are substitutes.

This equation can be estimated by OLS and by a 2SLS instrumental variables procedure, as long as there is an exclusion restriction on the determinants of the practices.

3.5 Estimation

The presence of ability bias in income-schooling models is well-documented – those with a higher innate ability are likely to do better at school and therefore receive a higher level of education. At the same time, these same innate abilities and talents lead these individuals to do better in the workplace and have more successful careers, increasing their incomes. Not accounting for innate abilities therefore overstates the return to schooling in OLS models. Instrumenting for education using costs and other determinants of the amount of schooling received that are uncorrelated with innate abilities permit a consistent estimation of the actual returns to schooling.

The same ability bias is likely to occur when estimating the returns to being a project leader, and therefore the joint returns to schooling and OS/FS contributions. More talented programmers, and those who simply enjoy coding, are more likely to lead OS/FS projects. However, these same talents are likely to make them more successful at careers in IT or software, and increase their earnings.

For this reason, college tuition in the respondent's native country as of 2002 (or the average for the years when the respondent was aged 20-25, when available), average level of enrollment in tertiary education in the respondent's native country for the years when the respondent was aged 20-25, and level of compulsory education, were used as instruments for years of schooling. Average manufacturing wages in the respondent's country was used as an instrument for the project leader dummy, as a cost of time.[4] Additionally, whether or not the respondent signs their name to their code was used as an instrument for being a project leader, as an indicator of willingness to be recognized for one's work. These instruments were used in all the subsequent IV estimations as well. Since we are interested in labor market outcomes with college completion as a determinant, we only include those respondents between the ages of 21 and 65.

[4] Data on college tuition was obtained from a number of different sources, including the US National Center for Educational Statistics IPEDS database, the University of Michigan Survey on Human Capital Investment, and various news and information pieces. Data on manufacturing wages was obtained from ILO Labour Statistics. Data on average and compulsory education and enrollment levels, and minimum wages, was obtained from World Bank EdStats.

Table 3.1: Variable Names Used

Variable	Description
lnolead	Respondent has not completed college and does not lead a project
llead	Respondent has not completed college and leads a project
hnolead	Respondent has completed college and does not lead a project
hlead	Respondent has completed college and leads a project
age	Respondent's age
agesq	Square of respondent's age
employed	Respondent is currently employed
selfemployed	Respondent is currently self-employed
student	Respondent is currently a student
unemployed	Respondent is currently unemployed
consultant	Respondent works as a consultant
programmer	Respondent works as a programmer
sengineer	Respondent works as software engineer
nonIT	Respondent works in a non-IT related field
audio	Respondent primarily develops audio applications
games	Respondent primarily develops games

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Variable	Description
graphics	Respondent primarily develops graphics software
home	Respondent primarily develops home desktop software
multimedia	Respondent primarily develops multimedia applications
networking	Respondent primarily develops networking applications
office	Respondent primarily develops office productivity software
webservices	Respondent primarily develops web services
nomoneyos	Respondent does not earn any income from OS/FS development
single	Respondent is not married or in a committed relationship
kids	Number of children respondent has
yrschool	Years of schooling completed
college	Respondent has completed an undergraduate education
projleader	Respondent leads at least one OS/FS project
mult	Interaction term of college and projleader
USA	Respondent resides in the USA
France	Respondent resides in France
Germany	Respondent resides in Germany
India	Respondent resides in India
Australia	Respondent resides in Australia

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Variable	Description
Canada	Respondent resides in Canada
UK	Respondent resides in the UK
	Instruments used:
tuition	Average college tuition in respondent's home country
enrollment	Percentage of population in respondent's home country enrolled in tertiary education when respondent was aged 20-25
compeduc	Level of compulsory education in respondent's home country
ch	Average hourly manufacturing wage in respondent's home country
dirmoneyos	Respondent earns a direct income from OS/FS development
indirmoneyos	Respondent indirectly earns an income as a result of OS/FS development
dontmark	Respondent does not sign his or her name to OS/FS code written
	Reasons Respondent Contributes to OS/FS:
earnmoney	To earn money
cooperation	To participate in a new form of cooperation
newskills	To learn new skills
shareknow	To share knowledge
participate	To participate in the OS/FS scene
jobopp	For improved job opportunities

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Variable	Description
otheros	To improve OS/FS products of other developers
reputation	To get a reputation in the OS/FS scene
nonmktsware	To distribute non-marketable software products
helpidea	To get help realizing an idea for a software product
solveprob	To solve a problem that could not be solved by proprietary software
largecos	To limit the power of large software companies
notprop	Respondent believes software should not be a proprietary good
Inverse Mills Ratios:	
lambda	Coefficient on Inverse Mills ratio in income selection model
imaudio	Inverse Mills ratio for audio
imgames	Inverse Mills ratio for games
imgraphics	Inverse Mills ratio for graphics
imhome	Inverse Mills ratio for home desktop
immultimedia	Inverse Mills ratio for multimedia
imnetworking	Inverse Mills ratio for networking
imoffice	Inverse Mills ratio for office
imwebservices	Inverse Mills ratio for web services

3.5.1 The Arora-Gambardella Model

When testing for complementarity, first, the Arora-Gambardella model was estimated. Regressions were run on the years of schooling and the number of projects as leader, and the coefficient of correlation of their residuals was computed. From table 3.2, we see that a preliminary estimation of the model indicates that practices may indeed be complementary. The coefficient of correlation between residuals of the two regressions on the contributions of OS/FS and years of schooling respectively is 0.17, which is significantly different from zero at the 99% level. This result is robust to specification – adding in more dependent variables improves the R^2 but the coefficient of correlation, the complementarity parameter, remains positive.

Table 3.2: Estimation results : Arora-Gambardella model

	Dependent Variables:		
Regressors	**Years of Schooling**	**No. of Projects as Leader**	**Hours/Week on OS/FS**
age	0.612***	0.07	-0.28
	(0.082)	(0.051)	(0.24)
agesq	-0.007***	-0.001*	0.003
	(0.001)	(0.0007)	(0.003)
nomoneyos	-0.184	-1.004***	-6.61***
	(0.187)	(0.117)	(0.54)
employed	1.058**	0.019	-1.32
	(0.511)	(0.32)	(1.47)
student	0.254	0.257	-3.01*
	(0.577)	(0.362)	(1.67)
selfemployed	-5.18***	-0.7**	-1.73
	(0.525)	(0.329)	(1.52)
Intercept	3.85***	1.96**	20.4***
	(1.478)	(0.927)	(4.27)
Correlation between residuals:		0.169	0.048
P-value:		0.00	0.027

*significant at 90% level ** significant at 95% level ***significant at 99% level
Standard errors are in parentheses

This initial evidence is enough to proceed and test for complementarity using the Ichniowski et al. (1997) model. When the estimation used hours per week spent on OS/FS contributions, the evidence of complementarity was slightly weaker, but still present. Hours worked, in this case, need not be any indicator of the quality of code produced, and being unverifiable, are unlikely to serve as a signal of any sort. On the other hand, whether or not a respondent is a project leader is clearly observable, verifiable, and more likely to indicate ability and perhaps better-quality code. Henceforth, the project leader indicator is used in estimation, rather than hours worked.

3.5.2 The Ichniowski-Shaw-Prennushi Model

A note on normalization

Given that the model relies on a set of dummy variables, and $D^i_{00}+D^i_{01}+D^i_{10}+D^i_{11}=1$, the standard procedure would be to leave out one dummy variable as the reference group and estimate the model with a constant. However. all of the coefficients are required to estimate the parameter of interest κ, making this infeasible. An alternative would be to leave out the constant, but this relies on an arbitrary restriction given the presence of many other dummy variables as regressors in the model. The model is:

$$\begin{aligned} lnY^i &= \beta_0+\gamma_{00}D^i_{00}+\gamma_{01}D^i_{01}+\gamma_{10}D^i_{10}+\gamma_{11}D^i_{11} \\ &\quad +\beta X^i+\sum_{j=1}^{2}\alpha_j Z^i_j+\sum_{j=1}^{n}\delta_j H^i_j+\xi_i \end{aligned} \tag{3.14}$$

where Z_j and H_j are sets of dummy variables. If Z_1 and H_1 are the left-out reference groups, and the model was estimated without the constant β_0, this would imply the restriction $\beta_0=\alpha_1+\delta_1=0$, which need not be the case in the true model.

Instead, following (Gardeazabal and Ugidos, 2004), the coefficients on the dummy variables are normalized so that $\gamma_{00}+\gamma_{01}+\gamma_{10}+\gamma_{11}=0$. Similarly, $\Sigma_j\alpha_j=0$, $\Sigma_j\delta_j=0$, and so on. This way, $\gamma_{11}=-\gamma_{01}-\gamma_{10}-\gamma_{00}$, $\alpha_1=-\alpha_2$, and so on. Substituting for γ_{11}, α_1, and so on in equation 14, we obtain:

$$\begin{aligned} lnY^i &= \beta_0+\gamma_{01}(D^i_{01}-D^i_{11})+\gamma_{10}(D^i_{10}-D^i_{11})+\gamma_{00}(D^i_{00}-D^i_{11}) \\ &\quad +\beta X^i+\alpha_2(Z^i_2-Z^i_1)+\sum_{j=2}^{n}\delta_j(H^i_j-H^i_1)+\xi^i \end{aligned} \tag{3.15}$$

Since $\gamma_{11} = -\gamma_{01} - \gamma_{10} - \gamma_{00}$, it and all the other coefficients on the dummy variables are still identified. Since $\kappa = \gamma_{11} + \gamma_{00} - \gamma_{01} - \gamma_{10}$, we now have $\kappa = -2(\gamma_{01} + \gamma_{10})$. All the dummy variables in the regressions follow this normalization, and the reported coefficients are on the normalized variables.

The estimate of κ in the OLS estimation – see table 3.3 – is not significantly different from zero. This is robust to specification in terms of regressors and whether or not those with an income of zero are dropped from the estimation. The results are the same when hours worked on OS/FS is used instead of number of projects as leader, with a cutoff value of 8 hours a week or more being considered a high level of contribution.

As discussed earlier, we see that while the correlation is strictly positive, the estimated values of κ are equal to zero. Going back to the Athey and Stern (1998) model, we see it is possible that the estimates of κ are downward biased, when the χs, the unobserved components of the practice-specific exogenous variables affecting productivity (benefits) are not equal to zero but are independent from one another, and the ωs, the unobserved components of the practice-specific exogenous variables which do not affect productivity (costs) are equal to zero.

This would imply that controlling for these disturbances would lead to more precise estimates of κ. This is what has been attempted with by estimating an instrumental variables model with heteroskedasticity-robust standard errors. The practice-combination dummies were instrumented for with the set of instruments described earlier, along with an additional variable – whether or not the respondent signs their name to the code they write, as the best available proxy for ability. The assumption is that not even desiring credit for the code one writes is an accurate indicator of either pure altruistic motives, or code that one does not want to admit is one's own. The first-stage results (appendix D) show that while the instruments are perhaps weaker than would be liked in terms of the partial R^2, which is fairly low, they do have reasonable predictive power, as evinced by the F statistics. For this reason, as suggested by Stock and Yogo (2002), a Limited Information Maximum Likelihood (LIML) procedure is also used, since this results in more consistent IV estimates in the presence of weak instruments.

There remains the fact that incomes are reported as zero for about 500 respondents, some of whom are students, some unemployed, and others self-employed. Therefore a first-stage selection equation is required to account for the probability of having a non-zero income, in a standard Heckman selection setup with robust standard errors (Wooldridge, 2002). The model being estimated is therefore:

$$lnY^i = \sum \gamma_{jk} D^i_{jk} + \beta X^i + \rho\sigma_\xi \lambda^i + \xi^i \tag{3.16}$$

where λ_i refers to the Inverse Mills ratios of the selection probabilities obtained from the probit estimation of whether or not a respondent has a zero income.

The estimated κ from the instrumental variables estimation is positive and significantly different from zero – it is about 2.7 (table 3.3, column c), indicating complementarity between college education and being an open-source project leader. The estimated κ from the LIML procedure is 3.14 (table 3.3, column d), and also significantly different from 0.

Table 3.3: Estimation results : Ichniowski-Shaw-Prennushi Model: Dependent variable is ln(income)

	(a) **OLS**	(b) **Heckit**	(c) **IV**	(d) **LIML**
lnolead	-0.049	-0.033	1.488*	1.729*
	(0.044)	(0.045)	(0.831)	(1.04)
llead	-0.162***	-0.116***	-0.505	-0.573
	(0.035)	(0.036)	(0.395)	(0.462)
hnolead	0.119***	0.086***	-0.843*	-0.996
	(0.031)	(0.031)	(0.517)	(0.647)
age	0.1***	0.137***	0.141***	0.14***
	(0.009)	(0.015)	(0.033)	(0.036)
agesq	-9x10^{-4}***	-0.002***	-2x10^{-4}***	-0.002***

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	(a) **OLS**	(b) **Heckit**	(c) **IV**	(d) **LIML**
	$(12\text{x}10^{-5})$	$(2\text{x}10^{-4})$	$(44\text{x}10^{-5})$	$(5\text{x}10^{-4})$
single	-0.1***	-0.065***	-0.086***	-0.089***
	(0.018)	(0.019)	(0.031)	(0.035)
kids	0.044**	0.049**	0.042	0.041
	(0.021)	(0.022)	(0.032)	(0.035)
migrant	0.091***	0.078***	0.159***	0.171***
	(0.027)	(0.028)	(0.054)	(0.063)
Australia	0.083	0.029	-0.110	-0.132
	(0.09)	(0.093)	(0.175)	(0.194)
Austria	-0.031	0.097**	0.176*	0.189*
	(0.045)	(0.047)	(0.092)	(0.103)
Canada	0.15	0.098	-0.004	-0.019
	(0.103)	(0.116)	(0.181)	(0.2)
France	-0.094**	-0.126***	-0.098	-0.095
	(0.045)	(0.046)	(0.078)	(0.086)
Germany	0.053	0.043	-0.041	-0.053
	(0.049)	(0.051)	(0.1)	(0.112)
India	-0.879***	-0.836***	-0.625***	-0.593***
	(0.117)	(0.117)	(0.181)	(0.206)
UK	0.22***	0.22***	0.291***	0.302***
	(0.061)	(0.063)	(0.091)	(0.1)
USA	0.526***	0.518***	0.534***	0.537***
	(0.048)	(0.05)	(0.072)	(0.078)
indirmoneyos	0.057**	0.054**	0.055*	0.054
	(0.024)	(0.024)	(0.033)	(0.036)
dirmoneyos	0.01	0.008	-0.005	-0.006

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	(a) **OLS**	(b) **Heckit**	(c) **IV**	(d) **LIML**
	(0.028)	(0.028)	(0.043)	(0.047)
consultant	0.2***	0.223***	0.276***	0.287***
	(0.041)	(0.04)	(0.065)	(0.074)
programmer	-0.082**	-0.096**	-0.187**	-0.2**
	(0.041)	(0.042)	(0.08)	(0.092)
sengineer	0.216***	0.165***	0.236***	0.245***
	(0.029)	(0.029)	(0.054)	(0.062)
nonIT	21x10^{-5}	-0.007	0.072	0.083
	(0.026)	(0.027)	(0.055)	(0.063)
lambda	–	-0.556***	-0.649***	-0.662***
	–	(0.061)	(0.121)	(0.134)
Intercept	5.518***	5.078***	5.419***	5.486***
	(0.164)	(0.268)	(0.57)	(0.64)
$\widehat{\kappa}$	0.086	0.059	2.696*	3.138*
	(0.078)	(0.08)	(1.499)	(1.883)
Hansen J statistic			1.05	0.98
χ^2 (2) P-value			0.592	0.613

*significant at 90% level ** significant at 95% level ***significant at 99% level

Standard errors are in parentheses

We notice that the coefficient on λ, the selection parameter, is negative. On the surface this implies that if those who are not earning were to earn a positive income, their income would be higher than the income of those who do currently earn an income. However, we must remember that this was an online survey with self-reported incomes. It may well be that a portion of highly educated open source contributors earning a high income were simply not comfortable reporting their income in the survey. If we do not account for selection at all, the IV estimates of $\widehat{\kappa}$ do not change dramatically; they remain positive and significant.

3.5.3 Selection into area of OS/FS

One of the rich features of the FLOSS dataset is that it records contributions into various areas of OS/FS, namely audio, games, graphics, multimedia, home, office, networking, and web services. These choices are, by definition, endogenous, and can be controlled for in two ways – by instrumenting for them, or by controlling for selection. Table 3.9 contains the results after they have been instrumented for using the answers to a number of the attitude and motivation questions contained in the survey. These included whether the respondent contributes in order to earn money, improve job opportunities, participate in a new form of co-operation, learn new skills, share knowledge, build a reputation, help others, receive help on a new idea, work on another operating system, solve a problem, defeat large companies, or because they believe that software should not be proprietary. Instrumenting for the areas shows that the estimate of κ remains positive, but it is no longer significant. The area dummies are neither individually nor jointly significant, as shown by a Wald χ^2 test, and the instruments used are extremely weak, with even the F-statistics failing to reject the null that they are invalid[5].

Following Lee (1983), a selection procedure is therefore used for selection into area, using a multinomial logit (appendix E, tables E.1 and E.2) to calculate the predicted probability of selecting into each area, for which Inverse Mills ratios are then calculated. As above, following Wooldridge (2002), robust standard errors are calculated in the usual way using the heteroskedasticity-robust Huber-White procedure.

Selection model:

$$lnY^i = \sum \gamma_{jk} D^i_{jk} + \beta X^i + \rho\sigma_\xi \lambda^i + \sum_m \alpha A^i_m + \sum_m \theta_m \mu^i_m + \xi^i \tag{3.17}$$

where the A^i_ms are dummies representing individual i's choice of area A_m, and the

[5]The results are therefore not reported, but are available on request.

μ_m^is are the Inverse Mills ratios associated with each choice. Following Lee (1983):

$$\mu_m^i = \frac{\phi(\Phi^{-1}(Prob[A_m^i = 1]))}{Prob[A_m^i = 1]}$$

This is equivalent to estimating separate wage equations for each of the areas being estimated, using the Inverse Mills ratio for each one as a regressor, and constraining the coefficients on all the other variables to be equal.

Results from this model, shown in table 3.4, show that the coefficient of complementarity is about 2.5 and also significant with a P-value of 0.053 in the IV case (table 3.4, column b) and 2.98 and significant in the LIML case (table 3.4, column c). The coefficients on the Inverse Mills ratios are jointly significant according to a Wald Chi-square test with 8 degrees of freedom – the test statistic for the Inverse Mills ratios, is 51.52 in the IV case and 42.6 in the LIML case. In both cases, we reject the null that they are jointly zero. We therefore find that selection into area of OS/FS is crucial and should not be omitted.

Table 3.4: Estimation results : Ichniowski-Shaw-Prennushi Model with Selection: Dependent variable is ln(income)

	(a) **Heckit**	(b) **IV**	(c) **LIML**
lnolead	-0.027	1.109*	1.352
	(0.047)	(0.682)	(0.887)
llead	-0.112***	-0.475	-0.545
	(0.04)	(0.341)	(0.408)
hnolead	0.079**	-0.768*	-0.944
	(0.033)	(0.46)	(0.602)
age	0.135***	0.147***	0.143***
	(0.016)	(0.036)	(0.041)
agesq	-0.002***	-0.002***	-0.002***
	(0.001)	(0.0004)	(0.001)
single	-0.066***	-0.147***	-0.149***
	(0.019)	(0.036)	(0.04)
kids	0.05**	0.009	0.007
	(0.02)	(0.032)	(0.036)
migrant	0.079***	0.225***	0.241***
	(0.028)	(0.058)	(0.07)
Australia	0.02	1.967***	1.992***
	(0.114)	(0.584)	(0.636)
Austria	0.099*	0.198*	0.215
	(0.056)	(0.120)	(0.136)
Canada	0.103	0.336	0.338
	(0.123)	(0.704)	(0.765)

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	(a) **Heckit**	(b) **IV**	(c) **LIML**
France	-0.12***	-0.572**	-0.574**
	(0.042)	(0.254	(0.277))
Germany	0.038	-0.405	-0.419
	(0.051)	(0.266)	(0.294)
India	-0.831***	-1.424	-1.430
	(0.1)	(0.979)	(1.076)
UK	0.224***	0.123	0.129
	(0.062)	(0.293)	(0.32)
USA	0.514***	0.277	0.271
	(0.054)	(0.259)	(0.284)
indirmoneyos	0.057**	0.01	0.011
	(0.024)	(0.048)	(0.052)
dirmoneyos	0.004	-0.007	-0.005
	(0.029)	(0.1)	(0.108)
consultant	0.217***	0.183**	0.199**
	(0.037)	(0.089)	(0.102)
programmer	-0.085**	-0.153	-0.172
	(0.041)	(0.136)	(0.153)
sengineer	0.167***	0.144**	0.15**
	(0.028)	(0.059)	(0.066)
nonIT	-0.003	0.034	0.042
	(0.03)	(0.075)	(0.083)
lambda	-0.54***	-0.676***	-0.694***
	(0.08)	(0.122)	(0.138)
Intercept	5.102***	6.601***	6.88***
	(0.274)	(1.616)	(1.84)

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	(a) Heckit	(b) IV	(c) LIML
Area Dummies:			
networking	0.073**	0.092*	0.101*
	(0.035)	(0.05)	(0.057)
office	0.069*	0.118*	0.129*
	(0.041)	(0.063)	(0.072)
home	-0.003	-0.020	-0.026
	(0.046)	(0.066)	(0.073)
webservices	-0.074**	-0.092*	-0.093*
	(0.036)	(0.049)	(0.054)
games	-0.078	-0.130	-0.146
	(0.062)	(0.094)	(0.108)
graphics	-0.04	0.002	-0.001
	(0.057)	(0.085)	(0.096)
multimedia	0.037	0.049	0.061
	(0.085)	(0.122)	(0.138)
Coefficients on Inverse Mills Ratios:			
imnetworking	–	-0.295	-0.293
	–	(0.220)	(0.242)
imoffice	–	0.116	0.084
	–	(0.186)	(0.212)
imhome	–	-0.210	-0.255
	–	(0.226)	(0.262)
imwebservices	–	-0.372	-0.397
	–	(0.248)	(0.274)
imgames	–	-0.026	-0.032
	–	(0.129)	(0.142)

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	(a)	(b)	(c)
	Heckit	**IV**	**LIML**
imgraphics	–	0.635***	0.657*
	–	(0.148)	(0.168)
immultimedia	–	-0.506***	-0.516***
	–	(0.139)	(0.153)
imaudio	–	-0.060	-0.063
	–	(0.208)	(0.227)
$\widehat{\kappa}$	0.067	2.485**	2.976*
	(0.084)	(1.282)	(1.685)
Hansen J statistic		1.345	1.354
χ^2 (2) P-value		0.511	0.508

*significant at 90% level ** significant at 95% level ***significant at 99% level
Standard errors are in parentheses

3.5.4 Direction of bias

Athey and Stern (1998) show the following:

As long as the exclusion restriction and all of the assumptions above hold, χ equals zero, and the ωs are independent random vectors, then if we observe positive correlation and $\kappa \geqslant 0$, $\widehat{\kappa}$ as estimated by OLS and 2SLS is the true measure of complementarity. However, the results clearly show that in each case, $\widehat{\kappa}^{OLS}$ is not significantly different from 0, and is much less than $\widehat{\kappa}^{IV}$. The fact that the IV estimate of κ is greater than the OLS estimate can imply that the OLS estimate is downward-biased, or that there is measurement error.

If the exclusion restriction and all of the assumptions above hold, ω equals zero, but the χs namely the unobserved returns from each practice, are independent random vectors, and the true $\kappa \geqslant 0$, then the OLS and 2SLS estimates of $\widehat{\kappa}$ are downward-biased, and the observed correlation is positive. We can write this out as under:

$$E[ln(Y_i)|s_i] = E[\gamma^{00}D_i^{00}] + E[\gamma^{01}D_i^{01} + E[\chi_P|s^* = (0,1)]]$$
$$+E[\gamma^{10}D_i^{10} + E[\chi_C|s^* = (1,0)]]$$
$$+E[\gamma^{11}D_i^{11} + E[\chi_P|s^* = (1,1)] + E[\chi_C|s^* = (1,1)]] + E[\beta X_i]$$

χ_C and χ_F refer to the unobserved returns from the two practices: completing college, and being a project leader, respectively. They only impact the income when the practice in question is selected, which is why they are not counted when $D_i^{00} = 1$.

The bias in $\widehat{\kappa}^{OLS}$ can therefore be written out as under:

$$E[\widehat{\kappa}^{OLS}] = \kappa + E[\chi^C|s^* = (1,1)] - E[\chi^C|s^* = (1,0)]$$
$$+E[\chi^P|s^* = (1,1)] - E[\chi^P|s^* = (0,1)]$$

The last 4 terms on the right-hand side, will equal zero if and only if $\kappa = 0$ *and* the χs equal 0. If they are independent, these 4 terms will sum to zero but the bias will remain in the unobservable portion of the estimation, so that $\xi_i = \chi_i^C s^C + \chi_i^P s^P + \epsilon_i$. These unobservables will bias $\widehat{\kappa}^{OLS}$ and $\widehat{\kappa}^{IV}$ downwards. [6] The true κ, in this case, is even larger than $\widehat{\kappa}^{IV}$, which is clearly positive.

If the χs are strictly correlated, then even if the above assumptions hold, the estimated $\widehat{\kappa}$ from OLS and 2SLS will be strictly greater than zero when the true κ equals zero and estimated correlation is positive – they will be upward biased. In this case, that would mean that practice-specific unobservable returns are strictly correlated, and are driving the simultaneous adoption of the practices, not actual complementarity between them. One might hypothesize what these returns may be, other than income. They are most likely to be related to intrinsic motivation, like an enjoyment of learning and tinkering with software may well go together. In the selection models, these have been controlled for

[6] A positive correlation between the practices with a negative κ occurs when the unobserved costs of the practices, the ωs are strictly correlated. Due to the nature of the practices, this can mostly be ruled out – the costs of education, with the exception of opportunity cost, are exogenous, and once again except for opportunity cost, unlikely to be correlated with the costs of contributing to OS/FS. Since opportunity cost is proxied for, I will assume the ωs are zero.

to an extent by using the "attitude" variables, and qualitatively the results do not change. It may therefore be reasonable to assume that affiliated or strictly correlated unobserved returns are not a serious concern.

Athey and Stern (1998) recommend a structural GMM estimator to eliminate these biases and accurately estimate the magnitude of the complementarity measure. However, due to the difficulty of finding suitable exclusion restrictions for each combination of practices, which is what the structural estmation as a system of equations would require, an instrumental variables procedure has been used instead. What is more important in this case is perhaps accurately estimating the sign of the complementarity parameter, rather than the exact magnitudes of all coefficients.

In sum, we see that there is evidence of complementarity between education and OS/FS contributions as a project leader, which is driving the positive correlation and the κ estimate. However, looking at the coefficients to tease out the individual effects of education and leading an OS/FS project turns up some interesting results – in each case, the coefficient on going to college but not leading a project is *less* than the coefficient on not going to college but leading a project. This would imply that if a developer goes to college but does not lead a project, she might as well have not gone to college. Between project leaders, however, it helps to have gone to college.

How might this result, which is counterintuitive at first glance, be explained? It is worthwhile to remember that this sample is entirely comprised of OS/FS developers. Those who aren't college graduates but are project leaders are more likely to be, in pure correlation terms, unemployed. So overall, choosing both activities together or neither of the two appears to have stronger positive effects on income than choosing just one of the two. In a way, this fact provides the strongest positive effect of complementarity, and also supports the signaling results obtained by (Roberts et al.).

Crucial to explaining the above results is the context of the IT industry recession which began at the end of 2000 with the dot-com crash and continued for another two years at least in most parts of the world. This survey, conducted between February and April 2002, occurred long before most countries surveyed had recovered. Might the results be indicative of a lack of initiative displayed by those who go to college, code OS/FS, but don't care to lead a project? It may well be a negative job-market signal when compared to other OS/FS developers. On the other hand, maybe they were simply hit very badly by the recession, and may well have suffered pay cuts if not a loss of their jobs. The signaling story is therefore more complex than originally imagined by Lerner and Tirole (2002), but still works in the same direction.

3.6 Conclusions and Further Research

The current estimation shows there is evidence of complementarity in terms of the basic correlation, which also indicates that there may be an unobserved practice-specific component to productivity, which is not being captured by the OLS κ estimates. The IV estimates do indeed add further evidence to support the hypothesis of complementarity. So existing evidence appears to be consistent with the hypothesis of job-market signaling, specifically that of open-source contributions as a signal of ability. Even if they are both complementary human capital investments, it would be consistent with the job-market signaling and ability hypothesis.

However, the intention of an OS/FS developer may be more than to simply signal ability to a prospective employer. While it has been shown that altruism is not a driving force at all, there is growing evidence that releasing a piece of software one has written as open-source may actually help build a business around it, offering ancillary services like training and consulting. Open-source creates a community of like-minded people in the same field who can help the network around a particular application to grow. Given the importance of positive network effects in a good like software, this is not to be underestimated. While the rents to be earned from a particular application are not restricted by copyrights or patents and are spread widely, increasing the possibility of free-riding, this is less worrying for the OS/FS developer than it initially apears. Firstly, the strong network effects mean that free-riding is actually encouraged – Weber (2004) refers to OS/FS software as "anti-rival" in consumption. Also, the consulting, training, and other services can be localized, leading perhaps to smaller individual returns than in the case of a *successful* proprietary application, but a larger number of people and potentially larger total gains.

The empirical evidence in this paper also supports the above hypothesis. If OS/FS contributions are increasing in ability, rather than altruism, then incentives based on earning potential, even if it is not direct job-market signaling, will lead to increased contributions. Developing a model to capture this particular market mechanism remains a subject for further research in the future.

APPENDIX A

Proof of Sequential Reciprocity Equilibrium

Proof that 3 defects faced with D-D:

We need to find 1's kindness to 3, which is the same as 2's kindness to 3. This is:

$$6.7q_3 + 10(1 - q_3) - \frac{1}{2}[6.7q_3 + 10(1 - q_3) + 13.3q_3 + 16.7(1 - q_3)]$$
$$= -3.3$$

assuming the other person's contribution is held constant, and where q represents 3's belief of what 1 and 2 believe is the probability that she contributes. If 3 contributes, her kindness to 1 which is the same as her kindness to 2 is:

$$16.7 - \frac{1}{2}[16.7 + 10] = 3.3$$

whereas if she doesn't, her kindness to 1 and 2 is $10 - \frac{1}{2}[16.7 + 10] = -3.3$. So 3's utility from contributing is:

$$U_3(C) = 6.7 + 2Y(-3.3)(3.3) = 6.7 - 21.78Y$$

Her utility from not contributing is $U_3(C) = 10 + 2Y_3(-3.3)(-3.3) = 10 + 21.78Y_3$, which is unambiguously higher than that from contributing. So she will defect.

Proof that 3 defects faced with either C-D or D-C:

The kindness to 3 of the person who contributed is:

$$13.3q_3 + 16.7(1 - q_3) - \frac{1}{2}[13.3q_3 + 16.7(1 - q_3) + 6.7q_3 + 10(1 - q_3)] = 3.3$$

The kindness of the person who did not contribute is:

$$13.3q_3 + 16.7(1 - q_3) - \frac{1}{2}[13.3q_3 + 16.7(1 - q_3) + 20q_3 + 23.3(1 - q_3)] = -3.3$$

3's kindness from contributing is, to the person who contributed: $13.3 - \frac{1}{2}[13.3 + 6.7] = 3.3$, and to the person who did not contribute: $23.3 - \frac{1}{2}[16.7 + 23.3] = 3.3$. Her kindness from not contributing is, to the person who contributed: $6.7 - \frac{1}{2}[13.3 + 6.7] = -3.3$, and to the person who did not contribute: $16.7 - \frac{1}{2}[16.7 + 23.3] = -3.3$.

So her utility from contributing is: $U_3(C) = 13.3 + Y_3(3.3)(-3.3) + Y_3(3.3)(3.3)$, and her utility from not contributing is: $U_3(D) = 16.7 + Y_3(-3.3)(-3.3) + Y_3(-3.3)(3.3)$. So $U(C) - U(D) = -3.4$, and she never contributes.

Proof that 3 contributes facing C-C if $Y \geqslant 0.05$: 1's and 2's kindness to 3 is measured as:

$$20q_3 + 23.3(1 - q_3) - \frac{1}{2}[20q_3 + 23.3(1 - q_3) + 10] = 6.7 - 1.7q_3$$

As above, we see that her kindness from contributing is 3.3 and from not contributing is -3.3. So her utility from contributing is: $U_3(C) = 20 + 2Y_3(3.3)(6.7 - 1.7q_3)$, and her utility from defecting is $U_3(D) = 23.3 + 2Y_3(-3.3)(6.7 - 1.7q_3)$. She contributes if $Y_3(6.7 - 1.7q_3) > 0.25$. In equilibrium, this must hold for $q_3 = 1$, and in that case we must have $Y_3 > 0.05$. We must have $Y_3(6.7 - 1.7q_3) < 0.25$ for 3 to defect, so that $q_3 = 0$. In that case, we must have $Y_3 < 0.0375$.

For $0.0375 \leqslant Y_3 \leqslant 0.05$, we have $Y_3(6.7 - 1.7q_3) = 0.25$, so $q_3 = 4 - \frac{0.15}{Y}$.

A similar proof applies to show that player 2 always defects if player 1 does, since she knows that even if she contributes, player 3 will defect. Her utility is therefore higher from not contributing. However, if 1 contributes:

1's kindness to 2, where 1 and 2 believe 3 contributes with probability p_3 is:

$$20q_2p_3 + 13.3q_2(1-p_3) + 23.3(1-q_2)p_3 + 16.7(1-q_2)(1-p_3) - \frac{1}{2}[23.3p_3 + 20(1-p_3+10]$$

$$= 3.3 - 1.7q_2 + 3.3p_3$$

Similarly, 3's kindness to 2 is:

$$p_3[20 - \frac{1}{2}(20 + 13.3)] + (1 - p_3)[13.3 - \frac{1}{2}(20 + 13.3)] = 6.7p_3 - 3.3$$

As earlier, 2's kindness to 1 and 3 from contributing is 3.3, and from not contributing is -3.3. So:

$$U_2(C) = 20p_3 + 13.3(1 - p_3) + Y_2(3.3)(3.3 - 1.7q_2 + 3.3p_3) + Y_2(3.3)(6.7p_3 - 3.3)$$

and

$$U_2(D) = 23.3p_3 + 16.7(1-p_3) + Y_2(-3.3)(3.3-1.7q_2+3.3p_3) + Y_2(-3.3)(6.7p_3-3.3)$$

So $U_2(C) > U_2(D)$ if $-3.3 + 6.7Y_2(10p_3 - 1.7q_2) > 0$. This holds in equilibrium for $q_2 = 1$ if $Y_2 > \frac{1}{20p_3-3.3}$. This needs $p_3 > 0.17$, or $Y_3 > 0.039$ (substituting for p_3), and $Y_2 > 0.06$. For 2 to defect, we must have $-3.3 + 6.7Y_2(10p_3 - 1.7q_2) < 0$ for $q_2 = 0$ in equilibrium. This always holds if $p_3 = 0$, and requires $Y_2 < 0.05$ if $p_3 = 1$ (or $Y_3 > 0.05$), and $Y_2 > 0.3$ as $p_3 \to 0$, or $Y_3 \to 0.0375$.

For a mixed strategy, we have indifference between contributing and defecting, so that $Y_2 = \frac{1}{20p_3-3.3q_2}$. This occurs when $0.05 \leqslant Y_2 < 0.3$, and we get $q_2 = 26.7 - \frac{1}{Y_3} - \frac{0.3}{Y_2}$, substituting for p_3.

Let q_1 be 1's belief that 2 and 3 believe that 1 plays C. As above, p_2 and p_3 are 1's beliefs that 2 and 3 respectively play C. 1's material payoff from contributing is therefore:

$$\begin{gathered} q_1[20p_2p_3 + 13.3p_2(1-p_3) + 13.3p_3(1-p_2) + 6.7(1-p_2)(1-p_3)] \\ +(1-q_1)[23.3p_2p_3 + 16.7p_2(1-p_3) + 16.7p_3(1-p_2) + 10(1-p_2)(1-p_3)] \\ = 6.7(1+p_2+p_3) \end{gathered}$$

If 1 defects, 2 and 3 will also defect, so 1's material payoff from defecting is 10. 2 and 3's kindness to 1 when 1 contributes is therefore measured as:

$$6.7(1+p_2+p_3) - \frac{1}{2}[20q_1 + 23.3(1-q_1) + 6.7q_1 + 10(1-q_1)] = 6.7(p_2+p_3) + 3.3q_1 - 10$$

Their kindness to 1 from defecting when 1 defects is:

$$10 - \frac{1}{2}[20q_1 + 23.3(1-q_1) + 6.7q_1 + 10(1-q_1)] = 3.3q_1 - 6.7$$

1's kindness to 2 from contributing is:

$$20p_2 + 23.3(1-p_2) - \frac{1}{2}[20p_2 + 23.3(1-p_2) + 10] = 6.7 - 1.7p_2$$

Similarly, 1's kindness to 3 from contributing is $6.7 - 1.7p_3$.

1's kindness to 2 from defecting is:

$$10 - \frac{1}{2}[20p_2 + 23.3(1-p_2) + 10] = 1.7p_2 - 6.7$$

Similarly, 1's kindness to 3 from defecting is $1.7p_3 - 6.7$.

So we have:

$$U_1(C) = 6.7(1 + p_2 + p_3) + Y_1[6.7(p_2+p_3) + 3.3q_1 - 10](6.7 - 1.7p_3)$$

$$+Y_1[6.7(p_2+p_3) + 3.3q_1 - 10](6.7 - 1.7p_3)$$

and

$$U_1(D) = 10 + Y_1(3.3q_1 - 6.7)(1.7p_2 - 6.7) + Y_1(3.3q_1 - 6.7)(1.7p_3 - 6.7)$$

so that $U_1(C) > U_1(D)$ if $q_1 > \dfrac{1 - 2(p_2+p_3)}{2Y_1[13.3 - 1.7(p_2+p_3)]} + 2.5 - (p_2+p_3)$. This holds in equilibrium for $q_1 = 1$ as long as $(p_2+p_3) > \frac{1}{2}$. For 1 to defect, we must have $q_1 < \dfrac{1 - 2(p_2+p_3)}{2Y_1[13.3 - 1.7(p_2+p_3)]} + 2.5 - (p_2+p_3)$ in equilibrium for $q_1 = 0$. This always holds if $(p_2+p_3) < \frac{1}{2}$. If $(p_2+p_3) > \frac{1}{2}$, 1 will contribute with some positive probability $q_1 = p_1 = \dfrac{1 - 2(p_2+p_3)}{2Y_1[13.3 - 1.7(p_2+p_3)]} + 2.5 - (p_2+p_3)$. Substituting for (p_2+p_3), we get $q_1 = \dfrac{\frac{2.3}{Y_3} + \frac{0.6}{Y_2} - 59.7}{Y_1(\frac{4}{Y_3} + \frac{1}{Y_2} - 77.7)} - 28.2 + \frac{1.15}{Y_3} + \frac{0.3}{Y_2}$. Substituting for the values of Y_2 and Y_3 which give us $\frac{1}{2} < (p_2+p_3) \leqslant 2$, we see that player 1 plays a mixed strategy when $0.004 \leqslant Y_1 \leqslant 0.5$.

In the same manner, we calculate equilibria for the heterogeneity case. We find that when 3's opportunity cost is 1.25, she will contribute if $Y_3 > 0.117$, and will defect for $Y_3 < 0.066$, contributing with a probability $p_3 = 2.29 - \frac{0.15}{Y_3}$ if $0.066 \leqslant Y_3 \leqslant 0.117$. When her opportunity cost is 0.75, she will contribute if $Y_3 > 0.016$, and will defect for $Y_3 < 0.015$, contributing with a probability $p_3 = 10.375 - \frac{0.15}{Y_3}$ if $0.015 \leqslant Y_3 \leqslant 0.016$. So not only does she need a lower reciprocity coefficient to contribute when her opportunity cost is lower, but when she plays a mixed strategy, her probability of contributing is higher. Using backward induction, we see that this holds for all three players, and we should therefore see higher contributions when player 3's opportunity cost is low. This will lead to more mixed strategies being played and overall higher contributions in the heterogeneity case even if one player in the group has a high opportunity cost.

APPENDIX B

Subject Instuctions

In this experiment you will be asked to make a series of choices about how to allocate a set of tokens. You and the other subjects will be randomly assigned to groups, and you will not be told each others identities.

There will be a total of three people in each group. In each choice, you will have 10 tokens to allocate. You must choose whether you wish to keep these tokens or invest them.

You will make your choices sequentially. You will be randomly assigned to either the first, second, or third position in your group. Your position and the composition of your group will be randomly re-assigned in every period, so that you might play at either the first, second, or third position in every round. Your position may be different in each round, as will the other members of your group, whose identities will never be revealed. Since your group members will be randomly selected in each round, they may be the same between periods, or different, or a few of them may be the same. You might be Player 1, 2, or 3 in any round, and might be at the same position in consecutive rounds.

The amount of money that you earn depends whether you keep or invest your tokens, and whether the others in your group keep or invest their tokens.

Each round of the game proceeds in three steps as follows:

1. Player 1 first decides whether to invest the tokens.

2. Player 2 is informed whether Player 1 has chosen to invest or keep the tokens. Player 2 now decides how whether to invest the tokens.

3. Player 3 is informed whether Player 1 and Player 2 have chosen to invest or keep their tokens. Player 3 now decides whether to invest the tokens.

At the end, each player will be told their earnings for that round, which are calculated as under:

(My Endowment My Investment) + [2/3 x (Sum of everyone's investments)]

What this means is:

If I invest and:

- No-one else invests: I get 6.67 tokens
- One other person invests: I get 13.34 tokens
- Everyone in the group invests: I get 20 tokens

If I don't invest and:

- No-one else invests: I get 10 tokens
- One other person invests: I get 16.67 tokens
- Both of the others invest: I get 23.34 tokens

Note: These values hold regardless of your playing position in the group.

There will be three practice rounds, and twenty paying rounds. At the end, one token will be drawn from 20 in a bingo cage. The number on this token will determine which of the twenty paying rounds will count, so that each of you will be paid the exact amount of your earnings in that round in cash along with your show-up fee. So if the token drawn is number 12, then each of you will be paid the amount you earned in the twelfth round. In this manner, 1 experimental token = $1.00 for the round which is randomly selected to be paid out.

Treatment

:

In this experiment you will be asked to make a series of choices about how to allocate a set of tokens. You and the other subjects will be randomly assigned to groups, and you will not be told each others identities.

There will be a total of three people in each group. In each choice, you will have 10 tokens to allocate. You must choose whether you wish to keep these tokens or invest them.

You will make your choices sequentially. You will be randomly assigned to either the first, second, or third position in your group. Your position and the composition of your group will be randomly re-assigned in every period, so that you might play at either the first, second, or third position in every round. Your position may be different in each round, as will the other members of your group, whose identities will never be revealed. Since your group members will be randomly selected in each round, they may be the same between periods, or different, or a few of them may be the same. You might be Player 1, 2, or 3 in any round, and might be at the same position in consecutive rounds.

At the start of each round, you will be told your opportunity cost, which will be either 0.75 or 1.25, and will be randomly chosen for you in each round. Both values have an equal chance of being drawn. The number is drawn separately for each person in a group, so the three people in a group may or may not have the same opportunity cost. The amount of money that you earn depends on your opportunity cost, whether you keep or invest your tokens, and whether the others in your group keep or invest their tokens.

Each round of the game proceeds in three steps as follows:

1. Player 1 first decides whether to invest the tokens.

2. Player 2 is informed whether Player 1 has chosen to invest or keep the tokens. Player 2 now decides how whether to invest the tokens.

3. Player 3 is informed whether Player 1 and Player 2 have chosen to invest or keep their tokens. Player 3 now decides whether to invest the tokens.

At the end, each player will be told their earnings for that round, which are calculated as under:

[(My Endowment My Investment) x My Opportunity Cost] + 2/3 x [Sum of everyone's investments]

Let's see how this would proceed. Everyone's endowment is 10 tokens, and suppose the opportunity cost for Player 1 is 0.75, for Player 2 is 1.25, and for Player 3 is 1.25.

If Player 1 invests, Player 2 keeps the tokens, and Player 3 invests, then each player earns as under:

Player 1: [0 x 0.75] + [2/3 x (10 + 0 + 10)] = 13.34

Player 2: [10 x 1.25] + [2/3 x (10 + 0 + 10)] = 12.5 + 13.34 = 25.84

Player 3: [0 x 1.25] + [2/3 x (10 + 0 + 10)] = 13.34

Note: These calculations hold regardless of your playing position in the group. So if Player 1 had kept the tokens, Player 2 had invested, and Player 3 had invested, each player would earn as under:

Player 1: [10 x 0.75] + [2/3 x (0 + 10 + 10)] = 7.5 + 13.34 = 20.84

Player 2: [0 x 1.25] + [2/3 x (0 + 10 + 10)] = 13.34

Player 3: [0 x 1.25] + [2/3 x (0 + 10 + 10)] = 13.34

If Players 1 and 2 had kept the tokens, but Player 3 had invested, each player would earn as under:

Player 1: [10 x 0.75] + [2/3 x (0 + 0 + 10)] = 7.5 + 6.67 = 14.17

Player 2: [10 x 1.25] + [2/3 x (0 + 0 + 10)] = 12.5 + 6.67 = 19.17

Player 3: [0 x 1.25] + [2/3 x (0 + 0 + 10)] = 6.67

If Players 1 and 3 had kept the tokens, but Player 2 had invested, each player would earn as under:

Player 1: [10 x 0.75] + [2/3 x (0 + 10 + 0)] = 7.5 + 6.67 = 14.17

Player 2: [0 x 1.25] + [2/3 x (0 + 10 + 0)] = 6.67

Player 3: [10 x 1.25] + [2/3 x (0 + 10 + 0)] = 12.5 + 6.67 = 19.17,

and so on.

If no-one had invested, each player would earn as under:

Player 1: [10 x 0.75] + [2/3 x (0 + 0 + 0)] = 7.5

Player 2: [10 x 1.25] + [2/3 x (0 + 0 + 0)] = 12.5

Player 3: [10 x 1.25] + [2/3 x (0 + 0 + 0)] = 12.5

If everyone had invested, each player would earn as under:

Player 1: [0 x 0.75] + [2/3 x (10 + 10 + 10)] = 20

Player 2: [0 x 1.25] + [2/3 x (10 + 10 + 10)] = 20

Player 3: [0 x 1.25] + [2/3 x (10 + 10 + 10)] = 20

Please feel free to use the calculator provided in the experiment software interface to calculate your potential payoff before making your decision.

There will be three practice rounds, and twenty paying rounds. At the end, one token will be drawn from 20 in a bingo cage. The number on this token will determine which of the twenty paying rounds will count, so that each of you will be paid the exact amount of your earnings in that round in cash along with your show-up fee. So if the token drawn is number 12, then each of you will be paid the amount you earned in the twelfth round. In this manner, 1 experimental token = $1.00 for the round which is randomly selected to be paid out.

APPENDIX C

Summary Statistics and Graphs

Table C.1: Summary statistics

Variable	**Mean**	**Std. Dev.**
Age	28.572	8.606
No. of projects led	1.215	1.768
Leads at least 1 project	58.48%	–
Years of schooling	14.447	4.821
Completed college	68.18%	–
Employed	53.79%	–
Unemployed	3.45%	–
Self-employed	27.77%	–
Student	14.99%	–
Work in non-IT field	13.98%	–

Figure 1

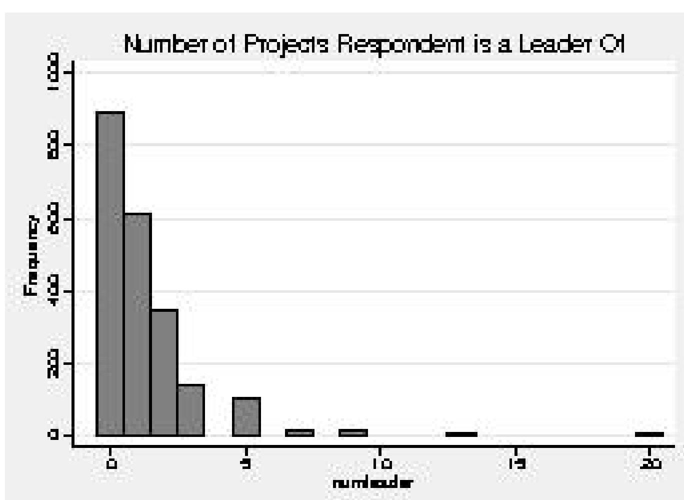


Table C.2: Nationalities in the sample

Country	**Frequency**	**Percent**
Australia	55	2.53
Austria	331	15.22
Belgium	86	3.95
Canada	46	2.11
Denmark	34	1.56
France	346	15.91
Germany	267	12.28
Greece	7	0.32
India	42	1.93
Ireland	12	0.55
Italy	168	7.72
Luxembourg	2	0.09
Netherlands	141	6.48
Norway	29	1.33
Portugal	16	0.74
Spain	142	6.53
Sweden	77	3.54
Turkey	9	0.41
United Kingdom	140	6.44
United States of America	225	10.34

Figure 2

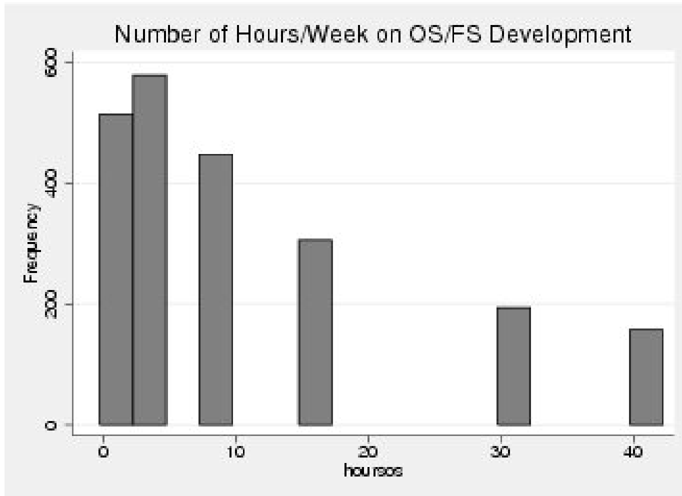


Figure 3: Age

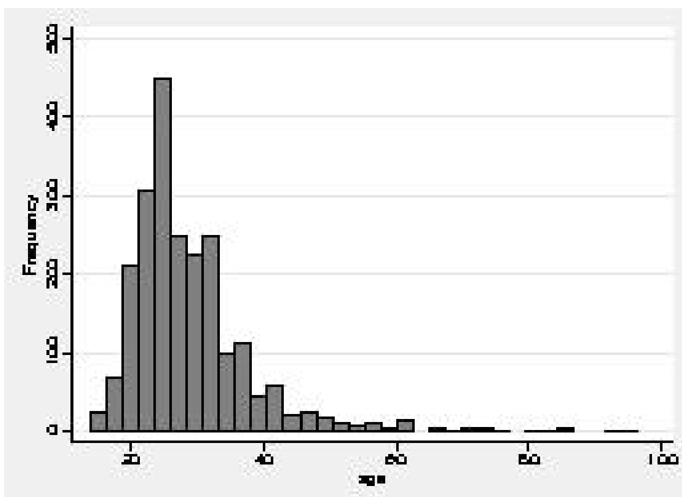


Figure 4: Years of schooling

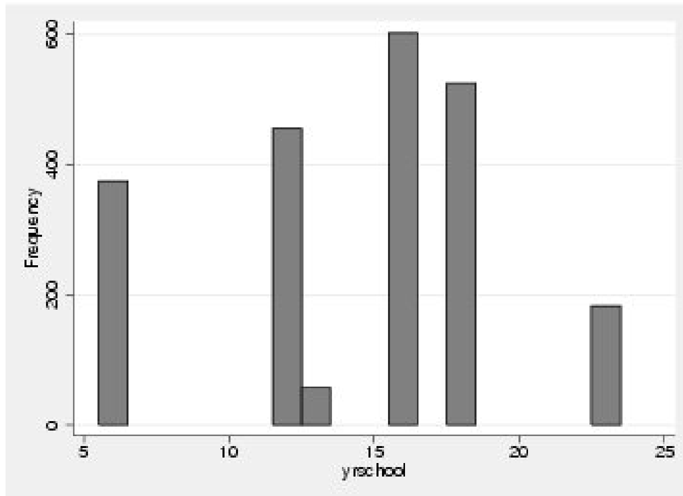


Figure 5: Age and Years of Schooling

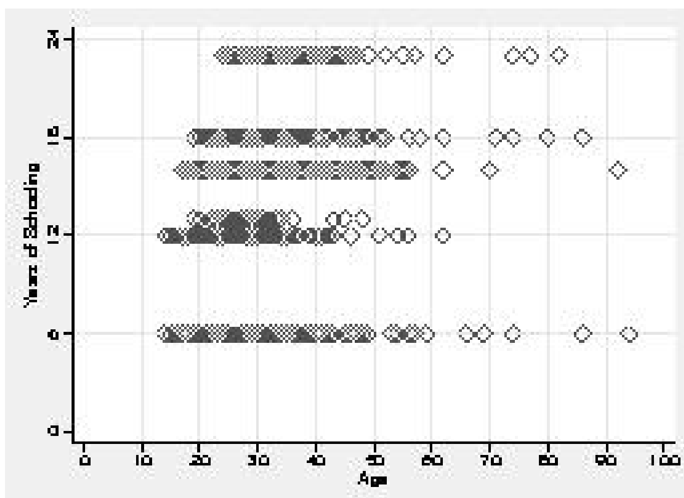
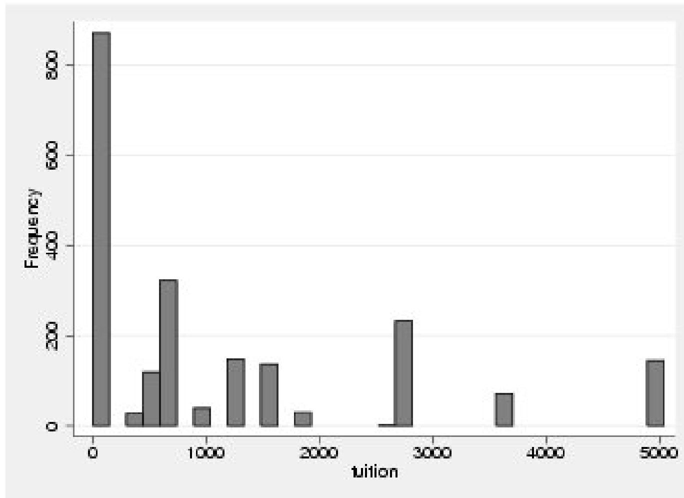


Figure 6: College tuition



APPENDIX D

First-stage regressions for Heckit and instrumental variable estimations

Table D.1: Estimation results : Probit for selection first stage, dependent variable is 1(income > 0)

Log likelihood:	-380.089	
LR $\chi^2(16)$	1190.04	

Variable	**Coefficient**	**(Std. Err.)**
age	0.036	(0.047)
agesq	-21 x 10^{-5}	(64 x 10^{-5})
single	-0.231	(0.059)
kids	0.149	(0.087)
migrant	0.178	(0.113)
student	-1.642	(0.772)
selfemployed	-1.931	(0.819)
unemployed	-2.302	(0.823)
Australia	0.536	(0.390)
Austria	-0.874	(0.079)
Canada	0.376	(0.333)
France	0.049	(0.176)
Germany	0.258	(0.159)
India	-0.549	(0.367)
UK	-0.202	(0.214)
USA	0.314	(0.188)
Intercept	1.577	(1 x 10^{-5})

Table D.2: Estimation results : First-stage regressions for IV estimation: lnolead

Variable	**Coefficient**	**(Std. Err.)**
age	-0.046	(0.014)
agesq	65 x 10^{-5}	(18 x 10^{-5})
single	0.059	(0.017)
kids	0.018	(0.020)
migrant	-0.032	(0.026)
Australia	-0.013	(0.086)
Austria	0.216	(0.047)
Canada	0.190	(0.109)
France	-0.061	(0.048)
Germany	0.141	(0.062)
India	-0.250	(0.120)
UK	-0.115	(0.057)
USA	-0.081	(0.067)
indirmoneyos	-0.032	(0.021)
dirmoneyos	-0.017	(0.023)
consultant	-0.036	(0.038)
programmer	0.065	(0.039)
sengineer	0.016	(0.026)
nonIT	-0.066	(0.025)
lambda	0.421	(0.044)
tuition	0.000	(0.000)
compeduc	-0.050	(0.021)
enrollment	-0.001	(0.002)
ch	0.006	(0.003)
dontmark	0.153	(0.030)
Intercept	0.865	(0.326)
Tests of excluded instruments:		
Partial R^2	0.0257	
F(5, 1421)	7.07	
P-value	0.0000	

Table D.3: Estimation results : First-stage regressions for IV estimation: llead

Variable	**Coefficient**	**(Std. Err.)**
age	-0.086	(0.015)
agesq	$11 \text{ x } 10^{-3}$	$(2 \text{ x } 10^{-4})$
single	0.049	(0.019)
kids	0.021	(0.023)
migrant	0.012	(0.029)
Australia	-0.014	(0.096)
Austria	0.073	(0.052)
Canada	0.128	(0.120)
France	-0.094	(0.053)
Germany	0.365	(0.069)
India	-0.335	(0.133)
UK	-0.031	(0.063)
USA	-0.146	(0.074)
indirmoneyos	0.003	(0.023)
dirmoneyos	-0.037	(0.026)
consultant	-0.008	(0.042)
programmer	0.104	(0.043)
sengineer	-0.050	(0.028)
nonIT	-0.020	(0.028)
lambda	0.244	(0.049)
tuition	0.000	(0.000)
compeduc	-0.073	(0.023)
enrollment	0.000	(0.002)
ch	0.003	(0.004)
dontmark	0.058	(0.033)
Intercept	1.881	(0.361)
Tests of excluded instruments:		
Partial R^2	0.0229	
F(5, 1421)	6.35	
P-value	0.0000	

Table D.4: Estimation results : First-stage regressions for IV estimation: hnolead

Variable	**Coefficient**	**(Std. Err.)**
age	-0.051	(0.017)
agesq	75 x 10^{-5}	(22 x 10^{-5})
single	0.038	(0.021)
kids	0.014	(0.026)
migrant	0.046	(0.033)
Australia	-0.122	(0.108)
Austria	0.201	(0.059)
Canada	0.154	(0.136)
France	-0.044	(0.060)
Germany	0.067	(0.078)
India	-0.102	(0.150)
UK	0.003	(0.071)
USA	-0.046	(0.084)
indirmoneyos	-0.034	(0.026)
dirmoneyos	-0.061	(0.029)
consultant	0.034	(0.047)
programmer	0.008	(0.049)
sengineer	-0.012	(0.032)
nonIT	-0.015	(0.031)
lambda	0.015	(0.055)
tuition	0.000	(0.000)
compeduc	-0.065	(0.026)
enrollment	-0.001	(0.002)
ch	0.003	(0.004)
dontmark	0.184	(0.037)
Intercept	1.515	(0.408)
Tests of excluded instruments:		
Partial R^2	0.0214	
F(5, 1421)	6.02	
P-value	0.0000	

APPENDIX E

First-stage multinomial logit regression for selection estimations

Table E.1: Estimation results : Multinomial logit for selection into area, networking as base category

	Multimedia		**Graphics**		**Audio**		**Games**	
Variable	**Coeff-icient**	**(Std. Err.)**	**Coeff-icient**	**(Std. Err.)**	**Coeff-icient**	**(Std. Err.)**	**Coeff-icient**	**(Std. Err.)**
indirmoneyos	0.1	(0.244)	0.03	(0.189)	-0.229	(0.142)	-0.037	(0.206)
dirmoneyos	-0.414	(0.319)	-0.222	(0.244)	0.805	(0.137)	-0.436	(0.273)
age	-0.038	(0.135)	0.046	(0.114)	0.092	(0.086)	-0.046	(0.109)
agesq	$45 \text{x} 10^{-5}$	(0.002)	$44 \text{x} 10^{-5}$	(0.002)	-0.001	(0.001)	0.001	(0.001)
single	0.24	(0.183)	-0.197	(0.141)	0.07	(0.115)	0.212	(0.134)
kids	0.156	(0.222)	-0.047	(0.188)	-0.116	(0.159)	0.01	(0.206)
migrant	0.067	(0.286)	0.26	(0.189)	-0.067	(0.184)	0.149	(0.215)
student	-0.598	(0.633)	1.037	(0.37)	0.457	(0.336)	0.603	(0.34)
selfemployed	-0.049	(0.406)	-0.677	(0.372)	0.266	(0.276)	-0.403	(0.342)
unemployed	0.689	(0.551)	-0.406	(0.601)	-0.596	(0.590)	-0.203	(0.514)
Australia	-14.402	(0.0001)	2.655	(0.538)	4.978	(0.438)	0.552	(0.629)
Austria	0.507	(0.290)	0.283	(0.287)	1.102	(0.167)	-0.124	(0.289)
Canada	5.612	(0.992)	3.922	(0.631)	-13.145	(0.0001)	0.493	(1.023)
France	5.166	(0.386)	2.000	(0.315)	3.814	(0.270)	0.161	(0.317)

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	Multimedia		**Graphics**		**Audio**		**Games**	
Germany	5.090	(0.411)	1.978	(0.321)	3.998	(0.267)	-0.552	(0.396)
India	-14.363	(0.0001)	-16.710	(0.0001)	-13.794	(0.0001)	0.116	(0.638)
UK	4.359	(0.671)	2.487	(0.398)	5.047	(0.311)	-0.033	(0.491)
USA	3.879	(0.567)	1.883	(0.352)	4.431	(0.277)	-0.522	(0.448)
dontmark	0.403	(0.3)	0.09	(0.265)	0.143	(0.208)	0.241	(0.264)
earnmoney	-0.096	(0.655)	0.163	(0.445)	-0.492	(0.328)	-1.113	(0.753)
cooperation	0.081	(0.331)	-0.251	(0.268)	0.046	(0.202)	0.043	(0.255)
newskills	-0.285	(0.346)	-0.071	(0.288)	-0.180	(0.208)	0.062	(0.285)
shareknowledge	-0.263	(0.334)	0.539	(0.307)	-0.355	(0.199)	-0.094	(0.271)
participate	0.377	(0.341)	0.303	(0.265)	0.082	(0.208)	0.044	(0.263)
jobopp	-0.367	(0.376)	-0.229	(0.291)	-0.483	(0.225)	-0.023	(0.273)
otheros	-0.367	(0.348)	-0.416	(0.273)	-0.039	(0.199)	-0.216	(0.268)
reputation	-0.572	(0.639)	-0.062	(0.425)	0.149	(0.296)	0.659	(0.34)
nonmktsware	0.185	(0.492)	0.379	(0.373)	0.373	(0.312)	0.739	(0.341)
helpidea	0.145	(0.359)	0.054	(0.291)	-0.242	(0.226)	-0.173	(0.299)
solveprob	0.182	(0.333)	-0.05	(0.273)	-0.394	(0.212)	-0.729	(0.314)
largecos	0.120	(0.353)	0.337	(0.273)	0.126	(0.215)	0.334	(0.261)
notprop	-0.452	(0.348)	-0.156	(0.266)	0.062	(0.199)	0.558	(0.251)

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	Multimedia		Graphics		Audio		Games	
consultant	-0.867	(0.575)	-0.735	(0.421)	-0.178	(0.298)	-0.741	(0.417)
programmer	1.151	(0.426)	0.771	(0.342)	-0.088	(0.395)	0.946	(0.308)
sengineer	0.514	(0.316)	0.269	(0.237)	0.339	(0.205)	0.04	(0.234)
nonIT	0.856	(0.309)	0.598	(0.197)	0.676	(0.169)	0.149	(0.217)
Intercept	-4.873	(2.404)	-4.300	(2.040)	-6.080	(1.536)	-0.6	(1.932)
Log likelihood:			-3143.646					
LR $\chi^2(217)$		753.2		P-value:		0.000		

Table E.2: Estimation results : Multinomial logit for selection into area, networking as base category, contd.

	Office		**Web Services**		**Home**	
Variable	**Coeff-icient**	**(Std. Err.)**	**Coeff-icient**	**(Std. Err.)**	**Coeff-icient**	**(Std. Err.)**
indirmoneyos1	-0.11	(0.108)	0.194	(0.098)	-0.174	(0.127)
dirmoneyos1	0.016	(0.128)	-0.038	(0.12)	-0.296	(0.155)
age	0.246	(0.069)	0.066	(0.064)	0.023	(0.076)
agesq	-0.003	(0.001)	-0.001	(0.001)	-0.001	(0.001)
single1	-0.135	(0.086)	-0.11	(0.079)	-0.041	(0.089)
kids	-0.043	(0.098)	0.023	(0.093)	0.021	(0.12)
migrant1	0.114	(0.126)	0.088	(0.122)	-0.033	(0.146)
student1	0.363	(0.249)	0.013	(0.232)	0.485	(0.231)
selfemployed1	-0.015	(0.194)	0.031	(0.170)	-0.084	(0.205)
unemployed1	-0.269	(0.350)	0.239	(0.279)	-0.228	(0.341)
Australia	0.106	(0.419)	-0.649	(0.496)	-0.206	(0.541)
Austria	0.251	(0.148)	0.230	(0.139)	0.218	(0.158)
Canada	0.554	(0.601)	0.610	(0.568)	0.576	(0.659)
France	-0.081	(0.224)	0.194	(0.204)	-0.358	(0.256)

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	Office		**Web Services**		**Home**	
Germany	-0.354	(0.238)	-0.431	(0.235)	-0.108	(0.246)
India	-0.473	(0.541)	-0.003	(0.420)	-0.791	(0.598)
UK	0.107	(0.305)	0.15	(0.291)	0.488	(0.308)
USA	-0.015	(0.240)	-0.002	(0.227)	0.299	(0.255)
dontmark	0.122	(0.157)	0.134	(0.153)	0.202	(0.167)
earnmoney	0.423	(0.237)	0.504	(0.215)	-0.198	(0.315)
cooperation	0.197	(0.157)	0.043	(0.149)	-0.169	(0.173)
newskills	-0.072	(0.168)	0.182	(0.163)	0.054	(0.189)
shareknowledge	-0.387	(0.163)	-0.294	(0.156)	-0.156	(0.178)
participate	0.041	(0.165)	0.024	(0.155)	0.286	(0.171)
jobopp	-0.246	(0.174)	-0.149	(0.16)	-0.272	(0.184)
otheros	-0.075	(0.159)	0.059	(0.149)	0.146	(0.168)
reputation	-0.585	(0.290)	0.242	(0.219)	0.148	(0.249)
nonmktsware	-0.415	(0.287)	0.139	(0.237)	0.104	(0.267)
helpidea	-0.072	(0.176)	-0.089	(0.165)	0.34	(0.179)
solveprob	-0.39	(0.166)	-0.37	(0.156)	-0.381	(0.183)
largecos	0.231	(0.166)	-0.028	(0.161)	0.134	(0.182)
notprop	-0.342	(0.164)	0.074	(0.150)	0.011	(0.172)

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	Office		**Web Services**		**Home**	
consultant	-0.339	(0.185)	-0.226	(0.167)	-0.552	(0.249)
programmer	0.730	(0.21)	0.738	(0.195)	0.455	(0.249)
sengineer	-0.102	(0.134)	-0.053	(0.124)	0.256	(0.154)
nonIT	0.332	(0.133)	0.286	(0.133)	0.449	(0.137)
Intercept	-3.854	(1.231)	-0.664	(1.130)	-0.430	(1.334)

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